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Comparative Analysis of CNN Based Depression Detection Techniques for Social Media Text

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Abstract*:* The address of depression through social media analysis has emerged as a promising field, which can lead to an early identity of mental health concerns using signs of natural language. This work studies the existing work in the field of depression analysis and provides brief literature review on machine learning techniques and compares the result achieved with social media text. On the basis of review proposes a novel approach, for Depression Detection using better recurrent neural architecture using gloves embedding. The study examines a promotional recruitment neural network (RNN) model designed to classify depressive manifestations in user-related materials. By integrating the gloves (global) embedding, the model captures the deep semantic relationships and micro-linguistic characteristics prevalent in the social media text. The combinations greatly enrich the understanding of the subtle emotional signals associated with depression and the model of linguistic patterns. A Twitter-based training was used using a dataset and a twitter was evaluated on a dataset to ensure a strong cross-platform generality. The proposed model achieved an impressive test accuracy of 98.45%, showing its effectiveness and ability as a reliable tool to detect automatic depression in real -world social media applications..

Keywords: *Depression Classification, RNN , Social Media Text , Glove Embedding , Twitter Dataset , Mental Health.*

1. Introduction

A mental disorder is described as a syndrome that impedes a person's cognitive functions, emotional regulation, or behavior, which indicates a laxity in the psychological, biological or developmental system that supports mental processes [1]. According to the Canadian Mental Health Association [2], one of the five Canadians of various demographic background has experienced mental illness at some point in his life, with about 8% of adults suffering from the major depressive episode. The World Health Organization [3] reports that about 20% of children and adolescents worldwide have faced mental health issues, half of which are emerging before the age of 14. In addition, mental and material use disorders contribute to about 23% of global deaths. This dangerous effect is also clear in Canadian suicides - 4,000 individuals die of suicide annually, 90% of which are diagnosed with a mental illness [4].

Beyond his serious impact on a person's mental and physical welfare, mental disorders are also surrounded by social stigma and discrimination, such as "mental illnesses cannot be cured." This leads to separation and necessary treatment by individuals affected. It is a complex task to detect mental disorders through social media data, as exposed in existing research, where several attempts have been made to identify relevant indicators using various natural language processing (NLP) techniques. To build an accurate future model requires deep domain knowledge, and even successful feature extraction, it is not guaranteed that the accuracy of prediction in those characteristics will significantly increase. As a result, this study examines the ability of deep learning models, where the feature learning process is naturally made in architecture.

In this research, we focus on a set of deep nerve network models aimed at identifying mental health conditions, especially depression. We use data from computational genderwistics and clinical psychology (CLPSYCH) 2015 shared work [5], including three sub -groups: PTSD and control, depression and control, and difference between PTSD and depression. Our primary goal is to detect depression using the most effective model among two widely adopted deep learning patterns in NLP: unproductive nervous network (CNN) and recurrent nervous network (RNN), given the limited availability of unnecessary text data.

This research work contributes to the following ways: Adaptation of Word Embeding: We introduce a novel method to enhance the word embeding to better classifying users with depression based on our social media content, such as tweet. This approach is tested at twitter dataset [6]. Comparative model assessment: We assess and compare the effectiveness of many deep teaching models used in NLP functions, especially to detect mental health. The evaluation also considens the variation in the effect of the term embeding and hyperpame tuning.

2. Literature Review

The widespread impact of depression, in the initial diagnosis, combined with challenges and strong stigma around mental health within Arab societies, for new strategies. Social media platforms are rapidly benefiting to detect mental health issues, along with increasing body of research - especially in English - on detection of depression. In a study [7], researchers analyzed Twitter posts from the Gulf region to identify signs of depression using supervised machine learning techniques such as random forests and naive bays. Instead of relying only on clinical symptoms, the model was trained on the behavioral pattern seen in users' online activity. In particular, the Livnier Classifier gained 87.5% accuracy in identifying tweets related to depression, showing its ability to effectively detect mental health indicators in the Arabic speaking population. This study emphasizes the ability of digital platforms in early detections around mental health issues in Arab communities and promoting cultural awareness.

In another study [8], researchers combined deep teaching models with traditional machine learning approaches to distinguish between specific and Atipical social media users. The study made a comprehensive review of mental health indicators, using behavioral signals and media materials. Integration of deep learning increased classification accuracy, achieved 89% accuracy rate, and reduced error margin compared to traditional techniques. This highlights the value of deep learning in advancing psychological assessment through social media analysis.

A separate investigation [9] demonstrated a 90% accuracy rate in detecting depression using a proposed model, which significantly reduced the existing systems, exceeding the error rate 30%. The system effectively analyzed linguistic emphasis in user texts and also showed promising results in real -world settings. Research underlines the importance of multi-modal strategies in improving accuracy and reliability of depression through social media content.

Another research effort [10] addressed the boundaries of traditional clinical methods based on self-reporting of the patient as alternative sources of behavior data by discovering social media platforms such as Twitter, Facebook, Reddit, and Tumbller. The study developed a machine learning framework to identify the linguistic markers of depression on Twitter, compared to the performance of the support vector machine and the random forest algorithms. Random forest model showed better performance with 77% accuracy rate, which proved effective in identifying patterns related to depression in tweet materials.

In a related study [11], Twitter posts were analyzed using machine learning and linguistic methods to estimate the possibility of users to experience depression. The model used the Bhavna score and gained 78% accuracy using Xgboost classifier. When features such

Table 1. Review of Existing Work

Author	*Title*	*Dataset*	*Problem Addressed*	*Proposed Method*	*Result Achieved*
S. Almouzini [7]	Detecting Arabic Depressed Users from Twitter Data	Arabic Twitter data: 2,722 tweets from 89 users (27 depressed, 62 non-depressed).	no prior work using Arabic data to detect depression among online Arabic users.	Random Forest, Naïve Bayes, AdaBoostM1, and Liblinear.	Liblinear classifier at 87.5%.
J. Deepali [8]	Mental health analysis using deep learning for feature extraction	Labeled Twitter data: 100 normal users and 100 non-normal users	inability to prove the accuracy of unsupervised models on real datasets.	Utilized deep learning feature extraction (sentence embedding, Word2Vec CBOW model)	Tweet classification (structural features only) achieved 90% accuracy.
T. Gui [9]	Cooperative Multimodal Approach to Depression Detection in Twitter	Multimodal Twitter dataset: D1 (Textual) and D2 (Multimodal).	Difficulty in automatically selecting relevant "indicator" texts and images and lack of specific labels at the text and image level.	Proposed a novel cooperative multi-agent model (COMMA) and image features by pre-trained VGG-Net.	Achieved 90% accuracy and F1-measure.
F. Azam [10]	Identifying Depression Among Twitter Users using Sentiment Analysis	Twitter data: 82,077 depressed tweets from 400 users	Self-reported symptoms, making them susceptible to patient manipulation. These methods are slow and prone to misdiagnosis,	Bag-of-words for feature extraction. Support Vector Machine (SVM) and Random Forest models	Random Forest achieving an accuracy of 0.78. SVM achieved 0.73 accuracy.
P. Kumar [11]	Feature Based Depression Detection from Twitter Data Using Machine Learning Techniques	Twitter data: Twitter APIs, comprising 256 depressed users (3,082 tweets) and 218 non-depressed users (4,687 tweets)	A significant barrier is that many individuals do not seek professional help or clinical advice due to social stigma.	Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost classifiers.	Achieved an accuracy of 89% using the Support Vector Machine (SVM) classifier.
S. Pachouly [12]	3. Depression Detection on Social Media Network (Twitter) using Sentiment Analysis	Twitter data: 15,000 tweets collected via Twitter API	The lack of effective methods in diagnosis makes it challenging to predict suicidal acts based on depression levels.	Feature extraction used Bag-of-Words and TF-IDF. Classifiers included Naïve Bayes, Support Vector Machine (SVM), and Decision Tree.	Achieved optimal accuracy of 87.5% with the linear classifier.
H. Kour [14]	An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM	Benchmark Twitter dataset: D1 (Depression) with 1,402 depressed users (292,564 tweets) and D2 (Non-depression) with 300 million active users (10 billion tweets).	Technical challenges include handling unstructured Twitter data (images, videos, emojis, foreign languages), and the time-consuming nature of professional data labeling.	Developed a hybrid Deep Learning (DL) model (CNN-biLSTM) for depression prediction.	Achieved an accuracy of 94.28% on RNN with the benchmark depression dataset.
R. Safa [15]	5. Automatic detection of depression symptoms in twitter using multimodal analysis	Twitter data: 553 users in the diagnosed group (self-reported "I was diagnosed with depression" 570 users in the control group	underutilization of multimodal features, especially visual data, and novel textual features like bio-description and header images.	Novel multimodal framework to predict depression symptoms from user profiles. Applied Singular Value Decomposition (SVD).	Tweets alone showed 91% accuracy (with Catboost and Gradient Boosting).
D. B. Victor [16]	Machine Learning Techniques for Depression Analysis on Social Media-Case Study on Bengali Community	Bengali community data: 35,000 messages collected from Facebook, Twitter, and chat applications.	difficulty in creating and accurately labeling a Bengali dataset and imbalanced nature of the dataset	Support Vector Machine (SVM), Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Naïve Bayes (Multinomial Naive Bayes), and Logistic Regression.	accuracy, averaging 90% for test data and 91% for train data.

as TF-IDF, N-Grams and LDA were combined, the support vector machine model achieved better accuracy of 89%. Conclusions underline the important role of convenience selection and integration in promoting model performance to detect depression.

Another investigation [12] applied machine learning techniques to distinguish depressed individuals from others based on extracted tweet features. The classification model, developed to process and evaluate social media data, achieved an 87.5% accuracy rate. This research supports the use of predictive algorithms for early identification of depressive symptoms and other mental health conditions through social media behavior.

In study [13], researchers evaluated depression severity and suicidal ideation by collecting demographic and symptom-related data similar to the PHQ-9 survey. Using this dataset, the XGBoost classifier achieved an accuracy of 83.87%, while logistic regression reached 86.45% accuracy in detecting depressive language in tweets [17]. The study successfully categorized users into five depression severity levels, confirming the effectiveness of machine learning in mental health classification.

Studies [14] focus on separation of depressive and non-disdain tweets using deep learning models. By applying CNNS and LSTMS to text data, a hybrid model was developed which gained 94.28% accuracy on a Twitter dataset related to the mental crisis. The combined CNN-LSTM approach improved the RNN and other base lines, demonstrating its better future stating abilities. The analysis emphasized the value of deep learning in identifying emotional patterns and increasing mental health monitoring through social media platforms.

A different approach [15] used users-generated materials to predict the symptoms of depression through a self-report-based method using tweets. The study introduced an N-Gram model, LIWC dictionary, image tagging and a multi-model structure employed by bag-off-words technology. The relationship-based feature selection in nine performance categories resulted in high accuracy: 91% for tweet and 83% for text input. The results highlight the ability to reduce dependence on medical records by analyzing social media content for mental health assessment.

Finally, the study [16] discovered Bengali-language tweets to identify discussions related to depression on social platforms. Various machine learning algorithms - such as SVMs, decisions trees, random forests, naive bays, kNN, and logistic region - were tested. Using TF-IIDF and random one classifierfier, the study gained 90.3% accuracy. Conclusions display the future ability of these algorithms in analyzing material related to depression, strengthening the importance of cultural and linguistic diversity in mental health research.

3. Depression Detection

Determining proper treatment for mental health disorders is a complex clinical process affected by multiple variables, including the intensity of symptoms, the cause of the crisis, the possible benefits and side effects of the available treatments, the functional loss due to the disorder, and how these symptoms can affect medical conditions [1]. Properly assessing the severity of a mental disorder is also a fine task that demands highly skilled professionals using techniques such as detailed text analysis, clinical interview and expert decision [1]. Given the necessary complexity and expertise in formal diagnosis and treatment schemes, using web mining and emotional analysis on social media platforms can be considered an early method for raising awareness about mental health issues.

However, moral use of social media data is a significant concern, especially in terms of user privacy. Researchers working with such data should apply strict measures to maintain the privacy and psychological welfare of users. Some scholars have effectively anonymous user data; For example, Coppermith et al.] Although the user name and URL were interrupted using salty haveh functions, there is a risk that they can be reverse-engineer using Twitter data stored. To address this, participants required to sign privacy agreements to protect user privacy.

Given that social media is present in naturally expressive environment, it is important to evaluate how much personal information users have voluntarily revealed and whether this information is sufficient and accurate to identify mental health conditions. The longitudinal content shared on these platforms has been offered a significant value [18–20], which often involves high-level self-completion [21].

Most of the researches have focused on feature engineering on detection of mental health disorders through social media. One of the most common techniques involves linguistic examination and extracting lexical features using Word Count (LIWC) tools, which classifies words into more than 32 psychological dimensions [23]. LIWC-based Lexicon has played an important role in identifying various situations such as insomnia, emotional crisis [24], postpartum depression [18], depression [25], and PTSD [5]. In these cases, researchers often identify overlapping and unique indicators for each situation. For example, the first-person pronouns have a high use [26] and the second and third-person pronouns were reduced [18] are common markers of crisis and depression. Additionally, demographic features such as age have proved useful in distinguishing between depression and disorders such as PTSD [27].

Working with Twitter data causes challenges due to its unbearable nature. User-related tweets often include informal language, spelling errors, syntax issues, and are forced by character boundaries. An effective solution is using the character N-Gram model, which are strong in handling unnecessary text. For example, [28] used PTSD, bipolar disorder, depression and seasonal affectionate disorder (SAD) to identify users suffering from Unigram and Character N-Gram models to remove features. Similarly, character N-Gram has shown effectiveness in detecting rare disorders such as ADHD, generalized anxiety disorder, and even schizophrenia [5] [29]. To increase model accuracy, subject modeling techniques such as latent dirichlet allocation (LDA) are often employed, although more advanced supervised subject modeling approaches [30] and clustering methods using Word2vec or glove term vector [27] have shown better credibility in identifying mental health issues. Clpsych 2016 shared work [31] was presented further innovations, where post embeding [32] was used to classify the severity of the forum post into levels such as crisis, red, amber and green.

In addition to text and syntax features (eg, character N-Gram, POS tag, dependence parsing), behavioral patterns such as posting of frequencies and retweet rates, as well as demographic factors such as age, gender and personality symptoms [27], are recognized as important to detect mental illness. The region has gradually developed up to advanced language and subject models by basic laxicon-based methods. The current state -of -the -art approach now takes into account vector space embeding and recurrent nervous network (RNNs), with a meditation mechanism [33] to better identify and interpret the material related to the crisis [33].

In our own research, we propose a model designed to detect depression at a user level (instead of post level) using a limited dataset and without relying on comprehensive feature engineering.

Our approach provides competitive performance by taking advantage of the strength of deep learning architecture.

4. Proposed method

4.1. LSTM

Long Short-Term Memory (LSTM) networks, a specialized form of Recurrent Neural Networks (RNNs), are designed to effectively capture long-range dependencies in sequential data. Initially introduced by Hochreiter and Schmidhuber in 1997, LSTMs have undergone substantial refinement over the years, becoming widely adopted across a variety of deep learning tasks due to their robust performance.

Unlike traditional RNNs, which often struggle with learning long-term dependencies, LSTMs are explicitly engineered to overcome this limitation. Their architecture allows them to retain information over extended sequences as a default behavior rather than a learned exception.

All the RNN network modules are created from the sequences of repeating. In traditional RNN, each module usually has the same TANH layer. In contrast, LSTM units are more complex and structured, with four interacting layers that work together in a careful designed manner.

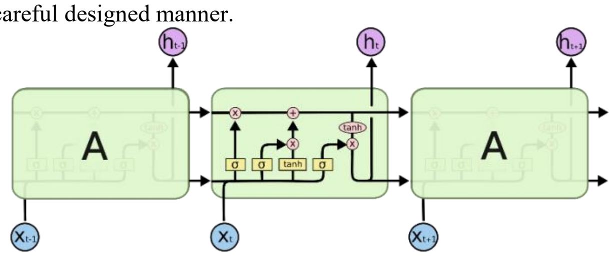


Fig. 1. LSTM architecture.

4.2. Word Embedding

In intensive teaching applications associated with text data, it is necessary to transform the text suitable for processing by algorithms into a numerical format. This is because the machine learning models cannot directly explain the raw text input. Traditionally, this change has been obtained through predetermined vocabulary or methods such as index assignments from a-hot encoding [34]. In an encoding, each word is represented as a unique binary vector, where only one position is marked as "1", with all others "0." with all others "0." Is set on. Alternatively, the vector space model (VSM) represents documents in multi-dimensional location, where each dimension matches the word frequency [35].

While these traditional encoding techniques are straight, they suffer from boundaries such as high al -alternatives, poor handling of meaning equality and disability with rare or rare dataset. To remove these shortcomings, the word embeding has emerged as a more advanced approach. They provide dense vector representation of words that catch sentence composition and meaning relationships, which increase the performance of the classification model.

4.2.1. Word2Vec

Unlike one-hot encoding, where each word is treated as a separate and unrelated feature, Word2Vec creates vector representations that reflect the relationships between words. This is achieved using two main strategies: Continuous Bag of Words (CBOW) and Skip-Gram.

CBOW predicts a target word based on its neighboring context, while Skip-Gram does the reverse—it predicts surrounding context words given a target word. Both techniques leverage the local context of words, defined by a fixed-size window, to capture meaningful linguistic patterns. This contextual learning enables Word2Vec to produce embeddings that are more semantically informative for NLP tasks.

4.2.2. Glove

The glove embeding uses vector differences to express the possibility of co-event of two words and their relationship. The method reduces the difference between two word vectors and the co-event frequency of their dot product [36], which is represented

$$J = \sum_{i,j=1}^{V} \quad f(X_{ij})(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij})^2$$

by J, using the purpose function of a weighted minimum classes.

Gloves (global global global global for word representation) catch the word relationship by analyzing the data of co-event in a large corpus. The term uses the objective function of a weighted least classes to reduce the gap between the dot product of the vector and the co-event frequency [37].

Each word in the model is associated with a vector and a prejudice word. By calculating how often the words appear together, the model refines the word representation so that embeding space in equal words has similar orienta vectors. This approach balances the effects of rare and frequent words pairing using a waiting function, which improves the quality of embeding.

Gloves embeding are particularly effective in modeling fine language, such as found in social media posts about depression. The capacity of glove to normalize the cementic meaning allows the model to identify the material related to depression even when facing less frequent or unseen words. This increases the strength of the classifier and contributes significantly to analyzing social media for mental health applications.

4.3. Data Pre-processing

4.3.1. Data Preproseing

The dataset carefully preprosasting to remove irrelevant materials such as URL, special characters and numerical data. Subsequently, the text material was token, and the normal stop words were abolished to emphasize important words. To normalize the vocabulary, lamematization was applied, reducing the words of words and allowing model accuracy to increase. The issue of a square imbalance - where about 53% of examples were labeled as "not sad" and 47% "sad" - addressed using resampling techniques. In particular, at least the "sad" class was enhanced by generating synthetic samples to balance the distribution. The text data was then converted into numerical format using A-Gap encoding. Finally, the dataset was divided into training, testing and verification the best for model development and performance evaluation with a partition ratio of 60:20:20.

4.3.2. LSTM and RNN models

The recurrent nerve network (RNN) is capable of capturing dependence in sequential data using a memory mechanism that stores the necessary information in the stages of time. The architecture revolves around a cell state, which maintains or stops the information from the back of the previous time and prevents selective information based on the input and hidden state. The basic design of a standard RNN includes a single memory cell that operates gradually to manage data flow.

4.3.3. Model Training

Each RNN version was trained with a batch size of 32 for 10 ages on a dataset. Adam optimizer, known for its adaptive learning rate mechanism, was employed to adapt model parameters. The binary cross-entropy loss function was used to measure the error between the estimated and real class labels.

4.3.4. Model Assessment

The model was evaluated using a separate test dataset. The performance metrics included F1-score, accurate, recall and accuracy. Each model had confusion to imagine predicting results. Visualization techniques were also used to identify the most effective one to compare model variants and classify social media texts into "sad" and "non-immortal" categories.

5. Results and Discussion

The study was conducted using the python and deployed on the Kagal platform, taking advantage of T4 GPU for quick calculation. Various RNN architecture was systematically compared to social media-related datasets, which provides significant insight into the relative performance of various models to detect depression from lesson data. Dataset

The first step in the suggested method is data collection. The dataset consists of Twitter tweets collected from work [38] which are available on Kaggal. Depression and non-depression categories are indicated by the following information. DER: depression, N-DEPR: Non- depression

Data extracted from Kagal repository consists of unbalanced and dirty tweets [39]. There is an imbalance in the number of records in the dataset between depression and non-immunization categories. Many data sampling techniques are available, and no technique works well for all classification models. To preserve data balance, only 6164 records are recovered instead of using a sampling technique to recover the exact balance in each categories. The number of records created by depression and non-depression categories is 3082 out of 6164.

Tables 2 display how the data was balanced and filtered. Tables 3 and 4 display some of the tweets and terms from the datasets.

Table 2. Number of records of each category in dataset from Twitter

Category	Number of posts
DEPR.	3082
N-DEPR.	3082

Table 3. Some Depressive /Non-Depressive Tweets/Posts from a Dataset

Tweet /Statement/Sentence	Category
my thoughts always destroy my mood	DEPR.
i seriously over think everything which make me stress myself out and it create problems that be not even there in the first place	DEPR.
happy i will always be grateful for the friends i make and the experience i have that all start on summoners rift	N-DEPR.
merry Christmas from my little dog and our little tree	N-DEPR.

Table 4. Number of records of each category in dataset from Twitter

Words	Category
Over thinking, sad, anger	DEPR.
Joy, happy, fun	N-DEPR.

5.1. RNN Glove model

The model used a prepromous embeding matrix based on gloves (global global global global for Word representation) with 300 suppresses. Architecture included relay and tanah activation work for hidden layers, employed both Softmax in the output layer, and Adam and RMSPROP. A dropout rate of 0.5 was applied to prevent overfiting, and training was conducted over 50 ages. The learning rates of 0.001 and 0.0001 were tuned to the eight model configurations to assess their impact on the dynamics of training. Learning rate - One of the most important hyperpamators - controls the magnitude of weight updates during training and significantly affects convergence behavior. Figure 2 shows model architecture of proposed model Layered architecture designed on kaggle IDE.

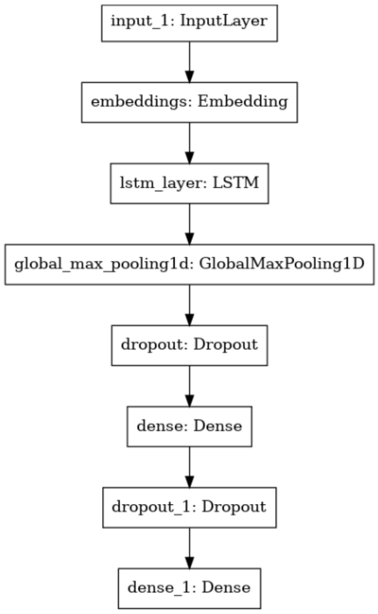


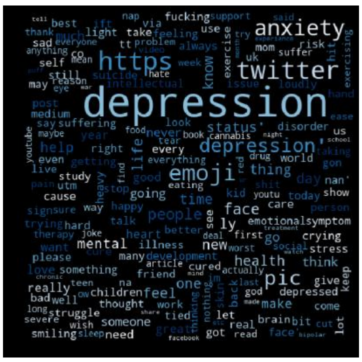
Fig. 2. Model Architecture..

5.2. Results

Twitter the effectiveness of the model on the Kaggle platform was validated using a dataset. The results showed that the integrated RNN model with glove embedding achieved excellent performance with 97.84% training accuracy and 97.22% test accuracy. These figures suggest strong generalization and minimal overfiting, confirming the strength of the proposed approach.

Word cloud generated from twitter dataset shown in figure 3. It's easy to spot words from word cloud that are indicative of depression in these tweets: depression, treatment, suffering, crying, help, struggle, risk, hate, sad, anxiety, disorder, suicide, stress, therapy, mental health, emotional, bipolar.

Fig. 3. Word cloud generated from twitter dataset.



The model was trained and evaluated on Twitter dataset, which was implemented on the Kagal platform using the python. Experimental results as shown in figure 4 performed remarkable performance, 98.85% training accuracy and 92.62% test accuracy. In the detailed analysis of classification metrics presented in Table 4, for the posts related to depression-risk respectively, 0.98090, 0.99959, and 0.99016 accurate, recall and 0.98090, 0.99959 and 0.99016 and 0.99016 and 0.96394, 0.9984, 0.9984, 0.99844, 0.99016 and 0.96396 Find out.

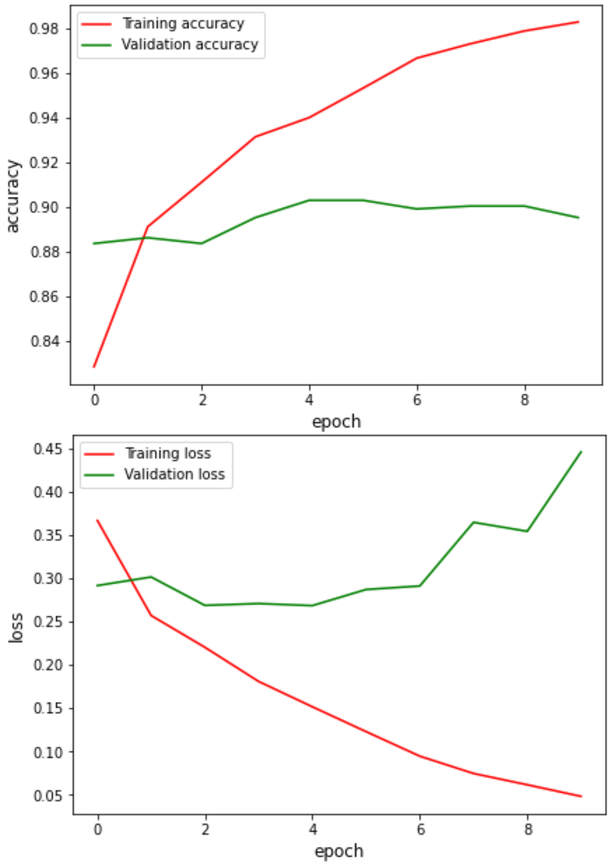


Fig. 4. Proposed Model accuracy and loss graph for training and testing classification.

These results highlight the ability of the model to correctly identify the material related to depression with minimal errors, ensuring both high sensitivity and uniqueness. These results were emphasized in training and testing data confusion matrix. The model's ability to differentiate between posts with some flaws that are associated with depression and which are not displayed by these results.

Table 4. Classification report

	precision	recall	f1-score	support
Class 0	0.98090	0.99959	0.99016	2415
Class 1	0.99844	0.93179	0.96396	689
Accuracy			0.98454	3104
macro avg	0.98967	0.96569	0.97706	3104
weighted avg	0.98480	0.98454	0.98434	3104

Comparing models with other models that are currently in use on a general Twitter dataset, are displayed in Figure 5 and Table 5. The results obtained show how effective the RNN model is made with glove embeding.

The study underlines the important role of glove embeding in increasing the performance of deep learning models for classification tasks. By bridge between linguistic understanding and machine learning, the proposed approach provides a strong and efficient framework to detect initial depression from the social media text. This research contributes to the extensive goal of taking advantage of technology to carry forward mental health analysis and intervention strategies.

Table 5. Performance of Proposed model compared to other Existing Models

Model	Accuracy	F1 score	Precision	Recall
Proposed Model	**0.98**	**0.99**	**0.98**	**0.99**
SBERT-CNN [40]	0.86	0.86	0.85	0.87
CNN [41]	NA	0.79	0.72	0.87
LSTM [41]	NA	0.77	0.74	0.79
XLNET a [42]	NA	0.70	0.74	0.67
BERT a [42]	NA	0.68	0.73	0.66
RoBERT a [42]	NA	0.68	0.71	0.60

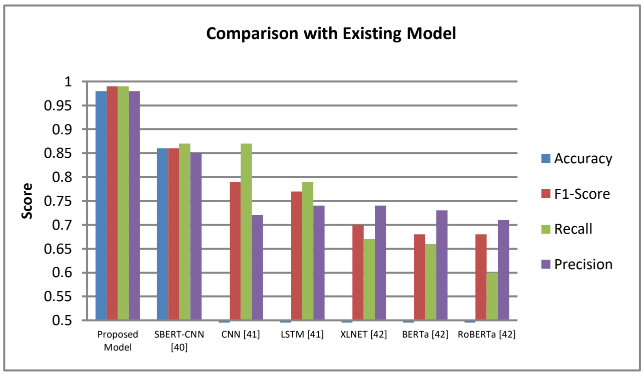


Fig. 5. Proposed Model Results comparison with existing models.

The study underlines the important role of glove embeding in increasing the performance of deep learning models for classification tasks. By bridge between linguistic understanding and machine learning, the proposed approach provides a strong and efficient framework to detect initial depression from the social media text. This research contributes to the extensive goal of taking advantage of technology to carry forward mental health analysis and intervention strategies.

5.3. Result Discussion

The effectiveness of the better RNN model proposed with glove embeding was evaluated using the redit dataset, which was executed through the python on the Kagal platform. The model received high training accuracy of 98.85% and a strong test accuracy of 92.62%, indicating effective generalization for solid learning and unseen data during training.

A detailed classification report suggests that for class 0 (post-related posts), the model received an accuracy of 0.98090, remembering 0.99959 and F1-score of 0.99016. For class 1 (post related to depression), accurate, recall and F1-shore were 0.99844, 0.93179 and 0.96396 respectively. The overall accuracy in both classes is 98.45%, with macro and weighted average equally high performance, reflecting balanced predictive abilities.

These results display the exceptional performance of the model in accurate identification of both depression and non-avasad materials. High recall for non-avasad positions indicates that almost all true examples were classified correctly, while very high precision for posts related to depression suggests that the model rarely misleads non-invalid positions as a depression. This balance between accurate and recall is essential for real -world applications where both false positivity and false negative results can be important.

Overall, the effectiveness of the model confirms that incorporating gloves embeding in an RNN framework greatly enhances the abilities of detection of depression. Results validate the strength of the proposed approach and its suitability for practical deployment in automatic mental health monitoring systems.

6. Conclusion

This research presents a better RNN-based model for depression classification from social media text, which uses gloves embeding to increase performance. The study suggests that integrating the glove embeding in the RNN framework leads to considerable improvements in the model's ability to understand and classify the text by capturing the meaning and relevant nuances contained in the social media posts. It is particularly valuable for detecting material related to depression, which often includes emotions, complex language patterns, and subtle expressions of colloquial language.

Glove embeding, pre-educated on the large corpora, brings many advantages to the model. First, they offer the rich meaning representation of words, which enables the RNN model to differentiate between different words and effectively understand their relationships. Second, by maintaining significant linguistic characteristics, gloves increase embedding computational efficiency by reducing the alternative of the word representation and also reduce the risk of overfiting with small datasets. Thirdly, their ability to encoded the similarity between semantics related words allows models to be better normal to ignore data, improving its strength and accuracy in real -world scenarios.

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