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Hybrid Artificial Intelligence-Based Models for Prediction of Death Rate in India Due to COVID-19 Transmission

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ABSTRACT

COVID-19 prediction models are highly welcome and necessary for authorities to make informed decisions. Traditional models, which were used in the past, were unable to reliably estimate death rates due to procedural flaws. The genetic algorithm in association with an artificial neural network (GA-ANN) is one of the suitable blended AI strategies that can foretell more correctly by resolving this difficult COVID-19 phenomena. The genetic algorithm is used to simultaneously optimise all of the ANN parameters. In this work, GA-ANN and ANN models were performed by applying historical daily data from sick, recovered, and dead people in India. The performance of the designed hybrid GA-ANN model is validated by comparing it to the standard ANN and MLR approach. It was determined that the GA-ANN model outperformed the ANN model. When compared to previous examined models for predicting mortality rates in India, the hypothesized hybrid GA-ANN model is the most competent. This hybrid AI (GA-ANN) model is suggested for the prediction due to reasonably better performance and ease of implementation.

KEYWORDS

ANN, Artificial Neural Network, COVID-19, Genetic Algorithm, Hybrid Model, MLR, Pandemic, Prediction

INTRODUCTION

COVID-19 is a novel coronavirus that causes a highly contagious illness. It was found in Wuhan, China, at the end of 2019. The WHO (World Health Organization) declared the virus a global hazard in January 2020. The virus affects people in a variety of ways. Older persons and other persons with chronic illnesses are more vulnerable to severe disease (Worldometers-COVID-19). As a result, governments,

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health systems, and their limited resources have been put under a lot of strain. The global death rate is gradually increasing which is a cause for concern. Transmission is divided into four phases based on the dissemination technique and the time frame. Each nation implemented various methods to counteract the spread of the disease, including sitting at home, face masking, reducing travel, shunning social gatherings, handwashing routinely, and sterilizing the environment (Sujath et al., 2020). The WHO received reports of 290,959,019 confirmed COVID-19 cases as of January 4, 2022, with a total of 5,446,753 fatalities. 8,693,832,171 vaccination doses have been distributed since January 2, 2022.

The spread of the disease poses significant hazards to human life and civilization. There is currently no precise remedy for the pandemic, and several antiviral drugs, plasma transfusions, and other medications have been examined in the clinical field with caution (Muhammad et al., 2020). The coronavirus outbreak in India has affected societal functioning. Everyone was advised to social distancing to escape the dreadful transmission. Cases that have been confirmed are those that have come back from overseas in the early stages, followed by local transmission. A lot of infections are caused by the present COVID-19 outbreak due to severe acute respiratory syndrome worldwide (SARS-CoV-2). Governments and public healthcare systems are under tremendous stress as infection and death rates rise exponentially. Identifying significant mortality determinants is necessary to maximize patient treatment strategies. The COVID-19 death rate was also thought to be strongly correlated with hospital capacity; the higher the death rate, the lower the hospital capacity. As a result, individuals at increased mortality risk must be prioritized (Sujatha and Chatterjee, 2020; Du et al., 2020; Chen et al., 2020, Aljameel et al., 2021; Ko et al. 2020). A total of 28 blood biomarkers, as well as gender and age attributes, were selected using analysis of variance (ANOVA) and available data. An assembly strategy was utilized to achieve a specificity value of 0.91, sensitivity of 1, and accuracy value of 0.92 by combining a deep neural network and Random Forest models to increase the number of patient points and the researchers also developed an online web tool (BeatCOVID-19) that forecasts mortality using blood test data which could benefit from data upgrades (Khan et al., 2021; Dhamodharavadhani et al., 2020). Planning for considerable increases in the capacity of standard hospital beds and intensive care unit (ICU) beds in the event of a pandemic is essential to enable patient identification and speedy isolation procedures (Phua et al., 2019).

The artificial neural network (ANN) is a technique for modelling epidemiological events, anticipating epidemic peaks, and assessing disease risk and scope (Pal et al., 2020; Torrealba-Rodriguez et al., 2020; Castro et al., 2020; Braga et al., 2021). The main advantage of ANN is that it itself learns by analyzing correlations between the inputs and output variables and solving the complicated nonlinear issue (Schmitt et al., 2018). This is due to neurons' extensive and concurrent processing and noise tolerance (Egrioglu et al., 2014). In addition, unlike manual ways, the ANN aims at developing learning technique through pattern recognition so that it can learn from data and predict outputs The ANN method's ability to incorporate many predictor factors concurrently, like incidence curves and information on demographic,which is another benefit that enables researchers to understand better the dynamics of viral transmission in cities over time (Adiga et al., 2020; Zeng et al., 2016; Wang et al., 2020; Tamang et al., 2020). Tamang et al. (2020) showed that ANN is an effective method for processing massive amounts of data by modelling the frequency of COVID-19 events in India, the US, France, and the UK (Saba and Elsheikh, 2020). Another application of short-term ANN prediction, an artificial intelligence (AI) based model, was used to predict the domination of the COVID-19 epidemic in Egypt (Grasselli et al., 2020). This AI-based study performed well compared to the traditional Autoregressive Integrated Moving Average (ARIMA) traditional regression method, which shows high agreement with preliminary data in predictions that were confirmed up to 17 days in advance.

AI is a promising alternative to conventional methods like deterministic, linear, and nonlinear regression and conceptual models that successfully address complex issues and are employed by numerous researchers across a wide range of fields (Miranda et al., 2022; Venaik et al., 2022; Yadav et al., 2022a). The desired tasks have been carried out using artificial intelligence (AI) techniques based on human perception, decision-making, reasoning, and learning (Dzeroski et al., 1997; Tiwari, 2018). The AI is a "black box" model that converts input to output without regard for what occurs in reality. In AI models, the structure is learned from the data, and no assumptions are made about the structure. It is helpful for modelling when the physical incidence of a process is unknown, there is no mathematical form for expressing the process, and valid experimental data is available (Reddy, 2014). Due to poor model parameter selection, AI may have some drawbacks when dealing with non-stationary data.

The genetic algorithm (GA) is a population-based optimization algorithm based on Darwin's theory of evolution used to find the best parameters for AI based models like ANN models (Holland, 1975). It is a well-known global search optimization algorithm that is used in a variety of applications. Over- and under-fitting is the main limitation of AI-based techniques such as ANN. Fitting issues are typically caused by poor selection of neural network-based parameters. Traditional trial-and-error methods have been used in ANN models to select learning parameters and network topology; however, these techniques may not provide the best parameter and topology selection in ANN models. Furthermore, trial-and-error methods are time-consuming. As a result, selecting learning parameters and network topology in ANN models is a critical task in developing robust neural network models.

The problems of ANN are solved by combining them with GA (Yadav et al., 2018). The proposed hybridized approaches may be used for prediction and forecasting in other domains. Still, our hybridized GA-based ANN approaches are unique in the healthcare field for predicting the death rate due to the COVID-19 pandemic. In this research, all ANN parameters are optimized simultaneously using global optimization approaches, i.e. GA for covid date prediction with high accuracy, which is a unique contribution to the COVID-19 pandemic.The scope of the research is to develop very generic, fully autonomous AI-based models that can precisely predict the death rate caused by COVID-19 in India. The main objective of this research is to develop a novel hybrid AI model like a genetic algorithm-based artificial neural network (GA-ANN) model with automated parameter tuning approaches using daily data from confirmed and recovered factors to predict the death rate in India due to COVID-19 pandemic. The performance of this model is compared with other traditional models like ANN and MLR to check its predictive capability. The proposed hybrid GA-based ANN modelling approach can be recommended for predicting the death rate of COVID-19 transmission worldwide due to ease of implementation and superior performance.

METHODOLOGY AND DATA USED

The customized code for the model was written in 'MATLAB' software. The data were first normalized, and then the neural network parameters were selected. Data normalization was used to eliminate the dimensions of the variables to maintain their uniqueness during the training in the models. This study's input and output data are normalized between 0 and 1. To develop all prediction models for forecasting the death rate, the data were divided into training (70%), validation (15%), and testing (15%) sets.

Variations in various statistical variables can provide an overview of the model's performance (Melesse et al., 2011). Table 1 shows the statistical parameters of the input and output datasets. The skewness values range from 4.727 to 5.797. Death cases are skewed more than other variables. A high skewness value has a negative impact on ANN performance (Altun et al., 2007). Kurtosis values (35.68-40.53) are assumed to be increased. The normal distribution has a kurtosis of 3 (Gupta and Kappor, 2011). Kurtosis describes a distribution's relative peakiness or flatness compared to the normal distribution. The Pearson correlation coefficient of the recovered and confirmed cases with death cases are 0.906 and 0.907, respectively. It indicates that recovered and confirmed cases significantly correlate with the death rate due to the COVID-19 pandemic.

Due to numerous complex processes, determining the death rate using various conventional methods is inaccurate. For estimating death rates due to COVID-19 transmission, a traditional multiple linear regression (MLR) mathematical model was used. The MLR is a linear model that can capture any

Table 1.
The statistical parameters of hydro-climatic data

Statistics	Recovered	Confirmed	Deaths
Mean	174794	194282	2721
Standard deviation	364833	409518	7183
Maximum	4927480	5433506	83777
Minimum	0	0	0
Skewness	4.727	5.058	5.797
Kurtosis	35.68	40.53	40.31

linear relationship; however, it fails to model the presence of nonlinearity. The ANN is a data-driven approach in which the model is developed using training data. The ANN is one of the most widely used AI techniques. It is well suited to forecasting and predicting models of nonlinear and dynamic systems due to its low data requirements, simplicity, and low cost (ASCE, 2000; Yadav et al., 2017).

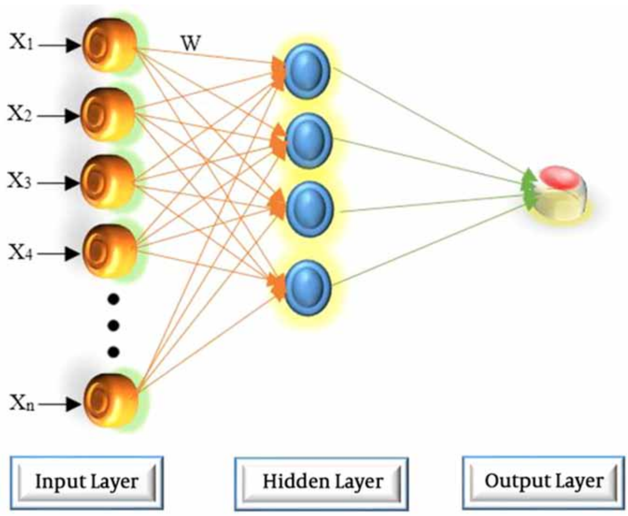
The artificial neural network (ANN) is a flexible and well-known mathematically and geometrically represented technique for approximating various complicated nonlinear situations. It is based on the biological brain and nervous system (Demuth and Beale, 1998). The death rate attributable to COVID was predicted using a multilayer perceptron (MLP) based ANN with a rapid convergence training strategy or the Levenberg-Marquardt (LM), a feed-forward back-propagation method. This strategy's key benefits are its versatility and fast convergence (Demuth and Beale, 1998).

All the neurons in a layer of the MLP transfer the total sum of the weighted input factors to the subsequent layer (Yadav et al., 2018; Yadav, 2019). In this study, the Levenberg Marquardt (LM) algorithm (FFBP-LM) was used to train neural network models using feed-forward back-propagation (FFBP) training algorithms (Pramanik and Panda, 2009). In terms of performance, training a multilayer perceptron feed-forward neural network with LM outperforms other types of ANN, such as gradient descent and radial basis function (RBF) (Kisi, 2008; Sahoo and Jha, 2013). Because of its fast response, the FFBP-LM algorithm is used for developing the reliable MLP based ANN model. Figure 1 depicts the architecture of an MLP-based ANN. The MLP is a feed-forward artificial neural network with three layers: input, hidden, and output. Each layer contains a specific number of neurons with an activation function—the activation function, which should essentially be monotonically rising and differentiable. Various literature describes the MLP-based ANN (Yadav et al., 2017; 2018).

This ANN approach changes the network's bias and connectivity weight, neurons, transfer function etc. The LM training approach was used to construct the MLP model because of its speed. As a result, despite requiring more random-access memory (RAM), it is a top choice for supervising the algorithm (Yadav et al., 2017; Yadav et al., 2018). Some fitting issues in ANN models are typically caused by poor selection of ANN parameters, like the combination coefficient and network topology, such as hidden node size, i.e. number of hidden layers, initial weights, and so on (Yadav et al., 2018; 2021). The GA solves the ANN models' problems (Yadav et al., 2022b). The predictive capability of the proposed hybrid GA-ANN model, which was developed by simultaneously optimizing all related ANN parameters in death rate prediction using a single objective, was also compared to that of traditional MLR and ANN models. For a comparative study, all models used the same test data set. The input, the activation function and the hidden layer nodes were used in each layer, and the beginning weight values all impact how well MLP-based ANN models predict data. If any of these components are selected improperly, a poor ANN model may result. In this research, we have considered the GA and simultaneously chosen the optimized value of all ANN parameters.

To find the optimal global parameters for ANN models, the GA applied a global optimization technique using the population, which is based on the evolution theory of Darwin (Yadav et al., 2021;

Figure 1.
The architecture of multilayer perceptron-based artificial neural network



2022c; Kumar, 2021). Utilizing genetic operators like mutation, selection, and cross-over creates variation in the population (chromosomes) of the given individual. The GA is a popular optimal solution for non-differentiable, discrete, stochastic, or highly nonlinear problems in a noisy environment (Yadav et al., 2020a; Yadav et al., 2020b; Yadav et al., 2021). This study implements GA in a feed-forward ANN with just one hidden layer (hereafter named GA-ANN). The neural network would be trained using the LM approach, and all parameter settings would be chosen using the GA method.

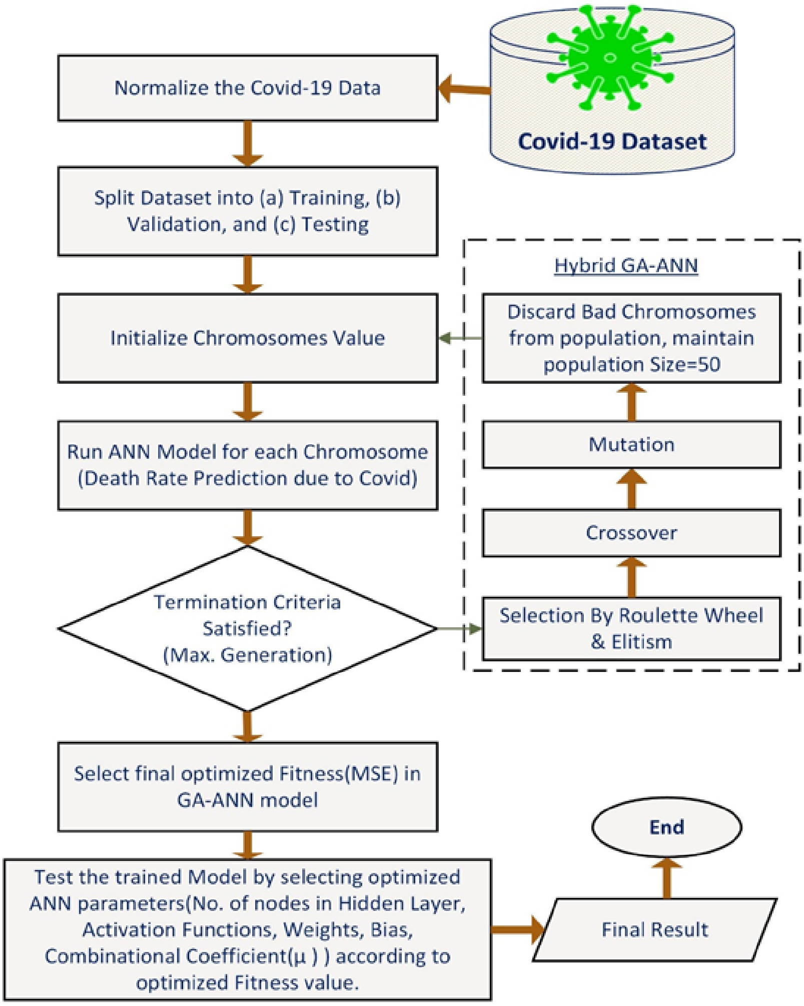
The parameter setting and ANN training were done concurrently using GA to obtain a more robust solution that is less likely to become stuck at the local optimum point. With the help of the GA method, successive populations of people with various qualities can be created. In this study, five crucial ANN technique parameters— the transfer function, inputs, hidden layer neurons, the combinational coefficient of LM, and bias and connection weights were chosen using the GA. There are representations of all five ANN parameters in a binary string. Over several generations, the least RMSE, or minimal change in the fitness function is found. The optimum solution value is found by minimizing the fitness function value (Root mean square error (RMSE)) from the most recent generation. The ANN model's optimal ANN parameters (transfer functions, input variables, hidden layer neurons, combinational coefficient of LM techniques, initial bias and connection weights) are determined by population matching to that optimum solution. Most previous models that approached the input selection and parameter optimization were time-consuming and had computational expenses. The general framework of the proposed hybrid GA based ANN technique is depicted in Figure 2. To build a stable convergence model, the GA model parameters such as mutation probability (0.05), cross-over probability (0.6), the highest number of generations (5), and the number of populations (50) were chosen using a trial-and-error process. The maximum number of generations are employed as terminating conditions.

RESULTS AND DISCUSSION

Hybrid GA-ANN Model

In this research, AI-based model like ANN is developed in which all of the ANN parameters (transfer functions, transfer functions, hidden layer neurons, combination coefficients, Input variables, and

Figure 2.
Flowchart of Hybrid GA-ANN Model for Prediction of the death rate due to COVID-19 transmission



network weights) were optimized concurrently using the GA, which is applied it for the Covid-19 death rate prediction. The GA-ANN model produced a set of finalized optimum solutions based on a predetermined stopping condition, that matched the maximum number of generations. Figure 3 shows the variation in mean fitness and best fitness value (RMSE) throughout each generation in the training period. The highest degree of fitness was identified across all generations. The best chromosome with the highest fitness function showed that all input parameters (data from infected and recovered persons) must be chosen before developing the neural network model. The results also showed that 11 neurons were the optimal count for the hidden layer. Tan-Sigmoid, an S-shaped activation function that is monotonically rising, is chosen as the optimized activation function in the hidden and output layers. According to the GA-ANN model, the combination coefficient (μ) of the LM algorithms has the best optimization at a value of 10. The initial bias terms and connection weights were chosen appropriately.

As per the distinct records from the test dataset, the generalization and prediction capabilities of the GA-ANN model were analyzed. The mean absolute error (MAE), mean square error (MSE),

Figure 3.
GA-based ANN learning with Generation-wise fitness function profile

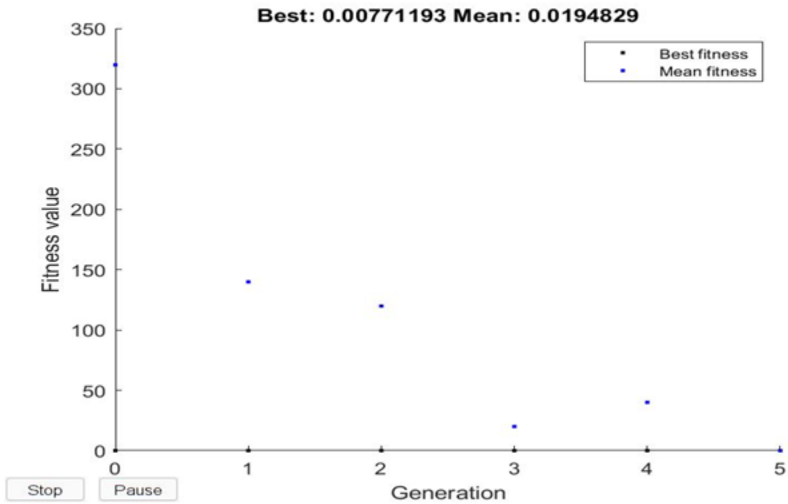


Table 2.
Error statistics data of hybrid GA-ANN model for prediction of the death rate due to COVID-19

Error Statistics	Testing	Training	Validation
RMSE	0.03698	0.025177	0.082512
Error variance	0.001293	0.000555	0.00617
r	0.961752	0.931169	0.915486
MSE	0.001368	0.000634	0.006808
MAE	0.024216	0.019114	0.037697

root mean square error (RMSE), error variance (VAR), and correlation coefficient (r) are standard statistical parameters used to measure the efficiency of the ANN and other models. Standard formulas are used to calculate the error statistics (RMSE, r, MAE, MSE and VAR) of the model's training, validation, and testing datasets (Legates and McCabe, 1999; Sahoo and Jha, 2013). If the model is perfect, RMSE, MSE, VAR, and MAE should be close to zero, and r should be close to one. In addition to quantitative evaluation using statistical measures, the effectiveness of the ANN technique in predicting the death rate in India due to the COVID-19 pandemic is evaluated using graphical indicators such as comparison plots and scatter plots between the forecasted modelled values and actual death rates due to COVID-19 transmission. Based on the model's observed and predicted death rates, Table 2 presents the statistical analysis of the errors for the validation, training, and testing of the GA-ANN model. While the correlation coefficient (r) is relatively high, the root mean square error (RMSE) and mean square error (MSE) for all three datasets are very low. Additionally, across all three datasets, the error statistics are consistent. According to the MAE, error variance, RMSE, r and RMSE values, it was found that this GA-ANN model performed well in predicting the daily death rate due to the COVID-19 pandemic.

It is also seen that the predicted death rate is closed the observed death rate values (Figure 4). Figure 5 depicts a scatter plot of the observed and forecasted death rates using the GA-ANN model. It can be noticed that most of the locations are situated near the straight bisector line, where both

Figure 4.
Comparison of Covid-19 death rate predicted by hybrid GA-ANN and observed death rate due to Covid-19

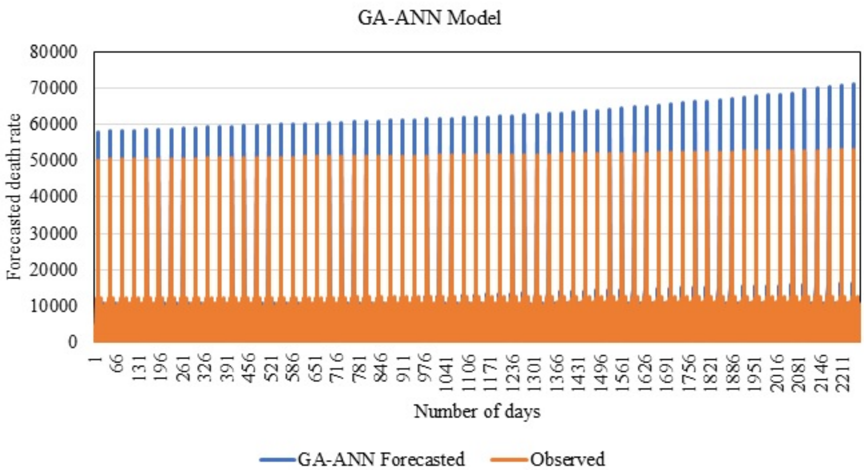
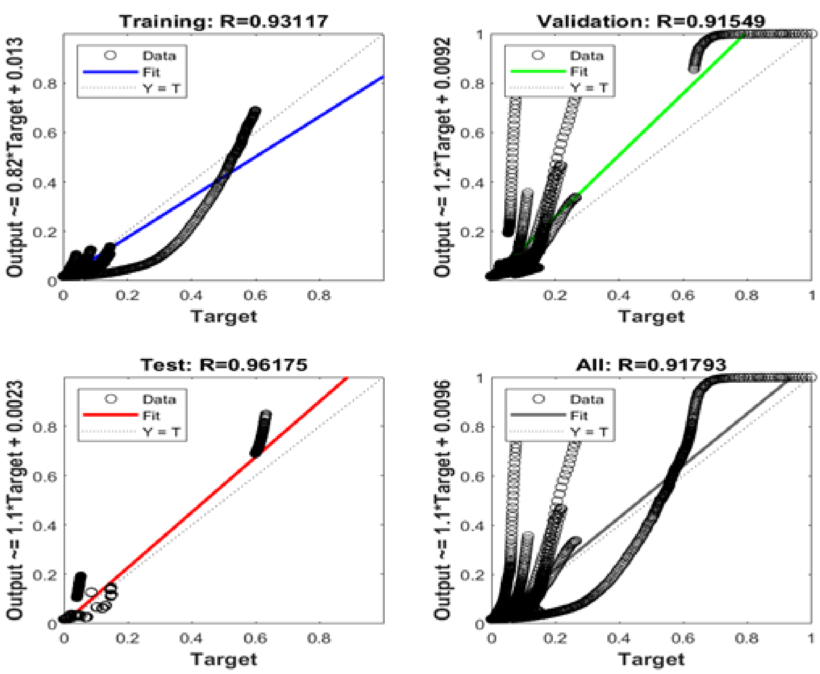


Figure 5.
Scatter graphs between the actual and predicted death rates from COVID-19 in GA-ANN



forecasted and actual values are almost equal. In addition, during the testing, validation and testing phases, the bisector line and regression line are very near to each other. It signifies that the proposed model performs satisfactorily. The hybrid GA-ANN model exhibits better generalization capability and performance, which might be attributed to using the GA to optimize all ANN model parameters simultaneously.

Figure 5 depicts a scatter plot of the observed and estimated death rates using the GA-ANN model. Most points are located along the regression and bisector line (45-degree line) straight line, where both actual and predicted values are roughly equal. The scatter plot shows that the GA-ANN results are closer to the 1:1 line, and the data points are scattered around the 1:1 during training, validation, testing, and combining all of these data sets. The 1:1 line is a bisector (45-degree line) where both predicted and observed values are the same. If the scatter points are close along this line, the predicted and observed values are roughly the same. If all scatter points fall along this line, the model is perfect. The scatter plot (Figure 5) of actual and model forecasted values in the test data set also shows that the maximum points are closest to the 45-degree line. All correlation coefficient values in the training, validation, testing and combined datasets are close to one and highly significant. If the model is perfect, it will be nearer to one and scatter points will lie on the 1:1 line. The scatter plot clearly shows that the coefficient of determination (R^2) is close to one. As a result, the proposed GA-ANN model is very effective for forecasting the death rate due to COVID-19 transmission.

Traditional ANN and MLR models

The results of the traditional models are described in this section. Table 3 shows the MLR model's error statistics. Table 3 shows that the values of MSE, RMSE, MAE, and error variance of MLR method are low, while r is high for all three training, validation, and testing datasets. Figure 6 represents the comparison of the forecasted death rate and observed death rates by the MLR model due to the Covid-19 pandemic. The MLR approach offers a negative death rate value at some points, as seen in Figure 7. This is unrealistic because the death rate can never be negative. Table 4 shows the error statistics of the ANN model. MSE, RMSE, MAE, and error variance of ANN are low, and r is high for all data sets. It indicates that underfitting and overfitting do not exist in these models. Figure 8 shows that the ANN-forecasted and actual death rates are closer. The scatter plot of the ANN forecasted and actual death rate values indicates that most points are nearer to the straight bisector line (Figure 9).

The scatter plots of the MLR model during the testing phase are shown in Figure 7. Figure 8 depicts the ANN model comparison plot based on the testing data set. The scatter plot of the ANN models during the testing phase is shown in Figure 9. The scatter plots (Figures 7 and 9) of the actual and model predicted values of the MLR and ANN models in the test data set show that the maximum points in the ANN model are closer to the 45-degree line than in the MLR model. The ANN model has a higher coefficient of determination (R^2) value than the MLR model, which is closest to one. This indicates that the ANN model outperforms the MLR model on the basis of R^2 value.

Comparisons of all models

The performance of the proposed GA-ANN, ANN and MLR model is analyzed using the distinct instances of the test dataset, which were unseen during the training step. To evaluate the proposed model's prediction capability, the ANN and GA-ANN models are compared to the conventional MLR

Table 3.
Error statistics data of hybrid MLR model for prediction of the death rate due to COVID-19

Error Statistics	Testing	Validation	Training
r	0.908681	0.928068	0.923819
RMSE	0.044376	0.097581	0.02446
Error variance	0.001952	0.04405	0.000598
MAE	0.022431	0.049736	0.012619
MSE	0.001969	0.009522	0.000598

Figure 6.
Comparison of Covid-19 death rate predicted by MLR and observed death rate

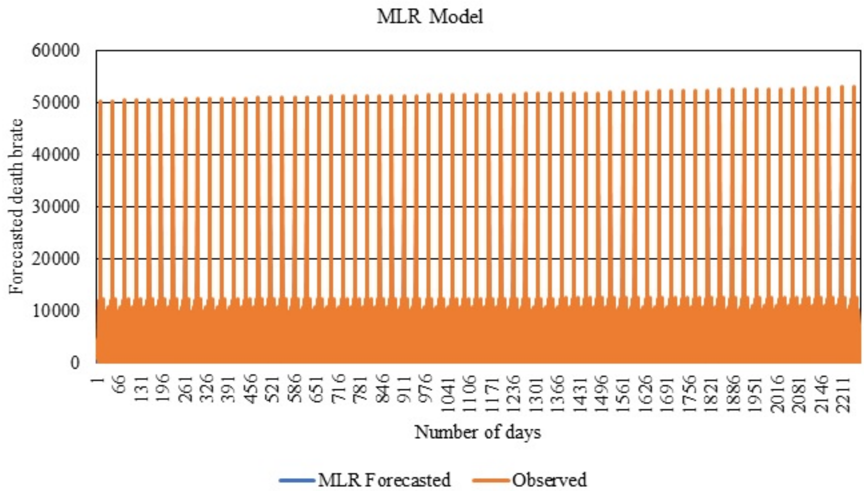


Figure 7.
Scatter graphs between the actual and expected death rates from COVID-19 in MLR

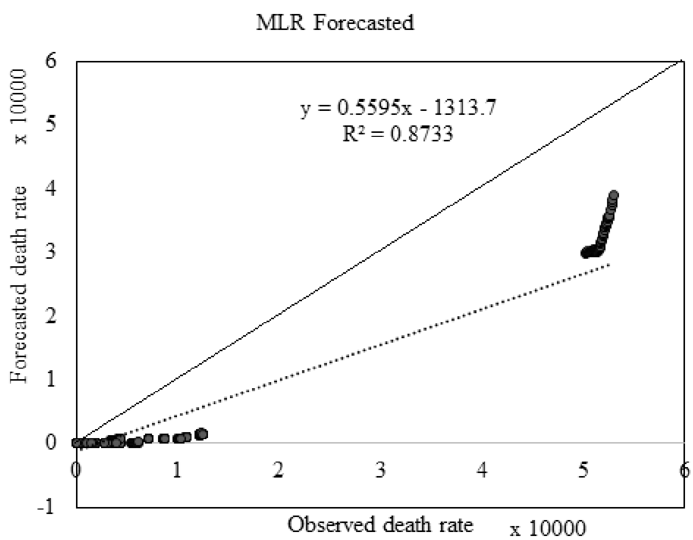


Table 4.
Error statistics data of ANN model for prediction of the death rate due to COVID-19

Statistics	Testing	Validation	Training
r	0.978757	0.908671	0.920102
RMSE	0.042075	0.122869	0.034062
MAE	0.0380	0.528	0.0273
MSE	0.00177	0.015097	0.00116
Error variance	0.000527	0.012508	0.000635

Figure 8.
Comparison between observed and hybrid ANN predicted death rate of Covid-19

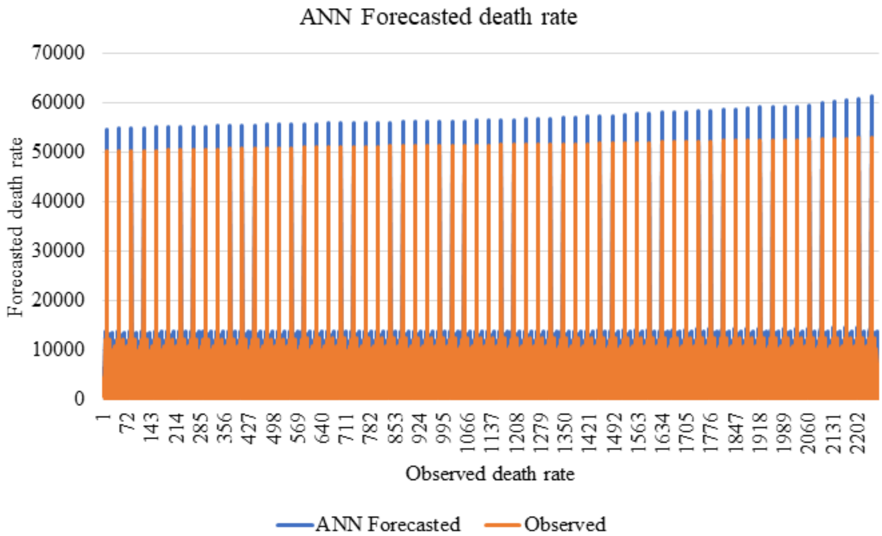
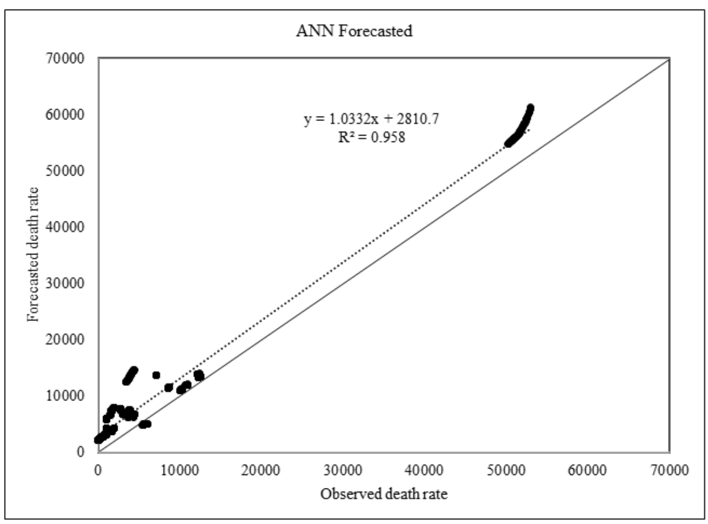


Figure 9.
Scatter plots between the observed and ANN predicted death rate due to Covid-19



regression method. Furthermore, the proposed hybrid GA-ANN model's performance and predictive capability were compared to conventional ANN and MLR models.

Table 5 shows the 'r' and RMSE error statistics of the MLR ANN and GA-ANN models during testing phase. Compared to previous models, the GA-ANN was found to perform better based on lowering the RMSE and maximizing the r. Table 5 further shows that when the ANN model is employed in association with the GA in the testing phase, the ANN model's forecasting model inaccuracy results are improved. Based on RMSE, the GA-ANN model outperformed the ANN and MLR models by considering the optimum ANN's related parameters. This dominance is achieved

Table 5.
Comparing the RMSE and r of hybrid GA-ANN, ANN and MLR models during testing time

Models	RMSE	r
GA-ANN	0.03698	0.9618
ANN	0.042075	0.9788
MLR	0.044376	0.9087

by using the GA to select all ANN parameters at the same time.. Even though r is relatively high (0.9618), the GA-ANN is still second to the ANN, which has the highest value of r (0.9788). It is not always viable to assess a model's capacity only based on r (Legates and McCabe, 1999; Yadav et al., 2018). Based on RMSE and r, it is also noticed that both AI models (GA-ANN and ANN) produced superior outcomes than the MLR model (Table 5). It is also observed that both AI models (ANN and GA-ANN) are provided positive forecasted values of death rate. On the other hand, the MLR model is generated the negative forecasting values of death rate which is unrealistic in nature because death rate can not be negative values. Thus, both ANN and GA-ANN models have more genaralisation forecasting capability as compare to MLR model.

CONCLUSION

This research is being carried out to track the growth of COVID-19 and forecast the death rate over time. Compared to countries with similar COVID cases, India is expected to have the lowest death rate due to its protective qualities against COVID-19. According to the findings of the results, the developed hybrid GA-ANN model outperformed the ANN and MLR model. It is also observed that both AI-based approaches, like ANN and GA-ANN, also provided a better death rate predictions than the MLR regression model. The MLR model generates some negative death rate values that are not real. It indicates that the MLR model failed to capture some complex nonlinear phenomena of the death rate due to the COVID-19 pandemic. On the other hand, the hybrid GA-ANN model is provided with all positive death rate values. It is also observed that the ANN model also provided positive death rate values. Thus, both AI models (GA-ANN and ANN) have more generalization capability for predicting the death rate. The hybrid GA-ANN models are the most suitable substitutes compared to other models. The predicted death rate and the actual death rate are pretty close. Because of its relatively improved performance and ease of implementation, this hybrid AI (GA-ANN) model is recommended for death rate prediction due to the COVID-19 pandemic. This study's limitation is using randomly chosen cross-over and mutation parameters and other GA-related parameters. However, since these parameters are crucial to the model's development, they will also be considered to enhance its capacity for estimation and forecasting. Future research will test different ANN models and intelligence-based methods, such as support vector machine hybridization with a single objective and multi-objective GA, and introduce new data sets to these hybrid models.

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CONFLICT OF INTEREST

There are no conflicts among the authors.

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