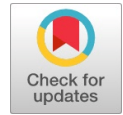# A Review Study on Outbreak Prediction of Covid-19 By using Machine Learning

Kamal Narayan Kamlesh

*Abstract: In December 2019, Wuhan City, China, discovered a new infectious disease, COVID-19. Over 70 million people have been infected and one million people have died as a result of COVID-19. Defeating such a deadly, infectious disease requires accurate models that predict COVID-19 outbreaks. Using prediction models, governments can plan budgets and facilities for fighting diseases, and take control measures to make better decisions and take control measures. For example, they can determine how many medicines and medical equipment to manufacture or import, as well as how many medical personnel are needed to fight the disease. The COVID-19 outbreak has subsequently been predicted in several countries and continents using regression and classification models. A recent study that incorporated statistical and machine learning techniques was reviewed to predict COVID-19 outbreaks in the future. Ground truth datasets are used, their characteristics are investigated, models are developed, predictor variables are identified, statistical and machine learning methods are applied, performance metrics are calculated, and finally comparisons are made. By applying machine learning methods, the survey results indicate that we can make predictions about whether a patient will become infected with COVID-19, how outbreak trends will develop, and which age groups will be affected the most.*

*Keywords: Machine Learning, Classification, Regression, COVID-19, ARIMA*

## I. INTRODUCTION

SARS-CoV-2 is also known as COVID-19. Infectious diseases like this are caused by Coronavirus. Over 71 million people have been infected and died from COVID-19, the first major respiratory pandemic in the history of humanity [1]. Symptoms of the pandemic began to appear on March 12, 2020, when the World Health Organization declared it a pandemic. For governments to make better decisions, COVID-19 outbreaks need to be predicted as accurately as possible. To combat disease effectively, the government can (a) set up a budget, (b) make sure that facilities are adequate before they become overcrowded, (c) select the amount of medical equipment and medicines to manufacture, and finally (d) determine how many doctors are needed. Other diseases, including dengue fever, H1N1 flu, and swine fever, have been studied for developing prediction models in the past decades [2].

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COVID-19's unique characteristics and unprecedented spread caused a number of measures that had never been taken before due to its unique characteristics. Curfews were imposed nationwide, businesses and public places were closed, masks were required outside of homes, and stadiums were converted into temporary hospitals.

To predict COVID-19 outbreaks, two types of prediction models are used: regression and classification. In regression models, continuous quantities are predicted. To assign them to appropriate classes, data are classified either by single-class labels (i.e., binary labels) or by multi-class labels. A time series prediction considers how values have evolved over time in order to predict future changes. The combination of regular regressions, regular classifications, time series-based regressions, and time series-based classifications is used to obtain regular regression models and regular classification models.

In the present study, recent statistical and machine learning studies have been conducted in order to predict the COVID-19 outbreak. A description of the statistical methods and machine learning algorithms used in each study is provided, along with performance metrics. In addition to describing these characteristics, the ground-truth dataset, the statistical models, predictor variables, and the machine learning methods are also described. Finally, we provide results and conclusions. Throughout the paper, the studies are organized as follows: Indian cases, Eurasian cases, African cases, American cases, and intercontinental cases. At the end of the paper, a scope for future research is presented.

## II. ANALYSES OF INDIAN CASES

A study was conducted to predict India's situation during the outbreak of global pandemic COVID-19. COVID-19 outbreak in India was analyzed using enhanced versions of the SIR epidemic model [3]. Rather than assuming values for parameters, sophisticated approaches based on curve fitting were applied on available data to achieve more realistic results. For optimal results, the Government of India implemented Zone bifurcation to identify susceptible patients. Compared with the number of people who should be tested for HIV, not enough people have been tested for HIV in India. According to the model, India has a low Ro value and a low fatality rate compared to other countries. In a single day, it is predicted that there could be around 800000 active cases and over 35000 deaths due to the outbreak. Another researcher believe that the situation in the country is acceptable compared to many other regions [4]. Lockdowns and distancing laws could have prevented this if enacted at the right time.

# A Review Study on Outbreak Prediction of Covid-19 By using Machine Learning

COVID-19 has been predicted by model to cause large numbers of deaths in India, even at lower values of R0, due to the relatively high population. The models assume that the same conditions will persist, which can lead to a mismatch between the number of tests and the number of confirmed cases if there are too few tests conducted and there are too many asymptomatic patients.

Humans are infected with the COVID-19 virus, which damages the lungs and causes illness. The COVID-19 virus has killed a lot of people around the world. Using navel coronavirus analysis to study five different tasks, we propose Support Vector Regression [5]. Rather than using simple regression lines, this work uses supported vectors to improve classification accuracy. The first thing that must be completed before trying to minimize virus spread is to determine the extent of the virus, so that the government and citizens can better prepare for future outbreaks. Based on this information, the government and citizens will be able to make appropriate plans to minimize its spread. We are more likely to be able to gain insight into the effectiveness of mitigation measures, the actions that have been taken so far, and the number of cases that have been prevented as a result.

Finally, by doing the third task, we will be able to estimate how many patients will be able to recover from this disease, since vaccines and cures have not yet been discovered. This will allow us to predict how long it will take for the pandemic to end by predicting how long all the patients will take to recover. In the fourth task, we will observe and analyze the speed of the virus's spread between regions, determining which areas need more attention [6]. To prevent the spread of infection, the environment of an infected patient should be improved. A warning can also be provided if humidity and high temperatures are to be avoided or not. Pearson's correlation method can be used to determine if disease spread is correlated with the weather. In comparison to other regression methods, the proposed Support Vector Regression method performed well in all tasks based on Coronavirus analysis.

Several nations have been devastated by COVID-19 outbreaks. COVID-19 has, however, recovered from India with an 88% recovery rate. Senapati used piecewise linear regression to predict the prevalence of positive cases and recovery cases in five Indian states. Instead of simple linear regression, we have used piecewise linear regression in the proposed scheme [7]. Consequently, both cases are accurately predicted by the proposed scheme. Therefore, our model can be applied to other COVID-19 parameters no matter where they originate or where they are used. We will develop advanced machine learning and deep learning models in order to enhance our response to COVID-19 and other pandemics [8]. Implementing piecewise linear regression involves finding where the data should be partitioned. Using the previous 7 days' data, we have heuristically observed the slope of the point in this paper to predict the next day. By finding an optimal partitioning point in the future, we hope to minimize errors.

COVID-19 poses a threat to thousands of people worldwide. All governments in all countries should pay close attention to this disease in order to reduce its effects [9]. A study has been conducted to analyse and train the outbreak of this disease in the Indian region until May 10th, 2020, as well as to ascertain how many cases there will be over the next three weeks. Government data collected between 29th January and 11th May was analyzed using a machine learning algorithm [10]. RMSLE was used to evaluate the models, and SEIR performed well with 1.52 and regression with 1.75. Regression and SEIR performed well with 2.01. Regression and SEIR performed well with 2.01. R0, which is the spread of the disease, was calculated at 2.86. The expected number of cases is 176K–210K for the three-week test period [11]. Doctors and the government will benefit from this study in preparing their future plans. A new coronavirus, COVID-19, was reported in Wuhan, China, on December 30, 2019.

This virus has an estimated fatality rate of 4.5%, but that increases to 8.1% in the 70-80 age group, and 14.9% in the 81+ age group, Diabetes, Parkinson's disease, and cardiovascular disease pose the greatest risk to elderly patients over 50 [12]. As a result of this disease, you may experience a fever, cough, shortness of breath, pneumonia, kidney failure, and even death. The virus spreads via respiratory droplets between people in close proximity, with an average number of infected individuals being 1.5–3.5 per patient, but it is not considered an airborne illness. As there is no vaccine against CoVID-19, flattening the epidemic curve and reducing the epidemic peak are critical to managing this pandemic [13]. Using data science and data mining, researchers can develop concrete plans and make accurate decisions by understanding viruses and their characteristics. In order to prevent future epidemics and develop infrastructure, facilities, and vaccines, more aggressive measures will be taken. In this study, regression and SEIR models are combined to predict the number of cases and estimate the spread of the disease in India. Our empirical results were analyzed using the data from the government web portal (https://www.mohfw.gov.in/) and the John Hopkins University, USA. Data for the training period will be available on 30/01/2020 and the test data will be available on 11/05/2020 and 31/05/2020. In the data, we include confirmed cases as well as deaths and recovered cases. Using data from Guhathakurata in his article analyses and predicts COVID-19 cases in India [14]. There have been fewer than one COVID-19 case per million in India, which represents approximately 18.6% of the world's population.

Artificial intelligence has been used to fight the COVID-19 pandemic. The definition of Artificial Intelligence given by Tamhane & team in Machine Learning, Natural Language Processing, and Computer Vision Applications [15]. Pattern recognition, prediction, etc. can be taught to computers using these models. This paper uses two machine learning techniques to predict COVID-19 outbreaks. Support vector regression and polynomial regression methods are used for data visualization and prediction. It would allow us to take precautions before COVID-19 spirals out of control without control by estimating future cases of the virus. In the fight against COVID-19, the use of artificial intelligence does require accurate data and human-computer interactions, but it has become a source of hope for the advancement of technology for the protection of mankind [16].

2

Here, a prediction model is developed for predicting the number of cases in the next 25 days. A polynomial regression model as well as a support vector regression model were used to obtain the results. The Python language simplifies the process of achieving desired results. As a result, it uncovers hidden insights that provide insights and predict future trends.

**Table 1**

| Author's | Publishing Year | Model | Technique of the study | Predictor variables of the study | Target variables of the study |
|---|---|---|---|---|---|
| Kumar et. al. | 2020 | Nested Exponential Statistical Model | Machine Learning | Confirmed Cases | Total Cases |
| Gupta et. al. | 2020 | Regression Model | Machine Learning | Expected Cases | All Cases |
| Yadav et. al. | 2020 | Support Vector Regression Model | Machine Learning | Active Cases | Recoveries |
| Guhathakurata et. al. | 2021 | Multiple Criteria Decision-Making (MCDM) Technique | Machine Learning | Covid-19 Cases | Total Death |
| Senapati et. al. | 2021 | Linear Regression | Machine Learning | Confirmed Cases | Total Cases |
| Hussain et. al. | 2021 | Convolutional Neural Network | Deep Learning | X-ray and CT Scan | non-COVID Bacterial pneumonia |

## III. ANALYSIS OF EURASIAN CASES

COVID-19 spread in Indonesia can be predicted using different models [17]. Both ARIMA and PROPHET algorithms were used to create the model, which is an Autoregressive Integrated Moving Averages (ARIMA) model. An ARIMA (p, d, q) formula is used to average a difference between two samples, where p is the lag time, d is the difference degree, and q is the size of the average window. Data for this study were obtained from the Kaggle website. They contain serial numbers, observation dates, provinces/states, countries/regions, last updates, confirmations, recoveries, and deaths. In the original dataset, 28.218 rows were included, but only 82 rows remained when only Indonesian data were included [18]. Due to the fact that ARIMA uses only univariate data, they separated confirmed, recovery, and death data frames. Afterwards, they checked if the data was stationary since ARIMA is better able to calculate results with stable data. There was no stationary trend in the data, according to their findings. As a next step, they transformed the data into stationary form using log-scale transformation and time-shifting transformation. The prediction of future death counts was based on past confirmed, recovered, and recovered death counts [19].

Metrics such as coefficients of determination (R2), mean square errors (MSEs), mean absolute errors (MAEs), and mean forecast errors (MFEs) are used to measure program performance. Between April 22, 2020, and May 21, 2020, both models were evaluated over a 30-day period. Both PROPHET and ARIMA are generally more accurate as more days are forecasted, but PROPHET is generally better than ARIMA. Using age, gender, nationality, and location as indicators of susceptibility, analyzed the demographics of individuals [20]. The dataset was provided by the Saudi Ministry of Health. Between January 2, 2020, and April 25, 2020, 229124 patient records in Saudi Arabia were included in the dataset. Cities, confirmatory results, dates of birth, genders, nationalities, subject identification numbers, result dates, screening results, and test dates are among variables that predict the outcome. You can substitute the date of birth with any of the following age groups: 0-8, 9-20, 21-29, 31-39, 41-49, 51-59, 61-69, 71-79, or 81+. A total of 15 Saudi regions replaced the city. For the positive class, random oversampling was used because the negative test results were overwhelmingly high, resulting in a database with 51% positive results and 49% negative results. Using age, gender, nationality, and location variables, we predicted COVID-10 outbreaks [21]. DTs (Decision Trees), RFs (Random Forests), and MLPs (Multi-Layer Perceptrons) were more popular in this study. Five cross-validations were performed on the models during training and testing. In study of 2021, AUC (Area under the Curve) was used as a measurement of accuracy, precision, recall, and recall [22]. A DT-based model has been determined to perform the best based on all performance metrics. In addition, only the mentioned predictor variables could be used to predict susceptibility without considering medical factors.

Among Italy, Spain, and France, COVID-19 is prevalent, according to Ceylan [23]. Ceylan, collected data for Italy, Spain, and France from the WHO website between 22.02.2020 and 15.04.2020. A time series ARIMA regression model was created using 45 samples in this study. There are a variety of architectures used in the ARIMA model, where confirmed cases are used as predictors and total cases as dependent variables [24].

A forecasting model was developed by Fang et al. to prevent and control COVID-19 outbreaks. Coronavirus resource center at John Hopkins University provided the dataset [25]. In the dataset, data are available from 30.01.2020 to 30.06.2020. A total of two categories of Russian cases were used in this study: confirmed recovery cases and confirmed death cases.

# A Review Study on Outbreak Prediction of Covid-19 By using Machine Learning

ARIMA forecasting was used to develop time series regression models. The MAPE metric is preferable for verifying the fit of the ARIMA model [26]. With a MAPE value of 0.65, the forecast model for confirmed cases is highly accurate and robust. It has been reported that death forecast models have a MAPE value of 3.90, while recovery forecast models have a MAPE value of 2.40 [27]. These models have also been reported as being reasonably robust.

**Table 2**

| Author's | Publishing Year | Model | Technique of the Study | Predictor Variables of the Study | Target Variables of the Study |
|---|---|---|---|---|---|
| Satrio et al. | 2021 | Time Series Regression | Prophet Forecasting Model | Death Confirmed, Recovered | Death Confirmed, Body Recovered |
| Althnian et al. | 2020 | Regular Classification | Decision Tree, MultiLayer Perceptron | Location, Age, Gender, and Nationality | Susceptibility |
| Ceylan | 2020 | Time Series Regression | Autoregressive Integrated Moving Average | Cases Confirmed | The Total Number of Cases |
| Fang et al. | 2020 | Time Series Regression | Autoregressive Integrated Moving Average | Death Confirmed, Recovered | Death Confirmed, Recovered |
| Fayyoumi et al. | 2020 | Regular Classificati | MultiLayer Perceptron | Test Result Positive For PCR, Age, Gender, Smoking, Positive X-Ray, Fever, Breathing | COVID-19 Positive or Negative |
| Gupta et al. | 2020 | Time Series Regression | Prophet Forecasting Model | Cases Confirmed, Death Cases, And Cases Recovered | Cases Confirmed, Death Cases, and Cases Recovered |
| Önder | 2020 | Time Series Regression | Sub Exponential Growth | Cases Confirmed | Reproductive Number |
| Pinter et al. | 2020 | Time Series Regression | Multi Layered Perceptron-Imperialist Competitive Algorithm | Cases and Deaths per Day | Mortality Rate and Number of Cases |
| Pourghasemi et.al. | 2020 | Time Series Classification | Support Vector Machines, Autoregressive Integrated Moving Average | Coldest Month's Maximum Temperature, Warmest Month's Maximum Temperature, Wettest Month's Precipitation Distance from Banks, Distance from Bakeries, Distance from Attraction Sites | Areas with High or Low Risk |
| Tamhane et al. | 2020 | Time Series Regression | Polynomial Regression, Support Vector Machines | Cases Reported | Amount of Cases |

For predicting the future occurrence of COVID-19, Fayyoumi developed a regular classification model based on machine learning and statistics [28]. This study utilized a dataset collected by an online survey conducted among various eligible Jordanians, of which 105 were selected for participation. Machine learning models were built with SVM and MLP, while statistical learning models were built with Logistic Regression [29]. The dataset also contains predictor variables such as the presence of a PCR test, age, gender, smoking, x-rays that show a positive result, a fever, bronchitis, diarrhea, feeling unwell, nasal congestion, dry

coughing, a lack of smell, aching and pains, and sore throat. Tenfold cross-validation was used to test all models. According to Kumar, this study aims to identify patients who are infected with COVID-19 [30]. Geometric Mean (G_Mean), precision, and accuracy were assessed for the models. Due to the performance metrics used, MLP was selected as the best model.

In the Fars Province of Iran, Pourghasemi investigated risk factors for COVID-19 using a SVM model [31].

The growth trends in COVID-19 in Fars Province were also compared with those elsewhere. Data from time series was classified with the help of these models. A combination of ARIMA and SVM was used. Analyzing COVID-19 spread patterns using ARIMA models and SVMs helped create a risk map of the outbreak. PWM (Precipitation of Wettest Month), PDM (Precipitation of Driest Month) and MTCM (Minimum Temperature of Coldest Month) are predictor variables. Road distance, mosque distance, hospital distance, petrol station distance, bus station distance, bank distance, bakery distance, attraction distance, ATM distance, footprints of people, density of towns. SVM coefficients were analyzed using accuracy metrics, AUC, and t-statistics, whereas ARIMA coefficients were analyzed using standard error, t-statistics, and probability metrics. COVID-19 risk mapping is moderately influenced by MTCM and village density, but ATMs, distances from attractions, fuel stations, mosques, and roads are least affected by climate factors. There is a strong correlation between MTCM and distance from bus stations, bakeries, and hospitals [32]. The infection isn't expected to demonstrate a rapid explosion, but the general trend may continue for some time, according to ARIMA.

To predict the number of cases for the next 25 days, Yeung used a time series regression model [33]. Using dates between January 1, 2020, and May 25, 2020, John Hopkins University provided the dataset. A polynomial regression (PR) model was constructed using SVM and Polynomial Regression (SVM), while the number of cases was used as a predictor [34]. For the purpose of analyzing the data, we divide it into two sets: test data and train data. A performance metric is measured by MAE and a performance metric is measured by MSE. A critical tool for dealing with the crisis may be machine learning, as demonstrated in this study.

## IV. ANALYSIS OF AFRICAN CASES

A prediction of COVID-19's future trends in Ethiopia was made by Gebretensaeby using ARIMA [35]. A study of confirmed, recovered, and death cases in Ethiopia was conducted using data from the Ethiopian Public Health Institute's website. During March 13, 2020, through August 31, 2020, data are included in the dataset. A time-series regression model was constructed using ARIMA. On the basis of Box and Jenkins' description, the authors estimated model parameters using least squares after determining the appropriate ARIMA order. We used Partial Autocorrelation (PACF) and Autocorrection Function 8ACF to confirm the stationary nature of the data in confirmed cases [36]. ACF and PACF graphs were used to select ARIMAs (5, 1, 0) and (3, 1, 2) for predicting confirmed and recovered cases. The Bayesian information criteria (BIC) and RMSE are not the only performance metrics we examined. It is predicted that Ethiopia will experience an increase in confirmed and recovered cases within the next 60 days under ARIMA (5, 0, 0) and ARIMA (3, 1, 2).

A deep learning algorithm was used by Marzouk to predict COVID-19 outbreaks [37]. It is an important source of confirmed, recovered, and fatal cases from Egypt according to the Egyptian Ministry of Health and Population. Over 504 days have passed since February 13, 2020, when the dataset was collected, and it covers the period from February 13, 2020, to June 30, 2021. There was a 90 percent training portion of the data, and a ten percent testing portion [38]. An analysis of time-series regression was conducted in this study. As part of our model building process, we used Multi Level Perceptrons, Convolutional Neural Networks, and Long Short Term Memory (LSTM). The past values of confirmed, recovered, and death counts were used to predict future counts. Performance metrics have been RMSE and R2. Based on their ability to capture nonlinear patterns in input data over time, LSTM models outperformed CNN and MLP models in predicting a week and a month ahead.

In a study published by Anki , Ethiopian cases were used to predict COVID-19 spread [39]. A dataset for this analysis can be found in John Hopkins University's official GitHub repository. This dataset only contains data about Ethiopia. Based on data collected on 25.01.2020, the dataset contains the following information. A training and testing set was created based on the dataset. Training data made up about two-fourths of the dataset, while testing data made up the rest. Time series regression models were developed using SVM and PR. A confirmed case, a recovered case, and a death case are the predictors and output variables. Performance evaluation was based on MAE and MSE metrics. In order to make predictions for COVID-19, a deep learning model using LSTMs, GRUs, and Bi-LSTMs is used. Journal of Chaos, Solitons, and Fractals, 141, 120232. Therefore, both confirmations, recovered cases, and death cases perform better with SVM than PR.

In Algeria, new COVID-19 cases were predicted by Ballı [40]. Using the Algeria health ministry's public health database, we obtained the dataset used in this study. An Extreme Learning Machine (ELM) method is used to build a time series regression model. New cases for COVID-19 were calculated using the cumulative number of confirmed cases, as well as the index day. A new COVID-19 case is generated by the model. A number of performance metrics were preferred, including MSE, RMSE, MAE, NSE, OI, and R2, as well as Nash–Sutcliffe coefficients of efficiency (NSE). It has been concluded that new COVID-19 cases can be predicted using the ELM architecture.

Authorities can make better decisions with the help of the short-term prediction model developed by Saba [41]. Based on data collected between March 10, 2020, and May 15, 2020, a dataset was obtained from the Egyptian Ministry of Health and Population. In order to develop time series regression models, NARANN and ARIMA algorithms were employed. A predictor variable was based on reported cases, and a target variable was based on new cases [42]. Model performance was evaluated using MAE, RMSE, R2, and coefficient of residual mass (CRM) analyses. Using NARANN as a predictor of COVID-19 case numbers outperforms ARIMA.

# A Review Study on Outbreak Prediction of Covid-19 By using Machine Learning

## Table 3

| Author's | Publishing Year | Model | Technique of the study | Predictor variables of the study | Target variables of the study |
|---|---|---|---|---|---|
| Gebretensae et al. | 2021 | Time Series Regression | Autoregressive Integrated Moving Average | Recovered, Confirmed, | All Confirmed, Recovered |
| Marzouk et al. | 2021 | Time Series Regression | Long Short-Term Memory | Confirmed, Recovered, Death | Confirmed, Recovered, Death |
| Ahmed | 2020 | Time Series Regression | Support Vector Machines | Death Confirmed, Recovered | All Confirmed, Recovered, and Dead |
| Djeddou et al. | 2020 | Time Series Regression | ELM | New COVID-19 Cases | Total Cases |
| Saba et al. | 2020 | Time Series Regression | NARANN | Cases Reported | New Cases |
| Takele | 2020 | Time Series Regression | Autoregressive Integrated Moving Average | Confirmed Cases | Total Confirmed Cases |

## V. ANALYSIS OF AMERICAN CASES

According to Luo, COVID-19 is predicted to be on the rise in the US in the near future [43]. We obtained this time-series dataset from the WHO website. As no isolation or treatment measures were initiated by the US between January and March, new confirmed cases were considered 19 or not between April 2, 2020, and September 29, 2020. The performance metrics used were precision, accuracy, recall, and AUC. Based on the results, MLP performed better than other methods.

COVID-19 had been predicted to spread across countries in the Americas by Jojoa [44]. An open data repository of the European Union was used to download the dataset. In order to build the models, we used regression-based prediction models based on MLPs and SVMs. As predictors and output variables, COVID-19 confirmed cases were used. In this study, Pearson's correlation coefficients, mean percent errors, and mean percent errors (MPEs) were used [45]. Using an optimization algorithm to determine the hyperparameters improves MLP performance; however, if not, SVM must be used. In Chile, Mexico, and the United States, MLP performed better than SVM. When the same performance metrics are used for Brazil, Colombia, and Peru, SVM performs better than MLP.

The COVID-19 pandemic was predicted by Moreau in a study he conducted [46]. Our World in Data Project provided the dataset used in this study. Daily modeling objects are included in the dataset. Ninety percent of the data were training data, while ten percent were testing data. With time-series regression, LSTM and XGBoost models were built. Based on past data, we forecast the number of confirmed cases over the next 25 days. A number of performance metrics have been used, including MAE, MSE, RMSE, and MAPE. When the MAPE value is lower, LSTM performs better than XGBoost, which means LSTM outperformed XGBoost.

Using machine learning, Gomes attempted to detect COVID-19 early using early symptoms [47]. A total of 55.676 patients are included in the dataset, which was created in Brazilian. Regular classification techniques were used along with RF, SVM, MLP, KNN, DT, Gradient Boosting Machine (GBM), and XGBoost. According to Mohammedqasim, sore throats, dyspneic, fevers, coughs, headaches, taste disorders, olfactory disorders, and the presence of sore throats were all used as predictor variables. COVID-19 infection can be predicted through the use of this study. In addition to precision, accuracy, recall, and AUC, performance metrics were used. A comparison of MLP with other methods revealed that it performed the best [48].

Various countries in America are affected by COVID-19, according to Jojoa [49]. A dataset from the European Union's open data repository was used for the analysis. Models based on time series regression and SVM were constructed for the prediction process. A COVID-19 case study serves as a predictor and output variable in this study. The performance metrics used in this study were Pearson's Correlation Coefficients, Mean Percentage Errors (MPE), and Mean Absolute Errors (MAE). A hyperparameter optimization algorithm improves SVM performance, whereas it deteriorates MLP performance [50]. MLP performed better than SVM in Chile, Mexico, and the United States. A SVM performance metric outperforms a MLP performance metric when applied to Brazil, Colombia, and Peru.

The COVID-19 pandemic was predicted by Moreau's study. The dataset for this study was provided by 'Our World in Data Project'. The dataset includes all confirmed cases and deaths each day [52]. Beginning with February 26, 2020, the first confirmed case in Brazil, this dataset includes data going back in time. Weibull Distribution models are derived using time series regression. We used the number of confirmed cases and deaths as an output, with no new cases or deaths being recorded on a daily basis as a predictor.

The diagnostic-death lag correlates with mortality rate, so we use this parameter.

You can calculate this parameter by measuring the distance between new cases and deaths on a given day. A total of four scenarios were tested in this study. Using the daily death rate as a basis, these scenarios were developed [51].

A At the maximum point of the curve, the first, second, third, and fourth scenarios would have daily death rates of 1250, 1550, 1760, and 250, respectively. Performance was evaluated using R2 [53]. According to this author's study, the first scenario produced the most optimistic results, while the fourth scenario produced the most pessimistic outcomes. A similar pattern of results was found in the second and third scenarios, which were based on actual daily data. The similar precision of these scenarios makes it impossible to select one over the other as the most likely. According to the diagnostic-death lag value, there are between 1750 and 2000 deaths per day in a prospective scenario.

Forecasting models were updated to include exogenous climatic variables by Silva [54]. Datasets for confirmed cases include cumulative cases for five states in the USA and Brazil. There is data available in the datasets until 29.05.2020. An API was used to collect COVID-19 information about all Brazilian states.

The National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration and Johns Hopkins University's climate data set were used to analyze the climate in the United States. The Brazilian National Institute of Meteorology provided meteorological data for this study. Precipitation and temperature minimums and maximums were exogenously input into each model. In this study, a variety of time series regression models have been developed, such as Bayesian regression neural networks (BRNNs), Cubist regression neural networks (CUBISTs), Kakura neural networks (KNNs), Quantile Random Forests (QRFs), SVRs, and variational mode decompositions (VMDs). Climate variables such as rainfall, maximum temperature, and minimum temperature were predictive of COVID-19 cases [55]. The output variable is the cumulative confirmations.

**Table 4**

| Author's | Publishing Year | Model | Technique of the study | Predictor variables of the study | Target variables of the study |
|---|---|---|---|---|---|
| Luo et al. | 2021 | Time Series Regression | Long Short-Term Memory | Confirmed Cases | Cases Confirmed |
| Santana et al. | 2021 | Regular Classification | MultiLayer Perceptron | Health Professional, Gender, Sore Throat, Dyspnea, Fever, Cough, Headache, Taste Disorder, Olfactory Disorder | Positive or Negative COVID-19 |
| Jojoa et al. | 2020 | Time Series Regression | MultiLayer Perceptron, Support Vector Machines | Confirmed Cases | Confirmed Cases |
| Moreau | 2020 | Time Series Regression | Weibull distribution | Confirmed New Cases, Confirmed New Deaths | Daily New Cases, Daily New Deaths |
| Silva et al. | 2020 | Time Series Regression | BRNN, CUBIST, KNN, QRF, SVR, VMD based Models | COVID-19 Cases, Precipitation, Maximum Temperature, Minimum Temperature | Cumulative Confirmed Cases |
| Souza et al. | 2020 | Regular classification | LogReg, LDA, XGBoost, Support Vector Machines | Symptoms Include Fever, Respiratory Distress, Coughing, Runny Nose, Sore Throat, Diarrhea, Headache, Pulmonary Disease, Cardiovascular Disease, Kidney Disease, Diabetes, Smoking. | is Patient Recovered or Dead |
| WollensteinBetech et al. | 2020 | Regular Classification | Support Vector Machines, LogReg, RF, XGBoost | Age, Pregnancy, Chronic Renal Failure, Diabetes, Immunosuppression, Chronic Obstructive Pulmonary Disease, Obesity, other, Hypertension, Tobacco Use, etc. | Hospitalization, Mortality, ICU Need, Ventilator Need |

7

## VI. ANALYSIS OF INTERCONTINENTAL CASES

In their work, Ayyubi investigate gated recurrent units and long short-term memories (LSTMs). COVID-19 outbreak forecast models proposed [56]. From the WHO website, several columns were included in the dataset, including dates reported, country codes, countries, regions, cumulative cases, and cumulative deaths. For the development of the models, Australian and Iranian data were combined. A period of data for the Australians covers January 25, 2020, to August 18, 2020, and a period of data for the Iranians covers January 2, 2020, to October 5, 2020 [57]. About 71% of the data came from training, while 29% came from testing. Our models were built by combining bidirectional extensions and time-series regression with GRU, LSTM, and Conv-LSTM. On the basis of new cases, cumulative cases, new deaths, and cumulative deaths, we predict new cases, cumulative cases, new deaths, and cumulative deaths in advance. The performance metrics used were MSLE, MAPE, RMSLE, and Explained Variance (EV). The performance of bidirectional models is usually better than that of non-bidirectional models most of the time. Moreover, the best-performed prediction method depends on the scenario one, three, and seven days ahead, so no technique may always produce the best predictions. An outbreak of COVID-19 is predicted in any country using a model developed by Bala [58]. Data on COVID-19 deaths and confirmed cases are available from All our World in Data (OWID). Published by Oxford University under the supervision of the European CDC, this dataset is updated daily. We developed time series regression models based on the date of each case and the number of cases. There was approximately 69:31 training time and 31 percent testing time for this database. XGBoost Regression was built using LinReg, SVM, RF, and RF. A performance evaluation metric was based on MAE and RMSE. According to the results of the tests, XGBoost performed best when compared to RF, SVM, and LinReg.

To help humanity survive the COVID-19 pandemic, Hassan proposed a prediction model for outbreaks of COVID-19 [59]. John Hopkins University provided the dataset on its GitHub repository. Between the beginning of the pandemic and October 15, 2020, daily data was collected on confirmed, recovered, and euthanasia cases worldwide. An initial training set of 225 days and an additional testing set of 39 days comprised our training dataset. In addition to MLP and SVM, Bayesian Networks (BN), Principal Regression (PR), and Linear Regression (LinReg) were used to build time-series regression models [60]. In order to predict future confirmation, recovery, and death counts, past values were used as inputs. R2 value, EV, RMSE, MAE, and MSE were used as performance metrics. MLP generally predicted confirmed cases more accurately than recovered cases and death cases, according to the results.

Using Apple Mobility Trends Reports, we compiled a dataset of mobility data. During the period of 13.01.2020 - 10.05.2020, data was collected to train the model. Data was collected for testing models between 13.05.2020 and 20.05.2020. The United Kingdom, the United States, Brazil, France, Germany, Italy, Spain, and the United Kingdom were among the countries analyzed. Data from a population database and a mobility index were used as inputs. A time series regression model as well as a Gaussian Process Regression model, SVM, and decision tree models were also developed. MAPE was used to assess the model's performance. The mobility index cannot predict daily cases across all countries using machine learning methods.

According to above discussions, a cloud-based prediction model offers more realistic predictions in real time. A daily WHO situation report is used to generate the dataset derived from Hannah Ritchie's "Our World in Data." This study was run on an Azure B1 single-core virtual machine with 1GB RAM and SSD storage, along with Windows Server 2016 64-bit. Using the FogBus framework, the HealthFog framework performed multiple analysis tasks to predict various metrics. In order to develop time series regression models, Robust Weibull Fit and Gaussian Fit were applied. New cases, new cases per year, and mortality rates are all determined by input and output variables. Metrics such as MSE, R2, and MAPE are used to evaluate performance. Weibull Robust models are more effective as performance evaluation metrics than Gaussian Fit models. A Robust Weibull model is found to work better than a Gaussian Fit model.

## VII. CONCLUSION AND FUTURE SCOPE

This study summarizes recent studies on COVID-19 outbreak prediction using machine learning and statistical methods. Numerous studies have been conducted recently in an effort to predict whether patients will become infected with COVID-19, which outbreak trend is most likely to occur, and which age groups are most at risk. A regression model based on time series data, a linear regression model, a semilinear regression model, and a classification model based on time series data are the four main types of regression models. COVID-19 outbreaks can be predicted by analyzing variables such as confirmed cases, recovered cases, and deaths, in addition to pre-existing conditions such as asthma, obesity, hypertension, tobacco smoking, chronic renal insufficiency, diabetes, pregnancy, and demographics, gender, nationality, and location. Additionally, it is important to take into account an individual's current health conditions, such as fever, breathing difficulties, diarrhea, vomiting, loss of smell, nasal congestion, dry cough, headache, and sore throat, in order to predict COVID-19 infection. There are many performance metrics that can be applied to a model, but the most commonly used performance metrics are regression, MAE, MSE, MAPE, and RMSE, while the most commonly applied performance metrics in classification are accuracy, precision, recall, and F1 scores. The MLP method has pretty good results in most models, but cannot be ranked between these methods. A case count, a recovered case, and a death are the most common variables.

A COVID-19 mutations may affect outbreak severity in the future, which is a potential research area. Additionally, the survey results indicate that most forecasting models are developed within a very short timeframe.

8

In order to build more accurate models, longer timeframes like six or nine months can be taken into account in new studies. In addition, future studies can consider new vaccines. Last but not least, it would be beneficial to conduct more studies based on feature selection to identify COVID-19's relevant indicators.

## DECLARATION STATEMENT

| | |
|---|---|
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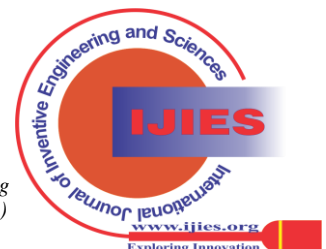
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10

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