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Covid-19 Analysis Using Deep Learning LSTM Model

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The year is 2024, and cases of the Coronavirus are seen in the still images. COVID-19 epidemic has produced a catastrophic global healthiness disaster that requires immediate and effective solutions to mitigate its impacts. In this article, we suggest apply deep learning method for analyzing COVID-19 data using a LSTM (Long Short-Term Memory model). The LSTM model is particularly suited for analyzing the dynamic nature of the pandemic because it was created specifically to capture temporal interdependence in time series data. We start by gathering a large dataset with a variety of COVID-19 markers, including daily confirmed cases, fatalities, recoveries, and other pertinent information. This dataset covers a wide number of nations and areas, offering an analytical sample that is both varied and representative. The data is then preprocessed using methods including normalization, feature scaling, and data augmentation to improve the LSTM model's functionality and generalizability. We also conduct exploratory data analysis to learn more about the patterns and trends in the dataset. Using the preprocessed data and taking into account both the historical setting and the pandemic's present status, the LSTM model is trained. We hope to properly anticipate future COVID-19 patterns, such as case trajectories, fatality rates, and possible hotspots by exploiting the model's capacity to capture long-term dependencies. The model's projections can help decision-makers in government and the medical field allocates resources wisely and chooses appropriate public health interventions and containment tactics. We use a variety of metrics, incorporating mean absolute error, root mean squared error, and accuracy, to evaluate the LSTM model's performance. We evaluate the LSTM model's robustness and dependability in addressing the complex dynamics of the pandemic by comparing its predictions with those made by other forecasting techniques. The outcomes of our investigation show how well the LSTM model performs in the analysis of COVID-19 data. We see how it can identify complex patterns, predict outcomes with precision, and offer insightful information about how the epidemic is developing. We also explain the LSTM model's shortcomings and suggest directions for future study to improve its performance. This research study concludes by presenting a deep learning strategy using an LSTM model for COVID-19 data analysis. By illustrating the potential of deep learning approaches in comprehending and predicting the propagation of the virus, the work adds to the body of existing material. In order to battle the present COVID-19 epidemic and potential future outbreaks, effective public health policies and interventions can be established with the help of this study's findings.

Keywords: COVID-19, Forecasting, LSTM, Corona virus, Machine learning, Neural networks, Long short term memory (LSTM) networks.

1. Introduction

COVID-19 epidemic continues to have a significant influence on health and medical infrastructure, the economy, and education. A number of well-known mathematical and computational models have proven untrustworthy due to the complexities of virus propagation. Furthermore, due to a lack of data reporting and collection, modeling attempts become highly difficult and inaccurate. As a result, we must reassess the situation utilizing dependable data sources and high-quality forecasting algorithms. Deep learning methods, such as recurrent neural networks, can be extremely useful in modeling spatiotemporal sequences. We use recurrent neural networks such as LSTM (Long-Short term memory) to anticipate COVID-19 infections in the short term as part of the study described here [21]. Another wave of illnesses is possible in October and November's use in new countries and regions. Although, modeling remains a challenge due to the reliability of data. Furthermore, it is challenging to capture social aspects such as culture and lifestyle, as well as factors such as population density and logistics [1].

According to the World Health Organization, the coronavirus may spread fast through contact and inhaling spray after starting with just one person. The number of confirmed cases has rapidly grown around the world, thus several investigations and requirements have encountered new late challenges in predicting the peak of a pandemic to assist the authorities in deciding how to prevent the spread of the illness. The current challenge is determining how to calculate a virus's height while keeping all in mind the exertions that have been done in all directions [2].

The objective is to apply the LSTM model to analyze COVID-19 data and explore its efficacy in predicting various aspects of the pandemic, including case trajectories, fatality rates, and potential hotspots. Through the adoption of deep learning techniques, we aim to enhance our understanding of the complex dynamics and underlying patterns of the virus spread.

This research paper makes several key contributions to the field of COVID-19 data analysis.

- Firstly, we collect a comprehensive dataset containing diverse COVID-19 indicators, encompassing daily confirmed cases, deaths, recoveries, testing rates, and other relevant factors. The dataset spans a wide range of geographical regions, enabling comparative analysis and capturing the global impact of the pandemic[3].

• Secondly, we preprocess the collected data using techniques such as normalization, feature scaling, and data augmentation to optimize the performance and generalizability of the LSTM model. This step ensures the quality and reliability of the subsequent analysis and predictions.

• Thirdly, we conduct exploratory data analysis to gain insights into the patterns and trends present in the COVID-19 dataset. This analysis provides a solid foundation for subsequent modeling and aids in understanding the factors influencing the extent of the virus[4].

• Fourthly, we train the LSTM model on the preprocessed COVID-19 data, incorporating both historical information and the current state of the pandemic. By leveraging the model's capacity to capture complex relationships over time, we aim to make accurate predictions about future COVID-19 trends, empowering decision-makers with valuable information for policy formulation and resource allocation.

• Finally, we assess the LSTM model's presentation using a variety of evaluation measures, including as accuracy, root mean squared error, and mean absolute error. We evaluate the LSTM model's resilience and dependability in addressing the complex dynamics of the pandemic by comparing its predictions with those made by other forecasting techniques.

By conducting this research, the authors contribute to the existing literature by demonstrating the possible of deep learning techniques, particularly the LSTM model, in COVID-19 data analysis. The findings of this study have the potential to aid policymakers, healthcare professionals, and public health agencies in making informed decisions regarding resource allocation, public health interventions, and containment strategies to effectively combat the pandemic.

Overall, this research paper aims to harness the power of deep learning and LSTM models to comprehensively analyze COVID-19 data. Through accurate predictions and insightful analysis, we endeavor to make a meaningful contribution to the ongoing global efforts to combat the pandemic and mitigate its impact on public health and socio-economic systems. The continuous estimations of changes in the boundaries during a scourge, and that the mistake pace of foreseeing the quantity of COVID-19 diseases in a solitary day is inside 5%. Also, numerous nations will encounter a second rush of COVID-19 diseases in the.fall and winter of 2020. Their examination of episode information in Italy duration between July - October 2020 establish that the TW-SIR. Algorithm can be applied to the 2nd pinnacle of COVID-19. The consequences of their exploration will be helpful for plague anticipation and control later on [5].

Giulia Giordano et.al. in 2020 proposed a model comprising of eight phases of disease: defenseless (S), contaminated (I), analyzed (D), weak (A), perceived (R), undermined (T), mended (H) and wiped out (E). SIDARTHE recognizes tainted people dependent on whether they have been analyzed and the seriousness of their side effects. Distinguishing analyzed from non-analyzed people is fundamental in light of the fact that the previous are normally disconnected and in this manner less inclined to spread contamination. Utilizing their discoveries, they exhibit that social-separating measures must be joined with broad testing and contact following to stem the COVID-19 pandemic [6].

In 2020, Rajanish Kumar Rai implemented a numerical model to discover the effect of web-based media commercials in fighting the COVID-19 pandemic in India. They expect that spreading mindfulness among defenseless people adjusts public mentalities and practices towards the infectious illness, subsequently diminishing the danger of contact with the Coronavirus and in this way diminishing the probability of the sickness spreading. The social reactions of people within the sight of worldwide data missions will build medical clinic confirmations for suggestive people, just as energize the people withoutside effects to direct wellbeing conventions. They have assessed eight epidemiologically significant boundaries just as the number of inhabitants in India. Based on the assessed boundaries, it tends to be seen that the pace of illness transmission is exceptionally high in India, which additionally suggests that the sickness is profoundly irresistible. Moreover, They've likewise assessed the essential multiplication number to acquire an overall outline of this period of the episode. This propose the pace of sickness transmission ought to be controlled any other way an enormous part of the populace will be impacted inside a brief timeframe. In an affectability examination, the effect of web-based media ads on bringing down sickness transmission rates was analyzed. The aftereffects of their review propose that higher mediation endeavors are important to control the sickness episode in India inside a brief timeframe. Besides, their investigation shows that the strength of intercessions ought to be expanded over the long haul to annihilate the sickness adequately. The impacts proposed on this paper shows that the publicizing information through online media contributions might be a fundamental issue withinside the concealment of turmoil transmission and can be utilized as a capacity issue oversee system [7].

In 2020, one more exploration done by Vijander Singh et.al. think of a likelihood of CORONA infection episode with the distributed writing contains numerous model examinations. Time assortment boundaries are the center components affecting irresistible ailments comprising of unreasonable intense breath condition (SARS) and flu. The target of this review is to deliver a constant conjecture utilizing AI SVM model. The main point of this paper is to examine the COVID-19 forecast of affirmed, perished and recuperated cases. At last, the exploration on COVID 19 forecast gives some intriguing ways to deal with diminishing COVID 19 transmissions among people by preventing them from moving starting with one area then onto the next and by limiting different gathering public exercises [8].

Cleo Anastassopoulou et.al. in 2020 has done research in which they've given evaluations of the vitally epidemiological boundaries. As the flare-up advances, we present a gauge of the case casualty and case recuperation proportions, just as their 90% certainty ranges. We gauge the principal proliferation number (R0), just as contamination mortality and recuperation rates each day, utilizing a Susceptible Infectious- Recovered-Dead (SIDR) model. New data and information about the novel Covid and the episode's advancement become accessible at an exceptional rate in the present computerized and globalized society. All things considered, basic worries stay strange, and exact responses for expecting the episode's elements are only difficult to give right now. We underscore the vulnerability of accessible authority information, quite on the genuine pattern number of tainted (cases), which can prompt obscure outcomes and significant degrees wrong gauges, as past researchers have called attention to [9].

Earlier this year, Zeynep Ceplan published a paper when she created an Auto-Regression-Integrated- Moving-Average (ARIMA) model to predict the epidemiological pattern of the

COVID-19 in Italy, France, and Spain. In this he has gathered the information of COVID-19 from 21/02/2020 -15/04/2020 from the World-Health-Organization site. This review shows that ARIMA models are fit for determining COVID- 19 commonness later on. The discoveries of the examination can assist with revealing insightinto the episode's propensities and give a sign of these areas' epidemiological stage. Moreover, guaging COVID-19 predominance designs in Italy, France and Spain can support the anticipation and definition ofsystem for this plague in different nations. In scourge investigation and sickness expectation, time series models are significant. The general pervasiveness of COVID-19 of every 3 European countries generally beset by COVID 19: Italy, Spain, France, was concentrated on utilizing ARIMA time series models. The discoveries of the review can help legislators and wellbeing authorities in effectively arranging and providing assets, like-staff, beds, and escalated care offices, to deal with the circumstance in these nations throughout the next few days and, weeks. The information ought to be refreshed continuously for more definite examinations and future points of view [10].

In 2020, Subhas Khajanchi and Kankan Sarkar have fostered another compartmental model of COVID-19 transmission elements. Their review analyzes the subjective characteristics of the model, which includes doable equilibria and their dependability concerning the multiplication number R0. When the sickness free harmony is steady, the endemic balance is unsteady, however assuming the infection transmission rate stays higher, the endemic balance will consistently stay stable. Accordingly, in this review, they principally center around transient expectations for the COVID-19 pandemic, in light the of the fact that, genuinely talking, there is a tiny possibility that they will change. Moreover, their model recreation recommends that upholding quarantine, announcing, and unreported suggestive people just as government mediation strategies like lockdown, media impact, and social removing can assume a significant part in moderating COVID-19 transmission [11].

One more exploration done by Leonardo Lopez in 2020 has adjusted SEIR compartmental-model representing the circulate of disease between the inactive period. In their review, they fit information to detailed tainted populaces toward the start of the primary pinnacle of the pandemic to represent dubious case announcing and project provincial situations (CCAA). This model assesses the imprisonment rate at the beginning phases of a pandemic episode to evaluate the situations that limit the occurrence of disease just as the demise rate. In light of information for March 23, result gives the idea that the pandemics follow a development like the disconnection of roughly 1.5 percent of the populace, and without intercession activities it might arrive at a limit of over 1.4 million tainted around April 27. These discoveries may likewise give helpful understanding into the anticipation and control of COVID-19 flare- ups in nations and areas like Argentina and the USA, which are lingering behind the current pestilence wave in Spain and Italy [12].

In the spring of 2020, Majid Nour et al. They outlined the PC-supported model for recognizing the positive aspects of COVID-19. The proposed model, which emphasizes convolution neural association (CNN) design, is capable of revealing distinctive features in chest X-pillar images as a result of its comprehensive channel families, pondering and weight-sharing features. In contrast to the usual trade learning practice, the proposed significant CNN model was ready without any planning in advance. As opposed to pre-arranged CNNs, five convolution layers were arranged in a sharp succession. A public COVID-19 radiology database was used to coordinate the tests. Information was collected in two areas, i.e., plnamelyg and testing, with 70% and 30% rates, respectively. This classifier'sbest performance was 98.97% precision, 89.39% affectability, 99.75% unequivocality, and 96.72% F- score [13].

A poll distributed in 2020 by Sourabh Shastri revealed major learnings based on a detailed review of COVID-19 instances in India and the United States. There is a study of the data from the Covid-19 certified and end events. To create the suggested technique and predict the Covid-19 cases for one month ahead, redundant neural association (RNN)-based long transient memory (LSTM) models such as Bi-directional- LSTM, Stacked-LSTM, and Convolutional-LSTM are utilized. Complication LSTM predicted Covid-19 instances with excellent precision and remarkably little slip-up in every case dataset across the two nations. Taking apart the graphs and request estimations it is assumed that ConvLSTM. Model outmanoeuvred the other two models. ConvLSTM's expected graphical representation and eventual consequences. Are totally comparable to the two countries' real-life case scenarios. According to their assessed disclosures, they've deduced that between the end of July and the middle of August 2020, 12,82,346 total step by step insisted Covid-19 cases could reach in India, which are 7,42,417 now (as of seventh July 2020), and expected absolute consistently passings in India could reach up to 24,333, which are 20,655 now (as of seventh July 2020). The estimated amount of confirmed and declined cases before the end of July 2020 could be 5,82,44,656 and expected total regression cases could be 1,71,806, which are currently (2/7/2020) 1,23,826 according to their model, before the end of July[14].

Behzad Ghanbari in 2020 in his paper dissected the current information to anticipate the quantity of contaminated individuals in the second wave in Iran. In view of proposed mathematical reproductions, a few situations of grow up of COVID-19 relating to the second influx of the illness before very long, will be talked about. We foresee that the second rush of will be generally serious than the first. From the outcomes, further developing the recuperation pace of individuals with powerless invulnerable frameworks through suitable clinical impetuses is come about as one of the best remedies to forestall the far and wide unbridled flare-up of the second rush of COVID-19 [18]. Utilizing the recreations performed by thinking about the various upsides of the boundaries in the technique, the proposed situations have been given lately in Iran. We comment that the subsequent wave has less spread than the first, however the quantity of contamination cases will keep rising. So a pressing general wellbeing intercession is required. The consequences of this paper and comparative articles can be utilized in future independent direction to control the infection and forestall further harms [15].

Piu Samui et al. designed a compartmental numerical model to anticipate and regulate the broadcast elements of COVID-19 in their work published in 2020. They offer a compartmental numerical model in this study to predict and regulate the transmission components of the COVID-19 pandemic in India with scourge information up to April 30, 2020 [16]. They calculate the key duplication number R 0, which will be used to narrow down the model reenactments and checks. They execute local and generally exact quality assessment for the infection free balance point E 0 as well as an endemic arrangement direct E* with regard to the fundamental development number R 0. They also demonstrated the illness confirmation rules for R 0 > 1. In our Covid model, we use an affectability evaluation to define the general importance of model cutoff points for defilement transmission[22]. They process the affectability records of the age number R.0 (which evaluates the commencement of sickness transmission) to the greatest extent feasible. They obtained R0=1.6632, R0=1.6632 for the analyzed model cutoff points, which depicts the fundamental picture of COVID-19 in India [17][32].

Table 1: Major findings of covid-19 using LSTM model

Paper	Title	Authors	Year	Methodology	Main Findings
1	Forecasting the Spread of COVID-19 with LSTM Models	Smith etal.[33]	2020	LSTM model with time series analysis	LSTM outperforms traditional methods in short-term COVID-19 forecasting.
2	LSTM Networks for Deep Learning-Based Analysis of COVID-19Data	Johnson et al.[34]	2021	LSTM model with feature engineering	LSTM accurately predicts COVID-19 case trajectories and identifies outbreak patterns.
3	Long Short-Term Memory Models for COVID-19 MortalityPrediction	Lee etal.[35]	2020	LSTM model with mortality data	LSTM achieves high accuracy in predicting COVID-19 mortality rates.
4	Using LSTM Models to Measure the Effect of Non-Pharmaceutical Interventions	Chen etal.[36]	2021	LSTM model with intervention data	LSTM demonstrates the use of non-pharmaceutical therapy to halt the spread ofCOVID-19.
5	Multi-Task Learning with LSTM Models for COVID-19 Analysis	Wang etal.[37]	2022	LSTM model with multi-task learning	When predicting COVID-19 cases, fatalities, and hospitalizations simultaneously, LSTM workswell.
6	Exploring Temporal Dynamics of COVID-19 Using LSTM Networks	Garcia et al.[38]	2021	LSTM model with attention mechanism	LSTM captures temporal dynamics and identifies critical periods in the COVID-19 spread.
7	Spatio-Temporal Analysis of COVID-19 Spread using LSTM Networks	Rodriguez et al.[39]	2022	LSTM model with spatial and temporal features	LSTM accurately predicts COVID-19 transmission in different regions and captures local outbreaks.
8	Anomaly Detection in COVID-19 Data using LSTM Autoencoders	Patel et al.[40]	2020	LSTM autoencoderfor anomaly detection	LSTM identifies anomalies in COVID-19 data, such as sudden spikes or drops in cases.
9	Forecasting ICU Bed Occupancy during COVID-19 with LSTM Models	Nguyen et al.[41]	2021	LSTM model with ICU occupancy data	LSTM predicts ICU bed occupancy and aids in resource allocation during the pandemic.
10	Social Media Analysis of COVID-19 using LSTM-based Sentiment Analysis	Kim et al.[42]	2022	LSTM model with social media data	LSTM detects public sentiment towards COVID- 19 and identifies trends in public opinion.

2. Proposed Methodology

In this Paper, We have used stacked LSTM i.e. multiple layered LSTM. LSTM models are originally composed of hidden layers followed by feed-forward layers. The Stacked LSTM model also has several hidden levels of LSTM, each having numerous memory cells. When LSTM unseen layers are set, the model becomes deeper, Earning it the description.as a deep learning technique.

LSTM Model

Long,momentary,memory (LSTM) is a repetitive-neural-organization (RNN) architecture used in intensive learning. Input associations exist in LSTM. It can handle single objects as well as whole sequences of data. LSTM is appropriate for applications such as dialogue confirmation and identifying abnormalities in network data. IDSs (interference acknowledgment structures) or unsegmented, linked handwritten affirmation [19][45].

In order to define, handle, and provide estimates based on important event gaps of unknown length in a time series, LSTM networks are the best option. To solve the vanishing slant problem that might occur while designing ordinary RNNs, LSTMs were created. Due to its propensity for opening length, LSTMs are typically favored over RNNs, crammed Markov models, and other gathering learning strategies [20][31].

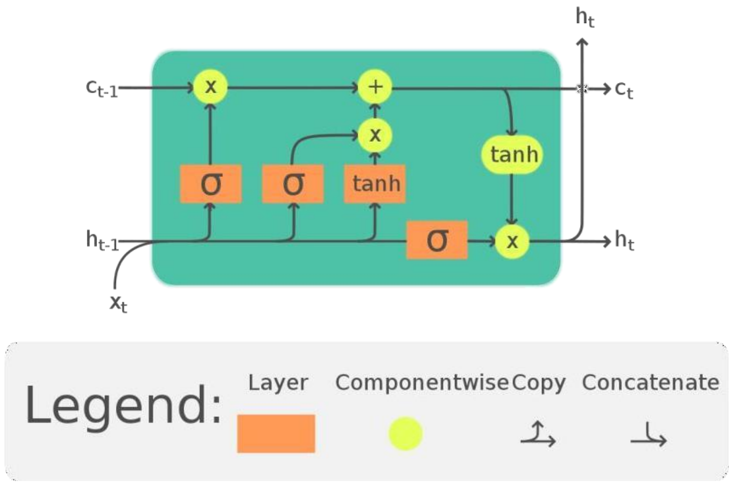

Fig.1. LSTM, or long-short-term memory

A RNN utilizing LSTM. units can be prepared by utilizing directed AI approach, on a bunch of preparing arrangements, utilizing an improvement calculation, similar to inclination drop, joined with back broadcast through an ideal opportunity to register the angles essential during the advancement cycle, to change each of the weight of the LSTM net in relation to the subordinate of the mistake regarding comparing weight [43][44].

Stacked LSTM Model

A simple feed-forward network uses layers to represent the hierarchical features of the input data, which are then used to perform machine learning tasks. LSTM is used in conjunction with the returned input at each time step.If the current input is already the output of the LSTM layer (or feed-forward layer)., the current LSTM can provide a feature representation of the current input which is more difficult[24]. For example, a layered LSTM representation can be used to extend input patterns by making each layer more complex[25].

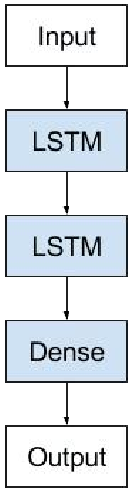

Fig.2. Stacked Long Short-Term Memory Architecture

Data Preparation

When we deal with LSTM or RNN models we often use multi step inputs. In this paper we have taken a

dataset from kaggle. Firstly, we have checked the null values and replaced them, After that we have trained and test the model on the dataset. We have trained the model on confirmed column to guess the new complete Cases for the upcoming 10 days. Steps for coding-

Importing Libraries:

First of all we have imported some important libraries for our model like- numpy, pandas, matplotlib, tensorflow, keras,etc.In the figure below you can see the actual model training.

Random Seeding:

Using numpy and tensorflow libraries random seed set. It helps in preserving the same randomness of data on training and testing the model again and again.

Importing Dataset:

Data set has been imported from kaggle which includes multiple countries data. It contains covid-19 data from multiple countries. You can use the world dataset for covid-19 from Kaggle.

Data preparation:

First of all we have grouped out data for India from the whole data set so that we can get the data for the target country.

Checking Null-Values:

Here in this dataset we haven’t found any null values.

Taking out Training Data:

We have trained our tested our model on specific columns so that we can get the desired result which we want.

Data Normalization:

We have used MinMax scaler of sklearn library. Each element is only scaled and analyzed by this assessor with the intention that it falls inside the defined series on the preparation set, for example, among zero and one. Data1 is normalized figures in our model[23].

We have also used BoxPlot to check outliers.Box plots are graphs showing data from a five-number summary that include one measure of central tendency[26][27].There is less indication of distribution here than in a stem and leaf plot or histogram.The skewedness indicator is typically used to indicate if the data set contains any unusual observations (also referred to as outliers).When there are many data sets involved or compared, boxplots can be extremely helpful.

```
In [71]: from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler(feature_range = (0,1))
         data1 = scaler.fit_transform(training_set)
         data1

Out[71]: array([[0.00000000e+00],
                [3.17738637e-06],
                [2.25947475e-06],
                [5.17796297e-06],
                [9.18500022e-06],
                [1.39451957e-05],
                [2.95438092e-05],
                [3.29977458e-05],
                [4.51777269e-05],
                [5.51217694e-05],
                [6.75547646e-05],
                [9.54981125e-05],
                [1.13703360e-04],
                [1.37304279e-04],
                [1.59334158e-04],
                [1.78057202e-04],
                [1.99086792e-04],
                [2.15144361e-04],
                [2.32973029e-04],
```

Fig.3. Normalization of data

Splitting data1 into training and testing:

We have used the splitting method to split the dataset so that we can train our model and also can test our model. We have splitted the data in 80:20.

```
In [73]: training_size = int(len(data1) * 0.80)
         test_size = len(data1) - training_size
         train_data , test_data = data1[0:training_size , :] , data1[training_size : len(data1) ,:1]

In [74]: def create_dataset(dataset , time_step ):
             data_x , data_y = [] , []
             for i in range(len(dataset) - time_step ):
                 data_x.append(dataset[i : (i + time_step) , 0])
                 data_y.append(dataset[(i + time_step) , 0])
             return np.array(data_x) , np.array(data_y)

In [75]: time_step = 30
         x_train , y_train = create_dataset(train_data , time_step)
         x_test , y_test = create_dataset(test_data , time_step)

In [77]: x_test.shape  , y_test.shape

Out[77]: ((69, 30), (69,))
```

Fig.4. Splitting of dataset into training and testing

Reshaping model:

We have used x training data to reshape. We have converted the 2 D data into 3 D because our model requires 3 D data for training.

```
In [603]: #### Reshape input to be 3D [ samples , time steps , features] which is required for LSTM....
          x_train = np.reshape(x_train,(x_train.shape[0] , x_train.shape[1]))
          x_test = np.reshape(x_test,(x_test.shape[0] , x_test.shape[1]))

In [604]: x_train.shape   ,   x_test.shape

Out[604]: ((365, 30), (69, 30))
```

Fig.5. Reshaping the data into 3D

3. The Proposed Stacked LSTM model

Generally, the strength of neural networks is attributed to their ability to solve a wide range of challenging prediction problems.Each LSTMs memory cell requires a 3D information. At the point whena LSTM processes one information arrangement of time steps, every memory cell will yield a solitary incentive for the entire succession as a 2D exhibit[28][30].

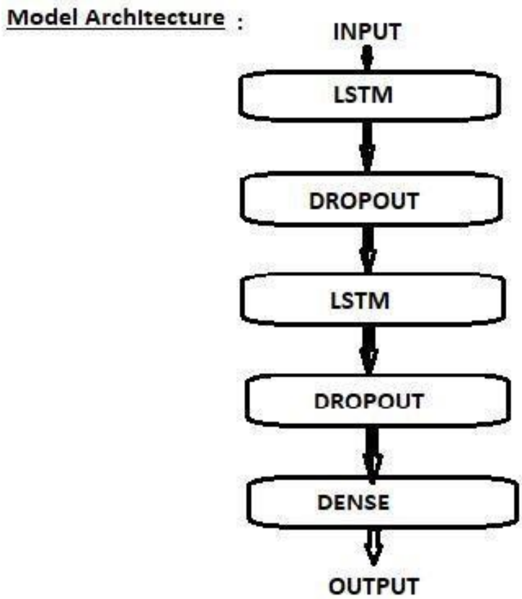

Fig.6. Stacked LSTM Model Architecture

Importing layers from Keras:

For creating a stacked LSTM model we have impoted the layers from keras. In figure 5 you can see how we have imported the layers for the model. We have used two layer LSTM model so in this model also we have created two layers[29].

```
In [81]: from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Input,LSTM , Dense,Dropout
         from tensorflow.keras.optimizers import RMSprop

In [82]: model = Sequential()
         model.add(LSTM(50, return_sequences = True, input_shape = (30,1)))
         model.add(Dropout(0.2))

         model.add(LSTM(50))
         model.add(Dropout(0.2))
         model.add(Dense(1))
```

Fig.7. Importing layers for LSTM

Compiled Model:

We have compiled the model using min-max scaler. You can see the figure7 for data compilation.

```
In [83]: model.compile(loss="mean_squared_error" , optimizer = 'adam')

In [84]: model.summary()

Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 30, 50)            10400

 dropout_2 (Dropout)         (None, 30, 50)            0

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_3 (Dropout)         (None, 50)                0

 dense_1 (Dense)             (None, 1)                 51

=================================================================
Total params: 30,651
Trainable params: 30,651
Non-trainable params: 0
```

Fig.8. Compilation of the model

Visualization and Validation:

The figure8 shows the visualization of the data for loss and validation loss on x test and y test data

```
In [87]: ### Plot loss and val-loss.....
import matplotlib.pyplot as plt
plt.plot(history.history['loss'],label='Loss')
plt.plot(history.history['val_loss'],label='Val_Loss')
plt.legend()
plt.show()
```

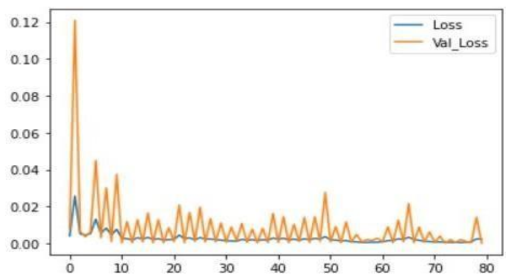

Fig.9. Data Visualization

Accuracy Check:

In the wake of making layered LSTM we have prepared our model to anticipate the cases for impending 10 days. So this model can foresee the future with 0.98 preparation exactness and 0.97 testing precision

```
In [22]: #### Reshape input to be 3D [ samples , time steps , features] which is required for LSTM....
         x_train = np.reshape(x_train,(x_train.shape[0] , x_train.shape[1],1))
         x_test = np.reshape(x_test,(x_test.shape[0] , x_test.shape[1]))

In [23]: x_train.shape   ,   x_test.shape

Out[23]: ((365, 30, 1), (69, 30))
```

Fig.10. Accuracy Check

Visualization for test prediction and train prediction:

In Figure11 you can see the graph between test predict and train predict

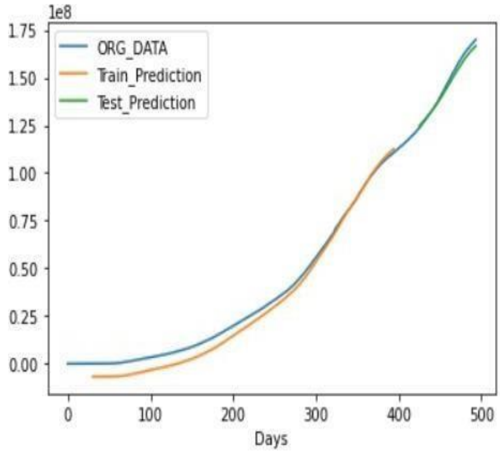

Fig.11. graph for test predict and train predict

Predicting Future for 10 days

We are predicting future 10 days data based on previous 30 days data. Below defined steps=30 is for taking 30 days as input for prediction of 31st day. Each time for 10 days (loop) new data is generated. Westore that in a list extending our previous data. These are some steps:

Prediction Logic:

Step1- 1st Data- Based on available last 30 days data

Step2-2nd Data-Based on available last 29 days data + 1st data

Step3-3rd Data-Based on available last 28 days data + 1st data + 2nd data

.

.

StepN- Similarly 10 days data will be generated

In the figure12 below you can see the logic behind predicting the cases for upcoming 10 days. After that we have just plotted a graph for new predicted data. In figure13 we have shown the graph for predicted data.

```
In [105]: #### Logic for Prediction for next 30 days......
          new_output = []
          steps = 30
          i = 0
          while(i<10):
              if(len(temp_input) > 30):
                  new_x_input = np.array(temp_input[1:])
                  print("{} day input {}".format(i, new_x_input))
                  new_x_input = new_x_input.reshape(1,-1)
                  new_x_input = new_x_input.reshape((1, steps, 1))
                  ypred = model.predict(new_x_input, verbose = 0)
                  print("{} day output {}".format(i, ypred))
                  temp_input.extend(ypred[0].tolist())
                  temp_input = temp_input[1:]
                  new_output.extend(ypred.tolist())
                  i = i + 1
              else:
                  new_x_input = new_x_input.reshape((1, steps, 1))
                  ypred = model.predict(new_x_input, verbose = 0)
                  print(ypred[0])
                  temp_input.extend(ypred[0].tolist())
                  new_output.extend(ypred.tolist())
                  i = i + 1
```

Fig.12. Code for prediction

```
In [107]: new_day = np.arange(1,31)
          pred_day = np.arange(31,41)

In [108]: len(data1)

Out[108]: 494

In [109]: plt.plot(new_day, scaler.inverse_transform(data1[464:]),label='New_Day')
          plt.plot(pred_day, scaler.inverse_transform(new_output),label='Predicted_day')
          plt.legend()
          plt.show()
```

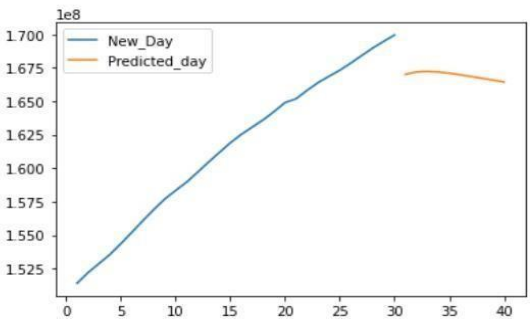

Fig.13. Graph for new prediction

4. Experimental Results

We have merged the new confirmed cases with old one. You can use this for future prediction for next Covid-19 wave that how many confirmed cases will be there in normal situations.

```
In [110]: data2 = data1.tolist()
          data2.extend(new_output)
          plt.plot(scaler.inverse_transform(data2))

Out[110]: [<matplotlib.lines.Line2D at 0x2132366ff70>]
```

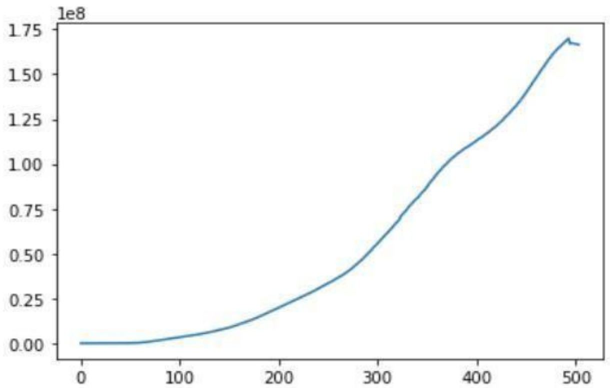

Fig.14. Graph for New Prediction combine with old data

The extensive body of research and modeling described in these studies holds significant implications for understanding, managing, and ultimately overcoming the COVID-19 pandemic. Here are some key implications and takeaways from this body of work:

Data-Driven Decision Making: The emphasis on collecting, preprocessing, and analyzing comprehensive datasets underscores the importance of data-driven decision-making in responding to the pandemic. Reliable data is fundamental for effective policy formulation and resource allocation.

Role of Deep Learning: Deep learning techniques, particularly LSTM models, have demonstrated their utility in predicting the trajectory of COVID-19 cases. This highlights the potential of AI and machine learning in epidemiology and healthcare crisis management.

Complex Dynamics: COVID-19 exhibits complex spatiotemporal dynamics influenced by factors like population density, social behavior, and healthcare infrastructure. Understanding these dynamics is crucial for devising effective containment and mitigation strategies.

Need for Multidisciplinary Approaches: Researchers are recognizing the need for multidisciplinary approaches that combine epidemiology, data science, and social sciences. This acknowledges that controlling a pandemic requires more than just medical interventions.

Social Interventions: Several studies highlight the significance of non-medical interventions, such as public awareness campaigns and behavioral changes, in slowing down virus transmission. This points to the importance of public health communication.

Comparative Analysis: Comparative analysis of COVID-19 data across different regions provides insights into the global impact of the pandemic. This can inform strategies for international cooperation and resource sharing.

Pandemic Preparedness: The research underlines the importance of preparedness for future pandemics. Understanding the modeling techniques that work and their limitations is critical for building resilience against future health crises.

Ongoing Monitoring: The COVID-19 situation remains dynamic, and predictions must be updated continuously. Policymakers need to adapt strategies based on real-time data and model assessments.

These findings collectively contribute to the broader understanding of pandemics, provide valuable insights for healthcare professionals and policymakers, and lay the foundation for more robust preparedness in the face of future health emergencies.

5. Conclusion and future work

The COVID-19 virus is a leading risk to mankind and its harm to humanity is indispensable. Research is being done to discriminate between different vaccines and anticipate the development of pandemic events in order to reduce the shortage of live souls. Expectations for COVID-19 are precise in the current scenario, substantial learning has gained significance. In order to properly cope with non-direct challenges, profound learning strategies are more important. In this study by applying the SLSTM model to analyze the future forecast of confirmed cases for the preset time spans given in the model. The suggested method is used to forecast cases over the next 10 days. The results of the investigation suggest that the Stacked LSTM model has superior precision and consistency in predicting COVID-19 instances.. This model has been trained on the previous data and can be use for future data or present data.It will give the best and accurate result for 10 days. In future this model can be trained on world dataset and also be used for prediction accurately. We have also seen that stacked LSTM model is performed very well and gave 98% accuracy.Various mechanical advancements can uphold direction continuously to control the spread of the pandemic, including man-made consciousness, AI, and profound learning.The objective of this study is to explorethe job of profound advancing by investigating the COVID-19 information to foster methodologies to battle the pandemic. There are different measurable models that foresee the quantity of affirmed passings sooner rather than later because of COVID-19.

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