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Deep learning based depression detection from social media text

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Abstract. Depression perception be a complex task on social media Complex properties associated with mental illness. There was a recent development in this area of research; social media platforms have established themselves as growing popularity. A basic part of people`s daily life. Social media platforms and their users share goals Relationships where the user's personal life is reflected on these platforms at several levels. Aside from the complexity associated with detecting mental illness through social media platforms, it is inherently difficult to obtain an enough annotated training data, so a supervised deep learning approach such as deep neural networks the implementation has not yet been widely implemented. We tried to find them for these reasons. The most effective deep learning model of the architectures selected in the previous architecture Achievements of supervised learning methods. The selected model will be used for recognition online users showing depression. Due to the limited amount of unstructured text data Extracted from social media text. Recently, Deep learning has been effectively used to a variety of application challenges, including stock market forecasting, traffic flow and accident risk forecasting, and mental disease diagnosis. Furthermore, deep learning has been used to predict sadness on social media and has outperformed classical machine learning method.

Keywords: Deep Learning, Depression Detection, social media, Bi- LSTM, RNN, LSTM, GRU.

1. Introduction

Depression, often known as depressive disorder, is a very prevalent illness. 3.8 percent of the world's population suffers from depression, with 5.0 percentages of adults and 5.7 percentages of people over the age of 60 suffering from it. Depression can have a significant impact on one's well-being and ability to function at job school, and in the family, and can even lead to self-harm [1]. Adolescent depression has been connected to mood disorders and major mental illness in adults. According to the World Health Organization, almost 0.8 million individuals commit suicide each year, and suicide is the fourth highest cause of death among 15–19-year-old. Five of the top major disorders that cause disability or incapacity are mental illnesses, with depression being the most common. As a result, the disease burden associated with depression is enormous. Depression affects around 5% of the adult population in the United States. Early recognition of depressed symptoms, followed by assessment and therapy, can greatly controls the symptoms and the existing condition, as well as attenuate harmful effects on personal, economic, and social life [5].

2. Existing system

Predicting Depression Severity Using Multimodal Functions [1] this study uses support vector machines and multi- characteristic selection strategies in stages to provide a real clinically valid 30 year database of depressed patients and use 30 health care courses. The authors state that the type of statistical features extracted, feature selection based on the t- test, is superior to other methods. Among the various conferencing methods used here, feature integration worked very well with moderate accuracy up to 88%. News and social media are always very cohesive examples of people's lives and conditions [2]. This is often a vast accumulation of knowledge about the behavior of some individuals and can be Victimization, linguistic processing, and deep learning are all employed to detect a range of mental diseases (in this example, depression). [3] The author applied a dictionary and machine learning-based approach to sentiment analysis of tweets using only Bangla's core text. In Recent years, deep learning methods, especially deep learning models based on recurrent neural networks, have led to many successes in mood and emotion analysis.

3. Proposed system

In order to capture the depression of an individual from social media comments, Bidirectional LSTM is a deep learning model that we used (Bi-LSTM) [4]. However, it can only save knowledge from the past and not from the future. We use the Bi- LSTM model for depression categorization on a given input text in the next section. The contextual information can be retained by the Recurrent Neural Network (RNN) for just a short period of time [5]. This problem can be solved by using LSTM, which uses a memory block rather than a simple RNN unit [6]. When compared to LSTM, use the GRU model to train the dataset as quickly as possible [7].

- Dataset Collection
- Data pre-processing
- Algorithm

3.1. Dataset Collection

Downloaded the dataset from kaggle (social media comments) in total, the dataset consists of nearly 4000 English text. Where60% of texts were used as a training dataset and 40% of texts were testing Datasets. Here, N and Y are denoted as labels.

3.2. Data Preprocessing

Data transformation and normalization are examples of pre- processing. URLs, Emojis, mentions, and stop-words were deleted from the dataset to clean it. The text in each row of the dataset was then tokenized by dividing it up into tokens or words. The tokenized words were then submitted to stemming and lemmatization. To extract characteristics from the stemmed input text, the One-Hot technique was applied to it. The characteristics were binary patterns that might be used to predict depression using a machine learning prediction model [8-9].

3.2.1. Tweet that needs to be pre-processed. I was 14 when I was diagnosed with PTSD and severe depression. I'm now almost 20. So I'll tell you what I'll do. I will take - @rregulusblack

3.2.2. Tweet after pre-processing. I was when was diagnosed with ptsd and severe depression I am now almost so I will tell you what i will do i will take

Predicting Depression Severity Using Multimodal Functions [10] this study uses support vector machines and multi- characteristic selection strategies in stages to provide a real clinically valid 30 year database of depressed patients and use 30 health care courses. The authors state that the type of statistical features extracted, feature selection based on the t- test, is superior

3.3. Architectures

3.3.1. Recurrent neural network. RNNs are a powerful and dependable type of neural network, and they are one of the states of art algorithms now in use as they are the only ones having an internal memory. The internal memory makes the RNNs recall important details about the input they receive, let them predict what will happen next with a high degree of accuracy. This is the reason for the choice for audio, video, weather, time series, speech, text, financial data and a variety of other sequential data types. In comparison with other algorithms, recurrent neural networks could develop a considerably more comprehensive grasp of a sequence and its environment [11]. A single time step of input is delivered to the network during RNN training. Then, using a set of current input and the prior state, determine its current state. For the next time step, the current ht becomes ht-1. To solve the problem, one can go through as many time steps as necessary and integrate information from all previous occurrences. The output is calculated using the final current state after all of the time steps have been completed. An error arises when the output is compared to the expected outcome. The error is then passed back to the network, which updates the weights and trains the network (RNN). The important aspect of a Recurrent NN is that each piece of information is remembered by RNN over time. Because of its ability to recall past inputs, it is only important for time series prediction. The recurrent neural network is paired with convolutional layers to increase the effective pixel neighbourhood. Gradient vanishing and exploding are two drawbacks of Recurrent Neural Networks. When using tanh or relu as an activation function, training an RNN is difficult since it cannot handle very long sequences. Gradient vanishing and exploding are two drawbacks of Recurrent Neural Networks. When using tanh or relu as an activation function, training an RNN is difficult since it cannot handle very long sequences. RNNs contain a kind of internal memory that allows earlier inputs to influence future predictions. If you know what the preceding words were, it's much easier to predict the following word in a phrase with greater accuracy. The sample RNN architecture is given in Figure 2.

3.3.2. Long Short Term Memory. A recurrent neural network is a type of long short term memory. In the current RNN *phase*, the output from the previous step is used as input. The LSTM was designed by Hoch Reiter & Schmidhuber [12]. It dealt with the problem of RNN long-term reliance, in which the RNN is unable to predict words stored in long-term memory but can make more accurate predictions using current input. As the gap length increases, RNN is not capable to deliver a better performance. By default, the LSTM can keep the information for a long time. It is used for time-series data processing, prediction, and classification. There are three gates in LSTM,

i. Forget Gate: The inputgate feeds important information to the cell state.
ii. Input Gate: The forget gate removes information from the cell state that is no longer helpful.
iii. Output gate: The output gate's job is to extract meaningful information from the current cell state and display it as output.

LSTMs are a great option for identifying suicidal ideation in social media texts. One of the strengths of LSTMs is the prevention of vanishing or explosive gradients commonly found in RNN models. In many areas, LSTMs outperform traditional feed- forward neural networks and RNNs. This is due to their ability to memories patterns selectively over long periods of time.

3.3.3. *Bidirectional Long Short Term Memory.* The practice of allowing any neural network to retain sequence *information* in both backwards (future to past) and forwards (present to future) orientations is known as bidirectional long-short term memory (bi-lstm) (past to future).

In this model input runs in two directions which distinguish it from a conventional LSTM. With a LSTM, input flows in one direction, either forwards or backwards. We may, however, have information flow in both directions with bi-directional input, maintaining both the future and the past information.

The results reveal that BiLSTM-based modeling, which incorporates additional data training, provides better forecasts than normal LSTM-based models. In particular, it was discovered that BiLSTM

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models outperform ARIMA and LSTM models in terms of prediction [13]. Bidirectional recurrent neural networks (RNN) are created by joining two separate RNNs. At each time step, this structure allows the networks to have both backward and forward knowledge of the sequence [14]. Your inputs will be handled in two directions when you use bidirectional: past to future and future to past. The difference between this technique and the unidirectional is that the backward LSTM saves information from the future, whereas to use both hidden states preserves information from the past and future at any period in history [15].

3.3.4. Gated Recurrent Unit. The Gated Recurrent Unit Network is a lesser-known but equally effective version (GRU) [16]. Differing from LSTM, it has three different gates and does not maintain track of the Internal Cell State [17]. The data stored in the Internal Cell State of an LSTM is given in the Gated Recurrent Unit's concealed state [18]. The data is consolidated and sent to the next Gated Recurrent Unit. The following are the several gates of a GRU:

i. Update Gate
ii. Reset Gate
iii. Current Memory Gate

The Update Gate(z) specifies how much past information must be passed on to future generations [19]. In an LSTM recurrent unit, it's similar to the Output Gate. The Reset Gate(r) specifies how much of the previous knowledge should be forgotten. It is similar the way how LSTM recurrent unit put together the Input Gate and the Forget Gate. Memory Gate currently in use on Gated Recurrent Unit Network, it is frequently disregarded [20]. It is considered as part of the reset gate component, much as the Input Modulation Gate of the Input Gate and it is used to bring non-linearity into the input as well as make the input Zero-mean [21]. The other important reason for making it as a sub-component of the Reset gate is to decrease the impact of previous data on current data being sent to the future. The amount of previous data that should be deleted is determined by the Reset Gate(r). It is similar to how an LSTM recurrent unit combines the IG and FG. Current Memory Gate is sometimes omitted in discussions of Gated Recurrent Unit Networks [22].

4. Result and discussion

We tested four kinds of deep learning architectures and also compared them. The proposed Bi-LSTM RNN model achieves 99.6% accuracy in our testing. Other LSTM architectures has 99.0 % accuracy, GRU also has 99.0 % accuracy, and RNN has 98.0 % accuracy. Bi-LSTM outperformed all these architectures in terms of accuracy. The graphs below demonstrate the accuracy of our models. Results are depicted in Table 1.

Table 1. Results of various models.

S.No	Model	Accuracy(%)
1	RNN	98
2	LSTM	99.0
3	GRU	99.0
4	Bi-LSTM	99.6

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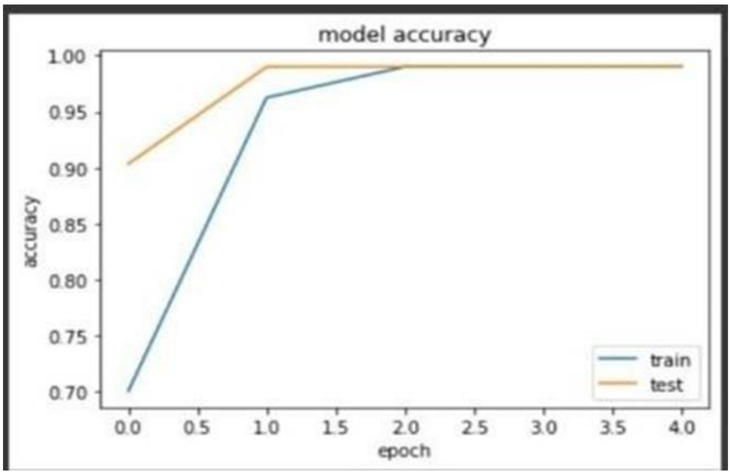

Figure 1. RNN – Accuracy vs Epoch.

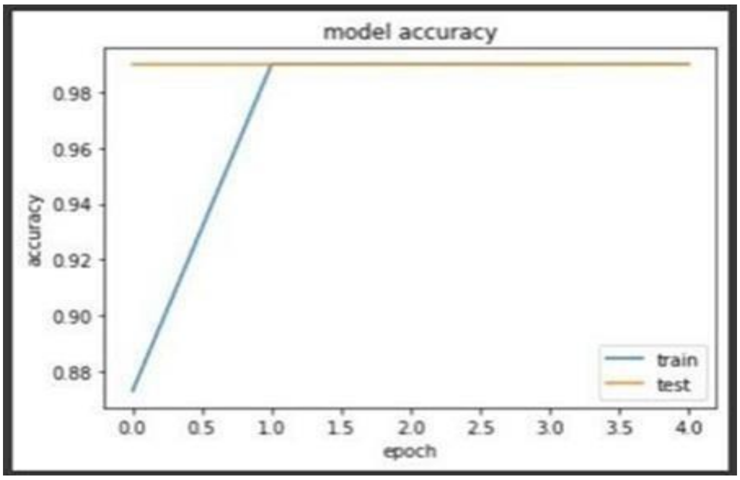

Figure 2. LSTM – Accuracy vs Epoch.

Figure 1 and 2 represents the graph of accuracy vs epoch for RNN and LSTM architecture respectively.

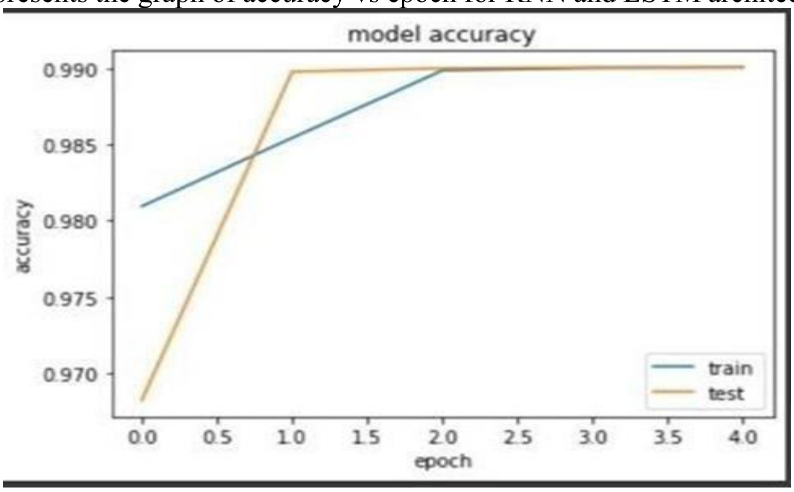

Figure 3. GRU Accuracy vs Epoch.

Figure 3 and 4 represents the graph of accuracy vs epoch for GRU and Bi-LSTM architecture respectively.

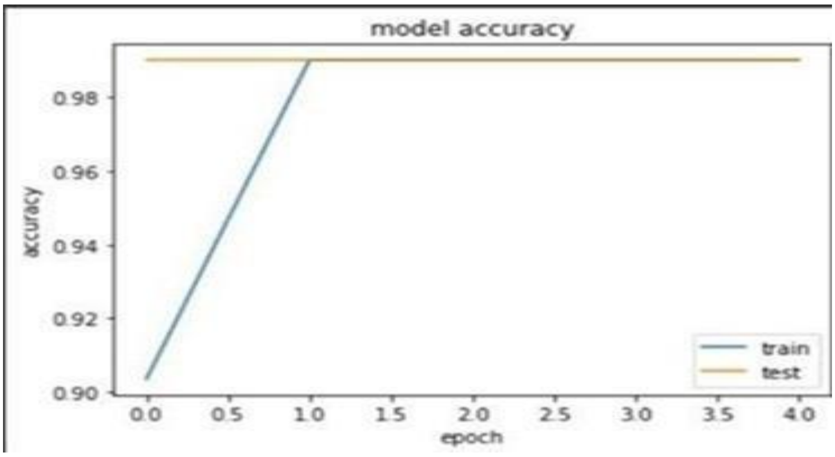

Figure4. BiLSTM Accuracy vs Epoch.

Figure 5 shows the comparison of different models.

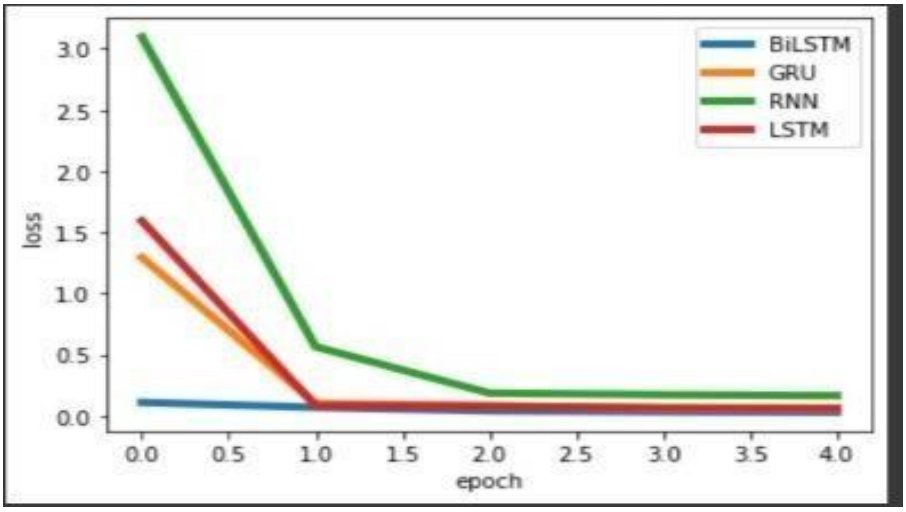

Figure 5. Comparison.

5. Conclusion

Among the most tough tasks to address is depression detection from language. Nonetheless, we attempted numerous ways to identify sadness in the text. Our goal was not only to properly diagnose sad people, but also to shorten the time it took to anticipate their status. After experimenting with several methodologies, we discovered that Bi-LSTM performs effectively. Our limits are that, even when users are accurately categorized, detecting them as depressed takes too long.

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