A Conventional & Deep Learning Strategy for Analyzing & Detecting Bengali Fake News in Online Medium

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

1. The thesis submitted is 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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Ethics Statement

As the author of this thesis paper, We would like to make a statement regarding the ethical considerations that have been taken into account during the writing process. Our work has been conducted in strict accordance with the principles of academic integrity and honesty. We have made every effort to ensure that our research is entirely original and free from any form of plagiarism. All sources used have been properly cited and acknowledged, and we have taken care to avoid any misrepresentation or distortion of the work of others. We believe that research ethics are of paramount importance in the academic community, and we have done our utmost to uphold these principles throughout the course of this project. We hope that our work will contribute to the advancement of knowledge in our field, while also serving as an example of the highest standards of ethical conduct in research.

Abstract

Nowadays, social networking sites like Facebook and Twitter have become an significant impact on our lives . We use such sites to remain in touch with one another and as a source of news to stay informed about current events. As a result, we frequently see news articles with click-bait headlines from various web portals that lack authenticity. The majority of these sites that share these sorts of links are used to manipulate people and spread false propaganda. We intended to utilize both traditional machine learning algorithms and deep learning algorithms on manually annotated data-sets to create effective approaches for spotting Bangla fake news on online media that included about 8,500 pieces of news data. In particular, in this project, we used classic machine learning algorithms for text classification such as “Naive Bayes Classifier”, “Support Vector Machines (SVM)”, “K-Nearest Neighbor (KNN)” as well as other classification-based algorithms such as “Decision Tree (DT)”, “Logistic Regression (LR)”, “Random Forest” and “AdaBoost”. We have also used deep learning models based on Feed-Forward Neural Networks such as “Convolutional Neural Network (CNN)” as well as a variety of Recurrent Neural Networks (RNN) such as “Long-Short Term Memory (LSTM)”, “Gated Recurrent Unit (GRU)” to detect fake news on online media. To conclude, our research focused on developing precise strategies for spotting fake news on social media sites.

Keywords: Conventional Machine Learning Models, Deep Learning Models, Classic Machine Learning Algorithms, Feed-Forward Neural Networks, Recurrent Neural Networks (RNN)

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Chapter 1

Introduction

1.1 Overview

The advancement of current technology has brought us to a point where information is as accessible as it has ever been. In only a few seconds, we can have the answers to our questions. The convenience is amplified for those who have access to mobile devices. This aspect significantly changed how individuals obtain news information. Every major news organization now has a website, a Facebook page, a Twitter feed, etc., so that the public can quickly and easily access the latest headlines.

Surprisingly, the news we receive is not always credible. However, due to the vast number of sources available online, many of which conflict one another, it is more difficult to verify information. As a result of all of this, fake news has spread. There are several websites devoted exclusively to promoting misleading information. They generate false news, propaganda materials, rumors, and conspiracy theories under the pretense of legitimate news.

The primary goal of fake news websites is to influence people's attitudes about controversial topics. Even false news has significant democratic and diplomatic implications. Every country in the world such as Ukraine, the UK, USA, Russia, Germany as well as many other countries [1] are examples of these global issue. Its disruptive and distorted effects on people's perspectives were on full display during the American presidential election [2]. Even now in Bangladesh, there are numerous unregistered online portals and websites operating under various aliases that seem to be liable for circulating misleading information. As a consequence, Bangladesh has experienced several disastrous incidents over the years. As reports of human sacrifice during the Padma Bridge's construction circulated, five persons were killed and 10 were injured by crowds in July of 2019 [3].

Artificial intelligence is considered to be capable of solving the biased news problem effortlessly and without external guidance. Researchers in the field of artificial intelligence have created more precise algorithms for machine learning to identify false or rumoured news for human evaluation [4]. Machine and Deep learning methods have shown that they can solve hard classification problems that are often not clear-cut.

This article will provide a basic false news detection technique based on 9 supervised machine learning algorithms: the Naive Bayes classifier (Multinomial Naive Bayes, Complement Naive Bayes, Bernoulli Naive Bayes), the Support Vector Machine

(SVM), Decision Tree (DT), Random Forest, Logistic Regression (LR), K-Nearest Neighbor (KNN), AdaBoost as well as 2 types of Modern Recurrent Neural Networks (RNN) architectures: Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) and commonly used Feed-Forward Neural Network architecture: the Convolutional Neural Network (CNN).

The article's objective is to explore how well fake news detection strategy using above algorithms would perform for tackling this specific social and global issue by giving a manually labeled unbalanced newspaper dataset to our models.

Throughout the rest of the article, we briefly presented our data set, methodology, model results and performances, and finished with our future plans and concluding remarks.

1.2 Problem Statement

The purpose of creating fake news is to mislead readers into believing fraudulent claims by making it challenging and laborious for readers to recognize based on news content. Hence, we must incorporate auxiliary information. As a result, we need to add some context. The mass circulation of false information can have devastating effects on both individuals and communities. Due to this, there is an increased interest in researching how to spot fake news on social media sites and stop it from spreading. Bengali is one of the largest and most widely used languages in worldwide, so an efficient method for locating and eradicating the erroneous information is required.

For some years, researchers have been researching automatic false news identification. Conroy et al. (2015) [5] proposed a hybrid technique that blends linguistic aspects of a language with network analysis. This strategy is not always appropriate since network information may be limited or unavailable. There are several implications of fake news that inflict damage on innocent individuals. Fake news can be created purposefully or unintentionally to hurt a person or a group for variety of reasons, such as political or religious reasons and so on. As a result, now is the time to recognize bogus news on every website.

All of these issues are the focus of our research. Our research is based on determining if a news article is fake or authentic using both classical supervised and deep learning methods. Additionally, a top goal for identifying fake news on the internet platforms is to find an improved approach with the best precision, recall, and F1.

1.3 Research Objective

This paper will introduce techniques to develop dependable machine learning system that can identify between true and fake news reports. Our goal is to utilise several data sources to identify incorrect information shared across social networking sites in real time, such as Fb and Twitter.

Our research aims to construct both conventional classification models with deep learning algorithms for identifying the earliest instances of false information on media platforms, before they have a chance to reach a significant audience.

For this we have,

1. Extracted features from the text data in our work. For that we used different word embedding techniques, which required less manual labor. We employed various machine learning models for the categorization tasks and examined the results.

2. We have applied the Naive Bayes theorem. Users may rapidly tell if a news article is legit or not by comparing its values to those from other datasets.

3. The term "Support Vector Machine", which can also refer to a "Support Vector Network" (SVN). Category assignment, spam detection, and sentiment analysis are just some of the text classification tasks that can benefit from SVM.

4. Another algorithm, Logistic Regression, was used to address the problem in this case. Because of its predictive strength in probability values, logistic regression is quite excellent at solving binary classifications. To recognize whether a news story was false or not, we tried to develop a basic machine-learning model using Logistic Regression.

5. The K-Nearest Neighbors (KNN) method has also been employed. A supervised machine learning method, using it to solve categorization issues. This maintains information about all previous instances in order to classify the new case based on similarities.

6. We have used decision trees for text classification task.

7. A random forest model was used during the prediction stage which assigned a probability as to whether the provided news article is true or false using the knowledge gained from the decision trees. The article was labeled as fake if the probability exceeded a predetermined threshold, otherwise, it was classified as real.

8. To gain the semantics of the text in a news article and generate predictions based on it, we applied commonly used RNN architecture like LSTM and GRU.

It's possible for fake news to have a huge impact and to go viral very rapidly. As more and more individuals join the social media revolution, everyone gains daily access to new viewpoints and news. The effects of spreading false information can last for a long time and might be difficult to undo. As a result, now is the time to recognize bogus news on every website.

In addition, we attempted to identify each model's strengths and limitations and explored ways to enhance their performances. We also attempted to identify important features and factors that contribute to each algorithm's success in classifying fake news in Bengali language.

All of these social and technical issues and constraints are the focus of our research.

Chapter 2

Detailed Literature Review

Researchers are inspired to investigate the problems currently faced by internet users by the increasing visibility and amount of bogus news. Although while interest in the topic is growing, academic research on it is just getting started. There has been a rise in the amount of studies looking at how to assess and detecting and countering false information requires research into fake news and rumour characteristics, yet this is an area with much space for development because no standard solution has yet been established.

For languages with little resources, like Bangla, Hossain et al. [6] developed a method for the automatic identification of misleading news. To develop this system, they looked at both standard linguistic traits and neural network-based methods. Linear classifiers with conventional language characteristics can outperform neural network-based models, according to their comparison. They relied on their own publicly available, annotated dataset with over 50K news articles.

Tanvirul Islam et al. [7] presented a study based on a method of spam identification in textual data. In order to word-level spam detection in Bangla text, they experimented via feature extraction and supervised machine learning methods using a Multinomial Naive Bayes (MNB) classifier. In order to identify spam, their method recommends examining the polarity of each relevant text. After further testing, it was determined that the algorithm can identify spammy Bangla text content with an accuracy of 82.44%.

Mohammed Al-Sarem et al.'s [8] study sought to develop a novel hybrid deep neural network technique for spotting COVID-19 rumors in online communities. (LSTM–PCNN). Based on LSTM and combined parallel convolutional neural networks, their proposed model is highly advanced (PCNN). The studies were carried out on an ArCOV-19 dataset that contained 46.87% rumors and 53.12% non-rumors. Efficiency, precision, recall, as well as F-score were all improved by the suggested model over previous approaches. GloVe, Word2Vec,and FastText were used as the static word embedding models in the testing. The results showed that the recommended LSTM-PCNN model outperformed the gold standard models with an accuracy of 86.37 percent when using the word embeddings skip-gram model.

The research of Farzana Islam et al. [9] makes use of data mining techniques to categorize fake and real news. They've also built a web-based interface on top of their classifier to evaluate Bengali news stories for authenticity. They facilitated the construction of a complete pipeline for data collection, ingestion, visualization, and fake news categorization on the web. The random forest model improves classification accuracy to 85%.

Khanom et al. [10] conducted a baseline study to recognize fake news from web portals by comparing both accurate and misleading stories. They likewise utilized sophisticated deep learning models (CNN, CRNN, GRU, and LSTM) that have demonstrated great promise in classifying fake news. Their research endeavor also provided two other models: Support Vector Machine and K-Nearest Neighbor. They tested random forest, SVM, and KNN on identical data and discovered that random forest surpasses the other two models by giving 76.37% accuracy.

In addition, A.Mandal and R.Sen [11] discussed four supervised learning techniques, including Naive Bayes,Decision Tree, KNN, and Support Vector Machine, for categorising content on the Bangla web (SVM). An experiment was performed by Jin,Z.(2008) [12] to replicate the progressive training of tailored spam filters. M. Hossain, I. Jui, and A. Suzana [13] used many classification techniques to determine whether Bengali newspaper headlines were negative or positive, with the Support Vector Machine (SVM) performing best. T.A.Almeida, T.P.Silva, I. Santos as well as J. M. G. Hidalgo [14] proposed a text processing strategy for semantic analysis and context identification. They tested their solution against a number of renowned machine learning algorithms that enhance instant messaging and short message service (SMS) spam filtering using an openly accessible, authentic, and unencrypted dataset.

Researchers Ahmed Fahmin, Sayeda Muntaha Ferdous as well as Shafayat Bin Shabbir Mugdha [15] used headlines to create a model that can accurately assess if a story is true or fraudulent. To achieve their goal, By employing the Gaussian Naive Bayes technique, they created a brand-new Bengali language data set. In their simulation, the Gaussian Naive Bayes Algorithm performed admirably.It accomplished this by combining an Additional Tree Classifier with a text feature that was determined by the TF-IDF distance metric. Compared to the other methods they tried, Gaussian Naive Bayes yielded the best results, with a dependability of 87% in their model.

A novel hybrid algorithm for deep learning combining both recurrent and convolutional neural networks is recommended by the authors Jamal Nasir, Osama Khan, and Iraklis Varlamis [16]. The model's performance was confirmed using both bogus news datasets (ISO and FA-KES), with accuracy in detecting outperforming nonhybrid techniques as the standard. CNN was used to extract features, and LSTM was used for classification in their model. Experiments with applying the proposed model to new data sets showed promising results.

The use of deep learning model by E.Amer,S.Girgis,and M. Gadallah [17] has been widespread, employing RNN and LSTM. To identify false claims Wang et al. [18] applied Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Logistic Regression, along with Long Short-Term Memory (LSTM). Victoria, L.,Rubin., et al. [19] implements the Support Vector Machine (SVM) Classifier. A simple technique was presented in the paper by K. Shu, X. Zhou, R. Zafarani, and H. Liu, [20] who employed the Naive Bayes (NB) Classifier to obtain 74% accuracy on the examination set. M. L. Della Vedova,E. Tacchini, G. Ballarin, S. Moret, and L.de

Alfaro [21] created a novel approach by fusing harmonic boolean label crowdsourcing with regression models. F.Frasca,F. Monti, M.M.Bronstein, D. Mannion, and D.Eynard, [22] utilized geometrical deep learning.

The new technique for identifying rumors is based on the GRU architecture and a dynamic time series approach. presented by Zhihong Wang et al. [23] The suggested framework employs the DTS algorithm to maintain social event distribution data over time and the GRU model with two layers to learn covert event descriptions. The results of their experiments on the real Sina Weibo dataset revealed that their solution beats five benchmark rumor event identification systems.

In his paper, Li et al. (2018) [24] present a Deep Bidirectional Gated Recurrent Units-based rumor detection system (D-Bi-GRU). In order to demonstrate the development of group reaction data in relation to microblog occurrences across time, they look at both forward and reverse cycles of microblog data movement along timelines concurrently. The development of multi-layer Bi-GRU stacks for rumor detection based on deep latent space descriptions, integrating semantic and affective learning. Weibo rumor detection has been improved by using both historical and anticipated group reaction data, based on research done on actual Weibo data collections. The text-hidden features of the experiment have also helped in rumor detection.

Our research utilises what we believe to be a currently accessible dataset [25] for Bengali fake news detection. In our work, we used a variety of embedding techniques and models including Bengali GloVe Model [26], Bengali Word2Vec Model [27] & Bengali Fast Text Model [28] to make feature extractions from text data. For the sake of our classification analysis, we tried various machine learning algorithms and compared their results.

Chapter 3

Description Of The Data

With an estimated 272.7 million native speakers, Bengali has been the 7th predominant language on Earth, according to the authors of ”Ethnologue” [29].In addition to Bangladesh, it is also spoken in other nations like France, Canada, and India. Despite this, finding a comprehensive library of the Bengali language is quite tough.

We obtained this dataset with the help from BanFakeNews [6] paper. This dataset contains news which has been annotated manually and verified by credible sources. On the contrary, articles from satire blogs and those that use misleading headlines are labeled as fake. There are two entity for true and false label: one of it contains 7,202 real articles classified as ”LabeledAuthentic-7K.csv,” and the other one contains 1,299 false ones classified as ”LabeledFake-1K.csv”.

headline	content	label
প্রবাসী আ.লীগের নির্বাচনী ভূমিকা নিয়ে স্পেনে সভা	বৃহস্পতিবার দেশটির রাজধানী মাদ্রিদে হোটেল পোর্...	1.0
ফিলিপাইনে জন্ম নিয়েই ভুল করেছি : একান্ত সাক্ষা...	বাংলাদেশ ব্যাংকের রিজার্ভ চুরির ঘটনায় ফিলিপাইন...	0.0
কুমিল্লা বিভাগের কাজ চলছে: কাদের	“কুমিল্লা বিভাগের কাজ হচ্ছে। আপনাদের দাবির বিষ...	1.0
এবার মশার বিরুদ্ধে গর্জে উঠলো ছাত্রলীগের কামান	সম্প্রতি ঢাকা বিশ্ববিদ্যালয় প্রাঙ্গণে ছাত্রলীগ...	0.0
রাজশাহীতে বনসাই প্রদর্শনী	রাজশাহীতে শুরু হয়েছে বনসাই প্রদর্শনী। রাজশাহী ...	1.0

Figure 3.1: Visualization of Sample Text Data

The dataset representation for the text data is shown in Figure 3.1. We focused on the headlines and content columns in the dataset as the features for our analysis. Before performing the pre-processing, we joined these two columns to create a single column.

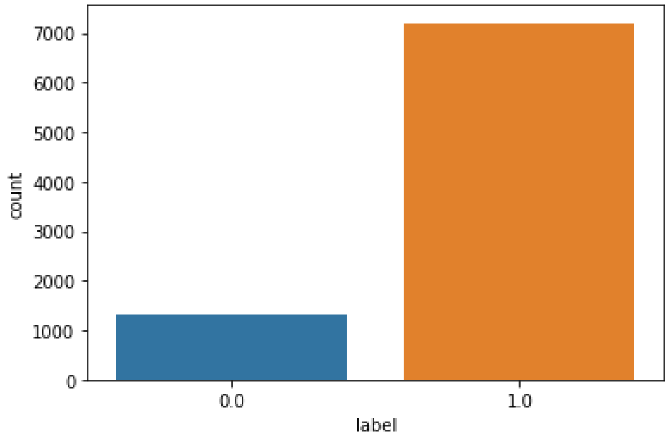

Figure 3.2: Relative Frequencies of Different Labels

Figures 3.2 illustrate an imbalanced ratio in the dataset, making classification difficult. The amount of fake news appears to be relatively small compared to credible news. Instead, our experiment's algorithms may have been better able to pick out differences between fake and genuine news if the dataset had been more uniformly distributed.

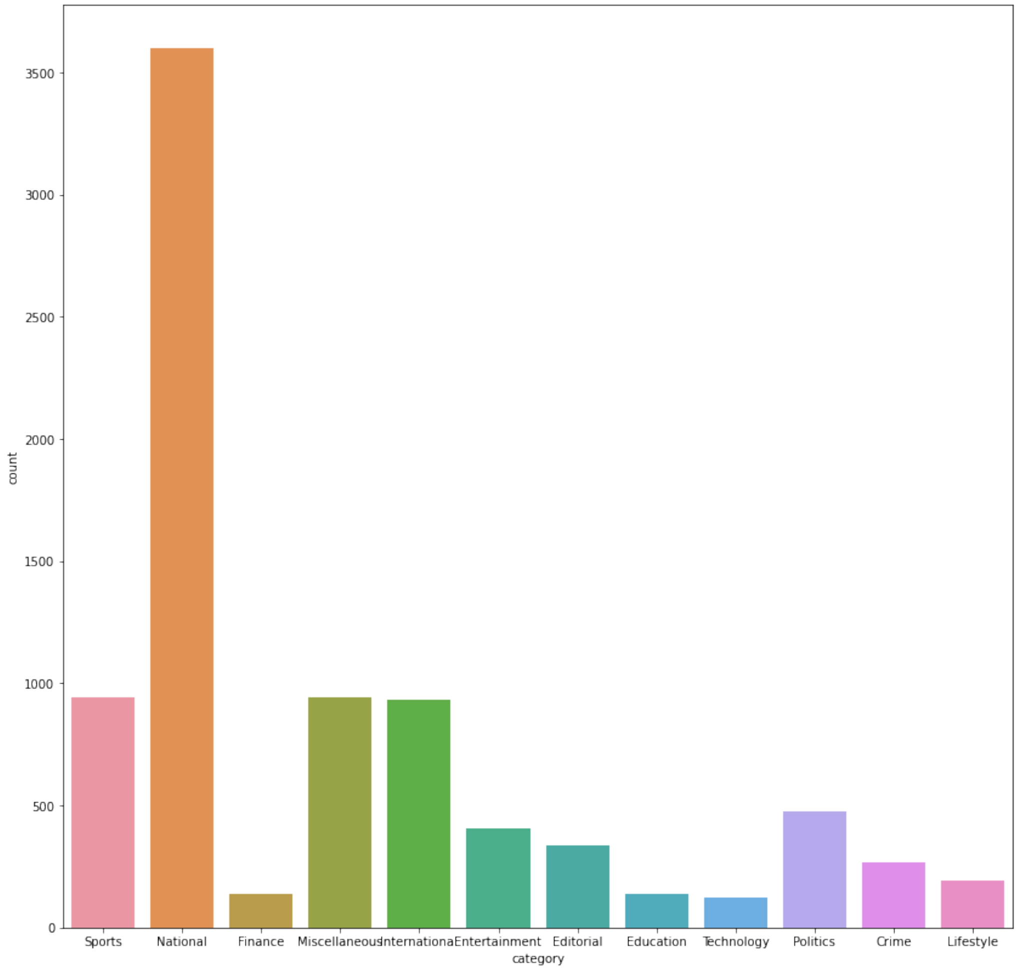

Figure 3.3: Relative Frequencies of Different Labels

The data is divided into twelve categories, which include entertainment, politics, sports and so on. Figure 3.3 illustrates the various news categories and the amount of news items in each category. The figure shows that the majority of the data falls under the “National” category, while only a small amount of data falls under the categories of “Finance”, “Education”, “Technology”, and “Lifestyle”.

Chapter 4

Methodology and Description Of The Implemented Model

4.1 Methodology

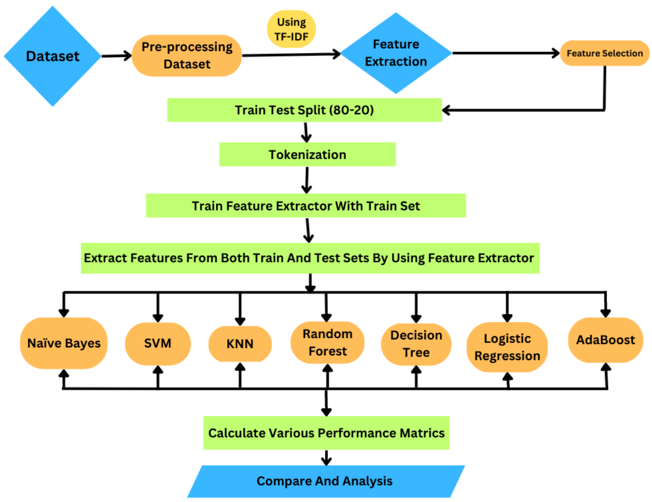

Figure 4.1: Work Flow for Supervised Learning

Figure 4.1 displays the approach we suggest for traditional machine learning models. In the beginning, we completed preprocessing of the dataset to obtain root words from sentences and concate those words. We then used TF-IDF to extract the features, and then we ran them through classifiers to determine the accuracy rate. Our dataset has been used to test 9 different types of traditional classifiers to identify fake news based on news headlines and content.

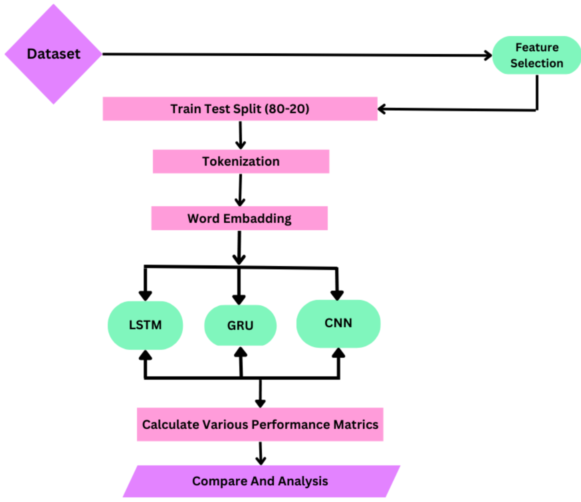

Figure 4.2: Work Flow for Deep Learning Models

Figure 4.2 displays the approach we suggest for deep learning models. In the beginning, we use variety of embedding models and techniques such as word2vec, GloVe, Fast Text to reduce the dimensionality of our data, and then we ran them through deep learning algorithms. On the basis of news headlines and content, our dataset has been used to evaluate three different kinds of neural network architecture.

4.2 Preprocessing

While preprocessing our dataset, we mostly eliminate stopwords and punctuation to produce a cleaner dataset. The preparation phase operates as shown in Figure 4.3 due to the lack of stopwords, text categorization, and lemmatization in the news' title section. The majority of our dataset's preprocessing procedures are performed to eliminate a more filtered dataset.

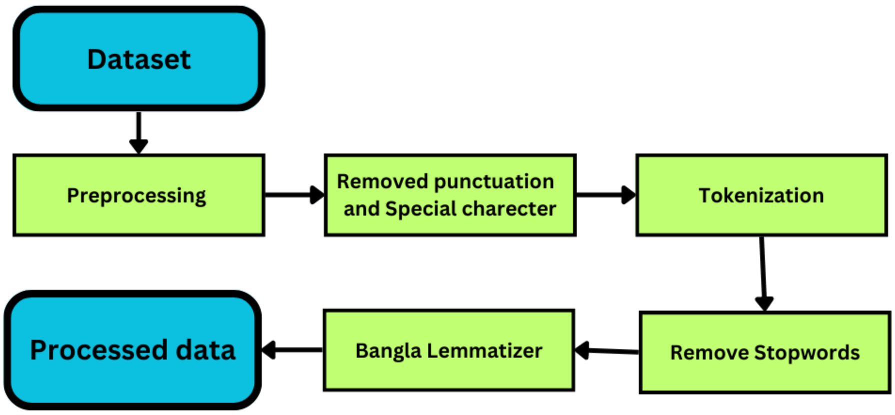

Figure 4.3: Pre-Processing Technique for Supervised Learning

4.3 Tokenization:

To prepare the texts for our supervised models, we got rid of all the special characters and numerical values from the text sequence. The remaining phrases were then broken up into words, and after tokenizing it from the text, we removed the frequent stop words using NLTK library. Thanks to filtering, we now have a large number of unique terms. Figure 4.4 showed a depiction of tokenizing texts and removing special letters.

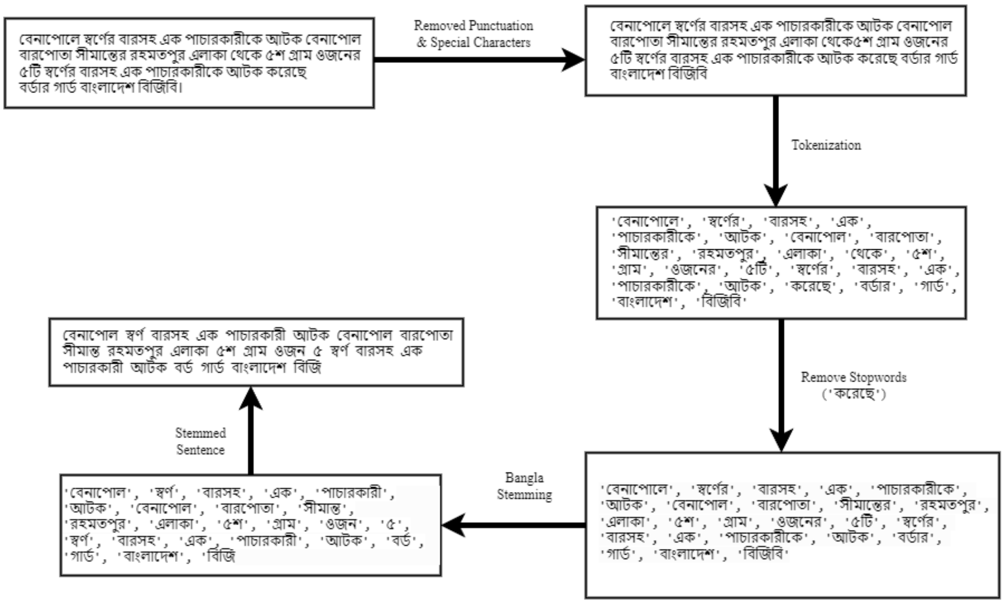

Figure 4.4: Visualization of Removing Special Characters and Tokenizing Sentence

After data has been tokenized, it must be converted to a uniform format. As a result of lemmatization, fewer word categories or classes exist, and the words are altered in their original form. The group of words we obtained after tokenization was utilized for lemmatization. Both the noun and the verb have been separately lemmatized. Our lemmatizers have just three steps each:

Step 1: In the first step, we got rid of the terms with accents.

Step 2:We eliminated the diacritical point from sentences.

Step 3: With a few modifications for the diacritical mark in consideration, special cases are managed.

4.4 Feature Extraction & Selection

Getting high dimensional information into text classifiers is one of the major challenges. A small number of concepts, words, and document-based explanations have a disproportionately large computational impact on the learning cycle.In addition, excessive or pointless emphasizing can reduce the classifiers' efficacy and performance.

4.4.1 TF-IDF

The Term Frequency-Inverse Document Frequency (TF-IDF) approach, also known as transformed text numerical representation, is commonly employed to determine a word's significance within a document. This feature extraction technique is commonly used in NLP applications. One of IDF's key characteristics is that it affects common terms while elevating unusual ones. In the event that we just employ TF, phrases like "the" and "at that point," for example, frequently appear in the content and will therefore govern the recurrence check. However, applying the IDF reduces the impact of these phrases.
The two divisions of the dataset were made at random. The classifiers are trained using 80% of the data in one section, and their effectiveness is tested using the remaining 20%.

4.4.2 GloVe Embedding

In order to produce word embeddings, dense vector representations of words that contain both syntactic and semantic information, the popular unsupervised learning method GloVe is employed (Global Vectors for Word Representation). Despite using a different method to record the statistical characteristics of word co-occurrences in a corpus of text, GloVe is comparable to other well-known embedding algorithms like Word2Vec.

GloVe's main principle is to factorize the word co-occurrence matrix into a product of two matrices, one representing the word-context matrix and the other representing the context-word matrix. GloVe learns embeddings that capture both local and global word relationships by minimizing the difference between the product of these matrices and the actual co-occurrence matrix.

4.5 Support Vector Machine

A common supervised learning technique is the use of the Support Vector Machine (SVM) for classification and regression. But it is primarily employed in machine learning to deal with classification-related issues. The SVM method's objective is to establish the optimum decision boundary for categorizing n-dimensional space so that fresh data points can be quickly added to the future categories. A hyperplane is used to visualize the optimal decision-making boundary. Use SVM to choose the hyperplane's extreme points and vectors. Support vectors are considered to be extreme situations, hence the method is known as SVM.

4.6 Decision Tree

One of the best and most commonly used methods for classification and forecasting is the decision tree (DT) . A decision tree's nodes and branches stand in for attribute tests, with each node denoting a test and each branch denoting the test's result. Each leaf node's end has a class label visible.

4.7 Random Forest

A well-known machine learning technique called Random Forest (RF) is a component of the supervised learning approach. It can be applied to Classification and Regression issues in artificial intelligence. This strategy makes use of ensemble learning, a method in which numerous classifiers collaborate to solve a particularly challenging problem. A decision tree is created for each subset of the provided data, and an average is used to increase prediction accuracy.The random forest uses the predictions from each decision tree to make a final forecast based on the votes cast. A larger forest is preferred since more trees indicate greater accuracy.

4.8 K-Nearest Neighbors

One of the most popular algorithms for supervised machine learning is K-Nearest Neighbor (KNN) . It can be used to solve both regression and classification issues, but the former is where it sees the most action.KNN is a non-parametric method that is also referred to as the "lazy learner algorithm" on occasion.

4.9 Logistic Regression

The discriminative linear model of the logistic regression classifier learns the independent feature coefficients via stochastic gradient descent. In order to calculate the loss function of the model and the term document matrix as input features, we employed cross entropy. In essence, logistic regression is a linear model that transforms its outputs into classification probabilities using the logistic function.

4.10 Multinomial Naive Bayes

A supervised machine learning algorithm for classification is called Multinomial Naive Bayes. It is founded on the idea that features are independent of one another, as stated by Bayes's theorem. Every class's probability is calculated, and the class with the highest likelihood is selected as the result.

4.11 AdaBoost

AdaBoost's core concept is the iterative training of a number of weak classifiers, each of which is trained on a different subset of the training data. AdaBoost increases the weight of incorrectly classified examples in each iteration so that the following weak classifier concentrates on correctly classifying these examples. All of the weak classifiers are combined and weighted based on accuracy to create the final classifier. Numerous applications, such as in face detection, text classification, and in bioinformatics, AdaBoost have demonstrated efficacy of.

4.12 CNN

The deep learning algorithm known as CNN, or Convolutional Neural Network, is frequently used for image recognition and classification tasks. The hierarchical and modular processing of visual information by the human visual cortex, which serves as an inspiration for CNN structure and operation.

Convolutional filters, which are compact matrices of weights that slide over the input image and carry out element-wise multiplication and sum operations, are the fundamental component of CNNs. CNNs can use local patterns and features in the image, like edges, corners, and textures, to make higher-level predictions about the image's content by learning these filters through backpropagation.

4.13 LSTM

The vanishing gradient problem, which is a frequent problem in conventional RNNs, is addressed by LSTM, a new type of RNN architecture [30]. In LSTMs, information is stored over time in memory cells, and information flow into and out of the cells is regulated by gating mechanisms. Activation functions like sigmoid functions regulate the gates, allowing the model to selectively remember past events and make room for new ones.

On many tasks requiring long-term dependencies, it has been demonstrated that LSTMs perform better than conventional RNNs. Additionally, they have been effective in NLP tasks like language modeling, sentiment analysis, and machine translation.

4.14 GRU

Long Short-Term Memory (LSTM) is a complex recurrent neural network (RNN) structure type that was designed as an alternative to the simpler GRU. To better represent sequential data, GRU, like LSTM, stores information about previous inputs in a hidden state that is updated at each time step. GRU simplifies the LSTM design by merging the forget and input gates into a single update gate, and the cell state and hidden state into a single hidden state. The result is a reduction in the total number of parameters and shorter training times compared to LSTM. GRU has been effectively used to several NLP applications, such as sentiment analysis, machine translation, and text synthesis.

Chapter 5

Result and Analysis

Utilizing supervised learning and deep learning techniques, we ran multiple algorithms with varying features. We grouped the title and content before training our models with the joined column. Below tables summarizes an overview of the findings created by traditional machine learning & deep learning algorithms. For our tasks, since our dataset is skewed towards positive labels, we have used precision, recall, F1 scores, and overall accuracy for classification metrics to measures the performance of our models. The precision, recall, and F1 scores have been calculated individually for the total data as well as the fake labeled data.

5.1 Analysis & Result using Uni-Gram Word Sequence

Algorithms	Precision	Recall	F1
Multinomial Naive Bayes	0.91	0.38	0.53
Complement Naive Bayes	0.70	0.86	0.77
Bernoulli Naive Bayes	0.68	0.90	0.78
Decision Tree	0.66	0.61	0.64
Support Vector Machine	0.89	0.75	0.82
Random Forest	0.98	0.55	0.70
Logistic Regression	0.93	0.64	0.76
K-Nearest Neighbor	1.0	0.03	0.06
AdaBoost	0.84	0.72	0.77

Table 5.1: Precision, Recall & F-Score on Fake class using Uni-Gram word Sequence

Table 5.1 displays the precision, recall, and F-score of traditional learning methods on a Fake class using a Uni gram word sequence. It reveals that Support Vector Machine (SVM) obtained the highest F-score of 82%, as well as moderate precision and recall of 89% and 75% on fake label data, respectively. This suggests that SVM is the best algorithm to employ on our fake news data. The F-scores of Multinomial Naive Bayes (MNB),Logistic Regression, Bernoulli Naive Bayes (BNB),and AdaBoost are all close, ranging from 76% to 78%, whereas the F-scores of the other methods are substantially lower. The table reveals that K-Nearest Neighbour (KNN) has the best precision (100%), lowest recall (3%), and lowest F-score. KNN has an exceptionally low f-score value of 6% when compared to all other algorithms.

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Multinomial Naive Bayes	0.90	0.90	0.68	0.74
Complement Naive Bayes	0.92	0.84	0.89	0.86
Bernoulli Naive Bayes	0.92	0.83	0.91	0.86
Decision Tree	0.89	0.80	0.78	0.79
Support Vector Machine	0.95	0.92	0.87	0.89
Random Forest	0.93	0.95	0.77	0.83
Logistic Regression	0.94	0.93	0.81	0.86
K-Nearest Neighbor	0.85	0.92	0.51	0.49
AdaBoost	0.93	0.89	0.85	0.87

Table 5.2: Overall Performance Result using Uni-Gram word Sequence

Table 5.2 illustrates the accuracy and overall resulting from the conventional machine learning algorithm utilized in our study using Uni gram word sequence. The findings of Table 2 confirm the results of Table 1, indicating that SVM has the best accuracy of 95%, as well as the highest F-score of 89%. Multinomial Naive Bayes, Logistic Regression, Complement Naive Bayes, and AdaBoost all have comparable accuracy, ranging from 92% to 94%, with F-scores ranging from 86% to 87%. In a similar manner as the Table-1, KNN ranks last with the accuracy of 85% and the least F-score value of 49%.

5.2 Analysis & Result using Bi-Gram Word Sequence

Algorithms	Precision	Recall	F1
Multinomial Naive Bayes	0.98	0.23	0.37
Complement Naive Bayes	0.77	0.79	0.78
Bernoulli Naive Bayes	0.69	0.85	0.76
Decision Tree	0.71	0.63	0.67
Support Vector Machine	0.92	0.68	0.78
Random Forest	0.92	0.54	0.68
Logistic Regression	1.0	0.23	0.37
K-Nearest Neighbor	1.0	0.03	0.06
AdaBoost	0.79	0.63	0.70

Table 5.3: Precision, Recall & F-Score on Fake class using Bi-Gram word Sequence

Based on Table 5.3, it can be observed that the precision, recall, and F-score vary significantly across different classification algorithms for the fake class using Bi-Gram word sequences. The Logistic Regression algorithm reached a perfect 100% precision, but a very poor F-score of 37%. However, it should be noted that these scores only apply to the fake class, and the performance of this algorithms on other classes may vary.

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Multinomial Naive Bayes	0.88	0.93	0.61	0.65
Complement Naive Bayes	0.93	0.87	0.87	0.87
Bernoulli Naive Bayes	0.91	0.83	0.89	0.85
Decision Tree	0.90	0.82	0.79	0.80
Support Vector Machine	0.94	0.93	0.83	0.87
Random Forest	0.92	0.92	0.76	0.82
Logistic Regression	0.88	0.94	0.62	0.65
K-Nearest Neighbor	0.85	0.92	0.51	0.49
AdaBoost	0.92	0.86	0.80	0.83

Table 5.4: Overall Performance Result using Bi-Gram word Sequence

Based on the performance results using Bi-Gram word sequence from Table 5.4, the Support Vector Machine (SVM) algorithm performs the best using an accuracy rating of 94% and an F-score of 87%. The Complement Naive Bayes algorithm also performed well with an accuracy score of 93% and an F-score of 87%. AdaBoost and Random Forest algorithms also had good performance with an accuracy score of 92% and F-score of 83% and 82% respectively. With an accuracy rating of 85%, K-Nearest Neighbor was the algorithm with the worst performance. and the lowest F1-score of 49%, indicating that it performed the worst among the algorithms tested. Although it had a high precision score of 92% and low recall score of 51%, which contributed to its overall low F-score.

Overall, the performance results suggest that SVM and Complement Naive Bayes are the top-performing algorithms for text classification using bi-gram word sequence, while K-Nearest Neighbor is the least effective. The results also suggest that accuracy and F1-score are important evaluation metrics to consider when selecting an algorithm for text classification tasks especially when running classification based algorithm on imbalanced data.

5.3 Analysis & Result using Tri-Gram Word Sequence

Algorithms	Precision	Recall	F1
Multinomial Naive Bayes	0.90	0.20	0.33
Complement Naive Bayes	0.54	0.79	0.64
Bernoulli Naive Bayes	0.35	0.96	0.52
Decision Tree	0.49	0.82	0.62
Support Vector Machine	0.88	0.35	0.50
Random Forest	0.62	0.77	0.69
Logistic Regression	0.95	0.20	0.33
K-Nearest Neighbor	0.20	0.97	0.33
AdaBoost	0.51	0.83	0.63

Table 5.5: Precision, Recall & F-Score on Fake class using Tri-Gram word Sequence

Based on Table 5.5, the algorithm with the highest F1-score on the fake class using Tri-Gram word sequences is Random Forest with a score of 69%. The second-best algorithm is Complement Naive Bayes with an F1-score of 64%, followed by decision tree with an F1-score of 62%. On the other hand,Multinomial Naive Bayes K-nearest neighbor, and Logistic regression performs the worst with an F1- score of 33%. In terms of precision, With a performance of 95%, logistic regression is the top-performing algorithm.%, followed by multinomial naive Bayes with a score of 90%. K-nearest neighbor is the worst performing algorithm with a precision score of 20%. When considering recall, K-nearest neighbor is the best performing algorithm with a score of 97%, followed by Bernoulli naive Bayes with a score of 96%. Logistic regression is the worst performing algorithm with a recall score of 20%. In conclusion, based on the analysis of the provided table, the algorithm with the best performance on the fake class using Tri- gram word sequences is Random forest. However, The efficiency of the algorithms is a high priority which may vary based on the dataset and the specific problem being addressed.

Table 5.6 shows how the traditional machine learning algorithm used in our research for the Tri gram word sequence performed in terms of accuracy and performance

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Multinomial Naive Bayes	0.87	0.88	0.60	0.63
Complement Naive Bayes	0.86	0.75	0.83	0.78
Bernoulli Naive Bayes	0.72	0.67	0.82	0.66
Decision Tree	0.84	0.73	0.83	0.76
Support Vector Machine	0.89	0.89	0.67	0.72
Random Forest	0.89	0.79	0.84	0.81
Logistic Regression	0.87	0.91	0.60	0.63
K-Nearest Neighbor	0.39	0.59	0.62	0.38
AdaBoost	0.85	0.73	0.84	0.77

Table 5.6: Overall Performance Result using Tri-Gram word Sequence

of the overall.The findings of Table 5.6 indicates that Both Random Forest and SVM has the best accuracy of 89%, and Random forest has the highest F-score of 81%. Multinomial Naive Bayes, Complement Naive Bayes, Logistic Regression, and AdaBoost all have comparable accuracy, ranging from 85% to 87%, with varied F-scores. In a similar manner as the Table 5.5, In terms of accuracy, KNN scores the least at 39%, while its F-score is the lowest at 38%

5.4 Analysis & Result using GloVe Embedding

Algorithms	Precision	Recall	F1
Long Short Term Memory	0.83	0.83	0.83
Gated Reccurent Unit	0.82	0.82	0.82
Convolutional Neural Network	0.92	0.82	0.86

Table 5.7: Precision, Recall & F-Score on Fake class using GloVe Embedding

The performance of deep learning techniques on a fake class employing GloVe embedding is shown in Table 5.7. The results demonstrate that Convolutional Neural Network (CNN) achieved the greatest F-score of 86%, as well as high precision and recall of 92% and 82%, respectively. This shows that the CNN algorithm is the most effective one to use with our fake news data. The F-scores for the Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), which are 82% and 83%, are also close. According to the table, Convolutional Neural Network (CNN) has the highest F-score and moderate recall of 82%, and the best precision of 92%.

Table 5.8 demonstrate the overall performance of the deep learning algorithm using GloVe embedding technique that was used in our study. Table 8's findings corroborate those of Table 5.7's findings, showing that CNN has the greatest overall F-score of 92%, as well as the best accuracy of 96%. The accuracy of LSTM and GRU is

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Long Short Term Memory	0.94	0.90	0.90	0.90
Gated Reccurent Unit	0.94	0.89	0.89	0.89
Convolutional Neural Network	0.96	0.94	0.90	0.92

Table 5.8: Overall Performance Result using GloVe Embedding

at 94% and 90%, respectively, with F-scores of 90% and 89%. In a similar manner as the Table 5.7, GRU has lesser F-score value of 89% than other deep learning architecture.

5.5 Analysis & Result using FastText Embedding

Algorithms	Precision	Recall	F1
Long Short Term Memory	0.82	0.84	0.83
Gated Reccurent Unit	0.89	0.81	0.85
Convolutional Neural Network	0.85	0.75	0.79

Table 5.9: Precision, Recall & F-Score on Fake class using Fast Text Embedding

Table 5.9 displays the effectiveness of deep learning techniques on a fake class using a Fast Text embedding. The outcomes show that Convolutional Neural Network (CNN) obtained the least F-score 79% and least Recall of 75%, together with moderate precision of 85%. The Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) have F-scores of 85% and 83%, respectively. GRU has the highest F-score, the and the best precision of 89%, according to the table

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Long Short Term Memory	0.95	0.90	0.90	0.90
Gated Reccurent Unit	0.95	0.93	0.90	0.91
Convolutional Neural Network	0.94	0.90	0.86	0.88

Table 5.10: Overall Performance Result using Fast Text Embedding

The accuracy and overall performance of the deep learning algorithm that was employed in our investigation are displayed in Table 5.10 using the Fast Text embedding method. The results of Table 5.10 support those of Table 5.9 and demonstrate that GRU has both the highest F-score of 91% and both LSTM and GRU has the best accuracy of 95%. CNN have accuracy of 94%, with F-scores of 88%.

5.6 Analysis & Result using Word2Vec Embedding

Algorithms	Precision	Recall	F1
Long Short Term Memory	0.85	0.81	0.83
Gated Reccurent Unit	0.83	0.88	0.85
Convolutional Neural Network	0.93	0.80	0.86

Table 5.11: Precision, Recall & F-Score on Fake class using Word2Vec Embedding

Table 5.11 displays the total effectiveness of deep learning techniques on a fake class using a word2vec embedding. The outcomes show that Convolutional Neural Network (CNN) obtained the lowest recall of 80% and the highest F-score 86%, together with good precision of 93%. This demonstrates that, when combined with our false news data, the CNN algorithm is the most useful. The Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) have F-scores of 85% and 83%, respectively. Convolutional Neural Network (CNN) has the highest F-score, the least recall of 80%, and the best precision of 93%, according to the table.

Algorithms	Accuracy	Precision(Macro)	Recall(Macro)	F1(Macro)
Long Short Term Memory	0.95	0.91	0.89	0.90
Gated Reccurent Unit	0.95	0.90	0.92	0.91
Convolutional Neural Network	0.96	0.95	0.89	0.92

Table 5.12: Overall Performance Result using Word2Vec Embedding

Table 5.12 displays the accuracy and overall performance of the word2vec embedding approach, a neural network-based learning procedure used in our analysis.The results of Table 5.12 support those of Table 5.11 and demonstrate that CNN has both the highest F-score of 92% and the best accuracy of 96%. LSTM and GRU both have accuracy of 95%, with F-scores of 90% and 91%, respectively. Similar to the Table 11, the lowest F-score number is 89% for LSTM.

5.7 Result Summary

Due to the established unequal distribution for both authentic and fake news, as illustrated in Figure 3.2 for the dataset, fake data is analyzed individually. Since our dataset includes both real and fabricated stories, the recall and preciseness scores may be deceptive due to the potential for large numbers of false negatives and positives. As a consequence, The F1 score most clearly illustrates an algorithm's efficiency since it takes into account both the recall and precision values. Contrarily, the F1 score provided for the individual fake labeled dataset declined significantly.

Nonetheless, Table 5.2, Table 5.4 and Table 5.6 demonstrate that Support Vector Machine (SVM) achieved the maximum accuracy of 95%, 94% and 89% respectively for classifying text using Uni, Bi and Tri Gram Sequencing. Meanwhile, if we only evaluate fake news data, the F1 score for Support Vector Machine (SVM) is high on Uni and Bi Gram word sequences and Random Forest Classifier has high F1 score for Tri Gram sequences. In addition, when contrasted with the conventional machine learning method, our F1 values for the fake label were significantly higher when we used a deep learning architecture.

Chapter 6

Future Plan and Concluding Remarks

6.1 Future Work

The future work for this thesis involves exploring the latest advancements in natural language processing (NLP) models. The current research utilizes LSTM, GRU and CNN models, but the performance of our Bangla false news detection technique could be enhanced by using more sophisticated models like BERT, RoBERTa, ALBERT, and other developing encoding technologies. Such advancements in NLP have shown promising outcomes in other fields, and they may be the source of our model's success. Additionally, the use of a better transformer model for Bangla language will be incorporated in the future to enhance the accuracy and effectiveness of the study. Additional research will be carried out to investigate the feasibility of incorporating other data sources, such as social networking sites, in order to enhance the quality and applicability of the research findings. These future endeavors aim to enhance the accuracy and effectiveness of the NLP models used in the study, ultimately leading to more comprehensive and meaningful results.

6.2 Conclusion

Based on this analysis, we can infer that the Support Vector Machine (SVM) algorithm performs more effectively and efficiently on imbalanced datasets than the other algorithms due to its high accuracy. Additionally we can also infer that deep learning models like CNN or GRU is better than traditional approaches when it comes to analyze false label data. However, if the datasets had a larger set of fake data, the performance could be boosted.

Also in this paper, we reviewed several previous studies on rumor identification, which demonstrated that even simple artificial intelligence algorithms may provide good results on such a complex subject as fake news identification. As a result, it implies that artificial intelligence as well as deep learning approaches might be successfully applied to address this critical issue. It also implies that, in the long term, the efficiency of success may be increased by conducting further studies with hybrid classifiers and neural networks.

In the future, we aim to employ more trendy models such as Transformers to boost text and sentiment analysis by using more powerful models that have already been trained, such the BERT & RoBERTa.

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