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A HYBRID MODEL FOR FORECASTING COMMUNICABLE DISEASES IN MALDIVES

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Abstract

The Maldives is an island nation and the islands are scattered over 26 atolls. The government of Maldives is trying to improve health services in the country and improve the accessibility of services throughout the country at the peripheral levels. The healthcare industry collects a large amount of healthcare information, which contains several patterns, such as outbreaks of diseases. However, this data frequently goes unexploited. Accurate forecasting using this past data could help healthcare managers in taking appropriate decisions especially in implementing preventing measures. Due to the geographical nature of Maldives, it is difficult to implement preventive measures in case of an outbreak. There is no single approach to be used for health forecasting; thus, various methods have been used to specific health conditions or healthcare resources. Healthcare comprises of both complex linear and nonlinear patterns, which can affect the forecasting accuracy if only linear models or neural networks are used. In this research, a hybrid of the ARIMA model and Neural Network has been proposed to forecast healthcare data. A dataset comprising of 10 diseases including unique cases reported for each disease, between the years 2012 and 2016 have been used in this research. It was found that the proposed model performed well on 7 out of the 10 diseases.

Keywords: Hybrid forecasting model, Linear models, Neural network.

1. Introduction

The Maldives is a country located in the Indian Ocean with a population over 393,500 and considered as one of the most geographically dispersed countries in the world and is the smallest Asian country in terms of both population and geographical area.

Healthcare in the Maldives is developed through a primary top-down approach. The Ministry of Health grades the Maldivian healthcare facilities into three levels depending on the range of the services available in the facilities [1]. The Ministry of Health is the primary body in charge of the healthcare sector in the Maldives. Together the Ministry of Health and the Government of Maldives continuously trying to improve the accessibility of healthcare services throughout the country, despite geographical challenges faced at very peripheral levels.

Due to dispersed nature of the country and population in very small islands, it exerts diseconomies of scale. Thus, providing healthcare services to all the islands has proven to be challenging and costly in terms of assigning resources. According to Shakeela [2], Maldives could make use of technology and disease prevention methods or tools to overcome several challenges and continue growth in the health sectors, as there is no system to routinely monitor trends in non-communicable and communicable diseases in the Maldives.

To ensure better access to healthcare and to provide financial security; all citizens of the Maldives are covered by a universal health insurance “Aasandha”. Aasandha health insurance scheme is provided by Aasandha Pvt. Ltd. It stores all the necessary information about the patients, such as the number of visits, medical history, diagnosis, medication, etc. Morbidity and mortality rates can be obtained from this collected data. Morbidity rates serve as an indicator of the health status of a community [3]. Morbidity rates or frequency characterizes the number of persons who are ill or who become ill at any given time. These trends can be utilized more effectively for forecasting and implementing appropriate action plans and preventive measures.

Forecasting is the process of predicting future events based on foreknowledge, which is essential for decision making [4, 5]. Forecasting as a science was first associated with weather forecasting and is credited mostly to Francis Beaufor and Robert Fitzroy [6]. Francis Beaufort developed the scale for measuring wind force (the Beaufort scale) and Robert Fitzroy, developed the Fitzroy barometer for measuring atmospheric pressure. According to Armstrong [7], decisions makers need to forecast only if there are uncertainties involved in the future. For example, there is a need to forecast the weather, while there is no need to forecast that the sun will rise and set tomorrow. Forecasting serves many needs and is widely used in various industries. Some of the areas of forecasting include forecasting currency exchange, stock prices, and weather report [8]. Forecasting methods can be classified as qualitative or quantitative [5].

Quantitative forecasting method is used when past or historical data is available, while qualitative forecasting method involves expert judgment to develop forecasts, where appropriate historical data on the variable being forecasted is unavailable. In forecasting, if the historical data is restricted to past values of the variable to be forecasted, the forecasting procedure is called a time series method and the historical data are referred to as a time series [9].

Time series forecasting has been used in several applications to predict future values using historical data. According to Song et al. [10], time series analysis of healthcare data is a good tool for the prediction of disease incidences. Healthcare forecasting is defined as “the prediction of health situations or disease episodes and forewarning future events” [5]. Healthcare data comprises of complex nonlinear and linear patterns making it difficult for forecasting with proper accuracy using only linear models or neural network models [3].

Four main principles; the measure of uncertainty and errors, the focus, data aggregation and accuracy of health forecasting and horizons of health forecasting are associated with healthcare forecasting [5]. According to Han et al. [11], health events and situations involve multiple meanings and variety of uncertainties, which would prevent from achieving an error-free prediction with 100% accuracy. The focus of health forecast is targeted towards a specific health-related issue or event that is being forecasted. The focus can be towards a specific individual which is the prognosis [12], which determines the course of an ailment or towards a population health outcome in terms of number events occurred within a duration.

The data used in health forecasting can be either the health condition or situation of an individual, group of people or of a population. A higher accuracy in health forecasting is obtained by using a pooled population data rather than that of a specific individual person. Aggregating data from a pool or a large group of people or a population can exhibit very stable characteristics even when individuals within exhibit randomness [5].

The horizon of health forecasting refers to the time period or duration that the forecast is intended to cover, no boundaries have been defined in reference to the health forecast horizon. However, in other areas a short-range forecast horizon refers to a period of one day to a quarter of a year; a medium-range forecast horizon refers to a quarter of a year to a year, and long-range forecasts refer to a year to five or more years.

2. Related Works

Healthcare forecasting has been focused on techniques for forecasting aggregate health conditions, total admissions, emergency visits, daily discharged patients, etc. [5]. Cao et al. [13] compared the accuracy of the linear Autoregressive Moving Average (ARMA) model and the nonlinear neural network model in producing forecasts of medical cost inflation rates, and that neural network models are more suitable for forecasting inflations in medical over traditional linear models.

Purwanto [3, 14] proposed a dual hybrid forecasting model for support of decision making in healthcare management and an optimally configured hybrid model for healthcare time series prediction. The author reported that the dual hybrid model is appropriate for obtaining accurate prediction results and generating appropriate decisions, while the optimized hybrid model is best suited for prediction of complex data which consists of both linear and non-linear patterns.

Hadavandi et al. [15] proposed a hybrid artificial intelligence model for outpatient visits forecasting in hospitals that used genetic fuzzy systems to construct an expert system for outpatient visits forecasting problems. The author reported that the proposed method was able to handle complex and nonlinear time series with a limited dataset. In addition, the proposed method was able to reduce the effects of noisy data and the complexity of the dataset to something more homogenous.

Hakan et al. [16] proposed a hybrid approach combining ARFIMA and Feed-Forward Neural Networks (FNN) to analyze long memory time series and improve forecasting accuracy and reported that FNN models are ineffective for long memory structured time series and ARIFMA models are not always adequate. Caruso [17] used the ARIMA method for forecasting hospital occupancy using time series data and obtained satisfactory forecasts of occupancy rates. The author also reported that it was impossible to obtain satisfactory results for patient's admissions. Côté et al. [18] forecasted emergency department arrivals using regression-based forecasting models and reported that the regression analysis alone is sufficient and flexible enough to handle a wide variety of forecasting needs.

Zhu et al. [19] compared three models; Seasonal Regression and ARIMA (SRARIMA), a Multiplicative Seasonal ARIMA (MSARIMA) model and a combinatorial model based on MSARIMA and weighted Markov Chain models in generating forecasts of daily discharges. The author reported that combinatorial model outperformed the other two models used for each value examined one-day ahead. The author also reported that utilizing the Markov Chain mode helped in capturing the nonlinear patterns in the dataset efficiently and dealing with large random fluctuations.

De Oliveira and Ludermir [20] proposed a hybrid forecasting model for time-series forecasting which comprised of ARIMA and support vector regression (SVR) models optimized by the Particle Swarm Optimization (PSO) algorithm is applied to perform predictions. The author reported that the proposed method was able to capture both linear and non-linear patterns in time-series data through the use of ARIMA and SVR model. The proposed method was able to achieve promising results for one-step-ahead predictions and achieved best results in three out of five datasets used for forecasting. Zheng et al. [21] used a combinatory model of ARIMA and Autoregressive Conditional Heteroscedasticity (ARCH) for forecasting tuberculosis in Xinjiang, China. The author reported that combinatory model is more effective compared to the use of ARIMA model alone and that ARCH model can be used to deal with time series heteroscedasticity.

Accurate prediction using the past data from healthcare sectors is very important to make proper decisions for the presentation of disease. The natural geography of Maldives makes it hard to develop a preventive plan for an outbreak. Healthcare includes complex linear and nonlinear patterns. Hence, the accuracy of forecasting model is not very satisfactory using linear models or neural networks. To bridge this gap, this research is established to propose and evaluate a hybrid model to forecast the communicable diseases in the Maldives.

3. Time Series

A time series is a sequence of data points, normally consists of successive measurements made over a time interval [9, 22]. The measurements can be made hourly, daily, weekly, monthly, yearly or any at any other regular interval. Time series data are also often found in scientific and engineering disciplinary which involves time-based measurements. Time series data are also seen in the following areas:

- Healthcare/Medicine - e.g., hospital admissions, ECG readings, etc.
- Economics - e.g., employment rates, etc.
- Finance - e.g., stock market prices, daily exchange rates, etc.
- Environmental - e.g., daily snow/rainfall, humidity, air quality etc.

The time interval between time series datasets varies with the problem that needs to be solved. The time interval for the dataset can be hourly, daily, weekly, etc. Thus, it can be said that time series data are based on specific time granularity. Time series data pattern is an important factor in identifying and selecting an appropriate forecasting technique or methodology. The pattern found in the dataset helps to understand how the time series data has behaved in the past over a specific period of time. Time series patterns can be classified into trend, seasonal and cyclic pattern [9].

3.1. Time series model

Time series modeling is separated into two classes; parametric and nonparametric [23]. Time series models are used for predicting future behavior of a specified variable, it can be used to make future observations, monitor and identify recent anomalies [24, 25]. There are three broad classes of time series models, which depends linearly on previous data points. The three models are:

- The autoregressive (AR) model
- The integrated (I) model
- The moving average (MA) model

3.2. **Autoregressive model**

Autoregressive (AR) model is a flexible model that can handle various different time series patterns [26]. It is also considered as a representation of a type of random process. The notation $AR(p)$ refers to the autoregressive model of order *p*. The $AR(p)$ model can be represented as

$$X_t = c + \sum_{i=1}^{p} \varphi_i \, X_{t-1} + \varepsilon_t \tag{1}$$

where are $\varphi_1, \ldots, \varphi_\rho$ parameters, c is a constant, and the random variable ε_ι is white noise. In AR forecasting is done by using a linear combination of past values of the variable that is being forecasted.

3.3. **Moving average model**

Moving Average (MA) model uses past forecast errors than using past values of the forecast variable [26]. MA is also considered a modeling technique for univariate time series data. MA can be represented as

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{2}$$

where μ is the mean of the series, the $\theta_1, \ldots, \theta_q$ are the parameters of the model and the ε_t , $\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are white noise error terms.

3.4. **ARIMA model**

Auto-Regressive Integrated Moving Average (ARIMA) is obtained by combining the difference with AR and MA model [26]. ARIMA model can be denoted as

$$y_t' = c + \emptyset_1 y_{t-1}' + \cdots + \emptyset_p y_{t-p}' + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \tag{3}$$

where y_t^t is the differenced series, p is the order of auto an regressive part, d is the degree of first differencing involved and q which is the order of the moving average part. This is also known as ARIMA (*p*,*d*,*q*) model.

3.5. **Neural network model**

Neural networks are flexible and adaptive learning systems that are used in various areas. Simon S. Haykin defines the neural network as “a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use” [27]. According to this definition, neural networks resembles the brain because it acquires its knowledge from its environment through a learning process and the inter-neurons are used to store the acquired or learned knowledge. When hidden layers exist in the neural network it becomes non-linear, making it a multilayer feed-forward neural network. The input and output variables in a feed-forward neural network model are linked through the hidden layers [13].

4. Methodology

Figure 1 shows the flowchart of the hybrid methodology that is used for forecasting. Firstly, the data is loaded from the healthcare database and formatted into time-series data. In the second step, the best fit ARIMA model is chosen by searching through the order parameters (p, d, q). Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) are compared when selecting the appropriate model, selecting a lowered or minimum value for both AIC and BIC. Next forecasting is done by using the selected ARIMA model.

Residual generated by ARIMA is provided to the neural network, which in turn generates its residual series. Finally, the residual series generated by the neural network is added to the predicted series generated by the ARIMA model producing a hybrid forecasted value.

Data validation ensures that a program or model operates on clean, correct and useful data, checking the correctness, the meaningfulness, and security of at used as input to the system [28]. Cross-validation is a common technique used in time-series data validation. In cross-validation, each of the training set consists of one or more observation than the previous and consequently, each test has one fewer observation than the previous one. According to Hyndman et al. [26], a minimum size of the training data set is needed to cross-validation, as it is often not possible to do any meaningful forecasts if enough data is available in the training set. The size of the training set depends on the complexity of the model used by the researchers. For example, if k observations are needed to produce a meaningful and reliable forecast, firstly observations at time $k + i$ are chosen as the test set. Then the observations are used at times $1, 2, \ldots, k + i - 1$ to estimate the forecast. Then the error on the forecast for time $k + i$ is calculated. This step is repeated for $i = 1, 2, \ldots, T - k$ where T is the total number of observations. Finally, the accuracy of the forecast is measured on the error values are obtained.

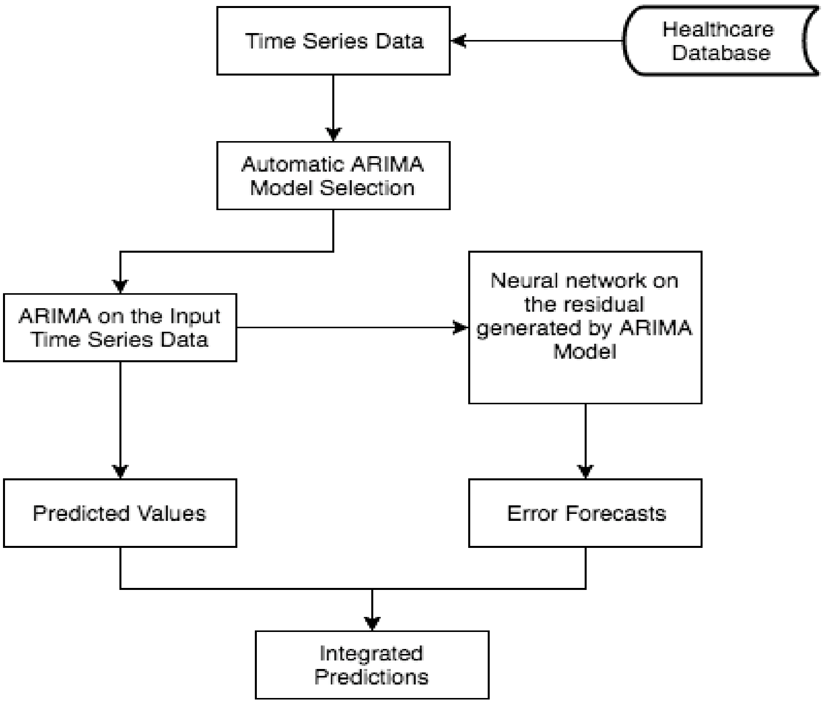


Fig. 1. Hybrid methodology.

Forecasting models should be evaluated in the situations for which they are meant to be used as and that most forecasting methods are based on commonly accepted methodological procedures, such as to prespecify criteria or to obtain a large sample of forecast errors [29]. Several performance measures are used to compare the forecasting performance of different models. Prediction models are evaluated in terms of their ability to predict the future values. The two most commonly used scale-dependent measures are based on absolute errors or squared errors [29]. The predictive validity of the model will be evaluated using the criteria of Root Mean Square Error (RMSE) and percentage variability in regression analyses (R2):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(X_t - \hat{X}_t)^2}{n}} \quad (4)$$

where Xi is the observed values, X_i is the corresponding forecasted values, and n is the number of observations. RMSE value lower than 1 represents a good model performance [10]. The second performance measure is Mean Absolute Error (MAE). The MAE is defined as:

$$MAE = \frac{\sum_{t=1}^{n}|X_t - \hat{X}_t|}{n} \quad (5)$$

Both performance measures are used for comparison and evaluation of the model accuracy. Lower values of *RMSE* and *MAPE* have better prediction results.

5. Data Set and Validation

A total of 10 diseases, including acute respiratory infection, viral fever, acute gastroenteritis, conjunctivitis, chickenpox, dengue fever, hand, foot and mouth disease, typhoid fever, scrub typhus, and mumps were used to train the model and used for forecasting. The dataset comprised of 4 years' data, a number of unique cases reported for each of the diagnosis between the year 2012 and 2016. The archival data collected in this research is provided by Aasandha Pvt Ltd., which is a Government company managed in a public-private partnership with Allied Insurance Company of the Maldives, thus the integrity of the dataset used in this research can be guaranteed. The archival/statistical data collected from Aasandha Pvt Ltd. consists of a number of transactions recorded in their system for the requested diagnostics.

6. Results and Discussion

The models tested were ARIMA model, neural network model and hybrid model comprising of both ARIMA and neural network model. Table 1 shows the forecasting results of different diseases for January and February 2017. The last column presents the actual value of disease reported in January and February.

Table 1. Forecasting results.

Disease	Forecasting for	Hybrid Model	ARIMA	Neural Network	Actual Value
Typhoid Fever	Jan-17	32	17	177	3
	Feb-17	43	23	0	0
Scrub Typhus	Jan-17	3	12	-22	12
	Feb-17	14	16	-28	1
Dengue Fever	Jan-17	118	124	43	75
	Feb-17	-103	174	49	20
Viral Fever	Jan-17	-6	28	111	19
	Feb-17	44	61	86	0
Chickenpox	Jan-17	118	176	167	176
	Feb-17	166	144	231	4
Hand Foot & Mouth Disease	Jan-17	105	132	149	83
	Feb-17	158	180	380	3
Mumps	Jan-17	10	14	5	3
	Feb-17	5	11	10	1
Conjunctivitis	Jan-17	479	873	727	554
	Feb-17	804	1054	863	38
Acute Respiratory Infection	Jan-17	7399	5711	5804	4585
	Feb-17	6095	7443	6867	335
Acute Gastro Enteritis	Jan-17	1035	817	767	363
	Feb-17	1696	1037	1002	28

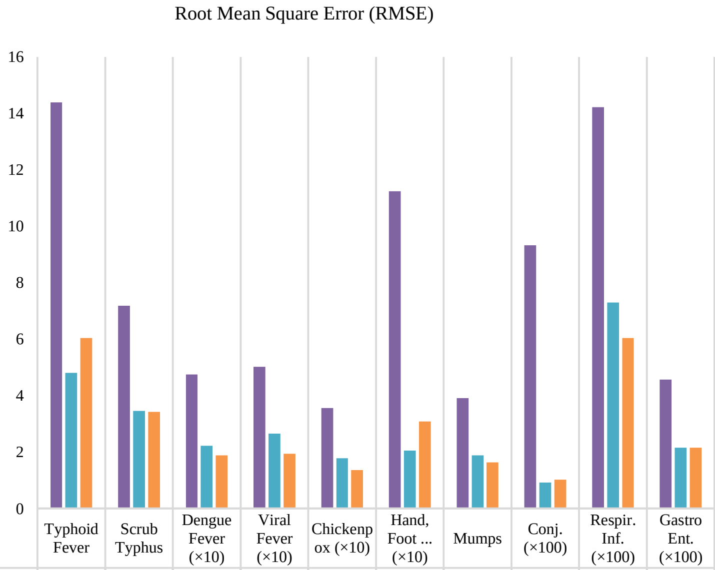
Table 2 presents error measures (RMSE and MAE) for the three tested models, ARIMA, neural network and the proposed hybrid model, separated for each disease. A comparison of these error measures is provided for RMSE and MAE in Figs. 2 and 3, respectively. From the results, it can be found that the hybrid model demonstrated better performance and produced higher accuracy values. Error measures for 7 diseases which are the scrub typhus, dengue fever, viral fever, chickenpox, mumps, acute respiratory infection and acute gastroenteritis. As for the other 3 diseases which are typhoid fever, hand foot and mouth disease and conjunctivitis, the neural network performed better. The ARIMA model had the worst performance among the three models when used for forecasting. However, if forecasted values are taken into consideration, the ARIMA model is more appropriate for forecasting scrub typhus and viral fever, while neural network is more applicable for dengue fever. In terms of RMSE and MAE values the hybrid model had better results, but because of negative value in the forecast, the neural network is more applicable.

Table 2. Error measures for diseases.

Disease	Model	RMSE	MAE
Typhoid Fever	ARIMA	14.3832	9.1666
	Neural Network	4.8011	3.4566
	Hybrid Model	**6.0377**	**4.0742**
Scrub Typhus	ARIMA	7.1863	5.158
	Neural Network	3.4622	2.7062
	Hybrid Model	**3.4291**	**2.588**
Dengue Fever	ARIMA	47.5137	33.2898
	Neural Network	22.291	15.555
	Hybrid Model	**18.8391**	**14.6418**
Viral Fever	ARIMA	50.2606	36.8167
	Neural Network	26.5745	18.6606
	Hybrid Model	**19.4366**	**15.1085**
Chickenpox	ARIMA	35.5901	29.2789
	Neural Network	17.8104	14.0455
	Hybrid Model	**13.6674**	**11.2725**
Hand, Foot and Mouth Disease	ARIMA	112.3858	58.2687
	Neural Network	20.5881	13.72
	Hybrid Model	**30.8664**	**18.9836**
Mumps	ARIMA	3.9105	2.9856
	Neural Network	1.8874	1.5139
	Hybrid Model	**1.6316**	**1.2799**
Conjunctivitis	ARIMA	932.2683	330.4286
	Neural Network	92.5847	68.6105
	Hybrid Model	**102.5741**	**72.0345**
Respiratory Infection	ARIMA	1421.689	1006.1608
	Neural Network	729.3717	540.9241
	Hybrid Model	**604.5021**	**452.5574**
Gastro Enteritis	ARIMA	457.1752	280.6103
	Neural Network	216.1251	140.5953
	Hybrid Model	**215.4472**	**147.0215**

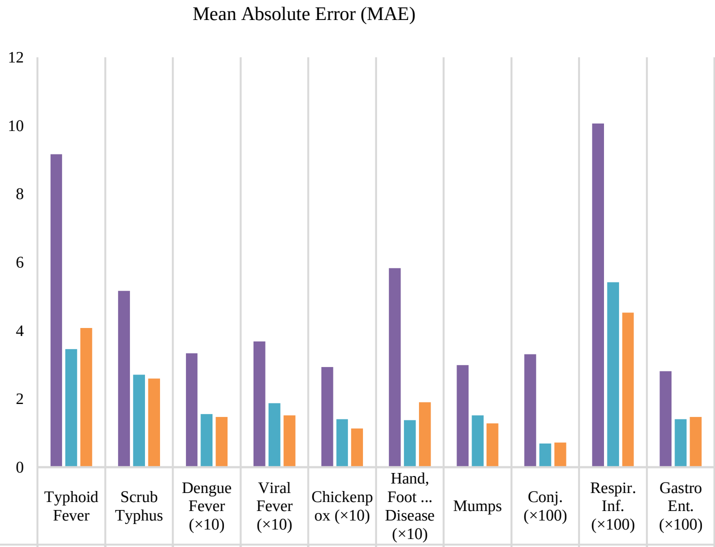
From the study, it can be found that hybrid models perform better than both the ARIMA and neural network models alone. It can be also concluded that a fixed parameter cannot be used for forecasting multiple variables, such as multiple diseases in this study. Therefore, both selection of ARIMA model and appropriate configuration for the neural network has to be automated to ensure that the model can be used for forecasting multiple diseases. Measures to overcome overfitting when using neural network also has to be taken into consideration when automating.

Accurate forecasting of healthcare can assist in policy, decisions makers for creating and developing appropriate action plans to implement preventive healthcare.



	Typhoid Fever	Scrub Typhus	Dengue Fever (×10)	Viral Fever (×10)	Chickenpox (×10)	Hand, Foot ... (×10)	Mumps	Conj. (×100)	Respir. Inf. (×100)	Gastro Ent. (×100)
ARIMA	14.3832	7.1863	4.75137	5.02606	3.55901	11.23858	3.9105	9.322683	14.21689	4.571752
Neural Network	4.8011	3.4622	2.2291	2.65745	1.78104	2.05881	1.8874	0.925847	7.293717	2.161251
Hybrid Model	6.0377	3.4291	1.88391	1.94366	1.36674	3.08664	1.6316	1.025741	6.045021	2.154472

Fig. 2. Comparison of RMSE for different methods.



	Typhoid Fever	Scrub Typhus	Dengue Fever (×10)	Viral Fever (×10)	Chickenpox (×10)	Hand, Foot ... Disease (×10)	Mumps	Conj. (×100)	Respir. Inf. (×100)	Gastro Ent. (×100)
ARIMA	9.1666	5.158	3.32898	3.68167	2.92789	5.82687	2.9856	3.304286	10.061608	2.806103
Neural Network	3.4566	2.7062	1.5555	1.86606	1.40455	1.372	1.5139	0.686105	5.409241	1.405953
Hybrid Model	4.0742	2.588	1.46418	1.51085	1.12725	1.89836	1.2799	0.720345	4.525574	1.470215

Fig. 3. Comparison of MAE for different methods.

7. Conclusion

In this study, a hybrid method comprising of the ARIMA model and the neural network is proposed for time-series prediction in healthcare domain. In this proposed method, the best ARIMA model is chosen automatically, and the neural network parameters are configured. This model can assist the decisions makers in creating and developing appropriate action plans to implement preventive healthcare.

Abbreviations

AIC	Akaike Information Criteria
AR	Autoregressive Model
ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractional Integral Moving Average
ARIMA	Autoregressive Integrated Moving Average Model
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criteria
ECG	Electrocardiogram
FNN	Forward Neural Networks
MA	Moving Average Model
MAE	Mean Absolute Error
MSARIMA	Multiplicative Seasonal ARIMA
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
SVR	Support Vector Regression

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