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Research Article

A Novel Multi-Modal Framework for Sentiment Driven Depression Intensity Assessment

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ABSTRACT

Introduction: Depression is a mental illness that can cause a low mood, loss of interest in doing things, and sudden behavioral changes. Major depression may lead to suicide. It is the life threatening problem to be addressed immediately. According to the World Health Organization (WHO), about 280 million people worldwide have depression, including 5% of the world's adults and 5.7% of adults above age 60. Once a person diagnosed with depression treatment continue by attending therapy sessions. All these traditional approaches will work on those who already diagnosed with the depression. Through the social media platforms vast data is generating, from the content taken from theses platforms by applying Large Language Models, which works on contest based rather than key based would give better results. So a preventive mechanism of finding depression severity from the text is a novel idea for earlier prediction.

Objectives: The main objective of the paper is to identify the depression intensity from the social media posts by applying the LLMs to find the behavioral and emotional patterns of posts. Identification of negative sentiments from the posts by using LLMs. PHQ-9 Questionnaire is used to find the t The LLM based models identifies the negative sentiments based on polarity. From these posts the seed terms were identified based PHQ-9 questionnaire. The next objective is to identify the intensity based the terms used in the posts.

Methods: This study proposes a multi-modal framework for depression intensity using NLP techniques. The data is extracted from twitter posted based on depression related hashtags. Preprocessing and feature extraction is done. Once data is ready after cleaning the transformer models like BERT, ALBERT techniques are applied fro depression severity estimation. Model is evaluated using deep learning models (BiLSTM, GRU) with accuracy, F1-score and loss estimation was evaluated.

Results: The bLSTM model achieved 92% accuracy, outperforming traditional methods. Transformer-based models (BERT, ALBERT) demonstrated improved classification performance.

Conclusions: The multi modal approach proved to be more accurate for earlier prediction purpose. The Same approach can be applied on various questionnaire based approaches for model evaluation. This approach can be used for self-assessment purpose.

Keywords: Health care, Depression, Sentimental Analysis, phq questioner.

INTRODUCTION

The healthcare industry produces a vast amount of data, including genomes, clinical records, and patient-reported outcomes. This data is organized using big data analytics, which also supports prediction models that foretell patient outcomes or disease course. Major applications of intelligent healthcare systems (IHS) include mental health monitoring and assessment, which use NLP and ML with social media [6], text, and speech patterns to detect signs of depression, anxiety, or stress; clinical decision support systems that analyze patient data and medical literature; remote patient monitoring via IoT systems; and personalized medicine that analyses genetic data, patient history, and environmental factors. IHS is improving the accuracy, effectiveness, and accessibility of medical care, thereby transforming the healthcare industry. The future of healthcare is changing to become more connected, data-driven, and patient-centric due to advances in AI, NLP, and IoT. This raises the standard of treatment and also makes it easier to identify and prevent illnesses in the early stages, changing the face of healthcare.

This paper focuses on using NLP and ML in social media to detect indications of stress, anxiety, or depression. Depression is a (chronic) mental illness, which manifests as a low mood, loss of enjoyment, or prolonged disinterest in routine activities. People's connections with friends, family, and the community may be impacted. It is mostly the outcome of issues encountered in early life, education, and the workplace. Depression is more likely to occur in people who have experienced abuse, substantial loss, or other worrying situations. Depression affects over 280 million people worldwide [1,7]. An estimated 7,000,000 individuals die by suicide each year. It is the fourth most common cause of mortality for those between the ages of 15 to 29. It can be difficult to distinguish between someone who is depressed and someone who is not. Due to social stigma and a lack of understanding of the problem's seriousness, people do not want to draw attention to their problems. Furthermore, clinical diagnosis is a drawn-out procedure. Thus, frequent medication and treatment sessions cause reluctance to seek professional assistance. Following the pandemic, most of them habituated to online social media platforms to express their thoughts and emotions. The amount of information generated about mental health [20] is enormous. Therefore, it is possible to identify the emotions from user-generated content on social media. The main objective of this chapter is to understand the role of social media in assessing mental health and identify those suffering from mental health issues, through Twitter. The computational process in end-to-end solutions, from relevant data extraction to mapping emotion tone, extends to assessing depression intensity.

BACKGROUND

A study to investigate the use of advanced NLP techniques [3] and sentiment analysis for the identification of depression from relevant content extracted from social media text (Twitter) is essential. Studies reveal that online well-being and social order are good signs for the mental health of individuals. The rise of social media platforms has fundamentally altered the way people share experiences, the way they communicate and express emotions. With millions of users generating vast amounts of text-based content daily, these platforms have become valuable repositories of human behavior and emotional expression. This digital footprint offers unprecedented opportunities for researchers to explore and understand various aspects of mental health, including the prevalence and intensity of depression. At present, mental health assessment is taken at crucial stages through self-reporting-based assessments like clinical interviews, self-report questionnaires, and other standardized tools in controlled environments. Evolving the mental health assessment frameworks with the inclusion of feature-based [6], text-based [7], language markers [8], and aspect-based sentiment models on social media content [10] to predict mental states ranging from depression to suicidal tendencies[18] with the help of deep learning [9] and NLP techniques.

2.1. NLP role in clinical health

Natural Language Processing (NLP) is a major tool for analyzing unstructured data from social media, clinical notes, and patient records to assess mental health conditions. Sentiment analysis can be used to extract emotions and behavioral patterns as well as interpret the language to figure out the intensity of depression, stress, and anxiety. NLP helps clinical professionals to detect the problem, provide timely intervention, and continuously monitor patients.

2.2. Computing on Structured Data

In the traditional approach diagnosing the state of mental health is based on the individual's self-report and an assessment is made based on the PHQ-9[5] records, DASS scores, etc., and interviews. Personal interviews give deeper insights into the patient's emotional state, which is not a realistic expression of mental state. In contrast to traditional data, social media platforms provide the thoughts and behaviors of the persons in a vague way. Users share their personal experiences, thoughts, and emotions daily, but the data is unfiltered and unstructured. The change from traditional approaches and structured analysis opens new avenues for understanding the status of mental health. NLP techniques like language models [4] and sentiment analysis identify the mental status.

Prominent NLP techniques such as sentiment analysis, emotion detection, and deep learning language models like transformers (e.g., BERT, GPT) help to understand depression symptoms and mind states.

Apart from all the issues and challenges, the integration modules of NLP with the context of social media analysis hold highly achievable and promising results for transforming the assessment of mental health. By employing real-time, large-scale monitoring of depressive symptoms, these mechanisms serve proactive, personalized, and accessible mental health care solutions, theoretically reaching individuals who are unable to seek help.

This chapter aims to provide a comprehensive understanding of the current state of the depression assessment and the ongoing evolution of mental health well-being. It majorly focuses on the following issues:

- The influence of social networks in assessing the state of mental health, specifically depression
- Computational process of unstructured data (social networks data) exemplarily with depression detection.
- Discussion on the ontology of advanced NLP techniques to process social media texts.
- A computational framework for assessing mental health like depression using social media data.

METHODS

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3.1. Data Description

3.1.1. Social Media Text Tones

Social media platforms such as Reddit, Twitter, Facebook, and Instagram have become rich sources of real-time data for assessing mental health trends. People frequently share their thoughts, emotions, and their experiences on these platforms, providing prised insights into their mental state. By analyzing the language, tone, and frequency of social media posts, researchers and clinicians can detect indicators of mental health conditions like depression, anxiety, and stress.

Sentiment Analysis- Aims to determine the emotional tone of a text, which can indicate a person's mental state. For instance, a consistent expression of negative sentiment over time in a person's social media posts could signal depression [12].

A depression dataset was created [15] by using web crawling from Twitter pages. It contains a total of 6562 users, out of these 1402 are labeled as *depressed* and 5160 as *non-depressed,* and a total of 4,245,747 tweets, out of which 292,564 are depressed and 3,953,183 are non-depressed.

Table 1. Datasets containing #Depression and #MentalHealth.

Dataset	Hashtag	Year	No. of Tweets	No. of Unique Users
D19	#Depression	2019	279,900	74,964
D20	#Depression	2020	276,830	78,888
M19	#MentalHealth	2019	995,770	219,119
M20	#MentalHealth	2020	1,304,112	302,496
M20S	#MentalHealth	2020	995,770	254,558

Timeframe for each dataset: 11 March to 1 December. M20S is a sub-sampled subset of M20 that matches the number of tweets of M19.

Figure 1. Datasets containing #Depression and #MentalHealth

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The various datasets that contain prominent hashtags like #depression and #mentalHealth with statistics are given in Figure 1. The timeframe for the dataset is from 11th March to 1st December. M20S is a subset of M20 that ties the number of tweets of M19 [15]. They labelled a user as depressed if their anchor tweets which satisfies the following regular expression “(I’m/I was/I am/I’ve been) diagnosed as depression.” They found 1402 depressed users and 292564 tweets within a span of one month. Similarly, the persons who did not marker any message having the word “depress,” were labelled as non-depressed. In this way, a non-depression dataset was also created. As the dataset is broadly classified into binary classes of depressed and non-depressed, these labels are not useful for finding depression severity estimation. Therefore, we develop our relabelling technique for the same dataset. Firstly, we compute a depression score based on the emotional division of tweets and LSA, as explained below. The scores are then mapped into four intensity categories. The technique for gathering and preparing social media data [16] is a pipeline of activities.

3.2. Pre-processing on Social media text

The pre-processing of Twitter data requires a pipeline of activities. It contains the removal of unwanted symbols, all entities, hashtags, symbols, URLs, multiple spaces and stop words. Figure 2 shows the pre-processing pipeline design.

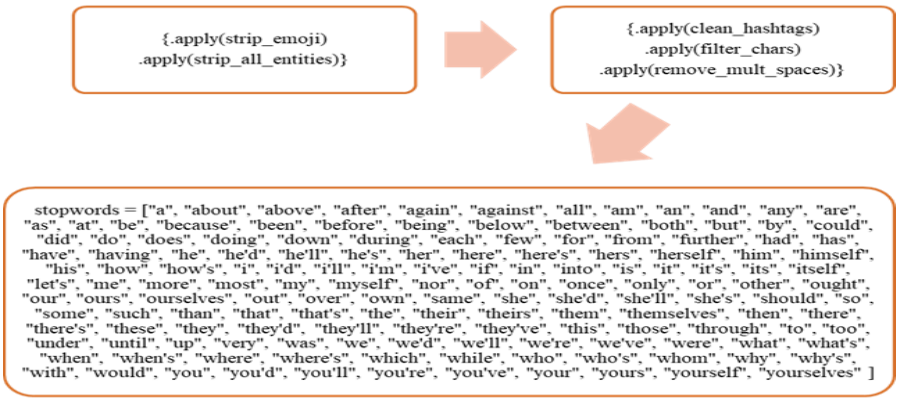

Figure 2. Pre-processing pipeline design

3.3 Feature Extraction and Representation

The aim is to identify the depressed users and their intensity of depression from their social media posts. In general, medical professionals extract information from the user through a questionnaire for diagnosis of depression. In online generated data we are identifying the emotions/behaviours of users and how they are posting messages and depression-related texts that are appropriate for depression intensity estimation. Figure 3 shows the features of Twitterdata.

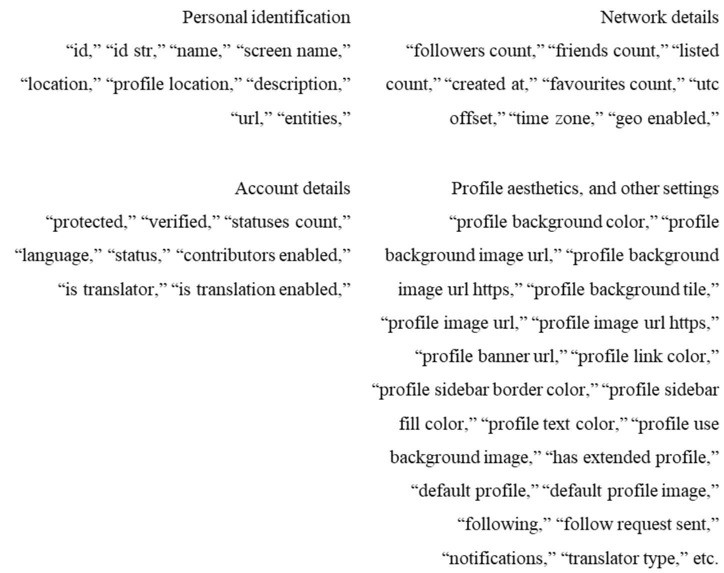

Figure 3. Illustration of Feature categories

The following features are considered by the user:

1) Emotional Features: These features include negative word count from tweets with the help of LIWC[8,9]. This feature includes both the sentence and word level. Emotion is measured in a 3-D plane called valance, dominance, and arousal. Valance represents the negative to positive effects of emotion, dominance represents control against emotional stimuli and arousal represents the intensity of emotion.

2) Event Features: Here we consider the events that trigger depression.

3) Online Behavioural Features: The time spent and no. of tweets posted, how they are interacting with other posts through comments, and posting behavior including the no. of tweets per hour and the ratio of posts per day to the total posts.

4) User Level Features: User features include user personal identification, network details, account details, profile aesthetics, and other settings.

The processing includes the removal of attributes like dates, URLs, and IDs, conversion of values from true/false to 0/1 and identification of unique value attributes; unique attribute sets having unique values will be treated with frequency-wise weightage.

For example, "time zone." Word2vec embedding for text attributes like "status".

Normalization: The attributes having integer values are normalized to specific ranges using min-max normalization; a 334-D vector corresponds to the user-level features.

Depression Related n-Gram: n-gram keywords and their emotions such as "anxiety", "stress", "depression", "sad" and "unhappy". A sample tweet for the reference is shown in Figure 4.

{"created_at":"Thu Jan 12 08:13:20 +0000 2017",
"id":819457219104280578,
"id_str":"819457219104280578",
"text":"\"I'm just a little boy from Bradford and now I''m smashingit\"\n#HappyBirthdayZaynMalik https://t.co/m9JyFqN0Nn",
"truncated":false,
"entities": {"hashtags":{"text":"HappyBirthdayZaynMalik",

{"created_at":"Thu Jan 12 08:13:20 +0000 2017",
"id":819457219104280578,
"id_str":"819457219104280578",
"text":"\"I'm just a little boy from Bradford and now I''m smashingit\"\n#HappyBirthdayZaynMalik https://t.co/m9JyFqN0Nn",
"truncated":false,
"entities": {"hashtags": {"text":"HappyBirthdayZaynMalik",
"indices":[63,86]}],
"symbols":[],"user_mentions":[], "urls":[],media":[{"id":819394017788043264,
"id_str":"819394017788043264","indices":[87,110],
"media_url":"http://pbs.twimg.com/media/C18ShJFWIAAxTSd.jpg",
"media_url_https":"https://pbs.twimg.com/media/C18ShJFWIAAxTSd.jpg",
"url":"https://t.co/m9JyFqN0Nn","display_url":"pic.twitter.com/m9JyFqN0Nn",
"expanded_url":"https://twitter.com/L0UlSCUL0N/status/819394032241623041/photo/1","type":"photo","sizes":{"small":{"w":400,"h":225,"resize":"fit"},"medium":{"w":400,"h":225,"resize":"fit"},"large":{"w":400,"h":225,"resize":"fit"},"thumb":{"w":150,"h":150,"resize":"crop"}},"source_status_id":819394032241623041,
"source_status_id_str":"819394032241623041", "source_user_id":1625800886,
"source_user_id_str":"1625800886"}]},
"extended_entities":{"media":[{"id":819394017788043264,
"id_str":"819394017788043264", "indices":[87,110],
"media_url":"http://pbs.twimg.com/media/C18ShJFWIAAxTSd.jpg",
"media_url_https":"https://pbs.twimg.com/media/C18ShJFWIAAxTSd.jpg",

Figure 4. Sample tweet mentioned about mental health

3.4. Sentiment-Driven Depression Intensity Detection Model

Depression is a condition of mental health with a frequent occurrence of emotional imbalance and chronic medical illness which negatively impacts one's feelings, thinking potential, and behaviour. It disrupts the active functioning of the nerve impulse to the cerebral cortex and leads to memory issues, malfunctioning of the learning module, and a poor mental state. It adversely affects appetite, causing sleep disorders, uncontrolled mood swings, and aggressive attitudes. The actions might also affect the individual's thinking hypothesis.

This research focuses on data collected from social media. People who are facing problems share their opinions online via social media. The data set contains tweets from a normal person and a depressed person. By applying NLP techniques [12], the work is progressing towards identification. The previous work is more focused on whether the person has depression or not, which is a binary classification; this is not of a high standard. The gap identified from the work is if a depressed person shares their emotions, then identification of the level of the depression is the aspect to focus on. The main objective of this research is to identify the intensity level of depression.

The proposed sentiment-driven depression model was a people's perceptions-centric model. The inclusion of large language models (LLMs)[4,6] like transformer model BERT[17,19] allows us to solve a range of NLP tasks with high accuracy.

3.5. Model evaluation Metrics

According to the current study, if a user tweets on a social media site related to emotional health, the tweet can show the tone of emotion and whether it is indicative of depression. The task becomes even more challenging because a tweet like that might be incomplete, unstructured, or even grammatically incorrect. The Diagnostic and Statistical Manual of Mental Disorders (DSM)[14] states that a set of symptoms present for a significant period of two weeks can be used to diagnose clinical depression. The Patient Health Questionnaire (PHQ-9) [5,14] suggests a series of surveys that are frequently used to identify the mental status of the person and gauge depression. PHQ-9 consists of 9 questions that address symptoms such as eating, sleeping disorders, lack of energy, hopelessness, failure, disinterest, and depression. It can be divided into four categories based on how frequently these symptoms occur: none, mild, moderate, and severe. Figure 4 illustrates depression intensity metrics based on symptoms and related keywords. The major symptoms of depression are mapped to related seed terms and keywords to define depression intensity. Three variants of transformer-based models, namely vanilla BERT, BERTweet, and AL-

BERT[17,19], have been proposed for predicting the intensity of depression into four different categories: non-depressed, mild, moderate, and severely depressed.

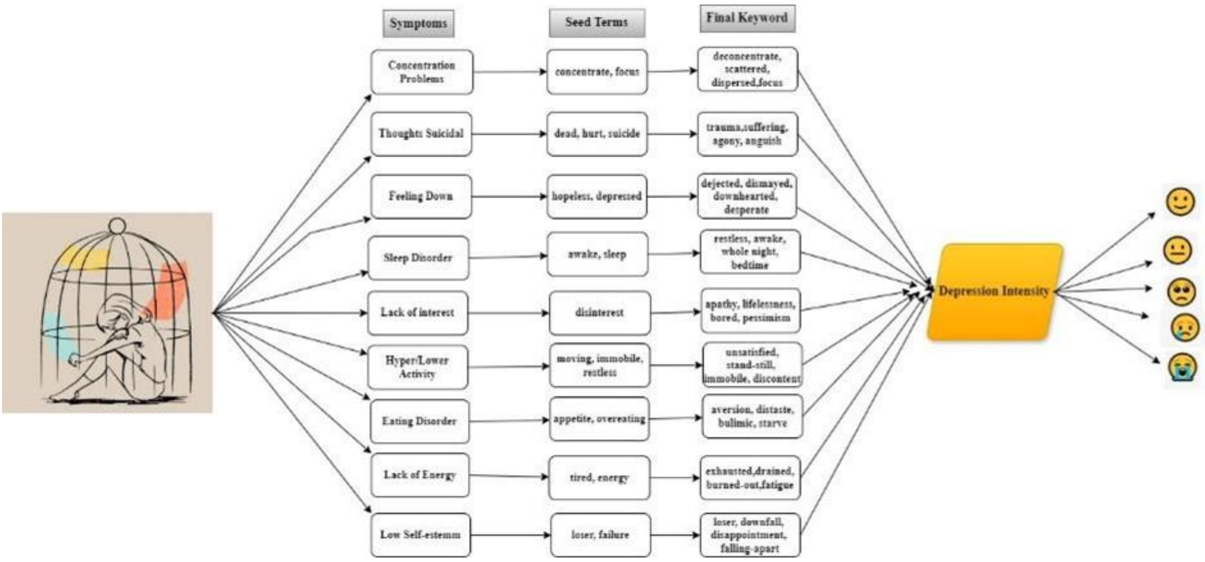

Figure 5. Depression intensity based on symptoms and related keywords

The framework for mental health clinical tools is illustrated in Figure 5. It contains a pipeline of activities to address the issues and concerns in clinical practice. It is an end-to-end solution containing social media data extraction, pre-processing, feature extraction, mental health score, and depression intensity prediction.

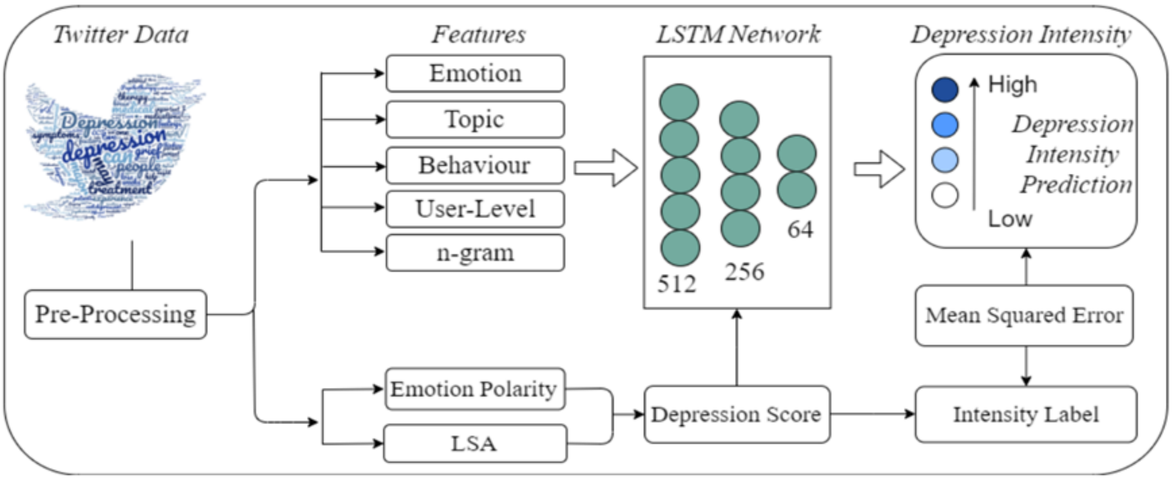

Figure 6. Mental Health Clinical Tool Framework

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RESULTS AND DISCUSSION

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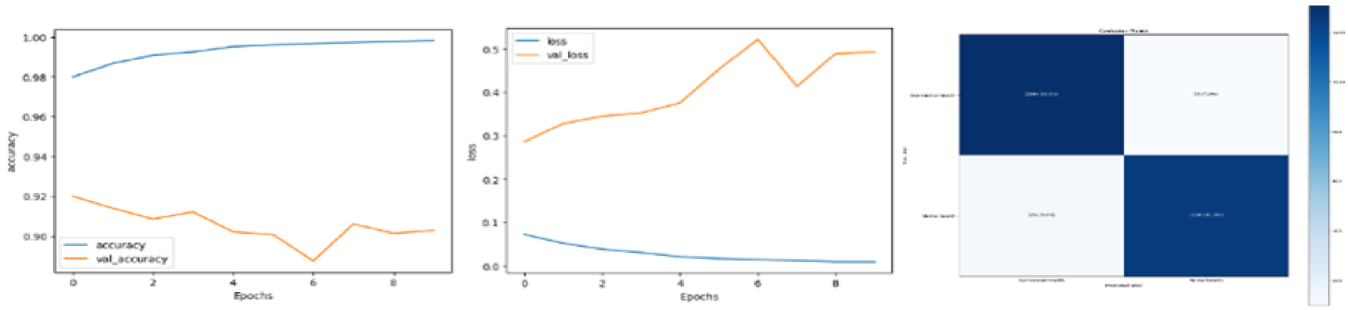
A bi-directional Long-short-term memory (bLSTM) depression prediction model performs with a 92% accuracy rate. The model design has 64 layers, with a dense layer activation function "Relu" and an output layer set with the "sigmoid" function. The model has been compiled with a loss function as "binary_crossentropy", and optimizer as "Adam" function. Figure 13 shows bLSTM model performance in terms of accuracy and loss.

Layer type	Output Shape	Param #
input_2 (InputLayer)	[(None, 1)]	0
text_vectorization	(None, 231)	0
embedding_2 (Embedding)	(None, 231, 300)	18819000
lstm (LSTM)	(None, 231, 64)	93440
lstm_1 (LSTM)	(None, 64)	33024
dense_1 (Dense)	(None, 64)	4160
dense_2 (Dense)	(None, 1)	65



(a) **(b)** **(c)**

Figure 7. bi-LSTM Model performance (a) accuracy b) Loss c) Confusion Matrix

Evaluation of the model Performance with variant deep learning approaches

The mental health model has been evaluated by using a range of deep learning models such as Dense network, Lon short-term memory (LSTM), Bidirectional - bLSTM, Gated recurrent unit (GRU), Bidirectional - bGRU, 1D Convolutional Neural network - conv1D and Unified semantic dependency (USD) parsing. It aims to focus on the mental health state in social media texts. Figure 14 shows the performance evaluation of variant neural network models in terms of accuracy and loss. The baseline model observed an accuracy of 85.6% and the USE model exhibited an accuracy of 93.2%. Figure 8 illustrates the comparison of neural network variants' accuracy.

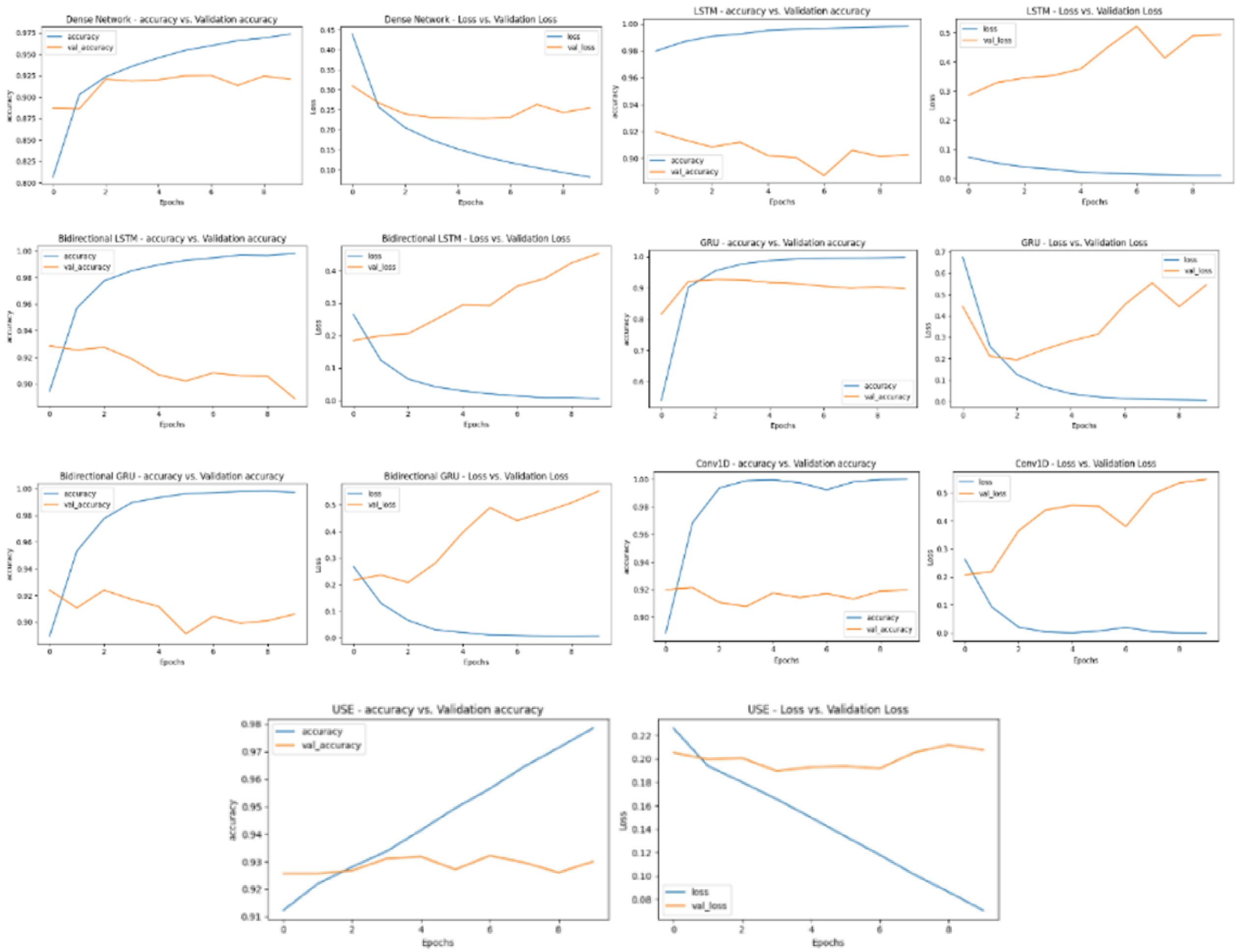


Figure 8. Performance evaluation of variant neural network models in terms of accuracy and loss

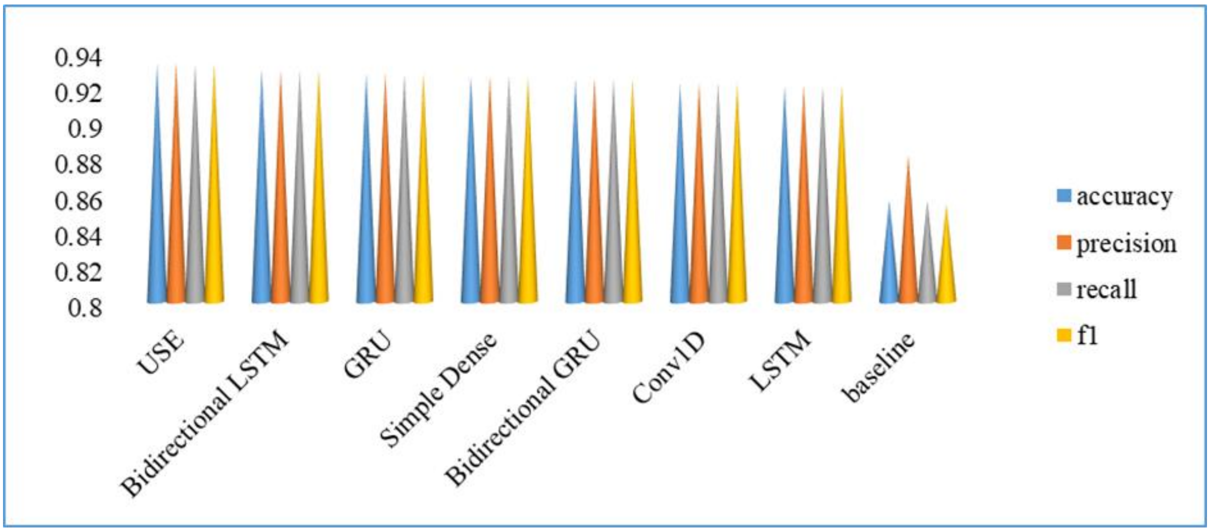


Figure 9. Comparison of Neural Network Variants Performance

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