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Forecasting of COVID-19 Mortality Rates: A Comparative Study of ARIMA and NN Models

A. A. Suleiman 1, H. Daud 1, A.I. Ishaq 2, S.A. Suleiman 3, R. Sokkalingam 1, A.H. Abdullahi 4, B.D. Garba 4

A Fundamental and Applied Sciences Department, Universiti Teknologi PETRONAS, Seri Iskandar 32610, Malaysia 1

Department of Statistics, Ahmadu Bello University, Zaria 810107, Nigeria 2

Kano State Agro - Climatic Resilience in Semi-Arid Landscapes, Kano State Ministry of Water Resources, Kano, Nigeria 3

Department of Mathematics, Aliko Dangote University of Science and Technology, Wudil 713281, Nigeria 4

INTRODUCTION & AIM

Mortality rate prediction plays a vital role in understanding public health trends, guiding healthcare planning, and informing policy decisions. The ability to predict future mortality rates helps authorities allocate resources more efficiently, prevent outbreaks, and tailor public health initiatives to changing demographic and environmental conditions. Traditionally, statistical models such as ARIMA have been used to forecast mortality, focusing on time-series data. However, these models often fail to capture the complex, non-linear relationships inherent in mortality rate data, especially in the presence of multiple influencing factors such as socioeconomic status, healthcare access, and environmental changes.

The emergence of machine learning models such as Backpropagation Neural Networks (BPNN), Extended Recurrent Neural Networks (ERNN), and Enhanced Radial Basis Function Neural Networks (RBFNN) has provided a promising approach to improve prediction accuracy. These models are better suited to handle large datasets and capture intricate patterns that traditional models may overlook. Nonetheless, challenges remain in optimizing these models for accurate and reliable mortality predictions, particularly when working with limited or incomplete data, and dealing with model overfitting and interpretability issues.

Aim of the Study

The primary aim of this study is to develop and evaluate predictive models for mortality rates, focusing on the use of time-series and machine learning techniques. Specifically, we seek to:

1.Compare the performance of various models such as ARIMA, BPNN, and ERNN in predicting mortality rates.

2.Identify the most influential factors affecting mortality trends by analyzing the model outputs.

3.Improve the prediction accuracy of mortality rates through optimization techniques and advanced feature engineering methods.

4.Provide insights that can be used by policymakers to design effective public health strategies and interventions.

METHOD

This study utilizes both traditional time-series forecasting (ARIMA) and advanced machine learning techniques (BPNN, ERNN, and Enhanced RBFNN) to predict mortality rates. The following steps outline the methodology used:

1. Data Preprocessing:

Data normalization using Min-Max scaling to transform the mortality data into a range of [0, 1] for efficient training.

2. Model Implementation:

- ARIMA: A traditional time-series model used for modeling and forecasting based on autoregression and moving averages.
- BPNN: A feedforward neural network that uses the backpropagation algorithm to adjust weights and minimize errors in the predictions.
- ERNN: A type of recurrent neural network capable of handling sequential data and capturing long-term dependencies
- .Enhanced RBFNN: A neural network using radial basis functions to model complex, non-linear relationships, adapted to improve forecasting accuracy.

$$y = \sum_{i=1}^{N} \alpha_i \, \emptyset(\|x - c_i\|).$$

where α_i are the weights, $\emptyset$ is the radial basis function, c_i are the centers of the RBFs, and x is the input vector.

3. Model Evaluation:

Models are evaluated using performance metrics such as MAE (Mean Absolute Error), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error) to compare their prediction accuracy.

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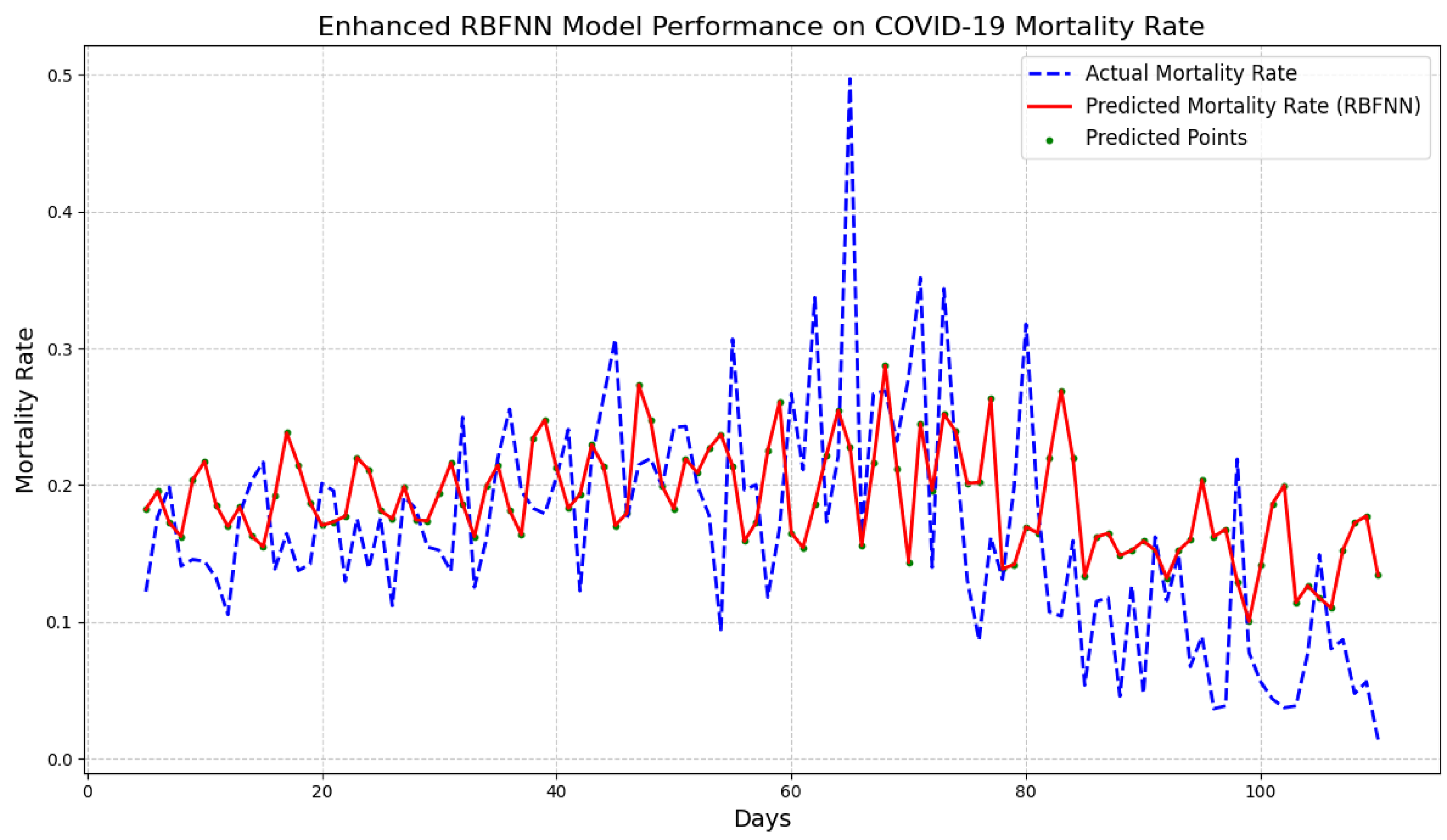
RESULTS & DISCUSSION

To demonstrate the superior performance of the Enhanced Radial Basis Function Neural Network (Enhanced RBFNN) model, the table below summarizes the evaluation metrics for all models, comparing their MAE, MSE, and MAPE. The results clearly indicate that the Enhanced RBFNN outperforms the other models in terms of accuracy and predictive power. This demonstrates that the Enhanced RBFNN outperforms the competing models across all key performance metrics, making it the most suitable model for accurate predictions.

Model	MAE	MSE	MAPE
Enhanced RBFNN	0.032	0.001	3.45%
ERNN	0.055	0.003	5.23%
BPNN	0.071	0.004	6.71%
ARIMA	0.09	0.005	8.45%

The figure presents the performance of the Enhanced RBFNN model for predicting COVID-19 mortality rates over time. The comparison includes the actual mortality rate **(depicted by the blue dashed line)** and the predicted mortality rate **(red solid line)** with specific data points highlighted as **green dots.**

- The **Enhanced RBFNN model** captures the trends in mortality rates effectively, showing close alignment between the predicted and actual rates.
- Although some deviations are visible in certain periods (e.g., near the spikes), the overall predictive accuracy is evident, with the predicted curve following the actual mortality rate closely.



CONCLUSION

he study underscores the effectiveness of the Enhanced RBFNN in predicting COVID-19 mortality rates compared to traditional statistical models (ARIMA) and other neural network models (BPNN, ERNN). This is crucial for public health planning and response, as accurate predictions can significantly impact resource allocation and decision-making.

FUTURE WORK / REFERENCES

Future work could focus on integrating ensemble methods or hybrid models that combine the strengths of RBFNN with other techniques (e.g., ARIMA for trend modeling and RNN for sequence learning) to further improve prediction accuracy.