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Analyzing Reddit Data: Hybrid Model for Depression Sentiment using FastText Embedding

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Abstract

Depression, a prevalent mental condition globally, exerts a substantial influence on various aspects of human cognition, emotions, and behaviour. The alarming increase in deaths attributable to depression over the past few years demonstrates the imperative need to address this problem through prevention and treatment interventions. In the era of thriving social media platforms, which have a significant impact on society and psychological aspects, these platforms have become a means for people to convey their emotions and experiences openly. Reddit stands out among these platforms as a significant place. The main aim of this study is to examine the feasibility of forecasting individuals' mental states by classifying Reddit articles on depression and non-depression. This work aims to employ deep learning algorithms and word embeddings to analyze the textual and semantic settings of narratives to detect symptoms of depression. The study effectively employed a BiLSTM-BiGRU model that applied FastText word embeddings. The BiLSTM-BiGRU model analyzes information bidirectionally, detecting correlations in sequential data. It's suitable for tasks dependent on input order or addressing data uncertainties. The Reddit dataset, featuring text concerning depression, achieved an accuracy score of 97.03% and an F1 score of 97.02%.

Keywords: *depression; social media; reddit; biLSTM; fasttext*

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1. Introduction

Social media, being a widely used platform, allows people to share their thoughts, feelings, and emotions, as well as their feelings of depression and dissatisfaction. Platforms like Reddit enable varied individuals to communicate and connect. While social media has had great consequences, it has also had side effects that pose potential risks to society [1]. Depression, often known as depressive disease, is a substantial negative impact of social media use. It is a common disease that many people suffer from and presents as depression, loss of interest or pleasure, guilt, low self-esteem, disturbances in eating and sleep, and difficulty concentrating. Depression can last for a long time or reoccur, wreaking havoc on a person's daily functioning. Depression, in its most severe form, can even lead to suicidal ideation. Depression is predicted to afflict 322 million people worldwide, with an 18.4% increase between 2005 and 2015 [2]. The Indonesian Basic Health Research revealed that there was a 6.2% prevalence of depression among individuals aged 15-24 years [3]. Based on an independent investigation, it has been observed that there exists a prevalence rate of 7.7% among students in Indonesia who have mental health challenges [4]. Unfortunately, a scant 9.2% of individuals aged 15 to 24 who experience depression actively seek therapy at a healthcare facility [5].

The significance of mental health and its associated issues is paramount across all developmental stages, spanning from early childhood to maturity. Depression is frequently linked to experiences of diminished self-esteem, which may manifest as either temporary or enduring states, resulting in a decrease in creative output and a diminished level of excitement for routine tasks [6]. If symptoms such as a persistent low mood and chronic stress are not addressed, they have the

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potential to develop into chronic or recurring issues that can have significant implications for one's health [7]. Individuals who suffer from depression frequently exhibit several symptoms, including but not limited to insomnia, social isolation, disruptions in appetite and sleep, impaired cognitive functioning in both professional and personal domains, and maybe even suicidal ideation or behaviour [8], [9]. Several factors have been identified as potential contributors to the development of long-term depression. These factors encompass a challenging upbringing, experiences of sexual abuse, excessive alcohol consumption, various medical conditions, occupational stressors, and societal concerns such as colonialism and caste inequalities [10]. If left unaddressed, depression has the potential to deteriorate progressively and give rise to severe health complications, such as sleep disturbances and cardiovascular issues. Despite the implementation of numerous incentives and programs by renowned organizations such as the World Health Organization (WHO) to tackle depression, substantial obstacles persist, particularly for persons hailing from lower-middle-income households [11], [12]. Furthermore, it is worth noting that in underdeveloped nations, the dearth of resources and financial support frequently poses significant challenges in delivering efficacious treatment interventions for those suffering from depression [13].

Although depression is a significant issue, a study indicates that individuals afflicted with it have not received sufficient treatment [14]. As a result, persons suffering from depression are often hesitant to seek treatment or professional support, resulting in a continual drop in the number of people obtaining proper care for their disease. According to studies, a significant majority of people suffering from depression, ranging from 75% to 85%, are unable to obtain the necessary treatment [15]. Social media may provide psychiatrists and psychologists with additional information before making decisions in the current environment, in cases where individuals frequently use it to discuss their problems. However, it also enables early prevention through the analysis of social media data [16]. Multiple studies of research projects [17]–[19] have shown that detecting depression using natural language processing and data mining poses considerable obstacles. This research investigated the identification of depression using approaches such as machine learning and neural network models. Various natural language processing (NLP) characteristics, such as emotion, sentiment, readability, and depression embedding, have been incorporated into studies on depression [17]. It is strongly recommended to develop a melancholy detection system using artificial intelligence and advanced learning techniques.

Analyzing Reddit data for depression sentiment analysis using FastText embeddings encounters challenges such as the prevalence of informal language and internet-specific jargon, which can lead to ambiguity in interpretation. Additionally, the contextual nuances inherent in depressive discussions may not be fully captured by FastText embeddings, potentially resulting in misinterpretation of sentiment. Imbalanced data distribution, inconsistent labelling, and the inclusion of multimodal content further complicate analysis. Domain adaptation techniques may be necessary to fine-tune embeddings for depression-related language while ensuring the ethical handling of sensitive data and addressing privacy concerns remains paramount. Effective strategies to mitigate these challenges include careful preprocessing, domain-specific fine-tuning, dataset balancing, and continual model evaluation and refinement.

Reddit is a social media framework that has 52 million daily active users and over 430 million monthly active users, ranking it as the sixth most popular social media website in the United States [20], [21]. Reddit had 2.8 million subreddits in 2021 [22]. The community network is specialized on particular themes, like depression, enabling users to engage and exchange with individuals who have similar perspectives, backgrounds, and life experiences [23]. The numerous subreddits on Reddit are a helpful tool for identifying persons with depression who need therapy [24]. Nevertheless, the large number of posts and responses would make it difficult for mental health specialists to manually sort through all the content to pinpoint those who need assistance. Therefore, there is a notable potential for creating artificial intelligence (AI) and natural language processing (NLP) techniques that can evaluate numerous social media posts and detect depressed users for help [25].

Previous investigations made use of the Reddit dataset [25]. This study employs the Self-Reported Mental Health Diagnosis (SMHD) dataset, which consists of publicly accessible Reddit posts from individuals who self-disclose mental health issues. The objective is to detect depression in users by integrating pre-trained Sentence BERT (SBERT) with a neural network (CNN). The hybrid model attained a precision and F1 score of 0.86%, surpassing the performance of current machine learning models [25]. The study uses natural language processing and machine learning techniques to examine Reddit postings and find traits that indicate depression. The method pinpointed particular terminology linked to depression, hence enhancing accuracy. Remarkably, the fusion of Bigram and Support Vector Machines (SVM) yielded an accuracy and F1 score of 0.80% [26]. The utilization of LIWC, LDA, and bigram features in conjunction with Multilayer Perceptron (MLP) resulted in the highest level of performance, with an accuracy rate of 0.91% and an F1 score of 0.93%.

Several research has utilized natural language processing (NLP) algorithms and classical machine learning approaches like logistic regression, random forest, and support vector machines (SVM) to identify sadness in social media posts [24], [26], [27]. Prior studies employed conventional machine learning techniques to detect depression by using features including n-grams, sentiment, and social traits via thorough feature engineering [28]. Advancements in utilizing deep learning for NLP tasks have inspired studies on detecting depression from social media posts. Techniques like convolutional neural networks (CNN) [29]–[31], recurrent neural networks (RNN) [29], [31], [32], dan Transformers [33], [34].

This work proposes a hybrid model named BiGRU-BiLSTM for depression sentiment analysis. The models have bidirectional processing abilities that allow them to successfully capture and use long-range dependencies in sequence data [35]. The concurrent use of BiLSTM and BiGRU models can create a more flexible and robust framework that is ideal for processing sequence data, as demonstrated in multiple research papers [35]–[37]. We will assess the depression dataset from Reddit using this model. Additionally, we will test it with other models like BiGRU-FastText and incorporate the glove weighting method in conjunction with BiGRU-BiLSTM models. We utilize word weighting to turn words into vectors, specifically using FastText. This approach enables the creation of robust models on extensive datasets by providing representations for words that may not have been encountered during the training process. The text is broken down into n-grams when a word is not present to obtain its embedding vector [38]. This strategy aims to offer prevention strategies for mental health issues, particularly depression, and deliver efficient therapy for individuals suffering from depression. This variable is anticipated to be beneficial for therapists in their treatment approach.

The proposed hybrid model, BiGRU-BiLSTM, addresses several challenges in depression sentiment analysis. Firstly, depression sentiment analysis involves understanding and categorizing text data based on emotional states related to depression, which can be complex due to the subtle nuances and context-dependent nature of language. Secondly, traditional methods like uni-directional recurrent neural networks (RNNs) or Long Short-Term Memory (LSTM) networks may struggle to capture long-range dependencies or contextual information effectively. Combining Bidirectional Gated Recurrent Units (BiGRU) and Bidirectional Long Short-Term Memory (BiLSTM) in the proposed hybrid model aims to overcome these challenges.

The novelty of the proposed solution lies in its combination of BiGRU and BiLSTM layers. BiGRU introduces gating mechanisms that help the model to capture relevant information from both past and future contexts simultaneously, enhancing its ability to understand the context of the text comprehensively. BiLSTM, on the other hand, excels at capturing long-term dependencies within the text data. By integrating these two architectures into a hybrid model, BiGRU-BiLSTM can effectively capture both short-term and long-term dependencies, thereby improving the accuracy and robustness of depression sentiment analysis.

The contributions of the proposed BiGRU-BiLSTM model are twofold. Firstly, it offers a more sophisticated and nuanced approach to depression sentiment analysis by leveraging the strengths of both BiGRU and BiLSTM architectures. This enables the model to better understand and categorize text data related to depression, leading to more accurate and reliable sentiment analysis results. Secondly, the proposed hybrid model contributes to the advancement of natural language processing (NLP) research by demonstrating the effectiveness of combining different neural network architectures for tackling complex NLP tasks.

2. Research Methods

In the present experiment, the first stage is to collect the dataset, which consists of depression-specific data. The dataset is then separated into two labels: label 1 indicates instances of depression, while label 0 indicates instances of non-depression. The data is then subjected to a crucial pre-processing step that functions to cleanse the dataset before its use in model training. This stage of pre-processing involves several essential procedures that contribute to improving the data's quality and suitability. After pre-processing, the dataset is split into two subsets: training data and testing data. The training data is utilized to train the algorithm by employing the designated model, whereas the testing data is employed to assess the model's performance and efficiency. Before commencing the training protocol, it is important to utilize a technique that transforms words into vector representations. FastText word weighting is a technique that enables the transformation of words into meaningful numerical representations. BiLSTM-BiGRU is implemented for the classification process and the determination of accuracy values. This model is essential for accurately categorizing and analysing the data, thereby facilitating the identification of patterns and relationships within the dataset. In the final phase of this research, words are predicted and designated labels based on the output classifications. Figure 1 provides a visual representation of the methodology used in this study, illustrating the sequential flow of each stage and their interconnections.

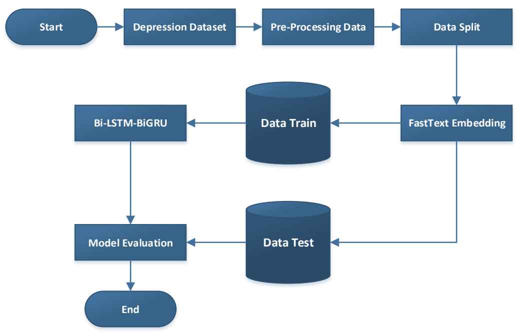

Figure 1. The general method of the depression classification task using Bi-LSTM-BiGRU

The proposed architecture of the Bi-LSTM-BiGRU FastText embedding classification task as its illustrated in Figure 2. The first stage is to collect a customized text dataset focused on depression. Following that, the dataset undergoes a thorough data cleansing process which involves converting all text to lowercase to ensure uniformity, removing punctuation to simplify the text, and reducing unnecessary symbols like commas and exclamation points. Additionally, stemming is performed to modify or eliminate word prefixes and suffixes, reducing words to their base form. This allows for a thorough examination of semantic meaning and minimizes duplication in the dataset by merging terms with a common root. Tokenization is the procedure of breaking down data initially presented as sentences or text into individual words or tokens. These safeguards are put in place to guarantee that the data is properly organized for further examination.

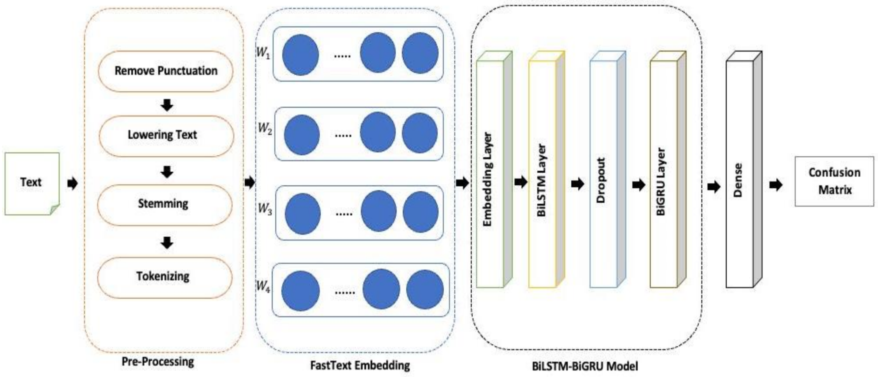

Figure 2. Proposed Architecture of Bi-LSTM-BiGRU fast text embedding classification task

Following the data cleaning phase, the following step concentrates on word weighting with FastText, which uses a 300-dimensional vector representation. This critical step turns the textual data into numerical vectors, allowing machine learning techniques to be applied. The word weighting method assigns weights to each word based on its significance in the dataset. The initial procedure is to place a value of 300 into the vector layer. The 300 dimensions in the embedding vector represent distinct features that capture the semantics of the phrase or content before being passed to the BiLSTM layer. In this particular stratum, the numerical information derived from the vector is processed in a bidirectional manner, increasing the number of units and the sequential processing from both ends. To mitigate the risk of overfitting, a dropout layer is implemented within the model. The LSTM layer utilizes the BiGRU layer to handle the sequences it generates. BiGRU analyzes the output of BiLSTM to enable the model to work with and incorporate the representations that were already analyzed by the preceding layer. This enables the model to enhance its comprehension of crucial characteristics inside the sequence data. Ultimately, the evaluation of the modelling outcomes is conducted by the utilization of a confusion matrix, which encompasses metrics such as accuracy, precision, recall, and the F1 score. The following metrics are utilized to assess the efficacy of categorization on compressed data. Overall, Figure 2 depicts the research approach in detail, illustrating the sequential phases of data collecting, data cleansing, data transformation through word weighting, and subsequent modelling. This rigorous technique culminates in the model's performance being evaluated, providing vital insights into the classification of depression literature.

2.1 Dataset

The first and most important phase in this research is to collect the relevant data. The dataset used in this study is text data that is specifically focused on depression, and it is labelled with two separate labels: 0 for non-depression and 1 for depression [39]. The dataset is then separated into two subsets to ease the analysis and evaluation processes: training data and testing data. It is worth noting that the dataset has 7731 instances, which provides a large amount of data for analysis and model development. The dataset is divided into two sections: one for training the model and the other for testing it. The dataset is split into 90% training data and 10% testing data, with 6957 samples in the training set and 774 samples in the testing set. This dataset as shown in Table 1 was obtained through Kaggle, a well-known site for sharing and accessing varied datasets.

Table 1. Depression Dataset

Text	Label
so as a kid, I moved around a lot because my dad was in the military but since my teen, I've lived in the same state and it has been a decade i am depressed and I want to travel and move to another place this isn t isolated I also have dysthymia social anxiety disorder and Asperger's I m just wondering cause it s hard to find others who relate to this	1
stupid year project feel like you've conquered something then you realise it’s only a year down	0

2.2 Pre-Processing

This stage includes the data cleansing procedure, which entails several crucial procedures to prepare the data for subsequent analysis. The pre-processing phase as shown in Figure 3 includes the following procedures: Lower text is used to convert all text to lowercase, ensuring uniformity and eradicating capitalisation variations. By eliminating case-related inconsistencies, this phase standardises the text and facilitates accurate analysis [40], Remove punctuation illustrates reducing unnecessary punctuation, such as commas, exclamation marks, and other symbols that do not add to the meaning of the text. By eliminating these punctuation marks, the dataset becomes clearer and more streamlined, allowing for a text-centric analysis [41], the essential phase of stemming involves modifying or removing prefixes and suffixes from words. The objective of this approach is to minimize words to their fundamental or foundational form, thus facilitating a more comprehensive exploration of their semantic significance. In addition, stemming reduces redundancy within the dataset by merging terms with similar root structures[42].

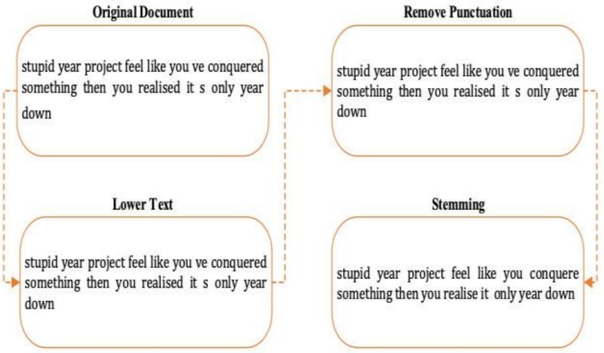

Figure 3. Pre-processing Result

2.3. *Tokenization*

The tokenization procedure is an important phase after the data cleansing phase. Once the data has been cleaned, which includes operations such as removing punctuation and stemming, it is available for tokenization. During this step, data that were initially provided in the form of sentences or text are broken down into individual words or tokens as shown in Figure 4.

Each word is regarded as a distinct unit, allowing for a more granular analysis of textual content [42]. Tokenization plays a crucial function in decomposing the data into its constituent parts, thereby enabling more precise linguistic analysis and following modelling tasks.

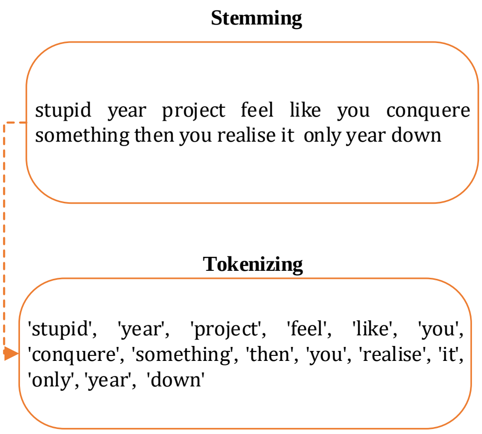

Figure 4. Tokenization Result

2.4 *Fast Text Embedding*

FastText is a word weighting method that can be was thinking as a modification of the word2vec model [43]. It was developed by Facebook's AI research team, who were inspired by Mikolov's work, to improve word representation capabilities. FastText's architecture is like the Continuous Bag-of-Words (CBOW) architecture used in word2vec. It uses a hierarchical framework to represent words as dense vectors that include semantic and grammatical information. FastText adds hidden layers in addition to the input and output layers, enhancing its ability to capture intricate patterns and relationships within data. This method is extremely efficient in handling words, allowing FastText to build meaningful representations even for uncommon or previously unknown terms. The resulting word vectors can be used to perform natural language processing tasks such as text categorisation, sentiment analysis, and information retrieval. Figure 5 shows FastText's architectural design, showing its layered structure and information flow between the input, hidden layer, and output levels [44].

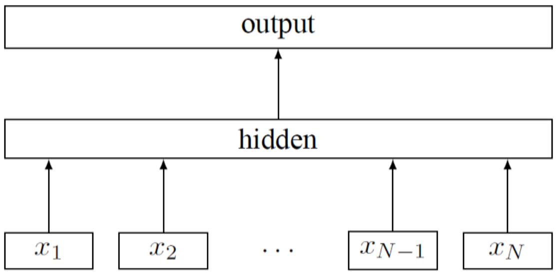

Figure 5. FastText Word Weighting [44]

The FastText technique investigates word representation research by including subword information, which aids in understanding shorter words and collecting word prefixes and suffixes. FastText expresses words as a succession of n-gram characters rather than as a single unit. Each character n-gramme is assigned its vector representation, which is then used to represent words. This method uses the CBOW architecture for training, allowing word vectors to be determined.

FastText disregards word morphology and instead focuses exclusively on word distributional characteristics by allocating a distinct vector to every word in the lexicon. This technique, however, has disadvantages for expressing linguistic terms with a large vocabulary and a high number of unusual words. FastText excels at performance, particularly when it comes to rapidly training models with large datasets. It also can produce meaningful word representations for words that are missing from the training data. When a word does not appear during training, its embedding vector can be deduced by dividing it into relevant n-grams [38].

2.5 BiLSTM

Recurrent Neural Networks (RNN) are an effective class of deep neural networks that are widely employed in natural language processing applications. It excels at processing variable-length input sequences and effectively capturing long-term dependencies within the data. Among the various RNN variants, Long Short-Term Memory (LSTM) stands out as a specialized architecture designed to address the challenge of modelling long-term dependencies by retaining information for extended periods. A cell, an input gate, an output gate, and a forget gate make up an LSTM unit. The cell maintains and improves its internal state at various time intervals, whereas the gates regulate the passage of information into and out of the cell, distinguishing between relevant and irrelevant data. The key advantage of LSTM is its ability to mitigate the issue of vanishing gradients, a prevalent issue in standard RNNs, allowing for more stable and effective training [45].

It is essential to note, however, that LSTM has limitations when it comes to accessing past information. The output of an LSTM unit is based solely on the data observed by the network in the current context, with no direct access to distant historical data. To overcome this limitation, bidirectional LSTM (BiLSTM) models have been developed. BiLSTM circumvents this limitation by training input data in both forward and backward orientations. By capturing contextual information from both past and future contexts, BiLSTM provides a deeper and more comprehensive understanding of the input data, resulting in greater efficiency in a variety of NLP tasks [46].

2.6 BiGRU Model

The utilization of a gated recurrent unit is a technique employed to manage short-term memory by incorporating two gates, specifically the reset gate and the update gate [47]. The utilization of these two gates serves as a means to regulate the occurrence of the vanishing gradient problem. The GRU model differs from LSTM in that it does not explicitly maintain a separate cell state, but instead maintains hidden cells. This characteristic of GRU contributes to its advantages in terms of ease and speed of training, particularly when dealing with small datasets. The GRU (Gated Recurrent Unit) is often regarded as a good model for processing sequential data, particularly when dealing with substantial volumes of data. The GRU model is capable of effectively processing long sequence data, a crucial requirement for natural language processing (NLP) tasks [48]. The bidirectional approach, as depicted in Figure 6, utilizes sequential data capture in both forward and backward directions. This architecture leverages the semantic information present in both directions, hence enhancing the performance of classification tasks. The bidirectional method is a data capture technique that consecutively gathers data in both the forward and backward directions. The forward layer in BiGRU is responsible for capturing sequential data that contains information about the subsequent sequence. In contrast, the posterior layer in BiGRU effectively collects sequential information from the preceding sequence.

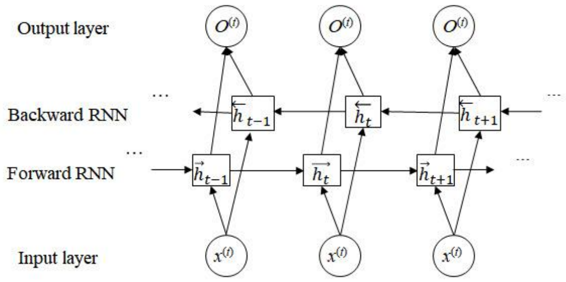

Figure 6. BiGRU structure [49]

2.7 Model Evaluation

In this study, the model's performance was evaluated using a confusion matrix, which is often used to examine classification problems. This tool can be utilized for both binary classification and multiclass classification jobs. Table 2 illustrates an instance of the confusion matrix.

Table 2. Confusion Matrix

Predicted			
		Negative	Positive
Actual	Negative	TN	FP
	Positive	FN	TP

The variations between predicted and actual values are represented by the confusion matrix. The term "TN" represents "true negative" in the context being discussed, denoting the accurate identification of negative instances. Likewise, the acronym TP denotes "true positive," signifying the quantity of accurately identified positive instances. The term FP represents "false positive," which is the number of actual negative examples categorized as positive, whereas FN denotes "false negative," which is the number of actual positive examples classified as negative. One of the most often-used classification metrics is accuracy, which is determined using Formula 1.

$$Accuracy = \frac{TN+TP}{TN+FP+FN+TP} \quad (1)$$

Model assessments that are frequently used in addition to accuracy include precision, recall, and F1 score. Precision assesses the accuracy of positive predictions, also known as the positive predictive value, by measuring how good the model is at predicting positive values. Recall, also known as sensitivity, is an important metric for determining a model's ability to anticipate favourable outcomes. The F1 score, commonly known as the F-value, combines a classifier's precision and recall values. The calculation of the spectrum of precision and recall is employed in this context. Formulas 2, 3 and 4 are used to create each of these evaluation metrics [50]:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

3. Results and Discussions

The data was processed using the BiLSTM-BiGRU model in this investigation. The dataset division in this research consists of 90% training data and 10% testing data. The initial step involves feature extraction via FastText, a technique that transforms the data into a vector representation. The vector is subsequently inputted into the embedding layer, which has a dimensionality of 300. Following the embedding layer, the data is next transmitted to the BiLSTM layer, which assumes the crucial role of processing the word order derived from the embedding layer. To mitigate the issue of overfitting, a dropout rate of 0.3 is implemented in this procedure. Subsequently, the input is fed into the bidirectional Gated Recurrent Unit (GRU) layer, which is employed to process the output sequence originating from the Bidirectional Long Short-Term Memory (BiLSTM) layer. The ultimate stage of the process entails the utilization of a thick output layer, which is responsible for producing probabilities about two distinct classes, specifically non-depressed and depressed. The training of the model was conducted over three epochs using the default parameters provided by the Keras API. The optimization algorithm employed in this study is Adam, and the batch size utilized for training the model is 32. The results presented in Table 5 demonstrate the best performance achieved through a series of experiments. The experiments involved manipulating various parameters, such as the number of epochs (3, 4, 5), the choice of optimizers (adamax, adam, rmsprop), variations in batch sizes (16, 32, 64, 128), adjustments to the number of neurons in the BiLSTM layer (32, 64, 128), and modifications in dropout rates (0.1, 0.2, 0.3). The objective of this experimental procedure is to identify the most effective configuration for attaining optimal performance outcomes for the assigned assignment. The most successful outcomes were attained in the compact dimension configuration, as described in Table 3, through a sequence of iterative trials that ultimately resulted in the ideal value, as shown in Table 5. Please refer to Table 3 for specific information regarding the parameter settings.

Table 3. Dense Dimension Setting

Layer	Type	Neuron
Input Layer	Embedding Layer	300
LSTM Layer	Bidirectional LSTM	64
	Dropout	0.3
GRU Layer	Bidirectional GRU	32
Output Layer	Dense	2

The classification training results utilizing depression data from Reddit are presented in Table 4. Two models are assessed in this study, specifically the Bidirectional Gated Recurrent Unit (Bi-GRU) model and the combination of Bidirectional Long Short-Term Memory (Bi-LSTM) and Bi-GRU models. The Bi-GRU model attains an accuracy rate of 96.90%. The combined model training yielded superior outcomes with an accuracy of 97.13%. Both model techniques utilize the RMSprop optimizer.

Table 4. Model Result

Model Algorithm	Optimizer	Accuracy	Loss
BiGRU	RMSprop	96.90%	0.0856
BiLSTM-BiGRU		97.13%	0.0823

The outcomes of training several models using FastText are presented in Table 5. The assessment utilized a dataset consisting of 774 samples, which were categorized into two groups: non-depressed and depressed. The BiGRU model attained a classification accuracy of 95.87% and an F1 score of 95.97%. The application of the combination model resulted in substantial improvements, as seen by the impressive accuracy rate of 97.03% and F1 score of 97.02%. Moreover, when employing the combination model with GloVe weighting as an option, it attains an accuracy of 96.51% and an F1-score of 96.59%. In a prior study [13], the utilization of the CNN-BiLSTM model in conjunction with the word embedding technique yielded a notable level of precision, with a 94.28% accuracy rate accompanied by an F1-score of 94.78%. In addition, several models were explored in the study, including the Recurrent Neural Network (RNN) model, which demonstrated a 90.66% accuracy rate and an F1 score of 91.78%. Furthermore, the Convolutional Neural Network (CNN) model attained an accuracy of 91.73%. The utilization of FastText as a technique for word weighting demonstrated a notable influence on the updating process of the employed model.

The BiLSTM-BiGRU model can analyze information in both forward and backward directions, enabling it to identify and utilize relationships that are distant in sequential data [35]. The model's bidirectional nature enhances its resilience to the input sequence, allowing it to effectively address tasks that rely on the sequence of input data or involve resolving ambiguities within the data [51].

FastText possesses the capability to effectively encode words that are absent from the training data or to address the challenge of out-of-vocabulary words. During the training process, words that are not recognized are broken down into n-grams, which are then combined to generate a sequence of syllables. This approach allows for the creation of an embedding vector that is effective in representing these words [38].

Table 5. Experimental Test Model Result

Model Algorithm	Accuracy	Precision	Recall	F1-Score
FastText-BiGRU	95.87 %	95.49%	96.46%	95.97%
FastText-BiLSTM-BiGRU	97.03%	99.21%	94.94%	97.02%
GloVe- BiLSTM-BiGRU	96.51%	96.46%	96.71%	96.59%
RNN [13]	90.66%	90.41%	93.19%	91.78%
CNN [13]	91.73%	92.29%	92.98%	92.64%
CNN-BiLSTM [13]	94.28%	96.99%	92.66%	94.78%

The findings of the class analysis, as depicted in Table 6's confusion matrix, demonstrate a high level of efficacy in identifying depression through text-based means. Both categories, namely non-depressed and depressed, exhibit an equivalent F1 score of 97%, so signifying that the model possesses a notable level of confidence in accurately detecting instances of depression. Put simply, the model demonstrates a high level of dependability when it comes to tasks involving the detection of depression based on text.

Table 6. BiLSTM-BIGRU+FasText Model Class Division Results

Class	Precision	Recall	F1-Score	support
Non Depression	95%	99%	97%	379
Depression	99%	95%	97%	395

The findings presented in Figure 7 demonstrate that the non-depression class achieved a high level of accuracy, with 376 out of the total 379 data points being correctly predicted. In contrast, the depression class exhibits 375 instances of true positives and 20 instances of false negatives, resulting in a cumulative count of 395 instances.

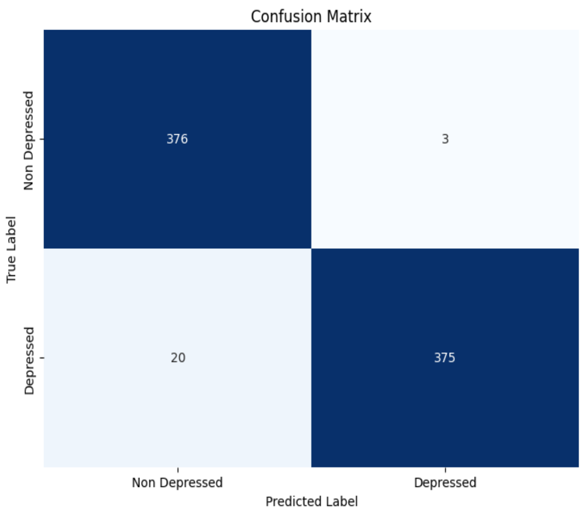

Figure 7. Results of the class division of the confusion matrix

According to the study's findings, the model demonstrates an impressive ability to minimize false positives, as indicated by only 20 cases. Consequently, the model exhibits a notable tendency to refrain from making erroneous positive predictions concerning depression. Hence, the model demonstrates a high level of reliability in its ability to predict depression using text-based analysis. However, the experimental results seem very doubtful when the results of accuracy, prediction, recall, and F1 score are at the same value and at the same time simultaneously, this could be with one class dominating the majority of the samples, it can skew the evaluation metrics, leading to uniform values across different metrics.

4. Conclusions

Depression ranks among the prevailing mental diseases on a global scale. Gaining a comprehensive understanding of depression is crucial at both the individual, community, and global levels. It is imperative to prioritize the resolution of this matter, encompassing the provision of suitable interventions for persons afflicted with depression, as well as implementing preventive measures for those exhibiting signs of depressive symptoms. The primary objective of this research endeavour is to employ data extracted from the online platform Reddit to forecast the occurrence of depression. The dataset is partitioned into two distinct categories: 0, representing the absence of depression, and 1, representing the presence of depression. This paper provides the implementation of a deep learning model that utilizes both Bidirectional Long Short-Term Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU) architectures to deal with the classification problem. The Bidirectional Long Short-Term Memory (BiLSTM) model is employed to effectively handle text data that contains longer sequences. This model is specifically designed to address the challenges associated with the vanishing gradient and exploding gradient difficulties. The BiGRU model is employed to extend the functionality of the BiLSTM layer, enabling a more comprehensive understanding of the contextual information. The utilization of FastText in the model further enhances its performance by addressing the challenge of out-of-vocabulary words by the conversion of such words into n-grams. The empirical findings indicate that the amalgamation of models presented in Table 5 yields the utmost accuracy of 97.03% and an F1 score of 97.02%. The utilization of GloVe weighting on the identical model yields an accuracy of 96.51% and an F1 score of 96.59%, which is notably inferior compared to the present enhancement.

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