COVID-19 Prediction through CNN and LSTM Deep Learning Models

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***Abstract*– The advances in the medical field have been crucial for the purpose of attaining the improvement in the health of the masses. A healthy populous for a nation has the ability to achieve the goals of productivity while reducing the efforts to combat the spread of diseases and other communicable ailments. If majority of the individuals are healthy and have a healthy lifestyle, it would be far easier to recover from a pandemic and also achieve effective realizations that can be useful in achieving the growth and advancements far more efficiently. The recent pandemic is a testament to this fact, the Covid-19 virus has led to the largescale deaths and destruction across the world. This pandemic could have been better handled if the healthcare sector had an idea about the scale and the severity of the pandemic which would let them be effectively prepared in response to the increasing infections. The progression of a pandemic is extremely complicated which can only be predicted using machine learning implementations. For this purpose, this research article deploys Pearson correlation and K Nearest Neighbor clustering along with the Convolutional Neural Networks and Decision Tree for precise Covid-19 predictions. The experimental outcomes have proved the improvement offered by the presented approach over conventional implementations.**

Keywords— *Covid-19 Prediction, Pearson Correlation, Convolution neural network, LSTM, K- Nearest neighbor Classifications.*

I. Introduction

COVID-19, a new coronavirus, caused an epidemic in Wuhan, China, in December 2019. It quickly expanded to over 200 nations throughout the world following its inception. The number of verified COVID-19 infected patients is expanding at an exponential rate throughout the world. COVID-19 has infected over 17 million individuals to far, with over 0.7 million people dying as a result. As a result of the lack of particular immunizations to prevent the disease from spreading further, numerous nations have entirely shut down their everyday operations. Lockdown has been implemented across the country. It controls the spread of the disease to some extent; yet, it has had a significant impact on the national and global health economy. The COVID-19 pandemic has mostly impacted small, medium, and big businesses, who are experiencing issues such as decreased demand, no exports, a scarcity of raw materials, and transportation and supply chain interruptions.

Thousands of COVID19 patients come every day in need of rapid help, which is frequently unavailable. As a result, it's critical to develop a technological tool that can estimate the number of infected individuals and foresee the worst-case situations, such as the economy collapsing and the healthcare system collapsing. The impact, on the other hand, is determined by the characteristics of the afflicted people, such as social connections, personal economic and educational levels, and government resources to deal with the crisis. Because there is no vaccine for COVID-19 and the disease is communicable, the number of afflicted persons is rising at a quicker rate. The tests that measure the Coronavirus to determine the presence of illness, are to be examined more since the range of symptoms of positive cases has been rising since the virus's discovery on the planet. As COVID-19 has achieved pandemic status and the number of patients continues to rise at an exponential pace, widespread diagnostic testing is critical in determining and controlling the spread of this rapidly spreading illness.

Fuzzy Rule-Based Systems (FRBS) are a type of artificial intelligence that uses fuzzy notions to make decisions. The goal of the methods is to describe knowledge as a set of fuzzy rules. For tackling difficult real-world issues, FRBS has been proposed [11]. The FRBS's performance is determined by its membership functions and rule base. Li- Xin Wang and Jerry M. Mendel proposed the Wang and Mendel (WM) fuzzy rule learning approach in 1992 [12].

Most of the preceding models take into account mortality based data, which is generally monotonic and has predictable behavior that can be explained by a quiet basic model. A distinct problem linked to COVID-19 will be addressed in this research. The goal of this study is to create a model that predicts the number of confirmed cases caused by COVID-19 in the selected region of india based on data from several countries. These data are not time-based in theory, and their states are typically random. LSTM and CNN supervised-based approaches are utilized and evaluated in terms of their prediction abilities to develop the best forecasting model.

In this research article related works are mentioned in the section 2. The proposed technique is deeply narrated in the section 3. The experimental evaluation is performed in section 4 and whereas section 5 concludes this research article with the scope for future enhancement.

II. Literature Survey

The hybrid AI framework developed by N. Zheng et al. et al. for predicting COVID-19 is dependent on the ISI model and includes an NLP module that incorporates important information gathered through the efforts of the central government and local governments, as well as widespread public participation in the prediction calculation process [1]. The model's predictions are very close to actual epidemic cases, demonstrating that the proposed hybrid model can analyze the virus's transmission law and development trend more accurately than previous models, and that language information processing of related news can drastically enhance the model's accuracy.

For estimating the danger of a worldwide COVID19 epidemic, a machine learning-based prediction method has been developed by F. Rustam et al [2]. The system uses machine learning algorithms to analyze a dataset including day-by-day actual historical data and create predictions for the following days. Given the type and amount of the dataset, the study's findings show that ES performs best in the present forecasting domain. LR and LASSO are also good at projecting mortality rates and confirming cases to some extent. The findings of these two models predict that mortality rates will rise in the following days, while recovery rates will slow. Because of the ups and downs in the dataset values, SVM delivers unsatisfactory results in all cases. It was quite tough to create an accurate hyperplane between the dataset's supplied values.

R. B. Duffey et al. introduced learning theory to describe the decline of pandemic illnesses like CoVid-19. The infection rate, as a metric of incorrect consequence, and time, as a measure of experience/knowledge collected or risk exposure that facilitates learning, are both important considerations. The CoVid-19 infection rate data almost closely follow the Universal Learning Curve outlining the falling trajectory of many other cases when people learn to deploy effective countermeasures, according to assessments of the already available data [3]. For other modern technical systems managed by people, the learning curve is approximately the same (with universal constant k3) as for any learning experience, minimizing outcomes, accidents, and incidents.

Michael Small et al. presented a framework that has a modest – possibly minimal – number of parameters and reflects the dynamics of pandemic illness spread as observed [4]. The model demonstrates strong qualitative agreement with observed data across population centers when applied to data from the worldwide coronavirus outbreak in 2019/2020. Despite this, similar simulations with different beginning circumstances produce dramatically different results. The presented model projections have a high variance, substantially higher than the variance found across different epidemiological parameter values. Therefore, selecting optimal transmission rates is a secondary consideration after properly describing contact patterns and devising a transmission mitigation approach. Their findings suggest that simulations of models claiming predictive capacity inside that prediction envelope may be prone to over-interpretation.

B. Wang et al. investigated how to use social relationships between mobile devices in SIoT to help limit infection rates by detecting probable COVID19 infections early [5]. Then, for dynamic network architecture, the authors converted the optimization issue into an MWVC problem and developed an RAI technique to solve it. Using two realistic datasets, they show that their method significantly decreases the epidemic infection rate in both large-scale and small-scale scenarios when compared to the benchmarks. Finally, by depending on the early detection of COVID-19 cases, the suggested approach is excellently appropriate for disease control and prevention.

The findings of X. Chen's study improve prior asymptomatic infector models based on issues, which are unique to the COVID-19 pandemic condition [6]. To begin, this framework takes into account a more realistic transmission pathway, in which the asymptomatic infector population is acquired from the affected population rather than the exposed population. Second, the recovery and death groups are studied separately, with the dead group acting as a key indicator of the impact of various response techniques. Third, evaluate the efficacy of various preventative and response techniques under a variety of implementation time restrictions, since this may provide useful information for choosing appropriate epidemic prevention and response measures in practice.

E. Karaçuha et al. wanted to offer practical advice on how to forecast case numbers to develop a better strategy for allocating health resources to patients in the face of the present pandemic [7]. This simulation may be utilized not just for today's COVID-19 situation, but also for future local or global outbreaks. The number of confirmed cases, fatalities, and recoveries from the COVID-19 epidemic are modeled and forecasted in this research for eight countries: China, France, Germany, Italy, Spain, Turkey, the United Kingdom, and the United States. First, the authors modeled the COVID-19 data from the first verified case date to April 19th, using their previously revealed Deep Assessment Methodology, which is based on Fractional Calculus. The DAM and Long-Short Term Memory (LSTM) were then utilized to evaluate DAM performance in a one-step prediction. The study's last portion focused on short-term pandemic prediction, with the Time-Dependent SIR model and a Gaussian model forecasting the next 30 days using the gradient of the continual number of reported cases obtained from DAM.

A. Ramchandani et al. offer a unique deep learning framework for examining diverse county-level characteristics and forecasting the future development of infected cases. The suggested technique uses both the spatial and temporal structure of the data to extract annotations from multivariate time series and multivariate spatial time series data in a unique way. Other deep learning studies might use this embedding extraction approach to analyze comparable types of data. In addition, unlike prior models, the proposed model incorporates a huge number of input features and learns relationships between them [8]. During the COVID-19 pandemic, the model's use was proved in forecasting the rise in the number of new cases in U.S. counties.

O. Tutsoy et al. create a Suspicious-Infected-Death (SpID) model with fully unknown dynamics [9]. The established SpID model is heavily linked since the suspicious, infected, and death casualties are all highly reliant on one another. Each sub-model of the produced SpID incorporates 2nd order internal dynamics to reflect the peaks and changes in the COVID-19 casualties. The exact bases corresponding to the model's parameter space are generated, and the unknown parameters are learned using a batch type Least Squares (LS) estimator to train the SpID model's unknown parameters. The model with the determined parameters has been carefully investigated using mathematical methods, and future COVID-19 casualties for Turkey have been anticipated using the constructed model.

COVID-19 was the subject of mathematical and numerical investigations of Y. -C. Chen et al. Not only is their time-dependent SIR model more adaptable than standard static SIR models, but it is also more resilient than direct estimation approaches. For the dataset published by the National Health Commission of the People's Republic of China (NHC), their numerical findings demonstrate that one-day prediction errors for the number of infected individuals Xt and the number of recovered persons Rt are within (nearly) 3%. Furthermore, they can exactly anticipate the future development of the COVID-19 epidemic in China by following the features of the transmission rate and the recovery rate over time [10].

To explain the transmission of pandemics, S. Dash et al. introduced the best ARIMA models for six high-incidence nations across the world and six badly impacted states in India forecast 90 days ahead of future values. Except for a few instances, the model predicts values that are fairly close to the precise values [11]. The ARIMA model utilized for the United Kingdom isn't the greatest fit. For all six nations, the anticipated RMSE, AIC, and BIC values are appropriate. Similarly, the ARIMA models built for Indian states have substantial projected RMSE, AIC, and BIC values. The ARIMA Model's efficiency is demonstrated through statistical performance indicators. The model's findings might be used to create possible measures to enhance the healthcare system and improve management.

Using data supplied by authorities daily, D. Gaglione et al. proposed a Bayesian sequential estimating and forecasting approach that can estimate the status of the epidemic and the parameters of the underlying model, as well as anticipate the evolution of the epidemiological curve [12]. The authors created a quick implementation of the aforementioned Bayesian framework that works well with the stochastic SIR pandemic evolution model. The proposed method is evaluated using both synthetic data representing two epidemic scenarios and real data obtained during the recent COVID-19 outbreak in Italy's Lombardia region and the United States. When the forecast is 7 days, the mean absolute percentage inaccuracy assessed after the lockdown is less than 5% and less than 10% when the prediction is 14 days.

To define the COVID-19 distribution in different nations, H. Friji et al. constructed an eight-state mechanistic model. The interactions between the different states are theoretically modeled using an ODE system. To establish correct fitting solutions and estimate the parameters of the ODE model, a curve fitting employing real-world observed data sets is constructed [13]. The ODE system parameters are solved and estimated using the LM technique. The authors have demonstrated that the techniques used outperform a reference model, BFGS. The fitting approach is shown alongside the model, which seeks to back up its predicting predictions by focusing on the data's most recent patterns, and so providing accurate results that are on the edge of these trends.

III PROPOSED METHODOLOGY

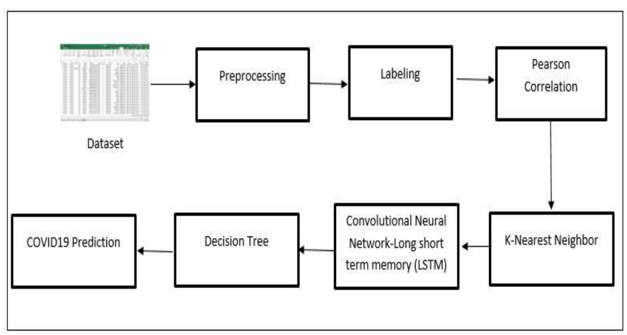

Figure 1: System Overview Diagram

The presented approach for the prediction of Covid-19 infections has been implemented using Convolutional Neural Networks and Long Short Term Memory. The procedure has been performed using a series of steps that have been displayed below.

Step 1: Dataset Collection and Data preprocessing - A district-by-district dataset is input into the system in.CSV format at the start of the proposed model. The following URL was used to collect this data: https://api.covid19india.org/csv/latest/districts.csv. Date, State, District, Recovered, Deceased, Other, and tested are all included in this dataset. The dataset path is supplied to the variable in the application as a hard coded value. Following the path, rows and columns are separated to read the dataset as a double-dimensional list.

Some extraneous columns, such as State, other, and tested, are removed from the list after the dataset is gathered in the double dimension list. Date, district, confirmed, recovered, and died are picked as preprocessed list elements in the Data segregation procedure, which is discussed in the following step.

Step 2: Data segregation – This phase takes the preprocessed list and changes it into a district-specific segregated list. The date is converted into ordinal values using a data segregated list; this procedure changes the string type of data of the durations into Date type of data. This finally aids the model in sorting or selecting the rows for the segregated list for the two supplied date intervals.

Step 3: Training and testing data Creation – Initially, the proposed model predicts the top ten districts for the given kind of case from the preprocessed list for creating the testing and training data list. This is accomplished using the sort values method, which takes two parameters: type and sorting value. Following the selection of the top ten districts, the train and test lists are created.

The data is picked from the preprocessed list between the two supplied date periods in a list. Then two lists are made, one for the date and the other for the specified district name. The test and train sets are then created using the function train test split(). Because the model is not rearranging the data according to date, this method takes the following parameters: X,Y, test size of 0.15, and rearranging boolean value of false. The random train and test data is then generated and assigned to four lists: train x, train y, test x, and test y.

These train and test collections are translated to ordinal values, allowing them to accommodate all data kinds with ease. The MinMaxScaler() function is used to equalize the test and training lists. This technique uses the upper and lower limits to normalize all of the data. Following normalization, the lists are reshaped into a single dimension using the reshape function ( ). The reshaped data is fed into several LSTM models to forecast infection levels for the next few days in COVID -19 patients.

Step 4: K nearest Neighbors – The data collected previously is being used for the purpose of achieving the effective clusters of the data. The K nearest clustering approach utilizes the dataset and finds the data points that are the closest to one another. This is done by calculation of the distances and the setting up of valid centroids through the value of K. The k number of classifications are formed according to the centroids which are then provided to the next step for the prediction through the use of the CNN-LSTM approach.

Step 4: Long Short Term memory – This is the neural network, which takes train x, train y, test x, test y, scalar object of normalization, test date, and case category as input parameters. Cases are capitalized for the first character at the start. The neural network's model object is then generated in sequential mode. The LSTM model is enhanced with 20 units of samples, a TRUE return sequence, and a one-dimensional space with a single feature. In addition to the additional parameters, a dropout () is employed between the final hidden layer and the output layer at a rate of 20% (or 0.2). This procedure of parameter addition and dropout is replicated at rates of 40, 80, and 80 units. After that, a dense layer with kernel size 40 and activation function 'ReLU' is implemented. The dense layer is a densely linked neural network that uses the activation function on neurons to effectively learn data. The basic LSTM neural network is built using two dense layers with kernel sizes of 40 and 1, respectively. The neural network is compiled with a batch size of 10 and 250 epochs. Similar to bidirectional LSTM and CNN LSTM, bidirectional LSTM and CNN LSTM are intended to train the model and architecture for the same, as demonstrated in the architecture diagrams in Figures 3 and 4.

Bidirectional LSTM	
Layer	**Activation**
Bidirectional 40 samples	
Dropout 20%	
Bidirectional 80 samples	
Dense 40	Relu
Dropout 20%	
Dense 40	Relu
Dropout 20%	
Dense 1	None
Adam Optimizer	
Batch size 10	
Epochs 250	

Figure 3: Architecture for Bidirectional LSTM

CNN LSTM	
Layer	**Activation**
CONV 1D 32 Samples,Kernel=1	relu
CONV 1D 32 Samples,Kernel=1	relu
Max Pooling 1D	
Dropout 30%	
CONV 1D 64 Samples,Kernel=1	relu
Max Pooling 1D	
Dropout 35%	
CONV 1D 128 Samples,Kernel=1	Tanh
Max Pooling 1D	
Dropout 40%	
LSTM 50	
Dropput 25%	
Flatten	
Dense 6	Tanh
Dropout 20%	
Dense 1	None
Adam Optimizer	
Batch size 10	
Epochs 250	

Figure 4: Architecture for CNN LSTM

The predict() method of the model object is used to identify predictions for a specific test list after establishing the LSTM neural network model. The predicted results are displayed in a graph created using the matplotlib API object.

The Mathematical Model for the COVID 19 Prediction has been depicted below.

Mathematical Model

1. S= { } be as system for COVID 19 Prediction System
2. Identify Input as S={ D_1, D_2, D_3….. D_n}
   Where D = Dataset
3. S={ D }
   Identify C_{PF} as Output i.e. COVID 19 Prediction
4. S= {D, C_P }
5. Identify Process P
6. S= { D, P,C_P }
7. P= { P,K_{NN},L_{STM} ,D_T}
8. Where
9. P=Preprocessing
10. K_{NN} =K- Nearest Neighbor
11. L_{STM} =Long Short Term Memory
12. D_T= Decision Tree

So the complete System of Covid 19 prediction can be explained depicted as

13. S = { D, P,K_{NN},L_{STM} ,D_T,C_P }

IV RESULT AND DISCUSSIONS

The proposed methodology for the prediction of Covid-19 infection rate prediction has been developed through the use of Python programming language. The Spyder IDE has been utilized to facilitate development of the proposed methodology. The development machine is equipped with 4GB of RAM and 500GB of Hard Disk which is supplemented by an Intel Core i5 processor. The Pandas API is being used for the purpose of enabling the interfacing of the dataset in a workbook format.

Experimental evaluation has been performed to allow an in-depth assessment of the prediction procedure for the presence of any errors. The error assessment derives the preciseness of the prediction that can be highly useful in describing the accuracy of the Covid-19 prediction system. The RMSE or the Root Mean Square Error performance metric has been used to extract the error of the prescribed prediction model.

The RMSE technique utilizes two continuous and correlated entities that are correlated to determine the error between these two variables. The variables utilized in our implementation are the expected Covid-19 infection rate predictions and the obtained Covid-19 infection rate predictions. The equation utilized to achieve the error are illustrated in the equation 1 given below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i} - x_{2,i}\right)^2}{n}} \qquad \_\ (1)$$

Where,

$\sum$ - Summation

$(x_1 - x_2)^2$ - Differences Squared for the summation in between the expected Covid-19 infection rate predictions and the obtained Covid-19 infection rate predictions

n - Number of samples or Trails

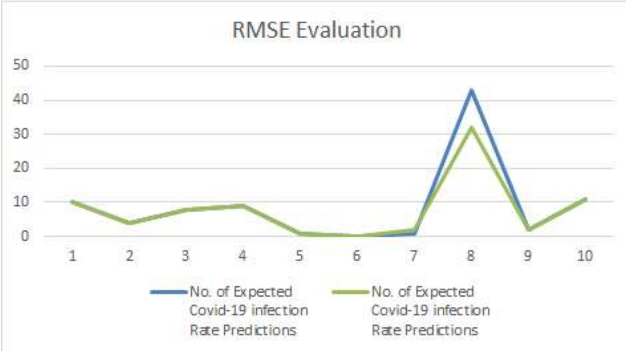

Table 1: Mean Square Error measurement

S no.	District	No. of Expected Covid-19 infection Rate Predictions	No. of Expected Covid-19 infection Rate Predictions	MSE
1	Anantpur	10	10	0
2	Guntur	4	4	0
3	Surat	8	8	0
4	Ambala	9	9	0
5	Faridabad	1	1	0
6	Palwal	0	0	0
7	Bandipora	1	2	1
8	Srinagar	43	32	121
9	Kasaragod	2	2	0
10	Palakkad	11	11	0

Figure 2: Comparison of MSE in between No of expected Covid-19 infection rate predictions V/s No of obtained Covid-19 infection rate predictions

The experimental evaluation and its outcomes have been depicted in the table 1 given above. The values obtained in the table are used to draw a line graph given in the figure 2 given below. Through close examination of the graphical representation and the tabulated values, we can come to a conclusion that the error achieve in this process of prediction is minimal. A collection of 10 experiments have been conducted with varying districts have been performed to achieve the assessment of MSE or Mean Square Error.

The assessment results declare that the error achieved in the prediction system is acceptable and reasonable. The error for the prediction is usually present in the prediction models which are work on a real world data. There are a number of different scenarios that affect the Covid-19 infection rate predictions. The achieved MSE and RMSE values of 12.20 and 3.49 respectively are highly satisfactory and describe an accurate deployment of the Covid-19 infection rate prediction model.

V CONCLUSION AND FUTURE SCOPE

The presented technique for the purpose of attaining accurate and precise predictions for covid-19 infection rate has been implemented through the use of Convolutional Neural Network-Long Short Term Memory. The input dataset is preprocessed to eliminate redundant data before being sent on to the next module for segregation. The preprocessed data is then partitioned into districts and sent into the N Nearest Neighbors module. The KNN method takes a preprocessed and segregated dataset and clusters it based on the dataset's nearest values. Through data normalization and data mapping, the CNN-LSTM module gets the segregated data, which is then separated into portions for training and testing purposes. Confirmed, recovered, and dead cases are used to train the CNN-LSTM module. In this case, the Deep Learning paradigm comes to the rescue, allowing for the effective prediction of Covid-19 infection rates with the use of three different types of LSTM models, namely conventional LSTM, Conditional LSTM, and Bi-Directional LSTM. The experimental results show that the Covid-19 infection rate projections are accurate.

In the future, the model may be applied to large sets of data encompassing hundreds of attributes for all parts of the world utilizing a cloud-based Generative Adversarial Neural Network.

REFERENCES

[1] N. Zheng et al., "Predicting COVID-19 in China Using Hybrid AI Model," in IEEE Transactions on Cybernetics, vol. 50, no. 7, pp. 2891-2904, July 2020, DOI: 10.1109/TCYB.2020.2990162.

[2] F. Rustam et al., "COVID-19 Future Forecasting Using Supervised Machine Learning Models," in IEEE Access, vol. 8, pp. 101489-101499, 2020, DOI: 10.1109/ACCESS.2020.2997311.

[3] R. B. Duffey and E. Zio, "Analyzing Recovery From Pandemics by Learning Theory: The Case of CoVid-19," in IEEE Access, vol. 8, pp. 110789-110795, 2020, DOI: 10.1109/ACCESS.2020.3001344.

[4] Small, Michael & Cavanagh, David. (2020). Modeling Strong Control Measures for Epidemic Propagation With Networks—A COVID-19 Case Study. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3001298.

[5] B. Wang, Y. Sun, T. Q. Duong, L. D. Nguyen, and L. Hanzo, "Risk-Aware Identification of Highly Suspected COVID-19 Cases in Social IoT: A Joint Graph Theory and Reinforcement Learning Approach," in IEEE Access, vol. 8,

pp. 115655-115661, 2020, DOI: 10.1109/ACCESS.2020.3003750.

[6] X. Chen, "Infectious Disease Modeling and Epidemic Response Measures Analysis Considering Asymptomatic Infection," in IEEE Access, vol. 8, pp. 149652-149660, 2020, DOI: 10.1109/ACCESS.2020.3016681.

[7] E. Karaçuha et al., "Modeling and Prediction of the Covid-19 Cases With Deep Assessment Methodology and Fractional Calculus," in IEEE Access, vol. 8, pp. 164012-164034, 2020, DOI: 10.1109/ACCESS.2020.3021952.

[8] A. Ramchandani, C. Fan, and A. Mostafavi, "DeepCOVIDNet: An Interpretable Deep Learning Model for Predictive Surveillance of COVID-19 Using Heterogeneous Features and Their Interactions," in IEEE Access, vol. 8, pp. 159915-159930, 2020, DOI: 10.1109/ACCESS.2020.3019989.

[9] O. Tutsoy, Ş. Çolak, A. Polat and K. Balikci, "A Novel Parametric Model for the Prediction and Analysis of the COVID-19 Casualties," in IEEE Access, vol. 8, pp. 193898-193906, 2020, DOI: 10.1109/ACCESS.2020.3033146.

[10] Y. -C. Chen, P. -E. Lu, C. -S. Chang and T. -H. Liu, "A Time-Dependent SIR Model for COVID-19 With Undetectable Infected Persons," in IEEE Transactions on Network Science and Engineering, vol. 7, no. 4, pp. 3279-3294, 1 Oct.-Dec. 2020, DOI: 10.1109/TNSE.2020.3024723.

[11] S. Dash, C. Chakraborty, S. K. Giri, S. K. Pani, and J. Frnda, "BIFM: Big-Data Driven Intelligent Forecasting Model for COVID-19," in IEEE Access, vol. 9, pp. 97505-97517, 2021, DOI: 10.1109/ACCESS.2021.3094658.

[12] D. Gaglione et al., "Adaptive Bayesian Learning and Forecasting of Epidemic Evolution—Data Analysis of the COVID-19 Outbreak," in IEEE Access, vol. 8, pp. 175244-175264, 2020, DOI: 10.1109/ACCESS.2020.3019922.

[13] H. Friji, R. Hamadi, H. Ghazzai, H. Besbes, and Y. Massoud, "A Generalized Mechanistic Model for Assessing and Forecasting the Spread of the COVID-19 Pandemic," in IEEE Access, vol. 9, pp. 13266-13285, 2021, DOI: 10.1109/ACCESS.2021.3051929.

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