

# A character gram modeling approach towards Bengali Speech to Text with Regional Dialects

by

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A thesis submitted to the Department of Computer Science and Engineering  
in partial fulfillment of the requirements for the degree of  
M.Sc. in Computer Science

Department of Computer Science and Engineering  
Brac University  
November 2024

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# Declaration

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1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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# Approval

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## **Ethics Statement (Optional)**

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We hereby acknowledge that all of the co-authors of this work are aware of the provided ACL Code of Ethics and honor the code of conduct. All procedures performed involving human participants were by institutional and/or national ethical guidelines. All participants in the study provided informed consent. All the annotators and transcribers were paid above the local minimum wage (2,000 BDT were paid for each hour of transcription).

# Abstract

The Bengali language, spoken in various regions of south-Asia and also among the Bengali diaspora, exhibits rich diversity with regional dialects or variations that reflect the cultural, geographic, and historical influences of different regional/socio-cultural communities. Based on phonology and pronunciation, Bengali is said to have 5 distinct major dialectal variations, such as Eastern Bengali Dialect, Manbhum, Rangpuri, Varendri, and Rarhi. For the dialects present in Bangladesh, even finer stratification can be done based on the used vocabulary, pronunciation, phonology, syntax, and morphology. These regional Bengali dialects are found in regions such as Bangladesh in the regions of Chittagong, Sylhet, Rangpur, Rajshahi, Noakhali, Barishal, etc possess unique phonetic, lexical, and syntactic features that set them apart from standard Bengali and also unique from each other. However, research and resources dedicated to understanding and harnessing the potential of natural language processing of regional Bengali languages remain limited. To bridge this gap, this work aims to investigate and document the characteristics of regional Bengali languages through comprehensive data-driven linguistic analyses, including phonetic and morphological studies. We also aim to study the feasibility of developing computational models, including Automatic Speech Recognition (ASR) systems, tailored to regional Bengali languages, which can facilitate applications like virtual voice command assistants and language processing tools. Our research findings will contribute to the understanding of regional Bengali languages, paving the way to foster the advancement of language technologies that can cater to the diverse linguistic needs of Bengali-speaking communities. Through this study, we intend to promote preservation of the regional dialects of the Bengali language, foster cultural inclusivity, and facilitate effective communication in the Bengali-speaking regions.

**Keywords:** Automatic speech recognition; Regional Bengali speech; Wav2Vec2; Bengali Dialects; Linguistic Analysis; ASR; Dataset Curation

# Acknowledgement

Firstly, I would like to thank my creator Allah, all praise to the Great creator. For making this journey possible for me and removing all the obstacles and major interruptions from the paths while completing my thesis.

Secondly, to my thesis supervisor, Professor Dr. Md. Golam Rabiul Alam sir for his support and advice during the thesis. He shared his wisdom and guidelines with me whenever I reached out to him with a query.

Also, a big thanks to Associate Professor Dr. Farig Yousuf Sadeque sir for playing a mentor role and for all the support, guidance, and wisdom.

Thirdly, the review panel of the conference “North American Chapter of the Association for Computational Linguistics”. Though our paper was not accepted there, their reviews helped us greatly in our later works.

Next, to my parents, friends, and acquaintances. It wouldn’t have been possible for me to continue this journey without their prayer and kind support.

A big thanks goes to team Bengali.AI, from team Bengali.AI I would personally want to thank Asif Shahriar Sushmit, Ahmed Imtiaz Humayun and Tahsin Reasat for their excellent guidance, Nazia Tasnim for helping with the modeling, and Trina Chakraborty for helping with few visualizations, Azmol Hossain, and Kanij Fatema for their linguistic support, Tanmoy Shome, Foriduzzaman Zihad, and Rubayet Sabir Faruque for logistic support; and Siha Hoque for being a helping hand in when and where needed.

And finally, a big thank to all the assigned data collectors and transcribers shown in table 1 for their efforts.

Table 1: Name of all the data collectors and annotators

| Rangpur              | Kishoreganj            | Narail             | Chittagong             | Narsingdi          |
|----------------------|------------------------|--------------------|------------------------|--------------------|
| Data Collectors      |                        |                    |                        |                    |
| Shaheen Alam         | Mosharrof Hossain      | Apon Sharif        | Sajid Ullah Chowdhury  | Monira Islam       |
| Data Annotators      |                        |                    |                        |                    |
| Monisha Rani Mohonto | Antora dey             | Md Apon Sharif     | Ashikul Islam Shagor   | Samad Mia          |
| Md Rakibul Hasan     | Mahjabin Rahman Maisha | S. M. Razoan Islam | Supratim Barua Koushik | M. M. Asif Yousuf  |
| Nurun Nahar Sraboni  | Rounake Afroze Eva     | -                  | Nure Mehjabin          | Tamima Islam Tonny |

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# Chapter 1

## Introduction

Language is fundamental for human expression and societal development, with structured language playing a pivotal role. In computer science, advancements in written and spoken language recognition have rapidly evolved. This evolution aims to enhance accessibility across various domains, including technology literacy and disability support [19].

Advancements in speech and writing recognition have spurred innovations in fields such as language education [38], language disorder assessment [21], and agricultural assistance [81]. Despite these advancements, the application of Speech-to-Text technology for regional variations of the Bengali language remains limited, largely as a result of the shortage of resources and available datasets.

Still, As per updated studies, there is a significant gap in both theoretical and computational linguistic studies focusing on regional Bengali variations, particularly in the context of automatic speech recognition tasks. Existing deep learning models have not adequately addressed these regional variations due to the lack of available datasets and resources [87]. Our research idea originated from this research gap in this domain and our research bridges these gaps by introducing an open-sourced dataset featuring diverse regional Bengali speech dialects and a modeling attempt that serves as a foundational resource for future research endeavors in this area.

Bengali, the fifth most spoken language globally [22], exhibits significant regional variations shaped by historical, geographical, and cultural influences. These dialectal differences encompass vocabulary, pronunciation, grammar, and cultural nuances, reflecting a sense of community identity and comfort among speakers.

1. **Vocabulary:** The standard Bengali language uses a consistent set of words that draw from both classical literature and modern usage. In contrast, re-

gional dialects often feature local expressions and slang that you might not encounter in formal or official contexts.

2. **Pronunciation:** How Bengali is spoken can vary significantly between the standard version and its regional dialects. Differences in how vowels and consonants are pronounced, as well as unique phonetic traits, can make each dialect distinct.
3. **Grammar:** The basic grammar of Bengali remains fairly uniform across different dialects, but there can be variations in how particles are used, verb forms are conjugated, and sentences are structured. Some dialects might simplify or modify certain grammatical rules.
4. **Cultural Influences:** Regional dialects often reflect local cultures and traditions, incorporating local sayings, idioms, and words borrowed from neighboring languages.
5. **Usage:** Standard Bengali is used in formal settings like education, media, and official documents. In contrast, regional dialects are more common in everyday conversations within communities and social groups, showing how people switch between different forms of the language based on the situation.
6. **Writing and Literature:** Formal writing, including newspapers, books, and academic work, typically uses standard Bengali. Regional dialects are rarely used in formal writing but might appear in casual communication like social media.
7. **Geographic Variation:** Different areas in Bangladesh and India have their own dialects, shaped by local cultures, histories, and landscapes.

Creating and implementing language policies that support standard Bengali while also respecting regional dialects is a challenging endeavor. This process requires a thoughtful approach, taking into account linguistic, cultural, and social factors. Language naturally evolves, and there can be resistance to changes in the standard form. Deciding which changes to accept or reject involves ongoing discussions and building consensus.

For an effective implementation model, it's important to recognize the rich linguistic diversity within Bengali. Many current datasets mainly focus on formal, standard

Bengali, which can limit users' ability to communicate in their natural style. This forces users to adapt to a more formal language, which can impede genuine communication. The distinct morphology and various accents within Bengali further complicate creating datasets that truly represent everyday language. Therefore, having large, diverse datasets is crucial for training comprehensive deep-learning models.

Progress in research and development has been hampered by a lack of resources, such as automatic speech-to-text systems for Bengali dialects, text-to-speech systems that include regional accents, and tools for dialect classification and transliteration projects. The absence of these resources presents major obstacles to advancing these technologies.

Accents are variations in pronunciation among speakers of the same language, while dialects have unique linguistic traits specific to certain groups or regions. These differences are shaped by geographic, cultural, and historical factors. For computational systems to effectively recognize and process these accents, it's essential to develop models that can accurately distinguish between them. This is crucial for tasks like speaker identification, emotion recognition, and understanding stress levels.

Alrehaili et al. [85] worked on analyzing Arabic dialects through a system that identifies dialects in audio recordings. They used a dataset of 672 audio samples from eight Arab dialects and applied Convolutional Neural Networks (CNN) for classification, achieving an accuracy of 83%. This work helps improve communication and translation across Arabic dialects.

Miao Wan et al. [83] focused on recognizing Chinese dialects using deep neural networks, with a special emphasis on regional accents. Their models achieved accuracies of 79.96% and 83.59%, enhancing applications like customer service and translation by addressing regional linguistic diversity.

In comparison, research on Bengali dialect recognition is still developing. Tomal et al. [82] are among the few to address this area. They focused on identifying regional Bengali dialects, which are primarily spoken and less documented. By analyzing extensive data from two dialects, Chatgaiya and Pabna, and using various data processing techniques, they achieved a high accuracy of 96%. Their work highlights the importance of preserving and understanding the diverse dialects within Bengali. Despite significant efforts in compiling datasets, existing resources face limitations in speech diversity, size, and accessibility. To tackle challenges related to regional

languages, it is essential to develop dedicated resources tailored to these needs.

The SHRUTI read-speech corpus, published by IIT Kharagpur in 2011 [27], [28], [30], includes 21.64 hours of audio featuring 7383 distinct Bengali phrases and 49 phonemes. The IARPA voice corpus, part of the Babel initiative, contains 215 hours of Bengali phone conversations and scripted communications from 2011 and 2012, complemented by transcripts [37]. The Linguistic Data Consortium for Indian Languages (LDC-IL) acquired 138 hours of continuous Bengali speech in 2019 and subsequently developed a series of speech corpora, as noted in a 2020 research paper [57]. The Technological Development for Indian Languages Initiative (TDIL) [50] provides access to Bengali words from over 43,000 audio recordings spoken by 1000 West Bengal native speakers. The European Language Resources Association (ELRA) offers a 70-hour Bengali speech corpus [44], although specifics such as publication date and corpus details remain undisclosed and unreviewed. A connected-word speech corpus [47] in 2018 was developed by Khan et al. comprising 62 hours of recordings from over 100 speakers. In the same year, Khan and Sobhan developed a second corpus focusing on isolated words, totaling 375 hours of recordings involving 150 speakers [46]. For the LVCSR challenge, Google released the "Large Bengali ASR training dataset" (LB-ASRTD) [48], a sizable Bengali speech corpus, in 2018 and made it accessible on the Open SLR website (Open SLR LB-ASRTD, 2018). It includes orthographic annotations in Bengali alphabets and consists of over 229 hours of conversation from 505 native Bangladeshis (323 men and 182 women), contributing a total of 217,902 utterances.

In 2020, Ahmed and Sadeq [54] utilizing publicly available audio and text data, constructed a 960-hour annotated speech corpus and proposed a method for automatic transcription generation from existing audio recordings. SUBAK.KO [78] is a Bengali speech corpus from Bangladesh, comprising 241 hours of recordings from local speakers across eight divisions and thirty four districts of Bangladesh. Data were sourced from online platforms such as YouTube.

Developed by Bhogale et al. [77] in 2022, Shrutilipi ASR Corpus is a labeled ASR corpus derived from news broadcasts in 12 Indian languages, including Bengali. It includes nearly 6400 hours of data, with the Bengali segment comprising 443 hours. On 2023, To support and advance research in this specific domain, a significant initiative has been undertaken by Fazle et al. [87] and Bengali.AI resulting in the

creation of the Domain Diversified Bengali Speech Corpus named OOD-Speech: A Large Bengali Speech Recognition Dataset for Out-of-Distribution Benchmarking. It includes Bengali sentences over 2000 hours of transcribed audio recordings collected across India and Bangladesh. The initiative aims to compile 5000 hours of audio data by 2023, addressing significant linguistic challenges in Bengali speech recognition. This corpus constitutes an integral component of an ongoing initiative with the overarching goal of amassing a total of 5000 hours of meticulously collected audio data by the year 2023. This corpus delves into a comprehensive examination of the notable linguistic challenges entailed in the development of Bengali speech recognition systems. Moreover, we provide insightful analyses and observations derived from the wealth of data at our disposal.

Additionally, the study includes a benchmark analysis of the **Word Error Rate (WER)** for an ASR algorithm stemming from Hidden Markov Models and Gaussian Mixture Models (HMM-GMM). The research is dynamic, open to updates, and incorporates the latest benchmarks from the Common Voice Speech Corpus..

In summary, the key contributions of this research to the field include,

1. Pioneering the integration of a novel dimension in natural language processing development for the **Bengali** language. This initiative aims to enhance understanding and comprehension of **Bengali** from both computational and linguistic perspectives, catering to deep learning engineers/researchers and linguistic researchers.
2. Establishment of a comprehensive and standardized research pipeline accompanied by protocols designed to guide the entire research process. Tailored for similar research endeavors, this framework anticipates application across diverse Bengali-speaking regions in future studies.
3. Creation of a meticulously designed and curated 39-hour open-source speech corpus. This corpus is intricately crafted to capture nuanced regional speech patterns, encompassing various dialectical forms and variations, aimed at supporting research and development in the speech recognition domain and dialectal studies.
4. Development of a finely calibrated model capable of accurately transcribing regional Bengali speech. The model accommodates diverse dialects, variations in speech patterns, and unique vocabulary, while strictly adhering to established orthographic protocols.
5. Conducting a comprehensive linguistic analysis focusing on regional variations of the Bengali language across diverse geographical regions within Bangladesh. This analysis aims to provide insights into linguistic diversity and evolution within the Bengali language landscape.

The remainder of this paper is structured as follows:

Chapter 2 provides a comprehensive review of the existing research and development in this domain. Chapter 3 details the background study relevant to the topic. Chapter 4 outlines the methodology employed in the research. Chapter 5 presents the analysis of the results and Chapter 6 offers concluding remarks and summarizes the findings of the study.

# Chapter 2

## Related Work

Speech represents the most fundamental mode of human communication, uniquely free from literacy constraints. Advances in the speech recognition domain hold the potential to democratize global access to information and services. By facilitating seamless interaction with technology through spoken language, these advancements empower individuals of varying literacy levels and language proficiencies to effortlessly engage with digital platforms, access educational resources, and utilize essential services. Research in speech recognition has not only rendered previously inaccessible technologies accessible but has also enhanced task efficiency and user experiences fostering societal equity by narrowing digital divides and promoting broader participation in the digital era. [11].

This chapter examines existing research within the domain of speech recognition, focusing on available corpora and modeling techniques.

### 2.0.1 Speech Recognition Corpus

#### 2.0.1.1 International speech corpora

Shivaprasad et al. [64] established a database for the Telugu language to facilitate a more comprehensive understanding of its dialects, addressing the absence of standardized resources for dialect study in speech recognition. They employed Hidden Markov Models (HMM) and Gaussian Mixture Models (GMM) to recognize these dialects based on speech patterns. Their findings indicated that the GMM technique outperformed HMM in this context.

MengEn Zhai et al. in their research [84], focused on the Yulin dialect, a lesser-studied regional dialect in China with inadequate data for speech recognition re-

search. Initially, they compiled and constructed a sole this specific dialect focused speech corpus, subsequently analyzing its phonological patterns and assembling a corresponding wordlist or dictionary. This methodology remarkably enhanced the Yulin dialect’s speech recognition accuracy, achieving a 15.42% improvement over traditional methods in low-resource dialect scenarios.

#### **2.0.1.2 Speech recognition modeling approaches for different languages**

S. Darjaa et al. [43] implemented a basic computer program to differentiate between the accents of the Slovak language and its various regional dialects. They amassed a substantial collection of recordings from speakers with different accents, creating a specialized database to train the program for improved accent recognition. Additionally, they trained the system to recognize standard Slovak spoken in a neutral manner. The results indicated that the system could effectively identify the primary accent groups in Slovak, demonstrating its practical utility. However, the researchers suggest that with more data and advanced techniques, further improvements can be achieved.

Imaizumi, Ryo, and Masumura [60] developed a computer model to recognize different Japanese dialects. Due to limited data, they utilized both standard and dialect-specific data for model training. Initially, they mixed both datasets, but this approach resulted in the loss of dialect-specific details. Subsequently, they employed a supervised learning method, which reduced the error rate by 19.2%.

Swiss German presents significant challenges due to its diverse writing styles and lack of standardization. Nigmatulina et al. [63] investigated the comprehension of Swiss German across various dialects. They employed two approaches: dialectal writing (transcribing Swiss German phonetically) and normalized writing (transcribing Swiss German to resemble standard German). They tested these approaches using a computer program and a dataset encompassing 14 different Swiss German varieties. The normalized writing approach yielded better performance in terms of word error rates, while the dialectal writing approach excelled at recognizing individual letters. This research provides insights into improving algorithmic understanding of Swiss German and offers potential applications for other languages lacking standardized orthography.

Nguyen et al. [13] developed a system to recognize tonal variations in standard Vietnamese, particularly the Hanoi dialect. They employed wavelet transforms to analyze pitch variations in a large speech dataset. Their approach involved using Hidden Markov Models (HMMs) to recognize tones, finding that accuracy improved when using one of the two monotonic tones as a reference. They also developed an initial version of a system capable of understanding individual Vietnamese words, effectively incorporating the tonal recognition methodology.

At the 2020 International Conference on Intelligent Systems and Computer Vision (ISCV), Abderrahim Ezzine and his team presented a paper [58] on a system for recognizing speech in the Moroccan Darija dialect. They focused on recognizing the first ten Arabic digits spoken in Moroccan Darija. Their system utilized Hidden Markov Models (HMMs) along with Mel-frequency cepstral coefficients (MFCCs). Through various trials, they achieved a recognition accuracy of 96.27

Omar Aitoulghazi et al. [74] proposed an approach to develop an Automatic Speech Recognition (ASR) system for low-resource languages in their paper. They utilized Baidu's advanced "Deep Speech 2" model and tested it with 24 hours of spoken language data, achieving a Word Error Rate (WER) of 22.7% and a Character Error Rate (CER) of 6.03%. While these results indicate that the system is not yet perfect, they represent a promising step toward understanding the widely spoken Moroccan dialect.

Hamzah A. Alsayadi et al. [76] discussed a method to enhance ASR model performance for Arabic dialects. They developed a hybrid model combining a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network with attention-based encoder-decoder techniques. Additionally, they created another language model using Recurrent Neural Networks (RNNs) and LSTMs, testing their approach on two sets of Arabic dialects. The experimental results showed that their methodology achieved a WER of 57.02

In a paper, Jooyoung Lee et al. [71] addressed the challenge of recognizing different dialects in the Korean language, which is complicated by a lack of research and resources. They proposed a novel approach focusing on intonation rather than individual syllables. They built a hybrid model combining spectral features such as fundamental frequency and trained it using a bidirectional LSTM (BiLSTM) network enabled with an attention mechanism. This approach helped identify dialect-rich parts of speech, even when mixed with non-dialect parts. Testing this model across

various ages and speech styles, they achieved an accuracy of 68.51

Vivek Bhardwaj et al. focused on improving ASR systems for Punjabi dialects in their research [69]. They used pitch acoustic features to enhance their system and tested it with two Punjabi dialects, Malwa and Majha. The results showed WERs of 23.25% and 25.91%, respectively, indicating that while there is room for improvement, the system represents progress in understanding these dialects.

In their research [40], N. D. Londhe et al. employed two prominent Machine Learning (ML) techniques, Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to develop an ASR system for the rare Indian dialect 'Chhattisgarhi'. They evaluated these methods using a dataset comprising 50 isolated words spoken by 15 individuals. The performance of ANN and SVM was compared to the traditional Hidden Markov Model (HMM). Additionally, they assessed the system's ability to recognize the same words spoken by different individuals. The results indicate that the ANN and SVM approaches are effective and reliable for recognizing this dialect.

### **2.0.1.3 Bengali speech corpora**

In both Bangladesh and India, the speech recognition domain has attracted considerable research interest due to its profound impact on academic and industrial sectors. Over time, various datasets have been made available or actively utilized for training speech recognition models. These datasets are meticulously annotated at multiple levels, including phoneme, word, utterance, and sentence levels. They serve the dual purpose of facilitating model development and enhancing the understanding of the linguistic richness and diversity inherent in the languages spoken in these regions.

Due to the scarcity of publicly accessible research and development resources dedicated to this linguistic domain, Bengali, also known as Bangla, continues to be classified as a low-resource language [70].

To develop highly precise and effective models for various applications, the fundamental prerequisite is the availability of a substantial training dataset. However, in the context of Bengali speech recognition, the available resources are notably limited, presenting a significant challenge. While numerous datasets do indeed exist, it is noteworthy that the majority of the larger and potentially more comprehensive ones remain confined within private domains and have not been made publicly avail-

able. Remarkably, there is a conspicuous absence of datasets that encompass over a thousand hours of recorded Bengali speech that is sufficiently diverse in terms of linguistic content and context.

In their research article, Shafkat Kibria et al. [61] examine the impact of regional accents on the accuracy of ASR systems, emphasizing how pronunciation variations due to accents can impede ASR performance. The study focuses on two distinct groups of speakers, analyzing the acoustic characteristics of their accents regarding Bangladeshi Bengali, with particular attention to vowels such as monophthongal and diphthongal. The research includes both male and female speakers from the Sylhet region, known for its pronounced dialect differences, and individuals from other districts in Bangladesh with relatively milder dialect variations.

The analysis investigates acoustic features regarding accents such as pitch slope, formant frequencies, and vowel duration to classify and differentiate accents. The findings reveal significant differences in formant frequencies and pitch slope steepness among accents, which negatively impact ASR performance. The study highlights the necessity for accent focusing acoustic models to better accommodate speakers from regions with distinctive dialects. It also underscores the importance of incorporating accent-related speaker variability in corpora development to improve ASR systems for Bangladeshi Bengali.

For Bengali, there are limited speech corpora available, that too as open-resource. The SUBAK.KO speech corpus [78] stands out as a notable exception in the domain of linguistic resources. It is a publicly accessible annotated Bangladeshi standard Bangla speech corpus designed for research in automatic speech recognition. This corpus comprises 241 hours of exceptional quality speech data, consisting of 229 hours and 12 hours of read speech and broadcast speech data, respectively. The read speech recordings are in standard Bengali and were conducted in a controlled studio environment, featuring contributions from 33 male and 28 female, a total of 61 native Bangladeshi Bengali speakers, representing 8 divisions and 34 districts of Bangladesh. Additionally, the read speech section includes 1 hour and 30 minutes of recorded speech from two second language (L2) speakers. A portion of the dataset samples was obtained from popular online platforms such as YouTube and Facebook. This approach reflects contemporary language usage and ensures that the dataset aligns with modern communication practices. Each segment of SUBAK.KO has undergone meticulous manual annotation to ensure the accuracy and reliability

of the provided labels.

Table 2.1: Available Speech Corpus for Bengali. Stats of the datasets taken from [73] mostly.

| Year | Corpus Name                                                                                 | Size of Dataset    | No. of Speakers             | Publicly Available                                                                                      |
|------|---------------------------------------------------------------------------------------------|--------------------|-----------------------------|---------------------------------------------------------------------------------------------------------|
| 2011 | SHRUTI [27], [28], [30]                                                                     | 21.64 hours        | 26 males,<br>8 females      | Yes.                                                                                                    |
| 2012 | IARPA-babel103b-v0.4b [37]                                                                  | 215 hours          | Not known                   | Not Publicly Available.<br>Access per application.                                                      |
| 2014 | LDC-IL [57]                                                                                 | 138 hours          | 240 males,<br>236 females   | No.                                                                                                     |
| 2014 | TDIL [50]                                                                                   | 43,000 audio files | 1,000 native speakers       | Not Publicly Available.<br>Available for TDIL members.                                                  |
| 2018 | OpenSLR [48]                                                                                | 229 hours          | 323 males,<br>182 females   | Not Publicly Available.<br>Accessible under<br>Attribution-ShareAlike<br>3.0 Unported (CC BY-SA 3.0 US) |
| 2018 | Bengali Connected Word Speech Corpus [47]                                                   | 62 hours           | 50 males,<br>50 females     | Not known                                                                                               |
| 2018 | Bengali Isolated Word Speech Corpus [46]                                                    | 375 hours          | 50 males,<br>50 females     | Not known                                                                                               |
| 2018 | OpenSLR [48]                                                                                | 229 hours          | 323 males,<br>182 females   | Publicly Available under<br>Attribution-ShareAlike<br>3.0 Unported (CC BY-SA 3.0 US)                    |
| 2019 | ELRA [44]                                                                                   | 70 hours           | Not known                   | Not Publicly Available.<br>Available for ELRA members.                                                  |
| 2020 | Bengali Speech Corpus from<br>Publicly Available Audio & Text [54]                          | 960 hours          | 268 males,<br>251 females   | No                                                                                                      |
| 2020 | Subak.ko [78]                                                                               | 241 hours          | 33 males,<br>28 females     | Yes                                                                                                     |
| 2022 | Shrutilipi [77]                                                                             | 443 hours          | All India<br>Radio archives | Yes                                                                                                     |
| 2022 | Common Voice Bengali Corpus [75]                                                            | 1000 hours         | 22.1k Speakers              | Not Publicly Available.<br>Accessible under<br>CC-0 Public Domain Attribution.                          |
| 2023 | OOD-Speech: A Large Bengali Speech Recognition<br>for Out-of-Distribution Benchmarking [87] | 2000 hours         | 25k Speakers                | Yes                                                                                                     |

Among the limited publicly accessible resources, the most prominent is the OpenSLR dataset developed by Google [48]. However, this dataset primarily focuses on the utterance level (Table 2.1) of speech recognition, leaving a considerable gap in broader linguistic and contextual coverage.

Accents are variations in how words are pronounced, even among the same language speakers. It is noteworthy that accents mainly involve differences in pronunciation, whereas dialects encompass variations in pronunciation, vocabulary, and grammar. Thus, dialects represent a broader and more comprehensive linguistic concept, with accents constituting just one aspect of overall dialectal diversity.

Bengali, as a language, exhibits remarkable diversity with numerous distinct regional dialects. These dialects show noticeable variations in pronunciation and accent across different regions, including various districts in Bangladesh. In locations such as Dhaka, Chattogram, Sylhet, Noakhali, Barishal, and Rangpur, multiple dialects can be observed. Interestingly, even a single word can undergo pronunciation changes [93] depending on the specific region.

For developing an effective ASR system, the acquisition of an extensive and diversified training dataset that comprehensively represents the linguistic variations inherent in the target language is paramount. This dataset must be robust enough to enable the ASR system to accurately identify and transcribe speech, encompassing the rich tapestry of regional dialects and accents within the linguistic landscape.

Regrettably, a significant impediment exists on this path to ASR system excellence when considering the current state of available resources for the Bengali language. The prevailing corpus of Bengali speech data, although valuable, is notably limited in terms of its scale and scope. This constraint renders it incapable of adequately encompassing the entirety of the diverse dialectal nuances and regional linguistic variants that are integral to the Bengali language’s linguistic diversity.

This inadequacy in available resources poses a significant challenge in constructing ASR systems that are both precise and reliable when dealing with the complexities of the Bengali language. This challenge becomes particularly pronounced in demanding ASR tasks, such as detecting spoken phrases within noisy acoustic environments or achieving speaker-independent speech recognition.

To overcome these impediments and enable the advancement of speech recognition technologies capable of effectively processing the spoken Bengali language, it is imperative to augment the existing resources. This augmentation should involve developing a more expansive, comprehensive, and representative Bengali speech corpus. These enhanced linguistic datasets would serve as the foundation for developing innovative ASR technologies, ensuring that the linguistic richness and diversity of Bengali can be effectively harnessed and understood by advanced speech recognition systems.

## 2.0.2 State-Of-The-Art (SOTA) Speech Recognition Systems

The emergence of modern deep learning technologies has catalyzed significant growth in the domain of speech recognition. Over the recent years, there has been substantial improvements in the speech recognition system’s accuracy. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have transfigured speech recognition task by enabling the development of more sophisticated models capable of learning from large-scale speech datasets.

Deep learning algorithms have enabled voice recognition systems to achieve unprecedented levels of speech recognition accuracy. These state-of-the-art models can now attain word recognition rates exceeding 95%, approaching human-like precision. This heightened accuracy has significantly improved the reliability of speech recognition systems and has opened up numerous new possibilities for the application of speech recognition technology.

A prime example of the advancement in speech recognition is the virtual assistants found on everyday devices. Google Assistant on Android, Siri on iOS, Amazon’s Alexa, and Windows’s Cortana are widely used to perform tasks such as note-taking, contacting individuals, or setting reminders. These virtual assistants are capable of perceiving voice commands and responding intuitively and spontaneously, thanks to the advanced development of voice recognition technology.

Other areas where speech recognition plays vital roles include recording and taking notes during meetings, translation and, transcription services, supporting video game interactions, and automating closed captioning for video indexing. Various companies offer such services through software or applications.

Automatic Speech Recognition is a research domain focusing on developing systems that can transcribe speech into text or other symbolic representations using models. ASR models are employed in numerous real-world applications, including powering voice-activated devices, facilitating language translation, and generating transcriptions for individuals with hearing impairments.

When constructing an ASR model, it is essential to consider several critical factors:

1. **Data collection and preparation:** ASR models require extensive audio datasets that accurately represent the target language and its regional dialects. These datasets must be transcribed and labeled for use in training and evaluation. Commonly used datasets include Common Voice [55], VoxCeleb [52], and LibriSpeech [36].
2. **Feature Extraction:** ASR models typically operate based on spectral features systematically derived from the raw audio waveform. These features enable the recognition and interpretation of spoken language with enhanced accuracy and efficiency.
3. **Acoustic Modeling:** This core component of an ASR system transforms audio information into textual output. Intricate statistical models map the extracted acoustic features from the input audio data to the corresponding textual representations. Deep Neural Networks (DNNs), known for their ability to model complex relationships within data, are frequently used for acoustic modeling in ASR systems.
4. **Language Modeling:** Language models predict the probability of different word combinations in the target language. They improve the precision and coherence of ASR output by infusing pre-existing linguistic knowledge into the recognition process. This involves methodologies such as n-gram models, which analyze word sequences up to 'n' words in length, and advanced neural network-based language models that leverage deep learning techniques to capture intricate linguistic patterns and relationships.
5. **Evaluation:** ASR models are typically evaluated using metrics such as WER or CER, which measure the degree of deviation from the reference transcripts. These metrics express the error rate as a percentage of incorrect words or characters.

Some of the top-performing models in the field include Whisper [79], Jasper [51], Wav2vec 2.0 [56], Conformer CTC [59], Kaldi ASR [31], and Google Assistant [25].

### 2.0.2.1 Wav2Vec 2.0:

Wav2Vec 2.0, developed by Facebook AI [56], represents a sophisticated ASR system. Its primary objective is to transcribe speech into written text accurately. The architecture is illustrated in Fig 2.1.

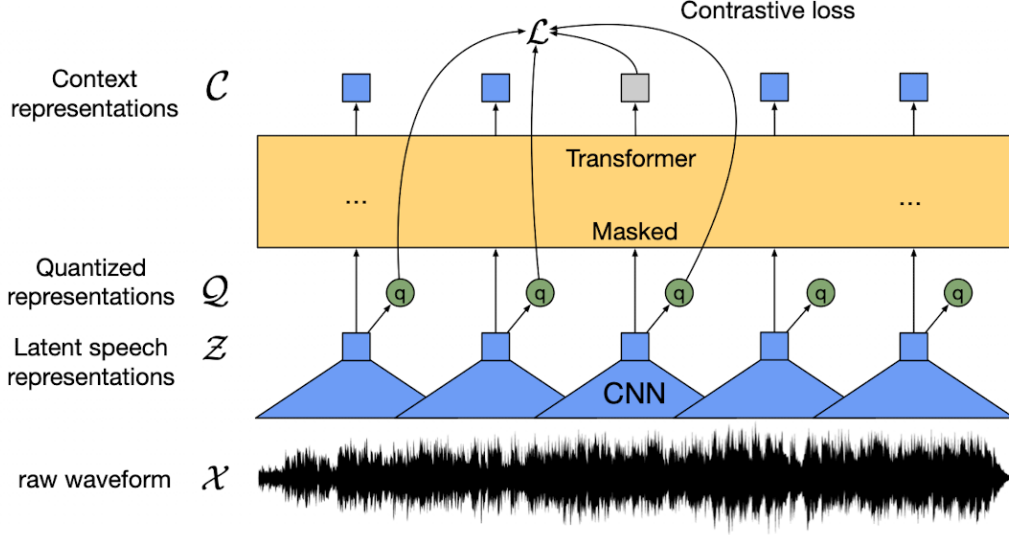


Figure 2.1: Illustration of the Wav2vec2 framework

A signature trait of Wav2Vec 2.0 is its innovative self-supervised learning approach, which enables the model to be trained without needing any transcribed speech data which makes the system particularly versatile, allowing it to be effectively applied to speech data with limited labelling.

Wav2Vec 2.0's core methodology requires a large corpus of unlabeled speech data to pre-train a neural network. Later a smaller, labeled dataset can be used to fine-tune this pre-trained network specific to a given ASR task. This approach has yielded exceptional performance across various speech recognition benchmarks.

Wav2Vec 2.0 marks a substantial improvement in ASR technology due to reducing the dependency on manual transcription efforts and improving the adaptability across different languages and domains. Its broad range of applications includes transcription services and voice assistants, making it an invaluable tool for the development of speech recognition systems.

What distinguishes Wav2Vec 2.0 is its self-supervised learning approach, which eliminates the need for transcribed audio data during training. This feature makes it particularly effective for languages and dialects with limited labeled data.

The foundational concept of Wav2Vec 2.0 involves pre-training a neural network

on a vast amount of unlabeled speech data. This pre-trained network is then fine-tuned with a smaller set of labeled speech data to perform specific ASR tasks. This methodology has demonstrated outstanding performance across various speech recognition benchmarks.

Wav2Vec 2.0 represents a significant advancement in ASR technology by reducing dependence on manual transcription efforts and enhancing adaptability across multiple languages and domains. Its applications are broad, ranging from transcription services to voice assistants, making it a valuable tool in the development of speech recognition systems.

The feature encoder output is discretized into a set of finite speech representations using product quantization [29], facilitating self-supervised training.

The Gumbel-Softmax technique facilitates the selection of discrete codebook entries in a fully differentiable manner [3], [34], [42]. The hard Gumbel-Softmax operations  $G$  [42] and the straight-through estimator [3] are employed to achieve this. The output of the feature encoder is projected onto  $\mathbf{l} \in \mathbb{R}^{G \times V}$  logits, and the equation below delineates the probabilities of selecting the  $v$ -th codebook entry for group  $g$ .

$$p_{g,v} = \frac{\exp(l_{g,v} + n_v)/\tau}{\sum_{k=1}^V \exp(l_{g,k} + n_k)/\tau} \quad (2.1)$$

In the equation 2.1,  $\tau$  is a non-negative temperature,  $n = \log(-\log(u))$  and  $u$  are uniform samples from  $U(0, 1)$ .

During the neural network training of the pre-trained model, codeword  $i$  is chosen by  $i = \arg \max_j p_{g,j}$ , and the true gradient of the Gumbel softmax outputs are used respectively in the forward and backward pass.

The pre-trained model has learned to represent the speech audio by optimizing two types of losses during its training, which are,

1. **Contrastive loss ( $L_m$ ):** Distinguishes the correct quantized latent speech representation from a set of distractors to learn representations.

$$L_m = -\log \frac{\exp(\text{sim}(c_t, q_t)/\kappa)}{\sum_{\tilde{q} \in Q_t} \exp(\text{sim}(c_t, \tilde{q})/\kappa)} \quad (2.2)$$

in 2.2,  $c_t$  is the context network output centered over masked time step  $t$ ,  $q_t$  is the true quantized latent speech representation in a set of  $K + 1$  quantized candidate representations  $\tilde{q} \in Q_t$  which incorporates  $K$  distractors along with

$q_t$  and  $\text{sim}(c_t, \tilde{q})$  is the cosine similarity between context representations  $c_t$  and quantized latent speech representations  $\tilde{q}$ .

2. **Diversity loss ( $L_d$ ):** Promotes diversity in the learned representations and to utilize all the codebook entries uniformly.

$$L_d = \frac{1}{GV} \sum_{g=1}^G -H(\bar{p}_g) = \frac{1}{GV} \sum_{g=1}^G \sum_{v=1}^V \bar{p}_{g,v} \log \bar{p}_{g,v} \quad (2.3)$$

In equation 2.3, Each of the  $G$  codebooks has  $V$  entries. This is done by ensuring to utilization of the maximized entropy of the averaged softmax distribution  $l$  for each codebook entry  $\bar{p}_g$  in an utterance batch. Note that the grumble noise is absent from the softmax distribution.

So, the total loss  $L$  becomes,

$$\mathcal{L} = L_m + \alpha L_d \quad (2.4)$$

In equation 2.4,  $\alpha$  is a tuned hyperparameter to optimize the significance of the two losses.

Upon showcasing the extraordinary performance of Wav2Vec 2.0 on the widely recognized English ASR dataset such as LibriSpeech [36], Facebook AI launched a multilingual variant known as XLSR (cross-lingual speech representations). This model extends Wav2Vec 2.0’s capabilities by enabling the acquisition of speech representations that are beneficial across multiple languages.

In November 2021, Arun Babu et al. released XLSR’s successor, XLS-R (short for ‘XLM-R for Speech’) [68] which was pre-trained using audio data spanning 128 languages that was almost half a million hours in duration and the model is available in model sizes ranging from 300 million to 2 billion parameters.

Fine-tuning is done by adding a single layer on top of an existing pre-trained network and then train the model using own custom dataset and refine the model’s performance on labeled data of audio downstream tasks like speech recognition/translation and audio classification as shown in the figure 2.2

XLS-R demonstrates significant outperformance over the existing state-of-the-art models in speech processing tasks like recognition/translation/diarization and language identification, as documented in the official report **XLS-R**.

**Jasper:** Developed by NVIDIA AI researchers [51], Jasper is an automatic speech recognition (ASR) system rooted in deep learning principles. Despite its modest

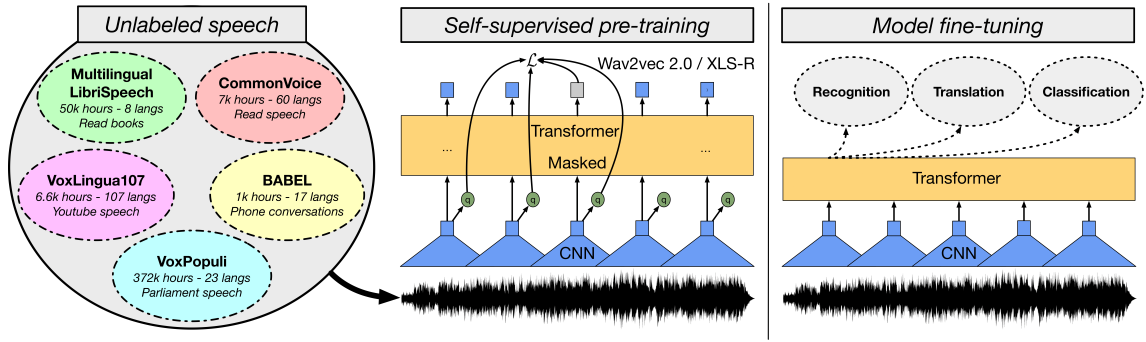


Figure 2.2: Wav2vec 2.0 / XLS-R

name, "Jasper" (Just Another Speech Recognizer) excels in converting spoken language into textual format with high efficiency.

A distinguishing feature of Jasper lies in its utilization of convolutional neural networks (CNNs) within its architecture. While recurrent neural networks (RNNs) have traditionally dominated ASR tasks, Jasper's adoption of CNNs enables parallel computation, facilitating faster audio data processing and potentially reducing computational overhead compared to conventional RNN-based ASR models.

Jasper has demonstrated competitive performance across diverse ASR benchmarks, underscoring its capability to accurately transcribe spoken language. Its versatile architecture supports adaptation to various languages and acoustic environments, enhancing its applicability across a broad spectrum of ASR applications.

To conclude, Jasper represents a significant advancement in the pursuit of efficient and precise ASR models. Recognized for its robust performance, Jasper contributes to ongoing advancements in speech recognition technology.

#### 2.0.2.2 Conformer:

Conformer, as described by Gulati et al. [59], constitutes a deep learning framework tailored for automatic speech recognition (ASR) and natural language processing (NLP) tasks. It excels particularly in converting spoken language into textual form for ASR applications. Conformer architectures have garnered attention for their

adeptness in handling sequential data and achieving impressive performance across various ASR benchmarks.

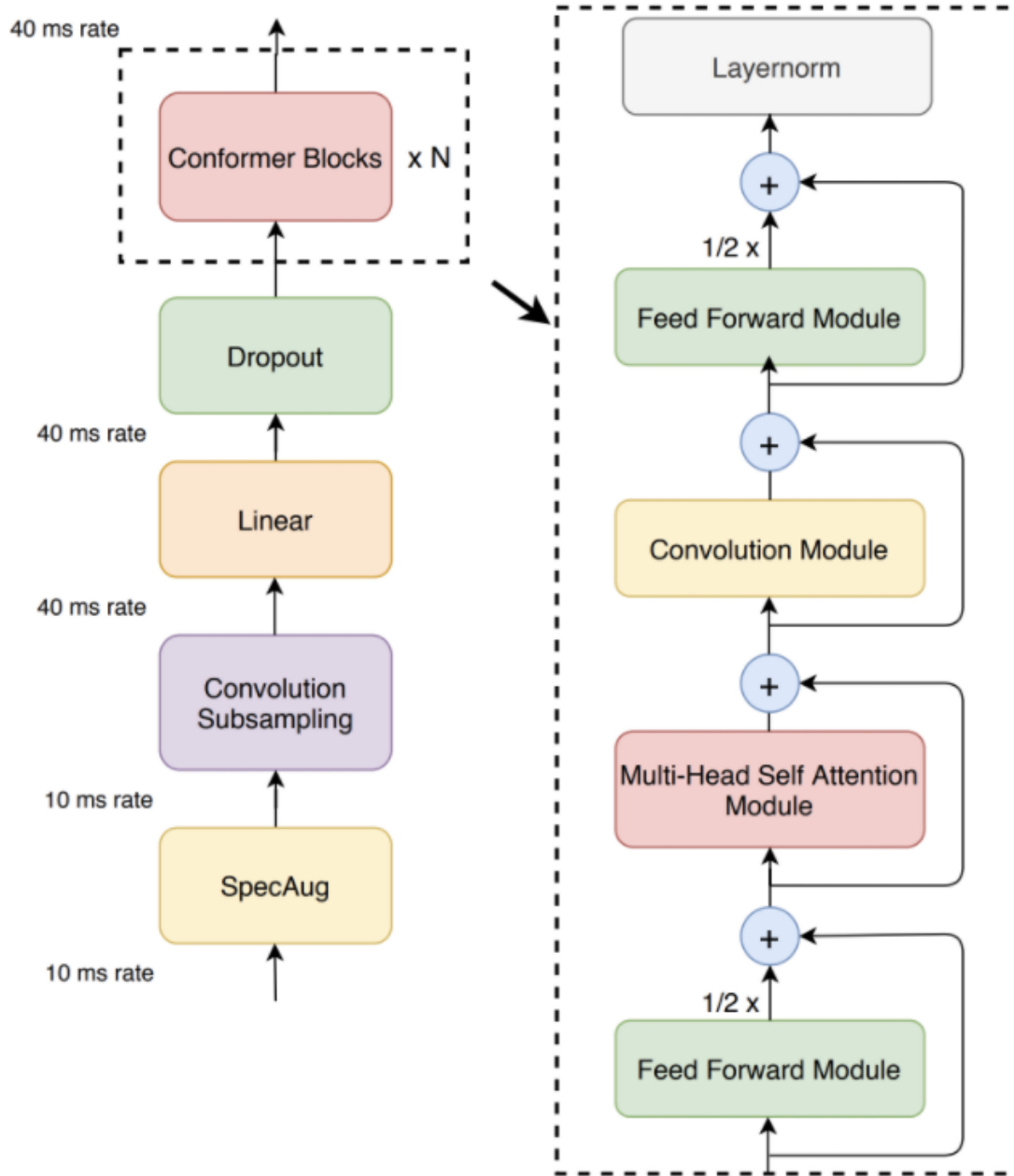


Figure 2.3: Conformer encoder model architecture

As depicted in Figure 2.3, the Conformer framework integrates several key components, including convolutional layers, a self-attention mechanism, and additional elements inspired by the Transformer architecture. The Conformer architecture consists of two macaron-like feed-forward layers that employ half-step residual connec-

tions, which encapsulate both multi-headed self-attention and convolution modules, followed by a post-layer normalization step.

The audio encoder first processes the input through a convolutional subsampling layer, subsequently passing it through multiple Conformer blocks, as illustrated in Figure 2.3. A distinctive feature of this model is the replacement of traditional Transformer blocks with Conformer blocks. Each Conformer block is structured with four stacked modules: a feed-forward module, a self-attention module, a convolution module, and a final feed-forward module.

This hybrid approach equips Conformer models with the capability to capture local and global dependencies within input audio data, thereby enhancing their efficacy in interpreting spoken language.

Key features of Conformer models include:

1. **Parallelization:** Conformer architectures are optimized for high parallelizability, facilitating accelerated training and inference processes. This attribute significantly enhances their efficiency in processing audio data.
2. **Self-Attention:** Leveraging a Transformer-inspired self-attention mechanism, Conformer models excel in capturing contextual dependencies across various segments of input sequences. This capability markedly improves their accuracy in speech recognition tasks.
3. **Depth and Stacking:** Conformer structures typically employ multiple layers stacked sequentially. This design enables them to effectively capture intricate patterns and features present in audio data, enhancing their robustness and performance.
4. **Adaptability:** By training on appropriate datasets, Conformer models can adapt seamlessly to diverse languages and dialects. This adaptability renders them versatile for a wide spectrum of ASR applications.

Conformer-based ASR models have consistently achieved state-of-the-art performance across numerous ASR benchmarks, underscoring their efficacy in comprehending and transcribing spoken language. Their adeptness in handling sequential data and their flexibility to accommodate various linguistic and environmental conditions have positioned them as a preferred choice for both academic research and

industrial applications in ASR.

### 2.0.2.3 Google ASR:

Google Automatic Speech Recognition (Google ASR) [25] is a robust speech recognition system developed by Google, integral to multiple Google services and products such as Google Assistant, Google Search, and Google Translate. This technology enables users to interact vocally with their devices, where Google ASR accurately transcribes spoken input into a textual format for subsequent analysis or actionable tasks.

Here are some key features and characteristics of Google ASR:

1. **Accuracy:** Google Automatic Speech Recognition (Google ASR) is renowned for its high precision in converting spoken language into text. It employs advanced machine learning algorithms and extensive datasets to continually enhance its recognition accuracy.
2. **Multilingual Support:** Google ASR offers robust support for a diverse array of languages and dialects globally, enabling users to interact with Google services in their preferred language.
3. **Voice Commands:** Google ASR drives voice-command functionalities, empowering users to manage devices, conduct web searches, schedule tasks, and perform various operations through spoken instructions.
4. **Voice Search:** Facilitating voice-based web searches, Google ASR enables convenient access to information and online resources without the need for manual typing.
5. **Accessibility:** Google ASR plays a pivotal role in accessibility initiatives, allowing individuals with disabilities to engage with technology through voice interactions.
6. **Natural Language Processing:** Integrated with sophisticated natural language processing (NLP) capabilities, Google ASR interprets spoken language in a conversational and context-aware manner, enhancing user interaction experiences.

7. **Cloud-Based Service:** Google ASR operates as a cloud-based service, offering developers the flexibility to integrate speech recognition functionalities into their applications and services.
8. **Privacy Considerations:** Google prioritizes user privacy and data security in its ASR implementations, ensuring users have control over their voice data and settings.

Google ASR continues to advance, fostering seamless and accessible voice interactions across a global user base. Its applications encompass a wide spectrum, encompassing voice assistants, search engines, transcription services, and voice-operated devices.

#### 2.0.2.4 Whisper:

OpenAI’s Whisper [79] currently stands as a discourse language model with significant potential that has garnered widespread attention. Similar to other models in the Whisper series, Whisper-medium comes pre-trained and is ready for use without the necessity for further fine-tuning. This makes it a practical option for numerous applications, including speech-driven interfaces and transcription services, where achieving a balance between speed and accuracy is essential.

Whisper has been meticulously trained and developed, exposed to a diverse dataset encompassing nearly 100 languages and over 680,000 hours of carefully curated multilingual and multitask supervised data sourced from the web.

There exist two varieties of the model. English-only and multilingual. The English-only models focus on speech recognition, where the predicted transcribed text and the spoken audio are in the same language. Multilingual models, on the other hand, are trained for both speech recognition and speech translation. In speech translation, these models predict text transcriptions in a different language from the spoken audio. It has many varieties. The varieties and details are shown in the table 2.2. Similar to Wav2Vec 2.0, it performed fair on standard Bengali but performed very poorly on Regional data. This is because although it was trained on a large-scale dataset built using contents from the internet for Bengali, it was less than 1.5 hours of audio data. Notably, the training corpus lacks substantial representation of spon-

Table 2.2: Whisper model types details

| Size   | Parameters | English-only model | Multilingual model |
|--------|------------|--------------------|--------------------|
| tiny   | 39 M       | Yes                | Yes                |
| base   | 74 M       | Yes                | Yes                |
| small  | 244 M      | Yes                | Yes                |
| medium | 769 M      | Yes                | Yes                |
| large  | 1,550 M    | No                 | Yes                |

taneous Bengali speech with distinct regional accents and dialects, a gap addressed by the dataset introduced in this research.

As depicted in Figure 2.4, The Whisper model architecture, developed by OpenAI for automatic speech recognition (ASR) and language translation, is structured around a transformer-based encoder-decoder framework. The following are its key components:

1. **Encoder-Decoder Structure:** The architecture comprises an encoder and a decoder, facilitating efficient processing of audio input and the generation of text output.
2. **Audio Input Processing:** Raw audio signals are initially transformed into spectrograms, representing the frequency content over time, thus enabling structured analysis of the audio data.
3. **Multi-Head Self-Attention:** The model employs multi-head self-attention mechanisms, allowing it to attend to multiple segments of the input audio simultaneously. This capability is crucial for capturing long-range dependencies and contextual information.
4. **Positional Encoding:** Positional encodings are incorporated to maintain the sequential characteristics of audio data, providing the model with information regarding the temporal order of input frames.
5. **Feed-Forward Layers:** After the self-attention layers, feed-forward networks are utilized to further process the output, applying non-linear transformations that enhance the model’s representational capacity.
6. **Layer Normalization:** Throughout the model, layer normalization is implemented to stabilize training and improve convergence rates.

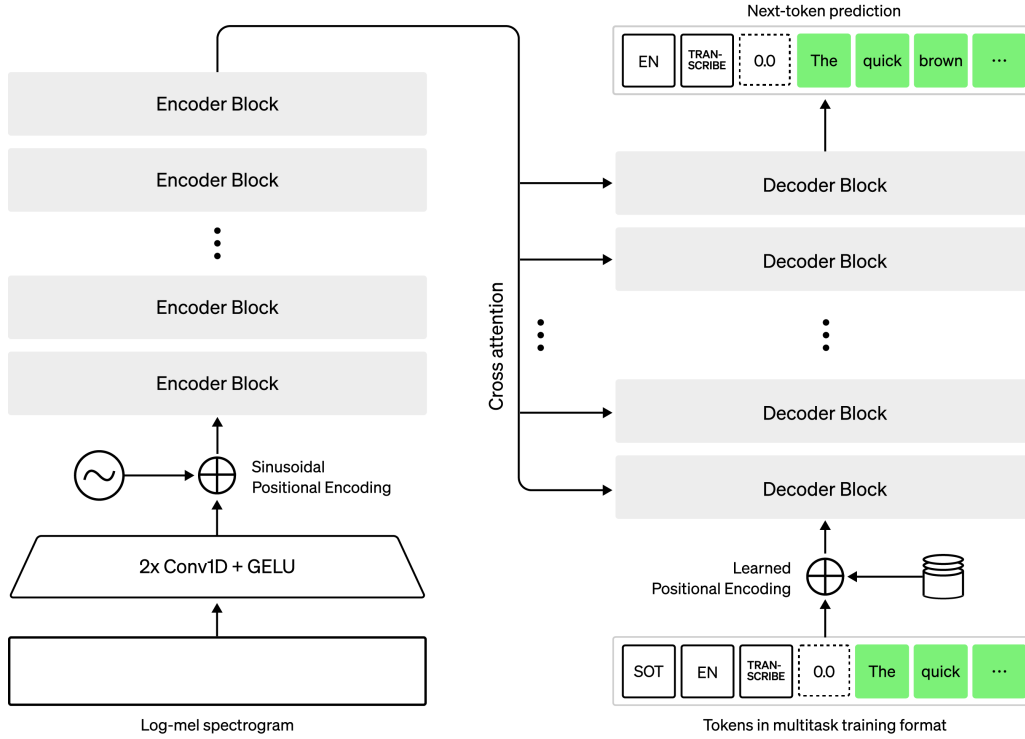


Figure 2.4: Conformer encoder model architecture

7. **Output Generation:** The decoder generates text sequences based on the encoded audio representation, utilizing both the attention mechanism and previously generated tokens to inform its predictions.
8. **Training Data:** The model is trained on a diverse and extensive dataset of multilingual speech, which significantly enhances its ability to handle various languages and accents.

In summary, the Whisper architecture leverages the strengths of transformer networks while being specifically optimized to address the challenges associated with speech recognition and translation tasks.

This work focuses specifically on augmenting the training dataset with regional Bengali accents and dialects, contributing significantly to ongoing research efforts. The dataset discussed herein highlights the manifold benefits of utilizing a comprehensive and diverse dataset, enhancing the model's robustness in navigating diverse accents, mitigating background noise interference, and understanding specialized technical

or regional languages such as Chittagong.

Beyond its contributions to speech recognition capabilities, Whisper’s versatility extends to transcription and translation tasks across multiple languages and dialects, transcending linguistic barriers and promoting cross-cultural communication.

Moreover, Whisper’s capability to expedite the translation of spoken content from various languages into English facilitates improved intercultural dialogue, fostering broader accessibility and understanding across diverse linguistic contexts.

Considering future developments, advancements in deep learning algorithms promise continued improvements in voice recognition accuracy, particularly in handling variations such as regional accents and dialects.

# Chapter 3

## Background Study

In this chapter, we will address the challenges associated with ASR modeling for regional dialects and provide a comprehensive linguistic analysis of each regional dialect.

### 3.1 Challenges with Bengali Speech Recognition With Regional Dialects

Bengali serves as the predominant language among the population of the Bengal region. Despite ongoing efforts towards standardization, regional dialects often prevail in everyday communication rather than the standardized form of Bengali. This trend is not exclusive to Bangladesh but mirrors similar patterns observed in other multilingual nations. Here, local dialects or languages are commonly used in daily interactions, contrasting with the use of standardized language reserved for formal settings such as education, media, and official documentation. As with many languages, variations in spoken language diverge significantly from the standardized norm in everyday contexts.

#### 3.1.1 Deviation Challenges

The standard form of Bengali encounters several challenges, including the preservation of cultural identity. As languages evolve, there is concern that the process of standardizing Bengali may diminish certain cultural nuances and regional characteristics inherent in various dialects and local variations. Accessibility and inclusivity of the formal standard language pose challenges for certain demographic groups,

particularly those with lower levels of education, impacting their ability to comprehend and utilize it effectively. This disparity can lead to social exclusion and hinder access to education, information, and opportunities. Moreover, proficiency in the standard language may confer advantages in education, employment, and other domains, thereby exacerbating linguistic divides within society.

Another challenge involves the lack of modern terminology. Like all languages, Bengali grapples with the adaptation of new technological, scientific, and academic advancements. Developing and integrating new terminology while maintaining linguistic integrity presents a complex undertaking.

#### **3.1.1.1 Regional Diversity**

In the Bengali-speaking world, diverse local dialects, accents, and colloquialisms abound, shaped by geographical, historical, cultural, and linguistic interactions with neighboring regions. Informal settings, familial interactions, and casual conversations typically witness the use of these local or regional dialects. Such variations often incorporate distinct vocabulary, pronunciation, and grammatical structures that may diverge from the standardized Bengali form.

This natural evolution of language underscores the dynamic nature of linguistic usage and adaptation across different regions. While the standardized form of Bengali serves as a common medium of communication among speakers from diverse backgrounds, the proliferation of dialectal diversity enriches the language and reflects the cultural vibrancy of Bengali-speaking communities.

#### **3.1.1.2 Cultural Diversity**

Media outlets generally aim to uphold the standard language, yet regional influences can introduce variations in pronunciation and word usage, occasionally resulting in misunderstandings. Strict adherence to language standards may potentially constrain creative expressions, including poetry, literature, and other art forms that often derive impact from bending linguistic norms.

The prevalence of the standard language in official and formal contexts can sometimes evoke tensions among individuals who perceive it as emblematic of cultural and linguistic imperialism, particularly in regions marked by robust regional identities.

### 3.1.2 Linguistic Challenges

Language constitutes a dynamic entity, continuously evolving and adapting to cultural shifts, technological progressions, and interactions with other languages. Bengali, shaped by centuries of linguistic evolution, literary contributions, and cultural identity formation, holds a pivotal position in the history of the Bengal region. Its linguistic complexity is underscored by several distinctive features intrinsic to its structure. These include a sophisticated writing system, intricate inflectional morphology, the occurrence of gemination, and a rich inventory of diphthongs and triphthongs [14].

A detailed analysis is discussed in the later part of this chapter of this dissertation.

### 3.1.3 Dataset Acquisition Challenges

The SUBAK.KO speech corpus [78] stands out as the singular reported speech corpus to date, involving participation from 61 native speakers representing all eight divisions and thirty-four districts of Bangladesh. But the recordings were uniformly in standard Bangla and were executed under controlled conditions within a studio environment.

Research and development in this domain have been hindered by insufficient datasets and resources.

### 3.1.4 Modeling Challenges

Utilizing advanced state-of-the-art (SOTA) models for training poses significant computational challenges, particularly for academic researchers with limited access to such resources. It should be noted that achieving convergence during training is notably more difficult for Bengali compared to languages like English, primarily due to the greater diversity of distinct tokens within the Bengali language. Bengali, as an agglutinative language, exhibits complex morphological variations where individual words can manifest phonetic similarities yet differ significantly in their written forms.

Moreover, Bengali encompasses a wide array of regional accents and dialects, further complicating linguistic modeling efforts. While quantifying phonetic variations across these diverse dialects remains challenging, addressing this linguistic diversity

is crucial for effective modeling. Our approach involves comprehensive data collection that captures a broad spectrum of linguistic nuances in both text and audio formats. This meticulous curation aims to ensure the training corpus reflects diverse linguistic characteristics, providing neural networks with a robust dataset essential for effective ASR development in Bengali.

## 3.2 Linguistic Analysis

A detailed analysis from a linguistic aspect is discussed in this section.

### 3.2.1 Grapheme Diversity

The Bengali writing system is distinct because it employs orthographic syllables as graphemes, a characteristic shared with other alpha-syllabary or Abugida languages. Consequently, in this text, we use the terms *orthographic syllables* and *graphemes* interchangeably.

The Bengali language is written in the Bengali script, which is renowned for its astounding grapheme diversity [67]. It intricately combines consonant characters with built-in vowel sounds to form an *abugida* script. The Bengali Unicode system introduces multiple encoding methods for the same alphabet, necessitating normalization [24] and contributing to the challenges related to text grapheme diversity. Several of these appear in infrequent words and can also result from spelling errors.[65]. There are 11 vowel characters that seamlessly combine with consonants to form syllables and 39 basic consonant characters that represent various consonant sounds. The script modifies vowel sounds with diacritical marks, providing a variety of vowel combinations. It also includes numerals and punctuation marks in its repertoire and allows the construction of complex consonant clusters using conjunct characters. Occasionally, specific consonant combinations are represented by ligatures as well. Besides the standard vowel, consonant, and conjunct local dialect offers various vowel combinations in local dialect [66].

A significant quantity of consonant combinations poses difficulties in associating written characters with their spoken forms. This can hinder the effectiveness of Text-to-Speech (TTS) or Speech-to-Text (STT) models, as these combinations may have varying pronunciations depending on their context.

For example, সামনে is pronounced  $\text{ʃemne}$  whereas it is pronounced both the same and differently in different regions from where I have collected my data such as it is pronounced in the same manner in Kishoreganj and Narsingdi but সামনোত ( $\text{ʃemnoʈo}$ ) in Rangpur, ছামনে ( $\text{c}^h\text{emne}$ ) in Narail and সামনো ( $\text{ʃemno}$ ) in Chittagong.

### 3.2.2 Inflection

In the field of linguistics, *inflection* refers to the process of creating different word forms by following a pattern derived from grammar, such as variations related to tense, or from the meaning of sentences, such as variations based on the gender of nouns. [9].

Similar to many other languages in the Indic language family, Bengali exhibits a high degree of inflection. Nouns, for instance, can manifest in more than 100 different case forms, while verbs can exhibit over 40 distinct variations. As a result, the count of whitespace-tokenized "words" in Bengali is notably high, reaching into the tens of millions, in stark contrast to the 188k words typically found in English [26]. Furthermore, Bengali's complex morphology allows for the creation of compound words, that results into the existence of substantial amount of Out of Vocabulary (OOV) words.

This issue poses considerable challenges for both TTS and ASR models, especially when dealing with languages with limited available resources, such as Bengali [49]. And when it comes to regional dialects, It exhibit unique inflectional patterns for gender, number, and case. For example, there are some distinctions in using singular and plural inflection in the Narsingdi and Kishoreganj dialects shown in the table 3.1

But the Chittagong dialect took some different inflection than the standard Bengali language shown in the table 3.2

Chittagonian dialects also exhibit unique inflectional patterns for gender variation shown in 3.3

Table 3.1: Morphological features of Narsingdi and Kishoreganj dialects

| Standard Bengali           | Inflection [IPA]       | Narsingdi/Kishoreganj  | Inflection [IPA] |
|----------------------------|------------------------|------------------------|------------------|
| আমটা [ $\text{emte}$ ]     | টা [ $\text{te}$ ]     | আমডা [ $\text{emde}$ ] | [ $\text{de}$ ]  |
| আমগুলা [ $\text{emgule}$ ] | গুলা [ $\text{gule}$ ] | আমডি [ $\text{emdɪ}$ ] | [ $\text{dɪ}$ ]  |

Table 3.2: Morphological features of Chittagong dialects

| Standard Bengali      | Bengali Inflection [IPA] | Chittagong           | Chittagong Inflection [IPA] |
|-----------------------|--------------------------|----------------------|-----------------------------|
| গরুগুলো [gorugulo]    | গুলো [gulo]              | গরুউন [goruʊn]       | উন [uʊ]                     |
| দাঁড়িগুলো [ḍeɽigulo] | গুলো [gulo]              | দাঁইরউয়া [ḍeɽiruʔe] | উয়া [uʔe]                  |
| গাছ থেকে [gɛcʰ tʰeke] | থেকে [tʰeke]             | গাছতুন [gɛcʰottun]   | তুন [tun]                   |
| বউয়ের [boʊer]        | এর [er]                  | বউঅর [boʊər]         | অর [ər]                     |

Table 3.3: Chittagong dialects inflectional patterns for gender variation.

| In English | In Standard Bengali [IPA] | In Chittagonian [IPA] |
|------------|---------------------------|-----------------------|
| He Does    | সে করে [ʃe kore]          | ইতে গরে [ɪte gore]    |
| She Does   | সে করে [ʃe kore]          | ইতি গরে [ɪti gore]    |

In the Rangpur region, This process includes combining the stem with a grammatical morpheme that does not produce new words but rather indicates aspects of the grammatical function of a word shown in the table 3.4

Another notable difference in the Rangpur dialect is observed in the inflections used in verb forms. The particular differentiation is outlined below in table 3.5

Table 3.4: Morphological features of Rangpur dialects

| Standard Bengali (IPA) | Root word     | Inflectional [IPA] | Rangpur [IPA]     |
|------------------------|---------------|--------------------|-------------------|
| অফিসে [ɔfise]          | অপিস [ɔpis]   | -এত [-et]          | অপিসেত [ɔpiset]   |
| মানুষের [menuʃer]      | মাইনষ [meɪnʃ] | -এর [-er]          | মাইনষের [meɪnʃer] |
| মানুষকে [menuʃke]      | মাইনষ [meɪnʃ] | -এক [-ek]          | মাইনষেক [meɪnʃek] |
| বাজারে [beʃere]        | বাজার [beʃer] | -ওত [ot]           | বাজারোত [beʃerot] |
| ছিল [cʰɪlo]            | ছিল [cʰɪlo]   | আ [ɛ]              | আছিল [ɛcʰɪl]      |
| বিছানায় [bicʰɛnɛɛ]    | বিছনা [bisnɛ] | -ত [t]             | বিছনাত [bisnɛt]   |

Table 3.5: Inflectional Verb Forms in Rangpur Dialect

| Standard Bengali [IPA]        | Rangpur Dialect [IPA]             |
|-------------------------------|-----------------------------------|
| (আমি) খাব [ɛmɪ kʰɛbo]         | (মুই) খাবু [muɪ kʰɛbo]            |
| (আমি) খেয়েছি [ɛmɪ kʰeʃeɪ]    | (মুই) খাইসি [muɪ kʰeɪsɪ]          |
| (কাজ) করবে না? [kəj kɔrbe nɛ] | (কাম) করবান নয়? [kɛm kɔrbɛn noɪ] |
| (আমি) শুনলাম [ɛmɪ ʃunləm]     | (মুই) শুননু [muɪ ʃununu]          |
| দেখি [dekʰɪ]                  | দেহং [dehɔŋ]                      |
| করার [korɛr]                  | করং [kɔrɔŋ]                       |

Table 3.6: Morphological features of Narail dialects

| Standard Bengali [IPA] | Root word [IPA] | Inflectional [IPA] | Narail Dialects [IPA] |
|------------------------|-----------------|--------------------|-----------------------|
| লোকজনকে [lokʃonke]     | লোকজন [lokʃon]  | রে [re]            | লোকজনরে [lokʃonre]    |
| মেয়ের [meɪer]         | মাই [meɪ]       | এর [er]            | মাইয়ের [meɪer]       |
| দোকানটা [dokɛntɔ]      | দুকান [dukan]   | ডা [dɛ]            | দুকানডা [dukɛndɛ]     |

### 3.2.3 Aspiration

*Aspirated* consonants খ, ঘ, ছ, ঝ, ঠ, ঢ, থ, ধ, ফ, ভ) [k<sup>h</sup>, g<sup>h</sup>, c<sup>h</sup>, ʃ<sup>h</sup>, t<sup>h</sup>, d<sup>h</sup>, t̪<sup>h</sup>, d̪<sup>h</sup>, p<sup>h</sup>, b<sup>h</sup>] are consonants that are accompanied by secondary articulation. [10]. In Standard Bengali, aspiration is found in voiceless and voiced stops. Both voiced aspiration and voiceless aspiration occur in the language. Aspirated consonants create difficulties in both ASR (Automatic Speech Recognition) and TTS (Text-to-Speech) modeling because of their subtle pronunciation nuances. This complexity is further compounded when dealing with exaggerated aspiration in breathy voices, making it particularly challenging to model natural speech [23]. Additionally, individuals with pronounced accents and non-native speakers tend to pronounce aspirated sounds differently, adding to the challenges of achieving accurate generalization.[39].

It is common to find aspirated sounds /k<sup>h</sup>/, /t<sup>h</sup>/, /b<sup>h</sup>/, /g<sup>h</sup>/, /d<sup>h</sup>/, /p<sup>h</sup>/ are changed into non-aspirated /k/, /d/, /b/, /g/, /p/ sounds. Shown in the 3.7, the entry in the first row is a case of bilabial plosive where <sup>h</sup> indicate a voiceless aspiration but the second and third entries are cases of voiced stop sounds where <sup>h</sup> is indicating a voiced aspiration.

Rangpuri, alternatively known as Kamtapuri or Rajbanshi, represents an Eastern Indo-Aryan language spoken in specific regions of Bangladesh and India, particularly within

Table 3.7: Inflection example of standard Bengali

| Voiceless<br>aspiration [IPA] | English<br>Translation | Voiced<br>aspiration [IPA] | English<br>Translation |
|-------------------------------|------------------------|----------------------------|------------------------|
| ডাকা [dʌkʌ]                   | Call                   | ঢাকা [dʱʌkʌ]               | Cover                  |
| দান [dʌn]                     | Donate                 | ধান [dʱʌn]                 | Paddy                  |

Table 3.8: Aspiration in Rangpur Dialect

| Rules                    | Standard Bengali [IPA] | Rangpur Dialect [IPA] |
|--------------------------|------------------------|-----------------------|
| /k <sup>h</sup> / - /kk/ | দুঃখের [dʊkʰer]        | দুক্কোর [dʊkkor]      |
| /t <sup>h</sup> / - /d/  | ওঠে [otʰe]             | ওডে [ode]             |
| /b <sup>h</sup> / - /b/  | লাভ [labʰ]             | লাব [lab]             |
| /dʱ/ - /d/               | বন্ধু [bondʱu]         | বন্দু [bondu]         |

the Rangpur division of Bangladesh. While it shares specific phonological and lexical features with Standard Bengali, it maintains a close mutual intelligibility. The widespread influence of the standard Bengali has led individuals from other communities and regions to adopt it across various aspects of life. Therefore, this shift in the use of language has resulted in a decline in the usage of their native dialect. From my collected and transcribed data of the Rangpur dialect, the following non-aspiration sounds are found which are shown in 3.8

For the district Kishoreganj, the table 3.9 shows that The palatal unaspirated sound c is changed into an aspirated sound c<sup>h</sup> sound at the syllable initial position without changing the meaning in the first entry and the bilabial plosive sound p is also changed into the aspirated p<sup>h</sup> sound at the syllable initial and positions are shown in the table's respectively second and third-fourth entries.

The aspiration in the language affects the definition of the term or word. The existence

Table 3.9: Aspiration in Kishoreganj Dialect

| Rules                   | Standard Bengali [IPA] | Kishoreganj Dialect [IPA] |
|-------------------------|------------------------|---------------------------|
| /c/ - /c <sup>h</sup> / | চার [cʌr]              | ছাইর [cʰʌr]               |
| /p/ - /p <sup>h</sup> / | পঞ্চাশ [poncaʃ]        | ফইঞ্চাশ [pʰoɪ̯ncaʃ]       |
| /p/ - /p <sup>h</sup> / | বাটপার [betpʌr]        | বাটফার [betpʰʌr]          |
| /p/ - /p <sup>h</sup> / | বাপ [bʌp]              | বাফ [bʌpʰ]                |

Table 3.10: Aspiration in Narail Dialect

| Rules                   | Standard Bengali [IPA]    | Narail Dialect [IPA]                    |
|-------------------------|---------------------------|-----------------------------------------|
| /p/ - /p <sup>h</sup> / | পারে [pære]               | ফারে [p <sup>h</sup> ære]               |
| /p/ - /p <sup>h</sup> / | প্রত্যেক [prottek]        | ফত্যেক [p <sup>h</sup> ottek]           |
| /p/ - /p <sup>h</sup> / | তারপরে [tərpore]          | তারফরে [tərp <sup>h</sup> ore]          |
| /c/ - /c <sup>h</sup> / | খরচ [k <sup>h</sup> ɔroc] | খরছ [k <sup>h</sup> ɔroc <sup>h</sup> ] |

of the same case is also observed in the dialect of Narail. However, the speaker of Narail also has a tendency to alter the unaspirated sound into an aspirated sound where this kind of change does not affect the meaning of the word. The examples are shown in the table 3.10. In the first two entries, the bilabial plosive sound p is changed into the aspirated p<sup>h</sup> sound at the syllable initial position. In the third entry of the table, the bilabial plosive sound p is changed into the aspirated p<sup>h</sup> sound at the syllable middle position and in the final entry, the palatal unaspirated sound c is changed into an aspirated sound c<sup>h</sup> without changing the meaning.

Chittagonian consonant is different from the Standard Bengali consonant. Some examples can be seen in the table 3.11. In the first and second entry, the bilabial plosive sound p and k is changed into the aspirated p<sup>h</sup> and k<sup>h</sup> sound at the syllable initial position. The bilabial plosive sound p is changed into the aspirated p<sup>h</sup> sound at the syllable medial position seen in the third entry of the same table and the bilabial plosive sound p is changed into the aspirated p<sup>h</sup> sound at the syllable final position is seen in the last entry of the same table.

Table 3.11: Chittagong dialect aspiration example

| Rules                   | Voiceless aspiration [IPA]      | Meaning in English | Voiced aspiration [IPA]         |
|-------------------------|---------------------------------|--------------------|---------------------------------|
| /p/ - /p <sup>h</sup> / | পরীক্ষা [p <sup>h</sup> orikka] | Exam               | ফরিক্কা [porikk <sup>h</sup> a] |
| /k/ - /k <sup>h</sup> / | কালো [kələ]                     | Black              | খালো [k <sup>h</sup> ələ]       |
| /p/ - /p <sup>h</sup> / | তারপরে [tərpore]                | Then               | তারফরে [tərp <sup>h</sup> ore]  |
| /p/ - /p <sup>h</sup> / | মাপ [mæp]                       | Measure            | মাফ [mæp <sup>h</sup> ]         |

One different characteristic of the Narsingdi dialect is the number of unaspirated consonants compared to aspirated ones. This indicates that, in contrast to certain other Bengali dialects, there is less of a noticeable burst of air (aspiration) when producing voiceless

stops like k, g, and c. Hence, in contrast to standard Bengali or other regional dialects, the speakers of the Narsingdi dialect pronounce words with a comparatively softer and less aspirated quality for these consonant sounds. Though Some  $p^h$  sounds are heard in the pronunciation of Narsingdi speakers. Some examples are in the table 3.12.

The bilabial plosive sound p is changed into the aspirated  $p^h$  sound at the syllable initial position in the first entry of the table. The same changes are made respectively at the syllable medial and final position in the second and third entries of the same table.

Table 3.12: Narsingdi dialect aspiration example

| Rules                   | Voiceless aspiration [IPA] | Meaning in English | Voiced aspiration [IPA]     |
|-------------------------|----------------------------|--------------------|-----------------------------|
| /p/ - /p <sup>h</sup> / | পড়া [pɔɽɐ]                | Read               | ফরা [p <sup>h</sup> ɔɽɐ]    |
| /p/ - /p <sup>h</sup> / | কাপড় [kəpɔɽ]              | Cloths             | কাফড় [kəp <sup>h</sup> ɔɽ] |
| /p/ - /p <sup>h</sup> / | কাপ [kap]                  | Cup                | কাফ [kəp <sup>h</sup> ]     |

### 3.2.4 Gemination

Gemination refers to the prolonged pronunciation of a consonant due to its consecutive occurrence in a sentence [15]. For instance, বাদ দাও [baɽ ɽaɽ] can also be pronounced as বাদ্দাও [baɽɽaɽ], with the latter being a geminated form. The distinction between these two pronunciations is subtle in spoken language but significant in written text. In Bengali, gemination can occur when similar phonemes are shared between words and within a single word, with a higher frequency between two consecutive words.

While this linguistic feature presents challenges for determining word boundaries in ASR algorithms for various languages [17], the specific modeling challenges it poses in Bengali have not been extensively explored in existing literature.

Gemination involves the extended pronunciation of a consonant sound in comparison to its typical length. The precise pronunciation and the use of germination may vary from dialect to dialect. We can see some examples of geminition for Rangpur, Kishoreganj, Narail, Chittagong and Narsingdi respectively in the table 3.13.

Table 3.13: Gemination examples of different regional dialects with IPA

| Rules              | Standard Bengali [IPA] | Dialect [IPA]      |
|--------------------|------------------------|--------------------|
| <b>Rangpur</b>     |                        |                    |
| /l + l/            | আল্লাহ [ɛllɛh]         | আল্লা [ɛllɛ]       |
| /t̪ + t̪/          | ওইতো [oɪ̯to]           | ওইত্তো [oɪ̯ttɔ]    |
| /t + t/            | এখানে [ekʰɛne]         | এট্টে [ɛttɛ]       |
| /t̪ + t̪/          | ওইগুলো [oɪ̯gule]       | ওইল্লা [oɪ̯lle]    |
| /n + n/            | শুনলাম [ʃunləm]        | শুনু [ʃunnu]       |
| <b>Kishoreganj</b> |                        |                    |
| /n + n/            | কিনে [kɪne]            | কিন্না [kɪnnɛ]     |
| /t̪ + t̪/          | কেটে [kɛtɛ]            | কাইট্টা [kɛɪ̯tta]  |
| /k + k/            | অপেক্ষা [opekʰkʰɛ]     | অপেক্কা [opekʰkɛ]  |
| /c + c/            | বেচে [bece]            | বেইচ্চা [beɪ̯cca]  |
| /t̪ + t̪/          | মথ্যা [mittʰɛ]         | মিভা [mittʰɛ]      |
| <b>Narail</b>      |                        |                    |
| /m + m/            | জন্মের [ʃɔnmɛr]        | জন্মের ʃɔmmɛr      |
| /t̪ + t̪/          | করতি [kɔrtɪ]           | কত্তি [kɔttɪ]      |
| /t + t/            | একটা [ɛktɔ]            | এট্টা [ɛttɔ]       |
| /d̪ + d̪/          | মধ্যে [mod̪d̪ʰɛ]       | মদ্দি [mod̪d̪ɪ]    |
| /n + n/            | এমনে [emne]            | এন্নে [enne]       |
| <b>Chittagong</b>  |                        |                    |
| /ʃ + ʃ/            | করেছি [korecʰɪ]        | গইজ্জি gɔɪ̯ʃʃɪ     |
| /l + l/            | এখন [ɛkʰɔn]            | এল্লা [ɛllɛ]       |
| /d̪ + d̪/          | মধ্যে [mod̪d̪ʰɛ]       | মইদ্দে [mɔɪ̯dd̪ɛ]  |
| /k + k/            | থেকে [tʰɛke]           | থাইক্কি [tʰɛɪ̯kkɪ] |
| /c + c/            | আচ্ছা [ɛccʰɛ]          | আইচ্চা [ɛɪ̯ccʰɛ]   |
| <b>Narsingdi</b>   |                        |                    |
| /n + n/            | কিনে [kɪne]            | কিন্না [kɪnnɛ]     |
| /k + k/            | টুকে [dʰuke]           | ডুইক্কা [duɪ̯kka]  |
| /m + m/            | এভাবে [ɛbʰɛbe]         | এম্মে [ɛmme]       |
| /l + l/            | খুলে [kʰule]           | খুইল্লা [kʰuɪ̯lla] |
| /t + t/            | হেঁটে [h̥ɛte]          | হাইট্টা [h̥ɛɪ̯tta] |

### 3.2.5 Diphthong

A diphthong refers to the combination of two vowels within a single syllable. The semi-vowel component of the diphthong can be found either at the beginning or the end of the syllable. Therefore, a diphthong is essentially a linguistic fusion of vowels and a glide sound.

The precise count of Bengali diphthongs has varied among different experts [32].

Sukumar Sen [8] noted that the Bengali language comprises two diphthongs, namely ঐ and ঔ. These combinations of two sounds are represented in written form but do not fit the conventional definition of diphthongs. In linguistic terms, they are referred to as digraphs [12].

On the contrary, Suniti Kumar Chatterji [2] claims that there exists 25 diphthongs in standard Bengali. In contrast, Md. Abdul Hai [4] asserts that there exists a total of 31 diphthongs, categorizing them into regular and irregular ones which are summing up to respectively 19 and 12. However, he also argues that there are only 18 diphthongs, as noted by Zinat Imtiaz Ali [12], who asserts that there are 17 diphthongs in Bengali. The government-approved IPA website acknowledges the regular 19 diphthongs, but they have used the diphthong /ui/ twice and excluded the /eq/ diphthong from considering.

A large number of loaned words from English, Arabic, Farsi, and others are used in Standard Bengali. These words are also spoken in the regional dialects as well. In English words with diphthongs, pronunciation is influenced by the presence of schwa/ə/ usually containing the neutral, unstressed vowel sound when appearing in unstressed syllables.

This leads to subtle variations in how diphthongs are articulated. For example, ‘power’- in the word, the diphthong /au/ is followed by the schwa sound in the unstressed syllable. Or for the word ‘water’, the first syllable may be reduced to a schwa sound, especially if it’s unstressed. It might sound like ”wuh-ter.” However, when these words are adapted by the Bengali speaker they will be pronounced like /pa.ɔ̃ˈar/ /õg̃.ter/.

Bengali speakers adopt English diphthongs that do not contain schwa and the pronunciation tends to align with the native English pronunciation. For example, হাই ‘high’ is transcribed in the Bengali as /hɛ̃i/, boil as /bɔ̃l/, and time as /tɛ̃m/.

The table 3.14 shows how a standard Bengali diphthong deviates region-wise. The diphthong entry cells that are left blank mean that those diphthongs do not exist in my curated

dataset or perhaps even in that regional dialect.

Note: Abdul Hai [4] categorized the regular diphthong /eɔ/ for words such as কেও, পেও and the irregular diphthong /eɔ/ for words like চেয়ো, পেয়ো. These words have orthographic differences but rarely do they have distinctions in their pronunciation. Which are marked as \* in the table 3.14

Table 3.14: Diphthong table of different regions The IPA transcription follows [89]

| Serial    | Standard Bengali | IPA | Rangpur         | Kishoreganj       | Narail                          | Chittagong          | Narsingdi         |
|-----------|------------------|-----|-----------------|-------------------|---------------------------------|---------------------|-------------------|
| Regular   |                  |     |                 |                   |                                 |                     |                   |
| 1.        | ইহ্              | iɪ  | নিই [niɪ]       | দিইয়া [diɪe]     | দিইয়া [diɪe]                   | -                   | কাকিইয়ে [kakiɪe] |
| 2.        | ইউ               | iʊ  | টিউবল [tiʊbɔl]  | -                 | -                               | ইয়ুত [iʊt]         | -                 |
| 3.        | এই               | eɪ  | গেইলে [geɪle]   | এইডা [eɪde]       | যেইডে [jeɪde]                   | এইক্কের [eɪkkere]   | এই [eɪ]           |
| 4.        | এও*              | eɔ* | -               | এও [eɔ]           | -                               | কেওরেতুন [keɔretun] | এও [eɔ]           |
| 5.        | এউ               | eʊ  | -               | কেউ [keʊ]         | কেউ [keʊ]                       | কেউ [keʊ]           | কেউ [keʊ]         |
| 6.        | অ্যাও            | ɛɔ  | দেও [deɔ]       | দেও [deɔ]         | দেও [deɔ]                       | -                   | দেও [deɔ]         |
| 7.        | অ্যাম্           | ɛɪ  | -               | দেয় [deɪ]        | দ্যায় [deɪ]                    | -                   | দেয় [deɪ]        |
| 8.        | আই               | ɑɪ  | রাইত [raiɪt]    | নাইগা [naiɪga]    | আইসে [ɑɪse]                     | আইবো [ɑɪbo]         | আইলে [ɑɪle]       |
| 9.        | আএ               | ɑɛ  | এলায় [elɑɛ]    | আয়ে [ɑɛ]         | পায় [pɑɛ]                      | গায়ে [gɑɛ]         | মায়ে [mɑɛ]       |
| 10.       | আও               | ɑɔ  | ইয়াও [iɑɔ]     | আও [ɑɔ]           | আওনে [ɑɔne]                     | -                   | আওয়াজ [ɑɔʒ]      |
| 11.       | আউ               | ɑʊ  | কাউরে [kɑʊre]   | আউজা [ɑʊʒa]       | আউলাত [ɑʊlat]                   | আগাউ [ɑʊgaʊ]        | আউশ [ɑʊʃ]         |
| 12.       | অয়              | ɑɪ  | কয় [kɑɪ]       | অয় [ɑɪ]          | অয় [ɑɪ]                        | নয় [nɑɪ]           | অয় [ɑɪ]          |
| 13.       | অও               | ɑɔ  | -               | কও [kɑɔ]          | কও [kɑɔ]                        | সওরি [sɑɔri]        | অওয়া [ɑɔʔ]       |
| 14.       | ওও               | oɔ  | ধোও [dʱoɔ]      | -                 | -                               | -                   | -                 |
| 15.       | উআ               | oʊ  | -               | -                 | যৌবন [joʊbɔn]                   | হউন [hoʊn]          | বউ [boʊ]          |
| 16.       | ওই               | oɪ  | কইলে [koɪle]    | মইদে [moɪdde]     | কইরে [koɪre]                    | চৈত [coɪt]          | কইরা [koɪra]      |
| 17.       | ওয়              | oɛ  | -               | -                 | -                               | -                   | -                 |
| 18.       | উই               | uɪ  | খুইয়া [tʰuɪɪa] | খুইতাম [tʰuɪtəm]  | দুইডে [duɪde]                   | উইদো [uɪddo]        | উইট্টা [uɪtte]    |
| 19.       | উউ               | uʊ  | খুউব [kʰuʊb]    | রুউবাইন [ruʊbɛɪn] | -                               | -                   | খুউব [kʰuʊb]      |
| Irregular |                  |     |                 |                   |                                 |                     |                   |
| 1.        | অআ               | ɔɑ  | -               | কয়া [kɔɑ]        | -                               | মআল [moɑl]          | অয়াতে [ɔɑte]     |
| 2.        | ইআ               | iɑ  | বালিয়া [baɪiɑ] | বিয়া [biɑ]       | দিয়া [diɑ]                     | মিয়া [miɑ]         | দিয়া [diɑ]       |
| 3.        | ইও               | iɔ  | -               | অইয়ো [ɔiɔ]       | দিও [diɔ]                       | কিওর [kiɔr]         | দিওন [diɔn]       |
| 4.        | ইএ               | iɛ  | -               | দিয়ে [diɛ]       | -                               | দিয়ে [diɛ]         | কিয়ের [kiɛr]     |
| 5.        | এআ               | eɑ  | যেয়া [jeɪɑ]    | নেয়া [neɪ]       | দেয়ার [deɪɑ]                   | গেয়া [geɪɑ]        | টেয়া [teɪ]       |
| 6.        | এয়ো*            | eɔ* | -               | -                 | -                               | -                   | -                 |
| 7.        | অ্যয়া           | ɛɑ  | -               | ট্যয়া [tɛɑ]      | দ্যয়াছে [deɪɑce <sup>h</sup> ] | -                   | -                 |
| 8.        | ওআ               | oɑ  | -               | হওয়া [hoɪɑ]      | -                               | নোয়া [noɪɑ]        | লওয়া [loɪɑ]      |
| 9.        | ওএ               | oɛ  | -               | -                 | -                               | -                   | -                 |
| 10.       | উয়ে             | uɛ  | -               | -                 | শুয়ে [ʃuɛ]                     | ফুয়ে [pʰuɛ]        | -                 |
| 11.       | উআ               | uɑ  | -               | দুয়া [duɑ]       | -                               | বুয়া [buɑ]         | আজুয়া [əʒuɑ]     |
| 12.       | উও               | uɔ  | -               | কুওন [kuɔn]       | -                               | উওর [uɔr]           | -                 |

### 3.2.6 Triphthong

Triphthong is described as "a combination of three vowel sounds, where the first vowel glides into the second, which, in turn, glides into the third," as defined by

Barman et al. [20]. The English language contains triphthongs, which is a rare case in the Bengali language. According to Suniti Kumar Chatterji [1], there are triphthongs in the Bengali language such as aeoi, aie, aio, aei, aoi, aui, eie, eio, eao, eoi, euo, iei, ieo, iae, oei, ooi, oeo, oie, ogi, oeo, oai, oae, oui, seei, uie, uio, uei, ueo, uae, uao, uoe.

However, the triphthongs in the Bengali language do not exist in the same way they exist in English. In the case of English triphthongs, native Bengali speakers tends to convert it into a diphthong and completely avoid pronouncing the triphthong word. For example, in English, the word ‘fire’ is pronounced as /fʌɪə/, which in Bengali is transcribed as /fɛ̃ɛ̃.ɐr/. Cases like these are found in these words as well - ‘hour’ /aʊər/, which is pronounced as /ɐ.õɔ̃ɔ̃r/, ‘prayer’ /preɪər/, pronounced as /prẽ.ɐr/, ‘pure’ /pjʊr/ pronounced as /pɪ̃ɔ̃r/. A Bengali speaker’s pronunciation of words can vary based on specific contexts and regional accents. Even a standard native speaker may pronounce certain words differently depending on the situation, which could lead to variations in IPA transcription. Unless the transcription is based on audio data, ensuring accurate contextual transcription can be a challenge. There are instances in dialectal languages where two vowels can appear together in a word, but they are treated as separate syllables.

For example, the word থুইলেও [tʰuileo] is used by the speaker of Rangpur. Here the vowel combination eo is part of the separate syllable as in tʰuile.o. Another similar case can be seen in দিয়াও [dɪəo] which is used by the speaker of other regions as well. These cases are unlike true triphthongs.

Excluding these, many grammatical features exists in Bengali that make ASR and TTS modeling challenging in this language. Brahmic Schwa deletion ambiguity [45] i.e. without an appropriate language model, trailing vowel sounds dropped by many Bengali words are difficult to model. Related to this issue, modeling is more challenging for a great amount of homographs in Bengali [72] [41]. Although the markers of Nasality [6] is often explicitly included in the written forms but in practice, it is often skipped while pronouncing done by any native Bengali speakers. Also, it has been reported [7] that the phonological phrases in Bengali correspond to no plausible constituent of syntactic representation which results as a challenge when modeling speech ensuring proper prosody.

In Bengali speech, the phone(s) associated with glide, diphthongs and emphasizeers often sounds similar. Where by definition, glides are sound that is phonetically similar to a vowel sound but operates as the syllable boundary. Diphthongs are the sounds formed when combining the two vowels and emphasizeers or modifiers that enhances to give the

auxiliary emotional context.

As each of these have different written narratives, high contextual information is often required when differentiating them from each other and this also results as a challenge when modeling. [18].

An inevitable instance in Bengali sentence structure is the position swapping of morpheme in the sentence. Bengali Language follows the SOV pattern of sentence structure. But in the daily life discourse or in literature, this pattern often alters to SVO, VSO, and OVS. [35] [33]

Also, a great deal of foreign words from different languages are used by Bengali speakers that often has no standardized pronunciation and spelling. This results as a practical challenge when working with diversified real-world data [5]

### 3.3 Available SOTA ASR Models

Numerous models have been fine-tuned using Bengali corpora; however, there is a notable absence of datasets specifically focused on Bengali speech incorporating regional dialects. Consequently, none of these models have undergone fine-tuning in this context. Several of these models were employed to benchmark performance against our developed corpus. A detailed description of these models is provided in the following sections.

#### 3.3.1 YellowKing

In July 2022, Bangladesh University of Engineering and Technology (BUET)’s Computer Science and Engineering (CSE) department initiated the first-ever Bengali Automatic Speech Recognition competition in Bangladesh, hosted on Kaggle under the title ”DL Sprint”<sup>1</sup>. The competition spanned from July to September and aimed to accelerate research in AI models for Bengali speech recognition. The significance of this initiative lies in the vast audience and potential business and educational applications associated with this field. The competition utilized a corpus of recorded sentences provided by volunteers through the Mozilla Common Voice platform.

The competition was sponsored by the ICT Division of the Bangladesh Government, with a prize of 200,000 Bangladeshi Taka awarded to the winning team.

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<sup>1</sup><https://www.kaggle.com/competitions/dlsprint/overview>

The competition consisted of two phases. In the first phase, participating teams used 400 hours of annotated Bengali speech data from Mozilla Common Voice to train their models. Teams competed to achieve optimal scores on a common voice test dataset. Upon completion of this phase, teams submitted their models and corresponding reports for evaluation. Performance was assessed on two distinct test sets, which remained confidential, accessible only to a select group of evaluators. The top-performing teams were subsequently invited to BUET CSE for the final phase, where they presented their work and received their awards. The judging panel, comprising industry professionals, government representatives, and academic experts, selected the winning model based on several criteria, including public and private Kaggle rankings, performance on a hidden test set, word error rate, runtime, and Kaggle score. The model named YellowKing[80] was ultimately chosen as the winner of the competition.

The project utilized a dataset comprising audio clips and corresponding transcripts, totaling 42,941 data points. However, approximately 13% of these data points were deemed unreliable and subsequently excluded based on a voting mechanism. The audio files were standardized by converting them to a 16 kHz MP3 format, while transcript characters were transformed into integer hashes. The team employed the Transformers library, optimizing batch training and matched the length of the longest sequence by padding all the other sequences in a batch.

To enhance the efficiency of the training process, portions of the audio arrays with low amplitude values at the beginning and end were removed. The dataset was further refined by selecting only sound files with durations between 1 and 9 seconds, resulting in a final dataset of 36,919 data points. The model was implemented using PyTorch, specifically leveraging a pre-trained Transformer model, \*facebook/wav2vec 2.0-large-xlsr-53\* fine-tuned for the task. The training procedure was conducted in two phases, ultimately achieving a Levenshtein Mean Distance Score of 2.60753.

The final model submission yielded a Connectionist Temporal Classification (CTC) training loss of 0.3172 and an evaluation WER of 0.2524. While further reductions in training loss were possible, the WER plateaued after approximately 77 epochs.

### 3.3.2 Google ASR

Google Automatic Speech Recognition (Google ASR) is an advanced speech recognition system developed by Google, serving as a crucial component of various Google services, including Google Assistant, Google Search, and Google Translate. This technology facilitates user interaction with devices through spoken language, transcribing speech into written text for a wide range of applications. Over time, Google ASR has undergone continuous enhancements, leading to increasingly seamless and accessible voice interactions for users globally. Its applications span multiple domains, such as voice assistants, search engines, transcription services, and voice-controlled devices. In essence, Google ASR is a powerful tool that significantly improves user interaction with Google’s services and products via spoken language.

In our study, We utilized the Google ASR API to transcribe the test audio samples from our dataset dataset.

While Google ASR performed adequately on standard Bengali, its performance deteriorated significantly when processing regional Bengali dialects. For instance, the system exhibited high CER and WER when transcribing audio from districts like Chittagong (CER: 0.943, WER: 0.984) and Kishoreganj (CER: 0.893, WER: 0.948). The primary reason for this decline in performance is that Google ASR has been trained predominantly on standard Bengali audio. Consequently, when confronted with audio clips containing regional dialects and out-of-vocabulary (OOV) words unfamiliar to the model, its transcription accuracy was markedly reduced.

### 3.3.3 Wav2Vec 2.0 Large

XLS-R has demonstrated significant advancements over previous state-of-the-art models for a range of applications, such as speech recognition, translation, diarization, and even language identification as detailed in the official documentation XLS-R and note that, YellowKing[80] was a fine-tuned version of Wav2Vec 2.0 Large XLS-R.

For our study, We conducted inferences on the test data samples from our developed corpus using a fine-tuned version of Wav2Vec 2.0 Large XLS-R, as hosted by Auditi Das on Hugging Face [91]. The Common Voice 11.0 dataset [55] was utilized to fine-tune this model.

Among the various configurations and iterations tested, the version referred to as "Yel-

lowKing” emerged as the most stable and robust performer. This Wav2Vec 2.0 model was then evaluated using the entire test split to assess its performance.

Although the model performed adequately in standard Bengali, its performance declined when applied to the regional speech dataset across all districts. This decrease in accuracy can be attributed to the model’s unfamiliarity with regional dialects, accents, and out-of-vocabulary (OOV) words.

### 3.3.4 Tugstugi (Whisper-Medium)

OpenAI’s Whisper-medium [79] is a language model designed to support a wide range of languages, including Bengali. Whisper’s capabilities extend to both transcription and translation of spoken content across multiple languages and dialects, thereby facilitating cross-linguistic communication and helping to overcome language barriers.

With training on a comprehensive dataset of 680,000 hours of labeled speech data, Whisper-medium is well-equipped to handle a wide array of languages and dialects. This variant performs robustly across both monolingual and multilingual tasks, delivering strong results in various linguistic contexts and domains. Its flexibility enables it to convert spoken language into text and translate speech across languages, enhancing cross-lingual communication.

In this study, we conducted inference on test data samples from our developed corpus utilizing a fine-tuned version of Whisper Medium, designated as Tugstugi [88], which is hosted on Hugging Face. Tugstugi emerged as the winner of the Bengali.AI Speech Recognition Competition `bengaliai-speech`. This model was fine-tuned using two distinct speech corpora, including OOD-Speech: A Large Bengali Speech Recognition Dataset for Out-of-Distribution Benchmarking [87].

### 3.3.5 Hishab-Conformer

The Conformer architecture represents a deep learning framework specifically designed for ASR and NLP tasks. Conformer models have gained significant attention due to their effectiveness in processing sequential data and their ability to achieve superior performance across various ASR benchmarks. The Conformer framework incorporates several essential components, including convolutional layers, a self-attention mechanism, and supplementary elements derived from the Transformer architecture. This hybrid approach not only allows Conformer models to efficiently handle sequential data but also

Table 3.15: Fine-tuned Conformer Parameters

| Parameters          | Value |
|---------------------|-------|
| epochs              | 16    |
| batch size          | 32    |
| sampling rate       | 16kHz |
| use start end token | True  |
| pin memory          | True  |
| number of workers   | 48    |
| trim silence        | False |
| max duration        | 18.5  |
| min duration        | 0.2   |

ensures their adaptability to diverse linguistic and environmental conditions, making them a preferred choice for both academic research and industrial applications in ASR. Conformer-based ASR models have consistently demonstrated state-of-the-art performance across numerous benchmarks, highlighting their efficacy in comprehending and transcribing spoken language.

In our study, we benchmarked a fine-tuned FastConformer model [86] developed by Hishab. This model was trained on the nearly 20,000-hour MegaBNSpeech corpus, created by the authors. The model, based on the NeMo Toolkit and utilizing a Conformer-CTC architecture, was further fine-tuned on 4,000 hours of transcribed YouTube data. A byte-pair encoding tokenizer [59] was initially developed utilizing the train split’s transcriptions.

The encoder’s weight initialization were done utilizing the pre-trained weights of Nemo English ASR during training. The training parameters are shown in the table 3.15

# Chapter 4

## Methodology

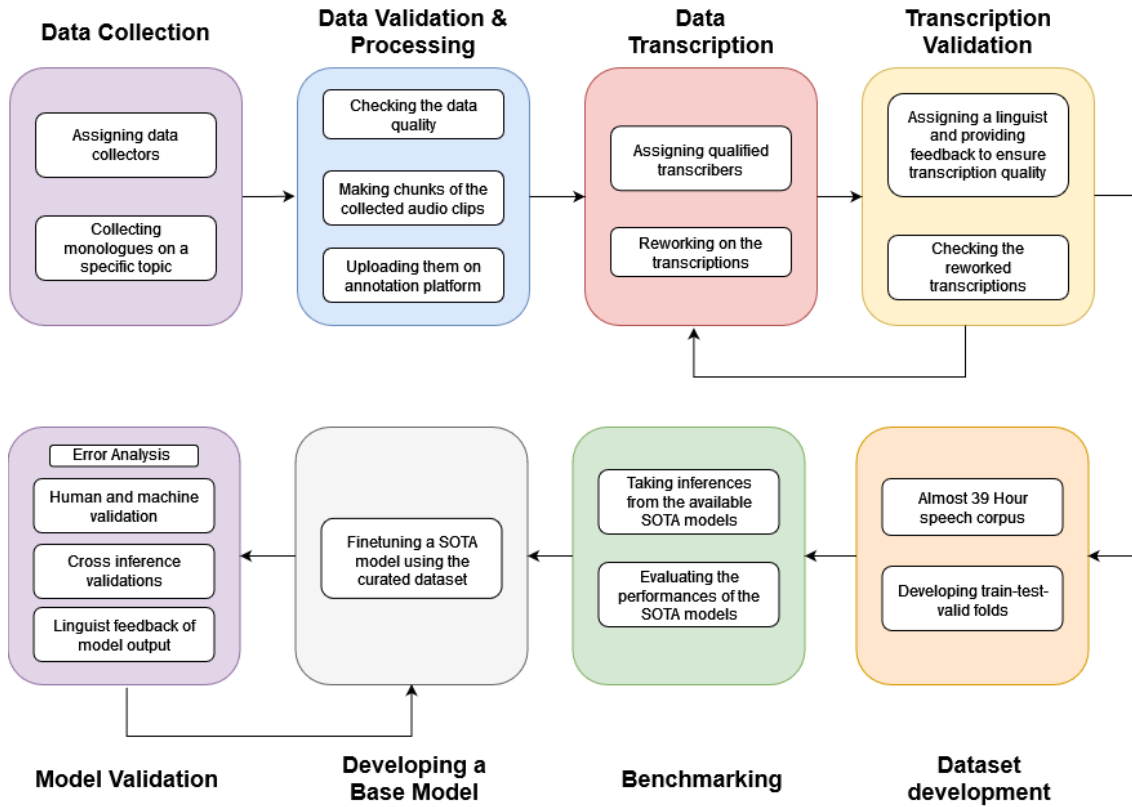


Figure 4.1: Top-level overview of the proposed methodology

In this research, we developed a speech corpus with a specific focus on regional dialects, along with a speech-to-text (STT) model designed to transcribe Bengali speech featuring regional dialectal variations, adhering to a standard orthography established by linguists. The pipeline depicted in Figure 4.1 delineates the comprehensive sequential steps to achieve our objective. This approach serves as an accelerated method for automating STT processes for low-resource languages, particularly those with numerous dialectal

variations and substantial linguistic diversity.

The diagram referenced above illustrates the comprehensive workflow for our project. In light of the absence of publicly available Bengali speech corpora specifically tailored to regional accents and dialects, we have undertaken the initiative to construct a corpus independently. This process involved the meticulous collection of data following established protocols designed to encourage spontaneous speech. Additionally, A compilation of monologues was obtained from individuals who were prompted to express their thoughts and sentiments without any restrictions or diffidence.

Following the audio data validation and processing phase, the recruitment of proficient transcribers from the different geographical regions relevant to the data was executed meticulously. This deliberate choice aimed to safeguard and enhance the quality of transcription by leveraging the transcribers' intimate familiarity with the nuances of accent and dialect present in the speech data. To ensure their linguistic competence, a comprehensive transcription examination was administered, encompassing both standard Bengali and the respective regional variations.

To further strengthen the quality assurance process, a dedicated linguist was appointed to rigorously review the transcriptions and provide constructive feedback. The transcribers then incorporated the suggested revisions and refinements, thereby fortifying the overall quality of the transcribed materials.

Following the aforementioned processes, we curated the dataset and employed an 80:10:10 partitioning strategy to divide it into training, testing, and validation subsets.

To optimize our model's performance, we fine-tuned a state-of-the-art (SOTA) model using our proprietary dataset as the training corpus. To evaluate the efficacy and competitiveness of our model, we conducted benchmark assessments by inputting our dataset into various other SOTA models and subsequently evaluating their transcription capabilities.

Additionally, we meticulously engineered an accent classifier capable of identifying and categorizing speech data based on the presence of regional accents and dialects.

Currently, our dataset comprises nearly 39 hours of speech data from five distinct districts within Bangladesh: Rangpur, Kishoreganj, Narail, Chittagong, and Narsingdi.

To summarize, through this work, we accomplished the following:

- Compiled nearly 39 hours of speech corpora specifically tailored to regional accents and dialects.
- Conducted both human and machine validation of the dataset.
- Generated benchmark results from various publicly available ASR models.

## 4.1 Data collection and validation

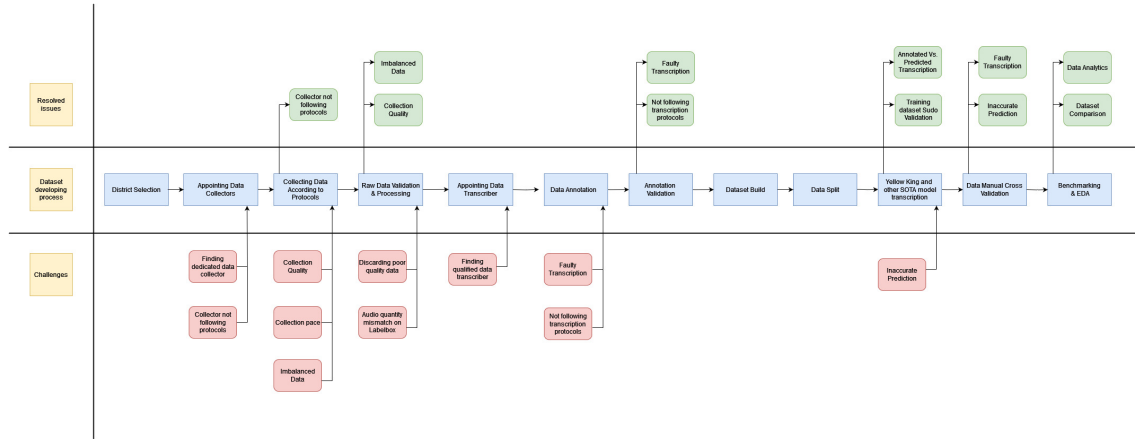


Figure 4.2: Detailed Workflow Diagram of Data Collection

Our objective was to develop a speech corpus that would enable any ASR model trained on it to accurately recognize Bengali speech from a variety of speakers across different topics, without exhibiting bias. To achieve this goal, several features were incorporated to ensure diversification, as outlined below.

1. **Voice Diversification:** To encompass a diverse array of voices and prevent bias towards any particular voice, we aimed to gather data from a wide range of individuals. Each audio clip was maintained at approximately ten minutes in duration. We targeted collecting at least 5 hours of data from each district.
2. **Gender Diversification:** To achieve a balanced gender representation, we aimed for a 50:50 ratio in the voice dataset. For a dataset comprising 5 hours of data, involving 30 individuals with each contributing 10 minutes of speech, we included 15 distinct male voices and 15 distinct female voices.
3. **Age Diversification:** Considering the changes in a person's voice with age, primarily due to reduced lung capacity and declining muscle strength and tone [90],

we incorporated age-related diversification into our speech corpus. This ensures that the ASR system trained on this corpus can effectively recognize the speech of speakers across various age groups.

4. **Topic Diversification:** To train an ASR system capable of recognizing speech across a wide range of topics and vocabulary, data collectors were guided to engage in conversations on everyday subjects. They were provided with a comprehensive list of topics, including sports, education, politics, family life, economics, and more. This approach aimed to ensure the system’s proficiency in recognizing speech on virtually any topic.
5. **Geographical Diversification:** Geography significantly impacts accent adjustment [92], affecting various aspects of human interaction and linguistic diversity.

Incorporating these diversification features, we initiated data collection from various regions. The procedure is illustrated in Figure 4.2, with details discussed below.

#### **4.1.1 District Selection**

Districts were selected based on two criteria:

1. **Available Acquaintances:** Districts where personal connections existed were chosen to receive direct assistance from known individuals or to delegate tasks as needed.
2. **Geographical Distance:** To ensure geographic diversity within the same language, districts or regions located at considerable distances from one another were selected, as languages tend to remain relatively consistent over short distances.

#### **4.1.2 Appointing Data Collectors**

In-person visits were avoided to obtain spontaneous speech samples. Additionally, being non-native to the region, there was a concern that speakers might not use their native accent while conversing with us and might not be as open compared to interactions with someone native to the area.

#### **4.1.2.1 Challenges**

1. Finding Dedicated Data Collectors: Identifying a dedicated data collector who adhered to all collection protocols was crucial to ensure the five types of diversification outlined above.
2. Collector Adherence to Protocols: Ensuring that the data collector diligently followed the protocols was essential for achieving the desired diversification in the speech corpus. Deviations in data collection could result in ASR models trained on this corpus not meeting the expected performance standards.

### **4.1.3 Collecting Data According to Protocols**

#### **4.1.3.1 Resolutions**

1. Collector Adherence to Protocols: Through manual validation of data collection, we could identify and correct potential data imbalances. This allowed us to guide the designated data collector in acquiring new data to ensure a balanced dataset.

#### **4.1.3.2 Challenges**

1. Collection Quality: The use of phone recorders by the designated data collector posed challenges such as low volume due to the device’s distance from the speaker’s mouth and the presence of background noise in the recordings.
2. Collection Pace: The rate of data collection could vary daily due to factors like weather conditions, illness, and personal commitments, affecting the consistency of data acquisition.
3. Imbalanced Data: Without adequate supervision during data collection, there was a risk of the dataset becoming imbalanced in various ways.

### **4.1.4 Raw Data Validation and Processing**

#### **4.1.4.1 Resolutions**

1. Collection Quality: At this stage, we reviewed the audio clips, categorizing those with consistently low speaker volumes and identifying clips with significant background noise.

2. **Imbalanced Data:** During manual validation, we precisely identified the nature of data imbalances and devised methods to rectify them.

#### 4.1.4.2 Challenges

1. **Discarding Poor Quality Data:** Upon thorough examination of all collected data, we excluded recordings that did not adhere to the specified protocols or exhibited notably poor quality.
2. **Audio Quantity Mismatch on Labelbox:** Following the segmentation of audio using the VAD algorithm, we force-split any segments exceeding 30 seconds, ensuring that all audio chunks conformed to this duration limit. We then processed all the samples through a filter designed to eliminate two specific types of chunks: those with sound activity but no speech, and those with speech that is inaudible. Subsequently, we uploaded these samples to the data annotation platform, Labelbox [94], in a single batch. Occasionally, a bug may prevent all chunks from being uploaded simultaneously without providing notifications. To address this, we had to run a script to verify that all chunks were successfully uploaded to Labelbox.

### 4.1.5 Appointing Data Transcribers

#### 4.1.5.1 Challenges

1. **Finding Dedicated Data Transcribers:** We hired transcribers who were residents of the same district where the data was collected. This choice provided them with an advantage as their ears were accustomed to the local accents and dialects. Applicants for the data transcription position underwent assessments with the assistance of a linguist who evaluated their scripts. The linguist selected candidates who demonstrated a strong command of Bengali spelling, grammar, and proficiency in their native accent. Following a thorough evaluation process, We selected several transcribers from the region to transcribe the audio data.

### 4.1.6 Data Annotation

I used the data annotation platform Labelbox to label the data. Transcribers were granted access to the data along with specific instructions and protocols provided by the linguist on handling the spellings of any out-of-vocabulary words. A screenshot of the interface of this annotation platform is shown in Figure 4.3.

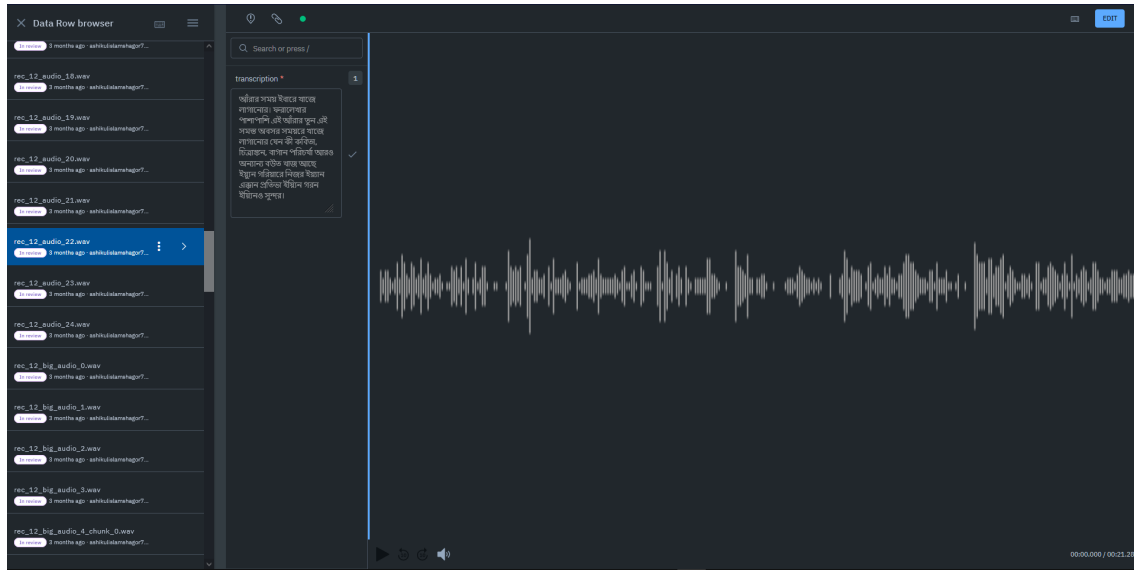


Figure 4.3: Interface of the annotation platform Labelbox

#### 4.1.6.1 Challenges

1. **Faulty Transcription:** Despite clear instructions and adherence to established protocols, human annotators may still make errors during the transcription process, even if they are minor and unintentional.
2. **Not Following Transcription Protocols:** Certain individuals might become confused and fail to grasp the protocols, resulting in errors during the transcription process.

#### 4.1.7 Annotation Validation

During the annotation process, a linguist diligently verifies spellings and transcriptions. Nonetheless, despite these efforts, occasional errors or inaccurate transcriptions may persist.

##### 4.1.7.1 Resolutions

1. **Faulty Transcription:** Once all transcriptions for a specific region are complete, they are consolidated into a CSV file along with relevant information. This file is then shared with linguists for a review and feedback process. Subsequently, transcribers revisit and rectify any erroneous transcriptions based on the linguist's feedback. This final review ensures that the dataset is accurate before its completion.

2. Not Following Transcription Protocols: If a transcriber encounters confusion or makes errors, they will rectify them through discussion with the linguist or by implementing the linguist’s feedback.

#### **4.1.8 Dataset Build**

After completing all transcriptions of the audio files, we removed entries that were null or had other problematic issues. This process resulted in a dataset that includes all relevant information for each audio clip, along with their transcriptions.

#### **4.1.9 Dataset Split**

After building the dataset, We performed 80:10:10 train-test-valid splits of the entire dataset.

#### **4.1.10 SOTA Model transcription inferences**

In this section, we performed inference on all audio samples within our dataset using cutting-edge models such as Google ASR, Wav2Vec2 large, A fine-tuned FastConformer which the authors claimed to have trained using 20,000 hours of pseudo-labeled Bengali speech data named, YellowKing (Kaggle Competition winner on the Bengali Common Voice Speech Dataset), and Tugstugi (Kaggle Competition winner on the Out-of-Domain Speech dataset). Additionally, we developed a base model by fine-tuning a pre-trained model using our proprietary training dataset.

##### **4.1.10.1 Resolutions**

1. Annotated Vs. Predicted Transcription: We computed the Word Error Rate (WER) and Character Error Rate (CER) scores for each of these inferences and our own fine-tuned model by comparing them with the human annotations in the dataset.
2. Training dataset sudo validation: During manual validation conducted by a linguist, we identified data imbalances and implemented corrective measures.

##### **4.1.10.2 Challenges**

1. Inaccurate Predictions:

We assigned a linguist to cross-check and validate the model's predictions based on several criteria:

- **Diffs.:** Comparison of the model's predictions with the human annotator's transcription to assess substantial discrepancies.
- **Word Error Rate (WER):** Quantifies the percentage of incorrect words in the predicted text compared to the human transcript.
- **Character Error Rate (CER):** Measures the percentage of inaccurate characters in the predicted text.
- **Word Insertion:** Number of additional words not present in the human transcription.
- **Word Deletion:** Number of words missing from the human transcription.
- **Word Insertion and Deletion Total:** Combined count of inserted and deleted words by the models.

Based on these criteria, samples were categorized during the manual validation process into

- **Incomplete Sentence:** Instances where the ASR models failed to transcribe all spoken words in the audio clip.
- **Incorrect Sentence:** Cases where the ASR models transcribed incorrect words or included spelling mistakes in their transcriptions.

#### **4.1.11 Data Manual Cross Validation:**

##### **4.1.11.1 Resolutions**

1. **Faulty Transcription:** At this stage, the occurrence of faulty transcriptions is minimal. Any remaining inaccuracies are identified during the comparison of model predictions with ground truths, and the annotators promptly resolve them.
2. **Inaccurate predictions:** Upon reviewing the model predictions, identified issues are documented and addressed through appropriate corrective actions. After resolving these issues, the models are retrained to improve prediction accuracy.

### 4.1.12 Benchmarking and EDA

After obtaining all predictions, we proceeded to benchmark them against predictions made by other state-of-the-art (SOTA) models developed in previous steps.

#### 4.1.12.1 Resolutions

1. Data Analysis: In this phase, comprehensive data analysis was conducted to assess metrics such as total correctly predicted words and characters. Additionally, visualizations were generated to provide insights into the dataset’s performance.
2. Dataset Comparison: We compared our dataset with other available datasets by training two different models under identical parameters on each dataset. Subsequently, we evaluated and compared their predictions to determine the suitability of our dataset for training models specific to this task.

For the modeling process, the dataset was divided and pre-processed before being input into the model. The specifics of these steps are detailed below.

## 4.2 Dataset Split

The entire dataset, totaling almost 39 hours, was divided into train, test, and validation splits with a ratio of 80:10:10. The dataset consisted of 6,667, 838, and 828 samples, totaling approximately 31:03:55, 3:51:11, and 3:51:43 hours of data, respectively. During this division, care was taken to ensure that recordings from a single speaker were included in only one of the splits. This approach facilitates a fair assessment of speaker generalization.

## 4.3 Modeling

We fine-tuned a large Wav2vec2.0 model [16], referred to as our proposed model, PX5. PX5 was fine-tuned from scratch for 100 epochs, with EarlyStoppingCallback enabled, and training concluded after 31 epochs.

### 4.3.1 Proposed Methodology

The standard implementation of Wav2vec2.0, in conjunction with the CTC algorithm, does not require a language model head or dictionary for transcription decoding. Models

like Wav2vec2.0 utilize the Wav2Vec2Tokenizer, which typically performs tokenization at the subword level as shown in the simplified architecture in Fig 4.4.

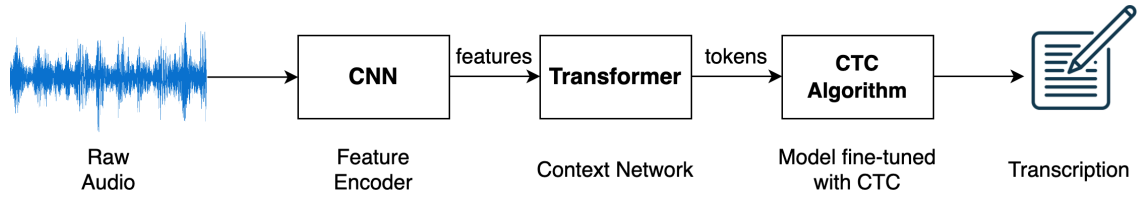


Figure 4.4: Simplified architecture of Wav2vec 2.0

While subword units can represent phonemes, syllables, or smaller linguistic elements, they effectively capture speech patterns and enhance the overall performance of the model in speech recognition/processing tasks. However, due to the significant diversity in local dialects and non-standard vocabularies in regional speech, we introduced a character-level n-gram language model. The architecture of our proposed methodology is illustrated in Fig 4.5.

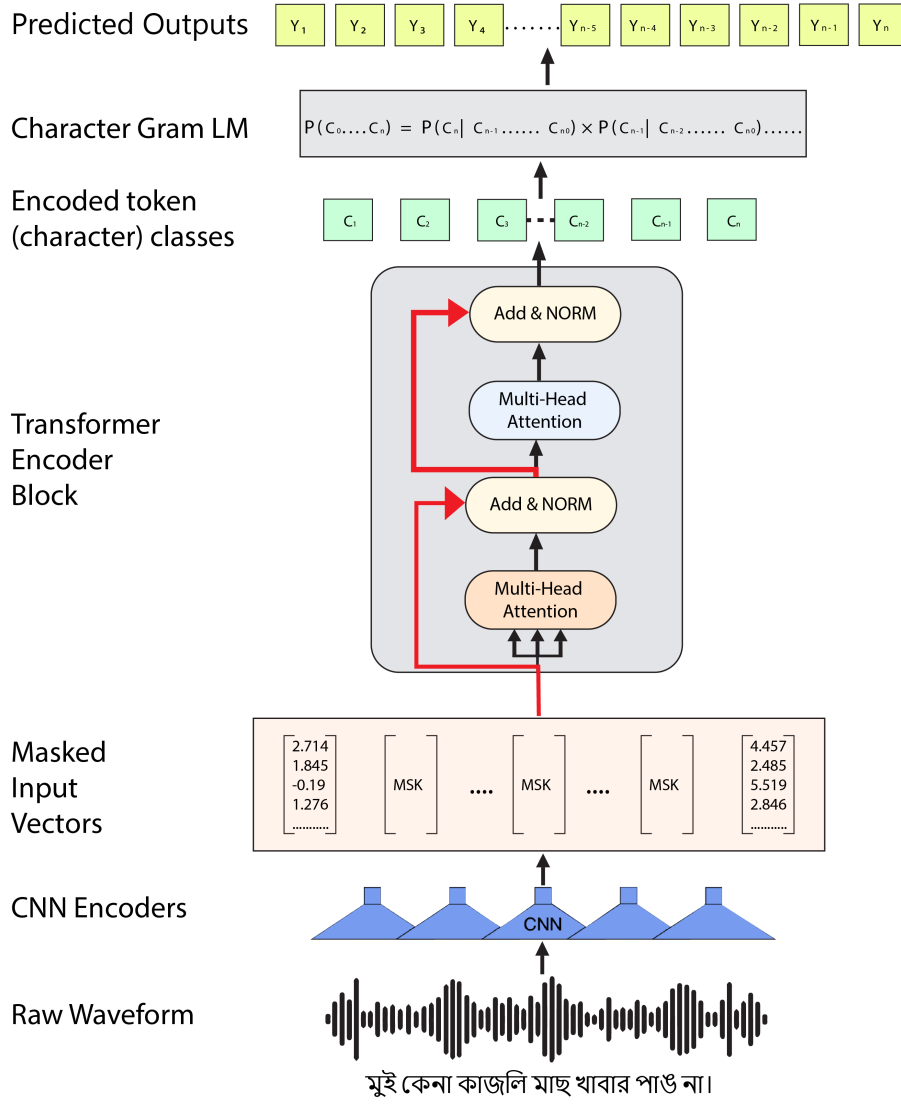


Figure 4.5: PX5 model architecture

This ASR system leverages self-supervised learning and transformers to efficiently decode audio signals into textual characters, making it particularly well-suited for low-resource languages like Bengali. The CNN encoders focus on feature extraction from the raw audio signal, while the masked modeling and transformer-based context capturing enable robust representations. The character gram language model further refines the output by modeling dependencies between characters, ensuring coherent transcriptions aligned with Bengali phonetics and grammar. A detailed breakdown of each component of this system is described below.

1. **Raw Waveform (Input):** The system begins by receiving the raw audio waveform as input, representing the speech signal of the speaker. The waveform is a continuous-time signal containing rich acoustic information, which must be pro-

cessed into discrete feature vectors for further analysis.

2. **CNN Encoders (Feature Extraction):** The raw waveform is passed through a series of CNN layers, which act as feature extractors. During this phase, the model learns a latent representation of audio, encoding it into high-level features that are abstracted from the raw signal converted by the CNN encoders. These features capture important information from the input audio, like speech patterns, and reduce the temporal dimension of the input, enabling the extraction of essential features such as phonetic information and temporal dependencies and are passed to the fine-tuning phase. However, they do not explicitly map to acoustic units like phonemes or syllables.

These feature vectors form the backbone of the speech encoding process, feeding into the subsequent layers for more abstract representation.

3. **Masked Input Vectors (Self-Supervised Learning):** In this stage, portions of the feature vectors are masked (hidden), indicated by the "MSK" markers. This is an essential part of the self-supervised pretraining phase in models like wav2vec 2.0. The model is tasked with predicting the masked portions of the input, forcing it to learn robust and informative representations of the speech signal without relying on labeled data. This method allows for efficient learning from large amounts of unannotated speech data, which is particularly beneficial for low-resource languages like Bengali.

4. **Transformer Encoder Block (Contextual Representation):** The masked input vectors are fed into a Transformer Encoder Block. The transformer architecture, featuring Multi-Head Attention mechanisms, enables the model to capture long-range dependencies within the speech sequence. It effectively models the global context by attending to different parts of the input sequence simultaneously.

This is crucial in ASR systems as speech sounds can have contextual dependencies that are far apart in time. By employing multiple attention heads, the transformer encoder can focus on various parts of the input sequence and integrate contextual information from diverse perspectives.

The Add and Normalize layers ensure that the model retains stable gradients during training and maintain layer consistency after the multi-head attention operations.

5. **Encoded Token (Character Classes):** The output from the transformer encoder block is a sequence of context-rich encoded tokens. These tokens represent high-

level abstractions of the input speech signal and are mapped to a specific class, which in this case, corresponds to characters in the Bengali alphabet. The model tries to predict the next character based on the acoustic features, and decoding happens on a per-character basis, where each encoded token translates to a character from the transcript. Each token is representing learned latent speech representations, an embedding containing both local acoustic information and global context, suitable for decoding into text.

6. Character Gram Language Model (LM): A character-level n-gram language model is used to decode the sequence of encoded tokens into a sequence of characters. This model estimates the probability of a character sequence given the context. The equation shown represents the joint probability of the character sequence  $C_1, C_2, \dots, C_n$  being the correct transcription, which is computed as the product of individual conditional probabilities:

$$P(C_1, C_2, \dots, C_n) = P(C_1) \times P(C_2 | C_1) \times P(C_3 | C_1, C_2) \times \dots \times P(C_n | C_1, C_2, \dots, C_{n-1}) \quad (4.1)$$

This ensures that the decoded output respects the character-level dependencies typical in Bengali regional scripts, improving the quality of transcription.

7. Predicted Outputs (Textual Representation): Finally, the system outputs the predicted sequence of characters, which forms the textual representation of the input speech. The model directly maps from audio features to characters as outputs without incorporating any acoustic unit discovery system. In this case, the predicted characters represent Bengali regional dialect texts, decoding the original audio input into a readable transcription in the target language.

## 4.4 Benchmarking

For benchmarking our fine-tuned model, We picked different state-of-the-art ASR models for Bengali. We involved popular speech API, and existing benchmark models used by the community. We do diverse benchmarking on our curated dataset. As the popular speech API, we used the Conformer-based `conformerModel` Google’s speech-to-text cloud service API.

Google’s cloud speech-to-text API was employed in its default configuration, without any fine-tuning. In contrast, a fine-tuned model [91] of Meta’s Wav2Vec 2.0, trained using the Bengali Common Voice Speech Dataset [55], was used for benchmarking purposes. We also benchmarked two competition winner models: Yellowking [80] (The winner of the DLSprint Competition `dlsprint` ) and Tugstugi [88] (The winner of Bengali.AI Speech Recognition Competition `bengaliai-speech`). Yellowking is a Wav2vec2 large [56] based and Tugstugi is a Whisper Medium [79] based finetuned model which was fine-tuned on 2 different speech corpus. Yellowking was fine-tuned on Bengali Common Voices Dataset [75] for about 70 hours on Kaggle GPUs and Tugstugi was fine-tuned on OOD-Speech: A Large Bengali Speech Recognition Dataset for Out-of-Distribution Benchmarking. [87] speech corpus. We also evaluated the Hishab Conformer [86] model which the authors have claimed to have trained on 20k hours of Pseudolabelled Bengali speech data.

We collected the inference results of all the available and traditional state-of-the-art deep learning models for automatic speech recognition using the samples from the test split of our curated dataset.

We evaluated their performance by calculating the average Word Error Rate (WER) and Character Error Rate (CER) of all the inference outputs from each of the models against human-annotated ground truth from regional sources and then compared it with our model performance. The outcomes are depicted in Table 6.2.

# Chapter 5

## Dataset Statistics, EDA and Feature Extractions

In this chapter, we delved deep into our developed speech corpus with regional Bengali dialects by showing all the statistics, exploratory data analysis, and relevant feature extraction from our corpus.

### 5.1 Dataset

This section shows all the corpus statistics of our corpus. In this section, we also illustrated how this regional speech corpus deviates from any standard Bengali speech corpus. We have used OOD-Speech: A Large Bengali Speech Recognition Dataset for Out-of-Distribution Benchmarking [87] as the reference corpus for standard Bengali.

#### 5.1.1 Bengali Speech Corpus with regional dialects

The dataset encompasses five districts in Bangladesh: Rangpur, Kishoreganj, Narail, Chittagong, and Narsingdi. Predominantly comprising spontaneous speech, it also includes a small amount of monologues and phone-recorded conversations from each district. Further details specific to each district are provided in the following table 5.1.

Table 5.1: Overview of Bengali Speech Corpus Regional Dialects

| Districts   | Duration            | Total chunks | Average chunk size | Type        |
|-------------|---------------------|--------------|--------------------|-------------|
| Rangpur     | 6 Hour 1 Minutes    | 1,298        | 16.55 seconds      | Spontaneous |
| Kishoreganj | 9 Hour 36 Minutes   | 2,048        | 16.71 seconds      | Spontaneous |
| Narail      | 8 Hour 36 Minutes   | 1,859        | 16.58 seconds      | Spontaneous |
| Chittagong  | 8 Hour 11 Minutes   | 1,757        | 16.67 seconds      | Spontaneous |
| Narsingdi   | 6 Hour 20 Minutes   | 1,371        | 16.51 seconds      | Spontaneous |
| Total       | 38 Hours 46 Minutes | 8,333        | 16.604 seconds     | Spontaneous |

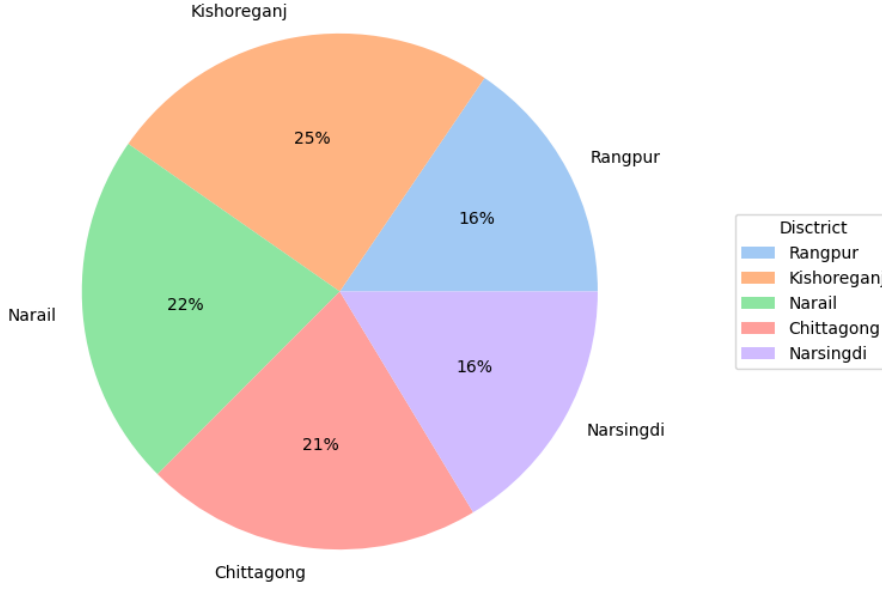


Figure 5.1: Pie chart of the corpus covering each district

### 5.1.2 About the corpus

The corpus has 8,333 chunk samples resulting from 178 speech recordings where the data was split into 80:10:10 train-test-valid split resulting in 31 hour 3 minutes, 3 hour 51 minutes, and 3 hour 51 minutes of audio data in each fold. In the metadata, Each chunk is accompanied by an 'External\_ID', 'Districts', and 'Contents' which is the chunk transcription done by human annotators.

A detailed overview of the corpus is shown in the table 5.2

Table 5.2: Regional Speech Corpus Statistics.

↔ denotes subsets | WPM = Avg. Words Per Minute | WPS = Avg. Words Per Sample | H:M:S = Hour(s) : Minute(s) : Second(s)  
| OOV = Words Out of Canonical Standard Bengali Vocabulary in comparison to the unique words of the corpus  
| Annotation Complexity is measured by the time needed to annotate every unit of data.

| Subset                               | Samples | Duration<br>(H:M:S) | Avg Rec.<br>len. | WPM     | WPS    | Uniq.<br>Words | OOV<br>% | Characteristic<br>Phones Pair Count | Avg. Phone<br>length perc(%) | Annot.<br>Compl. |
|--------------------------------------|---------|---------------------|------------------|---------|--------|----------------|----------|-------------------------------------|------------------------------|------------------|
| Bengali Regional Speech Dataset      |         |                     |                  |         |        |                |          |                                     |                              |                  |
| Die-alect Dataset (Cumulative)       | 8,333   | 38:46:49            | 16.754           | 132.429 | 36.965 | 41,878         | 70.125   | 12                                  | 0.982                        | 118.5            |
| ↔ Die-alect Train                    | 6,667   | 31:03:55            | 16.774           | 133.68  | 37.355 | 36,177         | 68.834   | —                                   | 0.987                        | 54.6             |
| ↔ Die-alect Test                     | 838     | 3:51:11             | 16.553           | 130.61  | 36.004 | 8,244          | 55.471   | —                                   | 0.999                        | 221.02           |
| ↔ Die-alect Valid                    | 828     | 3:51:43             | 16.791           | 124.74  | 34.801 | 7,393          | 55.079   | —                                   | 0.999                        | 221.02           |
| Region-wise breakdown of the dataset |         |                     |                  |         |        |                |          |                                     |                              |                  |
| Rangpur (Cumulative)                 | 1,298   | 6:00:57             | 16.685           | 134.022 | 37.171 | 8,827          | 51.263   | 5                                   | 0.989                        | 21.286           |
| ↔ Rangpur Train                      | 1,037   | 4:48:58             | 16.719           | 134.34  | 37.310 | 7,512          | 49.255   | —                                   | 1.025                        | 21.627           |
| ↔ Rangpur Test                       | 130     | 0:35:15             | 16.269           | 122.657 | 33.023 | 1,642          | 38.733   | —                                   | 1.038                        | 19.901           |
| ↔ Rangpur Valid                      | 131     | 0:36:44             | 16.822           | 146.25  | 40.191 | 1,761          | 38.785   | —                                   | 1.038                        | 19.901           |
| Kishoreganj (Cumulative)             | 2,048   | 9:36:51             | 16.90            | 116.651 | 32.808 | 13,149         | 64.864   | 2                                   | 0.987                        | 18.895           |
| ↔ Kishoreganj Train                  | 1,638   | 7:42:30             | 16.941           | 117.665 | 33.187 | 11,477         | 64.364   | —                                   | 0.987                        | 19.303           |
| ↔ Kishoreganj Test                   | 206     | 0:58:58             | 16.55            | 112.835 | 31.129 | 3,469          | 50.403   | —                                   | 0.998                        | 17.245           |
| ↔ Kishoreganj Valid                  | 204     | 0:55:23             | 16.287           | 108.327 | 29.206 | 1,778          | 53.993   | —                                   | 0.998                        | 17.245           |
| Narail (Cumulative)                  | 1,859   | 8:36:52             | 16.68            | 136.12  | 37.783 | 10,960         | 57.409   | 6                                   | 0.971                        | 8.74             |
| ↔ Narail Train                       | 1,488   | 6:52:29             | 16.63            | 138.442 | 38.332 | 9,478          | 56.552   | —                                   | 0.971                        | 8.576            |
| ↔ Narail Test                        | 188     | 0:51:57             | 16.69            | 127.262 | 25.402 | 3,387          | 44.133   | —                                   | 0.983                        | 9.387            |
| ↔ Narail Valid                       | 183     | 0:52:25             | 17.188           | 117.038 | 33.257 | 1,977          | 42.792   | —                                   | 0.983                        | 9.387            |
| Chittagong (Cumulative)              | 1,757   | 8:11:47             | 16.794           | 134.189 | 37.50  | 11,105         | 63.503   | 6                                   | 0.980                        | 13.35            |
| ↔ Chittagong Train                   | 1,406   | 6:35:54             | 16.89            | 136.618 | 38.381 | 9,517          | 61.868   | —                                   | 0.981                        | 12.02            |
| ↔ Chittagong Test                    | 177     | 0:47:26             | 16.26            | 125.010 | 33.901 | 3,379          | 63.482   | —                                   | 0.992                        | 18.91            |
| ↔ Chittagong Valid                   | 174     | 0:48:27             | 16.707           | 115.583 | 31.885 | 1,915          | 56.397   | —                                   | 0.992                        | 18.91            |
| Narsingdi (Cumulative)               | 1,371   | 6:20:23             | 16.65            | 148.597 | 41.187 | 10,745         | 53.160   | 2                                   | 0.982                        | 29.228           |
| ↔ Narsingdi Train                    | 1,098   | 5:04:04             | 16.616           | 148.0   | 40.976 | 9,160          | 52.336   | —                                   | 0.982                        | 28.319           |
| ↔ Narsingdi Test                     | 137     | 0:37:35             | 16.59            | 150.338 | 41.560 | 3,265          | 37.579   | —                                   | 0.992                        | 32.843           |
| ↔ Narsingdi Valid                    | 136     | 0:38:44             | 17.091           | 156.789 | 43.809 | 1,718          | 39.464   | —                                   | 0.992                        | 32.843           |

The phoneme deviation of the regional Bengali from the standard Bengali can be observed in the table 5.3 in (Standard Bengali, Regional Bengali) template.

Table 5.3: Regional Phoneme Characteristics Pairs (Standard, Region)

| Subset            | Phoneme characteristic pairs                                                                                                                                        | Count |
|-------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| Rangpur           | (h, <sup>h</sup> ), (h, <sup>h̃</sup> ), (k, t), (t, n), (n, p)                                                                                                     | 5     |
| Kishoreganj       | ( <sup>h</sup> , h), (j, z)                                                                                                                                         | 2     |
| Narail            | (h, <sup>h</sup> ), (h, <sup>h̃</sup> ), (k, t), (t, n), (n, p), (j, z)                                                                                             | 6     |
| Chittagong        | (c, ç), (cc, çç), (j, z), (p, f), (p <sup>h</sup> , f), (p <sup>h</sup> , ff)                                                                                       | 6     |
| Narshingdi        | ( <sup>h</sup> , h), (j, z)                                                                                                                                         | 2     |
| Die-alect Dataset | (h, <sup>h</sup> ), (h, <sup>h̃</sup> ), (k, t), (t, n), (n, p), (j, z), ( <sup>h</sup> , h), (c, ç), (cc, çç), (p, f), (p <sup>h</sup> , f), (p <sup>h</sup> , ff) | 12    |

### 5.1.3 Corpus statistics

The complete corpus consists of 8,333 audio segments, totaling 38 hours, 46 minutes, and 49 seconds of data collected from five regions. The average segment length is 16.754 seconds, with a speech rate of 132.429 words per minute and an average of 36.965 words per segment. The corpus contains 41,878 unique words, with 70.125% out of words vocabulary.

#### 5.1.3.1 Train fold statistics

The train split comprises 6,667 audio segments, amounting to 31 hours, 3 minutes, and 55 seconds of data collected from five regions. The average segment duration is 16.774 seconds, with a speech rate of 133.68 words per minute and an average of 37.355 words per segment. The corpus includes 36,177 unique words, with 68.834% out of vocabulary words.

#### 5.1.3.2 Test fold statistics

The test split consists of 838 audio segments, totaling 3 hours, 51 minutes, and 11 seconds of data gathered from five regions. The average segment duration is 16.553 seconds, with a speech rate of 130.61 words per minute and an average of 36.004 words per segment. The corpus contains 8,224 unique words, with 55.471% out of vocabulary words.

#### 5.1.3.3 Valid fold statistics

The validation split comprises 828 audio segments, totaling 3 hours, 51 minutes, and 43 seconds of data collected from five regions. The average segment duration is 16.791 seconds, with a speech rate of 124.74 words per minute and an average of 34.801 words per segment. The corpus includes 7,393 unique words, with 55.079% out of vocabulary words.

#### 5.1.4 Corpus Diversifications

#### 5.1.5 Word and Grapheme Diversity

Figure 5.2 displays the different regions from which the data were collected, and table 5.3 illustrates the unique phonetic elements from each of those regions. In each phoneme pair, the first phoneme represents the conventional standard, while the second is the local variant used by inhabitants as a substitute for the standard phonetic sound.

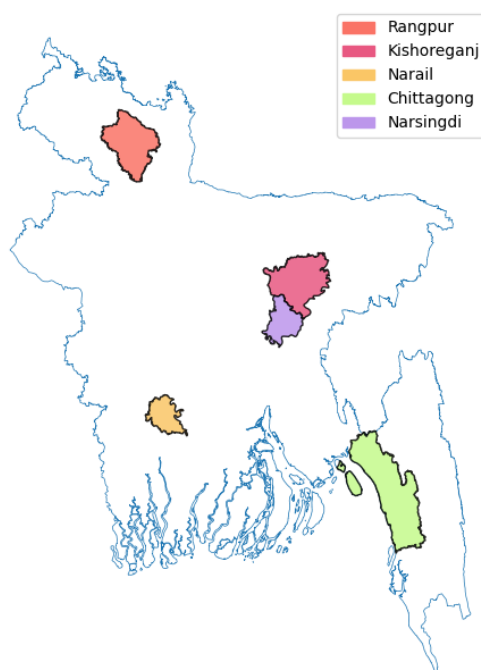


Figure 5.2: Mapped regions of the dialects along with reference point

Linguistic diversification is more conspicuous when two regions are geographically far apart from one other such as Rangpur, Chittagong, and Narail, which are farther from each other. Conversely, regions closer to each other or geographically adjacent regions such as Kishoreganj and Narsingdi, tend to exhibit similar levels of graphemic diversity. This suggests minimal linguistic variation within these neighboring areas, supporting the notion of mutual intelligibility [53].

Notably, the graphemic diversity observed in the Chittagong subregion is unique to that

area, reflecting a distinct collection of dialects specific to this region.

For a more comprehensive understanding, Table 5.4 demonstrates how an identical sentence is articulated differently across various regions, each employing a distinct set of words.

Table 5.4: Different pronunciation of the same sentence with IPA table

| Subset           | Bengali text                                | IPA Transcription                                |
|------------------|---------------------------------------------|--------------------------------------------------|
| Standard Bengali | সামনে ইদ, ইদের কেনাকাটা করতে হবে ভাই!       | ʃemne id̪, id̪er kenəkata kɔɽte hɔbe bʰaɪ!       |
| Rangpur          | সামনোত ইদ, ইদের কেনাকাটা কইরবার নাগবে, ভাই! | ʃemnoʈo id̪, id̪er kenəkati koɪrbar nəgbe, bʰaɪ! |
| Kishoreganj      | সামনে ঈদ, ঈদের কিনাকাডা করন লাগবো ভাই।      | ʃemne id̪, id̪er kinəkəɽə kɔron ləgbo bʰaɪ!      |
| Narail           | ছামনে ঈদ, ঈদির কিনাকাটা ওত্তি অবো ভাই!      | cʰemne id̪, id̪ir kinəkəɽə oʈʈi ɔbe bʰaɪ!        |
| Chittagong       | সামনো দি ঈদ, ঈদির কিনাকাটা গরন ফরিবু বাই।   | ʃemno d̪i id̪, id̪or kinəkəɽə gɔron pʰoribu baɪ! |
| Narsingdi        | সামনে ইদ, ইদের কিনাকাডা করুন লাগবো ভাই।     | ʃemne id̪, id̪er kinəkəɽə kɔrun ləgbo bʰaɪ!      |

### 5.1.6 Voice or speech Diversity

During the development of this corpus, we aimed to ensure maximum diversity and representation in the speech data. We attempted to standardize the length of each sample to approximately 10 minutes. If a sample exceeded 10 minutes, the data collector was instructed to balance this by gathering additional, shorter samples from other individuals. Conversely, if a sample was shorter than 10 minutes, the collector was directed to obtain longer samples from other participants. Recognizing that vocal characteristics vary with age, we also endeavored to collect speech data from individuals of all age groups within each region through our assigned data collectors.

### 5.1.7 Gender Diversity

This speech corpus comprises data from a minimum of 183 speakers, including approximately 50% male and 42.7% female participants. Additionally, 7.303% of the samples feature multiple speakers from both genders, resulting in 89 male speakers, 76 female speakers, and 13 clips with multiple speakers representing both genders.

### 5.1.8 Geographical Diversity

Although a single region may encompass multiple dialects [62], data collection was conducted across various subregions within each region to capture the diversity of dialects and ensure geographical representation. In total, 31 subregions were covered across

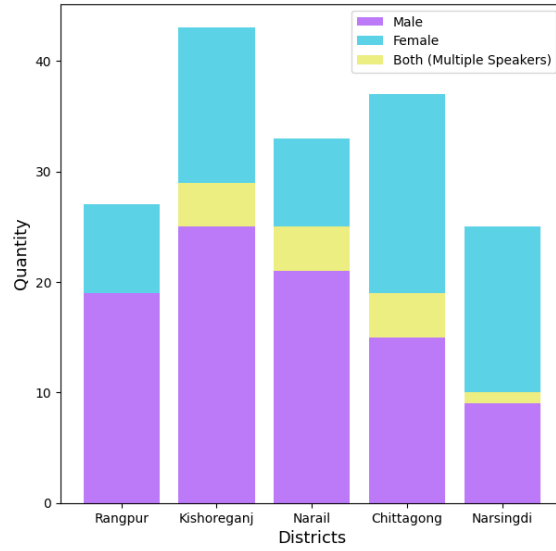


Figure 5.3: Gender quantity in the Regional Speech Corpus

the 5 districts from which speech was collected, namely Rangpur, Kishoreganj, Narail, Chittagong, and Narsingdi. These districts correspond to 1, 3, 17, 7, and 2 subregions, respectively, as detailed in Table 5.5.

Table 5.5: Subregions covered from each district

| Districts   | Subregions                                                                                                                                                                |
|-------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Rangpur     | Kamarpara                                                                                                                                                                 |
| Kishoreganj | Pakundia, Bhairab,Bogadiya                                                                                                                                                |
| Narail      | Barakalia, Chotta Kalia, Kartikpur, Mirzapur, Ramnagar, Joka, Baka, Patna, Chandpur, Uthali, Jogania, Kalabaria, Pahardanga, Bil Bauchh, Joypur, Baidhyarbati, Gachhbaria |
| Chittagong  | Nalanda, Satkania, Patharghata, Rangunia, Potiya, Hathazari, Boalkhali                                                                                                    |
| Narsingdi   | Polashtoli, Madhabdi                                                                                                                                                      |
| Total       | 30                                                                                                                                                                        |

### 5.1.9 Topic diversification

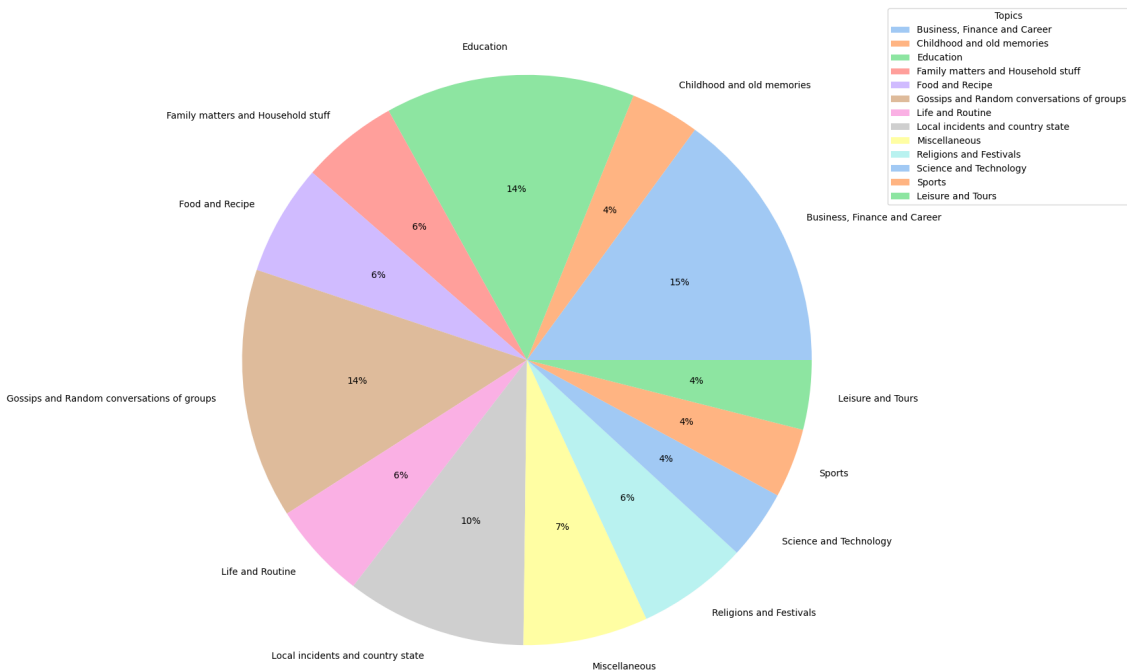


Figure 5.4: All subcategories of topics in the dataset

The dataset comprises speeches on 64 unique topics, categorized into 13 distinct categories. These categories are further organized into various subgroups of clusters, as illustrated in Figure 5.4.

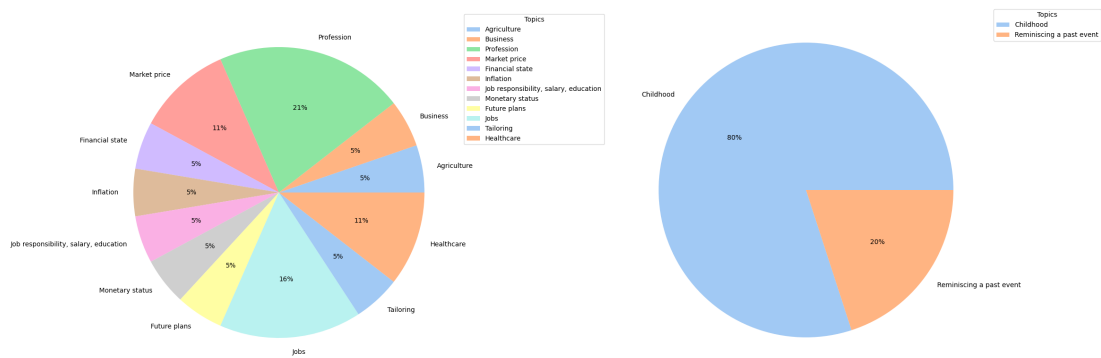


Figure 5.5: (Left) Topics in the "Business, Finance and Career" subcategory and (Right) Topics in the "Childhood and old memories" subcategory

#### 5.1.9.1 Business, Finance and Career

This subcategory encompasses topics related to Business, Finance, and Career, as detailed on the left of Figure 5.5. The majority of the topics pertain to individuals' professional

roles, job responsibilities, educational qualifications, and various professions through which they earn a livelihood. Given that a significant portion of the data was collected from rural areas, discussions frequently focused on agriculture, tailoring, and healthcare. Additionally, the subcategory includes topics such as market prices, inflation, financial conditions, and the monetary status of families or individuals.

#### 5.1.9.2 Childhood and old memories

This subcategory encompasses topics related to nostalgia, as depicted on the right of Figure 5.5. It includes discussions about childhood experiences, past living conditions, and reflections on various events from the past. The majority of the conversations focus on childhood memories.

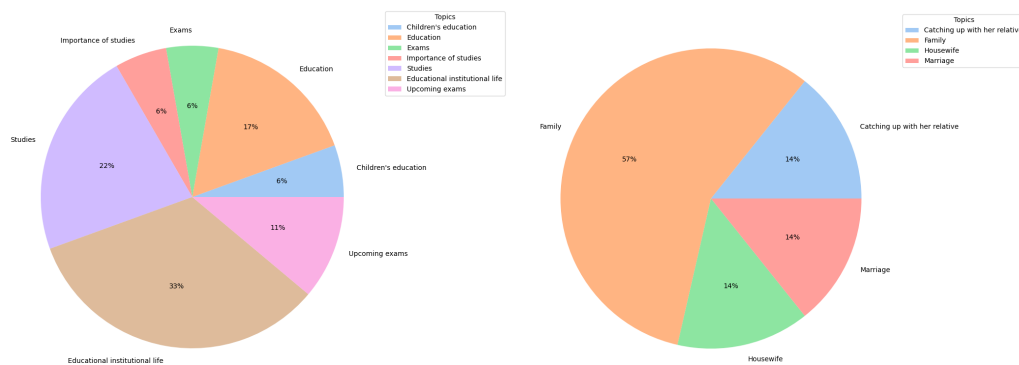


Figure 5.6: (Left) Topics in the "Education" subcategory and (Right) Topics in the "Family matters and Household stuff" subcategory

#### 5.1.9.3 Education

This subcategory addresses topics related to education, as detailed on the left of Figure 5.6. It primarily features discussions by students about their examinations, academic institutions, and the subjects they are studying.

#### 5.1.9.4 Family matters and Household stuff

This subcategory encompasses topics related to family and household affairs, as illustrated on the right of Figure 5.6. The discussions are predominantly conducted by older women and focus on familial matters and domestic issues within their households.

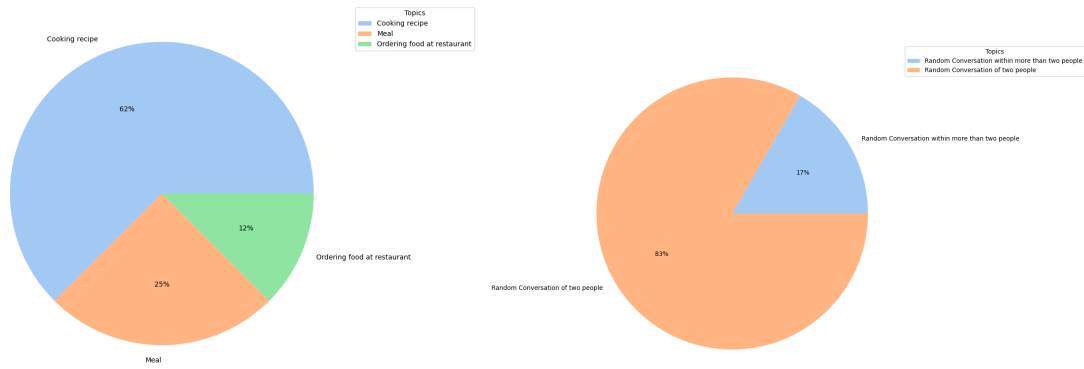


Figure 5.7: (Left) Topics in the "Food and Recipe" subcategory and (Right) Topics in the "Gossips and Random conversations of groups or individuals" subcategory

#### 5.1.9.5 Food and Recipe

This subcategory addresses topics related to culinary matters, as depicted on the left of Figure 5.7. The discussions are primarily conducted by women and housewives, focusing on various recipes and food-related topics.

#### 5.1.9.6 Gossips and Random Conversations of Groups or individuals

This subcategory primarily encompasses casual gossip or conversations among two or more individuals within a group, as illustrated on the right of Figure 5.7. The discussions often shift between topics, reflecting the spontaneous nature of the speech. The data collector was instructed not to interfere during these interactions. In some sample clips from this subcategory, there are more than two speakers, including the data collector.

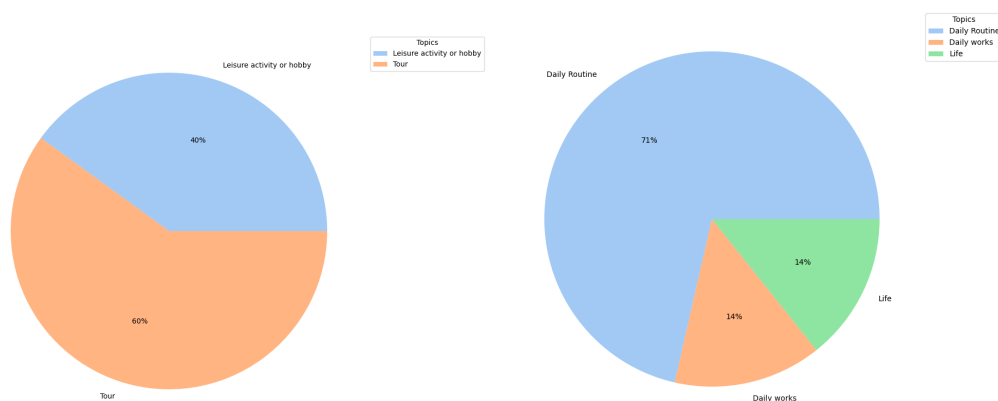


Figure 5.8: (Left) Topics in the "Leisure and Tours" subcategory and (Right) Topics in the "Life and Routine" subcategory

### 5.1.9.7 Leisure and Tours

This subcategory includes topics related to hobbies and travel, as shown on the left of Figure 5.8. The discussions cover various hobbies pursued by the speakers and the different trips they have planned or experienced with friends to various locations.

### 5.1.9.8 Life and Routine

This subcategory encompasses topics related to individuals' daily life and activities, as illustrated on the right of Figure 5.8. The majority of the speakers are students, and their discussions focus on the routine activities and daily experiences they encounter.

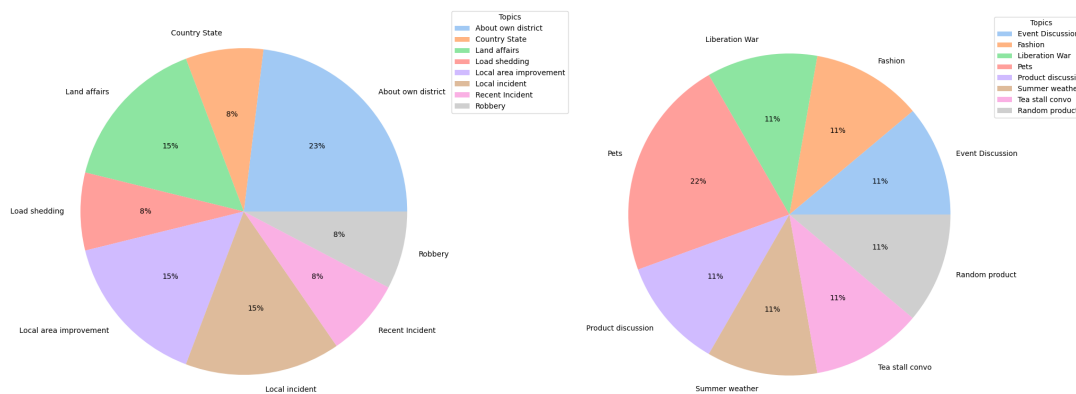


Figure 5.9: (Left) Topics in the "Local incidents and country state" subcategory and (Right) Topics in the "Miscellaneous" subcategory

### 5.1.9.9 Local incidents and country state

This subcategory addresses topics related to recent incidents occurring in the speakers' vicinity, as shown in Figure 5.9. The speakers, predominantly from rural areas, discuss various local issues, potential solutions, district-specific matters, local politics, and recent events within their communities.

### 5.1.9.10 Miscellaneous

This subcategory includes topics related to various miscellaneous subjects, as illustrated in Figure 5.9. The discussions encompass a range of topics, including different types of pets, fashion, and other diverse interests.

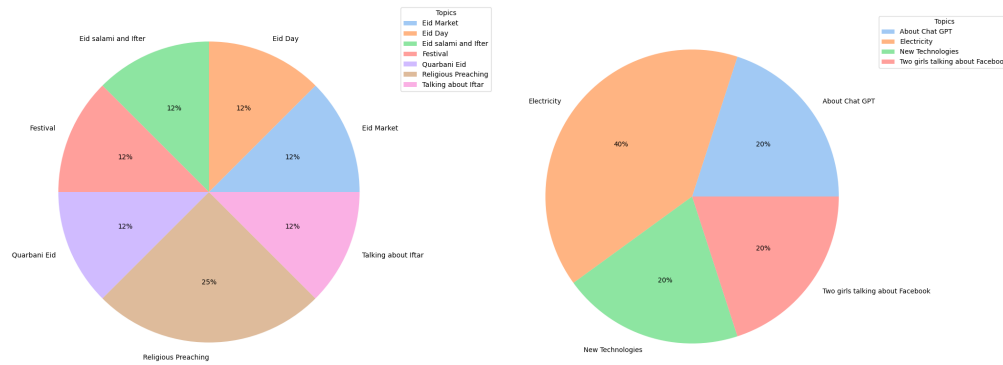


Figure 5.10: (Left) Topics in the "Religions and Festivals" subcategory and (Right) Topics in the "Science and Technology" subcategory

#### 5.1.9.11 Religions and Festivals

This subcategory addresses topics related to religious activities. Given the predominantly Muslim population in the regions, the conversations primarily focus on Eid and associated practices. The topics and their distributions are presented on the left of Figure 5.10.

#### 5.1.9.12 Science and Technology

This subcategory encompasses topics related to technology, as detailed on the right of Figure 5.10. Given that the majority of the data were collected from rural areas where stable electricity is a prevalent issue, discussions predominantly focus on this topic.

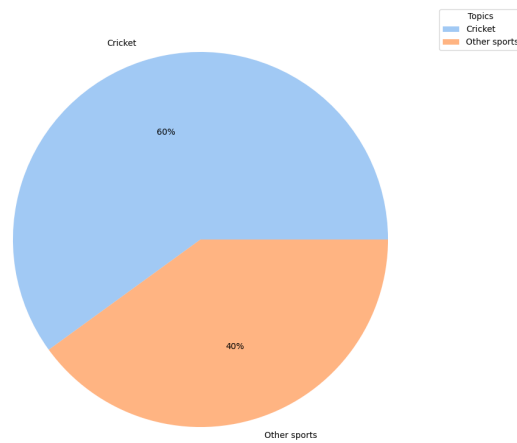


Figure 5.11: Topics in the "Sports" subcategory

#### 5.1.9.13 Sports

This subcategory includes topics related to sports, as shown in Figure 5.11. Given that cricket is the most popular sport in the subcontinent, the majority of discussions within this subcategory focus on cricket.

## 5.2 Exploratory Data Analysis and Feature Extraction

In this chapter, we delved deep into our developed speech corpus with regional Bengali dialects by doing some exploratory data analysis and relevant feature extraction and also illustrated how this regional speech corpus deviates from any standard Bengali speech corpus. We have used the OOD-Speech: A Large Bengali Speech Recognition Dataset for Out-of-Distribution Benchmarking [87] as the reference corpus for standard Bengali.

### 5.2.1 Exploratory Data Analysis

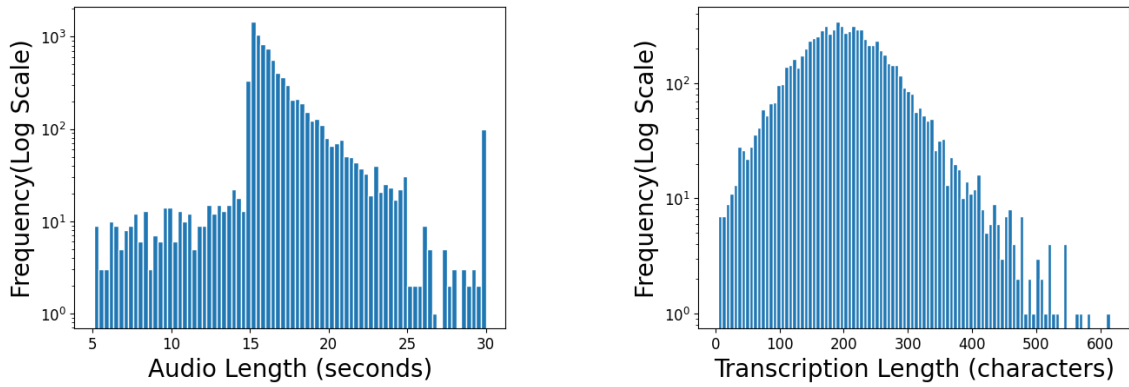


Figure 5.12: (Left) Audio length distribution of the regional Bengali dialect corpus (Right) Transcription length distribution of the regional Bengali dialect corpus

On the left of Figure 5.12 illustrates that the majority of the recordings have durations between 15 and 25 seconds, with a maximum length of 30 seconds. Additionally, on the right of Figure 5.12, it is demonstrated that there is no significant correlation between transcript character count and audio length.

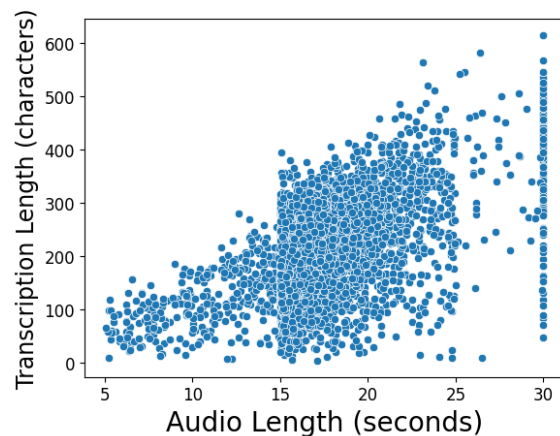


Figure 5.13: Transcription length vs audio length distribution of the regional Bengali dialect corpus

Although we do not observe any peculiar long transcripts for shorter audio recordings, the opposite is observed in several cases as we can see in Figure 5.13. Upon further investigation, these samples were found to be characterized by high levels of background noise, incomprehensible speech, or transcription errors.

## 5.2.2 Feature Extraction

### 5.2.2.1 Comparison with Standard Bengali

To evaluate the feature diversity within the Promito Bengali or Standard Bengali language dataset, we extracted Geneva speech features from 10,000 samples from the referred standard Bengali speech corpus [87] and compared them with our regional Bengali dialect speech corpus.

Figure 5.14 depicts the long-term spectral average (LTSA) across different dialects. The analysis reveals that dialects not only diverge semantically but also spectrally. This observation indicates a significant distribution shift between some dialectal data and others. Given that the same recording protocol was adhered to, this shift is likely attributed to prosodic variations inherent in the different dialects.

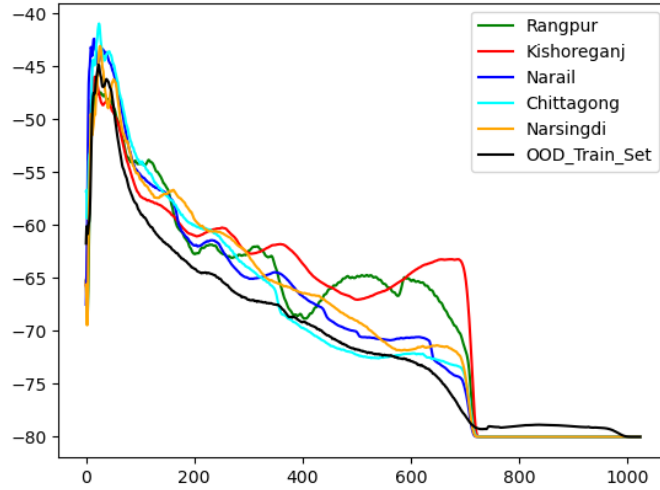


Figure 5.14: Long-Term Spectral Average plot of the regional Bengali dialect corpus

Additionally, we visualized the differences by plotting log-histograms of Geneva features for two sections: one representing regional district dialect speech data and the other representing Standard Bengali speech data. These comparisons encompassed various parameters, including pitch, loudness, and spectral attributes. The analysis revealed distinct variations in these parameters, as depicted on the left of Figures 5.15 for Bengali speech with regional dialects and on the right of 5.15 for standard Bengali speech. Each audio sample consisted of 88 features.

We further examined the distribution shift using Figure 5.16, which focuses on a specific feature, with 'ancholic' encompassing all the regional Bengali dialect audios and 'porimito' representing 10,000 samples from Standard Bengali speech data. Figure 5.17 illustrates the differentiation between dialects within the regional Bengali languages.

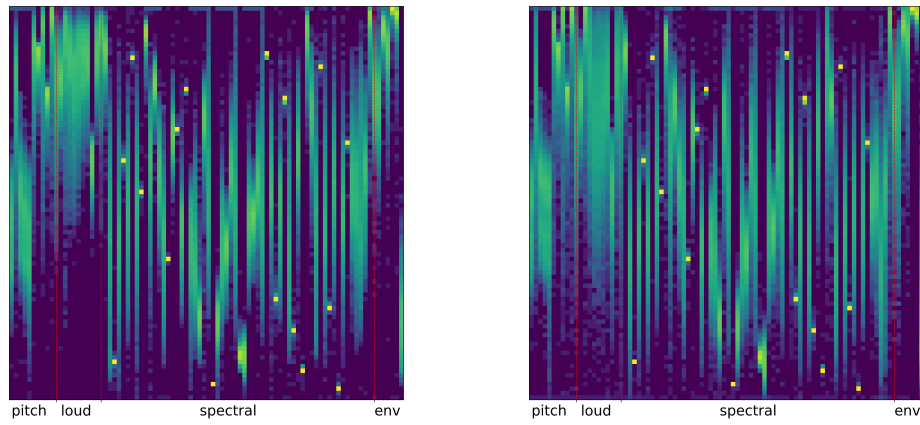


Figure 5.15: (Left) Stacked log-histograms of Geneva features for regional Bengali dialect (Right) Stacked log-histograms of Geneva features for Standard Bengali Dialect

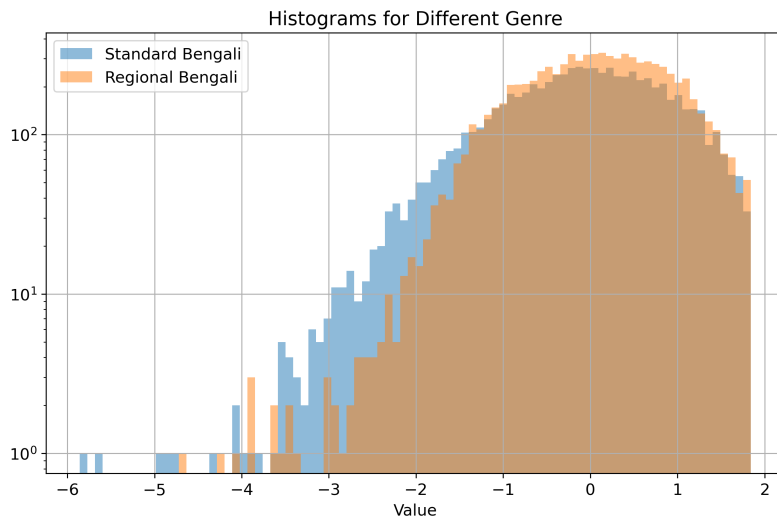


Figure 5.16: Histogram comparison between Geneva features of samples for Standard Bengali and Regional Bengali

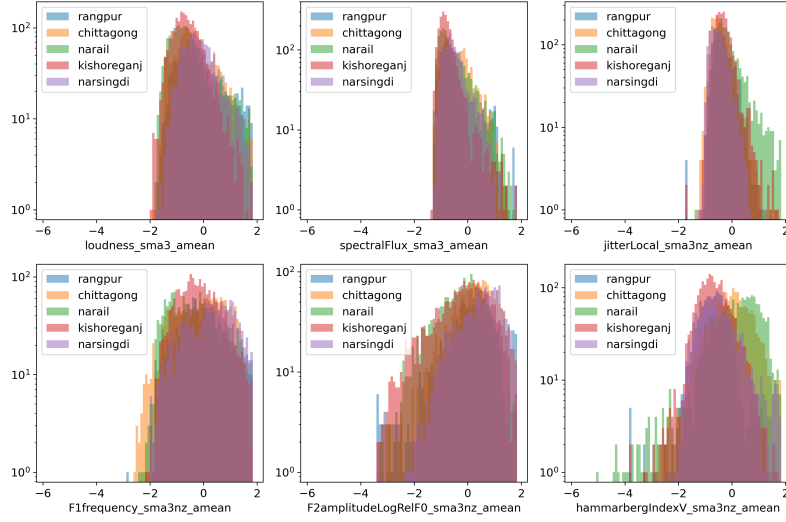


Figure 5.17: Histogram comparison between Geneva features of samples of different districts

To investigate the linguistic diversity of various regional dialects, we employed t-distributed Stochastic Neighbor Embedding (t-SNE) plots to visually represent the linguistic variation and distinct characteristics across different districts. By applying t-SNE to reduce the dimensionality of high-dimensional Geneva features and Wav2vec2 embeddings to two dimensions, we gained insights into the underlying structure of these dialect samples. The t-SNE plots based on Geneva features highlighted the distinctive linguistic characteristics within the Geneva dialect, allowing us to understand how these features cluster and relate to each other. In contrast, t-SNE plots using Wav2vec2 embeddings from various dialects provided a comparative perspective, enabling us to assess the similarities and differences between Geneva features and those from other dialects. The t-SNE plots of Geneva features extracted from five different districts in our dataset revealed clear separation between clusters, indicating significant differences in the Geneva feature space. A similar pattern was observed in the Wav2vec2 embeddings, with distinct clusters forming for different domains, as illustrated in Figures 5.18 and 5.19. These experiments were conducted using a perplexity of 40 and a 12-metric for clustering.

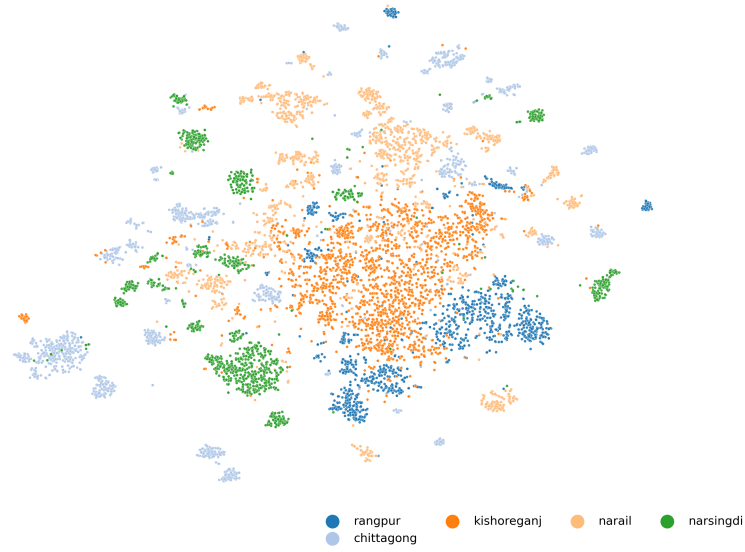


Figure 5.18: t-Schochastic Neighbor Embeddings of Geneva features of samples extracted from different dialect samples of the dataset.

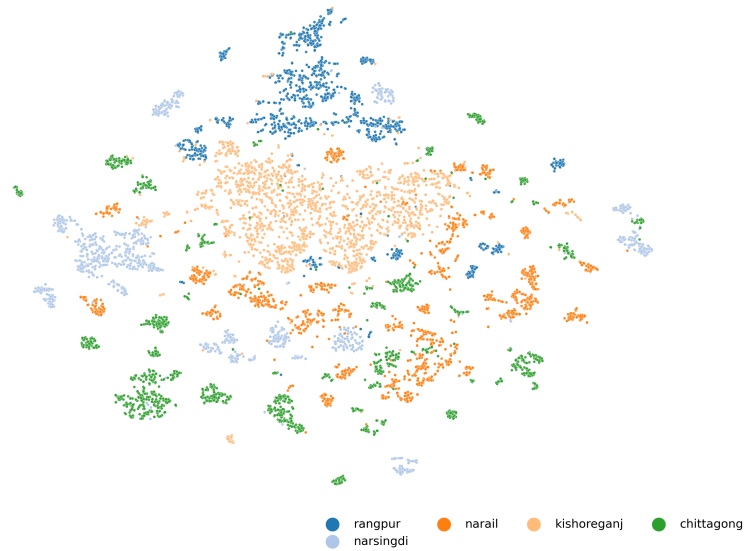


Figure 5.19: t-Schochastic Neighbor Embeddings of Wav2vec2 embeddings of samples extracted from different dialect samples of the dataset.

### 5.2.3 Spectrograms

A spectrogram visually represents how different frequencies in a signal vary over time. It comprises three dimensions: time, frequency, and the amplitude of each frequency, with colors or brightness indicating the strength of each frequency. Spectrograms are

commonly used to analyze audio signals, identify sound patterns, and study signal characteristics. Spectrograms of random samples from the dataset were plotted to assess the quality and diversity of the data, as well as to visualize the differences among audio clips from various regions.

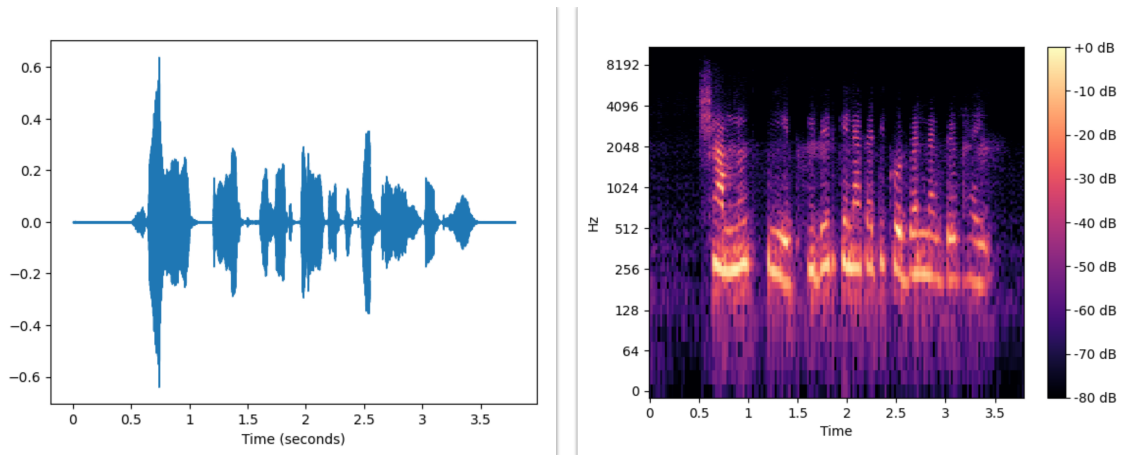


Figure 5.20: Waveform and Spectrogram of a sample from Rangpur

In Figure 5.20, a representative spectrogram for a data sample from the Rangpur fold is displayed. The spectrogram reveals that most temporal segments of this fold exhibit some level of energy, indicating fewer quiet periods. The high energy across a broad frequency range is evident from the bright regions, reflecting both the noisy nature of the recordings and substantial energy levels.

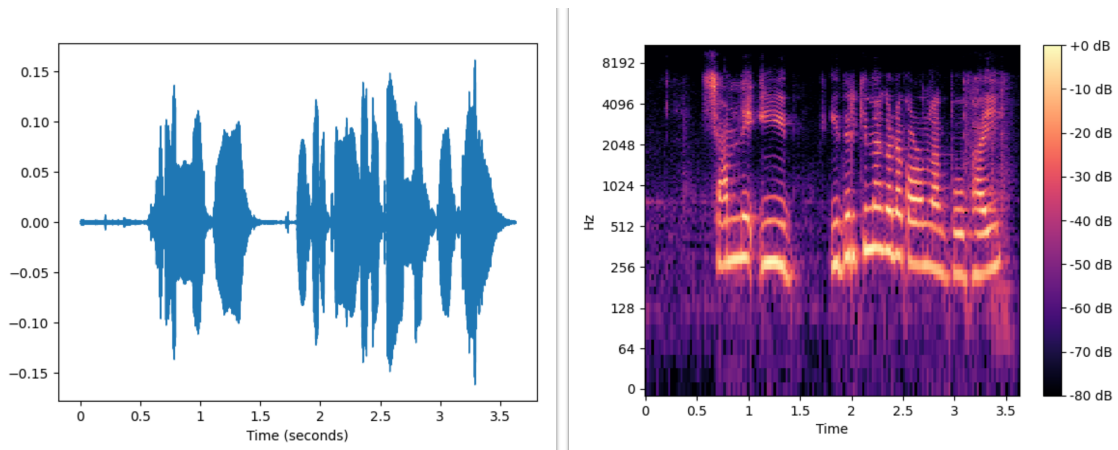


Figure 5.21: Waveform and Spectrogram of a sample from Kishoreganj

Figure 5.21 illustrates a spectrogram from the Kishoreganj fold, where the energy is clustered due to gaps between speech segments.

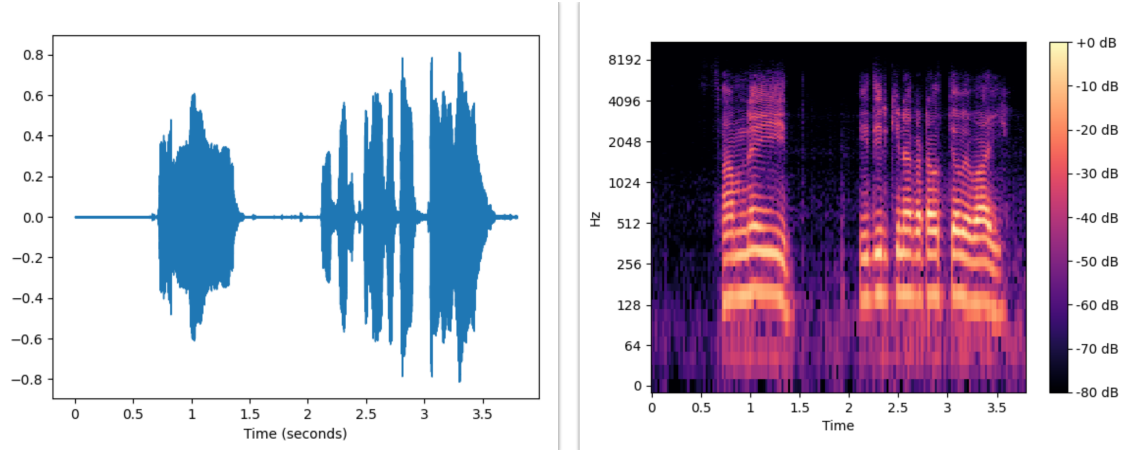


Figure 5.22: Waveform and Spectrogram of a sample from Narail

A similar observation is noted in the spectrogram from the Narail fold, shown in Figure 5.22, where the clustering of energy is more pronounced.

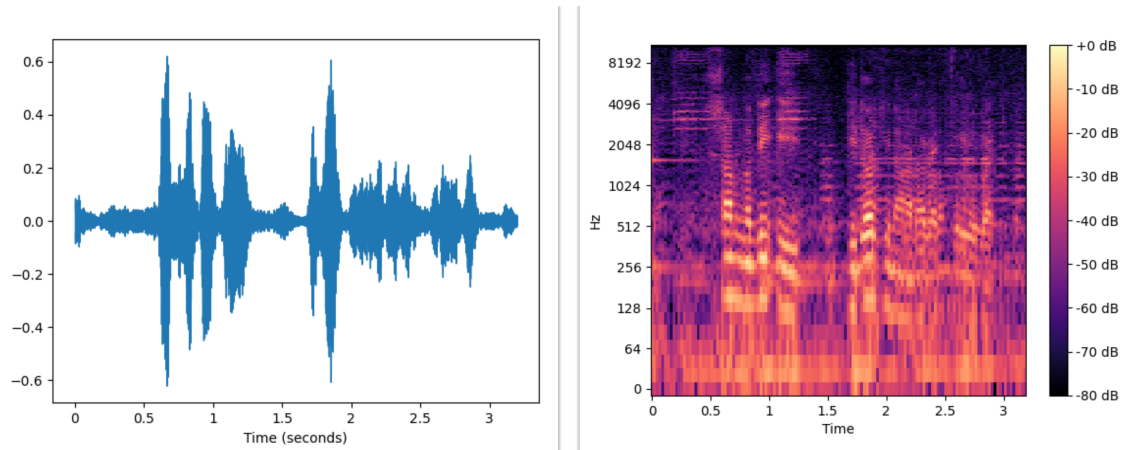


Figure 5.23: Waveform and Spectrogram of a sample from Chittagong

The spectrogram for the Chittagong region, depicted in Figure 5.23, shows significant energy, attributed to the emphasis or stress placed on particular syllables or segments by speakers from this region.

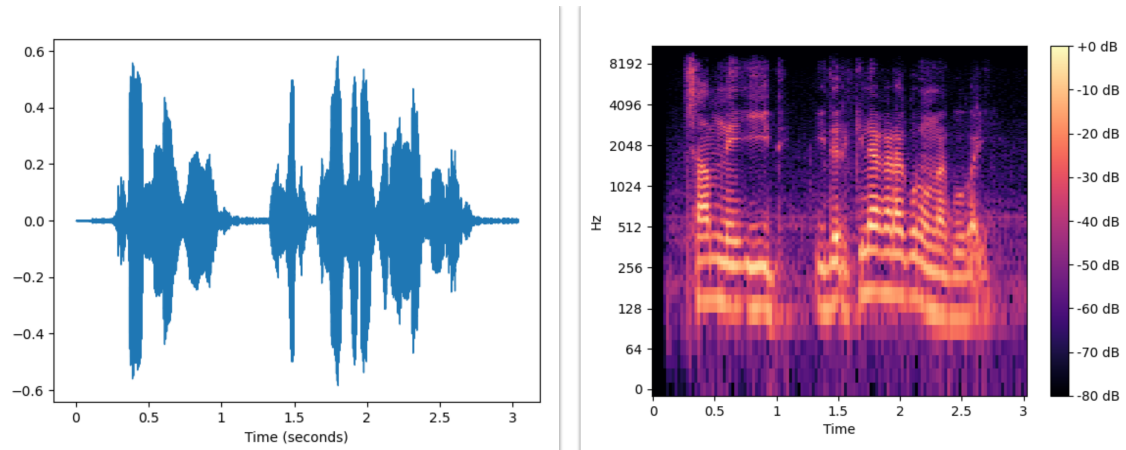


Figure 5.24: Waveform and Spectrogram of a sample from Narsingdi

Finally, Figure 5.24 presents the spectrogram for a data sample from the Narsingdi fold. The spectrogram indicates a consistent energy level across most temporal segments, with high energy over a broad frequency range, suggesting a noisy recording environment with substantial energy, as shown by the bright regions.

# Chapter 6

## Result Analysis

### 6.1 Evaluation Criterias

While fine-tuning the model, We evaluated model based on two evaluation criteria, Word Error Rate (WER) and Character Error Rate (CER).

The final WER and CER of this fine-tuned model are respectively 0.855 and 0.451. The table 6.1 shows District-wise WER and CER.

Table 6.1: Region-wise word error rate and character error rate

| District    | Word Error Rate (WER) | Character Error Rate (CER) |
|-------------|-----------------------|----------------------------|
| Rangpur     | 0.866                 | 0.466                      |
| Kishoreganj | 0.970                 | 0.557                      |
| Narail      | 0.757                 | 0.364                      |
| Chittagong  | 0.886                 | 0.471                      |
| Narsingdi   | 0.798                 | 0.399                      |
| Final       | 0.855                 | 0.451                      |

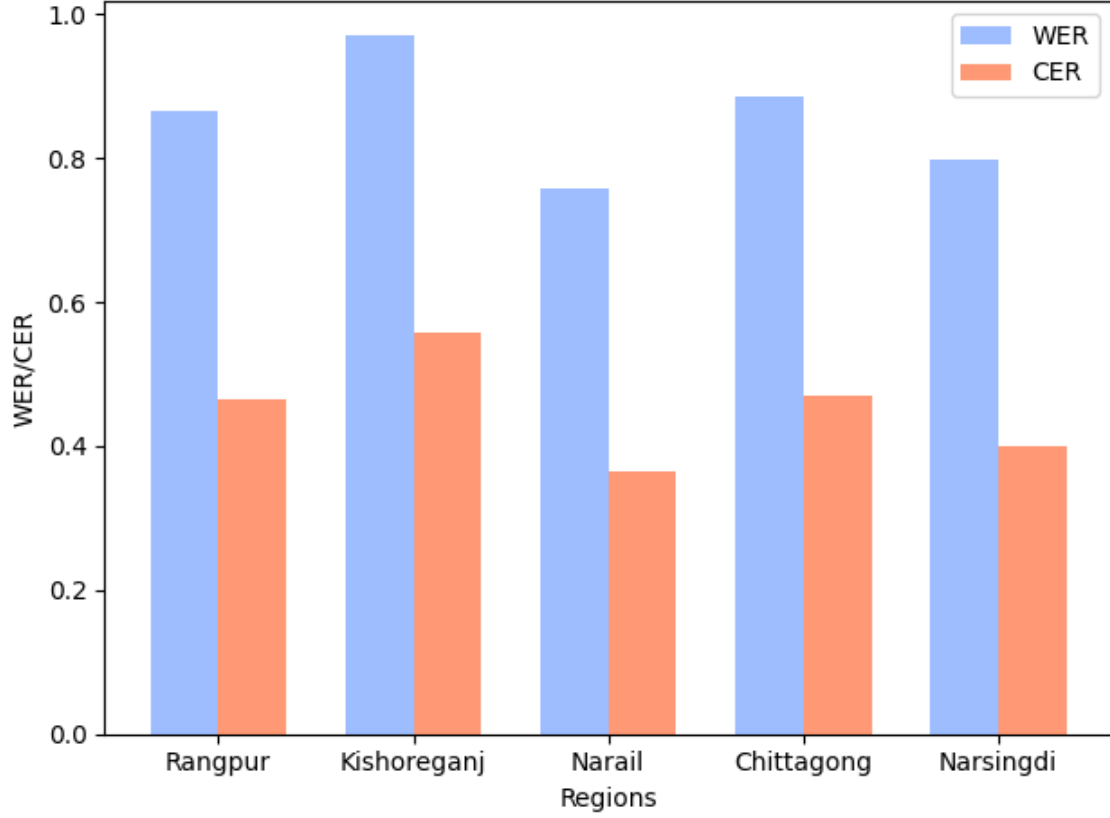


Figure 6.1: PX5’s performance for each region

## 6.2 Model Inferences

Some region-wise inferences of the samples from our fine-tuned model are shown below in the figures 6.2, 6.3, 6.4, 6.5, 6.6, for the respectively Rangpur, Kishoreganj, Narail, Chittagong, and Narsingdi test data from the corpus.

| A                      | B                              | C       | D                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              | E                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | F                                                                                                                                                                                                                           | G        | H        |      |
|------------------------|--------------------------------|---------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|----------|------|
| file_name              | External_ID                    | Region  | Transcriptions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Predictions                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | Split                                                                                                                                                                                                                       | WER      | CER      |      |
|                        |                                |         | লোখিয়া, কার্লি দিয়া, সেই সুন্দর করিয়া, এখন সেই সময় তো<br>মনে কর, সিরাজেরা আছিল রাজিল, গুয় রাজিল সাপোর্ট<br>করাছিল। একটা বিকিট ক্রপ ছিলো। হু ওরে কতা > বুজটি<br>বিষয়টি, ওয়ে তো এখনও বেরাজিল, বেরাজিরের সাপোর্ট করে।<br>বিয়র, ওই সময় আমর ওই কলির কলির করে। অতঃপর<br>একসাততে যখন কী হয়। হবিলি, ওই যে সুমন আর হবিলি<br>আমর > জাম্বা আর আমর। তো মনে কর তিনজন হিলাম<br>একসাততে যেমন, সিরাজ, আমি, তুই তিনজন হিলাম, পাশাপাশি<br>আমর সাতে                                                     | পলোয়া, কার্লি বিয়, সেই সুন্দর করি। এখন সেই সময় তো<br>মনে কর সিরাজেরা আছিল রাজিল, পর এটা বিনিমিত করলি,<br>তোমা' পনে কত আট। এ.এ.এ. ন। সাংজ করাবা সেটায়,<br>ওই বা ওয়ে, আমর ওই কলি মনের যাকোনা আটিলো এক<br>সাতম, যখন কী হয়। হবিলি, এবালা সুমন আর হবিলি আমর<br>বার্লি বা ও. জাম্বা। আর আমর। তো মনে কর কী। জলদিম<br>একসাততে। যম শুব, আমি তুই নভা ভলা, পাশা-পাশি আমর<br>সাতে                                                                                                          |                                                                                                                                                                                                                             |          |          |      |
| test_rangpur (1).wav   | rec_22_big_audio_0_chunk_0.wav | Rangpur | যারাগাছে হুবা > তাইলি হুয়া, জুমি জরুতে তো আবদ করেন<br>ন। আ পাও > না মোর জুমিন নাই। ও গরু কড়া আছে।<br>গরু আছ একটা। হাঁস-মুরগি আছে না। হাঁস-কুরগি আছে।<br>মুই কেনা কাজলি মাছ খাবার পাও না। কা? কাজলি মাছ তো<br>তোলো। মোক অত ভালো নাগে না। তোর খামা খামা কত সুন্দর।<br>খাইতে মাগে। মোর কাছে কল্যা গুলো ভালো নাগে। যামর<br>আমনে তো কাজলি আমনে। মোর কাছে কল্যা গুলো যামর<br>ভালো নাগে। >                                                                                                          | যারা কহেনঃ হুবা মুম্বি। তাইলি হুয়া জুমি জরুতে তো আবদ<br>করেন নাই। না আকা? না মোর জুমিন নাই। গরু কড়া আছে।<br>গরু আছ একটা। হাঁস-মুরগি আছে না। খাম-মুরগি আছে। ও                                                                                                                                                                                                                                                                                                                       | Test                                                                                                                                                                                                                        | 0.75     | 0.453222 |      |
| test_rangpur (10).wav  | rec_23_audio_5.wav             | Rangpur |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                | মুই কেনা কাজলি মাছ খাবার পাও না। কা? কাজলি মাছ তো<br>তোলো। মোক অত ভালো নাগে না। তোর খামা খামা কত সুন্দর।<br>খাইতে মাগে। মোর কাছে কল্যা গুলো ভালো নাগে। যামর<br>আমনে তো কাজলি আমনে। মোর কাছে কল্যা গুলো যামর<br>ভালো নাগে। >                                                                                                                                                                                                                                                          | মুই কেনা কাজলি মাছ খাবার পাও না। কা? কাজলি মাছ তো<br>তোলো। মোক অত ভালো নাগে না। তোর খামা খামা কত সুন্দর।<br>খাইতে মাগে। মোর কাছে কল্যা গুলো ভালো নাগে। যামর<br>আমনে তো কাজলি আমনে। মোর কাছে কল্যা গুলো যামর<br>ভালো নাগে। > | Test     | 0.633333 | 0.24 |
| test_rangpur (100).wav | rec_24_audio_39.wav            | Rangpur | তোমার উকুনো মাড়ো কাড়ে ঘাও পচড়া বন্ধায়। এবারে ><br>মাছগুলো পাওয়া যায় না তোমার এতদে। এখন পাওয়া যাইবে<br>পানি যখন হইবে তখন পাওয়া যাইবে। দুই একটা বুলি হইবে।<br>তখন পাওয়া যাইবে। নাঃ হুম। জনেকের ডিগির মাছ যাবে<br>আমিই তখন সেই সময়।<br>তোলাপ পানি আটকি থাকে না বিল গুল্যো? হুমনিচের বিল<br>ওইসে মাছ গুল্যো নামি আইসে। অতো থাকি বালিয়া পাওয়া<br>যায়। লোয়ায়? মেলা কলি ইয়েয় আগ বে বালিয়া যায়। আনু<br>নামো। টা।না. বালিয়া-ওটি হইল দ্যাকি বালিয়া যামর<br>বালায়। মাড়ো।           | তোমার উকুনো মাড়ো কাড়ে ঘাও পচড়া বন্ধায়। এবারে ><br>মাছগুলো পাওয়া যায় না তোমার এতদে। এখন পাওয়া যাইবে<br>পানি যখন হইবে তখন পাওয়া যাইবে। দুই একটা বুলি হইবে।<br>তখন পাওয়া যাইবে। নাঃ হুম। জনেকের ডিগির মাছ যাবে<br>আমিই তখন সেই সময়।<br>তোলাপ পানি আটকি থাকে না বিল গুল্যো? হুমনিচের বিল<br>ওইসে মাছ গুল্যো নামি আইসে। অতো থাকি বালিয়া পাওয়া<br>যায়। লোয়ায়? মেলা কলি ইয়েয় আগ বে বালিয়া যায়। আনু<br>নামো। টা।না. বালিয়া-ওটি হইল দ্যাকি বালিয়া যামর<br>বালায়। মাড়ো। | Test                                                                                                                                                                                                                        | 0.790697 | 0.502347 |      |
| test_rangpur (101).wav | rec_24_audio_40.wav            | Rangpur | মাঝে মাঝে যাবেন > ভম ভম ভম বোও। যাবের মেলা রে<br>মেলা। মেলা পাউকে যেতে আশপতন গেইসে মেলা। ওই মেলাত<br>গেইলি ওই খালার বোতা।                                                                                                                                                                                                                                                                                                                                                                      | তোমার > হ রে যাও পচে নো। এলামাগুলো পাওয়া যায় না<br>তোমার এতদে। এখন পাওয়াবিলে, বরুন হইবে তখনও দুই<br>একটার ডিগির তখন পাওয়া যাবে না। অনেকের ডিগির মাছ<br>যাবে। আইস তখন সেই সময়।                                                                                                                                                                                                                                                                                                   | Test                                                                                                                                                                                                                        | 0.666666 | 0.398148 |      |
| test_rangpur (102).wav | rec_24_audio_41.wav            | Rangpur | দুলাক পানি এটকি থেকে না বিলগুলো? হুমনিচের বিল<br>ওইসে পেয়ে ওই মাছ নামানি। হুই বে বাড়িও পাওয়া যায়,<br>নামো, মেলা পানি যাবের আগে বে বাড়িও মাছ নামানি। টি।না<br>বালিয়া > বুলি হইলো আটকি বালিয়া যামর খাওয়ার মাড়ো।                                                                                                                                                                                                                                                                         | দুলাক পানি এটকি থেকে না বিলগুলো? হুমনিচের বিল<br>ওইসে পেয়ে ওই মাছ নামানি। হুই বে বাড়িও পাওয়া যায়,<br>নামো, মেলা পানি যাবের আগে বে বাড়িও মাছ নামানি। টি।না<br>বালিয়া > বুলি হইলো আটকি বালিয়া যামর খাওয়ার মাড়ো।                                                                                                                                                                                                                                                               | Test                                                                                                                                                                                                                        | 0.85     | 0.427927 |      |
| test_rangpur (103).wav | rec_24_audio_42.wav            | Rangpur | মাঝে মাঝে যাবেন > ভম ভম ভম বোও। যাবের মেলা রে<br>মেলা। মেলা পাউকে যেতে আশপতন গেইসে মেলা। ওই মেলাত<br>গেইলি ওই খালার বোতা।                                                                                                                                                                                                                                                                                                                                                                      | মাঝে মাঝে যাবি আমরা চহ হু না বা। ধম দামাশুনা, মনোবে মেলা।<br>মেলা গাং হাং কত গেইসে মেলা? ওই মেলাত গেইলি ওইয়ার<br>খালার বাড়ত থেয়।                                                                                                                                                                                                                                                                                                                                                  | Test                                                                                                                                                                                                                        | 0.84     | 0.475    |      |
|                        |                                |         | আইজুপা বোতা মেলা? যামরও। তো শুনবার লাইসে মুই রোজ<br>কস, রজার মাশে, চলা যাই ঘরে। মেলা হইলে কামনে কী<br>হয়? কী মেলা মেলা যায়ে? আইজুকা যাইয়া গাওয়াও যাবান<br>না, বুয়াও যাবা > বুবার গেলেও ওটে কলজো। শুকাই যাইবে।<br>আমরা তো ওইবি যাইলি ওটে পেসিলাম। > না হইয়া যখন<br>আইজুপা বে হইলমে। তো শুনবার লায়গজা হট নেও। মেলা<br>হইলে কামনে কী হয়। কী কইরেবের মেলাগা য়েবে আইজুকা যে<br>খায়া খাটো গুয়া থিপা > না সুবিচে বুবে বুবার গেলেও ওটা<br>কলচে সুবি যাইবে। হমরা তো ওই যে গেইলি ওটে পেসিলাম। |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |                                                                                                                                                                                                                             |          |          |      |

| A                          | B                        | C           | D                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | E                                                                                                                                                                                                                                                                                                                                                                                                                   | F     | G        | H        |
|----------------------------|--------------------------|-------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|----------|----------|
| file_name                  | External_ID              | Region      | Transcriptions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | Predictions                                                                                                                                                                                                                                                                                                                                                                                                         | Split | WER      | CER      |
| test_kishoreganj (1).wav   | rec_41_audio_20.wav      | Kishoreganj | ৐ এয়েহে ওয়া। ৐ ছবি তুলানোই আস না ক্যা? দে<br>মানুষ অনন্য দুরাখার মইদে আস্তিগিয়া বেশি, নাইহাং কই, তুই ৐<br>৐ দিয়ালাগোই ৐                                                                                                                                                                                                                                                                                                                                                                                                                | া হুম, তুতে তর ফারাই। ত ত নাইগাহে<br>মানুষ নয়া গারির মইদে অশমক বেশি নোঁা কই? হেয়ে<br>মাগুর ছবি, হাইহাং বাহা হেঁগো<br>আস্হা দি পরমাঝে। ৐ হেই দেশে য়েছ গেলু কি মু না আইনা<br>কোঁ? না মুইনে<br>মুস হু কি? ক কি আবাদ? কি আবাদ? কি?<br>তা হম। ৐ এইএক কইইইই। ৐ একফক ফ উদিক বার,<br>৐ গারি তর খাদা বুদ্ধির পরগায়নে ৐ জিবের বিস্তারি জনা জাবি<br>পানির ভেত? নিরপাণী নিরপাণী, ৐ উদিক ৐ উদিকমুসা আর<br>ফনি কয়েন হময়ে কই | Test  | 1        | 0.659090 |
| test_kishoreganj (10).wav  | rec_41_audio_29.wav      | Kishoreganj | ৐ গারি কই এমন? না আইনা কালার? না, এমনই।<br>মুঠ কই, কি কইয়া বাতা। কিয়া বাতা? কি?<br>গারি ফরতাগছোই এনেত, ৐ জাগাত ওয়াছো নাহমফর, ফর, ফরা<br>উপ্তর তর খাদা বুদ্ধির পরগায়নে ৐ জিবের বিস্তারি জনা জাবি<br>পানির নিরপাণী নিরপাণী টিকাহে। উদিত বুজো আর প্রানি<br>কুজো এউজ কই                                                                                                                                                                                                                                                                    | উদিত। গাছপালা প্ানি। গরু সাগরে। ভূত রে ইসে গাছ পালা<br>পানি অহে। গরু সাউগলবা। পন শামশুই, টিকাহে। ৐<br>হেয়ে মাতরী দ বিত্তেকে বিভিন্নমানে ছুরির হেয়ে ছুরির পড়ার<br>হলাব বিত্তে? বিস্তরন বিভিজর? বিস্তরন, বিভিজ?                                                                                                                                                                                                    | Test  | 0.933333 | 0.494348 |
| test_kishoreganj (101).wav | rec_42_small_audio_1.wav | Kishoreganj | ৐ গারি কই এমন? না আইনা কালার? না, এমনই।<br>মুঠ কই, কি কইয়া বাতা। কিয়া বাতা? কি?<br>গারি ফরতাগছোই এনেত, ৐ জাগাত ওয়াছো নাহমফর, ফর, ফরা<br>উপ্তর তর খাদা বুদ্ধির পরগায়নে ৐ জিবের বিস্তারি জনা জাবি<br>পানির নিরপাণী নিরপাণী টিকাহে। উদিত বুজো আর প্রানি<br>কুজো এউজ কই                                                                                                                                                                                                                                                                    | উদিত। গাছপালা প্ানি। গরু সাগরে। ভূত রে ইসে গাছ পালা<br>পানি অহে। গরু সাউগলবা। পন শামশুই, টিকাহে। ৐<br>হেয়ে মাতরী দ বিত্তেকে বিভিন্নমানে ছুরির হেয়ে ছুরির পড়ার<br>হলাব বিত্তে? বিস্তরন বিভিজর? বিস্তরন, বিভিজ?                                                                                                                                                                                                    | Test  | 1.333333 | 0.975065 |
| test_kishoreganj (102).wav | rec_42_small_audio_2.wav | Kishoreganj | ৐ গারি কই এমন? না আইনা কালার? না, এমনই।<br>মুঠ কই, কি কইয়া বাতা। কিয়া বাতা? কি?<br>গারি ফরতাগছোই এনেত, ৐ জাগাত ওয়াছো নাহমফর, ফর, ফরা<br>উপ্তর তর খাদা বুদ্ধির পরগায়নে ৐ জিবের বিস্তারি জনা জাবি<br>পানির নিরপাণী নিরপাণী টিকাহে। উদিত বুজো আর প্রানি<br>কুজো এউজ কই                                                                                                                                                                                                                                                                    | উদিত। গাছপালা প্ানি। গরু সাগরে। ভূত রে ইসে গাছ পালা<br>পানি অহে। গরু সাউগলবা। পন শামশুই, টিকাহে। ৐<br>হেয়ে মাতরী দ বিত্তেকে বিভিন্নমানে ছুরির হেয়ে ছুরির পড়ার<br>হলাব বিত্তে? বিস্তরন বিভিজর? বিস্তরন, বিভিজ?                                                                                                                                                                                                    | Test  | 0.875    | 0.333333 |
| test_kishoreganj (103).wav | rec_43_audio_0.wav       | Kishoreganj | উদিত অহে। গাছপালা। প্রানি, গরু, ছাগল, মানুষ। উদিত অহে।<br>গাছপালা, প্রানি অহে। গরু, ছাগল, যাম মুরগী, মানুষ। গরু, ছাগল,<br>যাম মুরগী টিকাহে। হ্যাঁ। মাত উদিত তেকে বিভিন্ন স্থানে ছড়িয়ে এই<br>যে, এই জে জিবেই পরাই হলো বিত্তে বিস্তরন। বিত্তে?<br>বিস্তরন। বিভিজ?                                                                                                                                                                                                                                                                          | উদিত। গাছপালা প্ানি। গরু সাগরে। ভূত রে ইসে গাছ পালা<br>পানি অহে। গরু সাউগলবা। পন শামশুই, টিকাহে। ৐<br>হেয়ে মাতরী দ বিত্তেকে বিভিন্নমানে ছুরির হেয়ে ছুরির পড়ার<br>হলাব বিত্তে? বিস্তরন বিভিজর? বিস্তরন, বিভিজ?                                                                                                                                                                                                    | Test  | 1.035714 | 0.538043 |
| test_kishoreganj (104).wav | rec_43_audio_1.wav       | Kishoreganj | বিস্তরন টিকাহে। আই ফনি খাইলা। লা। ইয়া বই ল। সাধারন গ্যা্যান বই<br>লা। এইডা আর ফরতা। এইডা তো কয়ডা হো ফরহেছে। ফার আর<br>তিন কতো? আটা চাইহই এককো? তিন আর এক চাইহই। টিকাহে।<br>শুনা শুনা। হ্যাঁ। অইছে হাও সাধারন বই লও।<br>আগে আমারে এক দেও। পরে সাধারন গ্যা্যান বই। এইয়ে, জিবে,<br>জিবে বিস্তর নতুন উদ্ভিদে, নতুন উদ্ভিদকে আবার গেরে তুলতে<br>সাথায় করে। একায়েই পরিবেশের উদ্ভিদ ও প্রানি একে অপরের<br>উপর নির্ভরশীল। একায়েই পরিবেশের উদ্ভিদ ও প্রানি একে অপরের<br>উপর নির্ভরশীল।                                                        | বিস্ত টিক হে। ৐ সাটি ইহও অইল, এহই, সাটোজহসেন বইল।<br>কয়দে এহরো তো কয়ডা তো পাহাড়তুলে। চো চানি চিক অট।<br>চাইহ অইলে টিনারে? চাই। টিক আহে। সুশপনে, হ্যাঁ, ইসলা ইয়া<br>সাজাউ বইল                                                                                                                                                                                                                                    | Test  | 0.972972 | 0.484126 |
| test_kishoreganj (105).wav | rec_43_audio_2.wav       | Kishoreganj | উদিত অহে। গাছপালা। প্রানি, গরু, ছাগল, মানুষ। উদিত অহে।<br>গাছপালা, প্রানি অহে। গরু, ছাগল, যাম মুরগী, মানুষ। গরু, ছাগল,<br>যাম মুরগী টিকাহে। হ্যাঁ। মাত উদিত তেকে বিভিন্ন স্থানে ছড়িয়ে এই<br>যে, এই জে জিবেই পরাই হলো বিত্তে বিস্তরন। বিত্তে?<br>বিস্তরন। বিভিজ?                                                                                                                                                                                                                                                                          | উদিত। গাছপালা প্ানি। গরু সাগরে। ভূত রে ইসে গাছ পালা<br>পানি অহে। গরু সাউগলবা। পন শামশুই, টিকাহে। ৐<br>হেয়ে মাতরী দ বিত্তেকে বিভিন্নমানে ছুরির হেয়ে ছুরির পড়ার<br>হলাব বিত্তে? বিস্তরন বিভিজর? বিস্তরন, বিভিজ?                                                                                                                                                                                                    | Test  | 0.9      | 0.477157 |
| test_kishoreganj (106).wav | rec_43_audio_3.wav       | Kishoreganj | হাত দো গো বাইরে যাইলা কতো জানি ক। তিন কদম। (হেইদে, পুকা,<br>মাকর, উদ্ভিদ কেয়ে বেচে তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে<br>তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে তাকে।) আমরা অ<br>আবার<br>এই এহনি একটু ফরয়েনে। শুইনা শুইনা একটু ফরয়েনে। ফুনক<br>এই একটু ফরয়েনে। সকল প্রানীর শক্তি প্রত্যেক বা প্রত্যেক ভাবে<br>উদ্ভিদের উপর নির্ভরশীল। হুম<br>উদ্ভিদ সুচর আলো ব্যবহার কর ৐ নিজেই খাদ্য নিজেই তৈরি<br>করে। পোকামাকড় উদ্ভিদের, উদ্ভিদ যে খেয়ে বেচে থাকে। আবার<br>সারং, পোকামাকড়ের সার। নিমিষার একক করে। একায়েই পরিবেশের<br>উপর নির্ভরশীল। | আহুয়া জিবে, জিবে বিস্তার নতুন উদ্ভিদের নতুন উদ্ভিদের আবাশ<br>গরি তুলতে সাথায় করে। এবারে পরিসেই উদ্ভিদের পানি। একে<br>প রেইন হেয়ে। এগরদে আদাব পনি একপরি                                                                                                                                                                                                                                                           | Test  | 0.820512 | 0.506382 |
| test_kishoreganj (107).wav | rec_43_audio_4.wav       | Kishoreganj | হাত দো গো বাইরে যাইলা কতো জানি ক। তিন কদম। (হেইদে, পুকা,<br>মাকর, উদ্ভিদ কেয়ে বেচে তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে<br>তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে তাকে।) আমরা অ<br>আবার<br>এই এহনি একটু ফরয়েনে। শুইনা শুইনা একটু ফরয়েনে। ফুনক<br>এই একটু ফরয়েনে। সকল প্রানীর শক্তি প্রত্যেক বা প্রত্যেক ভাবে<br>উদ্ভিদের উপর নির্ভরশীল। হুম<br>উদ্ভিদ সুচর আলো ব্যবহার কর ৐ নিজেই খাদ্য নিজেই তৈরি<br>করে। পোকামাকড় উদ্ভিদের, উদ্ভিদ যে খেয়ে বেচে থাকে। আবার<br>সারং, পোকামাকড়ের সার। নিমিষার একক করে। একায়েই পরিবেশের<br>উপর নির্ভরশীল। | হুদককারি হইলা। তিন ৐ ইয়াম। হেয়ে, পুকামা কর উদিবিছে<br>বেইহা হাও পুকামা কর উদিবিছে বেইহা হাও। পুকামা ফর<br>উদিবিছে বেইহা হাও ৐ ইয়াম অহে।<br>এহনা কটু পোজান। পোজান। ফুনক ৐ ইটু উয়েনে। সকল<br>প্রণেজি, প্রন্তকফরাপ, পড়কফাবে, দুদ বিদের উপনির<br>বচনসম                                                                                                                                                             | Test  | 0.948717 | 0.568807 |
| test_kishoreganj (108).wav | rec_43_audio_5.wav       | Kishoreganj | হাত দো গো বাইরে যাইলা কতো জানি ক। তিন কদম। (হেইদে, পুকা,<br>মাকর, উদ্ভিদ কেয়ে বেচে তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে<br>তাকে, পুকা, মকোড উদ্ভিদ কেয়ে বেচে তাকে।) আমরা অ<br>আবার<br>এই এহনি একটু ফরয়েনে। শুইনা শুইনা একটু ফরয়েনে। ফুনক<br>এই একটু ফরয়েনে। সকল প্রানীর শক্তি প্রত্যেক বা প্রত্যেক ভাবে<br>উদ্ভিদের উপর নির্ভরশীল। হুম<br>উদ্ভিদ সুচর আলো ব্যবহার কর ৐ নিজেই খাদ্য নিজেই তৈরি<br>করে। পোকামাকড় উদ্ভিদের, উদ্ভিদ যে খেয়ে বেচে থাকে। আবার<br>সারং, পোকামাকড়ের সার। নিমিষার একক করে। একায়েই পরিবেশের<br>উপর নির্ভরশীল। | দুবিচুতুঘের আলব গের পনি। ই টু হাদো পি খেই ত বোকামাকর,<br>উদিবিরেই হাও। যে হেই হেইক আসার ন কয়ল ফর আসার                                                                                                                                                                                                                                                                                                              |       |          |          |

[illegible]

| A                         | B                   | C          | D                                                                                                                                                                                                                                                                                                                                                                                                            | E                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | F     | G            | H        |
|---------------------------|---------------------|------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|--------------|----------|
| file_name                 | External_ID         | Region     | Transcriptions                                                                                                                                                                                                                                                                                                                                                                                               | Predictions                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         | Split | WER          | CER      |
| test_chittagong (1).wav   | rec_29_audio_88.wav | Chittagong | গ্রামের মানুষ অল এলেনো। মারেয়া। ইন চায় দে ইতারা। যারগ ইন মাতি আইসসি দি এখন ন মাতিলেও নিজরতুঅ যারাক লায়। < ন মার্জিনি। তারফরে আর উইয়ার লয়ও এনে এটিওক্লিন হইজ্ঞা ঝগড়া <> আর নয় কি এডে? আর লাই তো বেকফুন ফরন দি ফেলায়।                                                                                                                                                                                  | গ্রামের মানুষ হল ইয়ে গেরে ডেব মারেথা ভ লো ইতারা। আরনইরে মাতি আইসসি দে এখন ন মাখিলে নিজিও যারাপ লাই বুঠিযরে ন খরেয় উই ইয়ান তিওক্লিন বখনে আআর নয় কি এডে? না, আরলা আছে বোয়াকওন ফরনে দি বেডে থ বেনা? হয় টেই ডেল ফাউয়ের ধরে বাইরেমোলাই পসাবে গরলো। ফুই সাব গরো না এনে কি খনকের খন না? ঘুরা ইয়ে খাইবা লরনি খন স। না না বয়া দুরেইয়ের খালাই আসে দে খালা, আই শইলো ন দি ট দিয়া দ ইর ংলেশি কাটাটাউলাম এগরে এ প্রাসসাইবু, এ প্রাস তুর দুরা থাক ও না আইয়া, মাইনে সাইয়েরে বং খাইবু। তো আমি, আইও ভাইয়া এরিমখুইবানাখারা আর তুই আইসসে দিসি। ই তো হইআইমানে হজেনো ইগলিশ মলো থোনাইথ, ভুলানি-টিয়া অখিয়ান | Test  | 0.7906976744 | 0.472222 |
| test_chittagong (10).wav  | rec_29_audio_97.wav | Chittagong | <> ডেইলি হওয়ার দুরে বাইঝতো লাইগগো, হিসাব গরো, তুই হিসাব গরো না, এন্তে হনে কি হর নো গুরাইয়া হাই ফেলার নে হেনো স, না না ওবা <> খালা আছেদেই, আই তো এনডিললা নদি তদি ইদানিও। আর ইংলিশত টাণেটি গজিল্লম এবারে -এ প্রাস আইবু। -এ প্রাস তো দুরত তাক, -এ ও ন আইয়া, -এ মাইনাস আইয়ারে বই তাইকি। আইও বাই ওইরইমানে ভাববিনাম, এখন আর তে আইসো দে অহল দে সি। তো আই মানে গজিল্ল অয়তো ইংলিশর মইদো হন ভুল ইয়া টিয়া অখিয়। | ফুই সাব গরো না এনে কি খনকের খন না? ঘুরা ইয়ে খাইবা লরনি খন স। না না বয়া দুরেইয়ের খালাই আসে দে খালা, আই শইলো ন দি ট দিয়া দ ইর ংলেশি কাটাটাউলাম এগরে এ প্রাসসাইবু, এ প্রাস তুর দুরা থাক ও না আইয়া, মাইনে সাইয়েরে বং খাইবু। তো আমি, আইও ভাইয়া এরিমখুইবানাখারা আর তুই আইসসে দিসি। ই তো হইআইমানে হজেনো ইগলিশ মলো থোনাইথ, ভুলানি-টিয়া অখিয়ান                                                                                                                                                                                                                                                      | Test  | 1.085714286  | 0.662650 |
| test_chittagong (100).wav | rec_31_audio_43.wav | Chittagong | আবার কেন গইজ্ঞেজেদে, <> দেখিদে সেভেনত সেইম, নাথার নলারের হরে, ও আইচা। তগগই, কি আরে গরওম, কুয়ালত থিয়ান আছে ইয়ান লইততাই চইততাই সামমাদি আই খাইবাগই। ন? অয়। গোর দাদা নাই? আছে তো। অফিসত ন-যায়? গিয়ে। আইচা আইয়ে তইলে। আই আড়া হ।                                                                                                                                                                           | আবার ইকান গইরাজি বাই কুনননীর্ খরমইনো দে ি দেখির দি তারফরে সেন। ইল নাথার নও লহরে ফরে। থ আইছে। তকুকি আর গুরওম, ওয়ালর দে নাখিয়ার লইসো চুইভে-এরে সামমইদে আই খাইব গই।                                                                                                                                                                                                                                                                                                                                                                                                                                  | Test  | 0.9069767442 | 0.527196 |
| test_chittagong (101).wav | rec_31_audio_44.wav | Chittagong | আরে তো মা ডায়ে? তরে? অয়। আইচা টিক আছে, রাই তইলে। রাখ তইলে। বাই বাই, চা চা। ভালো তাহিস। তই যাইলে, হতা অইবো তইলে কেন? আইচা। চাটা।                                                                                                                                                                                                                                                                            | নহ। আই। দুব দারা নাই? আছে তো অফিসত ন যাই? গিয়ে আইচা অখিয়া তইলে। ওয় ওডি থ।                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | Test  | 1.16         | 0.661971 |
| test_chittagong (102).wav | rec_31_audio_45.wav | Chittagong | আসসালামু আলাইকুম সালাম। কেন আইছো? আলহামদুলিল্লাহ, তুই কেন আইছো? আলহামদুলিল্লাহ গম আইছি।                                                                                                                                                                                                                                                                                                                      | আরে তো মা ডাহ। তোরে? অ আইছো টিক আছে? রাই ত ইলো বাঅলে বাই বাই চাটা। চাটা তাই? চাটা। তুই ভাউলা তাহিস। আইখন? আইছা আইছা।                                                                                                                                                                                                                                                                                                                                                                                                                                                                                | Test  | 0.75         | 0.346666 |
| test_chittagong (103).wav | rec_31_audio_46.wav | Chittagong | তুর আম্মতারা বেকওন কেন আইছে? আলহামদুলিল্লাহ গম আইছে। আইছা, আই তুরে হই, ওইদিন আইলদি, ফুয়া ইবা হতা নহয়নে, তো আইয়ে কি, এন্তে আইলদি <> আফুর হতা যেততে আর আম্ম তুইলনি। তো মানুষ ইবা সারা আফুর এদিন সাইতো চাইল, আই হর আইনতো গেইলাম দে।                                                                                                                                                                          | আসসালামু আলাইকুম সালাম। ওয়াল্লাইকুম ত না? কেন আইছো? আলহামদুলিল্লাহ তি কান আইছো? বাহম নে গমাছি। তুর আম্ম তরারে বেকওন কান আইছে।                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Test  | 0.8148148148 | 0.4      |
| test_chittagong (105).wav | rec_32_audio_0.wav  | Chittagong | কিন্তু হর আইনদে এদিন আরতুন এক ঘন্টা রাত্তি়া বঅই তাহন ফইরেগে, হর ইবরলাই, কারেক নআচাছিলদে, এগন ইল্লি গরন করিবা। তো আই এক ঘন্টা বই খাইকাকিলাম দে, এই সময়ত হদেদ, অনে মেয়ফুরে খুইনে মেয়ফুরে, থই আর মোবাইলত চার্জ নআচাছিলদে, আই ঘরত রাই পেইফাম।                                                                                                                                                                | লেগবাই। যা? আইসে আরতুরে খই। ওই ওইদিন আইলদি ফুয়াইবের খতা ন খয় না। তই কি? অ। এনড আইলদি চাক্তপুর্ খত তো তো মানুষ ইবে সালু আফরদি সাইতু সাইয়েল আই খর ইনতাম পেলাম দে                                                                                                                                                                                                                                                                                                                                                                                                                                   | Test  | 0.8947368421 | 0.362204 |
| test_chittagong (106).wav | rec_32_audio_1.wav  | Chittagong | কিন্তু হর আইনদে এদিন আরতুন এক ঘন্টা রাত্তি়া বঅই তাহন ফইরেগে, হর ইবরলাই, কারেক নআচাছিলদে, এগন ইল্লি গরন করিবা। তো আই এক ঘন্টা বই খাইকাকিলাম দে, এই সময়ত হদেদ, অনে মেয়ফুরে খুইনে মেয়ফুরে, থই আর মোবাইলত চার্জ নআচাছিলদে, আই ঘরত রাই পেইফাম।                                                                                                                                                                | কিন্তু খরাইলদি না তুন এক ঘন্টা আইলদি রাত্তি়ে বই বাহম ফরাগ। তুই খরিবার লাই কারন ন আইছি দি নিখারি গরম ফরিবু। তো আই এক ঘন্টা বই খাইকাকিলাম দে হই সময়ত হরদে অনে মেয়ফুরে খুইনে মেয়ফুরে, থই আর মোবাইলত চার্জ নআচাছিলদে, আই ঘরত রাই পেইফাম।                                                                                                                                                                                                                                                                                                                                                            | Test  | 0.9210526316 | 0.512562 |
| test_chittagong (107).wav | rec_32_audio_2.wav  | Chittagong | ইন লই অচি, বড়ত হতা হইয়ে আর আম্মারে, কি বলে. ব্যাংকার                                                                                                                                                                                                                                                                                                                                                       | খান লইয়ার আইলদি বড়ত খতা থই আই আম্মালে কী বলে                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Test  | 0.8780487805 | 0.424892 |

Figure 6.5: Model inferences samples on Chittagong data

| A                        | B                   | C         | D                                                                                                                                                                                                                                                                                                                       | E                                                                                                                                                                                                                                                                                        | F     | G            | H            |
|--------------------------|---------------------|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|--------------|--------------|
| file_name                | External_ID         | Region    | Transcriptions                                                                                                                                                                                                                                                                                                          | Predictions                                                                                                                                                                                                                                                                              | Split | WER          | CER          |
| test_narsingdi (1).wav   | rec_23_audio_46.wav | Narsingdi | জাৱে তো ওই য়াৱাপ খেইলাই আসে না। জাৱে ভালো, ওই লিগণ্ডলাতে ভালো খেলে, ডেমিস্টিকে ভালো খেলে। পরেই তো ওদেরকে জাদুয়ি দলে ডাকা হয়। হ। কিন্তু, কী করবি ক? প্রেয়ার তো আর একটা দুইটা না। প্রেয়ার তো অনেক।                                                                                                                   | জা তো ওই য়াৱাপ খেলার সেনা, জাৱে ভালো। ওই লিগণ্ডলাতে ভালো খেলে, ডেমিস্টিকে ভালো খেলে। পরে তো ওদেরকে রাক্ষস দলে ডাকা হয়। হ। কিন্তু কী করবু ক? প্রেয়ার তো আর একটা দুইটার না প্রেয়ার তো অনেক।                                                                                            | Test  | 0.5405405405 | 0.1631578947 |
| test_narsingdi (10).wav  | rec_23_audio_55.wav | Narsingdi | এটা বনতেই হবে। হ, এটা আমিও মানি। বাংলাদেশ উন্নতি করতেছে, আরও উন্নতি করবে। নতুন, নতুন প্রেয়ার আসবে। <> তবে, আমাদের যে পক্ষপাত্তব ছিলো, এরকম পাওয়া যাবেবা না রে আর।                                                                                                                                                     | এটা বলতিই আবাকরো। হ, এটা আমিও মার। মার ক্ষমতি করতেছে, আরও উন্নতি করবে। নতুন নতুন প্রেয়ার আসবে। ই তবে আমাদের ওইধে পক্ষ পত্রটিব ছিল, এরকম পাওয়া যাবে না রে আর।                                                                                                                           | Test  | 0.6206896552 | 0.21875      |
| test_narsingdi (100).wav | rec_24_audio_66.wav | Narsingdi | এজারে কী করব? থাকরা খেতাইওক, বাব দে। <> ফাচলে ছুয়া। ইদের ফরে তো হুরতে যাওয়ার খাঙ্গা এহে নাম বাউওই, না? নাহ। আর? আর কই? ইদে সালামি নিবা না কি আমাকো? সালামি।                                                                                                                                                           | ভাই কি কইম খাবলো? ওই বইডাই, বাতো মা। দেৱ ফরে তো সমুচে যবুদি বাহকজু বমাটে <- না না নাহ। আঁর। আর কই। দিৱে সালামিনিবার নাকি আমা কে? সালামিমি।                                                                                                                                               | Test  | 0.8387096774 | 0.417721519  |
| test_narsingdi (101).wav | rec_24_audio_67.wav | Narsingdi | সালামি, সালামি। কেউ সালামি দে না, বাই। ওই ছাচু যে দিতে ইদের মধ্যে? দিআইছে দিছে তো। হেইজা তো শপিংয়ের টাকা দিয়া দিছে। প্রায় দুই হাজার টেকা দিছে। সিরিয়ার্স একটা টেকাও আমার আতো আইতো না, বইনা। মা। মারে। ছাচু আমারে দিয়া দিছে। আমি সুন্দরভাবে ভদ্রভাবে মার আতো দিয়া নাইছি। হেদিন না আমার ভাযত আইছে বাইত। চুপ। আতে ক। | সালামি সালামি, কেউ সালামি দে না ভাই। ই ছাচুদর খদি ভদার মদ্যো দিস দিছে ভ। হেজা ত সবিংয়ের টাকার দারার। হুশ্রে দুই হাজার টেকা দিছে। শেসে সিরিয়ার্স একটা টেকাও আমার তোবই তো না ো। আমার হুসায় আমারে দে দিছে, আমি সুন্দর বদে জা মার জঁকি নাইছে। হেইদ্যো আমার জায় দিছে ভাই। আচ চু, আসতে কঙ। | Test  | 0.8070175439 | 0.3464052288 |
| test_narsingdi (102).wav | rec_24_audio_68.wav | Narsingdi | কিন্তু একটা ফ্যাঙ্কি কি, দেরি কইরা দিলে টেযাউ অন্ধরে রাইকা দিলোঅইলে। দিল জাৱা, জাৱা <> অবশ্য আমি আমার ইয়া এ আশুলিয়া যামু সময় দাদু এমানেও পচশো টাকা দিয়া দিবা একট্রা। মানে এখন ফরতেকবার আইলে এটা লাভ অইতোছে, পচশো টাকা কইরা দিয়া দেয়।                                                                              | কিন্তু একটা টাক কি। দিনবরে দিলে টিয়াডিয়া এক্লাভে রাইক্লা দি অইন। অ অজেনু, কিও অবে ি আবার ইয়া আসে যখন সময় দ দি দে পারশো টাকা দিয় দিবে। এস্ট্‌মন ুনে এখন ফরটে বাইলে এরা লাভ টা, মনে খাৱা আই য়া য়া                                                                                   | Test  | 0.8510638298 | 0.5133079848 |
| test_narsingdi (103).wav | rec_24_audio_69.wav | Narsingdi | জঁকি, ফান্দি কত। <> আৱাং আকরাবা। এ নুব্বা হু। ফাদুদা রানা শিখছে হু। তুই কী কী রানতরহ? আমি? হুম। <> গরম পানি করতারা। আর? <>।                                                                                                                                                                                             | অৱাংয়েকরা। এনে বা? অৱাদুরানা শিখচস। ইতু কি কি রানতরস? আমি? হুম। অয়। গরম পানি করতারা? হর                                                                                                                                                                                                | Test  | 0.88         | 0.484375     |
| test_narsingdi (104).wav | rec_24_audio_70.wav | Narsingdi | প্যাস পানি সিদ্ধ। হয়ার কি চার শেখ? না। ফালুদা না বানাইছিলি হেই দিন? কেমনে, কেমনে বানাইছছ রে? বইন, বইন, বিশ্বাস কর, এটা জাস্ট একটা কি কইতাম। মানে, আমি আমার মতো কইরে বানাইছ, ঠিক আছে? হু, হ।                                                                                                                            | জুসফানি সিদ্দে। হুয়ের কি চার শেখ? ন? অৱাদুরার বানাইছিলি এদিন কেয়ে এইমানে বানাইলে বইন বইন। বিশেষ কর, এডার জাস্‌টাকি কইতাম ডে, আমি আমার মত কইরে বানাইছি। ঠিক আছে? হই। ওডরা দুজের মদ্যো কফিচায়া ষ্া। কার পে কফি মা।                                                                      | Test  | 0.8260869565 | 0.2926829268 |
| test_narsingdi (105).wav | rec_24_audio_71.wav | Narsingdi | গুড়া দুধের মধ্যে কফি চাইলা, ব্লেক কইরা আসে কফি বান।                                                                                                                                                                                                                                                                    | কফিবার নাইছি, কুমক কেডো ই সিদ্দ নকড় স্র য়াচাইর ে। জিলিডাস। জলিইয়া জ্া, িথি টেনে শেলিডা। জাশ জেলিস। জাশ ট জুলি জাশওই ডেই কী আইছিলো। ককেন মঅফ পরি দাছে ফাস চার পুটিং ছেটা বাচনা খাৱ। মাংগু বন।                                                                                          | Test  | 0.9333333333 | 0.5196850394 |

Figure 6.6: Model inferences samples on Narsingdi data

### 6.3 Benchmarking Performances

The benchmarking performance of different models and our fine-tuned model on our developed regional speech corpus is shown in Table 6.2 and is visualized later in Figures 6.7, 6.8 and 6.9.

Table 6.2: Benchmarking Performance

|                  | Chittagong |       | Kishoreganj |       | Narsingdi |       | Narail |       | Rangpur |       | Average |       |
|------------------|------------|-------|-------------|-------|-----------|-------|--------|-------|---------|-------|---------|-------|
|                  | WER        | CER   | WER         | CER   | WER       | CER   | WER    | CER   | WER     | CER   | WER     | CER   |
| Google ASR       | 0.984      | 0.943 | 0.948       | 0.893 | 0.902     | 0.807 | 0.882  | 0.774 | 0.939   | 0.849 | 0.931   | 0.853 |
| Wav2Vec2 Large   | 0.989      | 0.671 | 1.032       | 0.754 | 0.958     | 0.575 | 0.952  | 0.574 | 0.967   | 0.646 | 0.979   | 0.644 |
| Hishab Conformer | 0.977      | 0.666 | 1.244       | 0.768 | 0.842     | 0.539 | 0.864  | 0.512 | 0.918   | 0.567 | 0.969   | 0.610 |
| Yellowking       | 0.983      | 0.803 | 0.959       | 0.801 | 0.932     | 0.720 | 0.903  | 0.652 | 0.937   | 0.712 | 0.943   | 0.738 |
| Tugstugi         | 0.942      | 0.633 | 1.058       | 0.887 | 0.791     | 0.476 | 0.758  | 0.453 | 0.830   | 0.549 | 0.876   | 0.599 |
| PX5 (Proposed)   | 0.886      | 0.471 | 0.970       | 0.557 | 0.798     | 0.399 | 0.757  | 0.364 | 0.866   | 0.466 | 0.855   | 0.451 |

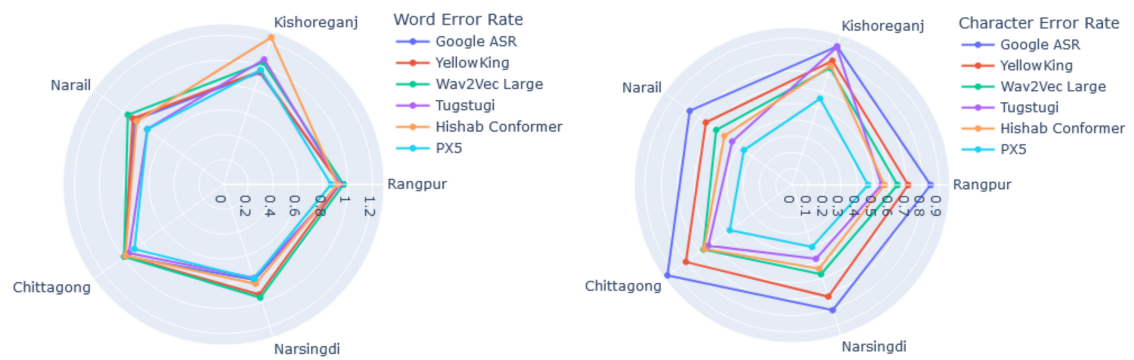


Figure 6.7: Radarplot of the model performances on regional speech corpus

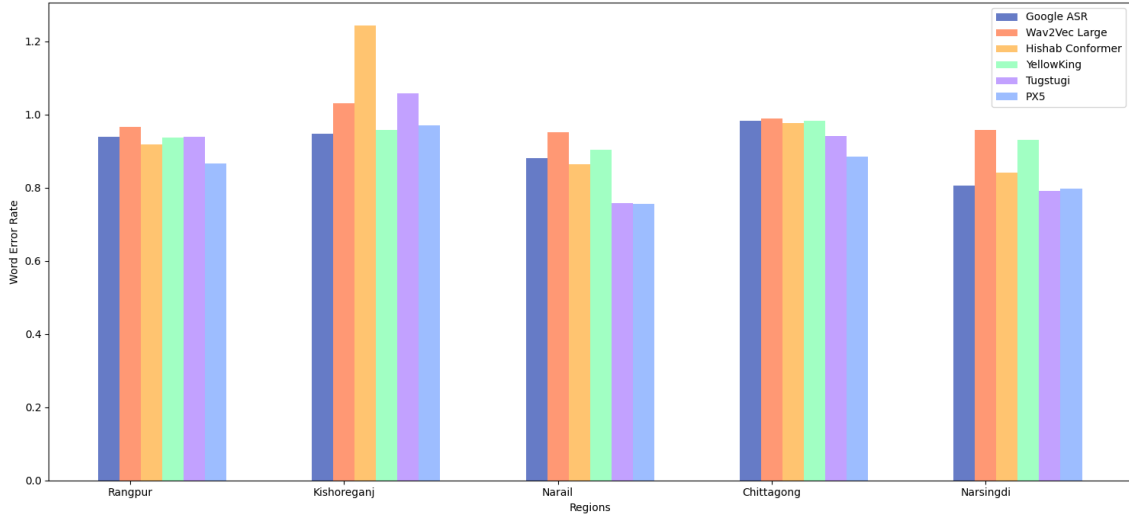


Figure 6.8: Barchart of the PX5’s performance based on WER compared to the other benchmark models on regional speech corpus

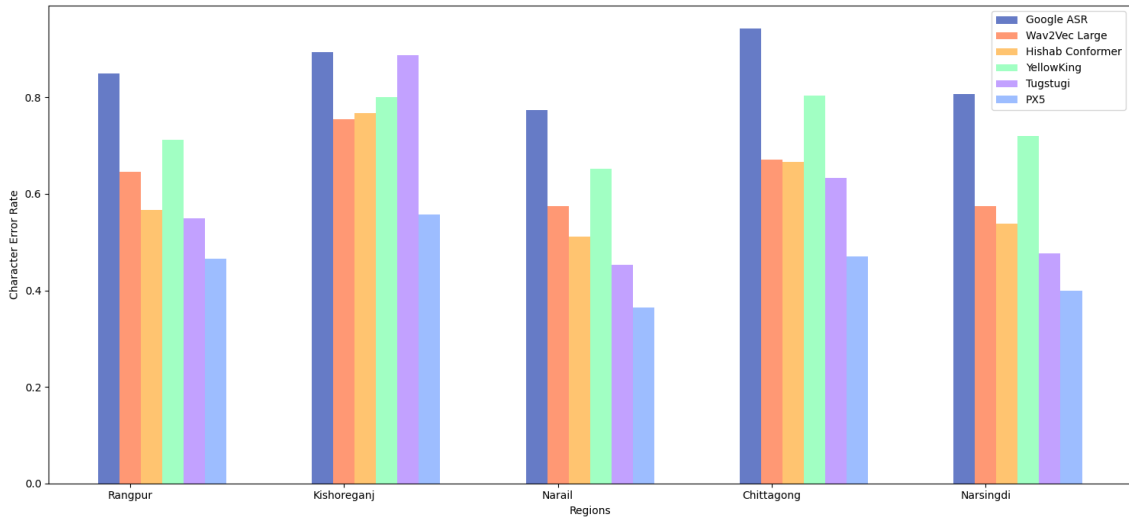


Figure 6.9: Barchart of the PX5’s performance based on CER compared to the other benchmark models on regional speech corpus

### 6.3.1 Region-wise Benchmarking Performances

As illustrated in Figure 6.7, the proposed PX5 model outperforms all existing state-of-the-art models, demonstrating a comparatively lower word error rate and a significantly reduced character error rate. This observation is consistent with Figure 6.8 and 6.9 , which illustrates the proposed model’s performance comparing with all the other benchmark models across various regions.

Region-wise model’s performances are also provided in the figures 6.10 and 6.11 for respectively Rangpur, Kishoreganj, Narail, Chittagong and Narsingdi regions.

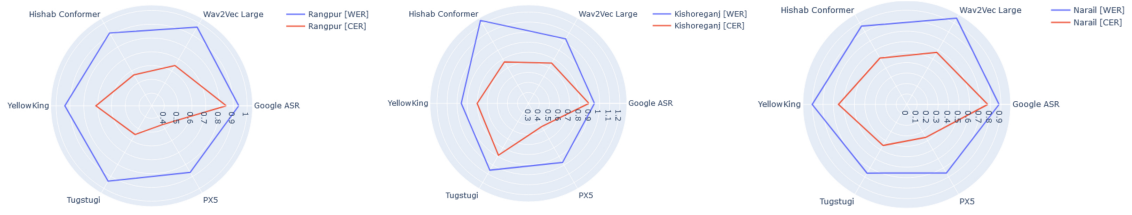


Figure 6.10: Radarplot of the model performances on Rangpur, Kishoreganj and Narail Data

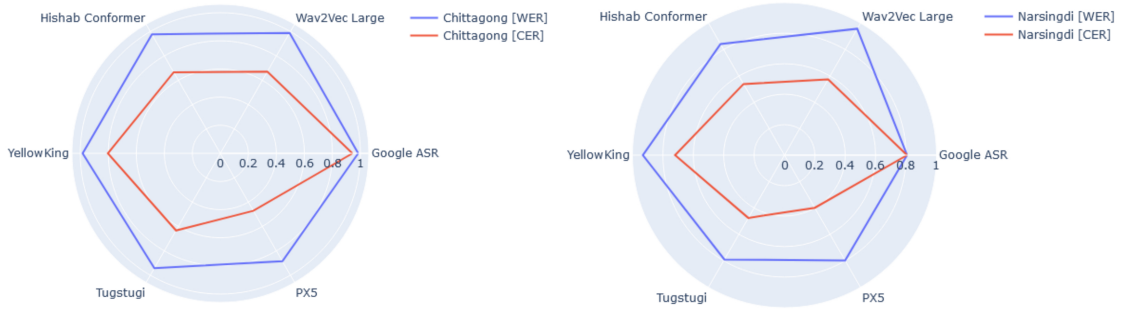


Figure 6.11: Radarplot of the model performances on Chittagong and Narsingdi Data

## 6.4 Inference Analysis of the Benchmark Models

Given that Bengali is a low-resource language, it has been observed that the model encounters significant difficulties in accurately transcribing named entities such as name of a person, animal, flower, fruit, or location. This issue is evident across transcription samples from different regions. Examples illustrating these challenges are provided below.

| Models           | Predictions                                                                                                                                               | Word Error Rate (WER) | Character Error Rate (CER) |
|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|----------------------------|
| Ground Truth     | হারাগাছে? হুম! তাইলে ইয়া, জমি জমার তো আবাদ করেন নাই, না আপা? না মোর জমির নাই, ও গরু কয়টা আছে? গরু আছে একটা। হাঁস-মুরগিও আছে না? হাঁস-মুরগিও আছে।        | N/A                   | N/A                        |
| Google ASR       | হারা করছে                                                                                                                                                 | 1                     | 0.939                      |
| Wav2Vec2 Large   | হারা গোছেপারাক নমুতিলিয়াজুমিযবাত আবদ করেন নাইনে আপা না আমুজ জামির নাইগুরু কোয়টে আছে গরু আছে এক তাককাশমুরগি আছে না রাসমুর দিয়ে আছে।                     | 0.828                 | 0.432                      |
| Hishab Conformer | হারা গেছে আর নাম তাহলে জমি জমার তো আবাদ করেন নাই না আপা না আমার জমির নাই গরু কয়টা আছে গরু আছে একটা মুরগি আছে না হাঁস মুরগি আছে                           | 0.69                  | 0.264                      |
| YellowKing       | কেরামত আবাদ করেন নাই না মামিনপুর কেটে গরু আছে কাশমুরের আছে।                                                                                               | 0.793                 | 0.655                      |
| Tutstugi         | তাইলে গিয়া জমিজমা তো আবাদ করেন নাই না পা গুরু কয়টা আছে গরু আছে একটা হাঁস মুরগি আছে না হাঁস মুরগিও আছে                                                   | 0.724                 | 0.365                      |
| PX5              | খারা কছেন? পরেখ না মুই। তাইলে ইয়া জমি জমার তো আবাদ করেন নাই। না আফা? না মোর জমির নাই। গরু কয়টা আছে? গরু আছে একটা। হাঁস-মুরগি আছে না? হাঁস-মুরগিও আছে। ও | 0.621                 | 0.209                      |

Figure 6.12: Inference results for all the models of samples from the corpus's Rangpur segment

In Table 6.12, which displays the ground truth alongside all model predictions for a sample from the Rangpur segment of the corpus, the term হারাগাছে is either missing or inaccurately transcribed as হারা করছে or হারা গেছে. While these terms demonstrate some phonetic similarity, they are orthographically distinct and incorrect. Our model predicted খারা কছেন, which deviates significantly from the expected transcription but the overall transcription quality of our model surpasses that of other models, as evidenced by its lowest CER and WER for this sample.

| Models           | Predictions                                                                                                                                                                                                                                                                                                                                                                       | Word Error Rate (WER) | Character Error Rate (CER) |
|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|----------------------------|
| Ground Truth     | ব্যাঙের দেহা যায় ফল মারে। লাল ফাডের মাঝে দেখবা <> ব্যাঙে ফল ফলা। লাল ভাঙলে দেখুনযে খালি ব্যাঙে ফলফলা। ফলফলায় কি খায়? ঘাসফড়িং। ঘাসফড়িং খায়। ঘাসফড়িং কি খায়? ঘাস খায়। আবার এই ঘাসফড়িং রে খায় কেলা? ব্যাঙে। ব্যাঙের খায় কেলা? সাফে। ব্যাঙের খায় কেলা? সাফে। সাফে। এভাবেই খাদ্য শৃঙ্খল। এভাবেই? খাদ্য শৃঙ্খল। নিচের কোন খাদ্য শৃঙ্খল সঠিক? এইযে দেহা এইনতে বৃহত্তা ফরবা। | N/A                   | N/A                        |
| Google ASR       | ভালো ফলাফল                                                                                                                                                                                                                                                                                                                                                                        | 1                     | 0.976                      |
| Wav2Vec2 Large   | ব্যাঙে দেহকে ভাল মারেদেলালা ওয়ারএ মরাজা তেক বা ধানকেব ব্যাঙেলে ভাল ফলালালা অংলেনের নিরসিবাসে ভান্ম হলাচিক ঘাস করিংকা রাসকইফেইকাগাসকা আর আবার এ গাস করিংযোকাকেনাব্যাঙে ব্যাঙে একাগেলা সহবে বেঙ্গের একা গেলাসাপে এভাবে কাশন হলেভাবে খাংশ নিচের পুর সার্থশপ কলে জটিকেন্যোন্দে বুডো হর মা।                                                                                           | 0.968                 | 0.566                      |
| Hishab Conformer | ভেঙ্গে হাল মারে লালারে দেখাম ভালো খা লাল গাছ শুইং গাছ শুই গাছ আবার এই গাছ শুইং একা খেলা ব্যাঙে ব্যাঙে একা গেলানে একা গেলা এভাবে খাদ্য শ এভাবে খাদ্য নিচে খাদ্যল বুতে ভ                                                                                                                                                                                                            | 0.921                 | 0.656                      |
| YellowKing       | ভালোভারে সিকারকে সেবা ভাবে কার্যকারিতে কোন সত্যাকিকে বুজে।                                                                                                                                                                                                                                                                                                                        | 0.984                 | 0.87                       |
| Tutstugi         | ভালা ভারে আমার দেখবা ধমকেবু ভাবে ভালা ফলা ভালা বাংলা দেনা ব্যাঙের ফলমার চিকা এ গাছ প্রোহিকা গাছ প্রোহিকা গাছ কা গাছ কা আবার এই গাছ প্রোহিঙ্গে একাকাল বেঙে একাকাল সাফে এভাবে খাদ্য শৃঙ্খল এভাবে খাদ্য শৃঙ্খল নিচে কুন খাদ্য শৃঙ্খল সত্যিক যেন দিবুটা ভাবা                                                                                                                          | 0.889                 | 0.561                      |
| PX5              | বেঙ্গে দেহো ফল মারে। জালা পারবা দেহ কইব? বো ালা কে লা ফলায। জালা ভাইঙগলে দেখন না গা। বেয়াঙগে ফল ালে। ফলফলা কি কা?। গাস শুড়িনকাও। গাস ফরিল্কে কা, গাস কা। আগা আবার এই ঘাস শুড়িঙ্গে কা কেলা? বেঙ্গে, বেঙ্গের কা কেলা? সাফেদ। বেইঙগের একা কেলা? সাফে, এইভাবেই খাদ্যসি কলেভাবে খাদ্যসিগা। নিজে কুনু খাদ্যসিন কলে শোটিক এ দে য নেন বৃহত্তা পারবা।                                   | 0.937                 | 0.477                      |

Figure 6.13: Inference results for all the models of samples from the corpus's Kishoreganj segment

In Table 6.13, which presents the ground truth and predictions for a sample from the Kishoreganj segment of the corpus, the term ব্যাঙের is inaccurately transcribed as ব্যাঙে or ভেঙ্গে, both of which represent distinct lexical items with differing meanings.

The model's prediction, বেঙ্গে, while orthographically divergent, exhibits phonetic similarity to the original ground truth.

| Models           | Predictions                                                                                                                                                                                                      | Word Error Rate (WER) | Character Error Rate (CER) |
|------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|----------------------------|
| Ground Truth     | না আসাদ মিয়ারে দিয়া ওইছেলো কিছু। বেচা ওইছেলো। তা ওত্তে আরও বেশি উনি অচ্ছে খায়। তা ওই দখলে? দখলে না। টাফি আমারে কলো যে ভাই এরকম এরকম। আমি ও নিয়ে আমার মাথা ব্যাথা নাই। আমি এর পিছনে দৈড়িছি। আগে এইটুকু দেহি। | N/A                   | N/A                        |
| Google ASR       | মাসুদ মেরে দিয়ে আইছিল কিছু বেশি বেচা আইছিল তা ওর থেকেও বেশি উনি আছে খায় তাও দখলে না উনি আমার মাথাব্যথা নাই আমি এর পিছনে ধরছি আগে ইউটিউব                                                                        | 0.756                 | 0.488                      |
| Wav2Vec2 Large   | নাসাদমেরে দিয়া ছুল কিছু বেশ বেশায় ছিল তা ওতের বেশিও নি আছে খায় তাওই তক হলেনাট অফি আমারে কলওজ বাইয়ে রকরম রকমতামি নি আমার মাথাপেথানাই আমিদের পিছনে দরও সে আগেই টোক দি।                                         | 0.927                 | 0.435                      |
| Hishab Conformer | দিয়া ছিল কিছু বেশি বেশি উনি আছে খায় তা দখলে না টাফি আমারে কল এরকমকম উনি আমার মাথা ব্যথা নাই আমি এর পিছনে দ আঙুকাই                                                                                              | 0.732                 | 0.488                      |
| YellowKing       | নাসের দিল কিছু বেসরকাটি আমারে বাইর রনি আমার মাথা বেথানি এর পিছনে ধরে আগে দেহি।                                                                                                                                   | 0.854                 | 0.671                      |
| Tutstugi         | নাসাদ মেয়ের দিয়ে আইস হল কিছু বেশি আইস হল তা ওটেরও বেশি উনি আসে খায় তা হই দখলে না টাফি আমারে কলও যে পাই এরকম রকম তা নিয়ে আমার মাথাব্যথা নাই আমি এর পিছনে দৌড়াছি আগে এটুকু দিহি                               | 0.707                 | 0.338                      |
| PX5              | নাসাদ মেয়ের দিয়ে আইস হল কিছু বেশি আইস হল তা ওটেরও বেশি উনি আসে খায় তা হই দখলে না। টাফি আমারে কলো যে ভাই এরকম রকম। তা আমি নি আমার মাথা ব্যথা নাই। আমি এরপিছনে দৌড়ছে আগে এইটুকু দেহি।                          | 0.537                 | 0.193                      |

Figure 6.14: Inference results for all the models of samples from the corpus's Narail segment

In a similar manner, Table 6.14, which presents the ground truth and predictions for a sample from Narail, indicates that the term আসাদ is inaccurately transcribed as নাসাদ by our model. This transcription exhibits a significant deviation from the expected output. However, it is noteworthy that the overall transcription, quality of our model exceeds that of alternative models, as demonstrated by its lowest CER and WER for this particular sample.

| Models           | Predictions                                                                                                                                                                                                                 | Word Error Rate (WER) | Character Error Rate (CER) |
|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|----------------------------|
| Ground Truth     | এই ইয়া সাদিয়া আইত ফারে বলে, সাদিয়ার মা ঢাখা গেলিল, যাইবো হইয়ে। অ, ইতারা বলে পাচটা বাজে উইঠা, আসতে আসতে এগারোটা, সাড়ে এগারোটা বাজিবু এন্ডে। ইয়া তুই যাইয়ারে, ইয়তুন তোর বড় হলামণির এডে যাইবু দে? অ। ফুপিরা বাসাত? অ। | N/A                   | N/A                        |
| Google ASR       | চোখের ভাষা                                                                                                                                                                                                                  | 1                     | 0.969                      |
| Wav2Vec2 Large   | তি লজনখাতাদিয়ায়েতরবল সাদিয়ার মা দাহাগের ব্যব্ব হযিকয়ত আবার পাচলা বা যদতি একপেস্তায়রাত সাহয় কঠা হবত সায কঠা বাসি বয়ান্ডেজুতুই জনারায়তুঃ বরাহলামনির বারা ব্যববও শুভির বাষা।                                           | 0.949                 | 0.604                      |
| Hishab Conformer | সাজিয়া এটার বলে সাজিয়ার মা হই হয় বলে পাচটা একটা জায়গাটা জায়গায় তোলা আমার নিজেরা যাব বোধহয় সুখের বাসায়                                                                                                               | 0.923                 | 0.656                      |
| YellowKing       | সাদা সাজিদাকে রাকা সানারিয়ার সুফির বা।                                                                                                                                                                                     | 1                     | 0.859                      |
| Tutstugi         | সাজিয়া এ তোর বলে সাজিয়ার মা দেখা যাব হই হয়তোর পরে পাচটা বাজুক বান্দায় যা তুই যাহারাই তো বলা হলামনি বেড়া যাব তাহা ফকির বাসায়                                                                                           | 0.923                 | 0.604                      |
| PX5              | ত তো ইয়া সাজিয়া ইতোর বলে সাজিয়ার মা ডাখা গেই যাবু খইয়ো। অয় তের বলে পাচটা বাজে উইঠতি, আইশযাইস টেগটা, সাড়া ঘটে ন আবার সাড়া ঘটে বাজিবাইনডোয় তুই যেডা তো বলে খলামনির এডে যাইবু দে? অ ফুফি বাষা। অ                       | 0.846                 | 0.432                      |

Figure 6.15: Inference results for all the models of samples from the corpus's Chittagong segment

In Table 6.15, which presents a sample from Chittagong, the term সাদিয়া is inaccurately transcribed as সাজিয়া. Although the erroneous transcription bears phonetic similarity to the ground truth, it differs orthographically. The Wav2Vec2 Large model transcribed the name accurately; however, our model demonstrated superior

overall performance.

| Models           | Predictions                                                                                                                                                                                                     | Word Error Rate (WER) | Character Error Rate (CER) |
|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|----------------------------|
| Ground Truth     | আসলে রুবলের জন্য খারাপ লাগে রে। আইও তো হিসাবে সিনিয়র প্রেয়ারই আমাদের। ওরে তেমন রেসপেক্ট দেওয়া হয় না। আর সাইফুদ্দিনের কথা বললি তো? সাইফুদ্দিন তো অইলো, মানে নিজেরে নিজে বড় মনে করলে যা হয় আর কি। এই আর কি। | N/A                   | N/A                        |
| Google ASR       | চলো রুবলের জন্য খারাপ লাগে রে ও তো হিসাবে দেওয়া হয় না নিজেরে নিজে বড় মনে করলে যা হয় আর কি                                                                                                                   | 0.641                 | 0.567                      |
| Wav2Vec2 Large   | সল রুবের জন্য খারাপ লাগে হতম হিসাবে সিনির প্রিয়ারী ম ধগরের তেমনর এক সপোক দেওয়া হয়নাআর্জখা ৃফ উদ্দিন কথাবলিত স্থায়ফুদ্দিন ত ল অনেদ নিজের নিজে পরমরনে গুলো যা হয় আকেএর।                                      | 0.872                 | 0.409                      |
| Hishab Conformer | রুবলের জন্য খারাপ লাগে হিসাবে সিনিয়রয়ার তেমন দেওয়া হয় না আর সাইফুদ্দিনের কথা বলি তোইউদিন তো নিজের নিজে বড় মনে করলে যা হয় আর কি                                                                            | 0.513                 | 0.356                      |
| YellowKing       | রূপের জন্য খারাপ লাগে হিসাবে সিনিয়র প্রেয়ার দে তেমন কসবা দেওয়া না সাইফুদ্দিনের কথা বলি ইদ্দিন নিজে নিজে পরনে যাওয়া হয়।                                                                                     | 0.821                 | 0.51                       |
| Tutstugi         | আসলে রোবারদের জন্য খারাপ লাগে রে প্রয়োগ হিসাবে সিনিয়র প্রেয়ার ই আমাদের ওর তেমন এক্সপেক্ট দেওয়া হয় না আর সাইফুদ্দিনের কথা বলিত সাইফুদ্দিন তো নিজের নিজের বড় মনে করলে যা হয় আর কি                          | 0.641                 | 0.279                      |
| PX5              | আসলে রুবের রে জনষ খারাপ লাগেরে। ওইষও তো হিসাবে সিনিয়র প্রেয়ার। ওরে। ওরে তেমন রব্রপেক্ট দেওয়া হয় না। আর সাইফুর দিনের কথা বলি তো, সাইফুর দিন তে অইলো মানে নিজেরে নিজের বড় মনে কলে যা হয় আর কি। এইআর।        | 0.641                 | 0.154                      |

Figure 6.16: Inference results for all the models of samples from the corpus's Narsingdi segment

Finally, in Table 6.16, which represents a sample from the Narsingdi segment of the corpus, the term *রুবলের* is inaccurately transcribed as *রুবের রে*. In contrast, some English terms, such as *সিনিওর* and *প্লেয়ার*, are transcribed accurately despite their lower frequency in the corpus. This accuracy is attributable to the model's prior familiarity with these English words, which facilitates more effective learning of their orthographic forms.

In conclusion, as demonstrated in Tables 6.12, 6.13, 6.14, 6.15, and 6.16 for a single sample, our model exhibits the lowest CER and, with the exception of the Kishoreganj sample, also achieves the lowest WER compared to all other SOTA models. Overall, the performance of our model indicates superior capabilities, as corroborated by the data presented in Table 6.2.

It is also observed that our model's inference lengths demonstrate a close alignment with the ground truth while also providing reasonably accurate orthographic representations of regional dialects as shown in the above tables. We believe with more data and more training, this can be overcome.

#### 6.4.1 Dialect Capturing Analysis

To evaluate the performance of the model in accurately capturing dialectal variations, we calculated the percentage of exact predicted words that match the ground truth dialectal transcriptions for each sample. This metric, referred to as the "Correct

Table 6.3: Dialect Detection Accuracy by District

| District    | Accuracy (%) |
|-------------|--------------|
| Rangpur     | 19.60        |
| Kishoreganj | 11.66        |
| Narail      | 24.17        |
| Chittagong  | 17.80        |
| Narsingdi   | 17.85        |
| Average     | 17.60        |

Dialect Percentage,” provides an interpretable measure of the model’s effectiveness in recognizing and predicting dialectal words accurately.

From the dataset, an average Correct Dialect Percentage of 17.6% was observed across all dialectal transcriptions. This suggests that while the model demonstrates some capability in identifying dialectal nuances, there is substantial room for improvement to ensure a more comprehensive representation of dialect-specific linguistic characteristics.

Further inspection reveals variability in performance across different samples, with some instances achieving relatively higher correct percentages, likely due to less dialectal complexity or better model alignment with the linguistic patterns of those specific dialects. Conversely, instances with lower percentages highlight challenges the model faces, such as highly nuanced or context-specific dialectal variations.

Average dialect capturing accuracy is shown in Table 6.3 and visualized in the Figure 6.17

This analysis underscores the importance of enhancing the model’s dialectal recognition capabilities, which may involve augmenting the training data with more diverse and representative dialectal examples or refining the linguistic features utilized in the model.

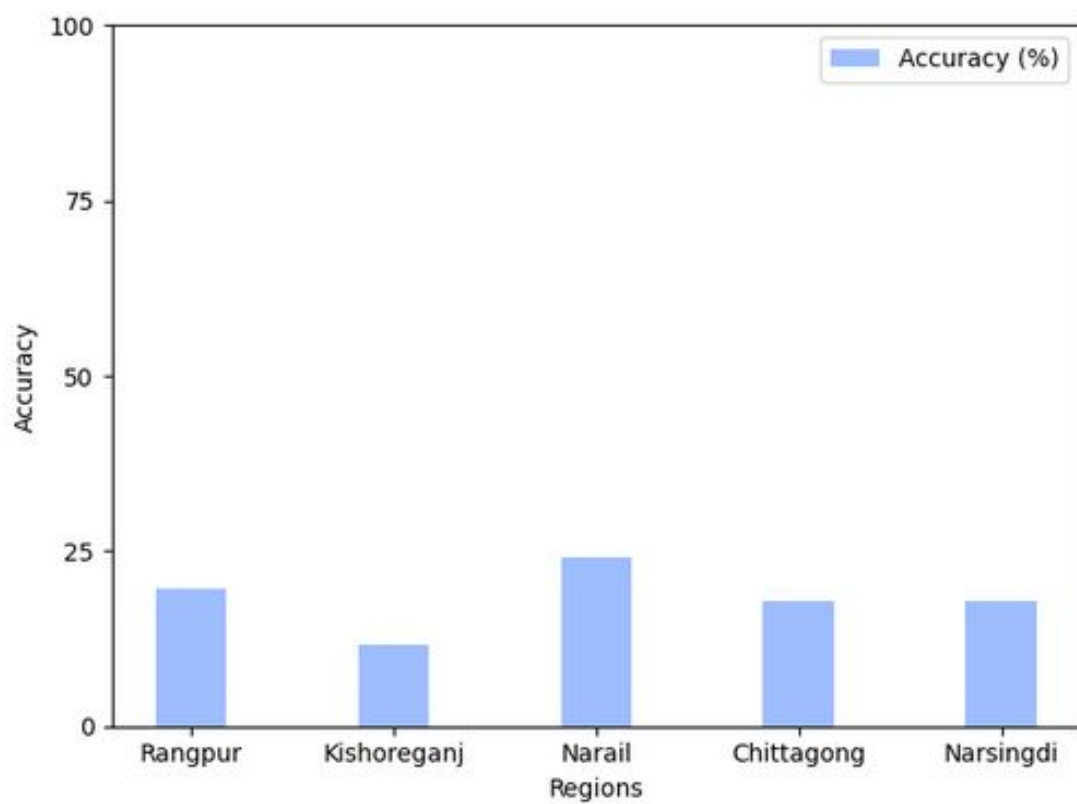


Figure 6.17: Bar chart of the PX5's dialect performance of dialect-capturing accuracy

# Chapter 7

## Conclusion

The research presented in this paper presents an all-encompassing framework for developing the first 39 hours of regional speech corpus specifically designed to address the various regional dialects of Bangladeshi Bengali. This dataset represents the only publicly available ASR (Automatic Speech Recognition) resource specifically focused on regional dialects. We also present a detailed analysis of the linguistic complexities involved in modeling Bengali speech with regional dialects using the developed regional speech corpus. It offers significant potential for applications in federated learning, meta-learning, text-to-speech systems, and other areas requiring further exploration. The corpus, dataset, and fine-tuned model are currently undergoing refinement and enhancement. Addressing challenges such as gender bias and diversifying sentence structures within the corpus will be crucial tasks for the development of future iterations of both the dataset and the model.

We are actively collaborating with an non-profit research community named Bengali.AI, where we are working to extend this effort to include speech corpora and datasets covering regional dialects from all 64 districts of Bangladesh. The data collection, transcription and validation processes will be comply by the guidelines and protocols established for the initial five districts.

Furthermore, a detailed linguistic analysis of regional Bengali will be conducted to enhance the understanding of this language for linguistic researchers. Future plans include the canonization of these transcribed data to enable machine transliteration between regional accents and standard Bengali. Additionally, We intend to develop a speech-to-text model capable of converting regional text data to its standard form and vice versa.

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