

Depression Detection From Social Media Text Using Embedding-Enhanced Long Short-Term Memory and Recurrent Neural Network Models

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Received: May 01, 2026 | Review began: June 04, 2026 | Review ended: July 10, 2026 | Published: July 13, 2026

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Abstract

Depression is a common neuropsychological condition that has a considerable influence on emotional stability, daily functioning, and general quality of life in various populations. Prompt detection of depressive symptoms is important for intervening effectively and reducing the chances of severe psychiatric effects. As digital platforms have rapidly expanded, especially social media, access to large volumes of user-generated textual content has provided new opportunities for automated mental health assessment. The current research paper discusses the results of state-of-the-art deep learning-based methods for early-stage depression detection on social media text. Recurrent neural networks (RNNs), long short-term memory (LSTM) models, and their embedding-based counterparts are built and trained on curated datasets of depressive and non-depressive posts. The methodology focuses on the derivation of linguistic and contextual signs that indicate underlying emotional conditions. It has been shown that embedding-enhanced deep learning models perform better than traditional methods, and that LSTM-based models yield ideal results in capturing and predicting temporal relationships and subtle emotional differences. The results show that there is potential to integrate deep learning algorithms into real-time mental health monitoring systems to assist clinicians and researchers in the early detection of depression.

Categories: Computational Science and Engineering, Computer Vision, Data Analysis

Keywords: depression detection, natural language processing, deep learning, rnn, lstm, sentiment analysis

Introduction

Depression is a serious mental health condition that affects emotional well-being, thinking patterns, daily functioning, interpersonal relationships, and overall quality of life. The World Health Organization reports that depression affects millions of people worldwide and contributes significantly to the global burden of disease [1]. Early identification of depressive symptoms is important, because timely intervention can reduce symptom severity and support better psychological and social outcomes [2]. In clinical practice, depression is commonly assessed through psychological questionnaires, structured interviews, and expert evaluation. Although these methods are useful, they are often time-consuming, subjective, and difficult to apply on a large scale.

With the rapid growth of digital communication, many individuals express their emotions, thoughts, and personal difficulties through online platforms such as Twitter, Reddit, and other social media communities. Textual communication is especially important because people often feel more comfortable sharing sensitive emotions anonymously through

How to cite this article:

Kumari P, Jijja A (July 13, 2026) Depression Detection From Social Media Text Using Embedding-Enhanced Long Short-Term Memory and Recurrent Neural Network Models. Cureus J Comput Sci 3 : es44389-026-00156-1. DOI <https://doi.org/10.7759/s44389-026-00156-1>

written posts. Previous studies have shown that people experiencing depression may use distinctive linguistic patterns, emotional expressions, and contextual cues that can reflect their mental state [3,4]. Therefore, social media text has become a valuable source for developing automated depression detection systems.

Artificial intelligence, machine learning, and natural language processing (NLP) have created new opportunities for detecting depressive symptoms from text. Traditional machine learning approaches usually depend on handcrafted features such as term frequency-inverse document frequency, bag-of-words, or lexicon-based features. Although these methods have shown useful results, they often fail to capture deeper semantic meaning, contextual relationships, and long-range dependencies in user-generated text. Recent deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have improved text classification performance, but many existing approaches still have limitations related to feature representation, contextual understanding, and generalization across different textual patterns [5,6].

The main research gap is that existing studies do not sufficiently explore how embedding-enhanced deep learning models can improve depression detection by jointly capturing semantic, contextual, and sequential linguistic information. Many previous methods either rely on sparse textual features or apply deep learning models without fully utilizing rich word embedding representations. To address this limitation, the present study proposes an embedding-enhanced deep learning framework for automated depression detection from social media text. The proposed framework aims to improve detection performance by using meaningful textual representations and deep learning-based pattern extraction, thereby advancing the current state of knowledge in text-based mental health analysis [7].

Motivation

The motivation of this study is based on the increasing need for scalable, reliable, and automated tools for early depression detection. Depression is a growing mental health concern, and traditional screening methods are not always sufficient for large-scale or early-stage identification. At the same time, social media platforms provide a large amount of user-generated text in which individuals often express emotions, stress, loneliness, sadness, and other psychological signals. This creates an opportunity to apply artificial intelligence and NLP for identifying depressive patterns from written language.

However, existing automated depression detection methods still face important limitations. Conventional machine learning models often depend on manually designed or sparse features, while some deep learning models do not adequately capture both semantic meaning and sequential context. This motivates the development of an embedding-enhanced deep learning framework that can learn more meaningful linguistic patterns from social media text and provide improved detection accuracy compared with existing approaches.

Objectives

The main objective of this research is to develop and evaluate an automated depression detection framework using social media text. The specific objectives are:

1. To analyze textual data from digital platforms for identifying linguistic patterns associated with depressive symptoms.
2. To develop an embedding-enhanced deep learning model capable of capturing semantic, contextual, and sequential features from user-generated text.
3. To address the limitations of traditional machine learning methods that depend mainly on sparse or handcrafted textual features.
4. To compare the proposed framework with existing baseline models in order to evaluate its effectiveness.
5. To improve the accuracy and reliability of automated depression detection and contribute to the development of AI-based mental health screening systems.

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Materials And Methods

Related work

Previous research has established a strong relationship between psychological well-being and linguistic properties in written communication, particularly in relation to markers of depressive behavior [8,9]. These studies indicate that depressed individuals often show identifiable language patterns, such as negative emotional expression, self-focused wording, and changes in the way thoughts and feelings are presented through text. Early detection of such depressive symptoms is important because it may reduce symptom severity and improve the quality of life of affected individuals. Picardi et al. [10] highlighted the value of symptom detection in minimizing severity, while Dickinson et al. [11] reported that early intervention may reduce absenteeism and improve workplace productivity. Although these studies provide important psychological and clinical motivation, they do not fully address how automated computational models can detect depressive signals from large-scale social media text.

With the rapid growth of digital communication, researchers have increasingly used social media data to study behavioral patterns related to health conditions [12,13]. Platforms such as Twitter and Facebook allow users to express personal experiences, emotions, and mental states, making publicly available textual data useful for observing depression-related indicators. To improve text-based analysis, word embedding techniques have been introduced to convert words into numerical representations that preserve semantic and contextual relationships. Popular embedding methods such as Word2Vec, GloVe, and FastText [14-16] have been adopted in both machine learning and deep learning models. These representations are useful for mental health-related tasks because they can capture meaningful relationships between emotional expressions, depressive indicators, and contextual word usage.

A number of studies have shown that social media analysis can be used in health monitoring. Prieto et al. [17] used Twitter data to identify health-related issues, while Chunara et al. [18] examined tweets related to cholera outbreaks and showed the broader usefulness of social media for population health monitoring. Similarly, Aladağ et al. [19] analyzed social media content to identify patterns associated with suicidal ideation, and Holleran [20] discussed the relevance of Facebook activity in understanding depression-related health concerns. These studies demonstrate the value of social media as a health-monitoring source, but they provide limited explanation of how textual representations can be improved for accurate automated depression detection.

Traditional machine learning methods have also been widely used for depression detection from text. Almouzini et al. [21] evaluated several machine learning classifiers on Twitter data and reported that the Liblinear algorithm identified 35 depressed users out of 97. Other studies have used support vector machines, logistic regression, and related classifiers for depression-related text classification [22-24]. These approaches helped establish the usefulness of computational techniques in mental health analysis. However, their main limitation is that they often depend on manually designed features, sparse word representations, and limited contextual understanding. As a result, such models may not effectively capture deeper semantic meaning, emotional context, and long-range dependencies present in social media text.

More recent studies have applied deep neural networks to complex data modalities such as text, speech, and images [25,26]. Orabi et al. [27] proposed a deep learning framework for depression detection using social media data and categorized users into depressed and non-depressed groups using data from 154 users. Recent work has also extended depression detection research to underrepresented languages such as Urdu [28-31]. Stephen and Prabu [32] applied RNNs, gated recurrent units, and CNNs to predict depression from Twitter data. Although CNNs are widely known for image processing, they have also been successfully applied to text classification tasks. Zahiri and Choi [33] demonstrated this by applying deep learning models to dialogue data from television scripts for emotion-state identification.

Overall, the reviewed studies show that social media text and deep learning methods are useful for depression detection, but several limitations remain. Existing studies are often descriptive, rely on handcrafted or sparse features, use small datasets, or do not clearly compare embedding-based and non-embedding deep learning models. Therefore, the main research gap is the need for a focused framework that combines word embedding representations with sequential deep

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learning models to capture semantic, contextual, and sequential patterns in depression-related text. The proposed framework differs from prior work by evaluating RNN and LSTM models with and without embeddings and by showing how embedding-enhanced models improve the reliability of automated depression detection from social media text.

The proposed methodology

Machine learning and deep learning methods were utilized to execute the experimental framework of this study on the Google Colab platform, which offers cloud-based computation tools and has a T4 GPU to train models faster. This environment was chosen to allow effective experimentation and reproducibility and to manage the computational requirements of deep learning models. A systematic, stepwise approach was followed in the evaluation and comparison of the performance of several neural architectures, such as RNNs, LSTM networks, and embedding-enhanced versions of such networks. All models were trained and tested on a collection of textual data gathered from social networks, the purpose of which is to understand the linguistic patterns of depressive expressions.

The recent progress in the fields of computational linguistics and representation learning opens up the possibility of analyzing textual data in greater detail, thus being able to identify subtle patterns associated with mental health problems. This task is best performed with deep learning models, which acquire hierarchical representations of language by using multiple processing layers. The different layers store varying degrees of semantic and contextual information, and the models can identify complex dependencies in a text. Such models have a high potential to identify depression-related indicators accurately when trained on large and diverse sets of data. These capabilities have driven the increased use of deep learning methods in the analysis of mental health, especially on tasks that require unstructured analysis of text in large volumes.

Data Gathering

The process of data acquisition is one of the essential steps of the given approach because the quality and the format of the dataset are the main determining factors of model performance. The data used in this research came from the publicly accessible Kaggle repository, and it consists of Twitter posts that were annotated based on the presence or absence of signs of depression. Each text instance is provided with a binary label as originally annotated in the Kaggle dataset: label 1 indicates that the post contains depression-related expressions, while label 0 indicates that the post does not contain depression-related expressions. Table 1 shows the record distribution between the two categories. There are 134,347 posts in the dataset; among them, 68,676 posts are characterized as being in the depressive category, and 65,671 posts are characterized as belonging to the non-depressive category.

Category	Number of Posts
Depression (1)	68,676
Non-Depression (0)	65,671

TABLE 1: Distribution of records in the Twitter depression dataset

The current work, as opposed to previous research where sampling was frequently used or smaller sets of data were employed, makes use of the entire dataset to maintain representational variety and minimize sampling bias. The gathered data are unstructured in nature and have a large variety of linguistic differences, informal expressions, and social media text noise. Consequently, extensive preprocessing is necessary prior to model training so as to guarantee coherence and efficient feature derivation.

Data Preprocessing

Before training the model, the textual data are subjected to various preprocessing steps designed to enhance the quality of the data and ensure consistency in input representation. These steps are required to minimize noise commonly found in social media text and to make downstream learning models more effective. First, the text samples are tokenized into individual words, and all tokens are converted to lowercase to maintain uniformity throughout the corpus. Social media-specific elements are also handled carefully: URLs and user mentions are removed because they usually do not contribute directly to depression classification, while hashtags are retained after removing the “#” symbol so that emotionally meaningful words can still be used. Emojis and emoticons are converted into their corresponding textual meanings wherever possible, as they may contain important emotional signals. Informal slang and abbreviated words are normalized to their standard forms, and negation words such as “not,” “never,” and “no” are preserved because they can change the emotional meaning of a sentence. Stop words with minimal semantic meaning are then filtered, while meaningful psychological and emotional terms are retained. Moreover, words are standardized to their root or base forms so that different inflections of the same word are treated as one word. These preprocessing tasks remove redundant and irrelevant material from the raw text while preserving important emotional and semantic information. The processed data therefore provide cleaner and more structured input to deep learning models, which supports more reliable learning and improved performance.

The complete preprocessing, embedding, model training, testing, and evaluation workflow is presented in Figure 7.

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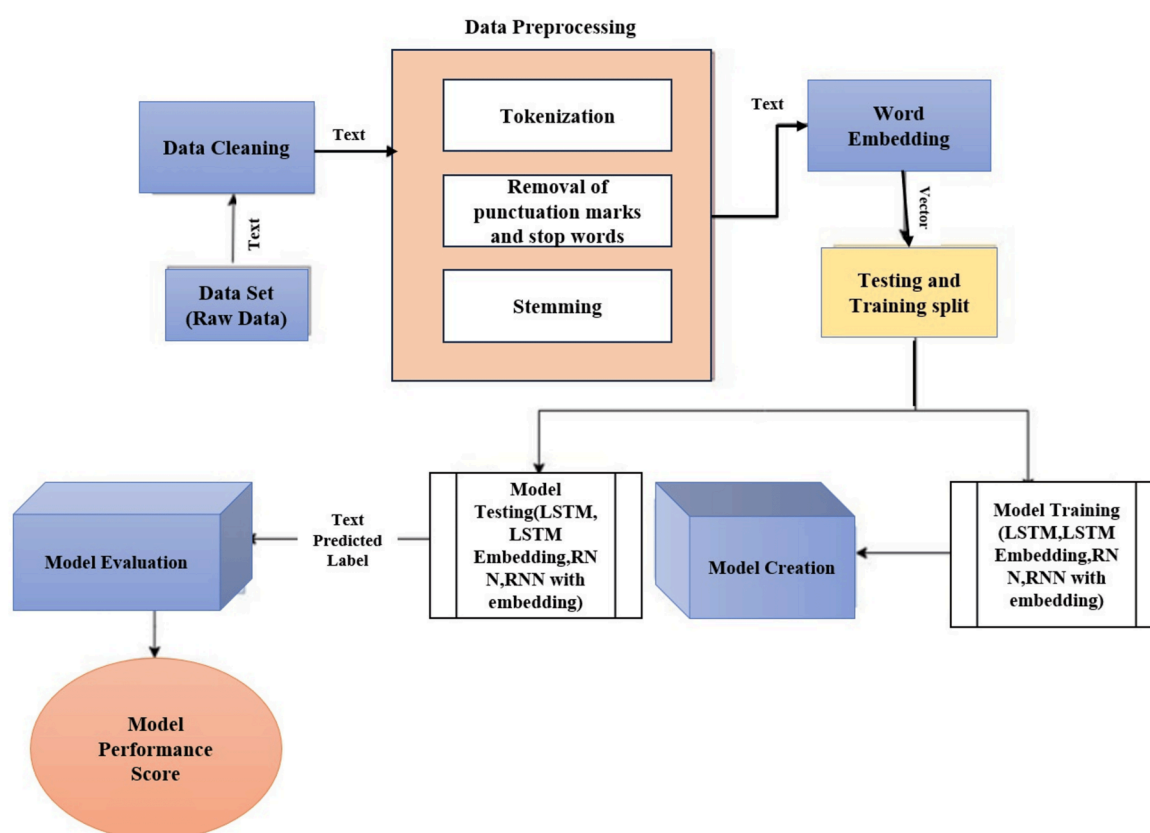


FIGURE 1: Procedure for depression detection using LSTM, LSTM with embedding, RNN, and RNN with embedding

Source: Authors' own illustration based on the experimental workflow used in this study.

LSTM, Long Short-Term Memory; RNN, Recurrent Neural Network

Model selection

This paper aims to critically review the performance of various popular deep learning networks in NLP tasks associated with depression detection. In this regard, the study focuses on four lightweight recurrent architectures: basic RNNs, RNNs with word embedding layers, LSTM networks, and LSTM networks with embeddings. RNN- and LSTM-based models were selected because they are suitable for sequential text modeling, can capture word-order information in short social media posts, and require fewer computational resources than transformer-based models. Transformer-based models are not included in the present scope and are considered for future work. All the models were executed in Python and the Keras deep learning framework, which guarantees coherence in experimental conditions. The choice allows the comparative study of sequential modeling with and without representation embedding. Each of the architectures is described in the subsections below, starting with the RNN model.

RNNs

RNNs are created to handle sequential data, such as text, speech, and time-series data. In contrast to feedforward neural networks, RNNs have recurrent connections within the network, which allow the network to store information related to the past time steps as a hidden state. RNNs can be used in situations where contextual relationships between sequences

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are required, as this mechanism can be used to model these relationships. This makes RNNs applicable to applications that involve knowledge of temporal or sequential relationships, such as language modeling and sequence prediction.

Despite their usefulness, standard RNNs face well-known challenges when applied to long sequences. In particular, issues related to vanishing and exploding gradients during training can hinder the network's ability to capture long-range dependencies. As a result, information from earlier time steps may be lost as the sequence length increases, leading to degraded performance. To overcome these limitations, more advanced recurrent architectures, including LSTM networks and gated recurrent units, were proposed. These models introduce specialized gating mechanisms that enable more effective retention and regulation of long-term contextual information in sequential data [34,35].

RNN With Embeddings

RNNs augmented with word embedding representations are widely used in NLP tasks because they combine semantic understanding with sequential modeling. Word embeddings represent words as dense numerical vectors that preserve semantic similarity and contextual relationships between terms [36]. These representations provide richer input than sparse encodings, allowing the model to better capture meaningful patterns in text.

When integrated with an RNN architecture, word embeddings enable the network to learn how semantic information from earlier tokens influences subsequent elements in a sequence. This integration improves the model's ability to interpret contextual dependencies within textual data and leads to more informative sequence representations compared to RNNs operating on raw or sparse inputs [34].

LSTM

LSTM networks extend the basic RNN architecture by explicitly addressing the limitations encountered when modeling long input sequences. Standard RNNs often fail to retain information from earlier time steps due to the vanishing gradient problem, which reduces the influence of distant inputs during the learning process. LSTM networks mitigate this issue by incorporating a structured memory component that enables selective retention, updating, and propagation of information over extended temporal spans.

An LSTM model is organized as a sequence of memory cells that process input data incrementally. Each cell contains a set of gating mechanisms that regulate the internal flow of information, namely the forget gate, input gate, and output gate. The forget gate determines which elements of the previous memory state should be preserved or discarded, while the input gate controls the extent to which new information is written into the memory. The output gate governs how much of the updated memory state is exposed as the hidden representation for the next time step. The overall structure and internal functioning of the LSTM network are illustrated in Figure 2 and Figure 3.

The forget gate evaluates the relevance of information from the previous cell state based on the current input and the preceding hidden state. Its operation is defined by Equation (1). The input and output gates further coordinate the memory update process and the generation of the hidden state, allowing the network to maintain long-term contextual information while adapting to new inputs. Through this gated mechanism, LSTM networks are able to effectively learn long-range dependencies and complex temporal patterns in sequential textual data.

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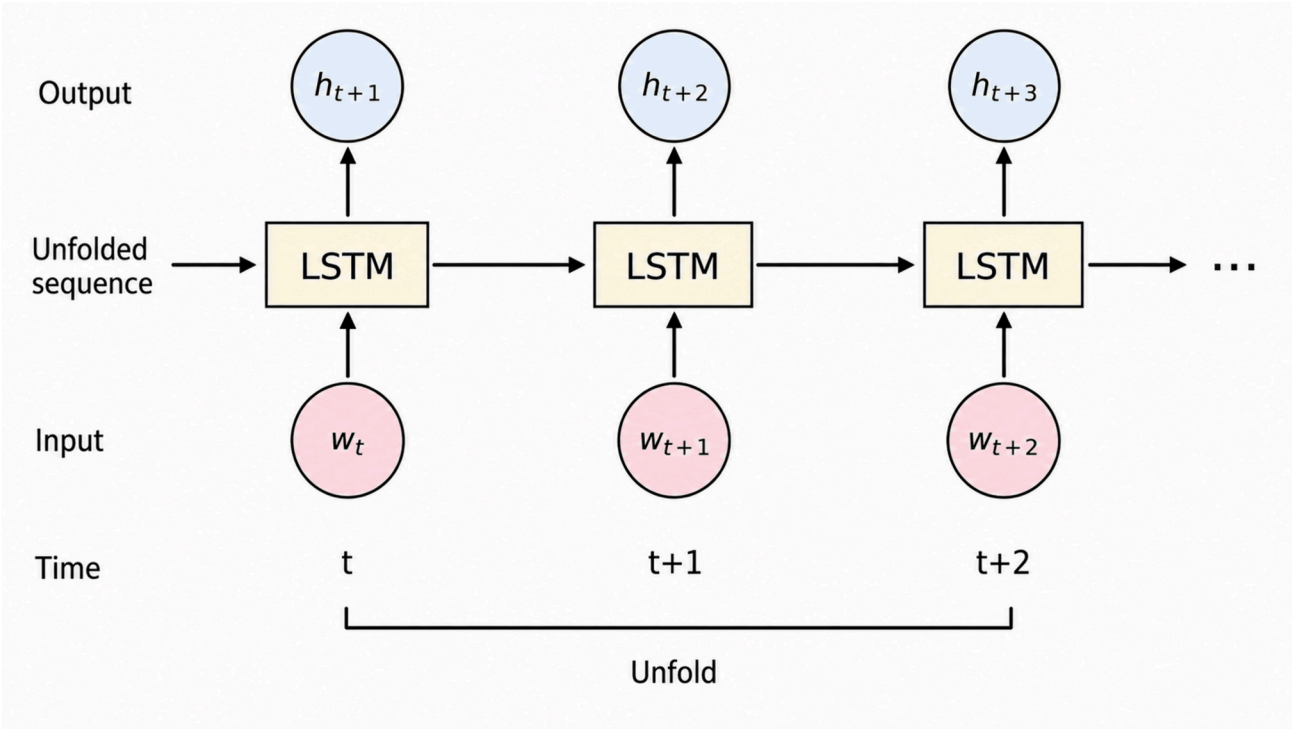


FIGURE 2: Surface architecture of Long Short-Term Memory (LSTM)

Source: [37]

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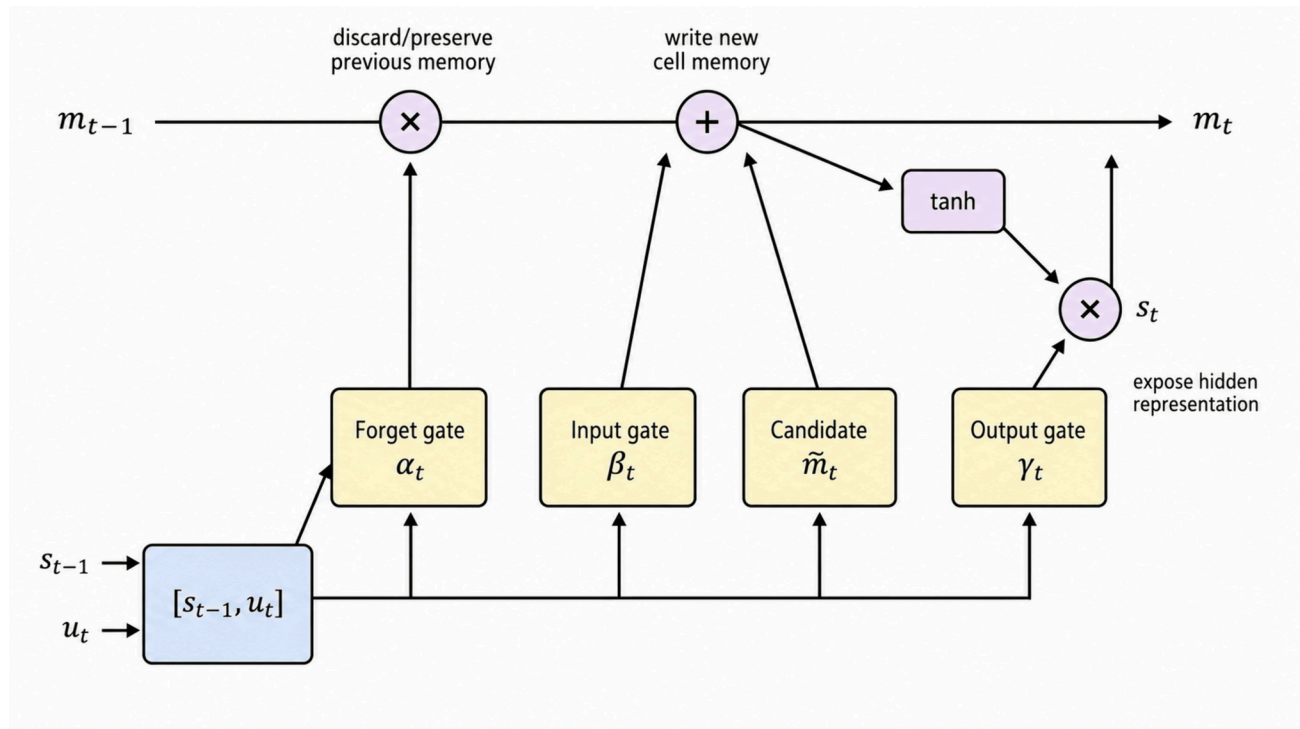


FIGURE 3: Single-cell architecture of Long Short-Term Memory

Source: [38]

The LSTM gate operations are mathematically expressed as follows:

[Forget gate: $\alpha_t = \sigma(A_\alpha[s_{t-1}, u_t] + d_\alpha)$

[Input gate: $\beta_t = \sigma(A_\beta[s_{t-1}, u_t] + d_\beta)$

[Output gate: $\gamma_t = \sigma(A_\gamma[s_{t-1}, u_t] + d_\gamma)$

[Memory cell state update: $m_t = \alpha_t \odot m_{t-1} + \beta_t \odot \tanh(A_m[s_{t-1}, u_t] + d_m)$

[Hidden state computation: $s_t = \gamma_t \odot \tanh(m_t)$

where α_t , β_t , and γ_t denote the forget, input, and output gate activations at time (t), respectively. The function $\sigma(\cdot)$ represents the sigmoid activation function. A_α , A_β , A_γ , and A_m are trainable weight matrices, while d_α , d_β , d_γ , and d_m are bias vectors. s_{t-1} is the previous hidden state, u_t is the input vector at time (t), and m_t and m_{t-1} represent the current and previous cell memory states, respectively. The function $\tanh(\cdot)$ denotes the hyperbolic tangent function, and $\odot$ represents element-wise multiplication.

LSTM With Embeddings

The LSTM with embeddings model combines two widely used components in NLP: distributed word representations and recurrent sequence modeling. Word embeddings map words into low-dimensional numerical vectors that encode semantic similarity and contextual relationships, such that words with related meanings are positioned close to one another in the embedding space [36]. These representations provide a richer and more informative alternative to sparse encoding schemes.

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LSTM networks complement this representation by modeling sequential dependencies in text. Through their gated memory structure, LSTMs retain relevant contextual information across time steps while selectively discarding less informative content [35]. When integrated, embeddings serve as meaningful inputs to the LSTM, enabling the network to learn both semantic and temporal patterns within textual data. This combined approach has proven particularly effective in applications involving emotion analysis and the early identification of mental health conditions, including depression.

Data and code availability

The dataset used in this study was obtained from the publicly available Kaggle dataset "Depressive/Non-Depressive Tweets Data" [39]. The dataset was preprocessed and used for training and evaluating the proposed deep learning models.

Model evaluation

The proposed models were evaluated using a held-out test dataset to assess their classification performance. Standard evaluation metrics, including accuracy, precision, recall, and F1-score, were employed to capture different aspects of model behavior in distinguishing between depressive and non-depressive text. In addition to these quantitative measures, confusion matrices were generated to examine the distribution of correctly and incorrectly classified instances across both classes.

Together, these evaluation criteria provide a comprehensive understanding of model performance and support a comparative analysis aimed at identifying the most effective approach for depression detection using social media text.

Results And Discussion

Experimental setup

All experiments were conducted in Google Colab using Python with the Keras/TensorFlow deep learning framework and T4 GPU acceleration. The full dataset contained 134,347 labeled tweets and was divided using an 80:20 train-test split, resulting in 107,464 training instances and 26,883 testing instances. Text samples were converted to lowercase, tokenized, cleaned by removing punctuation and stop words, stemmed, and converted into word embeddings where applicable. The processed data were then used to train four models: RNN, RNN with embeddings, LSTM, and LSTM with embeddings. The models were evaluated using accuracy, precision, recall, and F1-score to enable a clear comparison of classification performance.

The comparative evaluation showed noticeable performance differences among the evaluated models. In particular, the embedding-enhanced RNN and LSTM models achieved better overall performance than their corresponding non-embedding versions. The LSTM model with word embeddings produced the strongest classification results, as reflected in the confusion matrix shown in Figure 4. The improvements in accuracy, precision, recall, and F1-score indicate that word embeddings helped the models capture semantic meaning and contextual relationships within the text more effectively.

In contrast, the non-embedding RNN and LSTM models showed comparatively lower performance because they relied primarily on sequential word patterns without richer semantic representations. These findings support the observation that embedding-enhanced deep learning models are more effective for depression detection from social media text. Overall, the results indicate that combining recurrent architectures with word embedding representations improves the reliability and consistency of automated depression classification.

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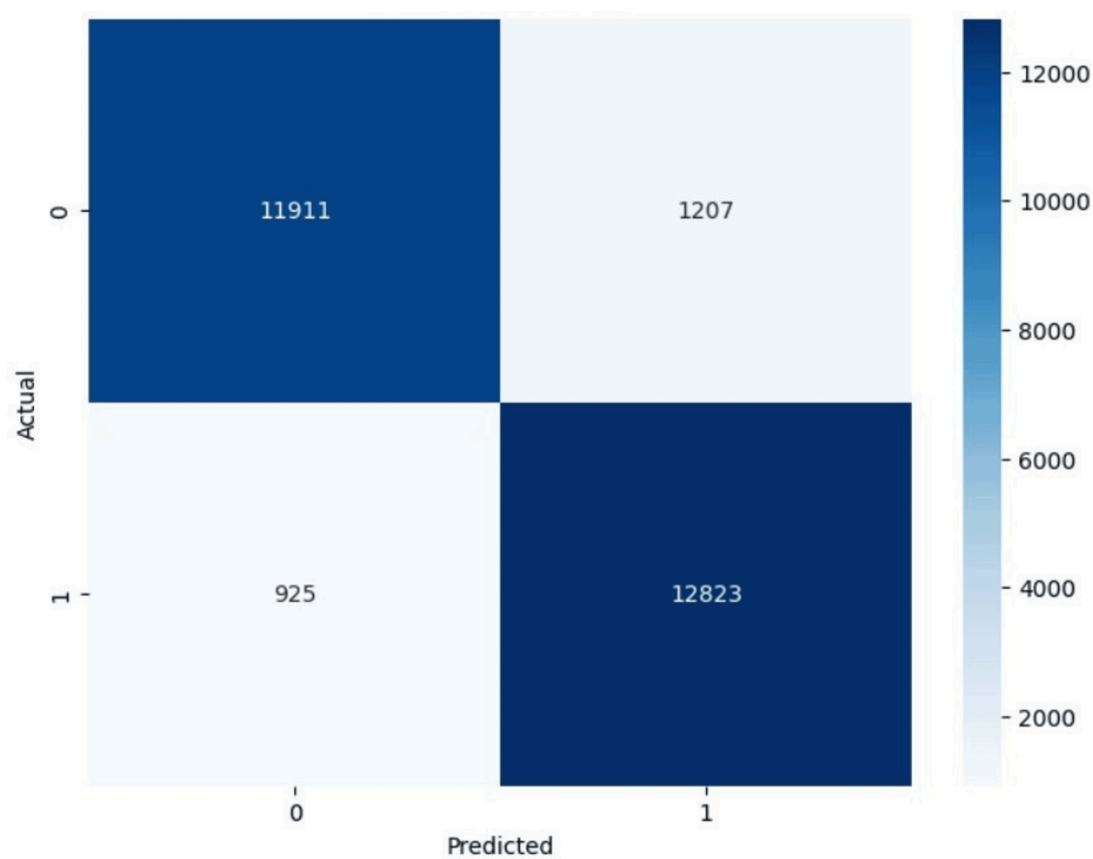


FIGURE 4: Confusion matrix of the Long Short-Term Memory model with embeddings

Source: Author-generated from the test-set predictions of the present experiments.

Figure 5 presents a comparative view of training accuracy across different models, highlighting differences in convergence behavior and learning efficiency.

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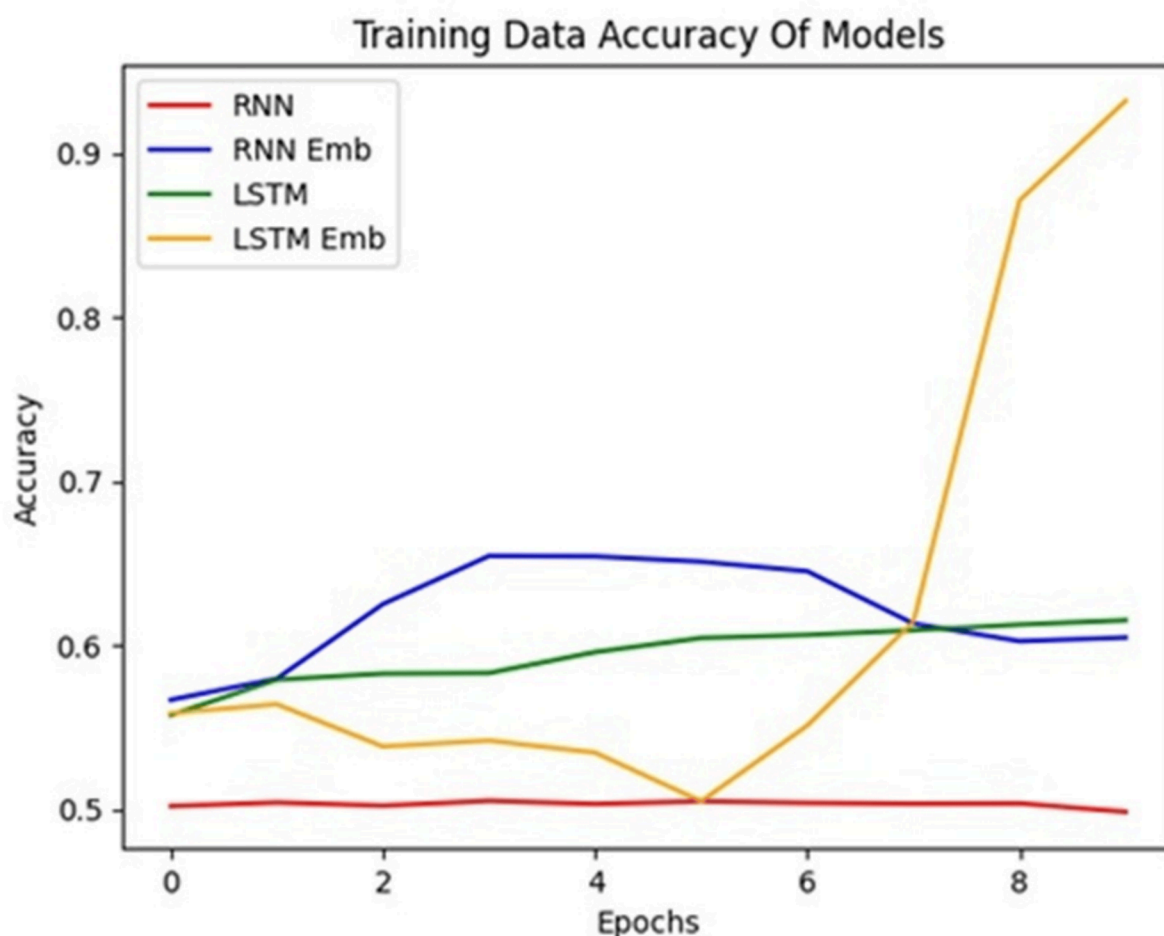


FIGURE 5: Training accuracy comparison of evaluated models

Source: Author-generated from the test-set predictions of the present experiments.
LSTM, Long Short-Term Memory; RNN, Recurrent Neural Network

Drawbacks

Even though the proposed approach shows promising results, several limitations should be acknowledged. User interaction patterns and linguistic expressions vary considerably across social media platforms, which may limit the external validity of models trained on data from a single source. Moreover, social media text is often informal, rapidly evolving, and highly contextual, making consistent feature extraction challenging. These limitations should be addressed in future research. Potential improvements include developing platform-specific modeling strategies and incorporating richer linguistic, temporal, and contextual features to enhance model robustness, adaptability, and generalization.

Conclusions

This paper explored how deep learning methods can be used to identify depression early on in social media text using NLP techniques. A set of neural structures was investigated, i.e., RNNs, LSTMs, and their variants with embedded features, so as to evaluate their comparative strengths in recognizing depression-related linguistic patterns. The experimental findings suggest that word embedding-based models always perform better than the non-embedding models because the former can semantically represent and understand the context better. The LSTM architecture with embeddings had the most consistent overall performance. These findings highlight the potential of NLP-based deep learning models as a

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supportive system in primary mental health diagnosis. The suggested framework is text-centric, but future studies can build upon the presented literature and add other types of data, including images and speech indicators. The use of multimodal information can also enhance the detection accuracy and help create more adaptable and comprehensive mental health monitoring models. These developments would provide improved support to clinicians and researchers in decision-making, but would still be ethically and responsibly oriented.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Parveen Kumari, Alpana Jijja

Acquisition, analysis, or interpretation of data: Parveen Kumari, Alpana Jijja

Drafting of the manuscript: Parveen Kumari

Critical review of the manuscript for important intellectual content: Parveen Kumari, Alpana Jijja

Supervision: Alpana Jijja

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

Acknowledgements

The authors gratefully acknowledge the 2nd International Conference on Engineering and Technology for Sustainable Future (ICETSF 2026) for selecting this research work and providing the platform for its submission for publication consideration in Cureus Journal.

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How to cite this article:

Kumari P, Jijja A (July 13, 2026) Depression Detection From Social Media Text Using Embedding-Enhanced Long Short-Term Memory and Recurrent Neural Network Models. Cureus J Comput Sci 3 : es44389-026-00156-1. DOI <https://doi.org/10.7759/s44389-026-00156-1>

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