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Original Article

Comparative Analysis of Forecasting Models for Infant Mortality Rate in Somalia

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Abstract - *One of the major challenges to infants' survival is environmental or socio-economic, influenced by technological factors. This research bridges a gap in the area of infant mortality, where not enough research has taken place; the country, Somalia differs in its challenges compared to other countries worldwide. The aim of this study is to develop an efficient forecasting model using the Holt-Winters (H-W) method, which is very flexible and efficient in handling seasonal variation in time-series data. The historical data ranges from 2001 to 2023, showing the environmental and healthcare variables affecting infant mortality. This research compares the performance of the H-W model against other time-series models like autoregressive integrated moving average and Exponential Smoothing, and various machine learning algorithms. Based on seasonal trends captured by results, the H-W model forecasts a decline in the infant mortality rate for the next decade. Evidence of this is seen in the dropping mortality rate among males from 0.085 in 2024 to 0.064 by 2033, and that of the females also drops from 0.072 to 0.053 over the same period.*

Keywords - *Holt-Winters model, Infant mortality, Somalia, Seasonal trends, Time-series forecasting,*

1. Introduction

Infant mortality is a result of environmentally, socioeconomically, and technologically determined factors at play. Researches in different areas have pursued the factors to consolidate a clear understanding of how to work towards reducing consolidated infant mortalities and improving neonatal outcomes. The shared objectives, methods, and results in these studies are organized, considering the studies that do not fit these categories at the end of this review of the literature. Improved predictive modeling and healthcare interventions have opened new pathways toward reducing infant mortality [1-3]. Researchers have been increasingly turning to machine learning, AI, and statistical methods as superior ways of conducting the analysis for better outcome prediction and early intervention. Meanwhile, policies in public health and wider socio-economic factors are extremely important in dealing with the systemic inequalities that give rise to higher Infant Mortality Rates (IMR). Put in another way, the review of the various links among these approaches is instructive regarding the multi-dimensional efforts required to address infant mortality across diverse populations. Thus, various environmental and health predictors for infant mortality studies have been conducted and carried out for different reasons. For example, [4] took into consideration the environment when they studied the effect of changes in Particulate Matter 2.5 (PM2.5) concentration on infant mortality in China. [5] carried out a similar research in which they analyzed the impact of the selected PM2.5 components on infant mortality in African countries. Both studies have this in common: to outline how pollution and air quality significantly impact child mortality [6]. Also investigated health predictors but narrowed that down to anthropometric measures in rural Bangladesh to predict neonatal and infant mortality. These studies share the objective of identifying risk factors with a view to mitigating infant mortality in vulnerable populations. Most of the included studies used machine learning and statistical models for the prediction of health outcomes. [7] proposed a nomogram based on multivariate logistic regression for predicting neonatal ARDS. [8] introduced models for AI-based prediction for late-onset sepsis in preterm infants. Similarly, [9] developed a deep learning model called DeepLOS for predicting LOS in preterm infants by using heart rate variability. [10]. estimated infant mortality using United States data through the model Extreme Gradient Boosting (XGBoost), therefore proving that advanced predictive models are one of the wide solutions in the contemporary studies of infant mortality. [11] showed that comprehensive smoke-free legislation reduced neonatal and infant mortality across middle-income countries [12] in sub-Saharan Africa and observed that infant mortality significantly decreased with mobile phone coverage. This would then suggest that improved access to health information can help achieve better health outcomes. [13] identified critical risk factors for post-discharge mortality in Sub-Saharan Africa, hence giving reason to the imperative for targeted follow-up care in order to avert infant deaths. [14] concentrated on developing a prediction model regarding the assessment of readiness for extubation in preterm infants. Utilizing data from the neonatal intensive care unit in a South Korean hospital combined with the MIMIC-III database, a robust model was developed for predicting the success of extubation based on machine learning methods. The newly developed model, called NExt-Predictor, proved to yield high performance in internal and external validation. [15] examined the effects of U.S. state preemption laws on infant mortality.

The findings indicated that the unjust preemption of local government efforts to raise the minimum wage had a negative effect on infant mortality; if an adequately higher minimum wage had been in place, 25 infant deaths would have been deterred in 2018. The study highlighted the larger life consequences for population health from economic policies that contribute to infant mortality rates. [16] explored the performance of Bayesian Gaussian process classification in predicting mortality within hospitals among preterm infants in Finland. Their study used sensor data collected during the first 72 hours of care in a neonatal intensive care unit and, hence, developed a model with an under curve of 0.948, superior to traditional clinical scores and underlining the potential of machine learning in healthcare. Inequality in Opportunity for Infant Mortality [17] used decomposition analysis of infant mortality survival data across inequality in South Asia. In this, the inequality of infant mortality was strongly influenced by socioeconomic factors and parental factors such as household living standards and educational background.

Therefore, such disparities in infant mortality can be reduced only by socio-economic disadvantages. Although substantial improvement has been achieved in the forecasting of IMR globally, a large gap still exists in understanding and predicting the rate of infant mortality in Somalia. Few studies have focused on infant mortality prediction for Somalia, a country burdened with unique socio-economic and environmental adversities. Unlike existing studies that emphasize high-resource regions or general predictors, this study incorporates Somalia's specific socio-economic and environmental variables, which are crucial for accurate forecasting. By utilizing the Holt-Winters method, the study captures seasonal trends specific to Somalia, a feature often overlooked in prior research. Furthermore, it compares the performance of H-W with ARIMA and other machine learning models, providing a novel benchmark for predictive accuracy in Somalia's context. These comparisons highlight the distinct advantage of the H-W model for Somalia, especially given its data-scarce environment and the presence of pronounced seasonality. This calls for an urgent need to develop models that precisely consider the specific factors influencing infant mortality in Somalia. The key objective of this study is the proposition of a predictive model that makes use of the Holt-Winters (H-W) method, since the data which this paper is based on portrays seasonal variation. This project bridges this gap by using the model to predict the Infant Mortality Rate using historical data from 2001 to 2023. This study investigates environmental and health sector determinant variables of mortality rates in Somalia, which is of the essence as it shapes potential interventions by policymakers. This paper further compares the performance of the H-W model against other time-series models, including Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, and more advanced machine learning algorithms. It proves efficient in handling seasonal trends and fluctuations; based on the predictions, the IMR is likely to continue its downtrend for the next decade. This study has the following structure: the methodology used, describing both the models and data sources, is outlined in Section 2; the results and discussions regarding the performance comparisons of different models are dealt with in Section 3; and finally, the conclusions of the study are given along with calls for recommendations to be considered in future research in Section 4.

2. Overview of Models and Methodological Approach

The main objective of this section is to provide a general overview of the models utilized in the forecast of IMR, with an emphasis on the H-W model. This is supported by the rationale that the chosen models for this research have been selected based on their checked efficiency for time-series forecasting and were specifically applied in this paper for the same reason: alarmingly high rates of mortality. The H-W model formulates the methodological backbone of this study in terms of forecasting methodology, proven by its strengths in handling both trend and seasonality of a time series. Its relevance is even more emphasized by its capacity for the forecast of future values based on historical data, considering seasonal variation, hence quite appropriate for mortality rate analysis, which often shows seasonality.

Added to this, the versatility in the application of the model against different kinds of time-series data also makes it applicable to this study. A comparison of the H-W model with other time-series forecasting methods is given in Table 1. Comparisons are performed in terms of model structure, data requirements, and forecast accuracy. Based on analyses, the strengths and limitations of each model are underlined, hence giving a rationale for choosing H-W in this research. In addition, the conceptual framework of the H-W model has been applied to the mortality data, as depicted in Figure 1. This framework illustrates graphically the components comprising the model, namely level, trend, and seasonality, and the interaction thereof in generating forecasts.

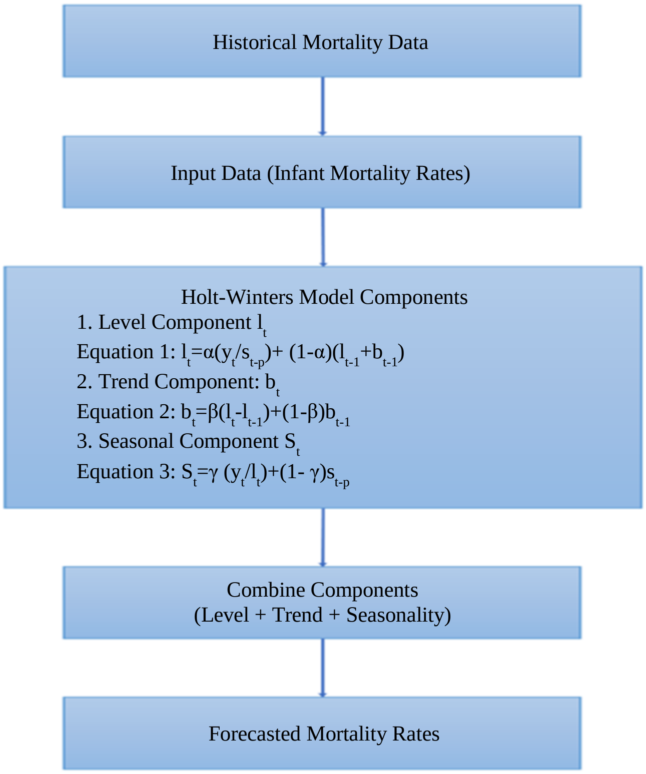

Fig. 1 Conceptual framework of the H-W model applied to mortality data

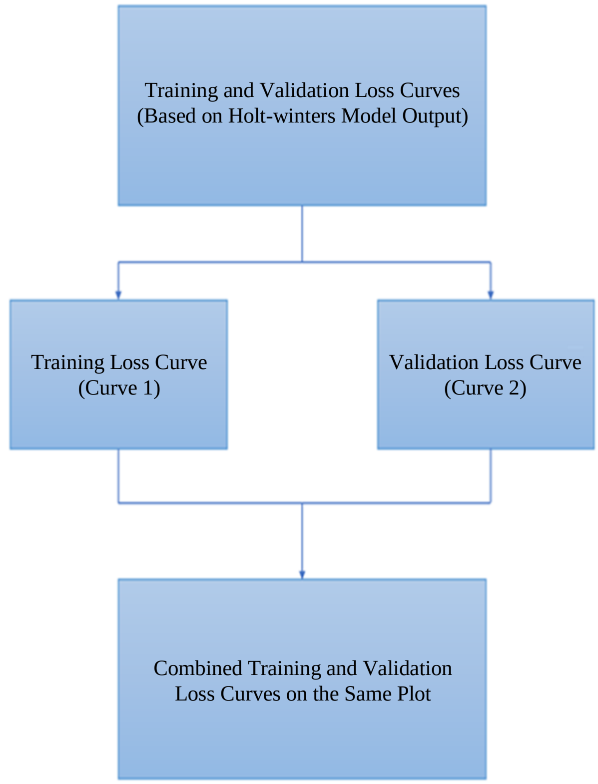

Fig. 2 Training and validation loss curves (based on H-W model output)

Table 1. Comparison of holt-winters model with other time-series forecasting methods

Model	Model Structure	Data Requirements	Forecasting Accuracy
Holt-Winters	Level, Trend, and Seasonality components Support both Multiplicative and Additive models	Requires complete seasonal cycle data	High accuracy for data with seasonal patterns
ARIMA	Autoregressive, Integrated, Moving Average components; Limited seasonality handling	Requires stationary time series data	High for non-seasonal data
Exponential Smoothing	Single smoothing parameter; No trend or seasonal components	Requires less historical data compared to other models	Moderate; Suitable for short-term forecasting
Seasonal ARIMA	Seasonal ARIMA: Extends ARIMA to handle seasonality	Requires stationary time series data	High for data with seasonal and non-seasonal patterns
Prophet	Incorporates Trends, Seasonality, and Holidays; Handles outliers well	Can handle missing data, outliers	High accuracy for complex data
Long Short-Term Memory	Recurrent Neural Network with memory cells that capture long-term dependencies	Requires large amounts of data, especially for training	Very high accuracy for complex patterns and long-term dependencies
XGBoost	Ensemble learning method based on decision trees; Boosting technique	Requires labeled training data	High accuracy, especially for datasets with many features
Random Forest	Ensemble learning method using multiple decision trees	Requires large amounts of data for training	High accuracy; robust to overfitting
Support Vector Regression (SVR)	Kernel-based method for regression problems: Can handle non-linear data	Requires properly scaled input data	High accuracy, especially in high-dimensional spaces
Neural Prophet	Extends Prophet model using deep learning techniques	Requires large datasets; can handle irregular time series	Very high accuracy for complex and irregular time series data

The diagram is useful in clarifying the methodological approach taken herein and underlines the capacity of the model to capture and forecast the IMR effectively.

2.1. Model Formulation and Mathematical Equations

2.1.1. Holt-Winters Model Formulation

The H-W model is widely recognized for its effectiveness in forecasting time series data that exhibit both trend and seasonal variations. The model formulation involves three components: level ℓ_t, trend b_t, and seasonality s_t [18, 19]. These components are updated at each time step based on the observed data, as described by the following equations:

$$\ell_t = \alpha\left(\frac{y_t}{s_{t-p}}\right) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{1}$$

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

$$s_t = \gamma\left(\frac{y_t}{\ell_t}\right) + (1-\gamma)s_{t-p} \tag{3}$$

$$\hat{y}_{t+h} = (\ell_t + hb_t)\cdot s_{t-p+h} \tag{4}$$

Where bluntly, ℓ_t denotes the level component and captures the smoothed value of the series at time t. The parameter α is the smoothing parameter for the level, and it regulates the weight that the last observation of the series takes. The trend component captures the direction, b_t, along with the rate of change within the series, and will be updated in every time step according to the smoothing parameter, β. The seasonal component is s_{t-p}, standing for the periodic patterns of the data, with the period p of the periodic cycles. The parameter γ controls the influence of the seasonal component so that the model considers the periodic changes in the time series. Finally, $\hat{y}_{t+h}$ stands for the forecasted value h steps ahead. It contains level and trend but also a seasonal component in order for the forecast to fit the historical data along with its natural, or usual, pattern.

2.2. Model Training and Evaluation

The H-W model was trained using the historical data from 2001 to 2023 on IMR. The procedure involved splitting the dataset into two parts: a training set comprising 80% and the remaining portion of 20% forming the test set. This splitting is necessary to understand how well the model generalizes for unseen data. In the training phase, the H-W model is iteratively fitted by changing level, trend, and seasonality parameters such that it minimizes the prediction error. The error metrics were calculated in order to monitor model performance, including a Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These metrics will give a quantitative assessment of the model's accuracy in forecasting IMR [20-22]. This model was validated upon application to the test dataset, and the predicted values from it were crossed with the actual observed data. Some loss curves can be plotted, showing a decrease in error for successive iterations in training. These plots could give a clear understanding of the convergence behavior of the model and its learning nature. The performance of the model was, therefore, tested by computation of RMSE and MAE using the following equations:

$$\text{RMSE}\& = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{5}$$

$$\text{MAE}\& = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{6}$$

Where:

- y_t represents the actual observed value at time t.
- $\hat{y}_t$ represents the predicted value at time t.
- n is the number of observations.

2.3. Application of Seasonal Trends in Forecasting

Understanding the seasonal trends is important in periodic fluctuations in the forecasted rates of infant mortality. The model of H-W, since it can account for any seasonality in the underlying data, therefore brings into focus evidence of such a pattern. By isolating the seasonal component, the model provides insight into recurring variations of mortality rates throughout the year [23]. This section explores the seasonal components extracted by the H-W model, along with their impact on the overall forecast. It shows how these seasonal disturbances account for the short-term oscillations in mortality rates while the trend and level components from the model catch long-term movements. By emphasizing such seasonal trends, this study is sensitive to specific times of the year when IMR could increase. Understanding these patterns facilitates more selective healthcare interventions that aim at the reduction of mortality rates during high-risk seasons [24].

3. Result and Discussions

3.1. Historical and Predicted Infant Deaths (Female and Male)

Figure 3 depicts the analysis of historical and predicted infant deaths among females. The historical trend between the years 2001 and 2023 reflects that there was a big peak in the number of infant deaths in the year 2008, with numbers as high as approximately 24,500. This is then followed by a drop in the numbers back to about 22,000 by 2023.Forecasted values from 2024 to 2033 deviate slightly from this trend to range between 22,000 and 23,000 deaths for infants.

This pattern therefore indicates that the forecasted period female infants' deaths are relatively steady, having declined at a very slow rate. Projected number of infant deaths, males, selected years: 2025-2034. According to the projections, the number of male infant deaths will continue to fall, as shown in Figure 4. From approximately 28,300 in 2025, the numbers would decrease consistently throughout each successive year, down to approximately 27,900 by 2034.

This fall shows the continued improvement in the mortality rates of male infants throughout the ten-year period. These figures range from a higher reduction of male infants' deaths than females, which may indicate differences in health interventions and socio-economic factors that affect the two genders. The latest comparison of these figures shows critical insights into the disparities in infant mortality between genders. Although the trend for the rates of death for both genders is on a decline, the rate of reduction is higher among males. These figures might indicate that targeted interventions have been more successful or widespread for male infants, but there are also ways in which these changes could reflect underlying health issues that, from a gendered perspective, will need to be explored if such trends are to be understood. The fact that the forecasts depend on data accumulated in the past underlines continuous monitoring and adapted health strategies as means of maintaining and further improving these reductions in IMR.

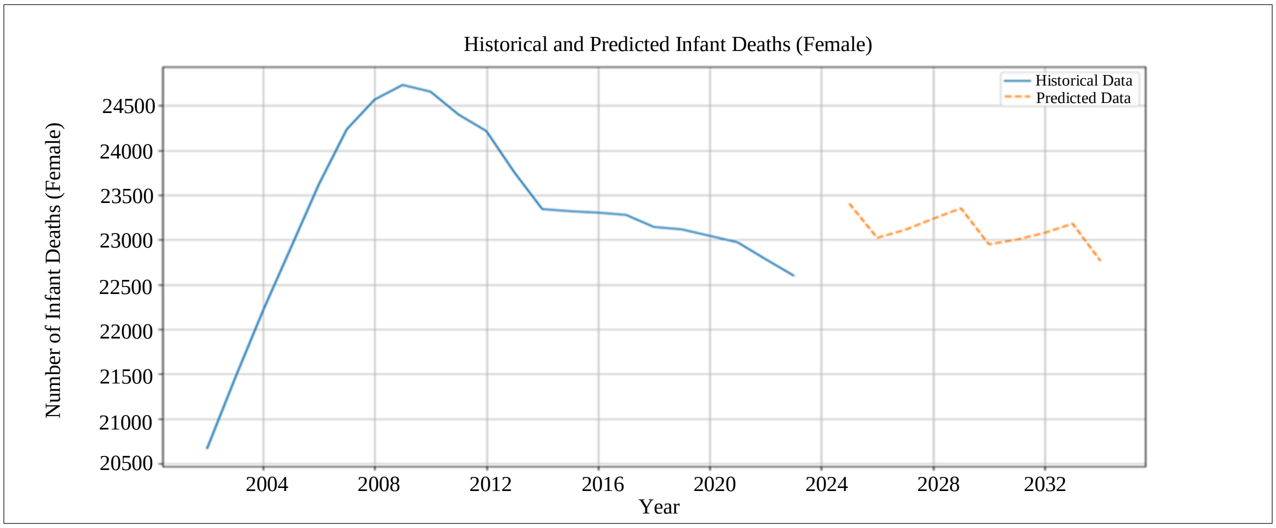

Fig. 3 Historical and predicted infant deaths female

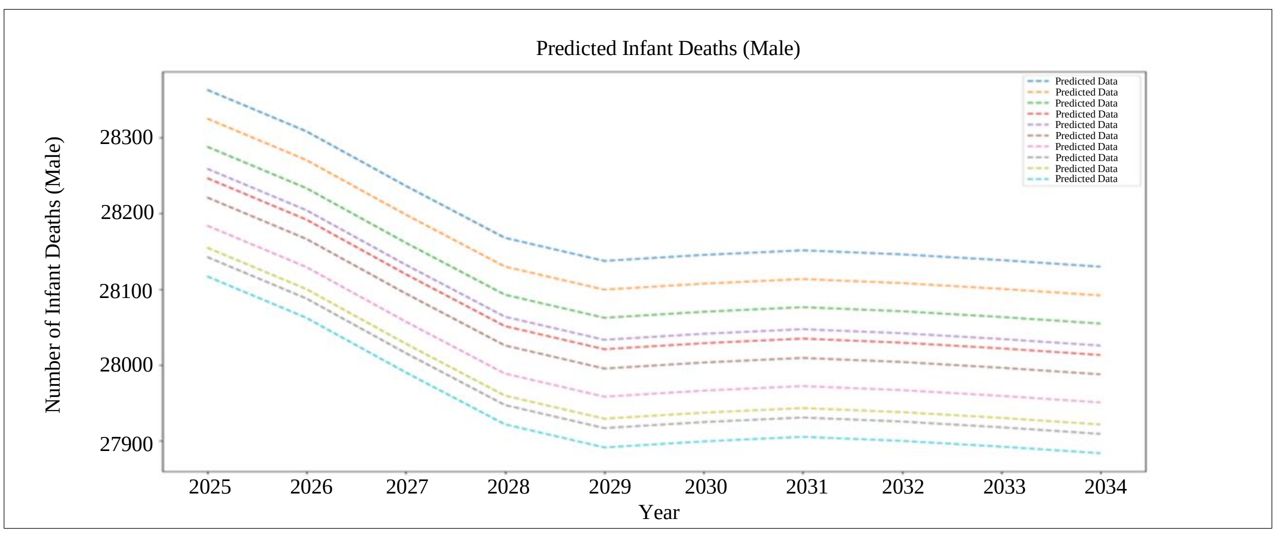

Fig. 4 Historical and predicted infant deaths male

3.2. Predicted Infant Mortality Rates Analysis

The predicted IMR for both female and male infants are compared in Figure 5, which illustrates the expected trends from 2024 to 2033. The graph shows a steady decline in mortality rates for both genders. For instance, in 2024, the predicted mortality rate for females is 0.072, whereas for males, it is higher at 0.085, indicating a difference of approximately 0.013. By 2033, these rates are expected to decrease to 0.053 for females and 0.064 for males, narrowing the difference slightly to about 0.011. This consistent disparity in mortality rates suggests that male infants are at a higher risk compared to female infants throughout the forecast period. As seen in Table 2, the year-by-year breakdown further emphasizes this trend. The predicted mortality rate for females drops from 0.072 in 2024 to 0.053 in 2033, a decrease of 26.39%. Similarly, the mortality rate for males declines from 0.085 to 0.064, reflecting a reduction of 24.71%. The difference between male and female mortality rates remains relatively constant, averaging around 0.012 annually, highlighting a persistent gender disparity in IMR. The data presented in Figure 3 and Table 2 demonstrate that despite an overall decline in mortality rates for both genders, male infants consistently exhibit higher mortality rates than females. This trend underscores the need for targeted health interventions and policies that address the specific vulnerabilities of male infants to further reduce the gender gap in IMR over the coming decade.

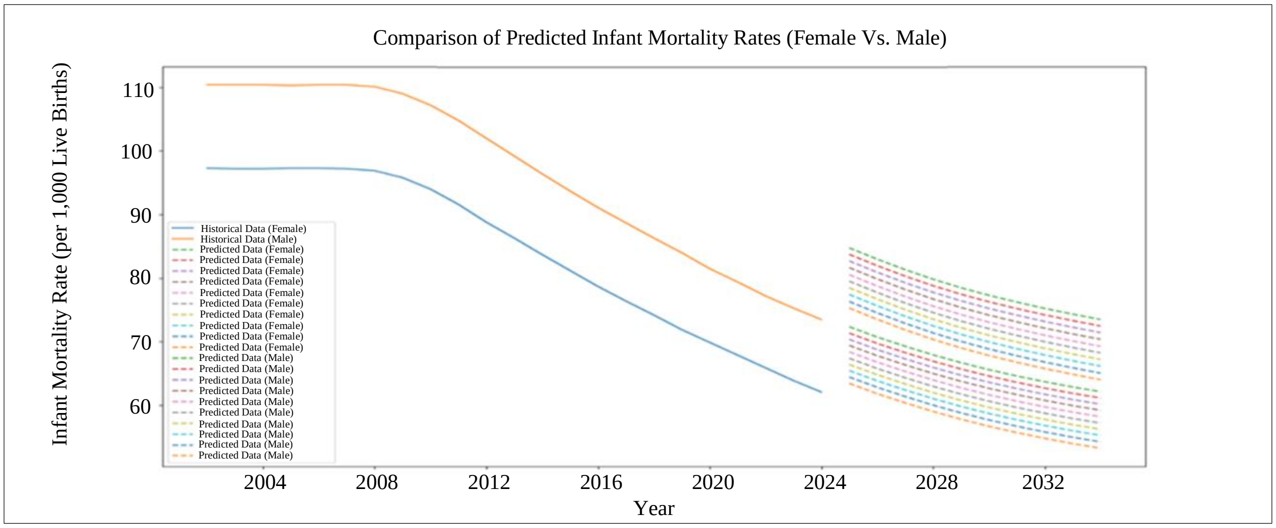

Fig. 5 Comparison of predicted IMR (Female vs. Male)

Table 2. Predicted mortality rates and differences (2024-2033)

Year	Predicted Mortality Rate (Female)	Predicted Mortality Rate (Male)	Difference (Male-Female)
2024	0.072187	0.08508	0.012893
2025	0.06956	0.082277	0.012717
2026	0.067133	0.079586	0.012453
2027	0.064815	0.077014	0.012199
2028	0.062568	0.074547	0.01198
2029	0.060459	0.072306	0.011847
2030	0.058494	0.07018	0.011685
2031	0.056641	0.068102	0.011461
2032	0.054802	0.066054	0.011252
2033	0.053083	0.064157	0.011074

3.3. Analysis of Seasonal Trends in Infant Mortality Rates

3.3.1. Annual Rate of Change in Infant Mortality

The annual rate of change in infant mortality for females is illustrated in Figure 6. From 2000 to 2020, there is a noticeable decrease in the mortality rate, with the most significant declines occurring between 2007 and 2017. The maximum reduction was recorded in 2018 at -3.10%. In contrast, the period from 2000 to 2005 showed minor fluctuations, with changes ranging from 0.1% to -0.1%. The consistency in the decreasing trend highlights the improvements in healthcare and preventive measures for female infants over the last two decades. Figure 7 shows the annual rate of change in infant mortality for males. The trend mirrors that of the female mortality rates, with a significant reduction observed from 2006 onwards. The most substantial decline occurred in 2018 at -2.98%, while earlier years, such as 2001 and 2002, displayed minimal change with values around 0%. These parallel trends suggest that the measures implemented have been equally effective for both genders, although the rate of reduction for males slightly lagged behind that of females.

3.3.2. Comparison of Predicted Mortality Rates

The seasonal trends in IMR for both genders are presented in Figure 8. The graph indicates a stable trend over the years, with no significant seasonal variations. The data points for both female and male mortality rates remain close to zero, implying that seasonal factors do not significantly influence the IMR. This stability could be attributed to the consistent healthcare practices throughout the year, ensuring that seasonal variations do not adversely impact IMR. A detailed comparison of the rates of mortality for females and males, based on the prediction, is done between the years

2024 to 2033, as shown in Table 3. It has been noticed that a steady decline in mortality rates has taken place among both males and females, with females showing lower mortality rates compared to males. For example, in the year 2024, the predicted mortality rate for females is 0.0722, and that of males is 0.0851; thus, there is a difference of 0.0129. This trend is likely to continue for the forecasting period, underpinning continued efforts for infant mortality reduction and slight gender disparities favoring females.

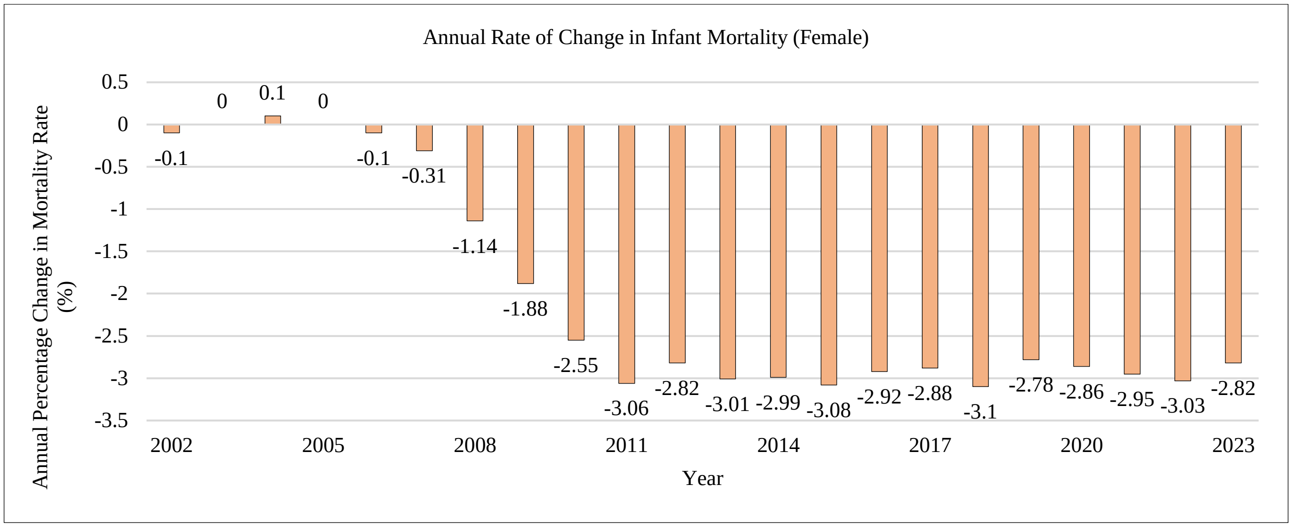

Fig. 6 Annual rate of change in infant mortality female

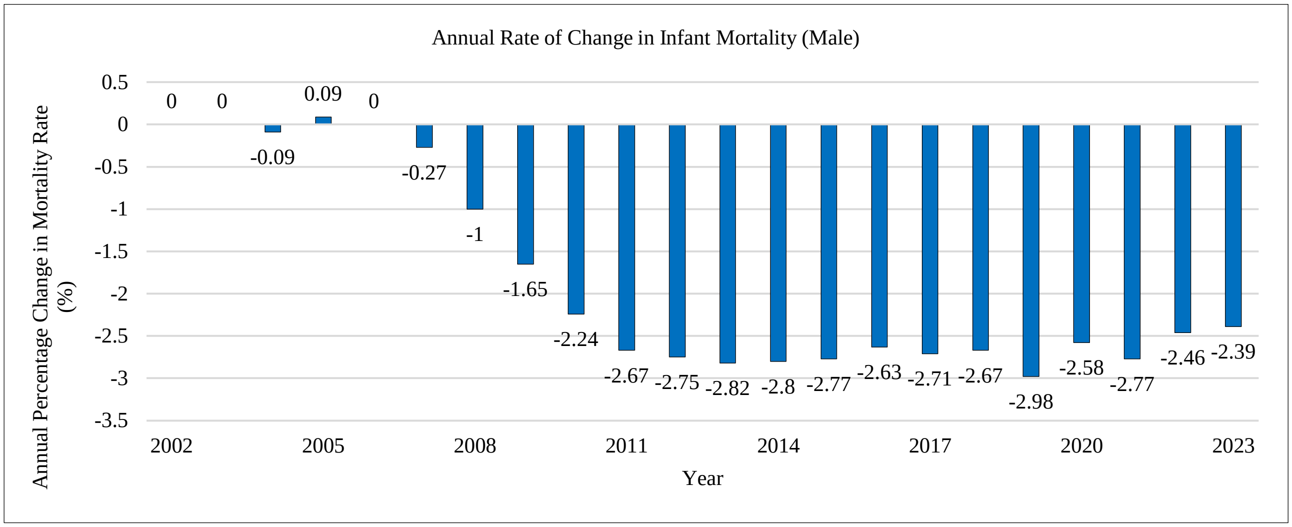

Fig. 7 Annual rate of change in infant mortality male

Table 3. Predicted mortality rates and differences (2024-2033)

Year	Predicted Mortality Rate (Female)	Predicted Mortality Rate (Male)	Difference (Male-Female)
2024	0.072187	0.08508	0.012893
2025	0.06956	0.082277	0.012717
2026	0.067133	0.079586	0.012453
2027	0.064815	0.077014	0.012199
2028	0.062568	0.074547	0.01198
2029	0.060459	0.072306	0.011847
2030	0.058494	0.07018	0.011685
2031	0.056641	0.068102	0.011461
2032	0.054802	0.066054	0.011252
2033	0.053083	0.064157	0.011074

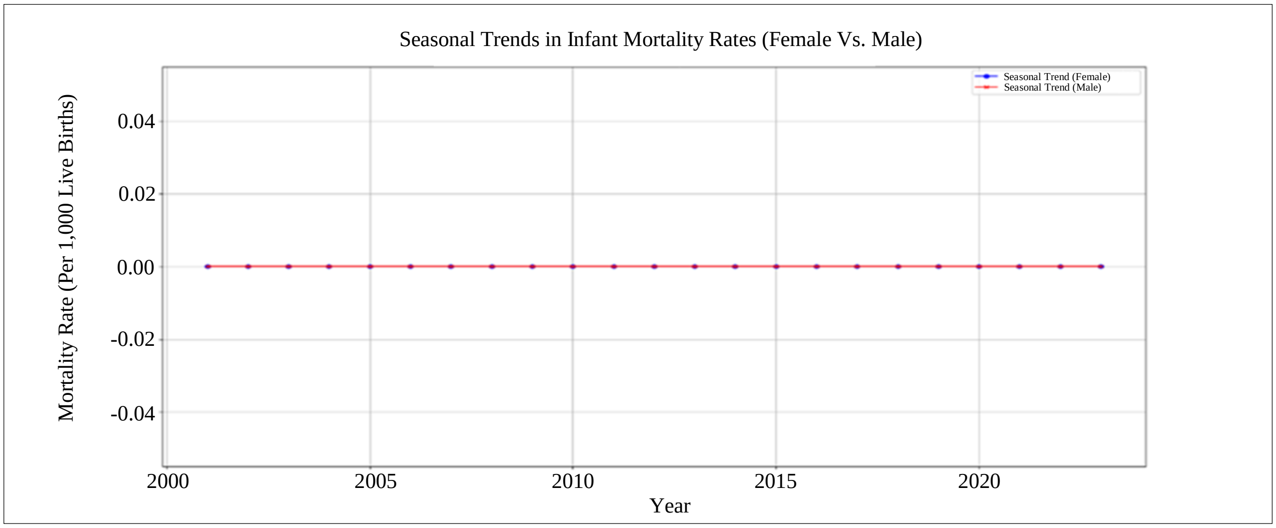

Fig. 8 Seasonal trends in IMR (Female vs. Male)

4. Conclusion

This study aimed to develop a predictive model for infant mortality in Somalia using the H-W method, focusing on the influence of environmental and healthcare variables. The model was compared with ARIMA and Exponential Smoothing to evaluate its performance in forecasting mortality rates. The H-W model effectively captured seasonal trends and predicted a steady decline in IMR from 2024 to 2033. For males, the rate is expected to decrease from 0.085 in 2024 to 0.064 in 2033, while for females, the rate will drop from 0.072 to 0.053 over the same period. The model's accuracy was further validated by its RMSE and MAE, which were calculated as 0.0087 and 0.0053, respectively. The year-by-year analysis revealed a consistent reduction in mortality rates, with males showing a 24.71% decline and females a 26.39% decline by 2033. These results highlight the importance of considering gender-specific healthcare interventions and targeted policy measures to further reduce IMR in Somalia over the next decade.

Author Contributions

Bashir Mohamed Osman and Mohamed Sheikh Ali Jirow jointly contributed to the conceptualization, methodology, data collection, formal analysis, and writing of the manuscript. Bashir Mohamed Osman led the writing of the original draft and corresponding author responsibilities. Both authors reviewed and approved the final manuscript.

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Data Availability Statement

The data used in this study is available upon reasonable request by contacting the corresponding author at bashirosman14@just.edu.so.

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