



Depression Detection from Social Media Text using RNN with GloVe Embedding

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How to Cite this Article:

Sharma, V. K. (2026). Depression Detection from Social Media Text using RNN with GloVe Embedding. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(05).

<https://doi.org/10.55041/ijcope.v2i5.240>

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<https://doi.org/10.55041/ijcope.v2i5.240>

Abstract—

The analysis of depression through social media platforms has become an important and promising research area, enabling early detection of mental health issues by identifying linguistic patterns in textual data. This study reviews existing research in depression detection and presents a concise overview of machine learning techniques applied to social media text, along with a comparative analysis of their performance. Based on this review, a novel approach is proposed for depression detection using an improved recurrent neural network (RNN) architecture combined with GloVe embeddings. The research focuses on developing an RNN-based model capable of classifying depressive expressions in user-generated content. By incorporating GloVe (Global Vectors for Word Representation) embeddings, the model effectively captures semantic relationships and subtle linguistic features present in social media text. This integration enhances the model's ability to identify nuanced emotional cues and complex language patterns associated with depression. The model is trained using a Twitter dataset and further evaluated on an additional dataset to ensure its robustness and cross-platform applicability. Experimental results demonstrate that the proposed approach achieves a high test accuracy of 98.45%, indicating its efficiency and reliability as an automated tool for depression detection in real-world social media environments.

Keywords— Depression Classification; RNN; Social Media Text; Glove Embedding; Twitter Dataset; Mental Health.



I. INTRODUCTION

A mental disorder is defined as a syndrome that disrupts an individual's cognitive functioning, emotional regulation, or behavior, reflecting dysfunction in the psychological, biological, or developmental processes underlying mental activity [1]. According to the Canadian Mental Health Association [2], approximately one in five Canadians from diverse demographic backgrounds experiences a mental health issue at some stage in life, with nearly 8% of adults affected by major depressive episodes. The World Health Organization [3] states that around 20% of children and adolescents globally encounter mental health challenges, with half of these cases emerging before the age of 14. Furthermore, mental and substance use disorders account for nearly 23% of the global disease burden. The severity of this issue is also evident in Canada's suicide statistics, where approximately 4,000 individuals die by suicide each year, and about 90% of these cases are associated with diagnosed mental illnesses [4].

In addition to their significant impact on mental and physical well-being, mental disorders are often accompanied by social stigma and discrimination, including misconceptions such as the belief that mental illnesses are incurable. Such stigma can result in social isolation and discourage individuals from seeking appropriate treatment. Detecting mental health conditions through social media data presents considerable challenges, as highlighted in previous studies, where multiple approaches have attempted to identify relevant indicators using various natural language processing (NLP) techniques. Developing an accurate predictive model requires substantial domain expertise, and even with effective feature extraction, improved prediction accuracy is not always guaranteed. Therefore, this study explores the potential of deep learning models, where feature extraction and representation learning are inherently integrated within the model architecture.

In this work, we investigate a set of deep neural network models for identifying mental health conditions, with a particular emphasis on depression detection. The dataset used in this study is derived from the Computational Linguistics and Clinical Psychology (CLPSYCH) 2015 shared task [5], which includes three categories: PTSD vs. control, depression vs. control, and PTSD vs. depression. The primary objective is to detect depression by evaluating and selecting the most effective model from two widely

used deep learning architectures in NLP: Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), especially in scenarios with limited labeled textual data.

This research makes the following contributions. Adaptation of word embeddings: A novel approach is proposed to enhance word embeddings for improved classification of depressive users based on social media content such as tweets. This method is evaluated using a Twitter dataset [6]. Comparative model evaluation: The study conducts a comprehensive comparison of various deep learning models applied to NLP tasks, particularly for mental health detection. The evaluation also considers the influence of different word embeddings and hyperparameter tuning on model performance.

II. LITERATURE REVIEW

The extensive prevalence of depression, along with difficulties in early diagnosis and the strong social stigma surrounding mental health in Arab societies, necessitates the development of innovative detection strategies. Social media platforms have increasingly become valuable resources for identifying mental health concerns, supported by a growing body of research—primarily in English—focused on depression detection. In study [7], researchers examined Twitter posts from the Gulf region to detect depressive tendencies using supervised machine learning techniques such as Random Forests and Naïve Bayes. Rather than relying solely on clinical indicators, the model incorporated behavioral patterns observed in users' online activities. Notably, the linear classifier achieved an accuracy of 87.5% in identifying depression-related tweets, demonstrating its effectiveness in capturing mental health signals within Arabic-speaking populations. This work highlights the potential of digital platforms for early detection and improving cultural awareness of mental health issues in Arab communities.

In another study [8], researchers integrated deep learning models with traditional machine learning approaches to differentiate between typical and atypical social media users. The study conducted a comprehensive analysis of mental health indicators by combining behavioral signals with textual content. The inclusion of deep learning techniques improved classification performance, achieving an accuracy of 89% while reducing error rates compared to conventional methods. These findings emphasize the



significance of deep learning in enhancing psychological assessment through social media analytics.

A separate investigation [9] reported a 90% accuracy rate for depression detection using a proposed model, significantly outperforming existing systems by reducing error rates by 30%. The model effectively analyzed linguistic patterns in user-generated text and demonstrated strong applicability in real-world scenarios. This research underscores the importance of multimodal approaches in improving the reliability and accuracy of depression detection using social media data.

Another study [10] addressed the limitations of traditional clinical methods, which rely heavily on patient self-reporting, by exploring social media platforms such as Twitter, Facebook, Reddit, and Tumblr as alternative data sources. The researchers developed a machine learning framework to identify linguistic markers of depression in tweets and compared the performance of Support Vector Machine and Random Forest algorithms. The Random Forest model achieved superior results with an accuracy of 77%, indicating its effectiveness in identifying depression-related patterns in textual content.

In a related work [11], Twitter data were analyzed using both machine learning and linguistic techniques to estimate the likelihood of users experiencing depression. The model incorporated sentiment-based features and achieved an accuracy of 78% using the XGBoost classifier. Furthermore, when features such as TF-IDF, N-grams, and Latent Dirichlet Allocation (LDA) were combined, the Support Vector Machine model achieved a higher accuracy of 89%. These findings highlight the importance of feature selection and integration in improving model performance for depression detection.

Another investigation [12] applied machine learning techniques to classify individuals as depressed or non-depressed based on features extracted from tweets. The developed classification model achieved an accuracy of 87.5%, supporting the effectiveness of predictive algorithms for early identification of depressive symptoms and other mental health conditions through social media behavior.

In study [13], researchers assessed depression severity and suicidal ideation by collecting demographic and symptom-related information similar to the PHQ-9

questionnaire. Using this dataset, the XGBoost classifier achieved an accuracy of 83.87%, while logistic regression attained 86.45% accuracy in detecting depressive language in tweets [17]. The study successfully categorized users into five levels of depression severity, demonstrating the effectiveness of machine learning techniques in mental health classification.

Studies [14] focused on distinguishing between depressive and non-depressive tweets using deep learning models. By applying Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to textual data, a hybrid CNN-LSTM model was developed, achieving an accuracy of 94.28% on a Twitter dataset related to mental health crises. This combined approach outperformed standalone RNN and baseline models, highlighting its superior predictive capability. The findings emphasize the value of deep learning in identifying emotional patterns and improving mental health monitoring through social media platforms.

A different approach [15] utilized user-generated content to predict symptoms of depression through a self-report-based framework using tweets. The study employed an N-gram model, Linguistic Inquiry and Word Count (LIWC) dictionary, image tagging, and a multimodal architecture based on bag-of-words techniques. Feature selection based on relational patterns across nine performance categories resulted in high accuracy levels of 91% for tweets and 83% for textual input. These results demonstrate the potential of reducing reliance on clinical data by leveraging social media content for mental health assessment.

Finally, study [16] explored Bengali-language tweets to identify discussions related to depression on social media platforms. Various machine learning algorithms—including Support Vector Machines, Decision Trees, Random Forests, Naïve Bayes, k-Nearest Neighbors, and Logistic Regression—were evaluated. Using TF-IDF features and a Random Forest classifier, the study achieved an accuracy of 90.3%. The findings highlight the effectiveness of these algorithms in analyzing depression-related content and emphasize the importance of incorporating cultural and linguistic diversity in mental health research.

III. DEPRESSION DETECTION

Identifying appropriate treatment strategies for mental health disorders is a highly complex clinical process



influenced by several factors, including the severity of symptoms, underlying causes, potential benefits and side effects of available treatments, the degree of functional impairment, and the interaction of symptoms with other medical conditions [1]. Accurately evaluating the intensity of a mental disorder is equally challenging and typically requires skilled professionals employing methods such as detailed textual analysis, clinical interviews, and expert judgment [1]. Given the complexity and expertise required for formal diagnosis and treatment planning, the application of web mining and sentiment analysis on social media platforms can serve as an early-stage approach for identifying and raising awareness about mental health issues.

Despite its potential, the ethical use of social media data remains a major concern, particularly with respect to user privacy. Researchers must implement strict protocols to safeguard both the privacy and psychological well-being of individuals. Some studies have attempted to anonymize user data; for instance, Coppersmith et al. anonymized usernames and URLs using salted hash functions. However, there remains a possibility of reverse engineering such anonymized data when combined with publicly available Twitter datasets. To mitigate these risks, participants are often required to sign privacy agreements to ensure the protection of sensitive information.

Given that social media platforms provide a natural environment for self-expression, it is essential to assess the extent to which users voluntarily disclose personal information and whether such data is sufficient and reliable for identifying mental health conditions. Longitudinal data shared over time on these platforms has proven to be particularly valuable [18–20], as it often includes rich self-reported information [21].

A significant portion of existing research has focused on feature engineering for detecting mental health disorders from social media data. One widely used approach involves linguistic analysis and the extraction of lexical features using tools such as Linguistic Inquiry and Word Count (LIWC), which categorizes words into more than 32 psychological dimensions [23]. LIWC-based lexicons have been instrumental in identifying various conditions, including insomnia, emotional distress [24], postpartum depression [18], depression [25], and PTSD [5]. Researchers frequently identify both overlapping and distinct linguistic markers across these conditions. For example,

increased use of first-person pronouns [26] and reduced usage of second- and third-person pronouns [18] are commonly associated with depressive states. Additionally, demographic attributes such as age have been found useful in distinguishing depression from other disorders like PTSD [27].

Analyzing Twitter data presents unique challenges due to its unstructured and noisy nature. User-generated tweets often contain informal language, spelling mistakes, grammatical inconsistencies, and are constrained by character limits. One effective solution to handle such data is the use of character N-gram models, which are robust in processing noisy text. For instance, study [28] utilized unigram and character N-gram features to detect users with conditions such as PTSD, bipolar disorder, depression, and seasonal affective disorder (SAD). Similarly, character N-gram techniques have proven effective in identifying less common conditions such as ADHD, generalized anxiety disorder, and schizophrenia [5][29]. To further enhance model performance, topic modeling techniques like Latent Dirichlet Allocation (LDA) are frequently applied. More advanced supervised topic modeling approaches [30], along with clustering methods based on Word2Vec or GloVe embeddings [27], have demonstrated improved effectiveness in detecting mental health issues. The CLPsych 2016 shared task [31] introduced additional advancements, including the use of post embeddings [32] to classify forum posts into severity levels such as crisis, red, amber, and green.

Beyond textual and syntactic features (e.g., character N-grams, part-of-speech tagging, and dependency parsing), behavioral patterns—such as posting frequency and retweet activity—as well as demographic factors like age, gender, and personality traits [27], are increasingly recognized as important indicators for detecting mental health conditions. The field has progressively evolved from basic lexicon-based methods to more advanced language and topic modeling techniques. Current state-of-the-art approaches incorporate vector space embeddings and recurrent neural networks (RNNs), often enhanced with attention mechanisms [33], to more effectively identify and interpret content related to mental health conditions. In this study, we propose a model aimed at detecting depression at the user level rather than at the individual post level, utilizing a limited dataset and minimizing reliance on extensive feature engineering. The proposed approach demonstrates competitive

performance by leveraging the strengths of deep learning architectures.

IV. PROPOSED METHOD

A. LSTM

Long Short-Term Memory (LSTM) networks are an advanced type of Recurrent Neural Network (RNN) specifically designed to capture long-term dependencies in sequential data. First introduced by Hochreiter and Schmidhuber in 1997, LSTMs have since been significantly improved and are now widely used in various deep learning applications due to their strong performance.

Unlike conventional RNNs, which often face difficulties such as vanishing or exploding gradients when learning long-term relationships, LSTMs are explicitly structured to address these limitations. Their architecture enables them to retain relevant information over long sequences, making memory retention a built-in capability rather than a learned behavior.

RNN architectures are generally composed of repeated modules. In standard RNNs, each module typically consists of a simple structure with a single tanh activation layer. In contrast, LSTM units are more sophisticated, comprising four interacting layers that regulate information flow through carefully designed gating mechanisms.

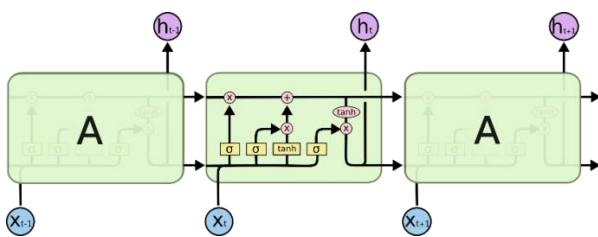


Fig. 1. LSTM architecture.

B. Word Embedding

In deep learning applications involving textual data, it is essential to convert text into numerical representations that machine learning models can process. Since models cannot directly interpret raw text, various encoding techniques are employed. Traditional approaches include predefined vocabularies and methods such as one-hot encoding [34], where each word is represented as a unique binary vector with a single active position. Another method is the Vector Space Model (VSM), which

represents documents as high-dimensional vectors based on word frequency [35].

Although these techniques are simple to implement, they suffer from several limitations, including high dimensionality, inability to capture semantic similarity, and poor handling of infrequent words. To overcome these challenges, word embeddings have emerged as a more effective solution. They provide dense vector representations that capture both syntactic and semantic relationships between words, thereby improving model performance in classification tasks.

1) Word2Vec

Word2Vec is an embedding technique that represents words in a continuous vector space, capturing relationships between them. Unlike one-hot encoding, where words are treated independently, Word2Vec learns contextual relationships using two main approaches: Continuous Bag of Words (CBOW) and Skip-Gram.

The CBOW model predicts a target word based on its surrounding context, whereas the Skip-Gram model predicts context words given a target word. Both approaches utilize a fixed-size context window to learn meaningful linguistic patterns, enabling the generation of semantically rich word representations useful for natural language processing tasks.

2) GloVe

GloVe (Global Vectors for Word Representation) is another widely used word embedding technique that captures global statistical information about word co-occurrence. It models the relationships between words by analyzing how frequently they appear together in a large corpus. The method minimizes the difference between the dot product of word vectors and the logarithm of their co-occurrence probability using a weighted least squares objective function [36][37].

In the GloVe model, each word is associated with both a vector representation and a bias term. By leveraging co-occurrence statistics, the model ensures that words with similar meanings are positioned close to each other in the embedding space. Additionally, a weighting function is applied to balance the influence of frequent and rare word pairs, enhancing the quality of the learned embeddings.

GloVe embeddings are particularly effective for capturing subtle linguistic patterns, such as those found



in social media text related to depression. Their ability to preserve semantic relationships enables models to identify depressive content even when dealing with rare or previously unseen words, thereby improving classification performance in mental health applications.

C. Data Pre-processing

The dataset was carefully pre-processed to remove irrelevant elements such as URLs, special characters, and numerical values. The textual data was then tokenized, and common stop words were removed to focus on meaningful terms. Lemmatization was applied to normalize words to their base forms, which helps improve model accuracy.

To address class imbalance—where approximately 53% of the samples were labeled as “non-depressed” and 47% as “depressed”—resampling techniques were employed. Specifically, the minority class was augmented using synthetic data generation methods to achieve a balanced dataset. The processed text was then transformed into numerical format using encoding techniques. Finally, the dataset was divided into training, validation, and testing sets with a ratio of 60:20:20 for effective model development and evaluation.

1) LSTM and RNN Models

Recurrent Neural Networks (RNNs) are designed to model sequential data by maintaining a memory of previous inputs through hidden states. This memory mechanism allows the network to capture temporal dependencies. The architecture includes a cell state that carries information across time steps, selectively updating or discarding information based on input and hidden states. A standard RNN typically consists of a single memory unit that processes sequences iteratively. LSTM extends this capability with more advanced gating mechanisms for better performance.

2) Model Training

The models were trained using a batch size of 32 over 10 epochs. The Adam optimizer was utilized due to its adaptive learning rate capabilities, which facilitate efficient convergence. Binary cross-entropy was employed as the loss function to measure the difference between predicted and actual class labels.

3) Model Evaluation

The trained models were evaluated on a separate test dataset. Performance was assessed using metrics such as accuracy, precision, recall, and F1-score. Confusion matrices were generated to visualize classification results. Additionally, comparative analysis and visualization techniques were applied to identify the most effective model for classifying social media text into “depressed” and “non-depressed” categories.

V. RESULTS AND DISCUSSION

The experiments were implemented using Python on the Kaggle platform, leveraging the NVIDIA T4 GPU to accelerate computation. Multiple RNN-based architectures were systematically evaluated on social media datasets to gain insights into their comparative performance for depression detection from textual data.

The initial stage of the proposed methodology involved data collection. The dataset comprised Twitter posts obtained from prior work [38] and made available on the Kaggle repository. Each record was labeled into two categories: DEPR (depression) and N-DEPR (non-depression).

The collected dataset was inherently noisy and imbalanced [39], with an unequal distribution between depressive and non-depressive samples. While several resampling techniques exist, none universally guarantees optimal performance across all models. Therefore, instead of applying aggressive sampling strategies, a balanced subset of 6,164 records was selected, consisting of 3,082 samples for each class.

Table 2 presents the balanced data distribution, while Tables 3 and 4 illustrate sample tweets and representative terms extracted from the dataset.



between depressive and non-depressive content with minimal misclassification. These results demonstrate the model’s effectiveness in identifying subtle linguistic cues associated with depression.

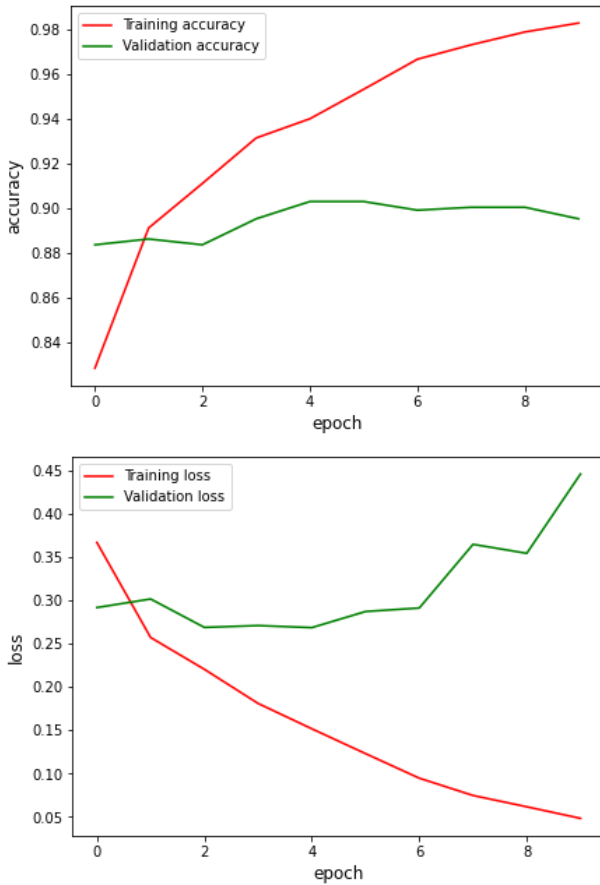


Fig. 4. Proposed Model accuracy and loss graph for training and testing classification

A comparative evaluation with existing models is presented in Figure 5. The results clearly indicate that the proposed RNN model with GloVe embeddings outperforms several baseline approaches on the same dataset.

Overall, the findings highlight the significant contribution of GloVe embeddings in enhancing deep learning model performance. By bridging semantic understanding with machine learning, the proposed approach offers an efficient and reliable framework for

early depression detection using social media data.

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

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

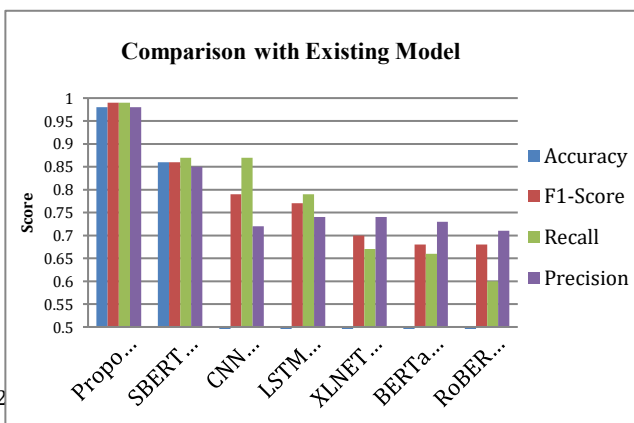
C. Result Discussion

The proposed RNN model with GloVe embeddings was further evaluated using a Reddit dataset, implemented in Python on the Kaggle platform. The model achieved 98.85% training accuracy and 92.62% test accuracy, demonstrating strong learning capability and effective generalization on unseen data.

The detailed classification report indicates that for class 0 (non-depressive posts), the model achieved a precision of 0.98090, recall of 0.99959, and F1-score of 0.99016. For class 1 (depressive posts), the precision, recall, and F1-score were 0.99844, 0.93179, and 0.96396, respectively. The overall classification accuracy reached 98.45%, with both macro and weighted averages reflecting consistently high performance.

These results demonstrate the model’s strong capability to accurately classify both depressive and non-depressive content. The high recall for non-depressive posts indicates that the majority of true negatives were correctly identified, while the high precision for depressive posts shows that false positives were minimal. Maintaining this balance between precision and recall is critical in real-world applications, where both false alarms and missed detections can have significant consequences.

In summary, the experimental results confirm that integrating GloVe embeddings within an RNN framework substantially enhances depression detection performance. The proposed model proves to be robust, accurate, and suitable for deployment in automated mental health monitoring systems, contributing to the





broader objective of leveraging technology for early intervention and mental health support.

VI. Conclusion

This study presents an improved RNN-based model for detecting depression from social media text, incorporating GloVe embeddings to enhance overall performance. The findings demonstrate that integrating GloVe embeddings within the RNN framework significantly improves the model's capability to interpret and classify textual data by effectively capturing semantic meaning and contextual nuances present in social media posts. This approach is particularly beneficial for identifying depression-related content, which often involves complex emotional expressions, informal language, and subtle linguistic patterns.

GloVe embeddings, pre-trained on large corpora, offer several advantages to the proposed model. Firstly, they provide rich semantic representations of words, enabling the RNN to better distinguish between terms and understand their contextual relationships. Secondly, by preserving essential linguistic features in a dense vector format, GloVe reduces the dimensionality of word representations, thereby improving computational efficiency and minimizing the risk of overfitting, especially when working with limited datasets. Finally, the ability of GloVe embeddings to capture semantic similarity between related words enhances the model's generalization capability, making it more robust when handling noisy and unseen data in real-world applications. Overall, the proposed approach demonstrates strong potential as an effective and reliable tool for automated depression detection using social media data, contributing to the advancement of technology-driven mental health analysis and early intervention strategies.

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