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# COVID-19 Time Series Forecasting of Daily Cases, Deaths Caused and Recovered Cases Using Machine Learning

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Abstract—A novel coronavirus (CoV) named '2019-nCoV' or '2019 novel coronavirus' or 'COVID-19' by the World Health Organization (WHO) is in charge of the current outbreak of pneumonia that began at the beginning of December 2019 near in Wuhan City, Hubei Province, China. COVID-19 is a pathogenic virus. From the phylogenetic analysis carried out with obtainable full genome sequences, bats occur to be the COVID-19 virus reservoir, but the intermediate host(s) has not been detected till now.Coronaviruses are a large family of viruses that are known to cause illness ranging from the common cold to more severe diseases such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). A novel coronavirus (COVID-19) was identified in 2019 in Wuhan, China. This is a new coronavirus that has not been previously identified in humans.

Keywords—— Deep learning, Artificial Neural Networks, LongShort-Term Memory (LSTMs), Pandemic, COVID-19, Coronavirus.

## I ] INTRODUCTION

A novel coronavirus (CoV) named '2019-nCoV' or '2019 novel coronavirus' or 'COVID-19' by the World Health Organization (WHO) is in charge of the current outbreak of pneumonia that began at the beginning of December 2019 near in Wuhan City, Hubei Province, China [1–4]. COVID-19 is a pathogenic virus. From the phylogenetic analysis carried out with obtainable full genome sequences, bats occur to be the COVID-19 virus reservoir, but the intermediate host(s) has not been detected till now. Though three major areas of work already are ongoing in China to advise our awareness of the pathogenic origin of the outbreak. These include early inquiries of cases with symptoms occurring near in Wuhan during December 2019, ecological sampling from the Huan Wholesale Seafood Market as well as other area markets, and the collection of detailed reports of the point of origin and type of wildlife species marketed on the Huanan market and the destination of those animals after the market has been closed.

COVID-19 respiratory disease caused by a novel (new) coronavirus that was first detected in China and which has now been detected in more than 150 locations internationally, including in the United States. The virus has been named "SARS-CoV-2" and the disease it causes has been named "coronavirus disease 2019" (abbreviated "COVID-19").

## I. LITERATURE REVIEW

### A. Artificial Neural Networks (ANN)

Artificial Neural Network ANN,ANN is an efficient computing system whose central theme is borrowed from the analogy of biological neural networks. ANNs are also named as "artificial neural systems," or "parallel distributed processing systems," or "connectionist systems." ANN acquires a large collection of units that are interconnected in some pattern to allow communication between the units. These units, also referred to as nodes or neurons, are simple processors which operate in parallel.

### B. Recurrent Neural Networks (RNN)

A significant increase in COVID-19 cases is already happening in many places because of the fast onset of winter. Mass vaccination programs are initiated in several nations to prevent the spread of COVID-19, yet unfathomable surges in COVID19 have significantly increased the challenges to public officials . As many parts of the world are reporting an increase in disease transmission and possible lethality, it has been reported that new and potentially more deadly strains have been found, and doubts have been already made about immunizations' ability to combat emerging lethal strains. Scientists have already predicted how awful the problem will get as fresh cases of COVID-19 continue to grow.

C . Long Short-Term Memory Networks (LSTMs)

Characteristically, an RNN is a very challenging neural net to train. Since RNNs make use of back propagation, they run into the problem of vanishing-gradient.Unfortunately, the vanishing-gradient is exponentially worse for an RNN. The reason being that, each time step is the equivalent to an entire layer in a feed-forward neural network. So, training an RNN for a 100time step is similar to training a 100 layer feedforward neural net. This results in exponentially small gradients and information decay through time. These problems can be solved using Long-Short-Term- Memory networks (LSTMs). LSTM are modules of RNN that can learn the longterm dependencies. By placing the LSTM modules inside an RNN, long-term dependency challenges can be avoided. linear-relationships. Traditional models do not work well for long-term.

D. Time series data (TS)

Time series data refers to the data that is collected over a regular time period and captures a series of data points captured at regular intervals of time where every data point is equally spaced over time. Trend, seasonality and error are the important components of a time-series data. Forecasting upcoming patterns and trends based on historical data set containing temporal features is known as Time Series prediction. Data with temporal components will be the best suited data to forecast the novel coronavirus transmission . A time-series data pattern can be noticed when a certain trend recurrences at regular time periods like confirmed cases, deaths, recovered cases etc. In many real-time situations, either seasonality or trend is absent. After finding the nature of time series data, different forecasting methods must be applied. The two categories of time-series data are nonstationary data and stationary data. A stationary series is independent of the time components such as seasonality, trends etc. Constant mean and variances are observed with respect to time. A non-stationary depends on the seasonality effects and trends in it and varies with respect to time. Statistical properties like mean, variance and standard deviation also changes with respect to time. Compared to non-stationary TS, stationary TS data is easier to analyze and provides good forecasting result.

E . Pytorch

Pytorch is a high-quality deep learning library with plenty of extensions and a support of a large community. Pytorch offers GPU support, the option to set up a deep net by configuring its hyper parameters. Once configured the deep net can be called from the routines of our programs. This library provides a powerful vectorized implementation of the math behind deep learning; In addition there are many libraries that extend Pytorch functionality for various applications.

## III SELECTION OF DEEP LEARNING MODEL

Time series forecasting is a challenging problem when working with noisy dynamic data. Deep learning models offer a lot of promise when working with time series data [8]. In this section different deep learning models are compared and why LSTMs are the better choice when compared to other models used for time series forecasting can be understood. A. Traditional Time Series Forecasting methods like ARIMA:

Traditional models like ARIMA require complete data, incomplete and noisy data as in this case cannot be applied to this model. Model works best for univariate and linear-relationships. Traditional models do not work well for long-term. x . Multi-layer-Perceptron's(MLP) for Time-series :

MLP's are best suited for problems having meaningful mappings unlike the problem statement presented in this paper. Static mapping functions and fixed inputs and outputs are required.

x . Convolution Neural Networks (CNNs):

CNNs are often used for image classification problems. CNNs though can extract import features from input sequence and enjoys benefits missing from traditional models and MLPs, it cannot learn from temporal dependency. CNNs are slow and fickle to train of time series data. The model also over fits easily x . Recurrent Neural Networks (RNNs):

RNNs suffer from long-range dependencies because of the vanishing gradient problem and exploding. Gradient vanishing in a Recurrent Neural Network (RNN) refers to the challenges where the long-term component's gradient norm decreases exponentially quickly to 0, hindering the ability of the model from learning longterm temporal correlations. The opposite event to this can be referred as gradient exploding. LSTM has been introduced to address the issue To address and mitigate the limitations of the above mentioned models, LSTMs have been chosen [4]. The benefits of using LSTMs are they establish temporal connections, define and maintain an internal memory cell state during the course of the entire life cycle of this model. In addition they are simple, well-understood, approximate non-linear functions, robust to noise, can handle multi-step forecasts and multivariate inputs. The LSTM is designed to estimate the movement of Covid-19s spread with consideration of uncertainties

## IV . METHODOLOGY OF TIME SERIES PREDICTION OF COVID-19 DATA USING Lively.

A. Data Exploration

The data in the paper contains different categories of time series data namely total no. of cases, deaths and no. of people who have recovered from novel corona virus. For Each category of data on exploring the .csv file structure the Province/State, Country/ Region/ Latitude, Longitude and cumulative number of virus cases, deaths due to the virus and recovered patients can be found as shown in Fig.3 and Fig.4 respect

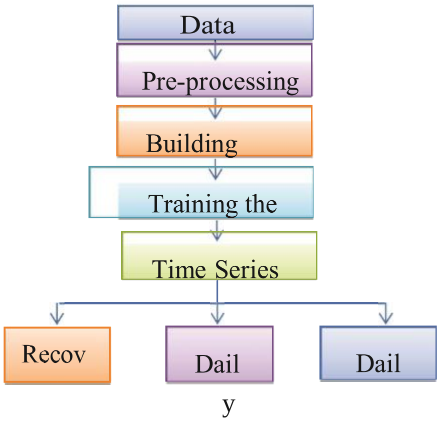



Fig.1.Represents the flowchart of the methodology used

| Province/State | Country/Region | Lat | Long | 1/22/2020 | 1/23/2020 | 1/24/2020 | 1/25/2020 | 1/26/2020 |
|---|---|---|---|---|---|---|---|---|
| Anhui | China | 31.8257 | 117.2264 | 1 | 9 | 15 | 39 | 60 |
| Beijing | China | 40.1824 | 116.4142 | 14 | 22 | 36 | 41 | 68 |
| Chongqing | China | 30.0572 | 107.874 | 6 | 9 | 27 | 57 | 75 |
| Fujian | China | 26.0789 | 117.9874 | 1 | 5 | 10 | 18 | 35 |
| Gansu | China | 37.8099 | 101.0583 | 0 | 2 | 2 | 4 | 7 |
| Guangdong | China | 23.3417 | 113.4244 | 26 | 32 | 53 | 78 | 111 |
| Guangxi | China | 23.8298 | 108.7881 | 2 | 5 | 23 | 23 | 36 |
| Guizhou | China | 26.8154 | 106.8748 | 1 | 3 | 3 | 4 | 5 |

Fig.2.Represents the three data sets for total number of cases.

| Province/State | Country/Region | Lat | Long | 1/22/2020 | 1/23/2020 | 1/24/2020 | 1/25/2020 |
|---|---|---|---|---|---|---|---|
| Hebei | China | 39.549 | 116.1306 | 0 | 1 | 1 | 1 |
| Heilongjiang | China | 47.862 | 127.7615 | 0 | 0 | 1 | 1 |
| Henan | China | 33.882 | 113.614 | 0 | 0 | 0 | 0 |
| Hong Kong | China | 22.3 | 114.2 | 0 | 0 | 0 | 0 |
| Hubei | China | 30.9756 | 112.2707 | 17 | 17 | 24 | 40 |
| | Afghanistan | 33 | 65 | 0 | 0 | 0 | 0 |

Fig.3.Represents the three data sets for total number of deaths.

| Province/State | Country/Region | Lat | Long | 1/22/2020 | 1/23/2020 | 1/24/2020 | 1/25/2020 |
|---|---|---|---|---|---|---|---|
| Hebei | China | 39.549 | 116.1306 | 0 | 0 | 0 | 0 |
| Heilongjiang | China | 47.862 | 127.7615 | 0 | 0 | 0 | 0 |
| Henan | China | 33.882 | 113.614 | 0 | 0 | 0 | 0 |
| Hong Kong | China | 22.3 | 114.2 | 0 | 0 | 0 | 0 |
| Hubei | China | 30.9756 | 112.2707 | 28 | 28 | 31 | 32 |
| | Afghanistan | 33 | 65 | 0 | 0 | 0 | 0 |

Fig. 4. Represents the three data sets for total number of people recovered from the virus respectively.

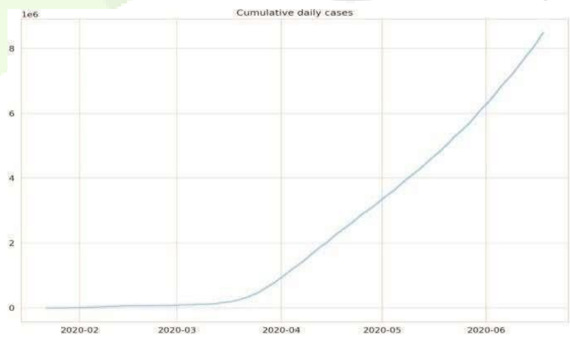



Fig.5.Plot of cumulative daily cases over the months.

Next the accumulation is undone by subtracting the present value from the preceding value and saving the sequ ence's first value. This results in an increase of cases on daily bases. Plot of the daily cases can be found in Fig.6.

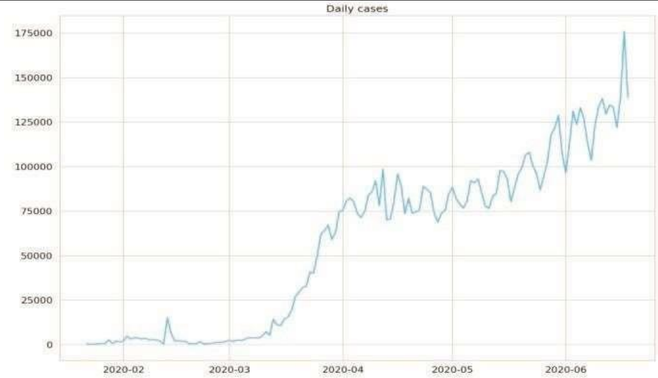



Fig.6.Plot of cumulative daily cases over the months.

B. Preprocessing the Data sequence of daily cases is converted to smaller ones. Every inputting a sequence of numbers or vectors and output a Split the data into training and testing data. In this paper a 80-20 split is used to separate training and testing data. Training data consists of 104 numbers of days. Next scale the training data between zero to one in order to improve the performance and training speed. In order to achieve this MinMaxScaler from scikit-learn is used. The big training sample comprises a sequence of five data points of history and a label for the real value that the model is required to predict. Now, create the actual sequences for the time sequence data to feed to our LSTM model, which work by

Since the Province/State, Country/ Region/ Latitude and Longitude are not required, operations can be performed to remove these columns. Next check for missing values in the data and sum all the rows to get cumulative daily cases. Then proceed to convert the date column into date time structure using Pandas. In the next step, plot the data. The results of cumulative daily cases can be seen in Fig. 5.

C. Building the model

The difficulty of the model is encapsulated into a class that belongs to torch.nn.Module. The model presented in this paper consists of three main methods namely

x Constructor method: To create the layers and initialize all helper the data.

x Rest hidden state method: A stateless LSTM is used, which requires the state to be reset after every example.

x Forward: To get the sequences, pass all the sequences through LSTM layer, at once. The output from the last time step is passed through linear layer to obtain the prediction.

D. Method for Training the model with limited data

A builder function is used to train the model. Observe that the hidden-state of the model is being reset at the beginning of every epoch. Batches of data are not used in this model; the model is exposed to all the examples at once. An instance of the model is created and trained. The train and test loss of the model is as shown in Fig. 7 and Fig. 8

E. Predicting daily case

At this stage based on how this model is trained, only a single day in the future can be predicted. A straight forward approach is employed to conquer this limitation. The next future days' output is predicted by inputting the previously

F. Predicting future cases

All the available data is utilized in training the model. The pre-processing and training steps are the same as explained above. The fully trained model is used to predict confirmed positive virus cases for next 12 coming days. In order to create charts containing historical and predicted cases the date index of the data frame is extended. Fig. 10 shows the predicted future cases.

```
Epoch 0 train loss: 23.527355194091797 test loss: 47.83329772949219
Epoch 10 train loss: 13.437393188476562 test loss: 27.69245719909668
Epoch 20 train loss: 13.142333984375 test loss: 25.96657943725586
Epoch 30 train loss: 13.00899600982666 test loss: 22.690153121948242
Epoch 40 train loss: 12.917614936828613 test loss: 25.685211181640625
Epoch 50 train loss: 12.946625709533691 test loss: 26.410751342773438
```

Fig.7.Represents the train and test loss with respect to epochs.

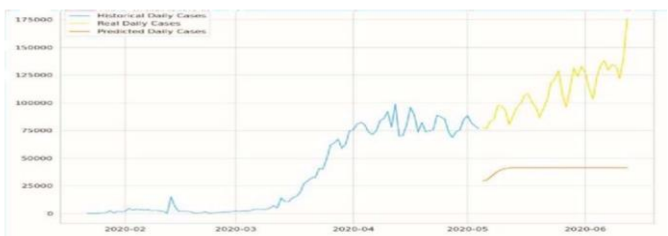
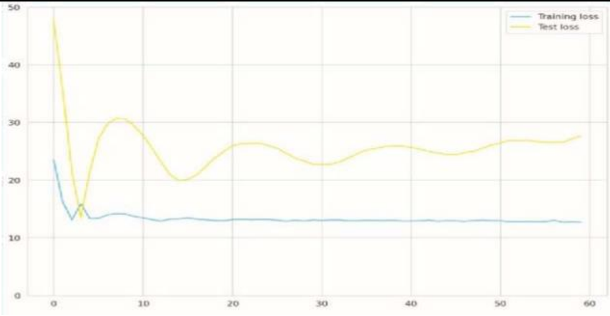



Fig. 8. Plot train and test loss




predicted values. Fig. 9 shows that the predictions seem to be around the same ballpark

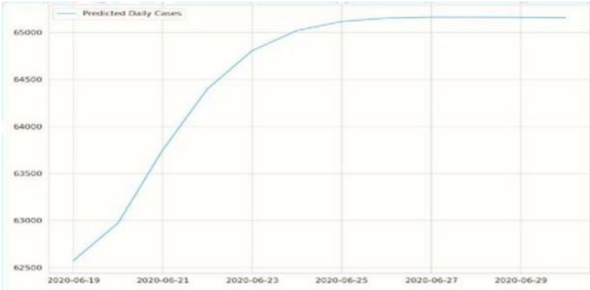



Fig.10.Plot of predicted future cases for next 12 days.

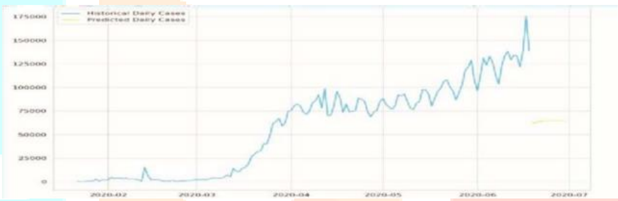


Fig. 11. All the data is used to plot the results

Fig.13. Plot of historical and predicted daily recovered cases

```
Accuracy of proposed model is:
77.895
```

The accuracy of the model proposed is 77.89% since the model is exposed to limited data, as the data increases and varies trends and patterns of the virus are exposed to the model and predicted values. Fig. 9 shows that the predictions seem to be around the same ballpark.

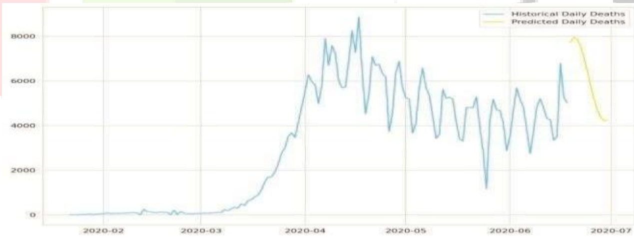



Fig.13. Plot of historical and predicted daily recovered cases

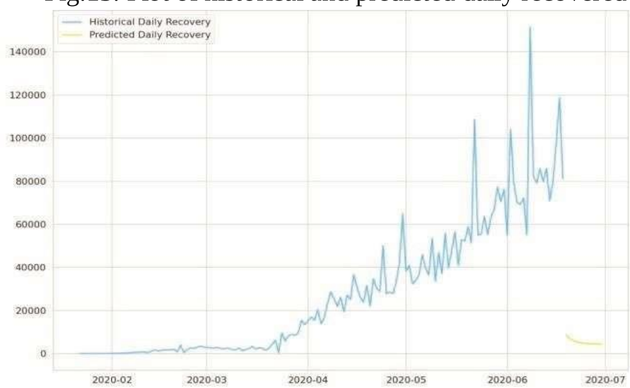



Fig. 14. Plot of historical and predicted daily deaths

All Europe North America Asia South America Africa Oceania

| # | Country, Other | Total Cases | New Cases |
|---|---|---|---|
| | World | 8,639,090 | +68,706 |
| 1 | USA | 2,275,229 | +11,578 |
| 2 | Brazil | 984,315 | +956 |
| 3 | Russia | 569,063 | +7,972 |
| 4 | India | 385,276 | +4,185 |
| 5 | UK | 301,815 | +1,346 |
| 6 | Spain | 292,348 | |
| 7 | Peru | 244,388 | |
| 8 | Italy | 238,159 | |
| 9 | Chile | 231,393 | +6,290 |
| 10 | Iran | 200,262 | +2,615 |
| 11 | Germany | 190,290 | +164 |
| 12 | Turkey | 184,031 | |

Fig. 15. COVID-19 stats on 19-06-20 from Wordometers.info

## V. CONCLUSION

Predicting COVID-19 cases has immense significance in the present dire scenario. In this work the growth patterns of the disease have been analyzed, data-driven estimations have been incorporated. Deep learning model based on RNN, LSTMs and time series analysis have been used to predict the trends in coming days such as the no. of confirmed positive viral cases, no. of deaths caused by the virus and number of people recovered from the novel corona virus. Encouraging experimental results have been obtained on the dataset used.

## VI. FUTURE SCOPE

The problem of predicting Covid-19 related data such as future cases, recovered cases and deaths is difficult, since we are amidst an outbreak . The future trends and patterns may vary widely based on myriad external conditions like quarantine measures, new behavior of the virus strain, population of a country etc., as the dataset becomes larger and we have more data to train our model, we can improve the accuracy. The same model can be used to predict any future pandemics that are similar in nature to SARS COVID19. This model can be integrated with an application that streams live data from government sites to view real time graphs of COVID-19 related data. Hope that everything will recover and get back to normal soon.

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