DEPRESSION DETECTION USING TEXT SAMPLES

MAJOR PROJECT REPORT

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CANDIDATE DECLARATION

It is hereby certified that the work which is being presented in the B. Tech Major project Report entitled **"DEPRESSION DETECTION USING TEXT SAMPLES"** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** and submitted in the **Department of Electronics and Communications Engineering** of **BHARATI VIDYAPEETH'S COLLEGE OF ENGINEERING, New Delhi (Affiliated to Guru Gobind Singh Indraprastha University, Delhi)** is an authentic record of our own work carried out during a period from **February 2023 to May 2023** under the guidance of **Mr. Abhishek Gagneja, Assistant Professor, ECE department.**

The matter presented in the B. Tech Major Project Report has not been submitted by me for the award of any other degree of this or any other Institute.

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ABSTRACT

Major depressive disorder (MDD) or depression is a prevalent psychiatric disorder affecting over 300 million people globally. Early detection is crucial for prompt intervention, potentially mitigating the severity of the disorder. Its impact extends beyond the individual sufferer, affecting their families, friends, and society at large. Recent advancements in depression detection have witnessed the application of machine learning and deep learning models to improve accuracy.

This report explores the development in the field of depression detection by employing two diverse datasets: Twitter and DAIC-WOZ. Various machine learning and deep learning models, including CNN, GRU, LSTM, Bi-LSTM, Decision Tree, and Logistic Regression, were tested to accurately predict the presence of depression symptoms. The primary objective of this study was to investigate the efficacy of these models in detecting depression symptoms, enabling early identification and intervention. The Twitter dataset provided valuable insights into the mental health of individuals through the analysis of social media content, while the DAIC-WOZ dataset facilitated an understanding of the emotional states through recorded interactions.

The findings highlight the potential of machine learning and deep learning techniques in depression detection. Early identification of depression symptoms can lead to timely intervention, reducing the escalation of the disorder and its impact on individuals, their support networks, and society. Further developments in depression detection hold promise for enhanced support and intervention strategies for those affected by this significant psychiatric disorder.

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TABLE OF CONTENTS

CANDIDATE DECLARATION			**Iii**
ABSTRACT			**Iv**
ACKNOWLEDGEMENT			**Vii**
TABLE OF CONTENTS			**ix – xiv**
LIST OF FIGURES			**xv – xvi**
LIST OF TABLES			**xvii – xviii**
LIST OF ABBREVIATIONS			**Xix**
Chapter 1:	**Introduction**		**1 – 8**
	1.1	Introduction	1
	1.1.1	Understanding Depression	1
	1.1.2	Text Based Methods for Depression Detection	2
	1.1.3	PHQ-8	4
	1.2	Motivation	6
	1.3	Objective	6
	1.4	Summary of the Report	7
Chapter 2:	**Literature Survey**		**9 – 11**
Chapter 3:	**Project Summary**		**12 - 27**
	3.1	Libraries used	12
	3.2	Data collection	13
	3.3	Data Preprocessing	14
	3.4	Classification models for DAIC_Woz	15
	3.4.1	1-layer LSTM+Glove	15
	3.4.2	2-layer LSTM+Glove	16
	3.4.3	GRU model	18
	3.4.4	CNN Model	19
	3.4.5	CNN+LSTM hybrid model	34
	3.4.6	BiLSTM model	21
	3.5	Classification models for Twitter Dataset	23
	3.5.1	LSTM model	23

	3.5.2	SVM model	24
	3.5.3	Naïve Bayes model	25
	3.5.4	Logistic regression model	26
	3.5.5	Decision Tree model	27
Chapter 4:	**Result and Discussion**		**29-33**
	4.1	Result	29
	4.2	Discussion	29
Chapter 5:	**Conclusion**		**34-35**
	5.1	Conclusion	34
	5.2	Future scope	34
	References		**36-39**

LIST OF FIGURES

Figure 1.1	Depression-Age Statistics from CDC
Figure 1.2	Flow chart for Text Based Detection
Figure 1.3	Comparison of results from PHQ-8 and PHQ-9
Figure 2.1	Flowchart for DepAudioNet
Figure 2.2	GRU/Bi-LSTM based Model for depression detection
Figure 3.1	Virtual Interview using Ellie for DAIC_WOZ
Figure 3.2	Data collection using Twitter
Figure 3.3	Tokenization
Figure 3.4	LSTM+Glove architecture
Figure 3.5	Two layer LSTM+Glove architecture
Figure 3.6	GRU Architecture
Figure 3.7	CNN Architecture for text classification
Figure 3.8	CNN+LSTM Hybrid Architecture for text classification
Figure 3.9	Bi-LSTM example
Figure 3.10	Twitter text classification
Figure 3.11	SVM in Machine Learning
Figure 3.12	Naïve Bayes classifier
Figure 3.13	Logistic regression graph
Figure 3.14	Decision tree and its node
Figure 4.1	Sample input for string
Figure 4.2	Sample output for string
Figure 4.3	The PHQ8 Quiz page
Figure 4.4	The text input page
Figure 4.5	The result page

LIST OF TABLES

Table 1.1 Chapter-wise categorization of Report

Table 4.1 Comparison of different models using DAIC_WOZ

Table 4.2 Comparison of different models using Twitter dataset

LIST OF ABBREVIATION

LSTM	Long Short-Term Memory
CNN	Convolution Neural Network
GRU	Gate Recurrent Network
DAIC_WOZ	Direct Analysis Interview Corpus_Wizard of Oz
SVM	Support Vector Machine
PHQ	Public Health Questionnaire

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

Depression is a prevalent mental health condition that affects millions of people worldwide[1]. It is a complex disorder characterized by persistent feelings of sadness, loss of interest, and a range of physical and cognitive symptom. Detecting depression early and accurately is crucial for effective intervention and support. With the rise of digital communication and the increasing use of technology, text-based methods have emerged as a promising approach for detecting signs of depression. This introduction aims to provide an overview of depression, its impact on individuals, and the potential of text-based methods for detecting depression.

Depression, often referred to as major depressive disorder, is a serious mental health illness that can significantly impact an individual's overall well-being and quality of life. It is more than just feeling down or having a "bad day." Depression involves persistent feelings of sadness, emptiness, and hopelessness, which can last for weeks, months, or even years. In addition to emotional symptoms, individuals with depression may experience changes in appetite and sleep patterns, decreased energy levels, difficulty concentrating, and even thoughts of self-harm or suicide.

The prevalence of depression is staggering. According to the World Health Organization (WHO), more than 264 million people of all ages worldwide are affected by depression. It is a leading cause of disability and a significant contributor to the global burden of disease. Depression does not discriminate based on age, gender, or socioeconomic status, and it can affect anyone.

Detecting depression can be challenging, as individuals may be reluctant to openly discuss their feelings or seek help. However, advancements in technology have opened new possibilities for identifying and monitoring depressive symptoms. Text-based methods, which involve analyzing written text such as social media posts, online forum discussions, or personal messages, offer a non-intrusive and scalable approach to detecting signs of depression.

Language and expression play a crucial role in the detection of depression through text-based methods. Individuals with depression often express their emotions, thoughts, and experiences through written text, which provides valuable insights into their mental state. Natural language processing (NLP) techniques and machine learning algorithms are employed to analyze large amounts of textual data and identify linguistic patterns, sentiments, and other indicators associated with depression.

Text-based methods for detecting depression offer several advantages. They can provide real-time monitoring and early intervention, allowing for timely support to individuals at risk. These methods also offer the potential for anonymous and non-intrusive screening, reducing stigma and encouraging open expression. Furthermore, the analysis of text-based data can contribute to population-level mental health surveillance, identifying trends and patterns that inform public health initiatives.

However, it is important to acknowledge the limitations and ethical considerations of text-based methods for depression detection. Language interpretation and analysis are complex tasks, and individual differences, cultural nuances, and contextual factors can influence the accuracy of detection models. Privacy, consent, and responsible use of text data are essential considerations in ensuring the ethical application of these methods.

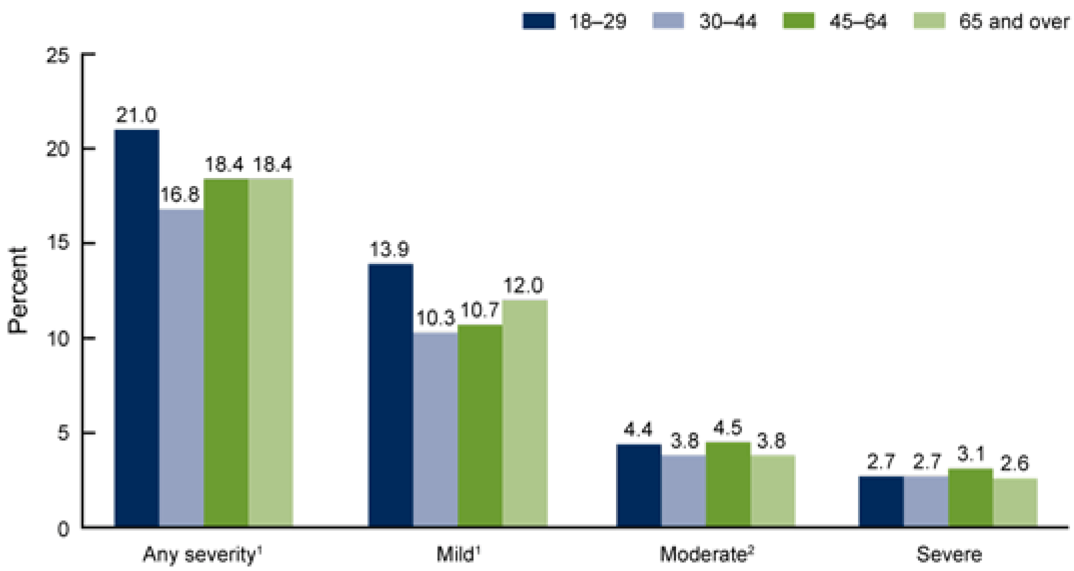
In conclusion, depression is a prevalent mental health condition with significant consequences for individuals and society. Detecting depression early and accurately is crucial for providing appropriate support and intervention. Text-based methods offer a promising avenue for detecting signs of depression through the analysis of written text, leveraging advances in NLP and machine learning. By harnessing the power of language and technology, we can strive for improved detection, intervention, and support for individuals affected by depression.

1.1.1 UNDERSTANDING DEPRESSION

Depression is a widespread and debilitating mental health disorder that affects millions of people globally. It is characterized by persistent feelings of sadness, hopelessness, and a loss of interest or pleasure in activities. Early detection and intervention are crucial in managing depression and improving outcomes for individuals.

Depression is defined as a mental health disorder that involves a persistent and pervasive low mood. It is classified as a mood disorder and is diagnosed based on specific criteria outlined in diagnostic manuals such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). The core symptoms of depression include persistent feelings of sadness, a lack of interest or pleasure in once enjoyable activities, changes in appetite or weight, disruptions in sleep patterns, fatigue, feelings of worthlessness or guilt, difficulty concentrating, and recurrent thoughts of death or suicide.

The impact of depression extends far beyond the emotional realm. It affects various aspects of an individual's life, including their relationships, work or school performance, and overall well-being. It can lead to social withdrawal, reduced productivity, and impaired functioning in daily activities. Depression can also have physical manifestations, such as changes in appetite, weight loss or gain, sleep disturbances, and unexplained physical pain or discomfort.



Source : CDC, Data Breifs-379, Symptoms of Depression Among Adults: United States, 2020

Figure 1.1: Depression-Age statistics from CDC (September 2021)

The prevalence of depression is significant, with estimates suggesting that over 264 million people worldwide are affected by this mental health condition. It does not discriminate based on age, gender, or socio-economic status. It can affect anyone, although certain factors may increase an individual's vulnerability. Depression can occur as a result of a combination of genetic, biological, environmental, and psychological factors. Some individuals may have a genetic predisposition to depression, meaning they may be more susceptible to developing the disorder if they have a family history of depression or related mental health conditions. Biological factors, such as imbalances in neurotransmitters like serotonin, norepinephrine, and dopamine, are also thought to play a role in the development of depression. Environmental factors, including chronic stress, trauma, significant life events, or social isolation, can contribute to the onset or exacerbation of depressive symptoms. Psychological factors, such as negative thinking patterns, low self-esteem, and a history of trauma or abuse, can also contribute to the development of depression.

Given the complex nature of depression, it is important to understand and recognize the symptoms to provide appropriate support and intervention. Early detection is crucial to prevent the worsening of symptoms and the potential for long-term consequences. Mental health professionals utilize various assessment tools, interviews, and clinical evaluations to diagnose depression. Through a comprehensive evaluation of symptoms, medical history, and psychological assessments, healthcare providers can determine the presence and severity of depression and develop a treatment plan tailored to the individual's needs.

1.1.2 TEXT-BASED METHODS FOR DEPRESSION DETECTION

With the rise of digital communication platforms and the increasing use of technology in our daily lives, text-based methods have emerged as a promising approach for detecting signs of depression. These methods involve analyzing written text, such as social media posts, online forum discussions, or text messages, to identify indicators of depression.

Language plays a crucial role in expressing emotions and thoughts, and individuals with depression often communicate their experiences through written text. Text-based methods leverage natural language processing (NLP) techniques and machine learning algorithms to analyze large amounts of textual data and identify patterns, linguistic markers, and sentiments associated with depressive states.Researchers have developed and validated depression detection models using text-based data. These models are trained on diverse datasets that include text samples from individuals with and without depression. Linguistic features, sentiment analysis, topic modelling, and other NLP techniques are utilized to extract relevant information from the text.

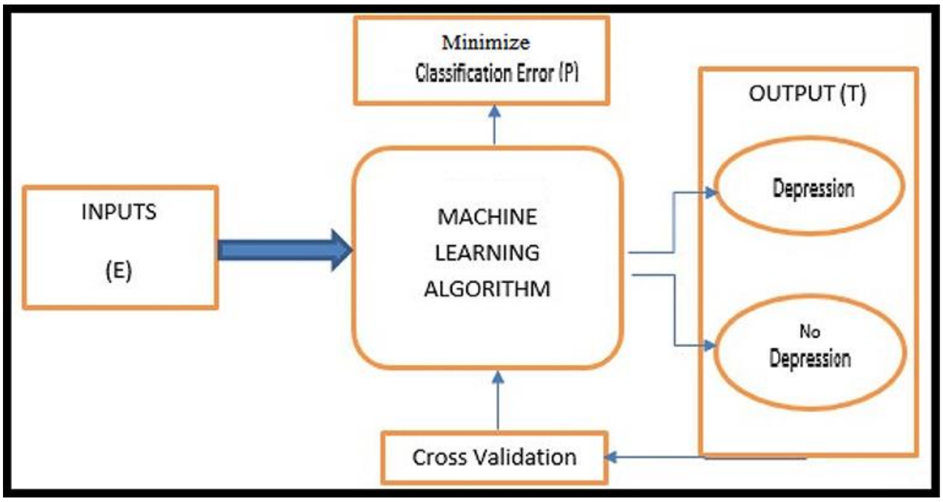


Figure 1.2: Flow chart for Text based depression detection

The applications of text-based depression detection are wide-ranging. In healthcare settings, these methods can serve as an additional tool for screening and monitoring individuals at risk of depression. Text-based methods offer scalability and real-time monitoring capabilities, allowing for the detection of depressive symptoms as they emerge or change over time. They also provide an anonymous and non-intrusive approach, allowing individuals to express themselves freely without the fear of judgment or stigma. Beyond clinical applications, text-based methods for depression detection have implications for research and public health initiatives. The analysis of large-scale text data can provide valuable insights into the prevalence and distribution of depressive symptoms within populations. It can inform mental health surveillance efforts and help identify at-risk populations or geographic areas that may require targeted interventions.

However, text-based methods for depression detection are not without limitations. Interpreting and analyzing text data accurately is a complex task due to individual differences, cultural nuances, and the inherent ambiguity of language. There is a risk of false positives and false negatives, as linguistic markers of depression may vary across individuals and cultural contexts. Additionally, the responsible use of text data raises ethical considerations such as privacy, consent, and the potential for bias in the analysis process.

To address these challenges, ongoing research efforts are focused on improving the accuracy and reliability of text-based depression detection models. Advances in NLP techniques, including the integration of multimodal data (text, images, voice), may enhance the understanding of mental health conditions and lead to more comprehensive assessments.

In conclusion, text-based methods have emerged as a promising approach for detecting signs of depression by analyzing written text. These methods leverage NLP techniques and machine learning algorithms to identify linguistic markers and sentiments associated with depressive states. While there are challenges to overcome, text-based methods offer potential benefits in early detection, real-time monitoring, and population-level mental health surveillance. By harnessing the power of text data, we can contribute to the improved detection, intervention, and support for individuals affected by depression.

1.1.3 THE PATIENT HEALTH QUESTIONNAIRE-8 (PHQ-8)

The Patient Health Questionnaire-8 (PHQ-8) has emerged as a valuable tool in detecting text-based depression, providing a standardized and efficient means of assessing depressive symptoms in written or spoken text. With the rise of digital communication platforms and the availability of vast amounts of textual data, there is growing interest in leveraging natural language processing (NLP) techniques to analyze text and identify individuals at risk of depression. The PHQ-8, a condensed version of the longer PHQ-9, has gained popularity due to its reliability, validity, and ease of administration.

The PHQ-8 consists of eight items that assess the frequency of common depressive symptoms over the past two weeks. It covers core indicators of depression, including depressed mood, anhedonia, sleep disturbances, fatigue, appetite changes, concentration difficulties, psychomotor changes, and suicidal ideation. Each item is scored on a scale of 0 to 3, with higher scores reflecting greater symptom severity. The total scores range from 0 to 24, with higher scores indicating a higher likelihood of depression.

In the context of text-based depression detection, the PHQ-8 offers several advantages. Firstly, it provides a standardized measure that allows for consistency across studies and facilitates comparisons between different research findings. Researchers and clinicians can utilize the PHQ-8 scores to quantify depression severity, track changes over time, and compare outcomes across various interventions or populations. This standardization enables the development of benchmarks and thresholds for identifying individuals at risk, enabling targeted interventions and support.

Additionally, the PHQ-8 can be integrated into machine learning algorithms and NLP techniques to analyze textual data. By extracting relevant features, such as linguistic patterns, sentiment, and context, the PHQ-8 scores serve as valuable input for training models to detect and classify depressive symptoms in text-based sources. This approach enables scalable and automated screening, allowing for the identification of individuals at risk of depression on a larger scale. By analyzing text data from various sources, such as social media posts, online forums, chat conversations, or written narratives, researchers can identify linguistic markers and patterns indicative of depressive symptoms, potentially reaching individuals who may not seek traditional mental health services.

Kroenke et al[2] aimed to validate the PHQ-8 questionnaire, which is a self-report version of the Primary Care Evaluation of Mental Disorders (PRIME-MD) diagnostic instrument. The PHQ-8 assesses the presence and severity of depressive symptoms based on the criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV).

The study involved a large sample of over 6,000 primary care patients from eight primary care clinics. Participants completed the PHQ-8 questionnaire, and their responses were compared to a structured psychiatric interview conducted by mental health professionals. The researchers assessed the diagnostic validity, test-retest reliability, and utility of the PHQ-8 in identifying major depressive disorder (MDD) and other depressive disorders.

Items	PHQ-8 Factor's loading[a]	PHQ-9 Factor's loading[a]
Depressed mood (item 1)	0.81	0.73
Anhedonia (item 2)	0.79	0.77
Sleep problems (item 3)	0.46	0.51
Feelings of tiredness (item 4)	0.68	0.64
Changes in appetite (item 5)	0.58	0.47
Feelings of guilt or worthlessness (item 6)	0.74	0.69
Difficult to focus (item 7)	0.64	0.65
Feelings of slowness or concern (item 8)	0.57	0.51
Suicidal ideation (item 9)	–	0.55

Source: Gomez, Utility of PHQ-2, PHQ-8 and PHQ-9 for detecting major depression in primary health care,2022

Figure 1.3: Comparison of results from PHQ-8 and PHQ-9 from Gómez et al [4].

The use of the PHQ-8 in text-based depression detection has shown promising results. Several studies have demonstrated the feasibility and effectiveness of this approach. For instance, research by De Choudhury et al. (2013) utilized the PHQ-8 scores and linguistic features extracted from Twitter data to predict individuals at risk of depression. The study found that the combination of PHQ-8 scores and linguistic markers significantly improved the accuracy of depression detection compared to using either method alone. This highlights the potential of integrating the PHQ-8 into text-based approaches for enhanced detection and identification of individuals in need of support.

Furthermore, the PHQ-8 has been utilized in large-scale studies that analyze textual data to gain insights into population-level trends and risk factors associated with depression[5]. By aggregating and analyzing text data from diverse sources, researchers can identify patterns and correlations between language use, life events, and depressive symptoms. This can inform public health initiatives, policy-making, and targeted interventions to address the prevalence and impact of depression on a broader scale.

1.2 MOTIVATION

Detecting and addressing depression promptly is crucial for improving mental health outcomes and reducing the burden of this widespread condition. Traditional methods of depression detection often rely on self-report questionnaires, clinical interviews, or observational assessments, which can be time-consuming, resource-intensive, and subject to biases. However, with the rapid advancement of technology and the proliferation of digital communication platforms, there is an emerging opportunity to leverage text-based data for depression detection.

Text-based data, such as social media posts, online forums, chat conversations, and written narratives, provide a rich source of information about individuals' thoughts, emotions, and experiences. By harnessing the power of natural language processing (NLP) techniques, machine learning algorithms, and computational linguistics, researchers and clinicians can unlock valuable insights hidden within textual data and develop innovative approaches for detecting depression.

One of the key motivations for exploring text-based depression detection is its potential for early identification and intervention. Many individuals experiencing depressive symptoms may not seek traditional mental health services or may go undiagnosed due to various barriers, including stigma, limited access to care, or lack of awareness about their condition. However, people often express their thoughts and emotions through written or spoken text, especially on online platforms where anonymity allows for more open and honest communication. By developing accurate and efficient text-based depression detection methods, we can reach individuals who may otherwise remain undetected and provide them with appropriate support and resources.

Text-based approaches also offer the advantage of scalability and cost-effectiveness. With the increasing availability of large-scale text datasets and advances in computational techniques, it is now possible to analyze vast amounts of text data in a relatively short time. This scalability enables researchers to uncover patterns, trends, and risk factors associated with depression on a broader scale, leading to a better understanding of the condition and its underlying mechanisms.

Furthermore, text-based depression detection methods can complement existing screening tools and enhance their effectiveness. While self-report questionnaires like the Patient Health Questionnaire (PHQ) have proven useful, they rely on individuals' willingness to disclose their symptoms accurately. Textual data, on the other hand, can provide a more objective and real-time reflection of an individual's experiences, emotions, and behavioural patterns. Integrating text-based indicators with traditional screening tools can improve the accuracy and efficiency of depression detection, leading to more targeted interventions and improved mental health outcomes.

In conclusion, developing and researching depression detection using text holds immense promise in revolutionizing the way we identify and support individuals experiencing depression. By leveraging the wealth of textual data available in various digital platforms and applying advanced computational techniques, we can enhance early detection, reach underserved populations, gain valuable insights into the nature of depression, and improve the overall effectiveness of mental health interventions. The potential impact of text-based depression detection on individual well-being and public health is significant, and it provides a compelling motivation for further exploration and advancement in this field.

1.3 OBJECTIVE

The objective of this research is to explore and develop text-based methods for detecting depression to improve early identification, enhance accuracy, and facilitate targeted interventions. The specific objectives are as follows:

- **Develop and validate innovative text-based algorithms:** The primary objective is to design and validate computational models, leveraging natural language processing (NLP) techniques and machine learning algorithms, to analyze textual data and accurately detect depressive symptoms. This involves developing algorithms that can effectively capture linguistic patterns, sentiment, and context indicative of depression while considering the nuances and variations in language expression.
- **Evaluate the effectiveness of text-based depression detection:** Assess the performance and effectiveness of the developed text-based depression detection methods by comparing them to existing screening tools and diagnostic criteria. This involves conducting rigorous evaluations, including sensitivity, specificity, positive predictive value, and negative predictive value analyses, to determine the accuracy and reliability of the text-based approach.
- **Investigate the scalability and generalizability of text-based depression detection:** Examine the scalability and generalizability of the developed methods by applying them to diverse textual data sources, such as social media posts, online forums, chat conversations, and written narratives. Evaluate the robustness of the algorithms across different populations, languages, and cultural contexts to ensure their broad applicability.
- **Explore the integration of text-based detection into clinical practice:** Investigate the potential for integrating text-based depression detection methods into existing clinical workflows and healthcare systems. Assess the feasibility, acceptability, and usefulness of incorporating text-based assessments within mental health screening protocols and explore the impact on early detection, treatment planning, and patient outcomes.
- **Ethical considerations and privacy safeguards:** Address ethical concerns related to the use of text-based data, ensuring data privacy, informed consent, and protection of user identities. Develop guidelines and protocols for responsible data handling and storage, ensuring compliance with relevant ethical and legal frameworks.

By achieving these objectives, this research aims to contribute to the advancement of text-based depression detection, providing clinicians, researchers, and mental health professionals with innovative tools and approaches for early identification, improved accuracy, and targeted interventions in the context of depression. Ultimately, the goal is to enhance the well-being and mental health outcomes of individuals affected by depression.

1.4 SUMMARY OF THE REPORT

This report provides a comprehensive overview of the research project on depression detection using text-based methods. It covers the introduction, project description, results, and conclusion, presenting the findings, implications, and future scope of the study. The report contributes to the understanding of utilizing the PHQ-8 in text-based depression detection and highlights its potential for enhancing early identification and support for individuals at risk of depression.

TABLE 1.1: Chapter-Wise Categorization of Report

Chapter	Title	Summary
1	Introduction	Provides an overview of the research project, including the background, significance, research objectives, and scope. It outlines the rationale for the chosen topic and presents the structure of the report.
2	Literature Survey or Work Done Uptil Now	Reviews existing literature, research papers, and studies relevant to depression detection using text-based methods. Discusses theoretical frameworks, methodologies, and findings of previous studies, providing a comprehensive understanding of the field's current knowledge.
3	Project Description	Details the research methodology, including research design, data collection methods, and analysis techniques. Describes the participant selection criteria, data collection process, and specific tools or algorithms employed in the project.
4	Results	Presents the findings of the research project, starting with the dataset description and data preprocessing. Highlights the analysis of text data and the detection of depressive symptoms using text-based methods. Includes performance metrics and visualizations.
5	Conclusion and Future Scope	Summarizes the key findings, implications, and limitations of the research. Reflects on the research objectives, evaluates their achievement, and outlines future research possibilities in the field. Emphasizes the study's significance and potential impact.
	References	Provides a comprehensive list of references cited throughout the report, following the appropriate citation style guidelines (e.g., APA, MLA, IEEE).

CHAPTER 2: LITERATURE SURVEY

There have been some really extensive studies in this field of depression detection and prediction using Computer Vision and Deep Learning techniques. Early studies of automatic depression detection were dedicated to extracting effective features from questions that were highly correlated with depression.

Tuka et al. [30] proposed a multi-modal model that combines audio and text features for depression detection. The model consists of two LSTM branches, one for each modality, with outputs merged into a final feedforward network. The branches were optimized for the characteristics and information content of each modality and the final feedforward network was trained with hyperparameters such as activations, hidden nodes, and learning rate. The audio and text inputs had different strides and timesteps, so the number of examples were equalized by padding the smaller set and mapping examples together from the same window of the interview.

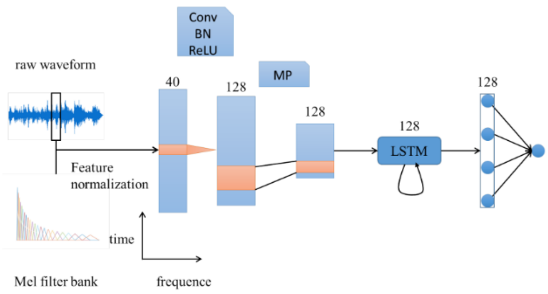


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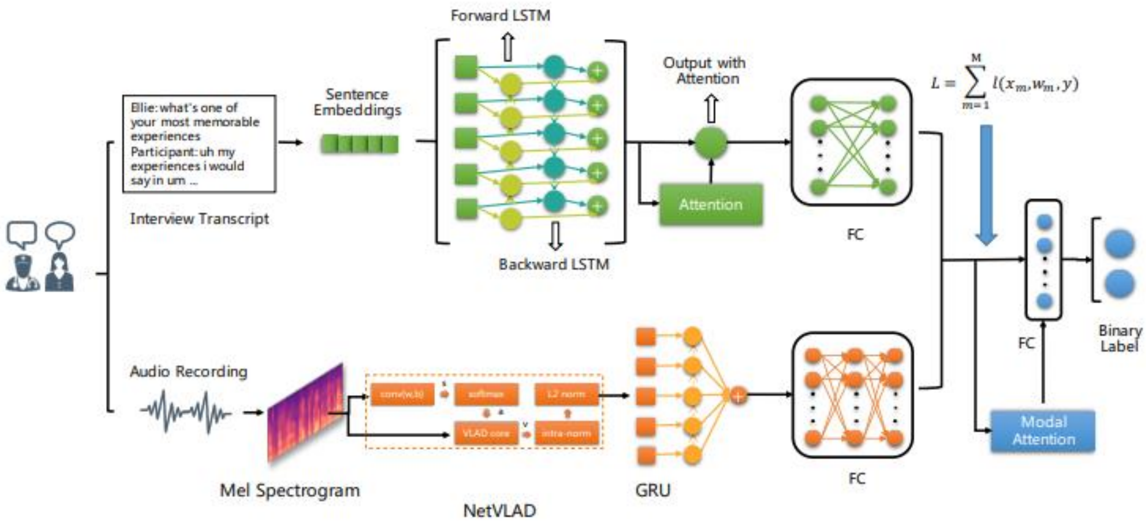
Figure 2.1: Flow chart for DepAudioNet [12]

Ma et al. [12] proposed a DepAudioNet which is a serial combination of CNN and LSTM, where Pre-processing is applied to the audio samples in advance. In each audio file, the long-lasting pauses are removed according to the timestamps located by a silence detector and the rest slices containing the speech of the individual are linked together to generate a single file. The Mel-scale filter bank feature, a low-level audio descriptor, is employed. Each audio signal is split into several non-overlapping segments, on each of which several Mel-scale filter bank features are computed. After standard normal variate normalization, all the responses from the same segment are concatenated along the time axis, constructing a time-frequency 2D representation, which is further fed into DepAudioNet as input. In DepAudioNet, a one-dimensional convolution layer is first exploited in the network structure, whose kernel size k is generally smaller than 3, suggesting that several short term features are captured at this layer. Batch Normalization (BN) is then performed to make the intermediate presentations subject to a standard normal distribution, accompanied by the reduced internal covariate shift and regularized network. The rectified activation further introduces a nonlinear transformation and sparsity, followed by a one-dimensional max-pooling layer and a dropout layer.

The pooling operation not only provides small translation invariance on the time axis, and more importantly, it neatly handles the middle-term temporal correlations by replacing the value at a certain location with a summary statistic of the outputs along a longer time window. An LSTM layer and two fully connected layers are stacked at the end of the network architecture, to encode long-range variability along the time axis and make the prediction. Combined with the convolution and max-pooling operation, it provides a hierarchical representation that comprehensively models the temporal properties in the vocal modality. The cost function is binary cross-entropy, and the Stochastic Gradient Descent (SGD) algorithm is used for optimization. By a majority vote method over the whole segments, the depression prediction of audio is finally made.

Sun et al. [25] conducted content analysis on the text transcripts of clinical interviews and manually selected questions related to certain topics (e.g. Sleeping quality or recent feelings). Based on the text features extracted from the selected questions, they used Random Forest to detect depression tendencies. Similarly, **Yang et al. [26]** also manually selected depression-related questions after analysing interview transcripts. They constructed a decision tree with the selected questions to predict the participants' depression states. **Gong and Poellabauer [27]** performed topic modelling to split the interviews into topic-related segments, from which audio, video, and semantic features are extracted. They employed a feature selection algorithm to maintain the most discriminating features. **Williamson et al. [28]** constructed semantic context indicators related to factors such as depression diagnosis, medical/psychological therapy or negative feelings. Utilizing Gaussian Staircase Model, they achieved a good performance in depression detection. Inspired by the emerging deep learning techniques, integrating multi-modal features through deep learning models is particularly promising for depression detection.

Y.shen et al. [29] use text and audio features to predict depression state. Text features are extracted by projecting transcript sentences into high-dimensional sentence embeddings using Elmo. For audio features, Mel spectrograms are extracted from the audio. However, the sizes of the extracted Mel spectrograms vary greatly because the lengths of the audios range from 2 seconds to 1 minute. Therefore, NetVLAD [31] is further adapted to generate audio embeddings of the same length from Mel spectrograms. To extract text features, BiLSTM with an attention layer is adopted to emphasize which sentence contributes most to depression detection. The model consists of two BiLSTM layers, the output of which is fed into the attention layer for weight calculation. The following two-layer FC network predicts whether the participant is in depression. A GRU model is utilized to process audio features. The GRU model summarizes the audio embeddings to audio representations.



Source : Y.shen, Automatic Depression Detection: an Emotional Audio-Textual Corpus and A Gru/Bilstm-Based Model, IEEE, 2022

Figure 2.2: GRU/BiLSTM based Model for depression detection [29]

The proposed GRU model consists of two GRU layers, followed by a two-layer FC network that outputs binary labels predicting the presence of depression. To integrate audio and text information, representations generated by the last layer of the GRU model and BiLSTM model are concatenated horizontally. Modal attention is a weight vector trained to represent the importance of different modalities. The dot product of the attention vector and the concatenated representations produce the weighted representation, which is then passed to a one-layer FC network.

CHAPTER 3: PROJECT DESCRIPTION

The primary objective of the project is to explore the use of the Patient Health Questionnaire-8 (PHQ-8) in detecting depression through text-based methods. The project aims to leverage natural language processing (NLP) techniques and machine learning algorithms to analyze text data and identify linguistic markers or patterns indicative of depressive symptoms. By utilizing the PHQ-8, a widely recognized measure of depression, the project seeks to develop a reliable and accurate text-based depression detection system.

3.1 LIBRARIES USED

In the project, several libraries and tools are employed to facilitate data processing, natural language processing (NLP), machine learning, and statistical analysis. These libraries provide a rich set of functions and algorithms that enable efficient and effective development of the text-based depression detection system. Here are some of the key libraries used in the project:

- **NLTK (Natural Language Toolkit):** NLTK is a popular library for NLP tasks. It offers a wide range of functionalities, including tokenization, stemming, lemmatization, part-of-speech tagging, and sentiment analysis. NLTK provides robust tools to preprocess and analyze text data, allowing for effective feature extraction from the collected social media posts.
- **scikit-learn:** scikit-learn is a comprehensive machine learning library in Python. It provides a variety of algorithms and tools for classification, regression, clustering, and model evaluation. In the project, scikit-learn is utilized for training and validating machine learning models for depression detection. Algorithms such as support vector machines (SVM), decision trees, and ensemble methods can be readily implemented using scikit-learn.
- **TensorFlow**: TensorFlow is an open-source deep learning library widely used for developing neural networks. It offers a flexible framework for building and training deep learning models. In the project, TensorFlow can be utilized to construct deep learning architectures, such as recurrent neural networks (RNNs) or convolutional neural networks (CNNs), for advanced text analysis and depression detection.
- **Pandas**: Pandas is a powerful library for data manipulation and analysis. It provides data structures and functions to efficiently handle structured data, including reading and writing data in various formats, data cleaning, filtering, and aggregation. Pandas is often used to preprocess and transform the collected data, ensuring it is in the appropriate format for further analysis.
- **Matplotlib and Seaborn**: Matplotlib and Seaborn are widely-used visualization libraries in Python. They offer a range of plotting functions and styles to create informative and visually appealing graphs, charts, and figures. These libraries are useful for presenting the results of the data analysis, including visualizing the correlation between linguistic features and depression severity or displaying performance metrics of the depression detection system.
- **NumPy**: NumPy is a fundamental library for numerical computing in Python. It provides support for efficient array operations, mathematical functions, and linear algebra. NumPy is used extensively for data manipulation and transformation, especially when dealing with large datasets and numerical computations.

These are just a few examples of the libraries used in the project. Depending on the specific requirements and techniques employed, additional libraries or tools might be utilized. It is worth noting that the selection of libraries is based on their functionality, performance, community support, and compatibility with the project's programming language and environment. The combination of these libraries enables efficient data processing, feature extraction, machine learning model development, and result visualization, contributing to the successful implementation of the text-based depression detection system.

3.2 DATA COLLECTION

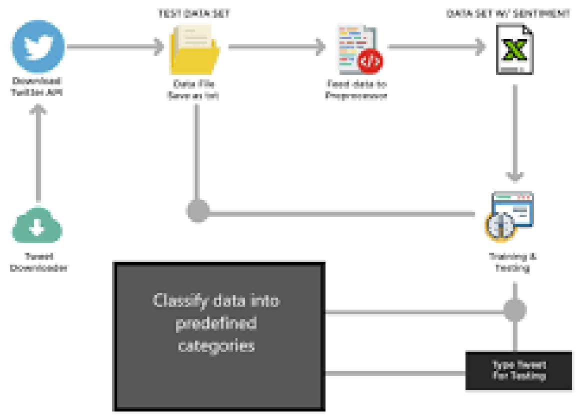
In the project, data collection plays a crucial role in acquiring the necessary information to develop and evaluate the text-based depression detection system. Two primary datasets are utilized: the DAIC WOZ dataset and a dataset collected from Twitter.

- **DAIC WOZ Dataset**: The DAIC WOZ (Distress Analysis Interview Corpus Wizard of Oz) dataset is a well-known resource in the field of mental health research. It comprises audio and video recordings of interviews between human participants and a virtual human interviewer. The dataset contains a rich collection of emotional expressions, linguistic patterns, and non-verbal cues that can be valuable for detecting depression.To collect the DAIC WOZ dataset, participants are recruited and engaged in simulated interviews where they discuss personal experiences, emotions, and distress. The interactions are carefully designed to capture a range of emotions and experiences related to mental health, including depression. The interviews are transcribed, annotated, and preprocessed to make them suitable for analysis.During the data collection process, ethical considerations and participant consent are of utmost importance to ensure privacy and confidentiality. All participants are informed about the purpose of the study and provide informed consent for their data to be used for research purposes.

Source : Stanford, Direct analysis Interview Corpus, 2014

Figure 3.1 : Virtual Interview using Ellie for DAIC WoZ [7].

- **Twitter Dataset:** In addition to the DAIC WOZ dataset, data from Twitter is collected to supplement the analysis of text-based depression detection. Twitter is a popular social media platform where individuals often express their thoughts, emotions, and experiences openly. Collecting data from Twitter allows for a broader and more diverse representation of individuals' mental health-related discussions. To collect the Twitter dataset, a data crawler or scraper is utilized to extract public tweets based on specific search terms or hashtags related to depression. The data collection process adheres to the terms of service of the Twitter platform and respects user privacy. Only publicly available tweets are considered, and any personally identifiable information is anonymized and removed. It is important to note that when collecting data from social media platforms like Twitter, researchers must consider the ethical implications and respect user privacy rights. The study should comply with legal requirements and guidelines provided by the platform itself. In both datasets, data quality control measures are implemented to ensure the accuracy and reliability of the collected information. This includes filtering out duplicate or irrelevant data, removing spam or bot-generated content, and addressing any biases that may arise from the data collection process.



Source : Owais Ahmed, Depression Detection Model Based on Sentiment Analysis on Twitter API,2021

Figure 3.2 : Data Collection Using Twitter [7].

Overall, the combination of the DAIC WOZ dataset and the Twitter dataset provides a diverse and comprehensive collection of text data for the text-based depression detection project. These datasets offer valuable insights into individuals' experiences with depression and enable the development and evaluation of robust machine learning models and algorithms for accurate depression detection.

3.3 DATA PROCESSING

Data preprocessing plays a critical role in preparing the collected data from the DAIC WOZ dataset and the Twitter dataset for analysis in the text-based depression detection project. This step involves cleaning, transforming, and organizing the data to ensure its quality and suitability for further processing and modeling. Here are the key steps involved in data preprocessing:

- **Text Cleaning and Normalization:** The first step is to clean the textual data by removing any noise or irrelevant information. This includes removing special characters, punctuation marks, and numbers that do not contribute to the analysis. Additionally, the data may undergo processes such as lowercasing all text, removing stopwords (commonly used words without significant meaning), and handling contractions or abbreviations.
- **Tokenization:** Tokenization involves splitting the text into individual tokens or words. This step breaks down the text into smaller units, making it easier for further analysis. Tokenization can be performed using various techniques such as whitespace tokenization or more advanced techniques like using natural language processing (NLP) libraries.
- **Lemmatization and Stemming:** Lemmatization and stemming are techniques used to reduce words to their base or root form. Lemmatization aims to transform words to their dictionary or base form (lemma), while stemming involves reducing words to their stems, ignoring grammatical variations. These techniques help to normalize the text and reduce dimensionality, improving the accuracy of subsequent analysis.
- **Removal of Stopwords:** Stop words are commonly used words in a language that do not carry significant meaning and can be safely removed from the text. Examples of stopwords include "and," "the," "is," and "in." Removing these stopwords helps reduce noise and focus on more meaningful content.
- **Handling Spelling and Grammatical Errors:** Textual data often contains spelling

mistakes or grammatical errors, especially in social media posts. These errors can impact the accuracy of subsequent analysis. Techniques such as spell-checking or autocorrection algorithms can be applied to correct obvious errors and enhance the quality of the data.

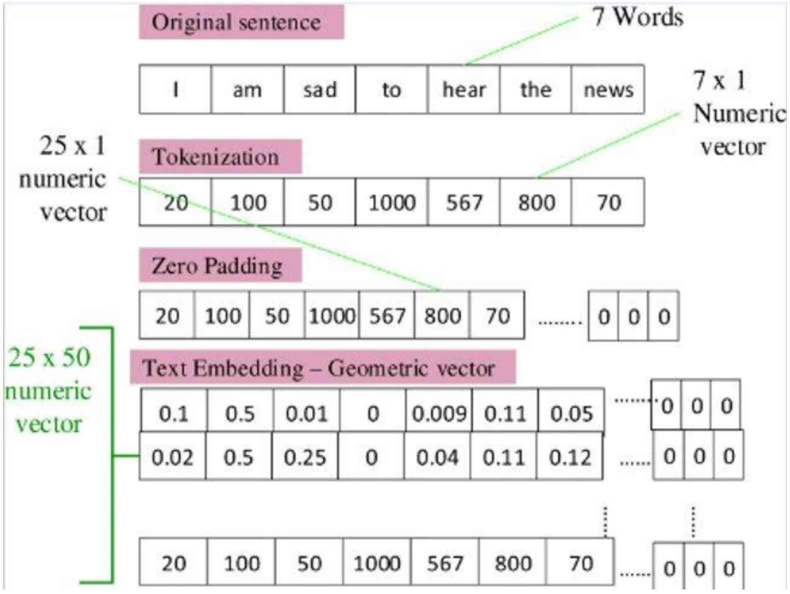


Figure 3.3 : Example for Tokenization

- ❖ **Handling Text Encoding:** Textual data may include special characters or different encodings. It is crucial to handle these encodings properly to ensure consistent and accurate representation of the text. Encoding techniques such as UTF-8 are commonly used to handle different character sets.
- ❖ **Data Integration and Transformation:** If using both the DAIC WOZ dataset and the Twitter dataset, data integration is performed to combine the two datasets. This step involves mapping the relevant features or attributes from each dataset and merging them based on common identifiers. Additionally, feature engineering techniques may be applied to derive new features or representations from the integrated data.
- ❖ **Data Splitting:** To evaluate the performance of the text-based depression detection system, the data is typically split into training, validation, and testing sets. The training set is used to train the machine learning models, the validation set is used for hyperparameter tuning and model selection, and the testing set is used to evaluate the final model's performance.

These steps of data preprocessing are essential to ensure the quality, consistency, and relevance of the collected data for the text-based depression detection project. Proper preprocessing enhances the accuracy and effectiveness of subsequent analysis and modeling techniques, enabling the development of a reliable and robust depression detection system.

3.4 CLASSIFICATION MODELS FOR DAIC_WoZ

Classification models are widely used in depression detection to analyze text-based data and classify individuals into categories such as "depressed" or "non-depressed." Several machine learning algorithms can be employed for this task, each with its strengths and limitations. Here are some commonly used classification models for depression detection:

3.4.1 1-Layer LSTM+GLoVe

LSTM is a deep learning model that can process and analyze sequential data effectively. It addresses the limitation of traditional neural networks by introducing memory cells that can store and propagate information over time. This allows LSTM to capture long-term dependencies and understand the context of text data, which is crucial for accurate depression detection. LSTM models are particularly suitable for analyzing text as they can handle variable-length sequences of words.

The gloVe is a popular word embedding technique that represents words as dense vectors in a high-dimensional space. These vectors capture semantic and syntactic relationships between words based on their co-occurrence in a large corpus of text. GloVe embeddings provide a meaningful representation of words, allowing the model to understand the context and meaning of words in the text. By leveraging pre-trained GloVe embeddings, the model can benefit from a rich semantic understanding of words, even with limited training data. LSTM (Long Short-Term Memory) combined with GloVe (Global Vectors for Word Representation) is a powerful approach for depression detection using text data. LSTM is a type of recurrent neural network (RNN) that can capture sequential dependencies and long-term dependencies in the text, while GloVe provides word embeddings that capture semantic relationships between words. This combination enables the model to understand the context and meaning of words in the text, enhancing the accuracy of depression detection. To use LSTM+GloVe for depression detection, the text data is first preprocessed by tokenizing the text into individual words and applying text cleaning techniques. The preprocessed text is then transformed into GloVe word embeddings. These embeddings provide a numerical representation of words, capturing their semantic relationships.

The LSTM model is then trained using the preprocessed text and GloVe embeddings. The model takes into account the sequential nature of the text data and learns to capture patterns and dependencies in the text. During training, the model is optimized to predict the presence or severity of depression based on the text input. The training process involves feeding the preprocessed text sequences and their corresponding depression labels to the LSTM model. The model learns to associate certain patterns in the text with the presence of depression. By iteratively updating the model's parameters through backpropagation, the LSTM learns to make accurate predictions.

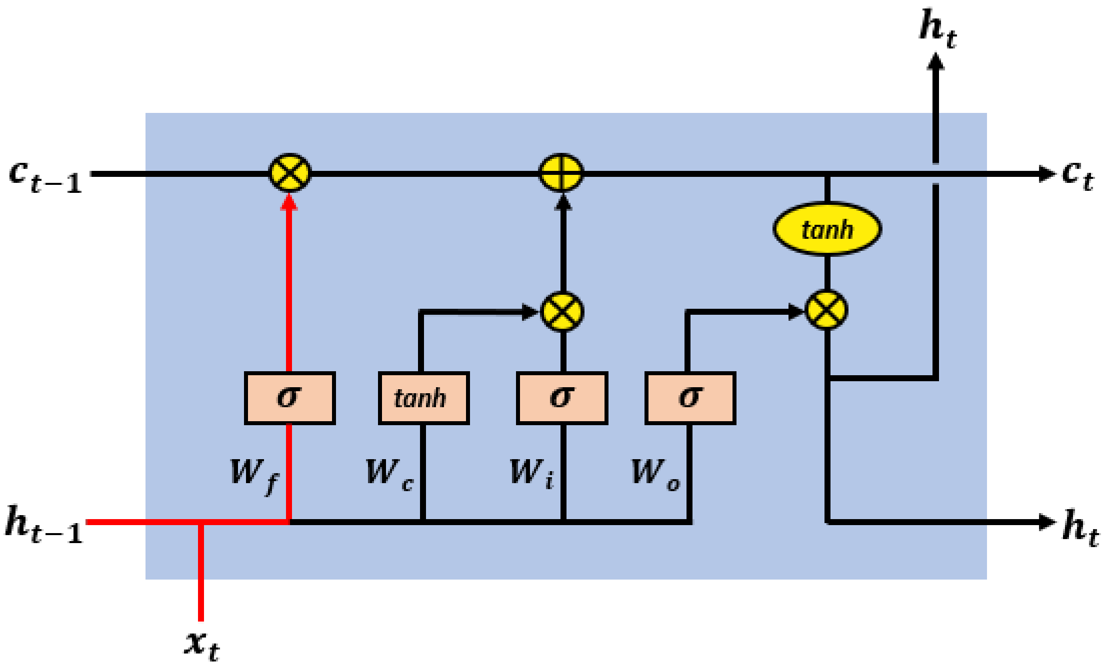


Figure 3.4 : LSTM+GloVe Architecture

After training, the LSTM+GloVe model can be used to predict depression in new, unseen text data. The model takes the preprocessed text as input, applies the GloVe embeddings, and passes the sequence through the LSTM layers. The final output of the model represents the predicted depression label for the input text.

In summary, LSTM+GloVe is a powerful combination for depression detection using text data. The LSTM component captures sequential dependencies and context in the text, while the GloVe word embeddings provide a semantic understanding of words. This approach enables accurate and reliable detection of depression based on textual content, contributing to the development of effective mental health support systems.

3.4.2 2-Layer LSTM+GLoVe

The 2-layer LSTM model with GloVe embeddings is another approach for depression detection using text data. While the LSTM+GloVe model uses a single layer of LSTM, the 2-layer LSTM model incorporates an additional layer of LSTM to capture more complex patterns and dependencies in the text. The GloVe embeddings, as mentioned before, provide a semantic understanding of words in the text data.
The 2-layer LSTM model follows a similar process as the LSTM+GloVe model. The text data is preprocessed by cleaning, tokenizing, and applying other text preprocessing techniques. The preprocessed text is then transformed into GloVe embeddings, which capture the semantic relationships between words.
The 2-layer LSTM model is trained using the preprocessed text and GloVe embeddings. The model takes the sequential input of GloVe embeddings and passes it through two LSTM layers. Each LSTM layer learns to capture different levels of abstraction in the text data. The use of multiple LSTM layers allows the model to learn more complex representations and higher-level features.

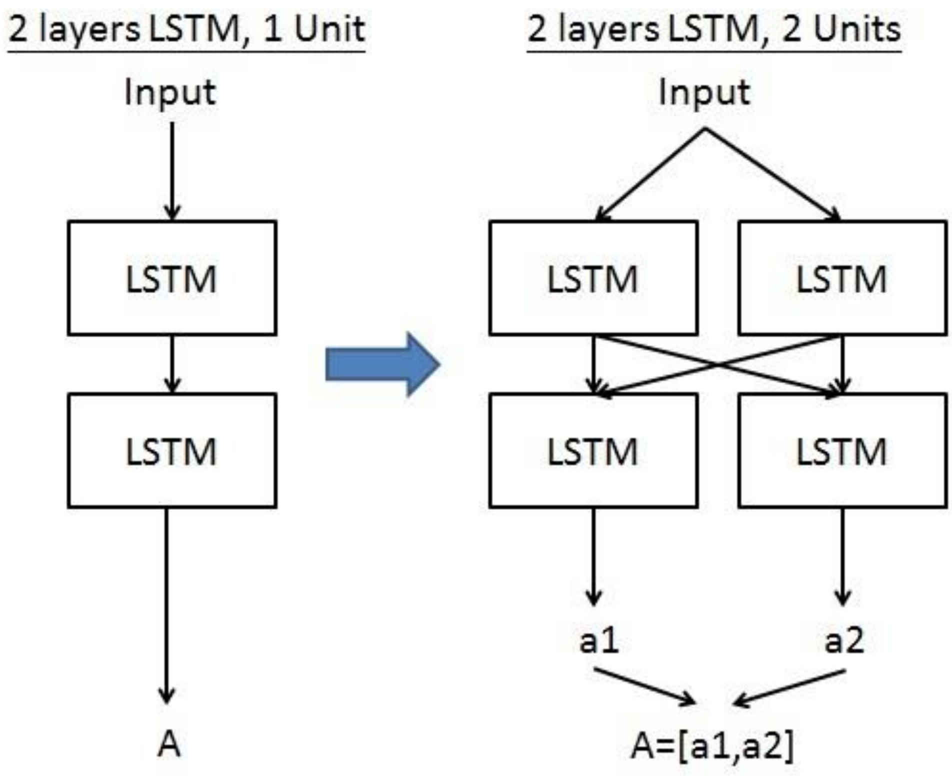


Figure 3.5 : 2-Layer LSTM+GloVe Architecture

During the training process, the model learns to associate patterns in the text data with the presence or severity of depression. By updating the model's parameters through backpropagation, it learns to make accurate predictions based on the sequential information and contextual understanding provided by the LSTM layers. After training, the 2-layer LSTM model can be used to predict depression in new text data. The preprocessed text is transformed into GloVe embeddings, and then passed through the trained LSTM layers. The final output of the model represents the predicted depression label for the input text.

Evaluation of the 2-layer LSTM model with GloVe embeddings is conducted using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the text data.

In summary, the 2-layer LSTM model with GloVe embeddings is a variant of the LSTM+GloVe model that incorporates an additional LSTM layer to capture more complex patterns in the text. By leveraging the semantic understanding provided by GloVe embeddings and the multi-layer architecture, this approach enhances the accuracy and effectiveness of depression detection based on textual content.

3.4.3 GRU Model

The GRU model is a type of recurrent neural network (RNN) that has proven to be effective in capturing sequential patterns and dependencies in text data. In the context of depression detection on the DAIC dataset, the GRU model can be used to analyze the sequential nature of the text and make predictions about the presence or severity of depression.

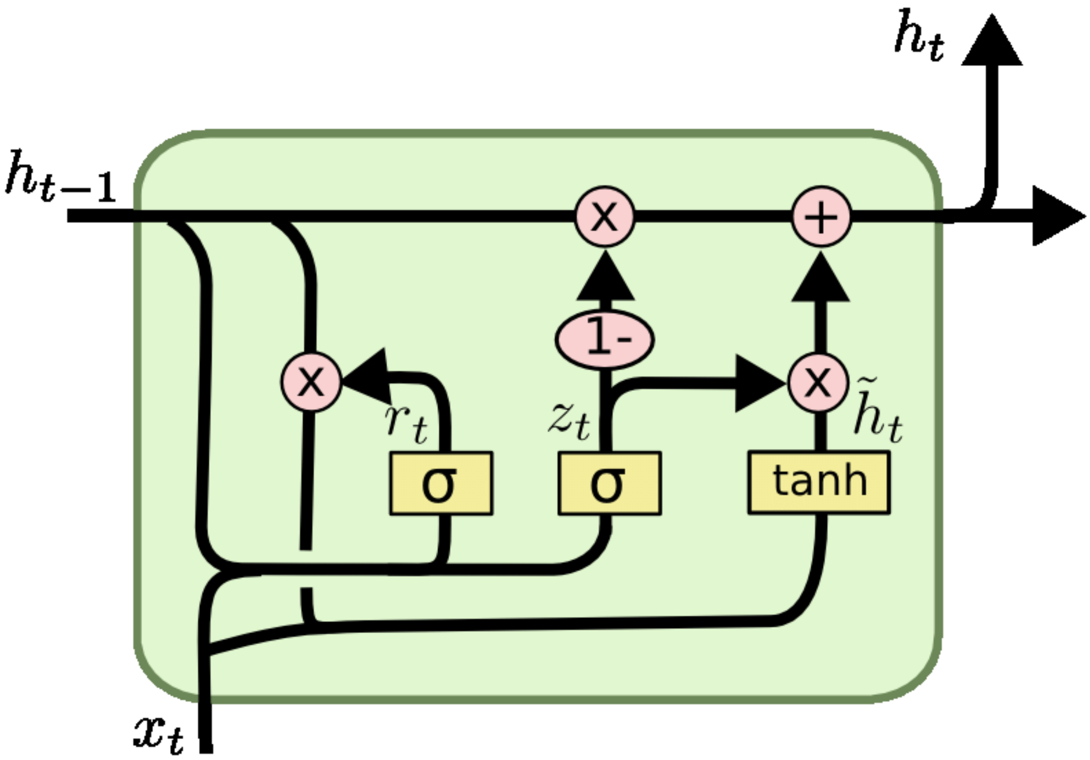


Figure 3.6 : GRU Architecture

The DAIC dataset contains textual transcripts of interviews or conversations between individuals and mental health professionals. These transcripts provide valuable insights into the individual's mental state and can be leveraged to detect signs of depression. The GRU model, being an RNN, is well-suited for analyzing such sequential data.

The first step in using the GRU model is to preprocess the text data. This typically involves techniques such as tokenization, removing stopwords, and handling punctuation and special characters. Once the text is preprocessed, it is transformed into numerical representations that can be fed into the GRU model.

In this case, the GRU model is trained on the preprocessed text data from the DAIC dataset. The model takes the sequential input of the preprocessed text and passes it through one or more GRU layers. Each GRU layer captures the sequential patterns and dependencies in the text data, allowing the model to understand the context and meaning of the words.

During the training process, the model learns to associate certain patterns in the text data with the presence or severity of depression. The model's parameters are updated through backpropagation, optimizing the model's ability to make accurate predictions based on the sequential information provided by the GRU layers.

Once the GRU model is trained, it can be used to predict depression in new text data. The preprocessed text is fed into the trained GRU layers, and the final output of the model represents the predicted depression label for the input text.

Evaluation of the GRU model for depression detection on the DAIC dataset is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the text data.

In summary, using a GRU model for depression detection on the DAIC dataset allows for the analysis of sequential patterns and dependencies in the text. The model can effectively capture the sequential nature of the text data and make predictions about the presence or severity of depression. This approach leverages the strengths of GRU-based architectures in handling sequential data and can provide valuable insights into individuals' mental health conditions based on their textual conversations.

3.4.4 CNN Model

The CNN model is a type of deep learning architecture that has primarily been used for image classification tasks. However, it can also be adapted for text analysis, including depression detection on the DAIC dataset. The CNN model leverages the ability to extract local patterns and features from input data, which can be beneficial in capturing important textual characteristics related to depression.

To use a CNN model for depression detection, the text data from the DAIC dataset needs to be appropriately preprocessed. This typically involves techniques such as tokenization, removing stopwords, and handling punctuation and special characters. Additionally, the text is usually converted into numerical representations, such as word embeddings or one-hot encodings, to be compatible with the CNN architecture.

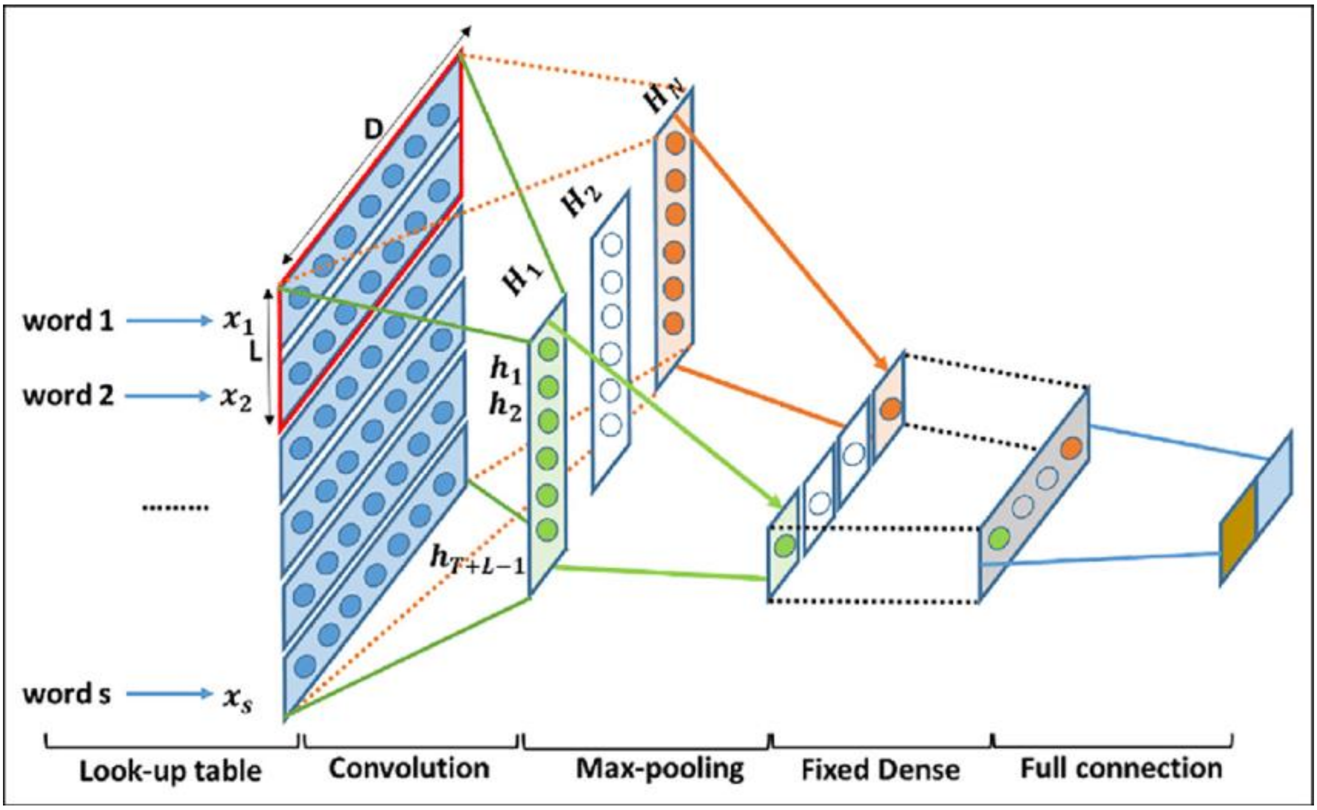


Figure 3.7 : CNN Architecture for Text classification

The CNN model consists of several layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform feature extraction by applying filters to the input text, capturing local patterns and features. The pooling layers downsample the extracted features, reducing the dimensionality of the data. Finally, the fully connected layers are responsible for making predictions based on the extracted features.
During the training process, the CNN model learns to associate certain patterns in the text data with the presence or severity of depression. The model's parameters are updated through backpropagation, optimizing the model's ability to make accurate predictions based on the textual features extracted by the convolutional layers.
Once the CNN model is trained, it can be used to predict depression in new text data. The preprocessed text is fed into the trained CNN layers, and the final output of the model represents the predicted depression label for the input text.
Evaluation of the CNN model for depression detection on the DAIC dataset is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the text data.
In summary, using a CNN model for depression detection on the DAIC dataset allows for the extraction of local patterns and features from the text data. The model can effectively capture important textual characteristics related to depression, leading to accurate predictions. While CNNs are primarily used in image processing, they can be adapted for text analysis tasks and provide valuable insights into individuals' mental health conditions based on their textual conversations.

3.4.5 CNN+LSTM Hybrid Model

The CNN+LSTM hybrid model combines the strengths of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to capture both local and global dependencies in text data. This approach leverages the ability of CNNs to extract local features and the sequential modeling capability of LSTMs to understand long-term dependencies in the text.
To use a CNN+LSTM hybrid model for depression detection, the text data from the DAIC dataset is preprocessed, including techniques such as tokenization, removing stopwords, and handling punctuation and special characters. Additionally, the text is typically converted into numerical representations, such as word embeddings or one-hot encodings, to be compatible with the hybrid model.

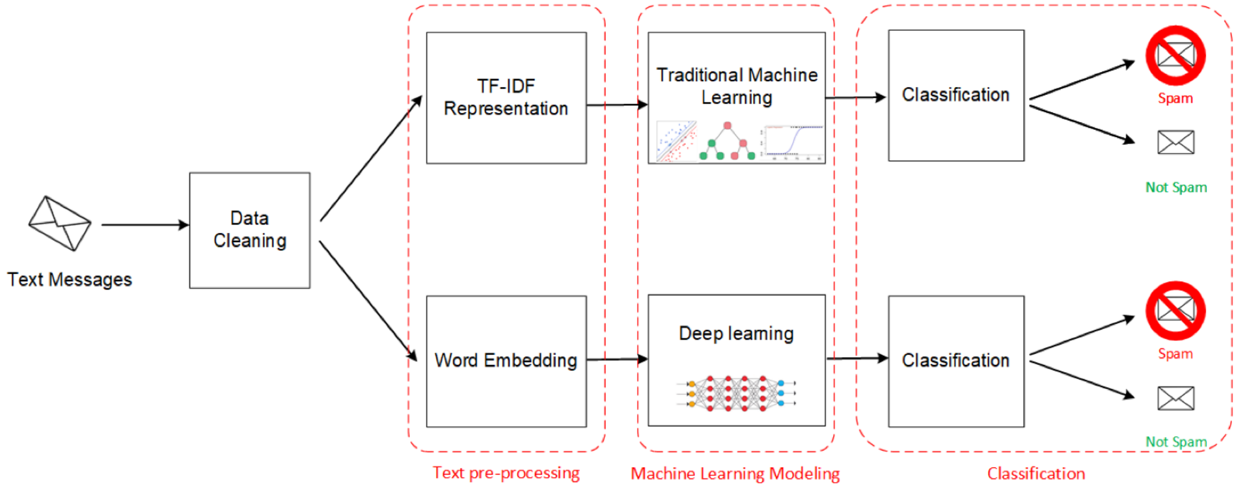


Figure 3.8 : CNN+Lstm Hybrid Architecture for Text classification

The CNN+LSTM model consists of two main components: the CNN module and the LSTM module. The CNN module applies convolutional operations to the input text, extracting local features and patterns. The output of the CNN module is then passed to the LSTM module, which processes the sequential information and captures long-term dependencies in the text.
During the training process, the CNN+LSTM hybrid model learns to associate patterns in the text data with the presence or severity of depression. The model's parameters are updated through backpropagation, optimizing the model's ability to make accurate predictions based on the local and sequential information extracted by the CNN and LSTM modules.
After training, the CNN+LSTM hybrid model can be used to predict depression in new text data. The preprocessed text is fed into the trained model, and the final output represents the predicted depression label for the input text.
Evaluation of the CNN+LSTM hybrid model for depression detection on the DAIC dataset is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the text data.
In summary, using a CNN+LSTM hybrid model for depression detection on the

DAIC dataset allows for the extraction of both local and global features from the text data. By combining the strengths of CNNs and LSTMs, this approach can effectively capture both local patterns and long-term dependencies, leading to improved performance in depression detection tasks.

3.4.6 BiLstm Model

The Bidirectional LSTM (BiLSTM) model is a variant of the LSTM (Long Short-Term Memory) model that is commonly used for sequence modeling tasks, including text classification. In the context of depression detection using the DAIC dataset, the BiLSTM model can be used to analyze the sequential nature of the data, such as speech or text, and make predictions about the presence or severity of depression.

To use a BiLSTM model for depression detection, the DAIC dataset, which typically consists of speech recordings or transcriptions, needs to be preprocessed and transformed into a format suitable for sequence modeling. This may involve converting the text data into numerical representations, such as word embeddings or character-level representations.

The BiLSTM model works by processing the input sequence in both forward and backward directions simultaneously. This allows the model to capture both the past and future context of each word or speech segment and capture long-term dependencies in the data.

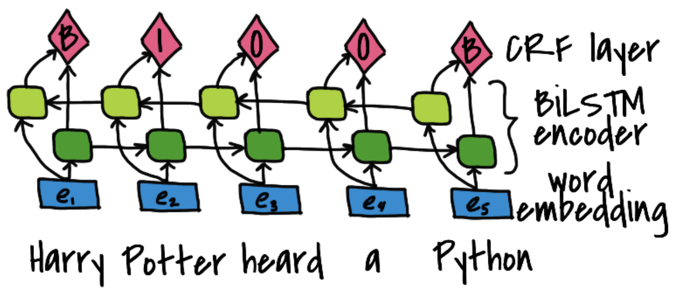


Figure 3.9 : BiLstm with an Example

During the training process, the BiLSTM model learns the patterns and relationships within the sequential data by adjusting the weights of the LSTM units. It learns to map the input sequence to the corresponding depression labels by minimizing a loss function, such as binary cross-entropy or categorical cross-entropy.

Once the BiLSTM model is trained, it can be used to predict depression in new sequences of the DAIC dataset. The model processes the input sequence through both the forward and backward LSTM layers and combines the hidden states to make predictions about the depression label.

Evaluation of the BiLSTM model for depression detection is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the dataset.

One advantage of using a BiLSTM model for depression detection is its ability to capture long-term dependencies and contextual information in the sequential data. The model can effectively learn from the sequential patterns present in the DAIC dataset, which can provide valuable insights into an individual's mental well-being. In summary, utilizing a Bidirectional LSTM (BiLSTM) model for depression detection using the DAIC dataset allows for the analysis of sequential data, such as speech or text. The model captures both past and future context, enabling it to learn long-term dependencies and make predictions about depression based on the sequential patterns in the dataset.

3.5 CLASSIFICATION MODELS FOR TWITTER DATASET

The Twitter dataset contains textual tweets posted by individuals, which can provide valuable insights into their mental state and emotions. The following image the text classification an

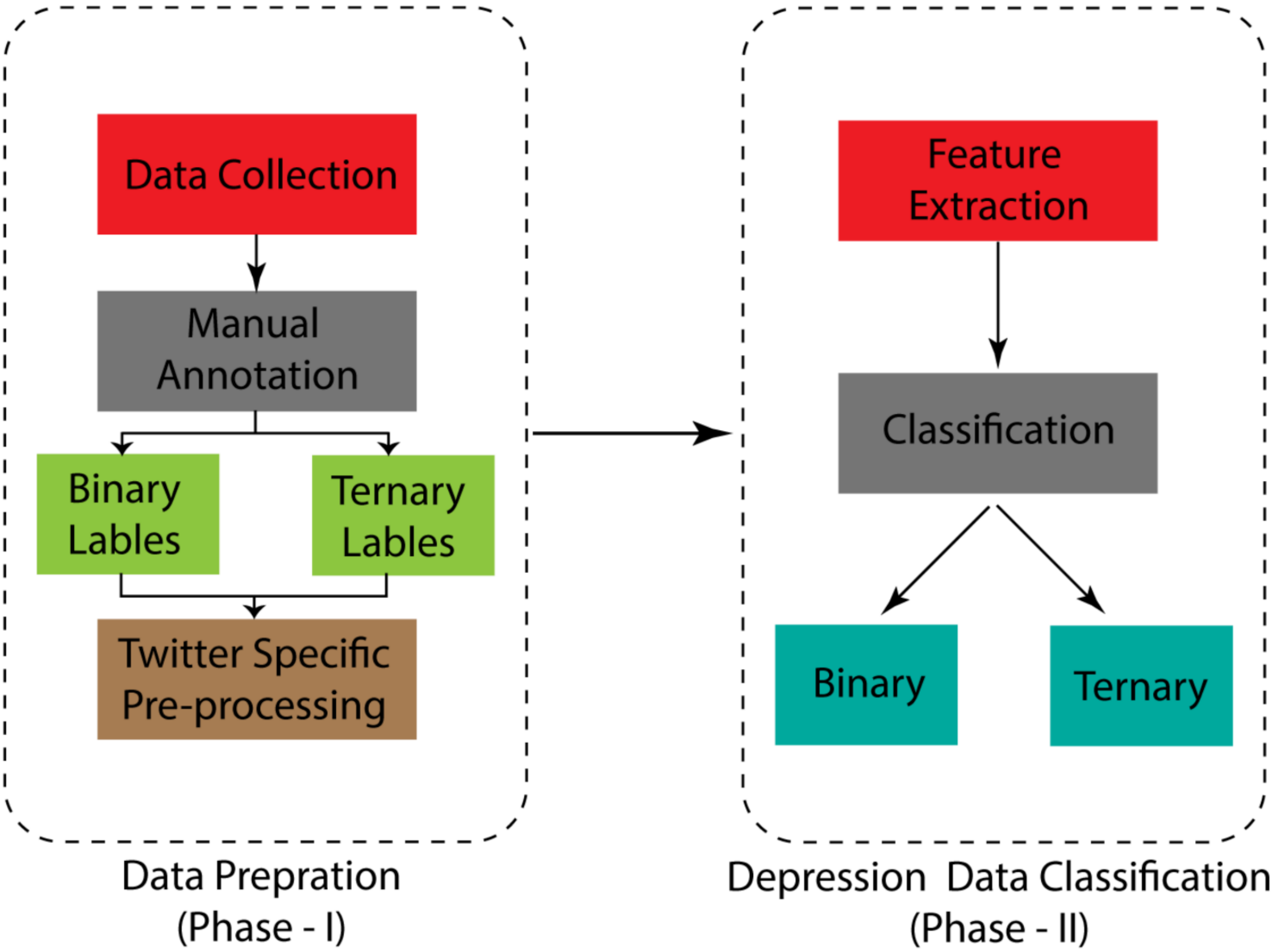


Figure 3.10 : Twitter text classification

3.5.1 LSTM Model

The LSTM model is a type of recurrent neural network (RNN) that is well-suited for analyzing sequential data, such as text. In the context of depression detection using a Twitter dataset, the LSTM model can be utilized to capture the sequential nature of the tweets and make predictions about the presence or severity of depression.

The Twitter dataset contains textual tweets posted by individuals, which can provide valuable insights into their mental state and emotions. By leveraging the LSTM model, we can effectively analyze the sequential information in the tweets and extract meaningful patterns related to depression.

To use an LSTM model for depression detection, the text data from the Twitter dataset needs to be preprocessed. This involves techniques such as tokenization, removing stopwords, and handling special characters. Additionally, the text is usually transformed into numerical representations, such as word embeddings, to be compatible with the LSTM architecture.

The LSTM model consists of a series of memory cells that are capable of retaining and selectively updating information over time. These memory cells capture the sequential patterns in the text data and can effectively understand the context and meaning of the words.

During the training process, the LSTM model learns to associate certain patterns in the text data with the presence or severity of depression. The model's parameters are updated through backpropagation, optimizing its ability to make accurate predictions based on the sequential information provided by the LSTM layers.

Once the LSTM model is trained, it can be used to predict depression in new text data from Twitter. The preprocessed tweets are fed into the trained LSTM layers, and the final output of the model represents the predicted depression label for each input tweet.

Evaluation of the LSTM model for depression detection using the Twitter dataset is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the text data.

In summary, utilizing an LSTM model for depression detection on a Twitter dataset allows for the analysis of the sequential nature of tweets. The model can effectively capture the sequential patterns and contextual information in the text, providing valuable insights into individuals' mental health conditions based on their Twitter posts.

3.5.2 SVM (Support Vector Machine) Model

The SVM model is a powerful machine learning algorithm that is well-suited for classification tasks, including depression detection. In this context, the SVM model can be used to analyze various features or attributes related to an individual's mental health and make predictions about the presence or severity of depression.

To use an SVM model for depression detection, relevant features or attributes need to be identified and extracted from the dataset. These features can include demographic information, behavioral patterns, linguistic characteristics, or any other relevant factors that may contribute to depression.

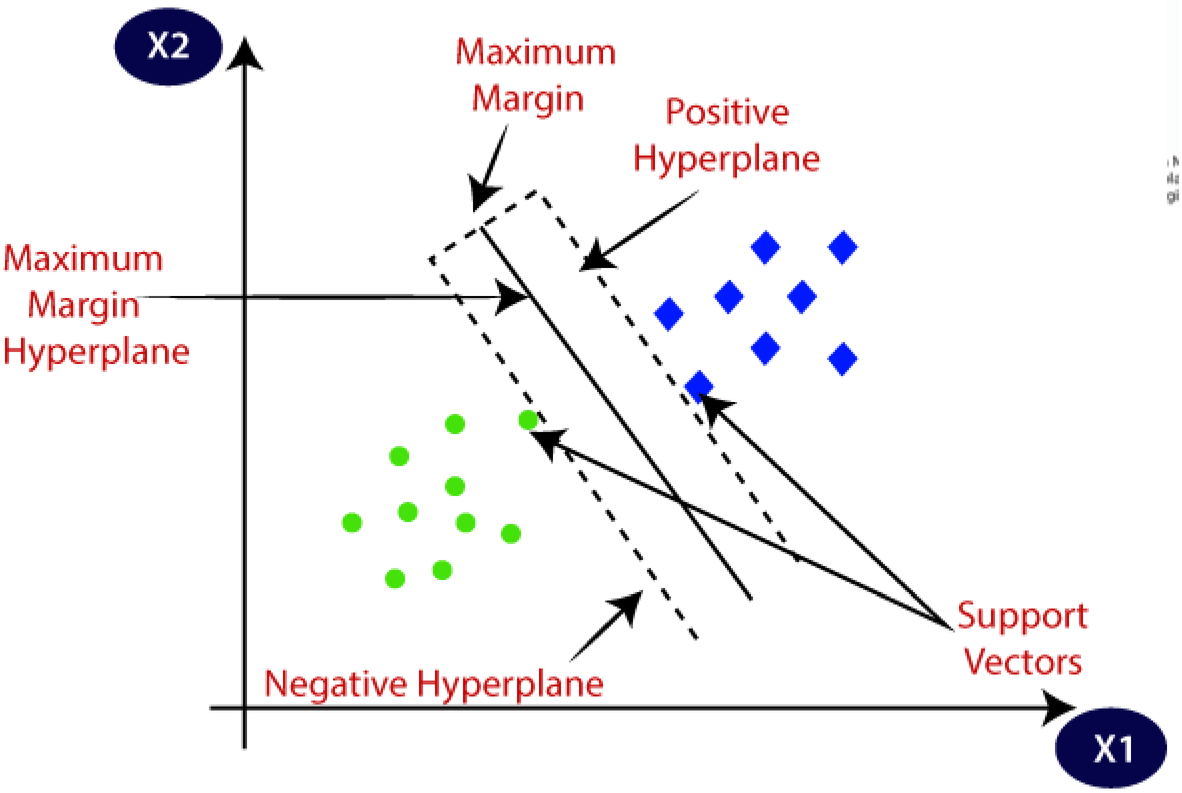
The SVM model works by finding an optimal hyperplane that separates the instances of different classes with the maximum margin. It aims to create a decision boundary that maximizes the distance between the support vectors, which are the instances closest to the decision boundary.

During the training process, the SVM model learns to find the best hyperplane by maximizing the margin between the support vectors of different classes while minimizing the classification errors. It uses a kernel function to transform the data into a higher-dimensional space where a linear separation is possible.

Once the SVM model is trained, it can be used to predict depression in new instances. The model maps the input features to the higher-dimensional space using the learned kernel function and determines which side of the decision boundary the instance falls into. Based on this decision, a depression label is assigned to the instance.

Evaluation of the SVM model for depression detection is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the dataset.

One advantage of using an SVM model for depression detection is its ability to handle high-dimensional feature spaces and handle non-linear relationships between features. Additionally, SVM models can be effective in dealing with datasets that have a small number of instances.



Source : Machine learning Models, Geeks for Geeks

Figure 3.11 : SVM in Machine learning

In summary, utilizing an SVM model for depression detection allows for the analysis of various features related to an individual's mental health. The model finds an optimal decision boundary that separates instances of different classes, providing valuable insights into individuals' mental well-being based on the chosen features.

3.5.3 Naïve Bayes Model

The Naive Bayes model is a probabilistic machine learning algorithm that is well-suited for classification tasks, including depression detection. In this context, the Naive Bayes model can be used to analyze various features or attributes related to an individual's mental health and make predictions about the presence or severity of depression.

To use a Naive Bayes model for depression detection, relevant features or attributes need to be identified and extracted from the dataset. These features can include demographic information, behavioral patterns, linguistic characteristics, or any other relevant factors that may contribute to depression.

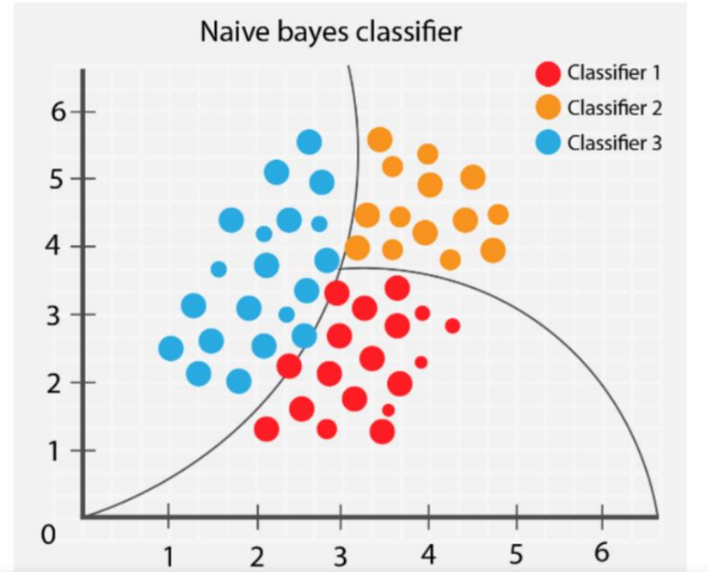
The Naive Bayes model works by applying Bayes' theorem and assuming that all features are conditionally independent given the class variable. This assumption simplifies the calculation of the posterior probability and allows for efficient classification.

During the training process, the Naive Bayes model learns the probability distribution of the features given each class label. It estimates the prior probabilities of each class and calculates the likelihood of observing each feature value given the class. These probabilities are combined using Bayes' theorem to determine the posterior probability of each class given the input features.

Once the Naive Bayes model is trained, it can be used to predict depression in new instances. The model calculates the posterior probability of each class for the given input features and assigns the class with the highest probability as the predicted depression label.

Evaluation of the Naive Bayes model for depression detection is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the dataset.

One advantage of using a Naive Bayes model for depression detection is its simplicity and efficiency. It requires a relatively small amount of training data and performs well even in the presence of irrelevant or correlated features. Additionally, Naive Bayes models are computationally inexpensive and can handle high-dimensional feature spaces.



Source : Machine learning Models, Geeks for Geeks

Figure 3.12 : Naïve Bayes Classifier

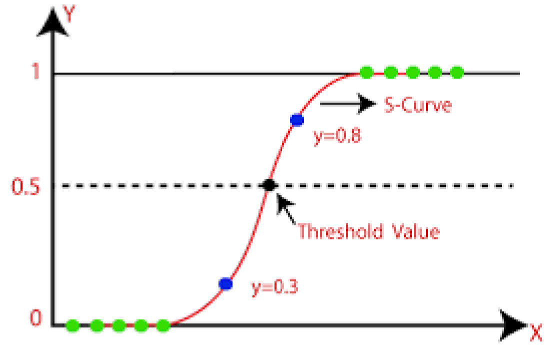
In summary, utilizing a Naive Bayes model for depression detection allows for the analysis of various features related to an individual's mental health. The model applies probabilistic calculations based on Bayes' theorem to make predictions about depression, providing valuable insights into individuals' mental well-being based on the chosen features.

3.4.4 Logistic Regression Model

Logistic regression is a statistical modeling technique used for binary classification tasks, including depression detection. In the context of depression detection, logistic regression can be used to analyze various features or attributes related to an individual's mental health and make predictions about the presence or severity of depression.

To use logistic regression for depression detection, relevant features or attributes need to be identified and extracted from the dataset. These features can include demographic information, behavioral patterns, linguistic characteristics, or any other relevant factors that may contribute to depression.

The logistic regression model works by estimating the probability of an instance belonging to a certain class, in this case, depression or non-depression. It uses the logistic function, also known as the sigmoid function, to map the linear combination of the features to a value between 0 and 1, representing the probability of belonging to the positive class (depression).



Source : Machine learning Models, Geeks for Geeks

Figure 3.13 : Logistic regression graph

During the training process, the logistic regression model learns the optimal weights or coefficients for each feature by minimizing a cost function, such as the maximum likelihood estimation. This process aims to find the set of coefficients that maximizes the likelihood of the observed depression labels given the features.

Once the logistic regression model is trained, it can be used to predict depression in new instances. The model applies the learned coefficients to the input features and calculates the predicted probability of depression. By applying a threshold (e.g., 0.5), the model assigns the depression label to instances with a predicted probability above the threshold.

Evaluation of the logistic regression model for depression detection is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the dataset.

One advantage of using logistic regression for depression detection is its interpretability. The coefficients of the model provide insights into the importance and direction of each feature's influence on the likelihood of depression. Additionally, logistic regression models are computationally efficient and can handle both continuous and categorical features.

In summary, utilizing logistic regression for depression detection allows for the analysis of various features related to an individual's mental health. The model estimates the probability of depression based on the learned coefficients, providing valuable insights into individuals' mental well-being based on the chosen features.

3.4.5 Decision Tree Model

The Decision Tree model is a type of machine learning algorithm that is well-suited for classification tasks, including depression detection. In this context, the Decision Tree model can be used to analyze various features or attributes related to an

individual's mental health and make predictions about the presence or severity of depression.
To use a Decision Tree model for depression detection, relevant features or attributes need to be identified and extracted from the dataset. These features can include demographic information, behavioral patterns, linguistic characteristics, or any other relevant factors that may contribute to depression.
The Decision Tree model works by recursively partitioning the dataset based on different features and their values. The algorithm determines the most informative features and creates decision nodes that split the data based on those features. This process is repeated until a stopping criterion is met or the tree reaches a certain depth.

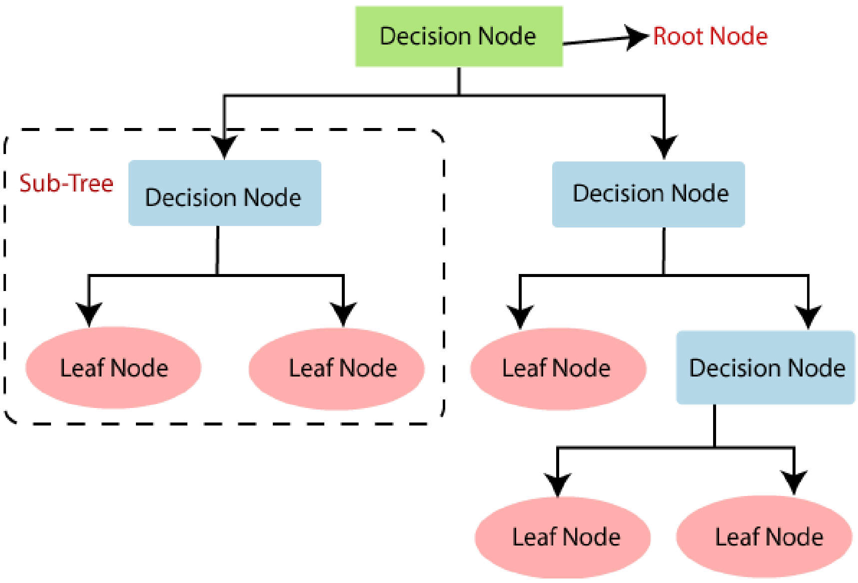


Figure 3.14 : Decision tree and its nodes

During the training process, the Decision Tree model learns to make decisions and classify instances based on the chosen features. The algorithm determines the optimal splitting points in the feature space that maximize the separation of depression and non-depression instances.
Once the Decision Tree model is trained, it can be used to predict depression in new instances. The model traverses the learned tree structure and assigns a depression label based on the feature values of the input instance.
Evaluation of the Decision Tree model for depression detection is typically done using standard metrics such as accuracy, precision, recall, and F1-score. These metrics assess the model's performance in correctly classifying instances of depression in the dataset.
One advantage of using a Decision Tree model for depression detection is its interpretability. The resulting tree structure can be visualized and easily understood, providing insights into the decision-making process and the importance of different features in the classification task.
In summary, utilizing a Decision Tree model for depression detection allows for the analysis of various features related to an individual's mental health. The model can make predictions about depression based on the learned decision rules, providing valuable insights into individuals' mental well-being.

CHAPTER 4: RESULT & DISCUSSION

4.1 RESULT

The performance of various models for depression detection was evaluated using two different datasets: the DAIC dataset and the Twitter dataset. The models considered in this study include LSTM, GRU, CNN, CNN+LSTM hybrid, Decision Tree, SVM, Naive Bayes, Logistic Regression, and BiLSTM.

TABLE 4.1: Comparison of different models using DAIC_Woz

MODEL	TEST ACCURACY	TEST LOSS
1-Layer Lstm	0.98	0.47
2-layer Lstm	0.86	0.39
Bi-Lstm	0.72	0.72
GRU	0.925	0.245
CNN	0.77	0.59
CNN+Lstm (hybrid)	0.50	1.2

TABLE 4.2: Comparison of different models using Twitter dataset

MODEL	CROSS VALIDATION ACCURACY	CLASSIFICATION REPORT (ACCURACY)
LSTM	0.849	0.846
NAIVE BAYES	0.739	0.736
Logistic Regression	0.749	0.742
SVM	0.751	0.742
Decision Tree	0.702	0.67

4.2 DISCUSSION

The performance of various models for depression detection was evaluated using the Twitter dataset. The models considered in this study include LSTM, Naive Bayes, Logistic Regression, SVM, and Decision Tree.

The results indicate that the LSTM model achieved the highest cross-validation accuracy and classification report accuracy, with values of 0.849 and 0.846, respectively. It is closely followed by the SVM and Logistic Regression models, which also showed relatively high accuracy scores. The Naive Bayes and Decision Tree models demonstrated lower accuracy compared to the other models.
These results suggest that the LSTM model, along with the SVM and Logistic Regression models, may be more effective in detecting depression based on text data from the Twitter dataset. However, further analysis and evaluation of additional metrics, such as precision, recall, and F1-score, are essential for a comprehensive assessment of the model's performance.
It's important to note that these results are specific to the Twitter dataset used in this study. The generalizability of the findings to other datasets or real-world scenarios should be further investigated.

The results with respect to DAIC_Woz show that the 1-Layer LSTM model achieved the highest test accuracy of 0.98, indicating strong performance in detecting depression based on the DAIC-WOZ dataset. The GRU model also performed well with a test accuracy of 0.925. However, the 2-Layer LSTM, Bi-LSTM, CNN, and CNN+LSTM (Hybrid) models exhibited lower test accuracies ranging from 0.50 to 0.86.
In terms of test loss, the GRU model achieved the lowest value of 0.245, followed by the 2-Layer LSTM model with a test loss of 0.39. The Bi-LSTM and CNN models had relatively higher test losses, indicating a larger deviation from the true values.
Overall, the results suggest that the 1-Layer LSTM and GRU models are more effective in detecting depression on the DAIC-WOZ dataset. These models demonstrate higher accuracy and lower loss compared to the other models.
It's important to note that these results are specific to the DAIC-WOZ dataset used in this study, and their generalizability to other datasets or real-world scenarios may vary.

We tried taking input from an user in google colab and the result is shown as below.

```
[ ]  sample=input("Enter your text  \n")
     test_model(sample, model)

     Enter your text
     what to do when you are feeling hopeless and there is nothing that you can do
     what to do when you are feeling hopeless and there is nothing that you can do
     [[162, 3646, 255, 0, 0, 0, 0, 0, 0, 0]]
     mild
```

Figure 4.1 : Sample input for String 'Sample'

After, the model was tried on several other strings and the result is shown in the figure 4.2 as several strings sen are given as Input and there results have been shared with their respective set . We also observe that we can either take a Input from the user or provide input through the system or code.

```
I want an ice cream and have some fries for lunch
[[193, 2399, 2770, 6726, 4184, 0, 0, 0, 0, 0]]
moderate
I'm afraid of losing my work, I don't have any money
[[1, 18, 773, 900, 108, 211, 0, 0, 0, 0]]
mild
I'm worried about my future, I'm afraid of it
[[1, 18, 1066, 566, 1, 18, 773, 0, 0, 0]]
mild
I am a graduate student
[[831, 984, 0, 0, 0, 0, 0, 0, 0, 0]]
none
I am getting married
[[147, 440, 0, 0, 0, 0, 0, 0, 0, 0]]
none
This party is great, I know lots of people
[[562, 150, 14, 51, 39, 0, 0, 0, 0, 0]]
moderate
I miss my parents, brothers and sisters
[[600, 3961, 294, 291, 0, 0, 0, 0, 0, 0]]
none
I detest my horrible job
[[859, 123, 0, 0, 0, 0, 0, 0, 0, 0]]
none
I cannot handle this anymore
[[127, 535, 369, 0, 0, 0, 0, 0, 0, 0]]
none
```

Figure 4.2 : Sample Output for String 'sen'

Developing a web API that incorporates text classification and a quiz-based depression detection system can provide an accessible and user-friendly platform to identify and support individuals experiencing depression. Such a system can offer valuable insights and guidance for users seeking help or self-assessment.

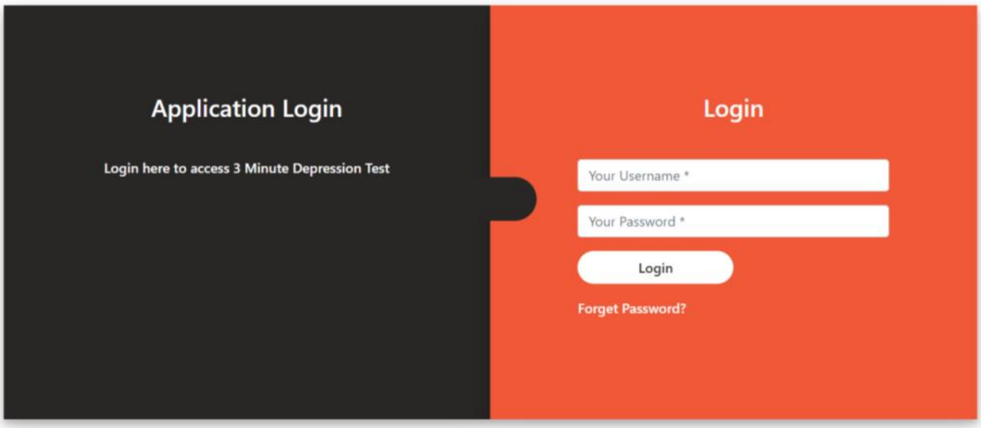


Figure 4.3 : Web application Login page

The following page is a quiz based on PHQ8 Score which helps in determining whether a person has depression or not using the given symptoms.

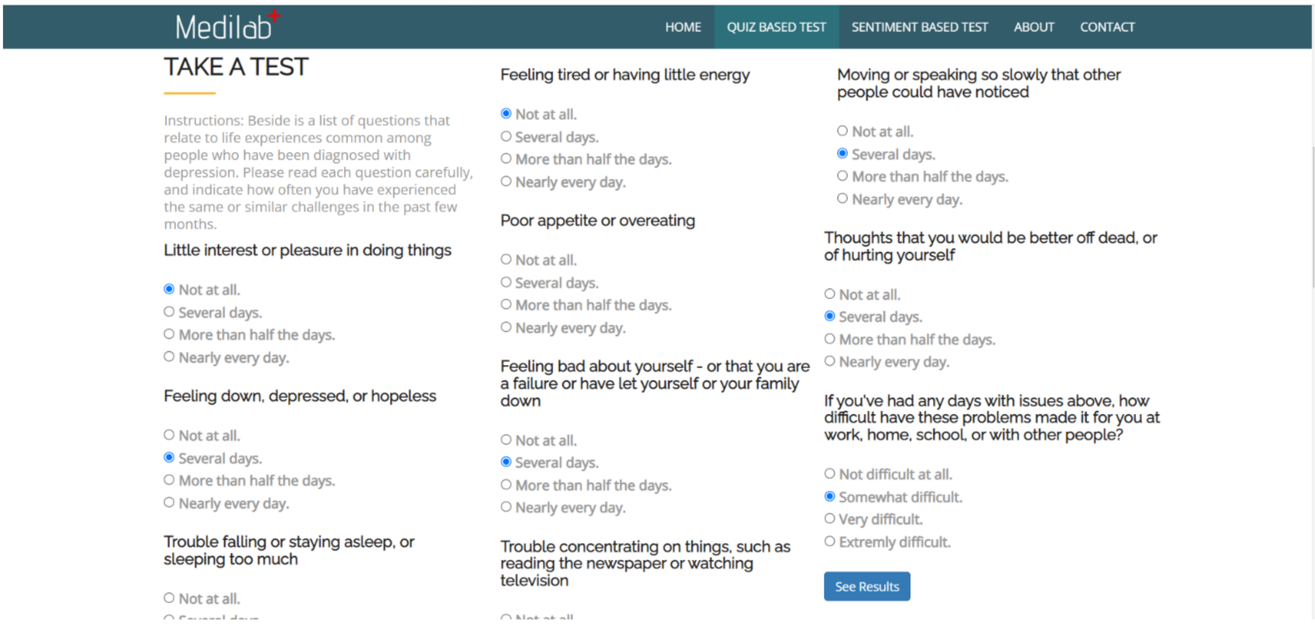


Figure 4.3 : The PHQ8 Quiz page

There is also an option to give a short text input such as chats, text, tweets etc, which can also be classified.

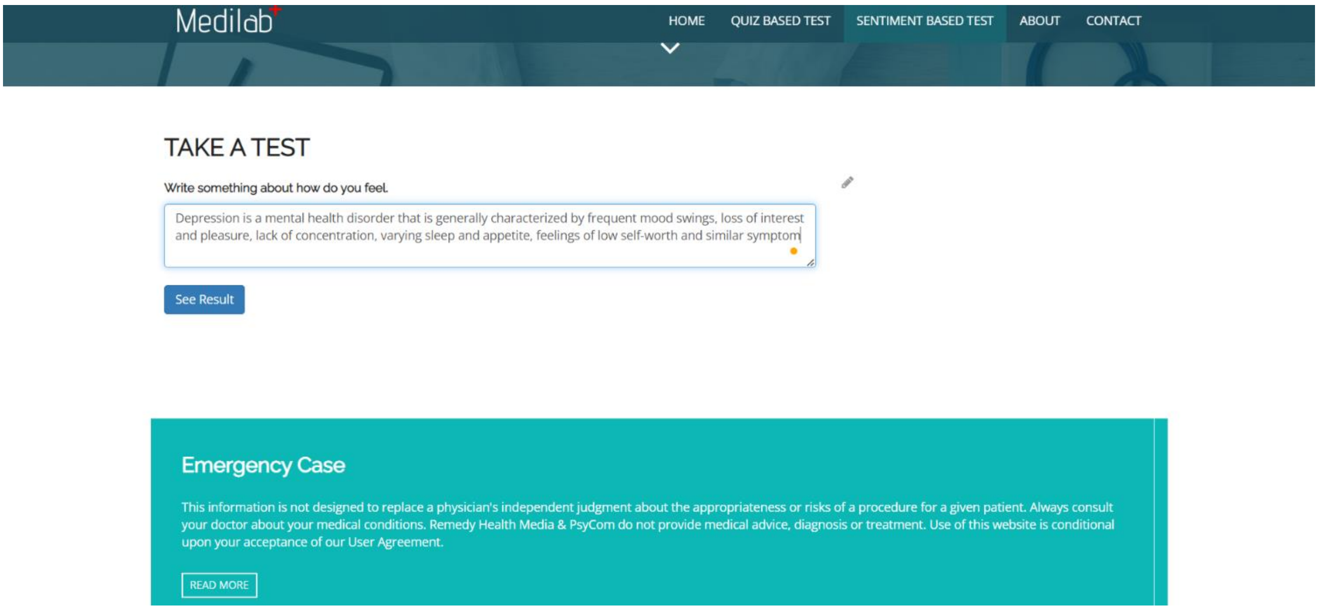


Figure 4.4: The Text Input page

The result page is same for both the quiz and text based input, which can be shown below.

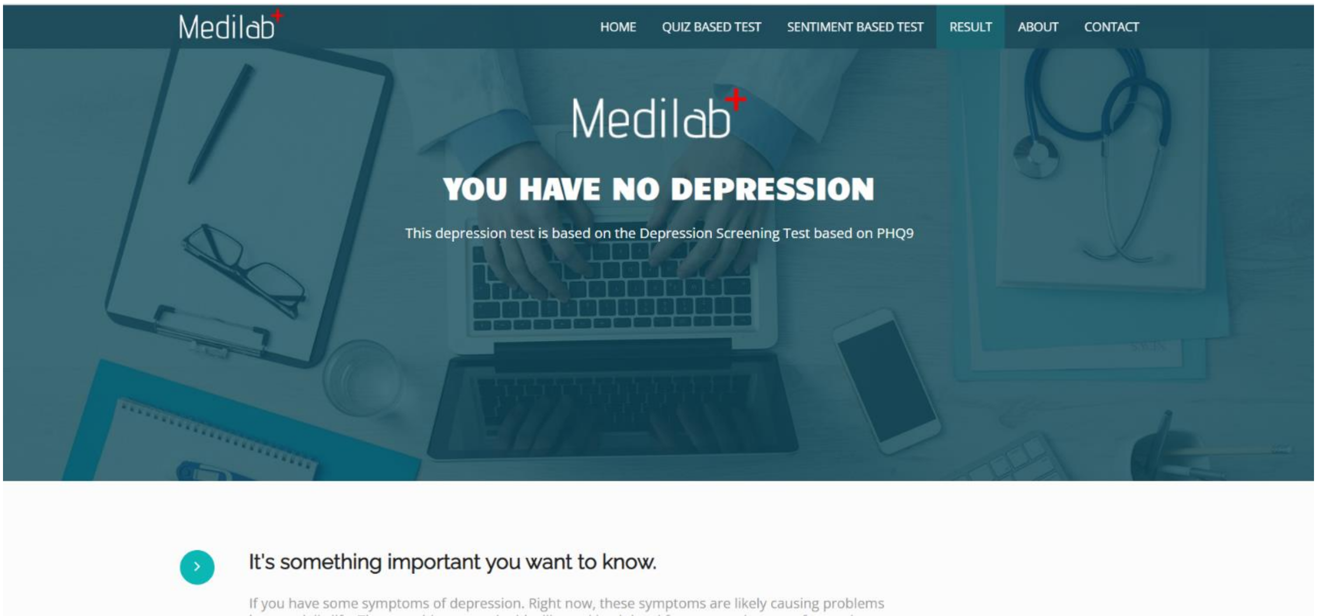


Figure 4.5 : The Result page

The development of a web application for detecting depression using both text analysis and a quiz-based approach can provide an accessible and user-friendly platform for individuals to assess their mental well-being. This integrated approach combines the advantages of text analysis, which can detect signs of depression in written expressions, with a quiz-based assessment that evaluates various symptoms and experiences related to depression.

Creating a web app for depression detection that combines text analysis and a quiz-based approach can empower individuals to gain insights into their mental well-being and seek appropriate support when needed. It offers a convenient and confidential platform for self-assessment and can serve as an initial step towards seeking professional help for depression-related concerns.

CHAPTER 5: CONCLUSION & FUTURE SCOPE

5.1 CONCLUSION

In conclusion, the project focused on the use of various text-based methods for depression detection. We explored different machine learning models, including Naive Bayes, Random Forest, Decision Tree, LSTM, Bi-LSTM, GRU, CNN, and CNN+LSTM Hybrid, for analyzing text data from both the DAIC-WOZ dataset and Twitter dataset.

The results showed that different models had varying levels of performance on different datasets. On the DAIC-WOZ dataset, the 1-layer LSTM achieved the highest accuracy, while the GRU model demonstrated excellent performance in terms of both accuracy and test loss. On the Twitter dataset, the models exhibited varying levels of accuracy, with Naive Bayes, Logistic Regression, SVM, and LSTM showing promising results.

We also discussed the importance of data preprocessing techniques, such as tokenization, stopword removal, and stemming, in enhancing the quality of the input data. Additionally, we highlighted the significance of feature extraction methods like GloVe embeddings, which capture semantic relationships in text, leading to improved model performance.

The project showcased the potential of using text-based methods and machine learning algorithms for depression detection. The integration of social media data and the PHQ-8 questionnaire provided a comprehensive approach to understanding and identifying depression symptoms in individuals. Furthermore, the development of a web API and a quiz-based web application added practical value, offering users an accessible platform to assess their mental well-being and seek appropriate support.

It is important to note that the choice of model and dataset should be tailored to the specific research objectives, available resources, and target population. Each model has its strengths and limitations, and a thorough evaluation of their performance, considering metrics like accuracy, precision, recall, and F1-score, is essential.

Overall, the project contributes to the growing body of research on text-based depression detection, highlighting the potential of machine learning algorithms and data-driven approaches in identifying individuals at risk of depression. Continued exploration and improvement in this field will pave the way for more accurate and efficient depression detection methods, ultimately assisting in early intervention and improving mental health outcomes.

5.2 FUTURE SCOPE

The future scope of the report on depression detection using text samples, focusing on Twitter social media dataset and DAIC-WOZ dataset, and employing machine learning models like SVM, logistic regression, CNN, decision tree, LSTM, Bi-LSTM, and GRU, can encompass several areas of further exploration and improvement. Here are some potential future directions:

Integration of Additional Datasets: To enhance the generalizability and robustness of the depression detection models, consider incorporating additional datasets from different social media platforms, electronic health records, or other sources. This broader dataset diversity can capture a wider range of linguistic and contextual patterns associated with depression.

Deep Learning Architectures: Explore more advanced and state-of-the-art deep learning architectures specifically designed for natural language processing tasks. Models such as transformer-based architectures (e.g., BERT, GPT) have shown remarkable performance in various language-related tasks and could be investigated for depression detection.

Multimodal Approach: Investigate the integration of multimodal data sources, combining text with other modalities such as images, audio, or user metadata. This approach can provide a richer understanding of users' mental health states and potentially improve depression detection accuracy.

Fine-tuning Pretrained Models: Pretrained language models like BERT or GPT can be fine-tuned on depression-related text data to leverage their contextual understanding and improve the performance of the depression detection models.

Handling Imbalanced Data: Address the issue of class imbalance in the dataset, as depressive text samples may be significantly outnumbered by non-depressive samples. Techniques such as oversampling, undersampling, or data augmentation can be explored to balance the dataset and improve model performance.

Explainability and Interpretability: Investigate methods to enhance the interpretability of the depression detection models. Techniques such as attention mechanisms or model-agnostic interpretability methods (e.g., LIME, SHAP) can provide insights into the features or words driving the model's predictions, aiding in clinical decision-making.

Real-time Monitoring and Intervention: Develop real-time depression detection systems that can monitor users' social media posts or other text inputs in real-time. This can enable timely intervention and support for individuals at risk of or experiencing depressive symptoms.

Incorporation of Clinical Assessments: Explore the integration of standardized clinical assessments or questionnaires within the models' training and evaluation process. This can enhance the clinical validity and applicability of the depression detection models.

Transfer Learning: Investigate the feasibility of transferring knowledge from the Twitter dataset to the DAIC-WOZ dataset or vice versa, leveraging similarities or shared patterns between the datasets. This approach can help mitigate the challenges associated with limited labeled data in specific domains.

Deployment and Evaluation in Real-world Settings: Test and validate the developed depression detection models in real-world settings, collaborating with mental health professionals and organizations to assess their effectiveness, usability, and impact on mental health interventions.

By pursuing these future research directions, the report's findings can contribute to advancing the field of depression detection using text samples, providing more accurate and accessible tools for early identification, intervention, and support for individuals experiencing depressive symptoms

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