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A Comparative Study of Deep Learning Methods for Depression Detection in Social Media Data

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Abstract

With the rise of social media platforms like Twitter, Reddit, and Facebook, individuals increasingly share personal information about their moods, behaviors, and mental states. This trend provides a unique opportunity to leverage large-scale textual data for understanding and monitoring mental health conditions, particularly depression, a prevalent and challenging mental health issue. Traditional depression assessments are often confined to clinical environments and lack the capacity for real-time monitoring. In contrast, social media provides a continuous, real-time stream of information that could be harnessed for early detection and intervention. This research aims to develop an advanced depression detection model tailored specifically for social media text by utilizing state-of-the-art Natural Language Processing (NLP) and deep learning techniques. Unlike traditional feature engineering-based methods, this study focuses on deep learning frameworks, which can capture nuanced linguistic patterns indicative of depressive symptoms without manual intervention. The research will explore various architectures, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models, incorporating strategies like attention mechanisms, transfer learning, and hybrid approaches to enhance accuracy.

Keywords: Machine learning, deep learning, depression, healthcare, mental health diagnosis

INTRODUCTION

Various mental disorders such as depression affect a person‘s emotional, social, and psychological well-being. Depression is one of the most widely known mental disorders and reports have stated that it might as well be the most prevalent mental disorder by 2030 [1]. Depression ranges from mild, temporary episodes of sadness to severe, persistent states often referred to as Clinical or Major depression (MD) [2]. Usually identified through symptoms of deep sadness, and loss of interest in day-to-day social activities, depression, if not properly diagnosed, may result in constant feelings of suicidal ideation and suicide attempts [3]. Therefore, the early detection of depression is of high importance.

For depression detection using machine learning techniques, two main steps are usually employed. Initially, implicit and explicit data are collected in various formats such as visual, acoustic, and textual formats, during the process of answering specific questions. Signal data can also be collected from wearable devices for this purpose. In some cases, like that of the Distress Analysis Interview Corpus (DAIC), one of the most popular open-access depression datasets, text transcripts were extracted from the recorded audio data to enhance diagnostic accuracy, and visual features were also extracted [4].

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In the second step, various machine learning/deep learning algorithms are then employed to analyze depression severity based on the collected data. Although with the high advancement of research in this area, and the development of new machine learning techniques, significant challenges remain in the practical implementation and attainment of diagnostic accuracy.

In recent years, Natural Language Processing (NLP), a branch of Artificial Intelligence (AI) technologies, has played an essential role in supporting the analysis and management of large scale textual data and facilitating various tasks such as information extraction, sentiment analysis, emotion detection, and mental health surveillance. Detecting mental illness from text can be cast as a text classification or sentiment analysis task, where we can leverage NLP techniques to automatically identify early indicators of mental illness to support early detection, prevention and treatment. Figure 1 provides an overview of textual mental illness detection from social media, which consists of datasets (such as Twitter, Reddit), pre-processing, model development (machine learning-based models or deep learning-based models) and model evaluation. Advances in NLP technologies and deep learning models explain the increased interest in investigating novel methods for detecting mental illness. Deep learning-based methods, for example, Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN) etc. are gradually replacing feature engineering-based methods since deep learning frameworks allow models to automatically capture features without the need for time-consuming feature engineering. Furthermore, when trained on mental healthcare datasets, pre-trained language models (PLMs) such as BERT, RoBERT a and Mental BERT, have achieved competitive performance on mental illness detection, demonstrating their potential value.

RELATED WORK

Previous studies have focused on exploring linkages between mental health symptoms and patient language to detect depression [5, 6]. Picardi *et al*. showcased the importance of early screening of depressive symptoms to increase the quality of life [7]. Rost *et al*. conveyed the importance of early intervention in the case of depression which leads to a decrease the absenteeism and ultimately helps in the growth of productivity [8].

With the increase in Internet usage [9, 10], researchers concentrated more on social networks to identify patterns and traits of various illnesses [11, 12]. The rapid expansion of social media usage has made it possible to study depression and mental illness. In particular, previous studies considered social media platforms as tools to observe how depressed people behave through the texts and messages they share.

Word embeddings are a way of word representation that enables similar-meaning entities to have comparable representations. These word embeddings are expressed as real-valued vectors in finite determined vector space. Many researchers choose popular embeddings like Word2vec, Glove, and fast text among the word embeddings [13–15]. Machine learning or deep learning models utilize these word embeddings to solve a specific task.

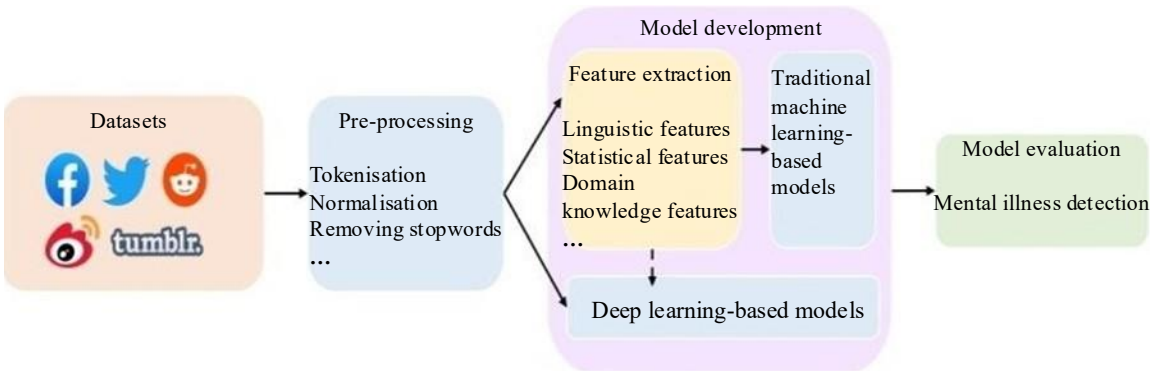

Figure 1. An overview of depression detection from social media text.

Twitter and Reddit held a solid position in popularity by attracting many users. Twitter data in Japanese was used by Tsugawa *et al*. to identify those who were suicidal as well as those who were depressed [16]. According to Reece *et al*., there is a 0.87 AUC chance that depression can be detected early from Twitter data [17].

Prieto *et al*. created a technique to identify health issues by examining the use of Twitter [18]. Chunara *et al*. concentrated on cholera-related tweets [19], and Aladağ *et al*. read the posts to identify the pattern for preventing suicide attempts [20]. Holleran concluded depression as a significant contributor to worldwide disease respective to work on Facebook [21]. Shen *et al*. created a multi-modal depressive model to identify those with depression [22].

The information gathered from a Reddit source was used in various tests by Pirina and Coltekin [23]. They clarified that the Reddit source is the ideal platform for producing more excellent results. They discovered that corpora are vital in identifying depression and that any divergence from the recommended choice may result in misunderstandings. Shen and Rudzicz described Reddit as the favored source for getting data on various aspects from which they extracted information for anxiety disorders [24]. They concluded that combinational models produce good results.

Islam *et al*. used Facebook to detect depression on social media [25]. They used the K-nearest neighbor for detecting depressed emotions. Peng *et al.* suggested a multi-kernel SVM-based model for extracting different forms of characteristics from social media accounts to represent users' circumstances [26]. To detect depression, Almouzini *et al*. employed Random Forest, Naïve Bayes, and Liblinear to find the depression from the tweets [27]. They found 35 depressed Twitter users and 62 non-depressed people. Liblinear algorithm is considered the best among the implemented algorithms. Most models used to identify depression are ML classifiers [28–30].

The advent of Deep Neural networks has shown its mark in various text processing, speech, and image analysis tasks [31, 32]. Deep neural network architecture was suggested by Orabi *et al*. to identify users who exhibit symptoms of mental illness [33]. The research is primarily concerned with identifying users suffering from depression. They used a test dataset of 154 users to diagnose them as controlled or depressed. Many researchers are trying to identify mental illness problems considering social media, including not frequently used languages such as Urdu [34–37].

With the help of deep learning approaches, including RNN, GRU, and CNN, Stephen and Prabu created a predictive model for depression by scraping tweets [38]. CNN has shown its incredible mark in image processing [39]. Its significance in that domain has also laid its path in text processing [40, 41]. Zahiri *et al*. examined TV show scripts to predict the carrying emotion in the script using deep learning techniques [42].

Some studies have focused on the extraction of features and then the train of shallow ML classifiers. For instance, Tadesse *et al*. extracted n-grams via the TF-IDF approach, LIWC features, and LDA topics [43]. Then, they trained LR, SVM, random forest (RF), AdaBoost, and multilayer perceptron (MLP). Results showed that the bigram features trained on an SVM classifier achieved 80.00% accuracy, while the best accuracy accounting for 91.00% was achieved by exploiting the MLP classifier with all the features, i.e., LIWC, LDA, and bigrams. Liu and Shi [44] extracted a set of textual features, namely, part-of-speech, emotional words, personal pronouns, polarity, and so on, and a set of features indicating the posting behavior of the user, i.e., posting habits and time [45]. Next, feature selection techniques were applied, including recursive elimination, mutual information, and extreme random tree [46]. Finally, Naive Bayes, the k-nearest neighbor, regularized LR, and SVM were used as base learners, and a simple LR algorithm was used as a combination strategy to build a stacking model [47].

Recently, deep learning approaches have been introduced, since they obtain better performance than the traditional ML algorithms and do not often require the tedious procedure of feature extraction. For example, Wani *et al*. represented words as word2vec and TF-IDF approach and trained a deep neural

network consisting of CNNs and LSTMs [48]. Park *et al*. collected a dataset consisting of posts written by people, who suffer from mental disorders, including depression, anxiety, bipolar, borderline personality disorder, schizophrenia, and autism [49]. This study developed six binary classification models for detecting mental disorders, i.e., depression versus non depression, and so on. Specifically, the authors utilized the TF-IDF approach and trained an XG Boost classifier. Next, the authors used the word2vec and trained a CNN model.

Naseem *et al*. reformulated depression identification as an ordinal classification problem, where they used four depression severity levels [50]. The authors introduced a deep neural network consisting of a text graph convolution network, bidirectional long short-term memory (BiLSTM), and attention layer. A similar approach was proposed by Ghosh and Anwar, where the authors extracted features and trained LSTMs for estimating the depression intensity levels [51]. A hybrid deep neural network consisting of CNN and BiLSTM was introduced by Kour and Gupta [52]. Zogan introduced the first dataset including posts from users with and without depression during COVID-19 and presented a new hierarchical CNN [53]. An emotion-based attention network model was proposed by Ren *et al*., where the authors extracted the positive and negative words and passed them through two separate BiLSTM layers followed by attention layers [54].

Ensemble strategies have also been explored in the literature. This means that multiple models are trained separately and the final decision is taken usually by a majority voting approach. For instance, an ensemble strategy was introduced by Ansari *et al*. [55]. First, the authors exploited some sentiment lexicons, including AFINN, NRC, SenticNet, and multi perspective question answering (MPQA), extracted features, and applied principal component analysis for reducing the dimensionality of the feature set. An LR classifier was trained using the respective feature set.

Next, the authors trained an LSTM neural network coupled with an attention mechanism. Finally, the authors combined the predictions of these two approaches via an ensemble method. Also, an ensemble approach was proposed by Trotzek *et al.* [56]. First, the authors trained an LR classifier using input user-level linguistic metadata. Specifically, the authors extracted LIWC features, the length of the text, four readability scores, and so on. Next, the authors trained a CNN model. Finally, the authors combined the outputs of these approaches via a late fusion strategy, i.e., by averaging the predictions of the classifiers. Figuerêdo *et al*. designed a CNN along with early and late fusion strategies [57]. Specifically, the authors exploited fast Text and GloVe embeddings. In the early fusion approach, multiple word embeddings were concatenated and passed to the CNN model. In the late fusion strategy, a majority-vote approach was performed based on the predictions of multiple CNN models. The CNN model comprised a simple convolution layer, max-pooling, fully connected layers, and concatenated rectified linear units as the activation function.

Explainable approaches have also been introduced. DeSouza *et al*. introduced a stacking ensemble neural network, which addresses a multi label classification task [58]. Specifically, the proposed architecture consists of two levels. In the first level, binary base classifiers were trained with two distinct roles, i.e., expert and differentiating. The expert base classifiers were used for differentiating between users belonging to the control group and those diagnosed with anxiety, depression, or co morbidity. The differentiating base models aimed at distinguishing between two target conditions, e.g., anxiety versus depression. In the second level, a meta-classifier uses the base models' outputs to learn a mapping function that manages the multi label problem of assigning control or diagnosed labels. The authors used LSTMs and CNNs. Finally, this study explored Shapley additive explanations (SHAP) metrics for identifying the influential classification features. Zogan *et al*. also proposed an explainable approach, where textual, behavioral, temporal, and semantic aspect features from social media were exploited [59].

A hierarchical attention network was used in terms of explainable purposes. A hierarchical attention network was also used by Uban *et al*., where the authors extracted a feature set consisting of content,

style, LIWC, and emotions/sentiment features [60]. An interpretable approach was proposed by Song *et al.*, where the authors introduced the feature attention network [61]. The feature attention network consists of four feature networks, each of which analyzes posts based on an established theory related to depression and a post level attention on top of the networks. However, this method did not attain satisfactory results [62–65].

Multimodal approaches combining both text and images have also been proposed. For instance, a multimodal approach was introduced by Bhattacharyya *et al*. for detecting depression in Twitter [66]. Specifically, the authors utilized the user's description and profile image. The authors used the IBM Watson Natural Language Understanding tool and extracted sentiment and emotion information for all user descriptions along with the possible categories (at most three) that the description may belong to. Next, the authors designed a neural network consisting of BiGRU, attention layers, convolution layers, and dense layers. The authors used GloVe embeddings. The proposed architecture can predict whether the user suffers from depression or not as well as predict the sadness, joy, fear, disgust, and anger score.

Li *et al*. exploited text, pictures, and auxiliary information (post time, dictionary, and social information) and used attention mechanisms within and between the modalities at the same time [67]. The authors exploited Text CNN, ResNet-18, and fully connected layers for extracting representation vectors of text, images, and auxiliary information, respectively. A multimodal approach was proposed by Cheng and Chen, where the authors exploited texts, images, posting time, and the time interval between the posts on Instagram [68]. Tang *et al*. collected multimodal datasets and extracted six depression-oriented feature groups, namely, social network, user profile, visual, emotional, topic level, and domain-specific features [69]. Gui *et al.* combined texts and images and proposed a new cooperative multi agent reinforcement learning method [70].

Multitask approaches have been introduced. A multitask approach was introduced by Zhou *et al*. [71]. Specifically, the authors proposed a hierarchical attention network consisting of BiGRU layers and integrated LDA topics. The main task was the identification of depression, i.e., binary classification task, while the auxiliary task was the prediction of the domain category of the post, i.e., multiclass classification task. Both multitask and multimodal approaches were introduced by Wang *et al.* [72]. The authors extracted a total of 10 features from the text, social behavior, and pictures. XLNet and BiGRU coupled with attention layers, and dense layers were used.

PROBLEM DEFINITION

Depression is a pervasive mental health disorder affecting millions globally, with severe consequences for individuals and society. Early detection is crucial for timely intervention, yet traditional diagnostic methods often fail to capture early signs due to stigma, limited access to mental health services, and the reluctance of individuals to seek help [4]. Social media has emerged as a platform where users frequently express their emotions, thoughts, and mental states, making it a potential tool for detecting early signs of depression. However, identifying depression from social media text presents several challenges.

This research aims to bridge this gap by developing a robust depression detection model tailored to social media text. By leveraging improved deep learning techniques, the model will capture subtle linguistic cues indicative of depression, surpassing limitations of conventional natural language processing (NLP) models. This investigation is particularly relevant given the unstructured and diverse nature of social media language, which requires advanced algorithms to discern meaningful patterns effectively. Furthermore, improved accuracy in detecting depressive language online could offer significant benefits in public health monitoring and early intervention strategies, ultimately contributing to more accessible mental health support systems.

There is a need for an improved, accurate, and scalable model capable of detecting depression in social media text, leveraging the latest advancements in deep learning and natural language processing

(NLP) [6]. By incorporating advanced architecture such as transformers and attention mechanisms, and addressing issues related to data imbalance and feature extraction, this research aims to build a robust system that can detect depressive tendencies more effectively and with greater sensitivity.

Despite significant advancements in natural language processing (NLP) and machine learning, several research gaps persist in the domain of depression detection from social media text. First, most existing depression detection models rely heavily on standard NLP techniques that may fail to capture the nuanced language used in social media, where expressions of mental health symptoms can be subtle, context-dependent, and highly varied across individuals. This leads to a substantial gap in the accurate detection of depression signals amidst the diverse and informal language commonly used online.

Secondly, a gap exists in models' generalizability and adaptability to new data, as the majority of current approaches do not effectively address the rapid evolution of online language, slang, or regional dialects. Most models are trained on static datasets, which may limit their effectiveness when applied to real-world, dynamic social media environments. Additionally, few studies have incorporated advanced deep learning methods, such as attention mechanisms, hybrid architecture, or Transformer models, that could offer a more robust understanding of context and sentiment in social media text.

Another key research gap is the limited use of multimodal data. Although text alone provides valuable insights, combining text data with other contextual signals, such as time-based activity patterns or interaction data, could yield a more comprehensive and accurate understanding of depression indicators. Furthermore, existing models often overlook the ethical considerations involved in analyzing social media for mental health insights, including user privacy and consent.

DEEP LEARNING TECHNIQUES FOR DEPRESSION DETECTION

In recent years, deep learning techniques have gained significant attention and success in a variety of domains, including natural language processing (NLP), where they are revolutionizing the way we analyze and interpret large volumes of text data. These techniques, which are a subset of machine learning, model complex patterns and representations in data, allowing systems to learn from raw data with minimal human intervention. For the task of depression detection from social media text, deep learning offers powerful tools to identify subtle patterns in language that may not be easily detectable by traditional approaches.

One of the primary deep learning techniques used in this domain is *Recurrent Neural Networks (RNNs),* specifically *Long Short-Term Memory (LSTM)* networks. LSTMs are designed to capture long-term dependencies and contextual information in sequential data, such as text. Social media posts often contain nuances and contextual information that require an understanding of previous words or sentences, making LSTMs ideal for modeling such dependencies. LSTMs have been widely used in sentiment analysis and emotion detection due to their ability to remember important information over long sequences of words, making them effective for depression detection in text.

To improve the model's performance and address challenges like vanishing gradients, *Bidirectional LSTMs (BiLSTMs)* and *Gated Recurrent Units (GRUs)* are also used. These models process the input sequence in both forward and backward directions, allowing them to capture context from both past and future words, enhancing their ability to understand the meaning behind the text more comprehensively.

Another important technique in this area is the use of *Convolutional Neural Networks (CNNs),* which are typically employed for image data but have also shown success in text classification tasks. In depression detection, CNNs are used to extract higher-level features from text representations, such as word embeddings, by applying convolution operations over the input text to detect relevant patterns in the sequence. CNNs can help identify local patterns in the text, such as recurring phrases or terms associated with depressive sentiment, which can be crucial for classification tasks.

Additionally, *Attention Mechanisms* have proven to be highly beneficial when combined with RNN-based models like LSTMs. Attention mechanisms allow models to focus on the most relevant parts of the input text while ignoring less important information. In the context of depression detection, attention can help the model identify which words or phrases in a social media post are most indicative of depressive thoughts, enabling more accurate predictions.

Furthermore, *transformer-based models,* such as *BERT (Bidirectional Encoder Representations from Transformers),* have become state-of-the-art in NLP tasks. These models leverage large-scale pre-trained language models to capture the semantic meaning of words in context, enabling them to understand subtle linguistic cues and tone, which are key to detecting emotions like depression in text. Fine-tuning these pre-trained models on depression-specific datasets has shown to significantly improve the performance of the detection models.

Hybrid models: Hybrid architectures combining CNNs with RNNs/LSTMs or Transformer layers will be explored to enhance feature extraction from social media text.

Various deep learning techniques, including LSTMs, BiLSTMs, CNNs, attention mechanisms, and transformer-based models, can be explored and integrated to develop a robust depression detection model. The goal is to leverage the strengths of these techniques to accurately identify signs of depression in social media posts, providing a powerful tool for early intervention and depression detection.

CONCLUSION AND FUTURE SCOPE

For various reasons, patients tend to give false reports on their mental status when answering questionnaires during depression screening, this tends to result in wrong diagnosis thereby putting such a patient at greater risk of the highly destructive state of suicidal ideations and suicide attempts. It is therefore important to develop methods that can be used to counter such negatives that come with using preset depression questionnaires. It is in this regard that we propose a variant of the cross-modal attention network to effectively capture telltale symptoms of depression from patients' speech and text. This research focuses on addressing the critical challenge of early depression detection from social media text using improved deep learning techniques. Social media has become a major platform where individuals express their thoughts and emotions, offering a rich source of data for mental health monitoring. However, the informal and often ambiguous nature of social media language presents significant challenges for traditional machine learning models in detecting depression accurately.

By leveraging advanced deep learning architectures such as transformers (e.g., BERT, GPT) and incorporating natural language processing techniques, this research aims to develop a more accurate and sensitive model for depression detection. The proposed model will not only enhance the ability to capture subtle linguistic patterns but also tackle common issues such as data imbalance in mental health datasets. This work holds the potential to offer a scalable and automated solution for identifying depressive tendencies, providing a tool that could support mental health professionals in making timely interventions. In conclusion, this research is a step forward in utilizing cutting-edge AI techniques for improving mental health care. By providing a more robust framework for detecting depression from social media text, it aims to contribute to the broader goal of early diagnosis and intervention in mental health treatment.

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