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An embedded LSTM based scheme for depression detection and analysis

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Abstract

Depression also known as depressive disorder is a serious and common medical condition that has an adverse impact on how you feel, think, and behave. But it can also be treated. Depression causes feelings of sadness or a loss of interest in activities once you enjoyed. It can impair your ability to perform at work and at home and cause a number of mental and physical issues. Therefore, it is important to provide some solutions to overcome the depression problem. These days' information and communications technology (ICT) is used in various domains to sort out their problems. In this paper, we propose an embedded long short-term memory (LSTM) based scheme for depression detection and analysis. It is a brain health mapping based system for the detection of depression. It is a first of its kind interdisciplinary brain cognition tool (software), which acts as a personalized support intelligence mechanism. It incorporates psychological traits for determining a user's mental health state. The proposed scheme utilizes natural language processing techniques to provide a novel framework to predict the sentimental and emotional state of the user based on the user's behavior in their interaction with the designed model. In order to actively track the user's mental state, proposed scheme analyses their text and identify specific keywords through the text that they input in different applications that the user utilizes in their machine. The practical implementation of the proposed scheme is provided and important results (i.e., accuracy and F1 score) are estimated. During the performance comparison, it has been observed that proposed scheme achieved better accuracy than the other existing schemes.

Keywords: Artificial Intelligence (AI); deep learning; depression detection; psychology;

1. Introduction

Artificial Intelligence (AI) as the name suggests, is the science and engineering of making machines intelligent, and enabling them to have the capacity to behave and act independently with minimal human interaction. AI uses the disciplines of computer science, psychology, sociology, philosophy, linguistics, human biology and various mathematical functions to solve problems that are generally not plausible for humans to solve with conventional

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methods. AI is an emerging trend being employed in every domain from medicine and home appliances to auto driving cars and armed forces. Using in conjugation with different fields like Internet of Things (IoT) and cyber security, it is becoming a part of every task that is done in technical and non-technical fields [1].

Deep Learning is the sub branch of Machine Learning using advanced computing techniques to help the computer learn trends and patterns that are used by human brains to learn by example. It consists of layers containing neurons mimicking brain neurons which get activated using mathematical activation functions and uses backward propagation to manage weights and improve accuracy using multiple rounds of training. These training or epochs uses massive data that undergoes many hidden layers and convolution layers to find relation between data values and the final predictive class. Specifically, we use Long-Short Term Memory (LSTM) networks, which are a category of neural networks that are capable of learning long-term dependencies and have a memory unit to store information called cell state [1], [2]. Depression, often known as a depressive disorder, is a serious mental illness that has an impact on a person's thoughts, feelings, and behavior in day-to-day situations. It typically results in a state of disassociation and an emotional low with feelings of grief, overload, and loss of desire in activities that were once enjoyed in the majority of circumstances, depending on the patient in context. It is crucial to identify this psychological disorder since it can cause unwelcome suffering, have major consequences if treatment or medication is not used to treat it, interfere with a person's daily activities, and even endanger their lives.

Typically, a depression detection mechanism can make the use of natural language processing and LSTM models to extract the tone and aspects like urgency and intentions based on predictive analysis of the user's mind [20].

Depression detection using sentiment analysis is done by training model to classify positive depression and related psychological disorders.

1.1. Motivation

Depression and related psychological disorders are on the rise and these conditions degrade a person's daily life. There is an urgent need to keep tabs on people's actions and mental health and using automated software that can operate in the background can help track this status with a high tolerance and accuracy. Also most of the pre-existing software tools don't have security schemes incorporated as they often send the data out of user's device and this private data could be misused to perform directed advertisement or leakage of banking and financial information. Therefore, in this paper, we focus on the designing of an embedded LSTM based scheme for depression detection and analysis.

1.2. Research contributions

The research contributions of the paper are given below.

- We propose an embedded neural network scheme that detects depression from text sequence that can extract the emotional context.
- In lieu of depression detection we propose a workflow that provides complete monitoring of a person's behavior and analyze it in background with calling and takes measure to not send the private data out of the user's device.
- We also evaluate the designed scheme on the Reddit data-set to evaluate its resilience and to retrieve exceptional results as compared to existing schemes due to involvement of batch normalization and dropout layers.
- The practical implementation of the proposed scheme is provided and important results are estimated.
- The performance comparison of the proposed scheme with the other similar existing schemes has also been conducted.

1.3. Structure of the paper

The details of other related schemes are given in Section 2. The architecture of the proposed scheme is given in Section 3. The details of the proposed scheme are given in Section 3. The details of the practical implementation of the proposed scheme are given in Section 4. The details of conducted comparisons are given in Section5. Finally, work is concluded in Section 6with some concluding remarks and future work.

2. Related work

Sentiment Analysis of tweets and data has been researched upon from the early 2010's[3]. However primarily depression detection from that sentiment has been researched upon from 2017 onwards with the advent of depression dataset [4][5].

Arora and Arora [6] used multinomial naive bayes and support vector regression and machine learning classifiers to detect depression and anxiety from tweets. Deshpande and Rao [7] used natural language processing (NLP) based emotional AI model working on a pre-computed wordlist to detect depression. On a slightly smaller volume of data specifically on Twitter users in the Indonesian region, Oyong *et al.* [8] demonstrated a lexicon's frequency for weighting calculations to predict depression. Trotzek *et al.* [9] uses an ensemble of both neural network and user-level linguistic metadata is used in combination for depression detection in text and evaluated results.

Vaci *et al.* [10] utilized a Natural Language Processing model on clinical depression related textual data and extract relevant information for detection. Polignano *et al.* [11] used a Bidirectional Long short term model (BiLSTM) in addition to a Convolution Neural Network(CNN) and self-attention with word embeddings for detection of emotion in text. Cong *et al.* [12] also use a BiLSTM model in conjugation with XGBoost algorithm. The XGBoost algoritm helps to deal with with reducing data imbalance issues and BiLSTM to use for classification.

Review Papers [13][14] summarizes work done in the field of sentiment analysis, and emotion detection including depression from text. There is also a discussion of challenges that are faced when research is done in sentiment and emotion analysis. Keshri *et al.* [21] used CNN based classification of human emotion through images based on recognition of facial features.

3. The proposed scheme: An embedded LSTM based scheme for depression detection and analysis

The designing of proposed scheme is done through several phases i.e., dataset acquisition, data preprocessing, and utilization of LSTM model. The architecture of proposed system is given in Fig.1. The details of the given phases are given below.

3.1. Dataset acquisition

We use the Reddit depression dataset [4] for training the deployed model. This dataset acquired by using PushShift API is retrieved from subreddits (online communities). The original dataset included posts from 28 subreddits, includ- ing 15 mental health subreddits. For the evaluation purpose, we use a smaller sized dataset available on Kaggle with 232074 unique posts separated into 116037 non-suicide and 116037 suicide posts. This structured data is full of special characters and is of raw format. It contains user's written posts and their related label of depressive or non-depressive.

3.2. Data preprocessing

To perform detection on the data this raw input data needs to pre-processed by tokenization, cleaning and stemming to make it compatible for our deep learning model. Without it sentiment will not be contextually extracted from the data efficiently.
This process is executed as follows.

3.2.1. Tokenization

Tokenization is the process of converting a piece of text into small units known as tokens. A token can be a word, a word fragment, or just characters such as punctuation. We can train the designed model in the better way through it. Because by analyzing the words in the text, we can easily interpret the meaning of the text because the entire data is better processed individually. We perform this conversion using NLTK library which splits the input data into an array of tokens.

3.2.2. Data-Cleaning

Dataset cleaning is performed to remove special and punctuation characters from the words. These words include symbols like (!./?) that will hamper the modelling of data and do not contribute in extracting the contextual meaning of the data. Cleaning and normalizing this data help to increase the accuracy of our model.

3.2.3. Stemming

Stemming is a technique for removing affixes from words in order to extract their base form. We utilize stemming mechanisms to store the meaning and usage of only the stems, not the entire words. By using stemming, there is reduction in size of the index and dataset with the increment in retrieval accuracy. The example is given below.

Assignment =Assign + ment (here stemmed word is Assign) Eating = Eat + ing (here stemmed word is Eat)
Observing = Observ + ing (here stemmed word is Observ)

These affixes are removed from data using PorterStemmer stemming technique. All these affixes are stored in an input array in the same sequential manner as the original input data.

3.2.4. Embedding

The word embeddings is a technique where textual tokens are converted into a numerical representation in the form of a vector. The vectors attempt to capture various aspects of that word in relation to the overall text. For textual data word embedding in our task, we use GloVe embedding. GloVe (global vectors for word representation) is an unsupervised learning algorithm that aggregates global word co-occurrence matrices from a given corpus of data to generate word embeddings. GloVe word embedding derives the relationship between words primarily from statistics.

GloVe embedding utilizes a Regression Model and is trained on global database of word co-occurrence counts to derive the statistical meaning of words and up to what extent are two words related.

3.3. Utilization of LSTM model

As a starting point, we use the document containing the text inputs. First, we use tokenization to convert the string data to a token of words. Then, we apply padding to convert each text data into a 50-word input array to the model.

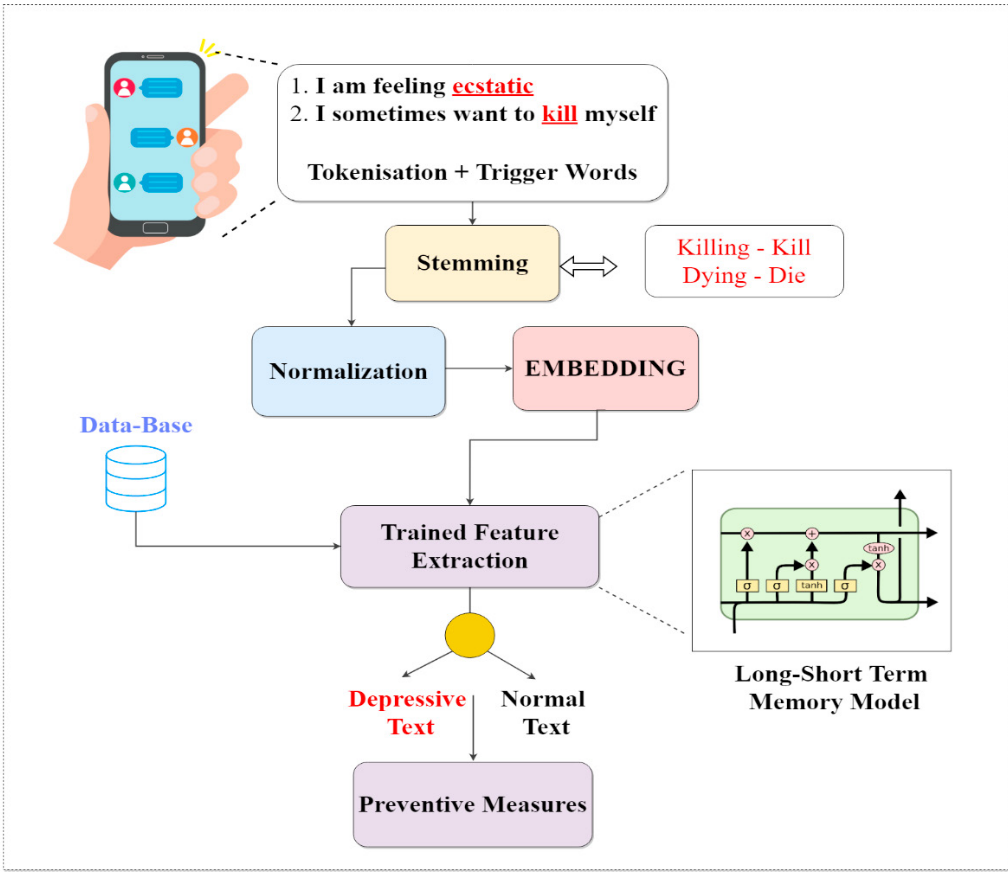

Fig. 1: Architecture of the proposed system

This padding converts the variable sized input data into a uniform sized sentence containing 50 tokens by resizing the input array due to the LSTM model's input layer only being compatible with it.

Next, all of the text is embedded using Glove embedding (global vectors for word representation).

After that we pass our embedded data to an LSTM [20] layer based model, an advanced recurrent neural network which is then passed to a *MaxPooling1D* layer. Our LSTM has 3 gates (Forget, Input and Output gate) for remembering the data while performing backpropagation. We then apply a dropout layer of 0.3 to avoid over-fitting of our data and send it to a dense neural layer that provides 512 as the output size. Then we apply batch normalization layer and repeat by applying a dropout layer of 0.2, followed by a dense layer that provides 256 as the output size. Finally, a dense layer is used that provides output of size 1, which represents the predicted class.

The learning rate, optimizer and epochs that the model has been implemented has been discussed in **Practical Implementation.**

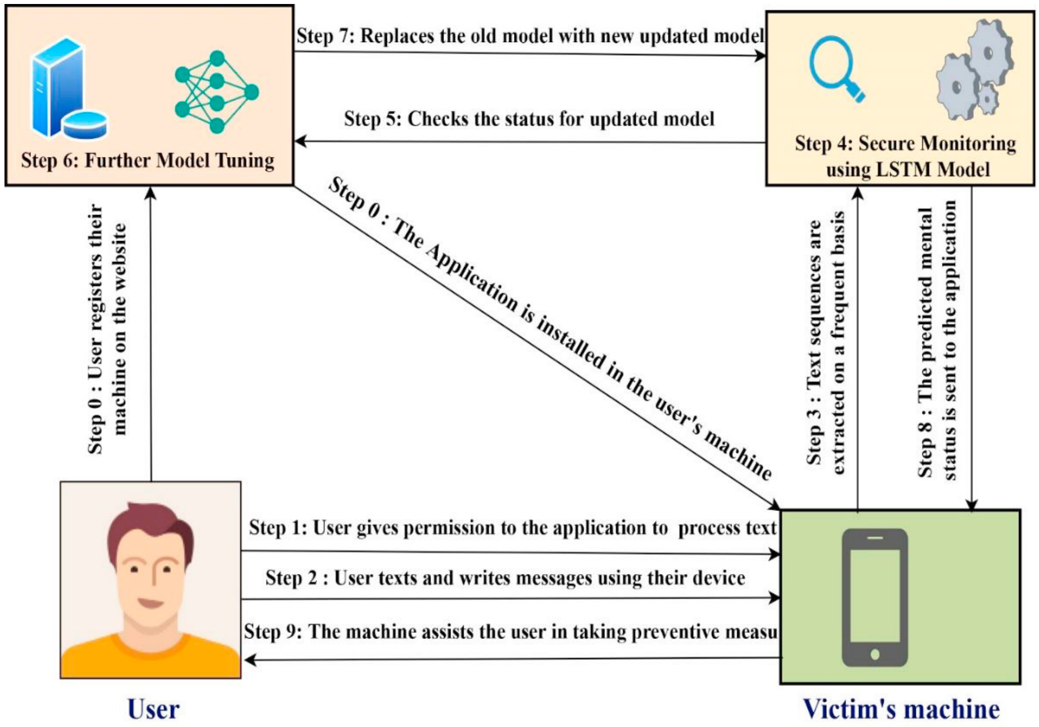

Fig. 2: Process flow diagram of the proposed scheme

Algorithm 1 Data preprocessing

for Given samples **do**
    All indexes and columns except post and class is removed from the dataset.
    Clean and normalize the data by removing stop-words, special characters (!, @, %,).
    Converting everything into lower case.
    The cleaned sequential data is tokenized and converted into stream of words.
    Padding is performed with limit 50 to convert tokenized data into uniform fifty sized input data blocks for the model.
    The processed "posts" columns is converted from words to vectors using GloVe embedding to extract the linear meaning from a global corpus.
    Class is converted from "depressive" and "non-depressive" to 1 and 0 using label encoding for classification.
    We'll get the preprocessed data.
end for

The details of the different activities of the proposed scheme are given in Fig.2. The activities are summarized as follows.

1. The user registers him/ herself via the designed software tool. It then gets installed on the user's device.
2. Next, user gives permission to the application to read and process text.
3. Then the user routinely reads and writes text on their device.
4. This text is extracted by the daemon process of application on a frequent basis.
5. The collected data is processed, embedded and its sentiment is predicted by the application, all without the data being sent out from the user's device.
6. Simultaneously, the application checks in server for any updated neural network model.
7. The model, which is deployed on the cloud server is regularly fine-tuned and updated by the organization.
8. If any new updated model is available, it is then installed in user's device.
9. Then the predicted user's mental status is delivered to the main application by the background daemon process.
10. Based on the analysed user's behavior, preventive measures are taken like suggesting mood-lifting content or booking appointment with their personal psychiatrist (i.e., available doctor).

The details of different processes of the proposed scheme are also given in Algorithm1 and Algorithm2.

Algorithm 2 Depression detection and analysis

1: **for** All users **do**
2: The user registers his/ her machine (device) with organization and installs the application.
3: The application asks for permission to extract the text and process it.
4: **if** Permission is given **then**
5: Goto Step 8.
6: **else**
Goto Step 3.
7: **end if**
8: Activates the daemon application and extracts the input text from user's machine.
9: Pre-processes the text using Algorithm1 and sends prediction back to the main application.
10: Based on the predicted sentiment performs preventive measures to uplift user's mood.
11: Repeat from Step 8 on hourly basis.
12: Check if update of neural network model is available in the cloud server.
13: **if** Yes **then**
14: Goto Step 17.
15: **else**
Goto Step 19.
16: **end if**
17: Fine tune the existing model with new collected dataset values in the cloud server.
18: Update the fine-tuned model in the user's machine.

```
19:     Repeat Step 12 on a weekly basis.
20: end for
```

4. Practical implementation

In this section, we provide the details of the practical implementation of the proposed scheme. The details of utilized simulation parameters are given in Table1. We have used processor of 2 X Intel(R) Xeon(R) with clock of 2.20GHz. The random access memory (RAM) size is of 12 GB. The training environment is Google colab environment. The Ubuntu 18.04.5 LTS platform is considered. The number of epochs have been considered to 120. The cloud server deployment is AWS G5g NVIDIA and T4G GPU. The user machine is Android 8.0 (Oreo) 6 GB. User machine application has been considered as Kotlin Gradle 6.0 version.

Table 1: Details of stimulation parameters

Parameter	Details
Processor	2 X Intel(R) Xeon(R) CPU @ 2.20GHz
Random access memory (RAM) size	12.7 GB (12 GB usable)
Training environment	Google colab environment
Operating system GPU	Ubuntu 18.04.5 LTS
Number of epochs	12 GB NVIDIA Tesla K80
Cloud server deployment	120 AWS G5g NVIDIA T4G
User Machine	GPU
User Machine Application	Android 8.0 (Oreo) 6 GB Kotlin Gradle 6.0 version

For the practical implementation of the proposed scheme, we have trained the neural network on the pre-processed embedded data over 120 epochs with Stochastic gradient descent (SGD) optimizer with 0.05 learning rate and 512 batch size. With these parameters and fitting data, the model provided 94.88% accuracy and 0.9492, 0.9496 and 0.9483 as precision, recall and F1 score respectively. The details are also given in Table2. Moreover, the details of accuracy and loss values in model training history over the 120 epochs are given in Fig.3a and Fig.3b.

Table 2: Obtained results

Accuracy	Precision	Recall	F1 Score
94.88%	0.9492	0.9496	0.9483

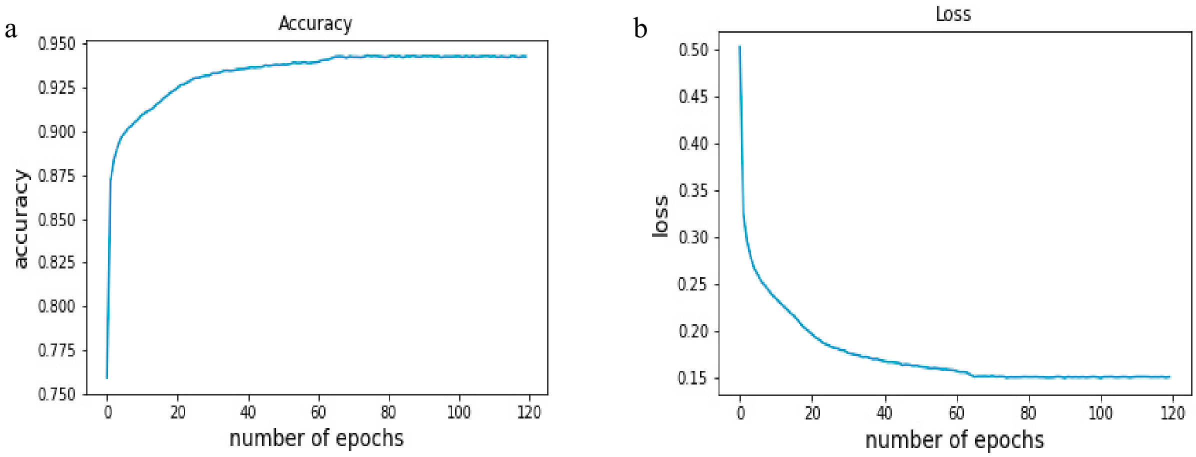

Fig. 3. (a) Accuracy in model training history; (b) Loss in model training history

5. Comparative study

In this section, we provide the details of performance comparison, which has been done among the proposed scheme and other existing schemes. The schemes of Imran *et al.* [15], Katchapakirin *et al.* [16], Cheng *et al.* [17], Rosa *et al.* [18], Ahmed *et al.* [19] and proposed scheme are 69.92, 85.00, 87.17, 89.00, 92.06 and 94.88, respectively. The details are given in Table3. From the Table3it is clear that performance of proposed scheme is better than the other existing schemes.

Table 3: Performance comparison of different schemes

Scheme	Accuracy (in %)
Imran *et al.* [15]	69.92 (with LSTM)
Katchapakirin *et al.* [16]	85.00 (with LSTM)
Cheng *et al.* [17]	87.17 (with BiLSTM)
Rosa *et al.* [18]	89.00(with CNN & BiLSTM)
Ahmed *et al.* [19]	92.06 (with LSTM & CNN)
Proposed scheme	94.88 (with LSTM)

6. Conclusion and future work

An embedded long short-term memory (LSTM) based scheme for depression detection and analysis was presented. It utilized natural language processing techniques to provide a novel framework to predict the sentimental and emotional state of the user based on the user's behavior in their interaction with the designed model. The practical implementation of the proposed scheme was also provided and important results i.e., accuracy, precision, recall and F1 score were computed. During the performance comparison, it was observed that proposed scheme achieved better accuracy than the other existing schemes.

In future, we would like to further improve the accuracy of the designed scheme.

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