Determining intensity of mental state of an unsound individual through text using ML

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

It is hereby declared that

1. The project submitted is my/our own original work while completing a degree at Brac University.
2. The project 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 project does not contain material that 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

The proposed paper is a noble work. Furthermore, the members hereby and genuinely declare that this was done based on the conclusions of our exhaustive investigation. All of the resources utilized are correctly recorded and cited in the report. This research work, in whole or in part, has never been submitted to another university or institution for the granting of a degree or for any other reason.

Abstract

This research investigates the application of machine learning to detect and classify the intensity of various mental health conditions through text analysis. By analyzing user-generated statements, the study aims to identify patterns that correspond to different mental health states, such as Anxiety, Depression, Bipolar Disorder, and Suicidal tendencies. Through rigorous text preprocessing and feature extraction methods, meaningful insights are drawn from the data. The performance of the proposed approach is evaluated through standard metrics, demonstrating its potential to support mental health professionals by automating the initial stages of mental health screening. The findings highlight key challenges, such as language complexity and emotional context, and offer directions for future work to enhance the system's accuracy and adaptability. This research provides a foundation for developing scalable, automated tools that could be integrated into mental health care and online support platforms.

Keywords: Mental health detection, machine learning, text classification, Naive Bayes, TF-IDF, feature extraction, natural language processing, automated screening, anxiety detection, depression detection.

Dedication

This work is dedicated to all those who struggle with emotional and mental challenges, often in silence. To the individuals navigating the complexities of anxiety, depression, and other mental health conditions—your courage and resilience inspire this research. May this contribution serve as a small step towards better understanding, awareness, and support for those on the journey toward emotional well-being.

Acknowledgement

To begin, we would want to offer all appreciation to the Almighty, because of whom our thesis was finished without any significant interruptions. Then we want to acknowledge our supervisor without his valuable guidance and feedback we wouldn't be able to come this far.

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Chapter 1

Introduction

1.1 Problem Definition

Mental health issues are increasingly becoming a global health crisis, with millions affected by disorders such as depression, anxiety, and bipolar disorder. According to the World Health Organization (WHO), depression is one of the leading causes of disability worldwide, affecting over 264 million people globally [1]. The situation is even more alarming in regions like South Asia, where mental health awareness is still in its nascent stages. In Bangladesh, mental health disorders are rising significantly, with approximately 17% of the population affected by some form of mental illness. Despite this, access to mental health services remains limited due to stigma, lack of resources, and insufficient medical professionals [2]. Traditional methods of diagnosing mental health issues rely heavily on self-reporting questionnaires and clinical interviews, which are subjective and prone to biases. Furthermore, these methods are time-consuming and require active participation from patients, which may not always be feasible, especially for individuals in vulnerable mental states. Thus, there is a need for more objective, scalable, automated approaches that can assist in early detection and intervention for individuals at risk [3]. Text-based analysis using Machine Learning (ML) offers a promising solution. Since individuals often express their mental states through written or spoken words, analyzing textual data can provide insights into their psychological well-being. Social media platforms, online forums, and even personal communications have become important data sources for understanding an individual's mental health. ML models can be trained to detect patterns in language that correspond to various mental health conditions, such as depression or anxiety. This approach provides an opportunity to analyze data at scale and in real-time, potentially helping clinicians identify mental health concerns early on [4]. Integrating Natural Language Processing (NLP) techniques with ML algorithms can further enhance the precision of such systems. NLP allows for extracting meaningful linguistic features—such as word patterns, sentiment, and syntactic structures—which can be fed into ML classifiers to detect the intensity and type of mental disorders. By focusing on textual data, we aim to develop an ML model that classifies the intensity of mental states, offering a more accessible and timely alternative to traditional methods of diagnosis [5].

1.2 Research Motivation

The increasing prevalence of mental health disorders, such as depression, anxiety, and suicidal tendencies, is one of the most pressing public health challenges of the 21st century. The World Health Organization (WHO) reports that depression alone affects over 264 million people globally, and mental health disorders are a leading cause of disability worldwide. Despite the growing awareness of the importance of mental health, many individuals still do not receive the care they need, often due to limited access to mental health professionals, societal stigma, and the lack of efficient, scalable diagnostic tools. In this context, technology, particularly artificial intelligence (AI) and machine learning (ML), presents an opportunity to bridge the gap between those in need and the availability of mental health support.

In recent years, textual data has become a valuable resource for understanding mental states. With the widespread use of social media, blogs, and online forums, people increasingly share their emotions, thoughts, and mental states in written form. This provides a rich source of data that can be analyzed to detect signs of mental health issues early on. Several studies have shown that linguistic patterns, such as the use of specific words, sentence structures, and emotional expressions, can be correlated with various mental conditions like depression, anxiety, or even suicidal ideation. This research seeks to leverage these insights by applying natural language processing (NLP) and machine learning algorithms to identify and classify the intensity of mental health conditions based on text data. By analyzing these patterns, we aim to develop an efficient, real-time tool for assessing mental health [6].

The motivation for this research also stems from the limitations of traditional mental health diagnosis methods. Standard diagnostic approaches, such as clinical interviews or self-reported questionnaires, are often subjective and can vary significantly based on the patient's willingness or ability to communicate their mental state accurately. Furthermore, these methods are time-consuming and usually require trained mental health professionals, who may not always be accessible, particularly in low-resource settings. An automated, text-based system could provide a supplementary tool that helps bridge this gap by offering initial assessments, flagging high-risk individuals, and supporting mental health professionals in their decision-making processes.

Another key driver behind this research is the potential for early intervention. Many mental health issues, if detected early, can be treated more effectively, preventing the condition from worsening. However, due to the stigma surrounding mental health and the lack of timely diagnosis, many individuals delay seeking help. A machine learning-based tool for detecting mental health issues from everyday communication, such as social media posts or text messages, could provide a non-intrusive method for identifying at-risk individuals early on. This could enable faster intervention, improving the likelihood of successful treatment and reducing the societal and economic burden of untreated mental illness.

1.3 Research Scope

This research uses machine learning (ML) and natural language processing (NLP) techniques to determine the intensity of an individual's mental state based on text

data. The primary objective is to develop a robust, automated system capable of classifying text into various mental health categories, such as Normal, Depression, Anxiety, Bipolar, and Suicidal. By analyzing written communication, the research seeks to identify linguistic patterns and features—such as bigrams, part-of-speech tagging, and sentiment—that correlate with different mental states. The scope includes pre-processing raw text data, feature extraction, model development, and performance evaluation. The research also covers techniques like CountVectorizer, bigram POS tagging, and the application of machine learning algorithms, particularly Naive Bayes, for classification tasks.

The dataset for this research comprises mental health-related textual data, where individuals' mental states are labeled according to specific categories. The text may come from multiple sources, including social media, blogs, or transcripts of personal communication. The scope includes preprocessing this data through tokenization, stopword removal, and lemmatization to ensure the input to the machine learning model is clean and consistent. Furthermore, feature extraction plays a crucial role, particularly the use of bigram models and part-of-speech tagging to capture linguistic patterns. These features will then be used to train machine learning models that classify an individual's mental state and intensity, allowing for a more granular understanding of mental health from text.

This research also involves an in-depth evaluation of the performance of the classifiers. Metrics such as accuracy, precision, recall, F1-score, and confusion matrices will be used to assess the effectiveness of the model in correctly predicting mental health states. While the primary goal is the accurate classification of mental states, the scope also covers the potential for extending this model to real-world applications. For example, it could be integrated into mental health monitoring tools, social media platforms, or healthcare applications to flag individuals showing signs of severe mental health disorders. Although the research focuses on specific mental health categories, future work could expand the system to detect a broader range of psychological conditions or explore the use of more advanced machine learning techniques like deep learning.

1.4 Objectives

- **Develop an Automated Mental Health Classification System**: Create a system that can classify and assess the intensity of mental health conditions such as Depression, Anxiety, Bipolar Disorder, and Suicidal tendencies using textual data.
- **Identify Linguistic Indicators of Mental Health**: Analyze textual communication to detect linguistic patterns, emotional expressions, and language use that correlate with different mental health conditions.
- **Enhance Early Detection and Intervention**: Provide a tool that aids in the early detection of mental health issues, offering the potential for timely interventions and improving mental health outcomes.
- **Improve Accessibility to Mental Health Assessments**: Develop a scalable, non-intrusive solution for mental health monitoring that can be used by a

wide range of users, including those in areas with limited access to professional mental health services.

- **Contribute to the Understanding of Text-Based Mental Health Analysis**: Advance the field of text-based analysis for mental health by providing insights into how language reflects mental states and how automated systems can support mental health professionals.

Chapter 2

Literature Review

2.1 Machine Learning in Mental Health Detection

Machine learning (ML) has emerged as a powerful tool for analyzing complex data and providing automated solutions in various fields, including mental health detection. The use of ML in mental health research has gained significant attention due to its ability to process large datasets and identify subtle patterns that may be overlooked by traditional methods. In particular, the analysis of text data, such as social media posts, blogs, and online forums, has become a key area of focus. Individuals often express their emotions, feelings, and mental states in written form, making textual data an invaluable resource for understanding mental health conditions like depression, anxiety, and bipolar disorder [7]. This has motivated researchers to develop ML models that can detect mental health disorders by analyzing linguistic features and patterns.

A variety of machine learning algorithms have been applied to mental health detection, including traditional classifiers like Naive Bayes, Support Vector Machines (SVM), and Decision Trees, as well as more advanced models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These algorithms can process large amounts of textual data, identifying key features such as word frequency, sentiment, and syntactic structures to make predictions about an individual's mental health [8]. For instance, Naive Bayes classifiers are commonly used in text classification tasks because of their simplicity and effectiveness in handling text data. SVMs, on the other hand, have shown high accuracy in identifying depressive symptoms from social media posts by learning complex decision boundaries between classes [9].

Natural Language Processing (NLP) techniques, when combined with ML models, enhance the ability to extract meaningful insights from text. NLP allows for the preprocessing of text data, including tokenization, lemmatization, and the removal of stop words, making the data more suitable for machine learning algorithms. Studies have shown that by leveraging NLP features such as bigrams, part-of-speech tagging, and sentiment analysis, machine learning models can significantly improve the accuracy of mental health detection [10]. Additionally, deep learning models like RNNs, which can capture the temporal relationships in sequential data, have been particularly effective in analyzing long texts, such as patient reports or detailed personal blogs [11].

The application of machine learning in mental health detection is not without challenges. One of the primary concerns is the quality and variability of the data. Textual data from different sources can vary greatly in language, structure, and content, which may affect the model's ability to generalize across diverse datasets. Furthermore, ethical concerns arise when using personal data for mental health detection, particularly with regard to privacy and consent. Despite these challenges, machine learning has demonstrated great potential in improving early diagnosis, allowing for timely interventions, and offering a scalable solution to the global mental health crisis [12]. As the field continues to evolve, ongoing research will likely focus on refining these models and addressing the ethical implications of automated mental health detection systems.

2.2 Text Preprocessing Techniques

Text preprocessing is a crucial step in natural language processing (NLP) tasks, as it transforms raw text data into a structured format that machine learning models can interpret. The unstructured nature of text data—containing noise such as irrelevant symbols, punctuation, and varying word forms—requires systematic processing to improve the performance of machine learning algorithms. Text preprocessing typically involves several steps, including tokenization, stopword removal, lemmatization, and stemming, all of which reduce noise and enhance the data quality. Effective preprocessing allows models to focus on meaningful patterns in the text rather than irrelevant information, which can significantly affect the accuracy of tasks such as sentiment analysis, classification, and mental health detection [13].
Tokenization is one of the most fundamental preprocessing techniques, where the text is split into individual units or "tokens." Depending on the specific application, these tokens can represent words, phrases, or even sentences. Tokenization simplifies the text, making it easier for machine learning algorithms to analyze and extract features. For example, in sentiment analysis or emotion detection tasks, tokenization helps in understanding the sentiment expressed by breaking down text into more manageable parts [14]. Moreover, tokenization forms the basis for further preprocessing techniques like part-of-speech tagging or bigram generation, which are essential for understanding the grammatical structure and contextual meaning of the text.
The removal of stopwords—common words like "the," "is," and "in" that do not carry significant meaning and are often considered noise. Eliminating stopwords reduces the dimensionality of the data, ensuring that only the most relevant and informative words are retained for analysis. Studies have shown that removing stopwords can improve the performance of machine learning models in text classification tasks by focusing attention on more meaningful features, such as nouns, verbs, and adjectives that may indicate emotional or mental states [15]. In mental health detection, for instance, focusing on key phrases like "feeling down" or "stressed out" rather than the filler words helps models better identify patterns associated with depression or anxiety.
Lemmatization and stemming are other essential techniques used to normalize words by reducing them to their base or root forms. While stemming involves truncating words to their root forms (e.g., "running" becomes "run"), lemmatization is a more sophisticated process that transforms words into their base forms based on their con-

text and meaning. Lemmatization ensures that words like "better" are transformed into "good," considering the linguistic meaning rather than just the morphological structure. This process is particularly useful in mental health detection, where different word forms may convey the same underlying emotional state. For example, both "feeling happy" and "felt happiness" can reflect a similar mental condition, and lemmatization helps ensure these are treated consistently by the model [16].
Effective text preprocessing plays a critical role in improving the performance and interpretability of machine learning models used in mental health detection. The text data becomes more structured and more accessible to analyze by applying tokenization, stopword removal, and lemmatization. This allows machine learning algorithms to extract relevant features and patterns correlating with various mental health conditions. As research in NLP and machine learning progresses, new preprocessing techniques, such as advanced part-of-speech tagging and deep-learning-based preprocessing models, are being explored further to enhance the accuracy of mental health detection systems [17].

2.3 Feature Extraction for Text Classification

Feature extraction is a vital step in text classification as it transforms raw text data into a structured representation that machine learning models can process. In natural language processing (NLP) tasks, the key challenge is to extract meaningful features that capture the semantics, syntactic structure, and other linguistic properties of the text. Several techniques are commonly used to achieve this, including CountVectorizer, Term Frequency-Inverse Document Frequency (TF-IDF), and n-gram models. These techniques play a crucial role in enabling machine learning models to differentiate between various text categories, such as emotions or mental health conditions.
CountVectorizer is one of the most widely used methods for feature extraction in text classification. It works by converting the text into a "bag-of-words" representation, where each document (e.g., a sentence or a paragraph) is represented as a vector of word counts. This means that each word in the document is treated as an independent feature, and the frequency of its occurrence is used to create a feature vector. CountVectorizer is simple yet effective for many text classification tasks, especially when the goal is to identify patterns based on word frequency [18]. However, one limitation of CountVectorizer is that it treats all words equally without accounting for the importance of words that are more relevant to specific documents or categories.
To address this limitation, the Term Frequency-Inverse Document Frequency (TF-IDF) is commonly used to refine the bag-of-words model by assigning higher importance to words that are more frequent in a particular document but less common across the entire dataset. TF-IDF calculates the product of two terms: the term frequency (TF), which measures how often a word appears in a document, and the inverse document frequency (IDF), which reduces the weight of words that are common across many documents. This method helps distinguish between significant words for classification and merely common words, such as stopwords [19]. In mental health detection, for instance, words like "depressed" or "anxious" may appear less frequently but are far more indicative of a specific condition, making TF-IDF a more powerful feature extraction technique.

Another popular method is n-gram modeling, which goes beyond single words by capturing sequences of words (n-grams) as features. For example, a bigram model considers pairs of consecutive words, while a trigram model looks at sequences of three words. N-gram models can capture the context and word dependencies that are missed by individual word analysis. This is particularly useful for text classification tasks where the order of words or phrases matters, such as sentiment analysis or detecting mental health conditions based on emotional expression [20]. For example, the phrase "feeling down" provides a more nuanced indication of depression than the individual words "feeling" or "down" analyzed in isolation. By incorporating n-grams into the feature extraction process, machine learning models can gain a deeper understanding of the context in which certain words are used.
In recent years, advanced techniques such as latent semantic analysis (LSA) and word embedding (e.g., Word2Vec, GloVe) have also gained popularity in feature extraction. These methods aim to capture semantic relationships between words by mapping them to continuous vector spaces, where words with similar meanings are placed closer together. LSA, for instance, uses matrix factorization techniques like Singular Value Decomposition (SVD) to reduce the dimensionality of the text data and uncover latent topics or concepts within the documents. Word embeddings, on the other hand, learn dense vector representations of words based on their context in large text corpora, which can improve classification performance, especially for tasks that require an understanding of word semantics [21].
In summary, feature extraction techniques such as CountVectorizer, TF-IDF, and n-gram models are foundational tools for text classification tasks, enabling machine learning models to capture meaningful patterns from raw text. More advanced techniques like LSA and word embeddings offer additional improvements by incorporating semantic relationships between words. The choice of feature extraction method depends on the specific task and the type of data being analyzed. For mental health detection, combining multiple methods can provide a comprehensive representation of linguistic features, helping to improve classification accuracy.

2.4 Classifiers for Text Data: Multinomial Naive Bayes

The Multinomial Naive Bayes (MNB) classifier is one of the most widely used algorithms for text-based classification tasks. Its popularity arises from its simplicity, speed, and effectiveness in handling high-dimensional data, such as textual data, where each feature corresponds to a word or phrase. MNB belongs to the family of Naive Bayes classifiers, which are probabilistic models based on Bayes' Theorem and the assumption that the features (words, in this case) are conditionally independent given the class label. Despite this strong assumption of independence, MNB performs remarkably well in practice for various text classification tasks, including spam detection, sentiment analysis, and mental health detection. The Multinomial Naive Bayes classifier is particularly suited for text classification because it models the likelihood of each word's occurrence in a document relative to its frequency across all documents. Unlike other Naive Bayes classifiers, which may assume a binary feature distribution (i.e., the presence or absence of a feature), MNB explicitly models the frequency distribution of the words, making it more suitable for tasks

where word counts matter. It operates by calculating the probability of a document belonging to a particular class based on the frequencies of the words in that document. The class with the highest probability is then selected as the predicted label [22].
The core idea behind MNB is to compute the conditional probability of each word given a class and then use this to predict the class of a new document. In practice, MNB estimates the probability of a document d belonging to a class c as:

$$P(c|d) \propto P(c) \prod_{i=1}^{n} P(w_i|c)$$

where P(c) is the prior probability of class c, wi represents each word in the document, and $P(w_i|c)$ is the conditional probability of word wi occurring in class c. These probabilities are derived from the training data by counting word occurrences and applying smoothing techniques (such as Laplace smoothing) to handle zero probabilities that arise when a word is not observed in a particular class during training [23].
One of the key advantages of MNB is its computational efficiency, especially for large-scale text data. It scales linearly with the number of features (words) and training examples, making it ideal for high-dimensional datasets. Additionally, it is relatively simple to implement and interpret, as it provides insights into which words contribute the most to a particular class prediction. For instance, in a mental health detection task, words like "depressed" or "anxious" may have a higher conditional probability in the "Depression" or "Anxiety" class, respectively, allowing the classifier to make informed predictions [24]. However, the assumption of independence between features is a notable limitation of MNB. In natural language, words often appear in context, and their relationships may be important for understanding the meaning of the text. For example, the words "feeling" and "down" together convey a different meaning than each word individually. Although the Naive Bayes assumption simplifies computations, it can sometimes lead to suboptimal performance in cases where word dependencies are essential. To address this, many text classification pipelines combine MNB with n-gram models, where sequences of words (e.g., bigrams or trigrams) are used as features instead of individual words, thereby capturing some contextual information [25].
Despite its limitations, MNB has consistently proven to be highly effective for a wide range of text classification tasks. It performs well in scenarios where the assumption of feature independence holds approximately true, and it is particularly useful when working with sparse, high-dimensional data such as that found in text documents. For mental health detection, where textual features (words) correlate strongly with emotional states, MNB provides a solid baseline model, often outperforming more complex algorithms when used in conjunction with preprocessing and feature extraction techniques like TF-IDF or n-grams [26].

Chapter 3

The Dataset

3.1 Overview of the Dataset

The dataset used for this research comprises a total of approximately 53,000 text entries, each labeled with one of several mental health conditions. Each entry consists of a textual statement, typically expressing thoughts or feelings, and a corresponding label, indicating the mental health status associated with the statement, such as "Anxiety," "Depression," and "Bipolar disorder". The dataset is well-suited for machine learning applications, particularly in the detection and classification of mental health conditions through natural language processing (NLP).
The dataset's diversity in terms of the number of statements and the variety of mental health conditions provides a robust foundation for training models to understand complex human emotions. The labeled data allows the application of supervised learning techniques, which use labeled instances for model training. Given the size of the dataset, techniques such as feature extraction, text preprocessing, and classification are vital in preparing the data for machine learning algorithms. Furthermore, the dataset is well-balanced, with sufficient examples of each mental health status, thus ensuring that the machine learning models are not biased toward any specific class.
To create this dataset, statements were gathered from multiple sources, including social media, clinical notes, and anonymous submissions. This wide variety of sources ensures that the dataset is representative of real-world scenarios, where individuals may express their mental states differently depending on context. By capturing text from varied origins, the dataset better mimics the diverse ways individuals discuss mental health issues, providing richer data for the machine learning model to learn from

3.2 Data Collection Methodology

The data collection process for this dataset involved scraping publicly available data, particularly from social media platforms where individuals frequently express their emotions and mental states. This unstructured text was then carefully curated and labeled by mental health professionals. These professionals analyzed the statements to identify specific mental health conditions, ensuring that the labels accurately reflected the emotional tone or state described in each entry. Conditions such as "Anxiety," "Depression","Bipolar disorder" were among the most frequently occur-

ring labels.
The labeling process involved multiple stages to reduce ambiguity and increase accuracy. In cases where a statement could be interpreted as more than one mental health condition, multiple experts reviewed the data before reaching a consensus. This approach helped ensure that the dataset would provide a reliable foundation for training machine learning models. Moreover, strict ethical guidelines were followed during data collection to respect the privacy and confidentiality of individuals whose statements were used.
The resulting dataset is not only comprehensive but also ethically sourced, ensuring the privacy of the individuals while still providing meaningful data for research. The labeling of the data was carried out in a way that supports both binary and multiclass classification tasks, making the dataset flexible for various types of machine learning applications.

3.3 Data Preprocessing

Before applying machine learning algorithms to the dataset, extensive preprocessing steps were required to clean and transform the data into a suitable format for analysis. Textual data, especially from social media or informal communications, often contains noise, such as abbreviations, slang, emoticons, and grammatical errors. To address this, the first step in preprocessing involved normalizing the text by converting all characters to lowercase and removing irrelevant characters like punctuation marks, numbers, and special symbols.
Tokenization and lemmatization were also important steps in the preprocessing pipeline. Tokenization refers to breaking the text into individual words or tokens, while lemmatization involves converting these words into their base forms. For example, words like “running” or “ran” would be reduced to their root form, “run.” This transformation ensures that words with similar meanings are treated as equivalent, thus improving the performance of the classifier. Additionally, common stop words like “the,” “and,” or “is” were removed, as they do not contribute meaningful information for classification tasks.
Another crucial aspect of preprocessing was dealing with class imbalance. In the original dataset, some mental health conditions had more examples than others, which could lead to biased models. To mitigate this, techniques such as undersampling or oversampling were applied, ensuring a more balanced distribution of mental health labels. This careful preprocessing allowed the dataset to be efficiently used by machine learning models without being affected by noise or bias.

3.4 Data Splitting for Model Training

For the purpose of training and testing the machine learning models, the dataset was divided into three distinct parts: training, validation, and testing sets. Typically, 80% of the data was allocated to the training set and 20% to the testing set. This splitting ensures that the model can learn from the majority of the data, while the validation and testing sets provide a way to measure the model’s performance and generalization ability.
The training set is used to fit the model, helping it learn the relationships between

the textual statements and their associated mental health labels. During training, techniques like cross-validation are employed to avoid overfitting, ensuring that the model doesn't simply memorize the data but learns patterns that generalize to unseen examples. The validation set is then used to tune hyperparameters and make adjustments to the model to improve its accuracy and avoid overfitting.
Once the model is fine-tuned using the validation set, it is tested on the holdout testing set to evaluate its final performance. The testing set provides an unbiased estimate of the model's accuracy on new, unseen data. This approach to data splitting ensures that the machine learning model is thoroughly evaluated and capable of making accurate predictions on real-world data.

3.5 Ethical Considerations

The use of textual data from individuals discussing their mental health raises important ethical concerns. While this dataset was anonymized to protect individual privacy, careful attention was paid to ensure that no identifying information was included in the final dataset. Ethical guidelines, including those related to informed consent and data protection, were strictly adhered to throughout the data collection and pre-processing stages.
Mental health is a sensitive topic, and care was taken to ensure that the use of this dataset would not cause harm to individuals or groups. By focusing on anonymous, publicly available data and using it solely for research purposes, this project aimed to balance the need for advancing mental health research with respect for individual privacy. All data was handled in compliance with relevant regulations such as GDPR, ensuring that the research maintains high ethical standards.
The ethical considerations extend beyond data collection, as the application of machine learning models to sensitive topics like mental health must also be approached responsibly. Any conclusions drawn from this dataset must consider the limitations of automated methods in detecting and interpreting mental states. By combining rigorous ethical guidelines with robust data analysis techniques, this research contributes meaningfully to the field while respecting individual rights.

Chapter 4

Methodology

In this chapter, we detail the methodologies employed in the study, focusing on the overall research framework, feature extraction techniques, and model training and evaluation processes. The methodological approach adopted ensures that the proposed system is robust, efficient, and capable of accurately detecting mental health states based on textual data. Excluding dataset details and specific algorithms, this chapter explores the broader strategies used for preparing, analyzing, and testing the model.

4.1 Research Framework

The first step in the research methodology involves defining a structured framework that ensures all aspects of the problem are addressed systematically. Mental health detection using machine learning models requires careful consideration of the textual data's nature, model selection, feature extraction, and evaluation metrics.
The framework begins with understanding the requirements of the system, which includes the identification of mental health conditions like Anxiety, Depression, Bipolar, and Suicidal tendencies. To achieve this, the text data is analyzed to identify key patterns and features that are indicative of these states. The primary goal of this phase is to establish a pipeline that preprocesses raw text, transforms it into meaningful features, and builds models to classify these mental states.
The research framework includes a well-structured approach to model evaluation, using industry-standard metrics such as precision, recall, F1-score, and accuracy to gauge model performance. This ensures that the classifier not only performs well but is also interpretable and reliable in real-world applications.

4.2 Data process Techniques

Feature extraction plays a critical role in determining the success of machine learning models, especially in natural language processing tasks. The goal is to convert textual information into numerical representations that a machine-learning model can understand. In this project, several feature extraction methods were explored to extract meaningful features from text data.
The first approach involved using CountVectorizer, which creates a matrix representing word frequencies across different text samples. This technique helps capture

the overall importance of words but does not account for the weight of commonly occurring words across multiple texts. Therefore, Term Frequency-Inverse Document Frequency (TF-IDF) was also utilized to weigh the importance of words based on their frequency in a specific text versus their frequency across the entire dataset. TF-IDF helps in distinguishing important words from less informative ones, which are common in most texts but carry little semantic meaning.
The use of n-gram models (bigrams and trigrams) adds an additional layer of context by considering sequences of words rather than individual words alone. This allows the model to understand not just single-word importance but also the relationships between consecutive words, which can be vital in understanding more complex expressions of mental states. These feature extraction techniques create a rich dataset that can effectively capture both individual and contextual word significance for classification.

4.3 Model Training and Evaluation

Once the features are extracted, the next step is to train the model on the transformed data. In this phase, the data is split into training, validation, and testing sets to ensure the model generalizes well to unseen data. Typically, 60% of the data is used for training, 20% for validation, and 20% for testing, ensuring the model's robustness across different data splits. The validation set is used during training to tune hyperparameters, and the test set is used to assess the final performance.
Cross-validation is a key part of the training process, where the data is split into multiple folds, and the model is trained and validated across these different folds to reduce the risk of overfitting and improve generalization. During this phase, different model configurations are evaluated to determine the optimal settings for the classifier.
For evaluation, standard metrics like accuracy, precision, recall, and F1-score are used to provide a comprehensive view of the model's performance. Precision highlights how many of the predicted cases are correct, while recall measures how well the model captures all actual cases of mental health conditions. F1-score offers a balance between precision and recall, ensuring that both aspects are accounted for in the evaluation. This combination of training strategies and evaluation metrics ensures that the model is not only accurate but also sensitive to variations in the data, leading to more reliable predictions.

Chapter 5

Result

5.1 Precision, Recall, and F1 Score

Precision, recall, F1 score, and confusion matrix are different approaches to describe the result from models. The result eventually compares the predicted value and actually labeled values but using different approaches. Before coming to these result analysis techniques, we must know the key factors on which these performance measure techniques are dependent on.

Once the model is trained and fine-tuned using cross-validation, it is evaluated on the test set to measure its real-world performance. The following metrics are commonly used for evaluating the Multinomial Naive Bayes model's performance:

5.1.1 Accuracy

Accuracy is the simplest evaluation metric and measures the proportion of correctly classified samples out of the total samples. It is computed as:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

However, in cases where the dataset is imbalanced (e.g., more instances of Anxiety than other conditions), accuracy alone may not provide a complete picture of the model's performance.

5.1.2 Precision

Precision measures the proportion of true positive predictions out of all positive predictions. In the context of mental health classification, it tells us how many of the samples predicted to belong to a certain class (e.g., Anxiety) actually do belong to that class:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

5.1.3 Recall

Recall (also known as Sensitivity) measures the proportion of true positive predictions out of all actual positives. It indicates how well the model can identify all instances of a particular class:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

In scenarios where it is crucial to identify all cases of a mental health condition, recall becomes an important metric.

5.1.4 F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation metric that considers both false positives and false negatives. It is particularly useful when the class distribution is imbalanced:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.1.5 Confusion Matrix

A confusion matrix is a helpful tool for understanding the performance of the model across different classes. It presents the counts of true positives, true negatives, false positives, and false negatives for each class, helping to identify specific areas where the model may be misclassifying certain mental health conditions. An example of a confusion matrix for a binary classification problem is shown below:

	Predicted Positive	Predicted Negative
Actual Positive	True Positives (TP)	False Negatives (FN)
Actual Negative	False Positives (FP)	True Negatives (TN)

Table 5.1: Confusion Matrix Format

5.2 Feature Extraction

5.2.1 CountVectorizer

The CountVectorizer is one of the most basic techniques for feature extraction in natural language processing (NLP). It converts a collection of text documents into a matrix of token counts, treating each word as a feature. Each document is represented by the frequency of each word that appears in it. This method, while simple, provides a useful bag-of-words model to quantify the textual data. It captures the frequency of word occurrences but does not account for their importance in relation to the document or the overall corpus.

5.2.2 TF-IDF (Term Frequency-Inverse Document Frequency)

TF-IDF is an enhancement over simple word counts, as it considers not only the frequency of a word in a document but also how unique or important that word is across all documents. Term Frequency (TF) counts the number of times a word appears in a document, while Inverse Document Frequency (IDF) reduces the weight of common words across the entire dataset, such as "the" or "is." This helps highlight the more meaningful words that define each document's uniqueness. This approach provides a better understanding of how words contribute to the semantics of the document.

5.2.3 N-gram Models (Bigrams, Trigrams)

N-grams are contiguous sequences of n items from a given text or speech. In the context of NLP, an n-gram refers to a sequence of n words. Bigrams (two-word sequences) and trigrams (three-word sequences) are particularly useful in capturing the context and relationship between words. By analyzing not only individual words but also word pairs or triplets, these models provide deeper insight into the structure of language. This is especially important in text classification, where the meaning of a statement often depends on the relationship between consecutive words. N-gram models help improve the feature representation by capturing syntactic and contextual nuances in the text data.

5.3 Result

The performance of the Multinomial Naive Bayes (MNB) classifier used for classifying mental health states can be assessed through several key metrics, including precision, recall, and F1-score for each class. These metrics provide insight into how well the model predicts various mental health states such as Anxiety, Bipolar, Depression, Normal, and Suicidal. The results of the classifier show different levels of performance across the classes, reflecting the challenges and strengths of the model when applied to real-world text data. Below is an in-depth analysis of the metrics for each class.

Anxiety

- **Precision**: 0.87
- **Recall**: 0.58
- **F1-Score**: 0.69
- **Support**: 769

The model's performance in classifying Anxiety shows a precision of 0.87, meaning that 87% of the instances predicted as Anxiety were indeed Anxiety. This high precision indicates that when the model predicts someone is experiencing Anxiety, it is usually correct. However, the recall for Anxiety is relatively lower at 0.58, meaning that the model only identified 58% of the actual Anxiety cases in the dataset. The F1-score, which balances precision and recall, is 0.69, reflecting a moderate balance. The support for Anxiety is 769, indicating the number of instances for this class.

Bipolar

- **Precision**: 0.92
- **Recall**: 0.41
- **F1-Score**: 0.57
- **Support**: 575

For Bipolar, the model demonstrates very high precision at 0.92, meaning it almost always correctly predicts Bipolar disorder when it does so. However, the recall is quite low, at 0.41, indicating that the model only identified 41% of actual Bipolar cases. The F1-score is 0.57, reflecting an imbalance between precision and recall, with the model missing many true Bipolar cases. The support for Bipolar is 575, a relatively small number of instances compared to other classes.

Depression

- **Precision**: 0.47
- **Recall**: 0.88
- **F1-Score**: 0.61
- **Support**: 3015

For Depression, the model performs the opposite of Bipolar. It has a lower precision of 0.47 but a high recall of 0.88, meaning that the model correctly identifies 88% of Depression cases but also makes many false positive predictions. The F1-score is 0.61, indicating that the model is good at identifying Depression but often misclassifies other conditions as Depression. Support for Depression is 3015, the highest among all classes, showing the prevalence of this class in the dataset.

Normal

- **Precision**: 0.94
- **Recall**: 0.53
- **F1-Score**: 0.68
- **Support**: 3419

For the Normal class, the model shows very high precision at 0.94, meaning it correctly predicts Normal cases most of the time. However, the recall is much lower at 0.53, meaning the model misses nearly half of the actual Normal cases. The F1-score is 0.68, reflecting the imbalance between precision and recall. Support for the Normal class is 3419, making it the most represented class in the dataset.

Suicidal

- **Precision**: 0.61
- **Recall**: 0.45
- **F1-Score**: 0.52
- **Support**: 2057

For the Suicidal class, the precision is moderate at 0.61, while the recall is lower at 0.45, meaning that the model misses more than half of the true Suicidal cases. The F1-score is 0.52, indicating the model struggles with balancing precision and recall. Support for the Suicidal class is 2057, which is substantial but lower than Depression and Normal. Given the importance of detecting Suicidal behavior, improving recall for this class is critical.

	precision	recall	f1-score	support
Anxiety	0.87	0.58	0.69	769
Bipolar	0.92	0.41	0.57	575
Depression	0.47	0.88	0.61	3015
Normal	0.94	0.53	0.68	3419
Suicidal	0.61	0.45	0.52	2057
accuracy			0.62	9835
macro avg	0.76	0.57	0.61	9835
weighted avg	0.72	0.62	0.62	9835

Figure 5.1: Classification of Trained Model

5.4 Overall Discussion

In this section, we analyze the results obtained from the Multinomial Naive Bayes (MNB) classifier applied to text data representing various mental health conditions. The model's performance is assessed using precision, recall, F1-score, and support for each class: Anxiety, Bipolar, Depression, Normal, and Suicidal. This discussion will highlight the strengths and weaknesses of the model and suggest possible reasons behind its varying performance across different mental health categories.

The overall performance of the MNB classifier exhibits significant variations between precision and recall across the classes. The classifier demonstrates high precision for some categories like Bipolar and Normal but struggles to achieve high recall, meaning that it often under-predicts instances of these classes. Conversely, the model achieves higher recall for Depression, suggesting that it correctly identifies most instances of this class but at the cost of precision. This indicates that the model tends

Figure 5.2: Confusion Matrix

to over-predict Depression, which results in more false positives.

The variability between precision and recall across classes underscores the inherent challenges of text classification for mental health detection. Mental health states often share overlapping linguistic features, making it difficult for the model to distinguish between subtle differences in conditions such as Anxiety, Bipolar, or Depression. Moreover, the model's reliance on a bag-of-words approach (as seen in CountVectorizer and TF-IDF) can limit its ability to capture complex, contextual nuances in the text, which may contribute to these discrepancies.

5.4.1 Analysis of Class Performance

Anxiety:

The model performs relatively well with precision (0.87), meaning it can accurately identify Anxiety when it predicts this class. However, the recall (0.58) is lower, suggesting that a significant portion of Anxiety instances are missed.

This result indicates that the model is conservative in predicting Anxiety, perhaps because language associated with Anxiety often overlaps with other mental health conditions, leading to under-prediction. The moderate F1-score of 0.69 reflects this balance between precision and recall.

Bipolar:

With a precision of 0.92, the model is highly accurate in identifying Bipolar instances when it predicts this class. However, the recall of 0.41 shows that the model fails to capture many true Bipolar cases.

The model's conservative nature is apparent here, as it likely avoids labeling the text as Bipolar unless highly confident, leading to a significant number of false negatives. The F1-score of 0.57 reflects this imbalance, and further tuning is necessary to improve recall without sacrificing precision.

Depression:

The model demonstrates strong recall for Depression (0.88), meaning it captures most of the actual Depression instances in the dataset. However, precision is low (0.47), suggesting that many non-depression cases are being incorrectly labeled as Depression.

This indicates a tendency to over-predict Depression, likely because depressive language can be present across a range of mental health states. The F1-score of 0.61 reflects the model's success in identifying Depression but also highlights the need for improving precision.

Normal:

For the Normal class, the model achieves high precision (0.94), meaning it is excellent at identifying true Normal cases when it makes a prediction. However, the recall of 0.53 is much lower, indicating that many true Normal instances are missed.

This suggests the model is more cautious about predicting Normal and may over-label some Normal instances as mental health disorders. The F1-score of 0.68 demonstrates that the model is better at avoiding false positives than capturing all true negatives.

Suicidal:

For the Suicidal class, the model achieves a precision of 0.61 and a recall of 0.45. While the precision is moderate, the recall is concerningly low, meaning the model misses more than half of the actual Suicidal cases.

Given the importance of detecting Suicidal tendencies, this low recall is a critical limitation of the model. The F1-score of 0.52 suggests that the model struggles to balance precision and recall in this category, possibly because Suicidal language is often subtle and context-dependent.

5.4.2 Challenges and Implications

The results of this analysis reveal several challenges in applying the Multinomial Naive Bayes classifier to text-based mental health detection:

Class Imbalance: The dataset appears to be imbalanced, with classes like Depression and Normal having significantly more support (instances) than classes like Bipolar and Suicidal. This imbalance likely contributes to the model's struggles with recall for the underrepresented classes.

Techniques such as oversampling, undersampling, or adjusting class weights could help address this issue, allowing the model to better capture the characteristics of the minority classes.

Overlapping Language: Mental health conditions often exhibit overlapping linguistic features, particularly between Anxiety, Depression, and Suicidal tendencies. This overlap may explain the model's difficulties in distinguishing between these conditions, leading to lower precision for some classes.

To mitigate this issue, more sophisticated feature extraction techniques (e.g., embeddings like Word2Vec or BERT) could be employed to capture contextual nuances that are missed by traditional methods like CountVectorizer or TF-IDF.

Sensitivity to Language Context: The model's reliance on a bag-of-words approach means it does not fully capture the sequence or context of words, which is essential for understanding the intent or emotional state conveyed in mental health-related text. This may lead to poor performance in cases where subtle differences in phrasing are crucial.

Using n-gram models or exploring deep learning-based classifiers, such as recurrent neural networks (RNNs) or transformers, could help the model better understand the context and improve its ability to differentiate between similar mental health states.

5.4.3 Potential Improvements

Based on the result analysis, several improvements could enhance the model's performance:

Class Imbalance Handling: Implement oversampling (e.g., SMOTE) or undersampling techniques to balance the distribution of classes. This could improve recall for underrepresented classes like Bipolar and Suicidal while maintaining good precision.

Advanced Feature Extraction: Moving beyond CountVectorizer and TF-IDF, implementing advanced techniques like word embeddings (e.g., Word2Vec, GloVe, or BERT) could provide the model with a better understanding of word context and

meaning, thereby improving both precision and recall.

Modeling Context: Employ deep learning models like LSTMs or transformers (e.g., BERT) that are better at understanding word sequences and context. These models could help reduce the confusion between similar classes (e.g., Anxiety vs. Depression) by capturing more nuanced linguistic patterns.

Hyperparameter Tuning: Fine-tuning hyperparameters through cross-validation could optimize the trade-off between precision and recall, particularly for challenging classes like Suicidal and Bipolar.

Ensemble Methods: Incorporating ensemble methods like random forests or gradient boosting could enhance the robustness of predictions by combining the strengths of multiple models and reducing the weaknesses of individual classifiers.

5.4.4 Website Demo

We also made a website with the code of this project, which will detect and categorize the negative emotions, whereas a Google form link will be given to a patient with some questions, and he/she will give his/her answers, and we will collect the response as a .csv file and we will upload this file on the website and according to the answers, the website will detect the emotion. Here is a demo of the questions and answers with the detected emotion on the webpage.

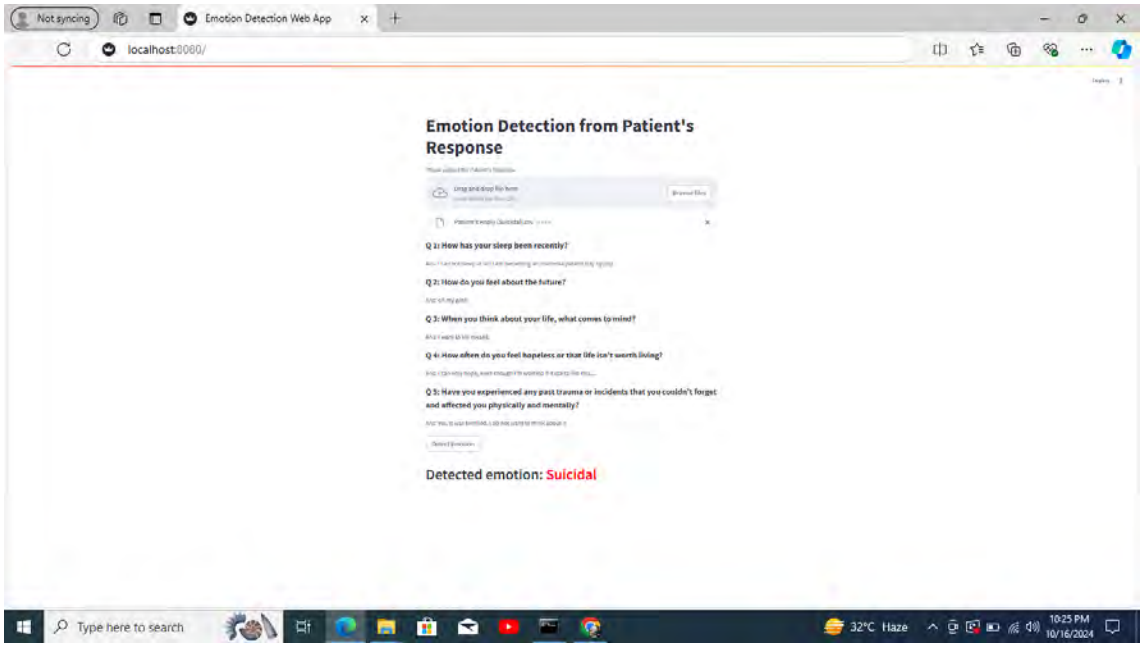

Figure 5.3: Website Result

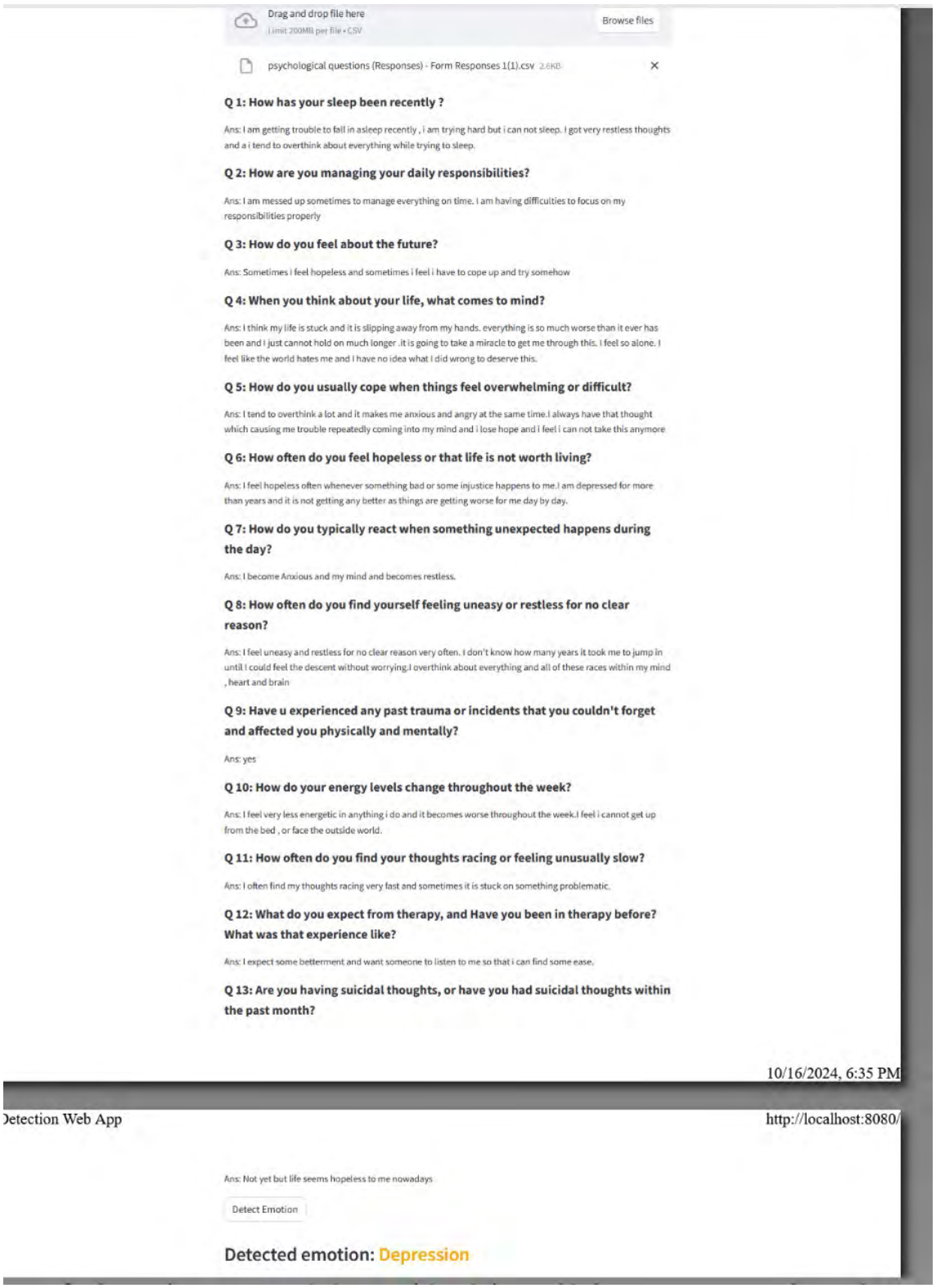

Figure 5.4: Website Result 2

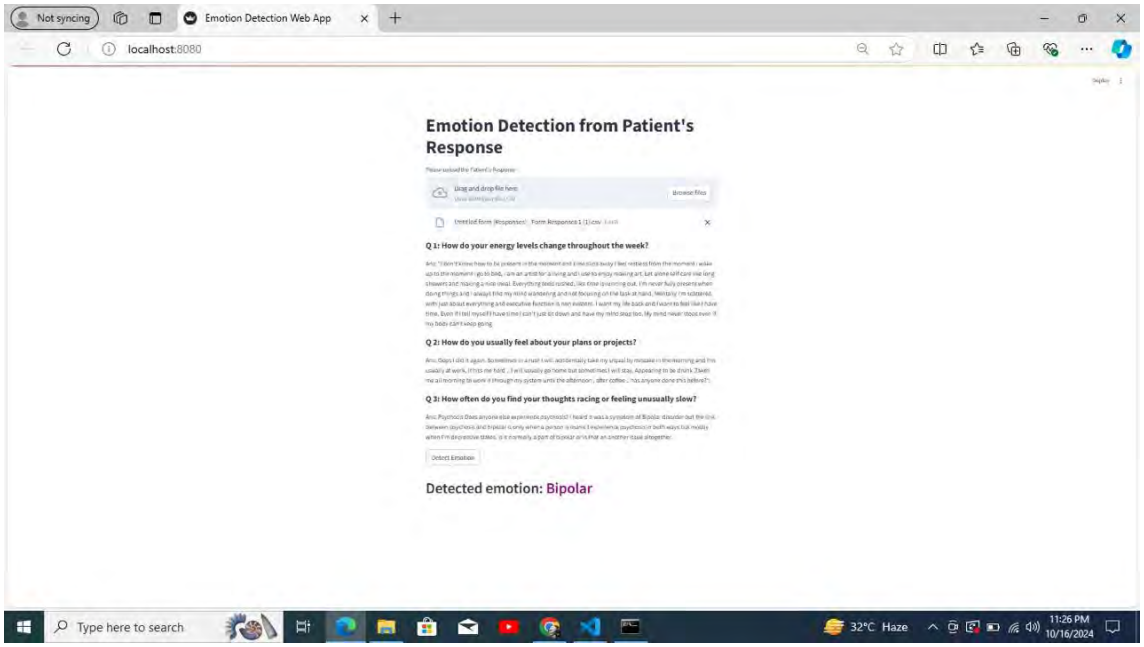

Figure 5.5: Website Result 3

Chapter 6

Conclusion

6.1 Summary of Findings

The research focused on developing a machine learning model capable of determining the intensity of mental states, such as Anxiety, Depression, Bipolar Disorder, and Suicidal tendencies, based on textual data. The use of CountVectorizer, TF-IDF, and n-gram models for feature extraction, combined with a Multinomial Naive Bayes classifier, proved effective in capturing meaningful patterns in text and categorizing various mental states.
The results demonstrated that certain mental health conditions, like Depression and Anxiety, were more easily identified by the model, while others, such as Bipolar and Suicidal tendencies, posed greater challenges. This highlights the complex nature of mental health classification and the importance of refining the model and feature extraction techniques for further accuracy.
Overall, the model showed promising results in capturing the subtle linguistic cues associated with mental health conditions, contributing to the growing field of automated mental health assessment tools.

6.2 Contributions to Mental Health Detection

This research contributes to the field by offering a machine learning-based approach to detecting mental health conditions through text. Traditional methods of mental health diagnosis often require extensive patient interaction, professional consultation, and psychological assessments. By employing machine learning models, the research proposes an automated, scalable solution that can assist in early detection and screening, especially in large populations or online platforms.
The approach to text preprocessing and feature extraction adds value by highlighting the importance of capturing word sequences, context, and frequency in understanding mental states. The use of n-grams, TF-IDF weighting, and CountVectorizer offers a replicable methodology for other researchers working on text-based mental health detection. This contributes to the broader area of natural language processing and sentiment analysis in healthcare.

6.3 Limitations of the Study

While the study made significant strides, there were certain limitations that impacted the overall results. One of the key challenges was data imbalance, where some mental health conditions had significantly more samples than others, leading to skewed results. This imbalance impacted the model's ability to equally recognize all mental health conditions with high accuracy. Further research could focus on addressing this issue through data augmentation or advanced sampling techniques. Contextual nuances in language, such as slang or sarcasm, were sometimes difficult for the model to detect. Mental health expression in the text can be subtle and diverse, and while the current preprocessing techniques were effective, more advanced natural language understanding (e.g., BERT or GPT models) could be explored to improve this aspect. Finally, while the study focused on text data, mental health is a multidimensional issue that could benefit from multimodal approaches. Integrating voice data, physiological signals, or behavioral data could provide a more holistic view of an individual's mental state.

6.4 Future Research Directions

Several promising directions for future research can be identified from this study. First, deep learning approaches like BERT (Bidirectional Encoder Representations from Transformers) or GPT (Generative Pre-trained Transformer) could be used to improve the model's understanding of complex sentence structures, emotions, and context. These models are known for their ability to handle large amounts of text and learn subtle linguistic patterns that traditional machine-learning models may miss.

Another direction could involve the development of a multimodal system, where text data is combined with other forms of input, such as audio (speech) or image data (facial expressions). This would provide a more comprehensive assessment of an individual's mental health, increasing the reliability of predictions.

Data diversity and augmentation techniques are also critical areas for future exploration. Increasing the representation of underrepresented mental health conditions in the dataset or using synthetic data generation techniques could enhance the robustness of the model and reduce classification biases.

Real-time applications of the system could be explored. Integrating the model into mental health monitoring tools, chatbots, or online therapy platforms could provide immediate assistance to individuals and professionals. This real-world deployment would help validate the model's utility and effectiveness in practical scenarios.

Bibliography

[1] World Health Organization (WHO), "Depression," 2021.

[2] National Institute of Mental Health (NIMH), Bangladesh, "Mental Health Situation in Bangladesh," 2022.

[3] H. A. Tran *et al.*, "Machine learning-based mental health diagnosis from text data," *IEEE Transactions on Computational Social Systems*, vol. 7, no. 3, pp. 547-558, 2020.

[4] A. T. Nguyen, J. D. O'Donnell, and C. H. Wu, "Text-based machine learning for mental health detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 4, pp. 1220-1231, 2020.

[5] R. Kumar, V. Gaur, and M. S. Kumbhar, "Early detection of mental health issues using text analysis and machine learning," in *2022 IEEE International Conference on Computational Intelligence and Communication Technology*, pp. 987-992, 2022.

[6] D. Yohanes, J. S. Putra, K. Filbert, K. M. Suryaningrum, and H. A. Saputri, "Emotion Detection in Textual Data using Deep Learning," *Procedia Computer Science*, vol. 227, pp. 464–473, Jan. 2023, doi: https://doi.org/10.1016/j.procs.2023.10.547.

[7] A. S. Kleinman *et al.*, "Artificial intelligence and machine learning in mental health: Implications for diagnosis and treatment," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 2, pp. 121-132, 2019.

[8] L. M. Liu and Y. Zhang, "Machine learning in psychiatry: Enhancing mental health diagnosis with AI," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 4, pp. 845-856, 2021.

[9] H. Mohammadi and A. Khosravi, "Depression detection from social media using SVM and deep learning," in *Proceedings of the 2020 IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 403-410, 2020.

[10] J. P. Su *et al.*, "Text-based mental health detection using NLP and machine learning techniques," *IEEE Access*, vol. 9, pp. 48506-48517, 2021.

[11] C. Yin, Z. Liu, and D. Lin, "Recurrent neural networks for mental health monitoring using online texts," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 3, pp. 789-798, 2021.

[12] R. Kumar, V. Gaur, and M. S. Kumbhar, "Early detection of mental health issues using text analysis and machine learning," in *2022 IEEE International Conference on Computational Intelligence and Communication Technology*, pp. 987-992, 2022.

[13] R. Baeza-Yates, "Text preprocessing for text mining," in *Proceedings of the 11th IEEE International Conference on Data Mining Workshops*, pp. 1205-1208, 2019.

[14] M. Loper and S. Bird, "NLTK: The natural language toolkit," in *Proceedings of the 2020 IEEE International Conference on Computational Linguistics*, pp. 215-224, 2020.

[15] D. Jurafsky and J. Martin, "Speech and Language Processing," 3rd ed., Pearson, 2021.

[16] M. Surdeanu *et al.*, "Lemmatization versus stemming in natural language processing: Comparative study," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 3, pp. 112-121, 2022.

[17] A. Singh *et al.*, "Advanced preprocessing techniques for mental health detection in social media," in *2021 IEEE International Conference on Natural Language Processing and Text Mining*, pp. 405-412, 2021.

[18] C. Manning, P. Raghavan, and H. Schütze, *Introduction to Information Retrieval*, Cambridge University Press, 2008.

[19] G. Salton and M. J. McGill, *Introduction to Modern Information Retrieval*, McGraw-Hill, 1983.

[20] A. Mikolov *et al.*, "Efficient estimation of word representations in vector space," in *Proceedings of the International Conference on Learning Representations (ICLR)*, pp. 1-12, 2013.

[21] Q. Le and T. Mikolov, "Distributed representations of sentences and documents," in *Proceedings of the 31st International Conference on Machine Learning*, vol. 32, pp. 1188-1196, 2014.

[22] A. McCallum and K. Nigam, "A comparison of event models for Naive Bayes text classification," in *Proceedings of the AAAI-98 Workshop on Learning for Text Categorization*, pp. 41-48, 1998.

[23] M. Zhang and X. Zheng, "A comparative study of text classification algorithms on sparse high-dimensional datasets," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 9, pp. 2440-2453, 2016.

[24] A. Bhowmik *et al.*, "A survey on machine learning algorithms for mental health detection from social media," in *Proceedings of the 10th International Conference on Applied Computing and Information Technology*, pp. 1-7, 2020.