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A review on the impact of mobility patterns and prediction on Covid-19 rates

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ABSTRACT

After the outbreak of COVID-19 several prediction models are being used by authorities and officials all over the world to implement appropriate control measures and to make well-informed decisions. Due to an enormous level of ambiguity and shortage of crucial data, conventional models have shown low efficiency for long-term prediction. As coronavirus is a contagious disease that is resulting in the massive growth of COVID-19 cases, therefore, we have used human mobility patterns as the effective factor to take preventive measures to thereby stop the outbreak. In this model, we have used methods such as exponential growth, and prophet models. We here demonstrate the impact of changes in mobility patterns by binding the data in Data Science to efficiently trace the disease, plan strategies, methods and foretell the future growth of the pandemic.

Keywords: *COVID-19, Prediction, Mobility, Lock-down, Cases.*

1. INTRODUCTION

The world is now suffering an unusual crisis due to the novel coronavirus, first discovered in Wuhan, China, in December 2019. China, along with other countries from all over the world implemented a quick strategy of suppression by locking down the provinces and implementing social distancing procedures nationwide, with a successful outcome. Still, the virus rapidly continued to spread across the world. India is a large country, with extremely changeable inter-state mobility, and dynamically varying COVID cases in different areas. The government in India announced non-pharmaceutical interventions (NPIs), such as forbidding gatherings, terminating schools, closing transports, barring down cities, inflicting curfews, and sealing areas, and still not able to adequately contain it. This paper exhibits a primary benchmarking to illustrate the potential of machine learning for ultimate analysis. According to our research and study, we discovered that spreading depends on the regional division of human mobility patterns, existing cases, and administrative decisions.

Google released Community Mobility Reports which aim to provide insights from across the globe, from which we extracted India's mobility data. The mobility data is estimated in 6 separate sections: retail and recreation, grocery and pharmacy, parks, transit stations, workplace, and residential. The COVID-19 Government Measures Dataset combines all the measures executed by states worldwide in response to the pandemic. The data set includes subsequent data reviews. The studied erudition available befalls into five categories: Social distancing, Public health measures, Social and economic measures, Lockdowns, Movement limitations. In this paper, we have tried to show a relationship between mobility patterns and measures taken by the government using the above data. We have used techniques such as exponential growth, and prophet models.
1) Exponential Growth is a verified function that can be used in various circumstances. This algorithm shows us the number of cases at a specific moment in time, in the case of Coronavirus, exponential growth gives us the number of infected people.
2) The Prophet library is an open-source library designed for making predictions for univariate time-series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.

2. LITERATURE SURVEY

According to [1], The data used in the research is from Google COVID-19 Community Mobility Reports, 2020, time series daily community mobility data made up of state and union regions (UTs). Data obtained by monitoring the number of requests made on Google Maps in countries, subregions and cities. This report has proven useful for understanding public health strategies, such as measures of social distancing, and how to slow down the rate of transmission. The data obtained here likely provides a cure to the impact of COVID-19 and also draws attention to daily changes from the core value of that day of the week in visits to places like grocery stores, pharmacies, workplaces, parks, etc. This research used data analysis to show how people moved in India during and before the lockdown. Using mobility data, a suitable line graph was plotted for each state and UT. To visualize and alter the spatial pattern of different societal mobility of pre-closure and during closure, the weighted distance inverse interpolation technique was used.

In [2], it is indicated that a mathematical model was proposed for the scenario of community spread of COVID19 in India. .A tree-based model is considered, in which some people are quarantined and few are left undetected (hidden nodes) because of various reasons like symptoms not shown, hiding travel history, etc.; and these hidden nodes spread the disease in the community. They proposed a mathematical model for constrained scenarios, i.e., with lock down,quarantine, self-isolation assumptions. This model can approximately predict the number of new COVID-19 cases and can tell the stage of COVID-19 in a particular country.We study the effect of these prevention techniques on the spread of COVID-19 mathematically, and we propose a new mathematical model to predict the new cases or total infected cases in practical scenario. These studies establish that fact that the proposed model can be used to predict the stage of COVID-19 also by matching the available data with analytical results.

In this paper, we have used data-driven estimation methods like long short-term memory (LSTM) and curve fitting for prediction of the number of COVID-19 cases in India 30 days ahead and the effect of preventive measures like social isolation and lockdown on the spread of COVID-19. Analysis on effect of the prediction of various parameters (number of positive cases, number of recovered cases, etc.) obtained by the proposed method is accurate within a certain range and will be beneficial for 90 days day-ahead estimation for various parameters tools for administrators and health officials. Forecasting and an insight towards possible situations in coming days[5].

This study attempts to develop a system for the future forecasting of the number of cases affected by COVID-19 has four standard forecasting models, such as linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), and exponential smoothing (ES) have been used in this study to forecast the threatening factors of COVID-19.The dataset used for the study contains information about the daily reports of the number of newly infected cases, the number of recoveries, and the number of deaths due to COVID-19 worldwide[4].

3. TOOLS

Jupyter notebook

4. LIBRARIES

1. Pandas
2. Numpy
3. Matplotlib
4. Seaborn
5. Datetime
6. Fbprophet

5. METHODOLOGY

In this section, we illustrate our model in detail. Initially, we brief the data set that we have gathered from various sources. Then we explain the mathematical and machine learning technique for foretelling the spread of the pandemic.

5.1 Data Collection and Preprocessing:

We have used COVID-19 data available on various platforms which are as followed:
i) COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/)
ii) COVID-19 Government Measures Dataset (https://www.acaps.org/covid-19-government-measures-dataset)
iii) Recovered Cases (https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_recovered_global.csv)
iv) Death Cases (https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_deaths_global.csv)
v) Confirmed Cases (https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_confirmed_global.csv)
vi) Global Forecasting test and train data **(https://www.kaggle.com/c/covid19-global-forecasting-week-3)**

5.2 Data Visualisation

In this section, the intuition we had, working on this problem, was that mobility could be a useful proxy for measures. In order to verify this hypothesis we first visualized mobility patterns and measures taken by the government. As a result we can see a strong impact of government measures on the mobility pattern. Then the total number of confirmed, recovered, death cases were visualized where we observed a huge spike in confirmed cases as the government started releasing lockdowns.

5.3 Prediction

Exponential Growth Model:

1. During the incipience of an epidemic, it is important to use an exponential growth model to understand the infection rates, and with fitting policy implementation and behavioral differences among the responsive groups of the population, the slope reduces and the curve flattens over time.
2. The formula tells us the number of cases at a certain moment in time, in the case of Coronavirus, this is the number of infected people.
3. A growth rate is calculated in the model, that is starting with the fundamental value of 1 infected person considering each sick person infects 2 other people, so the growth rate becomes 2. Therefore, we examined the development of the pandemic from time 0 to time 15.
4. We forecasted the infections for the fifteen days, and the deviation of the data points from the modeled exponential curve was captured using the exponential growth model.

Prophet Model:

1.Time series forecasting can be struggling as there are many diverse methods you can use and various hyperparameters for each system. Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
2.That is, we can make a forecast on data used as input to train the model. Growth forecasting is used to analyze how the COVID-19 cases have grown so far, and how they are likely to continue growing in the near future.

3. Prophet uses Fourier series to forecast the seasonality effects and the seasonality models are specified as the periodic functions of time. The models actively learn real-time data with current observations of COVID-19 in order to predict future outbreaks.

6. FLOWCHART

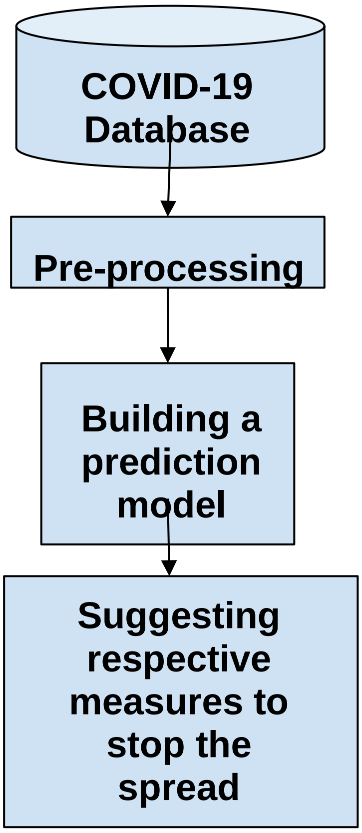

Fig 1. Implementation of Mobility Pattern and Prediction on Covid-19.

7. CONCLUSION

We have examined the predicament of Covid19 spread in India in practical situations. In this paper, the analysis was performed based on the data set gathered from various sources. The analysis work reported has tried to combine important variables concerning mobility patterns, confirmed cases, infected and death cases of the virus to foretell initial indications of containment. According to our study, it is proved that mobility pattern is an important factor for the prediction of covid-19 cases. A mathematical model has been established, using the exponential growth model which forecasted the number of infected cases. But when compared with the real-time data results show that the proposed model has a low ability to forecast the infected cases of the COVID-19 dataset. In contrast, a machine learning algorithm was deployed which is a time-series data technique, i.e, a prophet model which has a high ability to forecast the confirmed infected cases.

This study will be intensified continuously in the future course, we intend to explore the forecasting methodology, and use authentic and appropriate ML methods for forecasting.In this context, determining accurately the future trajectory of the pandemic will give the administration the expected tools to deal with the situation.

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