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Deep Learning in Pandemic States: Portrayal

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ABSTRACT: Pandemic is a global social outbreak of an infectious disease that can pose a serious hazard worldwide causing chronic economic shocks. This can generate a huge panic provoking the countries to pay special attention and be prepared to identify and manage a pandemic. Besides clinical tests and treatments, several new technologies like deep learning and machine learning algorithms are becoming increasingly prevalent in healthcare. Thus, infectious diseases can be predicted by optimizing deep learning techniques. This study analyses and showcases the prevalence of deep learning and its advanced technologies like LSTM (Long short term memory) and DNN (Deep neural network) in pandemic states. This study also incorporates the pervasiveness of other technologies namely machine learning in pandemic states prediction.

Keywords: Pandemic, Machine learning, Deep learning, LSTM (Long short term memory), DNN (Deep neural network)

I. INTRODUCTION

World Health Organization (WHO) defines pandemic as a worldwide spread of an infectious disease leading to consequential economic, social and political issues. A pandemic is a global epidemic which is highly unique and uncertain – an epidemic that has been spread to at least three or more countries in the territories recognized by WHO.

It is a world shattering event disrupting the lives of people and affecting the markets drastically, leading to long term changes in political and economic power. A pandemic could undoubtedly be the final stroke to economic globalization unless preventive measures are implemented.

Pandemic becomes threatening due to the rapid spread of an infectious disease against which no one is immune. Without the natural immunity to fight it off, it creates a sense of panic worldwide leaving people in an uttermost state of fear. Despite the pandemics being described by the spread of the disease, a major realisation of its growth rate can prepare the people for its paramount consequences. Knowing how quickly the disease is spreading, it can help in quickly moving on to slow down that spread.

The corona virus COVID-19 is much more than a global health crisis and the greatest challenge the world has faced after World War 2 [1]. It is potentially possible for the pandemic to create catastrophic economic, social and political crises all over the world. Keeping in line with the World Health organization report, as of 12th April, 2020 a total of 8447 COVID-19 cases have been confirmed in 31 states and union territories with 273 deaths in India. A pandemic has the potential to move like a wave- crushing those not able to cope [1].

Thus pandemics can easily cross borders to destabilize economic, political and regional stability. This marks the need for the countries to timely predict and brace against for a pandemic, otherwise leaving the country in a state of panic and provoking huge economic breakdown of the country.

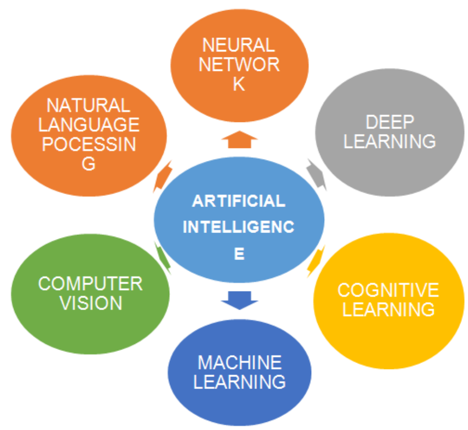

Fig. 1. Artificial Intelligence.

Although effective pandemic planning can give a rough time to the pandemic trying to spread like a wave worldwide. Pandemic planning consists of four stages mainly: Response, Recovery, Mitigation and Preparedness. All these stages require decision making skills at different levels to manipulate and process the information which marks the need for advanced technologies such as artificial intelligence, machine learning and deep learning and many more [2]. These techniques could help to track the growth and progression of the virus causing disease and recognize the areas or people with elevated risk of exposure.

Besides clinical tests and procedures, many advanced technologies are becoming pervasive in the prediction of pandemic state. Artificial intelligence is one of the most persuasive tool in prediction analysis thus making it potentially possible for AI to help people battle it against the pandemic. Application of Artificial intelligence plays a crucial role in analysing and decision making processes [3].

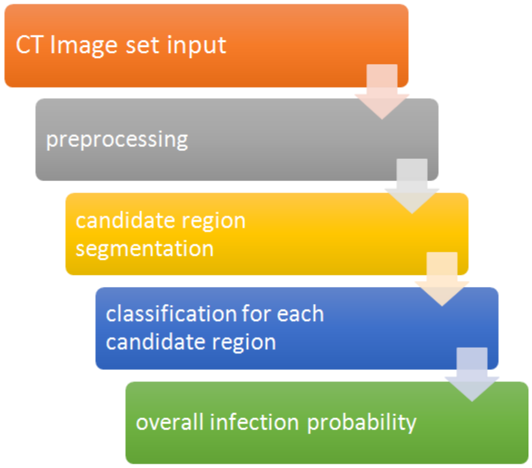

Fig. 2. Machine Learning Methods.

Machine learning is intended to gather more useful and important information from immense amount of data using its own method of computing specifically. This technology is one of the strongest approach to battle against a pandemic. The primary purpose of machine learning based approach is to recognize the factors contributing to disease outbreaks leading to a pandemic [3].

Logistic Regression is a supervised machine learning algorithm purposed for binary codification and predictive analysis. It is a particularly notable type of linear regression having discrete target variable [4]. It models the data using logistic function.

This model is mainly optimized in epidemiology to recognize the risk factors assosciated with the spread of a disease and predict the occurrence of the disease [3]. However, machine learning techniques require careful domain expertise to process the data from its raw form into some suitable feature respresentation or vector [5]. Deep learning is a budding technology that can turn some of our wildest dreams into reality making profound development all over the world [7].

Deep learning, an exciting new trend of machine learning, uses neural networks; layers of algorithms to learn from its own method of computing without any human interference. Layers of features do not require considerable domain expertise and any careful human engineering. It requires enormous amounts of data to learn from [5].

Recurrent neural networks or RNN's are deep feedforward networks which can be used formapping input sequence, preserving in their hidden units a vector that contains information about the prior sequence elements [5]. These networks convert the already subsisting information with the application of any function, thereby not adding new information. Thus, they cannot solve the issue of sequence handling completely. RNN's have indeed short term memory therefore cannot be dealt with long term dependencies. Also, training these networks are quite problematic due to the vanishing gradient problem during backpropogation,mapping input sequence, preserving in their hidden units a vector that contains information about the prior sequence elements [5].

Now, Long short term memory or LSTM are subsequently much more effectual than RNN's. These networks are propogated with an internal mechanism called Cell Gates for regulating the flow of relevant and useful information. These cell gates manage and subsidize the relevant information to make certain predictions [8]. Thus, the information is modified with certain mutiplications and additions.

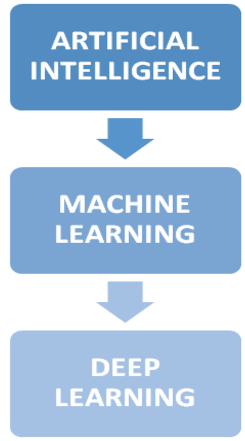

Fig. 3. Machine learning and Deep learning.

III. LITERATURE REVIEW

Chae *et al.,* developed a model aimed at predicting contagious diseases by utilizing the deep learning internal parameters and by using big data and social media data. This study incorporated deep learning techniques like LSTM and DNN models which were further compared with Autoregressive Integrated Moving Average (ARIMA) model [9].

Due to missing and lack of timely reports in medical organizations, it becomes problematic to retaliate quickly against an infectious disease. These frameworks can effectively reduce the reporting time differences in subsisting medical organizations and conventional surveillance systems and recognizing the extent of infectious disease trends can help in minimizing the costs to society.

The performance of this model is evaluated by comparing it with an advanced deep learning framework and a model based on time series analysis.This showcases the complete procedure of collecting data and the collation of models using DNN model, LSTM model, ARIMA model and ordinary least squares (OLS) model.

This study infered to the result that the already subsisting models can be made more effective in predicting the infectious diseases by manipulating the deep learning parameters. Thus, deep learning models yielded more accurate prediction performance in infectious diseases than the ARIMA model.

However, this study had rather short period for accumulation of data, predictions were consolidated over specific region and internal parameters were appraised over a limited array.

Tung Yang *et al.,* studied the prevalence of short term estimates and tried to determine the outbreak prediction methodology for influenza by using deep learning techniques. In this paper, LSTM is successfully implemented to solve the RNN vanishing gradient problem and to address the time series prediction case. This model can effectually calculate and predict the criteria of outbreaks like influenza during the last five years [10].

The model was based on the approach of combining chronical data with transitory forecast data which helps in a better understanding of instantaneous pollution data for the user. It also allows the user to understand the predicted rate of influenza disease in short term. This framework is used for forecasting causing death from influenza.

This study utilizes the outbreak calculation algorithms published by WHO by using the historical data of past 5 years. It also incorporates LSTM model to predict the influenza like isillness effectively.

Bhatia *et al.* designed a novel research on Deep data analytics which focused on encompassing smart devices in healthcare [17].

Liu *et al.,* implemented LSTM to predict influenza disease by using several data sources for the prediction case such as geographic spread of disease, environmental factors that affected the prediction of influenza like illnesses and google trends [10].

Akhtar *et al*., developed a neural network model for the prediction case of outbreaks and applied it to the Zika disease. This study implements RNN - a deep learning technique by using predictive modelling as a flexible tool for outbreak prediction for the zika epidemic and also incorporated the multi dimensional time series data at the country level. The proposed model being robust and accurately used a wide range of data to predict the spread of zika disease [12].

This model proved to be effective for shorter prediction windows and is suitable for isolated locations connected via air travel. However, this model had certain drawbacks as well which can be used to encourage model comparisons in future work. The data used vary regionally and cannot represent actual transmission lines. Also, this model has only accounted for air travel mode.

Zhu *et al.,* developed a deep neural network to predict the influenza like illness [13]. The previous research on this did implement deep learning methodGs but didn't conside the time series attribute of the data. This paper applied LSTM networks for the prediction case of influenza outbreak as influenza disease has the property of time series sequence. Using multi dimensional architecture to get the time series sequence, this model is highly flexible and competetive.

Jia *et al.* applied three mathematical models in their resarch for the prediction of corona virus : Logistic mdel, Bertalanffy Model and Gompertz model. The perfomance of the three models is tested by first analysing and fitting te SARS disease trends and the results so obtained were used to analyse the COVID-19 situation [4]. As both the viruses are similar coronaviruses, this paper first testifies the validity of this model with SARS trends. Thus, this paper also predicted the end of corona virus by proper estimation of SARS trends. The logistic model was proved to be the mose effectual than the other two models.

Wu *et al.,* developed a deep learning model for predicting the epidemics with time series perspective. This model applied RNN and CNN : RNN to get the temporal dependencies in data and CNN to capture the information from several different sources. This model effectively used a combination of RNN, CNN and residual links to increase the flexibility and and robustness of this framework [14].

Xi *et al*., proposed a deep residual framework comprising of four models : Linear regression, LSTM, spatiotemporal – LSTM and artificial neural network [15]. This study developed a deep learning model for infuenza disease prediction. This paper aimed at predicting influenza illness several neighbouring districts. The proposed model is highly effective and efficient as it is compared with four different models considering their accuracies in influenza disease trends.

Bhatia *et al.,* proposed a research which highlighted the fact that deep learning as a technique appeals a lot in Big data [16].

Varalakshmi proposed a mathematical framework for the detection of existence of coronavirus disease and and for analyzing the present epidemic states [18].

Gourisaria *et al.,* proposed the inclusion of technology in the detection of diseases leading to the confirmation of a disease [19].

IV. METHODOLOGY

Deep Learning embraces various processing layers that does not necessitate domain expertise and considerable human engineering, it comprehends with its own degree of computing. It develops its feature vector using its individual data which marks the need for enormous amounts of input data. Deep learning has outwitted machine learning algorithms in various other fields such as prediction of active drug molecules, natural language processing, sentiment analysis and many more [5].

Deep learning has the ability to calibrate its internal parameters by assessing an objective function to evaluate the error between the output obtained and the preferable or desired output. By adjusting these internal parameters, the error measured can be reduced to a certain extent [5].

Several prediction models incorporated deep learning to enhance its prediction perfomance but these models had definite shortcomings. This study attempts to address those pitfalls and conceptualize a framework using its most effectual form.

A novel model for forecasting infectious diseases using big data and deep learning technologies. This model divulged several attributes of the DNN and LSTM techniques however, this study had a short data collection period. Also, more internal parameters of deep learning model needs to be contemplated to ameliorate its prediction perfomance [9].

This framework forecasted outbreaks and contemplated it to the zika disease but this study relied on data for short periods of time and it diversified regionally [12].

Short data collection period and variation over region is one vital drawback in various researches on predicting the outbreak of contagious diseases. Prior researches were limited only to apprehend the time series characteristics of the data properly, thus proliferating its time and space complexity and abating its prediction accuracy.

For predicting the influenza like illness, the paper focused on developing a long short term memory neural network to forecast the influenza problem in Guangzhau, China as the data has time series aspects which fabricates this model robust and flexible. This study also devised an attention based multi channel architecture which ensures better apprehending of time sequence features of the data. LSTM capitulates a prediction perfomance better than the other models : it perpetrates the vanishing gradient complication in RNN's and elucidates the time series attributes of the data, thus working out well for long term sequence data. The influenza surveillance data used for this research is proffered by the Guangzhau Center for Disease control and Prevention which further include data for 9 years in 9 regions. This data set incorporates 6 different modules each containing various features. Due to suitable

stipulations of the data used, this model holds its applicability in several regions and is not just confined to an individual region [13].
Thus, this model surveys data for considerably longer period of time which breaks out the major drawback in other researches on deep learning.

Long short term memory neural network:
RNN's anticipate contextual data while processing IO sequences and it manoeuvre sequential information. However, training them is troublesome due to the vanishing problem of backpropogated gradient. LSTM can resolve this issue dealing with sequential data retaining time series attribute and in apprehending long-term dependencies. These networks comprises of cell gates for subsidizing the flow of relevant data miimizing the effects of short-term memory.

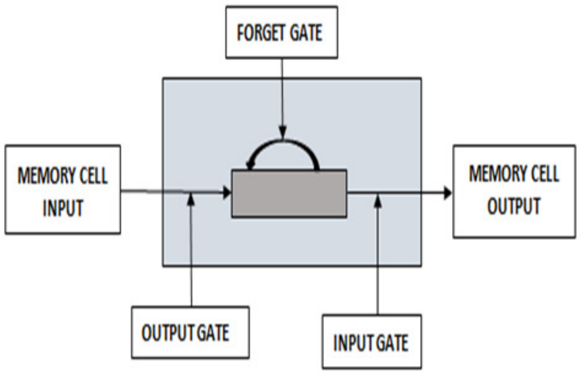

Fig. 4. Structure of LSTM.

The cell gates are non linear summation units that commands the activation of a cell and helps in regulating the flow of pertinent data. The forget gate can set to multiply the previous state of the cell. The input gate gets to choose the relevant data from the current state whereas the output gate decides the next hidden state.
The framework aims to forecast the expected number of cases contemplating a COVID-19 dataset which focuses on its practical and real implmentation.

Data Source:
The data set selected for this frameowork is COVID-19 data for Maharashtra state which shows the total number of cases in the state for 60 days i.e. from 11th March, 2020 to 9th May, 2020. The data for this research was proffered by an online platform kaggle for two different sets: training set and test set. The training data set is considered for 40 days and test data set is contemplated for next 20 days. Thus the model is first trained taking the training set and then expected number of cases are predicted for the next 20 days.

V. RESULTS

The given table shows the expected number of cases and the actual cases day wise which indicates the prediction accuracy of the framework. Table 1 provides the results for test data set for the 20 days after training period. As seen from the table, for 21st April, 2020 the expected cases and the actual cases are quite accurate. Similarly, same representation can be observed for 3rd May, 2020 as well giving us high prediction precision.
The expected cases are compared with the actual cases in order to get a precise framework. This model is highly robust and flexible as its prediction performance is quite satisfactory.

Table 1: Expected Number of Cases for Maharashtra.

S. No.	Date	Expected Cases	Actual Cases
1	20-04-20	4116	4203
2	21-04-20	4644	4666
3	22-04-20	5168	5218
4	23-04-20	5792	5652
5	24-04-20	6281	6430
6	25-04-20	7150	6817
7	26-04-20	7579	7628
8	27-04-20	8466	8068
9	28-04-20	8941	8590
10	29-04-20	9497	9318
11	30-04-20	10258	9915
12	01-05-20	10870	10498
13	02-05-20	11455	11506
14	03-05-20	12438	12296
15	04-05-20	13182	12974
16	05-05-20	13801	14541
17	06-05-20	15163	15525
18	07-05-20	15971	16758
19	08-05-20	16931	17974
20	09-05-20	17824	19063

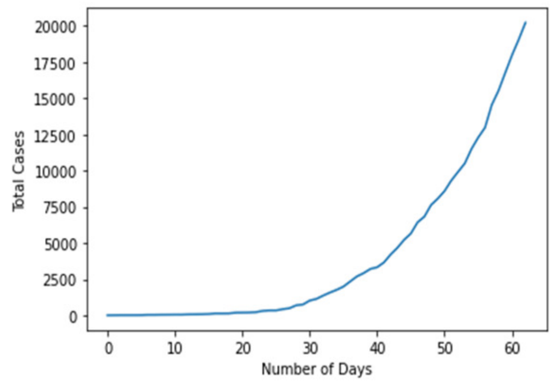

Fig. 5. Original Curve for Maharashtra.

Fig. 5 analyses the total actual number of cases in Maharashtra vs. the number of days. Here, the representation can be observed for a span of 60 days, i.e. from 11th March, 2020 to 9th May, 2020. This represents the number of actual cases in the state.

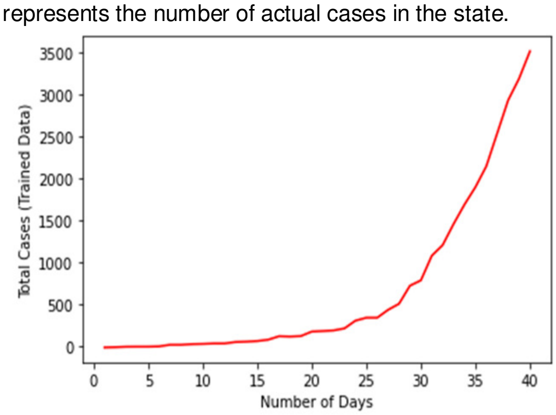

Fig. 6. Results against Training Data Set.

Fig. 6 showcases the results of implementing the model with the training data set for the first 40 days. It is represented considering two parameters: Number of days and the total cases against trained data set.

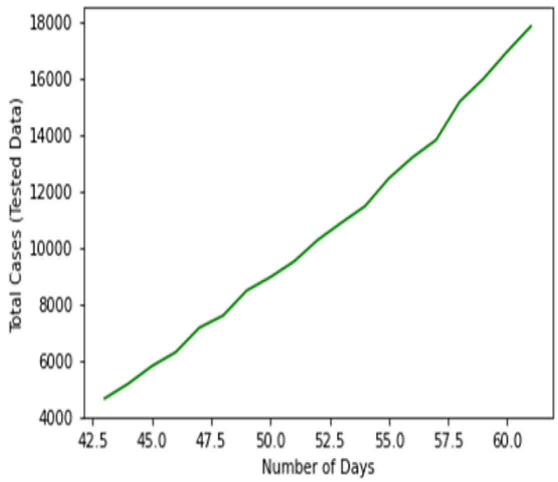

Fig. 7. Results against Test Data Set.

Fig. 7 shows the representation for results against test data set for the next 20 days once the training of the model is over. Thus, it can be seen that he number of days varies from 40 to 60.

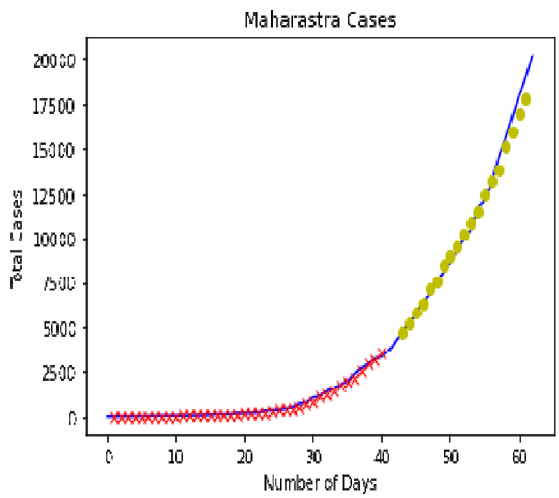

Fig. 8. Comparison.

Fig. 8 analyses and compares the expected cases obtained by implementing the model and the actual cases observed in the same period of time.
Here, Blue line represents the Actual Cases in 60 days. Yellow dots shows the expected cases for next 20 days.

VI. DISCUSSION

This model is based on LSTM approach that showcases the overall flexibility of this framework. The framework applies LSTM layers to predict the cases once the training period is over. This model considers the total number of cases on a particular date as input data and trains the model for 40 days. This models aims to predict the number of cases for the next 20 days after training the framework.
Keras, a neural network library is an API configured for humans. This python library is congenial with TensorFlow, making it facile to design neural network architectures. It's a direct, fast and flexible tool to implement deep learning for human beings rather than machines. It braces multi-input and multi-output training minimizing the cognitive load.

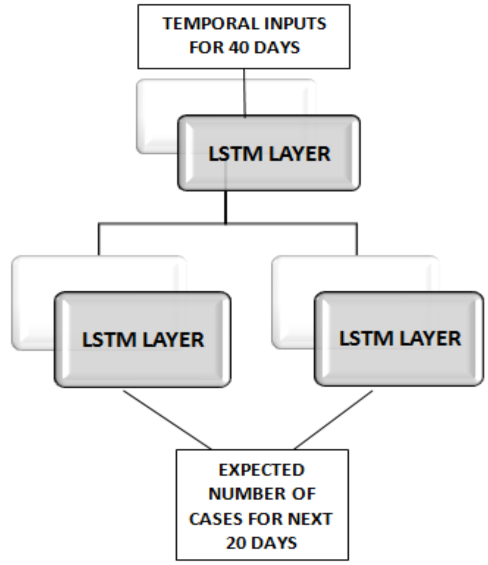

Fig. 9. System structure.

VII. CONCLUSION AND FUTURE WORK

In this paper, we try to incorporate the role and prevalence of deep learning and its complex area: LSTM for the prediction of a pandemic. This study aims to analyse a model which comprehends the time sequence attributes of the data for long term dependencies and effectively overcome the shortcomings of previous works. The proposed framework effectually succeeds in forecasting the expected number of cases of COVID-19, thus this model performed reasonably good enough giving high accuracies. The main objective of this framework is to develop a robust and flexible means to forecast the expected numbers accurately and precisely. As observed, the model prevails quite satisfactorily contemplating a COVID-19 dataset in the present scenario. Thus, LSTM in deep learning is high in its pervasiveness in forecasting a pandemic.This approach is based for relatively short data period which leads to less precised results. In future, this methodology will try to incorporate large time period.

Conflict of Interest: The authors proclaim no conflict of interest in this research work.

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