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Prognostic of depression levels due to pandemic using LSTM

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Abstract Depression is a medical illness that affects the way you think and how you react. It is a serious medical issue that impacts the stability of the mind. Depression occurs at many stages and situations. With the help of classification, the stage of depression the person is in can be tried to categorize. Nowadays, many users are sharing their views on social media, and it became a platform for knowing people around us. From the data that is shared on social media, the depressing posts are being classified using machine learning techniques. With these reports collected, the depressed person might be helped from making any sudden decisions. So, in our research study, the large datasets of the people in depression during the COVID-19 pandemic situations is analyzed and not in pandemic situations. Here to analyze the data, the neural networks have been trained with the current pandemic analysis report, and it has given a prediction that the people are less likely to get depressed when they are not in a pandemic situation like COVID-19.

Keywords:- Depression; Long short-term memory; Recurrent neural network; Preprocessing; Feature extraction; Visualization

1 Introduction

Depression is a common mental disorder. It is seen in all ages nowadays. According to the World Health Organization (WHO), 264 million people of all ages suffer from depression. Depression affects the functioning of the nervous system. It lasts very long. The major problem that comes with depression is the lack of proper diagnosis for this. There are different kinds and stages of depression. Some people did not identify the correct stage or suggest the correct type. The extreme stage of depression can lead the person to attempt suicide. In a study conducted, it is known that 7.2% people are affected with this disease starting at the age of 12. So, there is no age limitation for the depression. But it is considerably high in medieval people. The major depressive period is the highest among individuals between the age of 18 and 25 according to a study conducted. Women are said to have 8.7% depression rate while men are having a depression rate of 5.3%. This study shows that women are getting more depressed than men due to many factors.

Depression first affects the mood of the person[1], and it makes the person feel sad or depressed. It might affect the body as the person changes the appetite, losses interest in activities, and has trouble in sleeping. This may also lead to suicidal thoughts. Depression is different from having sadness and grief. Depression is the second most common illness in the world said by the World Health Organization (WHO). It is more prevalent in the world. It can be tested through direct physical interaction with the psychiatrist and analysis provided by them. It is believed that depression is caused due to chemical imbalance caused in the brain, but it is not caused due to that[2]. Many other factors can cause depression. It can be caused due to the stressful life, mental illness, and medications which add on lead to depression.

For this extreme point of the study, people interactions gave us a report of reasons for the cause of the depression which is joblessness, loss of loved ones, health problems, money issues, etc. The ultimate stage of their depression is that they start questioning their existence in life and starts comparing their life with others.

Many researchers made a strategical analysis by taking social media posts[3,4] and measuring the depression levels by different machine learning approaches[5]. This related work on the depression and getting an analysis of the data is the main approach of our research work. By comparing the report of depression levels in pandemic days and predicting that the depression levels would be less if there is no pandemic.

So, for all this analysis, the neurons have been trained with the current report of depression levels at the pandemic stage COVID-19. Based on those training, our model predicts that the depression rates will be less if there is no pandemic situation. In the final stage of predictions, the output is got in the form of graph model like a visualization report. Here, long short-term memory (LSTM) algorithm is used for training and building our model. This model can be used for prediction of stock prices[6] which recurrently checks the real price of stocks.
The LSTM RNN makes the classification of timely changing factors like the psychological series[7] which changes according to the reason of depression that they are in. After an in-depth survey on LSTM[8,9] RNN methods, it is found to implement this technique in providing statistics of depression levels by using the count obtained through the examination of depression.

2 Procedure

2.1 Importing All the Packages

To process our model, the required packages are needed to import for training the data in the LSTM algorithm. Here, in this model, NumPy has been imported for calculating high mathematical functions in making the data values into matrices and also for multidimensional array. The pandas, matplotlib, and sklearn for making regression and clustering algorithms have also been imported for the representation of the data in a graphical way. LSTM have been imported for this model for training the previous dataset sequentially to predict the next dataset within the provided constraints.

2.2 Importing Datasets

For making sure of our model, the dataset have been imported which have been got from the recent survey done with some individuals during the pandemic situations. This survey gave the data rate which contains the depression levels and their reasons for the depression. The dataset taken contains depression reason with the depression level value. The survey was taken during the pandemic situations like COVID-19.

2.3 Preprocessing and Feature Extraction

After importing packages and datasets, need to do scaling, centering, and also normalize the raw data in the dataset. The whole dataset is not needed for making predictions of depression levels if there is no pandemic situation. So, the data will be preprocessed by localization of depression levels of individuals and to scale it for feature extraction of raw data. Since this preprocessing and feature extraction role is the keen step for the entire model to progress the raw data.

2.4 Working Principle

When started to import all the necessary packages, datasets, preprocessing is the crucial stage for the extraction of the data and to allocate for sequential training of the available dataset. LSTM algorithm is a part of the recurrent neural network (RNN)[10]. This algorithm solves our daily ways of approaches by predicting the previous memory. For example, take cricket world cup matches which are held every year, having all the records of previous matches, if trying to predict which team is going to win this year's match, can be predicted it by the performance of that country in previous matches. It all happens in the gap while thinking of the winning possibility of that country. LSTM model here checks sequentially with every previous data.

The model is made to train with the dataset which selects the depression value as an attribute. This code of LSTM is trained with the dataset along with its reason for depression. So for further analysis of data, it keeps on training the data with depression value and reason for depression.

Here, in our model of code, the training of the previous report is made on depres-sion levels of the individuals during the pandemic situation. It stores the data of the particular person at that particular time. It is nothing like the history of depression levels which are trained in every iteration. For the LSTM[11] model, it stores the long-term memory, and it only happens because of their default nature. RNN makes the recurrent analysis of each neuron module with the data using every single layer[12]. The main point in LSTM is the cell state C_{S-1} which adds or removes the data if needed. The depression levels will not be high in the future if there is no pandemic situation. The possibility is that it can be high or cannot be high, but it will not be like '0' or '1.' So, these acts as gates for the process whether the data can be added as depression values at that period of time. This is like predicting the situation with no pandemic. So, if the model is trained with the depression values during pandemic days, then when tested with no pandemic days, the model forgets the old depression value and checks whether it can be the new value of depression or not, and finally adds that value as a new cell state C_S [13].

$$\text{forget layer}_s = \sigma\left(W_f.\left[h_{s-1}, x_s\right] + b_f\right) \tag{1}$$

Here, LSTM has the interactive layers where continuous or recurrent analysis is made with depression values. The state value is got by training the depression values of the pandemic situation based on their reason. The first step of the LSTM model is to decide whether to take the value for future prediction of data. So through Eq. 1, the model is being made to get into a decision either to keep the value for prediction of future or to neglect it. It is also called a decision taking layer as h_{s-1}, x_S together makes with sigmoid function[13].

Equation 2 acted as the input layer for taking data. This layer only takes values that are to be added to the data. However, in forget layer, activation vector is multiplied to the cell state and can set values to zero.

$$i_s = \sigma\left(W_i.\left[h_{s-1}, x_s\right] + b_i\right) \tag{2}$$

Equations 1, 2, and 3 used b_f , b_i, b_c which is continuously learned, and initialized with random numbers by neurons training biases. However, W_f, W_i, W_c are considered as neurons weights matrices to train the data with initializing random numbers.

The tanh layer in Eq. 3 is creating a function to add the value taken from the input layer to add in a new variable with a new state. For the final upgrading of a new state value, the new updated state value is being calculated through forget and input layer values (Eq. 4)

$$\widetilde{C}_s = \tanh\left(W_C.\left[h_{s-1}, x_s\right] + b_C\right) \tag{3}$$

$$C_s = f_s * C_{s-1} + i_s * \widetilde{C}_s \tag{4}$$

Fundamental analysis, statistics, linear regression, and all types of analysis can also be used, but they did not give us the correct idea on daily changes of mental health. So, this LSTM algorithm uses the recurrent approach of each neuron and predicts the next value to be placed. By this, the human changes recurrently based on their thoughts if the recurrent neural network approach is used to train every neuron with all the previously available data. If the person is more depressive in a pandemic situation and it tries to predict the depression rates when there is no pandemic situation, the basic motto of prediction is to identify the person's depressive levels in no pandemic situation based on the reason that they are into depression at pandemic days.

Step 1 Start.
Step 2 Import all the necessary packages, and the dataset is taken from a recent survey.
Step 3 Preprocessing and feature extraction of the dataset.
Step 4 Building the LSTM algorithm model.
Step 5 Training the model by passing through each neuron on the given data.
Step 6 Test the model with depression values when there is no pandemic situation.
Step 7 Displays the graph of predicting depression values after an analysis was done using the LSTM model.
Step 8 Prediction is done.
Step 9 Repeat the steps 1, 2, 3, 4, 5, 6, 7, and 8 if you want to see a random change in the depression values by passing the updated reports or datasets.
Step 10 End.

3 Flowchart

To visualize our process of approach, a flowchart has been given (Fig. 1). For the overview of our model, the packages and datasets required to train the LSTM model have been imported. Importing these packages in Python helps to do all types of high-level mathematical functions. After this, scaling, centering the dataset for feature extraction, will be performed, and also this stage is named for preprocessing the dataset. Now, the main stage of implementation takes place that is building the

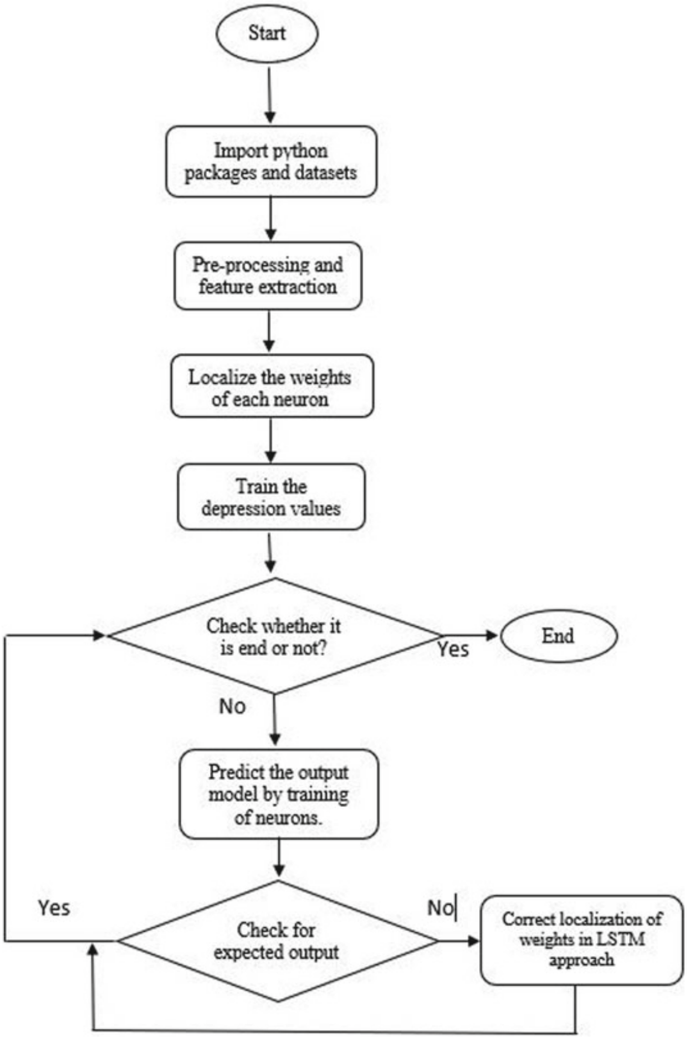

Fig. 1 Overview of the process

LSTM model. It localizes the weights of each neuron that needed to be trained for each recurrent iteration. A recurrent neural network predicts the possible output for the next stage by comparing it with all the previous data. If it does not identify the depression levels of a person, it corrects the weight of neurons and starts predicting the depression value again. This recurrent approach of the model gives the correct predictions by calculating the long-term memory of the model. Finally, it gives the prediction of depression value will be less in no pandemic situations like COVID-19.

4 Results

Figure 2 is a snapshot of our dataset that is taken to train our model. Here, we have trained our model that has been trained on the reason for the depression. Based upon their reason for depression during pandemic days, we have trained our model; if the reason does not have a long-lasting end, then the person's depression value will be the same irrespective of the pandemic situation. Predicting that if the reason is solved in the future, then depression values may decrease by taking all the possibilities in the approach of predicting depression values in the future.

Figure 3 shows preprocessing the dataset, and it is scaled for the training of dataset in the next stage of the LSTM model of approach. Figure 4 shows training each neuron with the passed dataset along with the reasonable value of depression and compares it with test data in a later stage. Then, it gives predictions for the depression levels when there is no pandemic situation like COVID-19 (Fig. 5).

depression.csv Open with

	A	B	C	D	E	F	G	H	I
1	Indicator	Group	Week	Week Label	Value	Low CI	High CI	Confidence Interval	Quartile range
2	Symptoms of Depres	National Estimate	1	Apr 23 - May 5	23.5	22.7	24.3	22.7 - 24.3	
3	Symptoms of Depres	By Age	1	Apr 23 - May 5	32.7	30.2	35.2	30.2 - 35.2	
4	Symptoms of Depres	By Age	1	Apr 23 - May 5	25.7	24.1	27.3	24.1 - 27.3	
5	Symptoms of Depres	By Age	1	Apr 23 - May 5	24.8	23.3	26.2	23.3 - 26.2	
6	Symptoms of Depres	By Age	1	Apr 23 - May 5	23.2	21.5	25	21.5 - 25.0	
7	Symptoms of Depres	By Age	1	Apr 23 - May 5	18.4	17	19.7	17.0 - 19.7	
8	Symptoms of Depres	By Age	1	Apr 23 - May 5	13.6	11.8	15.5	11.8 - 15.5	
9	Symptoms of Depres	By Age	1	Apr 23 - May 5	14.4	9	21.4	9.0 - 21.4	
10	Symptoms of Depres	By Gender	1	Apr 23 - May 5	20.8	19.6	22	19.6 - 22.0	
11	Symptoms of Depres	By Gender	1	Apr 23 - May 5	26.1	25.2	27.1	25.2 - 27.1	
12	Symptoms of Depres	By Race/Hispanic et	1	Apr 23 - May 5	29.4	26.8	32.1	26.8 - 32.1	
13	Symptoms of Depres	By Race/Hispanic et	1	Apr 23 - May 5	21.4	20.6	22.1	20.6 - 22.1	
14	Symptoms of Depres	By Race/Hispanic et	1	Apr 23 - May 5	25.6	23.7	27.5	23.7 - 27.5	
15	ymptoms of Depres	By Race/Hispanic et	1	Apr 23 - May 5	23.6	20.3	27.1	20.3 - 27.1	
16	Symptoms of Depres	By Race/Hispanic et	1	Apr 23 - May 5	28.3	24.8	32	24.8 - 32.0	
17	Symptoms of Depres	By Education	1	Apr 23 - May 5	32.7	27.8	38	27.8 - 38.0	
18	Symptoms of Depres	By Education	1	Apr 23 - May 5	25.4	23.9	26.9	23.9 - 26.9	
19	Symptoms of Depres	By Education	1	Apr 23 - May 5	25.6	24.4	26.9	24.4 - 26.9	
20	Symptoms of Depres	By Education	1	Apr 23 - May 5	17.6	16.8	18.4	16.8 - 18.4	
21	Symptoms of Depres	By State	1	Apr 23 - May 5	18.6	14.6	23.1	14.6 - 23.1	16.5 - 20.7
22	Symptoms of Depres	By State	1	Apr 23 - May 5	19.2	16.8	21.8	16.8 - 21.8	16.5 - 20.7
23	Symptoms of Depres	By State	1	Apr 23 - May 5	22.4	19.4	25.5	19.4 - 25.5	22.2 - 24.0

Fig. 2 Snapshot of our trained dataset

Fig. 3 Preprocessing and feature extraction snapshot

```
[ ] training_scaled

array([[0.35555556],
       [0.58271605],
       [0.40987654],
       ...,
       [0.57037037],
       [0.42962963],
       [0.58024691]])
```

```
[ ] regressor.fit(x_train,y_train,epochs = 100, batch_size = 32)

Epoch 1/100
1199/1199 [==============================] - 5s 4ms/step - loss: 0.0532
Epoch 2/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0221
Epoch 3/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0239
Epoch 4/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0215
Epoch 5/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0211
Epoch 6/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0214
Epoch 7/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0214
Epoch 8/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0217
Epoch 9/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0210
Epoch 10/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0212
Epoch 11/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0212
Epoch 12/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0200
Epoch 13/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0207
Epoch 14/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0206
Epoch 15/100
1199/1199 [==============================] - 4s 3ms/step - loss: 0.0215
```

Fig. 4 Training the model

Figure 5, for every prediction of an approach using LSTM algorithm, shows its model that trains recurrently with the data. So, for every change in epochs training, the output of depression levels gets varied in non-pandemic days. When 25 epochs is given, then the model trains the person depression might decrease based on the reason in non-pandemic days (Fig. 8). Figure 7 gives predictions of training the model with 50 epochs, and it also fluctuates data in raise and fall. So, this study of analytics on change of training epochs makes us learn that for every recurrent of data that are varying with the reason of the person's depression.

Hereby, changes in the prediction of data have been given with training data for every change of epochs like 100 (Fig. 5), 75 (Fig. 6), 50 (Fig. 7), and 25 (Fig. 8).

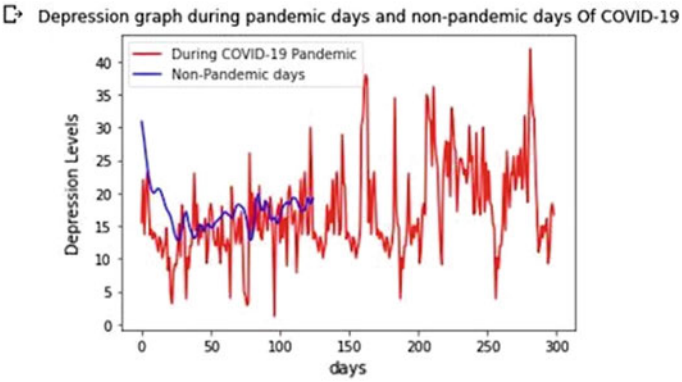

Fig. 5 Prediction of depression levels in non-pandemic days with 100 epochs

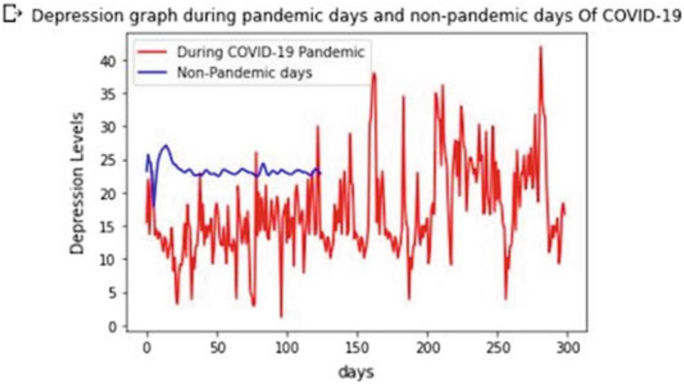

Fig. 6 Prediction of depression levels in non-pandemic days with 75 epochs

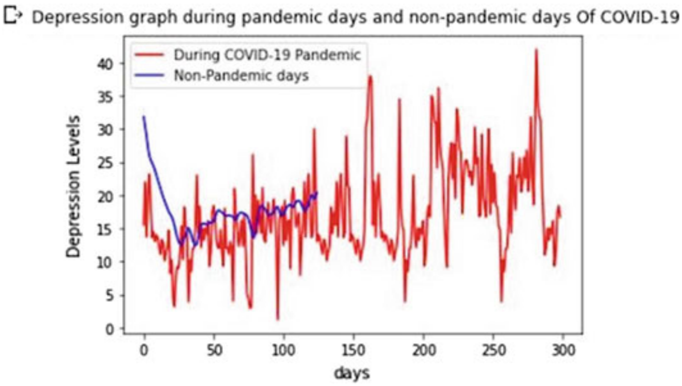

Fig. 7 Prediction of depression levels in non-pandemic days with 50 epochs

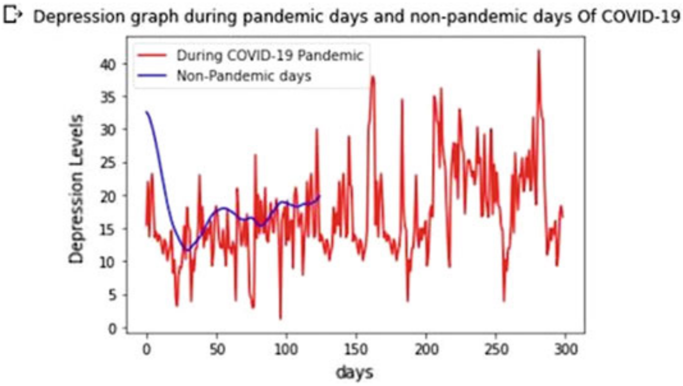

Fig. 8 Prediction of depression levels in non-pandemic days with 25 epochs

Type	Output shape	Number of parameters
Input	359, 1	0
LSTM(Forward)	125, 60	1470
LSTM(Backward)	125, 60	1470
Dropout	50	0
Epochs	100, 75, 50, 25	0
Fully connected (Sigmoid)	1	51

Fig. 9 Representation analytics of model

These changes in epochs make the model to train the LSTM algorithm and to learn for new data with each iteration on the reason of depression that they are in (Fig. 9).

5 Conclusion

Many methods have been implemented in the detection of depression. Depression can be detected by using neural network classification by taking the data available from social media. Depression has been substantially increased over a period of time. From the outbreak of the pandemic, it has increased exponentially than before, due to many factors such as hopelessness, loneliness, and joblessness. The data of depression have been compared during pandemic days. With this, it can be said that depressed people are getting more. Depressed people should be treated and taken care of to make them stay away from suicidal thoughts. Based on the reason for depression, the situation of depression might get low in the non-pandemic situation. From the study, it can be said that depression levels are higher in pandemic days than compared to normal days.

6 Future Scope

By considering this scenario of research, an app can also be built for further improvement of the research work. The depression levels of data from the social media posts[14-16] can be used to analyze the depression levels of the person. Through the analysis of the levels of depression that the person is in, the person can be helped and prevented from taking any serious action, and suggested something that can help the person.

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