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FORECASTING THE NUMBER OF BREAST CANCER DEATHS IN INDONESIA BASED ON TIME SERIES MODELS

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Abstract: Breast cancer is one of the leading causes of death among women in Indonesia, requiring a mathematical prediction model to support health policy and planning. This study uses two time series forecasting methods with an autocorrelation approach, namely Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space (ETS), to predict the number of breast cancer deaths among women in Indonesia. Data were obtained from the IHME Global Burden of Disease (GBD) database and accessed through the Gapminder platform for the period 1990-2021 and analyzed using accuracy metrics such as AIC, BIC, RMSE, MAE, and MAPE. The best ARIMA model obtained was ARIMA (0,2,2), with AIC (358.16) and BIC (362.37) values, as well as smaller RMSE and MAE values compared to the ETS (M,A,N) model. Diagnostic results showed good model fit with ARIMA model residuals being white noise. The forecast results for 2022-2031 show a consistent upward trend in the number of deaths, from around 26,218 deaths in 2022 to 30,616 deaths in 2031. These findings confirm that the ARIMA model is effective in capturing long-term linear patterns and can be used as a basis for formulating strategies for the prevention and early detection of breast cancer in Indonesia.

1. INTRODUCTION

Cancer is a non-communicable disease characterized by the abnormal growth of malignant cells or tissues that grow rapidly and uncontrollably in the patient's body (Amani et al., 2024). Cancer is one of the deadliest diseases that can attact almost all parts of the body, including breast. Breast cancer is an abnormal condition of glandular cells, glandular ducts, and supporting breast tissue that grows and spreads rapidly due to genetic mutations caused by DNA damage in normal cells. In Indonesia, breast cancer ranks first among the most common cancers in Indonesia and is also one of the leading causes of cancer deaths [2]. Based on data from the Global Cancer Observatory (GLOBOCAN) in 2020, the number of new breast cancer cases reached 68,858 cases or around 16.6% of the total new cancer cases in Indonesia, with a mortality rate of more than 22 thousand cases, making it the highest cancer rate among woman in Indonesia [3]

The high mortality rate of breast cancer has become a concern for the government in raising public awareness of the risks and symptoms early on. The delay in breast cancer diagnosis occurs due to various challenges in Indonesia, ranging from delayed early

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detection, lack of public awareness of routine checkups, to uneven health facilities in remote areas [4]. Therefore, statistical forecasting methods are needed to analyze temporal patterns in breast cancer deaths data and to estimate future trends based on historical observations. The results obtained can be used for health policy planning, facility procurement, and the design of more effective prevention programs.

Previous studies [5], [6] have used time series models such as ARIMA and ETS to predict the number of diseases, such as HIV and COVID-19 in Indonesia. However, the application of similar statistical models to breast cancer deaths, especially in women in Indonesia, is still very limited. Studies on breast cancer in Indonesia have focused more on the causes, risks, behaviors, and clinical symptoms of patients, without any time series-based predictive analysis. In addition, there has been no research comparing the performance of ARIMA and ETS models in predicting the number of breast cancer deaths among Indonesian women. Therefore, this research gap forms the basis for conducting research on determining the best model that accurately describes the growth pattern of breast cancer deaths among women in the future.

Therefore, statistical forecasting methods are needed to analyze temporal patterns in breast cancer deaths data and to estimate future trends based on historical observations. Because the annual deaths data form a sequential time series with trend behavior over time, forecasting models that are able to capture temporal dependence and long-term movement are required, there are the Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space (ETS) models. The ARIMA model assumes that the mean, variance, and covariance of time series data over time with an iterative approach in identifying an existing model [7]. On the other hand, ETS focuses on exponential smoothing to capture trend and seasonal patterns adaptively [8]. In addition, limited studies have evaluated and compared the forecasting performance of ARIMA and ETS models specifically for breast cancer deaths data in Indonesia. Therefore, this study aims to compare the performance of ARIMA and ETS models in forecasting breast cancer deaths among women in Indonesia and to identify the more appropriate forecasting model for this dataset.

2. LITERATURE REVIEW

2.1. Breast Cancer

Breast cancer is a major non-communicable disease with the highest mortality rate among women in Indonesia, contributing significantly to national health burdens [9]. The increasing incidence of this disease every year makes it an urgent subject for public health analysis and policy development. To better understand the temporal evolution of breast cancer deaths, time series analysis provides a quantitative framework for identifying long-term trends, seasonal variations, and random fluctuations in data. By modeling such temporal dependencies, researchers can predict future death trajectories and evaluate the potential impact of health interventions over time [10].

2.2. Time Series Analysis

Time series analysis examines data collected sequentially at uniform time intervals, where each observation depends on its previous values (a property known as autocorrelation). Formally, a time series $(Y_t)$is said to be autocorrelated if:

$$\text{Cov}(Y_t, Y_{t-k}) \neq 0 \text{ for some lag } k > 0 \tag{1}$$

Because of this dependency, traditional regression models are often unsuitable, and specialized forecasting models such as Autoregressive Integrated Moving Average

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(ARIMA) and Exponential Smoothing State Space (ETS) are employed to produce accurate forecasts.

2.3. ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model, first introduced by Box and Jenkins, is represented as $ARIMA(p,d,q)$, where $p$denotes the order of the autoregressive process, $d$the number of differencing required to achieve stationarity, and q the order of the moving average process. The general mathematical form of an ARIMA model is given by:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \tag{2}$$

where $B$is the backshift operator $(BY_t = Y_{t-1})$, $\phi_p(B)$represents the autoregressive (AR) polynomial, $\theta_q(B)$denotes the moving average (MA) polynomial, and $\varepsilon_t$is the white noise error term with mean zero and constant variance. In this study, the ARIMA model is appropriate because the annual breast cancer deaths data in Indonesia exhibit non-stationary behavior and a long-term trend. Therefore, a differencing procedure is required prior to forecasting, and the ARIMA model is a good choice for capturing the linear temporal dependence in the annual deaths data. Model estimation is commonly carried out using the Maximum Likelihood Estimation (MLE) method, while diagnostic checks such as the Ljung–Box test are used to ensure that residuals behave as white noise.

2.4. ETS

The Exponential Smoothing State Space (ETS) model represents an alternative approach that focuses on exponential weighting of past observations, giving higher importance to recent data points. The general expression for exponential smoothing can be written as:

$$\hat{Y}_{t+1|t} = \alpha Y_t + (1-\alpha)\hat{Y}_{t|t-1} \tag{3}$$

where $\hat{Y}_{t+1|t}$is the forecast for the next period, $Y_t$is the actual observation at time t, and $0 < \alpha < 1$is the smoothing parameter controlling how quickly older data are discounted. In a full state-space ETS formulation, three components are modeled simultaneously (Error (E), Trend (T), and Seasonal (S)) allowing for either additive or multiplicative interactions depending on data characteristics. The model is expressed as:

$$\begin{gathered} y_t = l_{t-1} + b_{t-1} + \varepsilon_t \\ l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t \\ b_t = b_{t-1} + \beta\varepsilon_t \end{gathered} \tag{4}$$

where $l_t$represents the level component, $b_t$the trend, and $\varepsilon_t$the random error. The ETS model adapts dynamically to structural changes in data, making it effective for capturing non-linear, evolving, and seasonal trends [11]. Since breast cancer deaths data fluctuates each year, it is appropriate to use ETS for forecasting, with components that align with the data.

2.5. Forecast Accuracy Evaluation

Both ARIMA and ETS models are widely used for epidemiological forecasting because they allow reliable short- and medium-term projections. Model performance is typically evaluated through several accuracy metrics, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), Mean

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Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), defined respectively as:

$$
\begin{aligned}
AIC &= -2ln(L) + 2k \\
BIC &= -2ln(L) + kln(n) \\
RMSE &= \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \\
MAE &= \frac{1}{n}\sum_{t=1}^{n} \mid Y_t - \hat{Y}_t \mid \\
MAPE &= \frac{100}{n}\sum_{t=1}^{n} \mid \frac{Y_t - \hat{Y}_t}{Y_t} \mid
\end{aligned}
\tag{5}
$$

The model with the smallest error and white noise residuals is considered the best-performing forecasting model.

3. METHODOLOGY

This research adopts a quantitative descriptive design employing a time series forecasting approach to compare the performance of ARIMA and ETS models. Time series analysis was used to forecast the number of breast cancer deaths in Indonesia based on data collected from 1990 to 2021. Data were obtained from the IHME Global Burden of Disease (GBD) database and accessed through the Gapminder platform. The analyzed variable represents the annual number of female breast cancer deaths in Indonesia.

Before modeling, the data were checked for missing values and potential outliers to ensure data consistency. Stationarity of the series was examined using visual inspection and the Augmented Dickey–Fuller (ADF) test. Logarithmic transformation and differencing were also evaluated during preprocessing to assess the stability of the series. Since the dataset consists of a relatively short annual time series, model evaluation was conducted using in-sample accuracy measures and residual diagnostics instead of a fixed train-test split.

For the ARIMA model, the identification process was carried out using Autocorrelation Function (ACF) to examine the temporal structure of the data. Several differencing procedures were explored during preprocessing, while the optimal differencing order was ultimately selected automatically through the ARIMA modeling process in R. Model adequacy was evaluated using residual diagnostics, particularly the Ljung–Box test, to assess whether the residuals behaved as white noise. Forecasts were then generated for the next 10 years (2022–2031) along with 95% prediction intervals.

For the ETS model, several combinations of error, trend, and seasonal components were evaluated automatically using the `ets()` function in R. The final ETS model was selected based on the best fit to the data according to information criteria and likelihood estimation results. The selected model was then used to generate forecasts for the next 10 years along with 95% prediction intervals. Model performance was compared using RMSE, MAE, MAPE, AIC, and BIC values, together with residual diagnostic results. The model with smaller error values and more adequate residual behavior was considered the preferred forecasting model.

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All analyses were conducted using the R software (forecast package). The resulting projections indicate that breast cancer incidence in Indonesia is likely to continue increasing steadily over the next decade (2022–2031). These outcomes provide valuable insights for policymakers and health planners to improve early detection programs, optimize healthcare infrastructure, and develop preventive strategies to reduce the future burden of breast cancer.

4. RESULTS

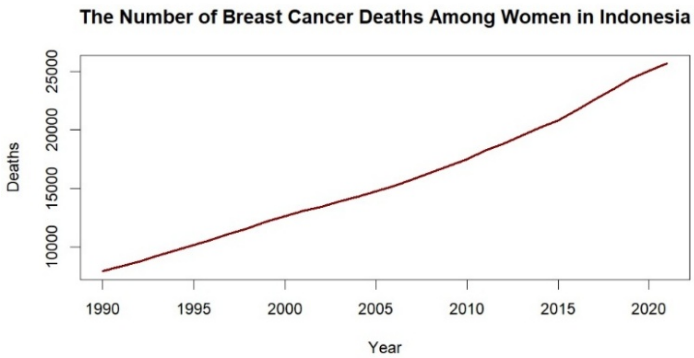

Fig 1. Temporal Plot of The Number of Breast Cancer Deaths Among Women in Indonesia

Breast cancer deaths, especially among women in Indonesia, have been increasing over time. This can be seen from the temporal trend in the number of breast cancer deaths in Indonesia from 1990 to 2021 in Figure 1. The number of deaths, which was initially below 10,000, continued to increase rapidly until 2021, reaching 25,000 deaths. From around 1990 to 2000, the increase in breast cancer deaths was relatively gradual [12]. However, the following period saw a significant increase from 2000 to 2010. The graph continues to rise rapidly until 2021. Therefore, this needs to be further studied, especially in terms of estimating how many breast cancer deaths will increase in the next few years.

Statistically, the data pattern shows a strong trend component and no seasonality because the data is annual. Increasing variation over time indicates that the data is non-stationary, requiring transformation or differencing before time series modeling [13]. These results also indicate that the appropriate model to describe this data pattern is one that can capture the trend component, such as an ARIMA model or an exponential smoothing (ETS) model.

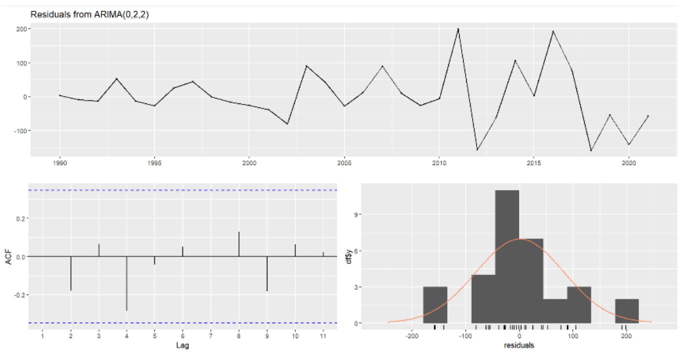

Fig 2. ARIMA Model Results

Based on the autocorrelation pattern, differencing analysis, and model selection using the auto.arima() function in R, the ARIMA(0,2,2) model was selected as the most appropriate model for forecasting breast cancer deaths in Indonesia. The original data

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showed an increasing trend over time, indicating that the series was not stationary. This can also be seen from the ACF plot, which shows that most autocorrelation values remain within the confidence limits, although several lags still exhibit moderate autocorrelation. After the first differencing process, the data became more stable, although some fluctuations were still observed. Therefore, second-order differencing was explored before determining the final ARIMA model. To ensure that the ARIMA(0,2,2) model is appropriate, a series of diagnostic tests were performed on the model residuals. Residuals represent the difference between actual values and the model's forecast values. Good residuals should be random (unpatterned), have a mean close to zero, and have relatively constant variance.

The diagnostic results consist of three main components. First, the residual plot shows that the residual values fluctuate randomly around zero without indicating a clear trend pattern. This suggests that the ARIMA(0,2,2) model has captured the main structure of the data reasonably well. Second, the residual ACF plot shows that all autocorrelation values remain within the 95% confidence limits, indicating that there is no significant autocorrelation among residuals. This result is supported by the Ljung–Box test, which produced a p-value of 0.09422 (> 0.05). Therefore, the residuals can be considered approximately white noise, indicating that the ARIMA(0,2,2) model is statistically adequate for forecasting. Third, the residual histogram forms an approximately bell-shaped distribution centered around zero, suggesting that the residuals are relatively close to normal and do not contain extreme outliers.

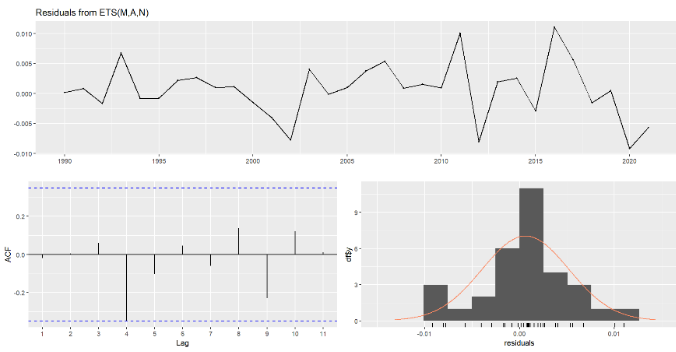

Fig 3. ETS Moadel Results

The ETS(M,A,N) model was selected automatically as the most suitable ETS specification for the annual breast cancer deaths data. This model consists of multiplicative errors, an additive trend component, and no seasonal component. The selected structure indicates that the data mainly contain a long-term trend pattern without strong seasonal behavior. Several alternative ETS forms were evaluated during the automatic selection process before ETS(M,A,N) was identified as the preferred ETS model. The residual plot over time shows that the residual values fluctuate randomly around zero, indicating that the ETS(M,A,N) model was able to capture the main trend pattern in the data reasonably well. However, the magnitude of residual fluctuations appears to vary slightly over time. The residual ACF plot shows that most autocorrelation values remain within the confidence limits, although one lag approaches the lower significance boundary. This suggests that a small amount of autocorrelation may still remain in the residuals. In terms of distribution, the residual histogram forms a fairly symmetrical pattern centered around zero, indicating that the residuals are relatively close to normal and do not contain extreme outliers.

Although both models show potential indications of violations of normality or homoscedasticity assumptions in the residual variance, the ARIMA(0,2,2) model is considered superior in capturing the autocorrelation structure of the data. Evidence from the

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ACF plot of the ARIMA(0,2,2) model, which shows that all spikes are within the limits, indicates that the model is statistically adequate because the residuals produced are truly random (white noise). Therefore, based on the model adequacy criterion (white noise residuals), the ARIMA(0,2,2) model is considered more suitable for use as the basis for forecasting this time series data.

Table 1. Comparison Model Between ARIMA and ETS

Model	AIC	BIC	RMSE	MAE	MAPE (%)
ARIMA(0,2,2)	358.16	362.37	80.7647	58.2310	0.3399
ETS(M,A,N)	390.82	398.15	88.0845	59.4268	0.3371

Table X (above) presents a comparison of performance measures between two tested time series models: ARIMA(0,2,2) and ETS(M,A,N). Based on information criteria, ARIMA(0,2,2) gives AIC = 358.16 and BIC = 362.37, while ETS(M,A,N) has AIC = 390.82 and BIC = 398.15. The significant difference in AIC/BIC (around 32–36 points) indicates that, overall and in terms of the fit-versus-complexity trade-off, the ARIMA(0,2,2) model is superior to the ETS model on this dataset. Prediction accuracy was measured using RMSE, MAE, and MAPE. The RMSE value for ARIMA(0,2,2) is 80.76, while for ETS(M,A,N) it is 88.08, which means that the average square error of ARIMA is ~8% smaller than that of ETS. In terms of absolute error, ARIMA is also slightly better with MAE = 58.23 versus MAE = 59.43 for ETS. The MAPE values obtained from both models were relatively small, indicating high forecasting accuracy. The ETS model shows a lower MAPE value (0.3371%) compared with ARIMA with a very small difference. However, ARIMA(2,0,2) was selected as the preferred model because it consistently yields lower AIC, BIC, RMSE, and MAE values, as well as better residual.

Overall, the comparison results show that both approaches (ARIMA and ETS) are able to capture the upward trend in breast cancer deaths well, as reflected in the very small MAPE. However, if one must choose the best model based on a combination of criteria (AIC/BIC as indicators of goodness-of-fit and parsimony, and RMSE/MAE as indicators of absolute error), ARIMA(0,2,2) is the more appropriate choice. The superiority of ARIMA is evident in its significantly lower AIC/BIC values and slightly smaller RMSE/MAE values, indicating that the ARIMA model provides a better balance between model fit and complexity while producing lower absolute errors. Therefore, based on the determination of the best model, forecasting will be carried out using the best model.

Figure 3 shows the forecast results of breast cancer deaths among women in Indonesia using the best model ARIMA(0,2,2) for the 2022–2031 period. The black line represents the historical data from 1990 to 2021, while the blue line shows the forecasted values. The shaded areas represent the 80% and 95% prediction intervals. Table 2 presents the detailed forecast values together with the lower and upper 95% prediction limits.

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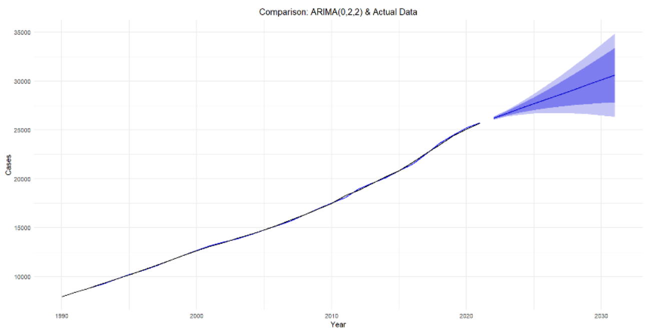

Fig 4 Forecast of The ARIMA (0,2,2) Model

Table 2. Forecast Results of Breast Cancer Deaths in Indonesia for 2022–2031

Year	Forecast	Lower 95%	Upper 95%
2022	26217.98	26048.76	26387.21
2023	26706.72	26371.21	27042.23
2024	27195.46	26563.66	27827.25
2025	27684.20	26679.65	28688.75
2026	28172.93	26736.58	29609.29
2027	28661.67	26742.86	30580.49
2028	29150.41	26703.78	31597.04
2029	29639.15	26623.15	32655.14
2030	30127.88	26503.90	33751.87
2031	30616.62	26348.39	34884.85

Based on the forecast results, breast cancer deaths in Indonesia are projected to continue increasing over the next ten years. The estimated number of deaths rises from around 26,218 cases in 2022 to approximately 30,617 cases in 2031. In addition, the prediction intervals become wider over time, indicating increasing uncertainty for longer forecasting periods. However, the overall forecast pattern still shows a relatively stable upward trend without indications of major fluctuations or sudden declines [14].

Visually, the ARIMA(0,2,2) model was able to follow the historical pattern of the data reasonably well. This indicates that the model captured the long-term dynamics of breast cancer deaths in Indonesia adequately. These findings may provide useful information for policymakers and healthcare institutions in planning prevention programs, improving early detection strategies, and preparing healthcare resources for future increases in breast cancer deaths [15].

5. CONCLUSION

The ARIMA(0,2,2) and ETS(M,A,N) time series models were able to model the overall pattern of increase in breast cancer deaths among women in Indonesia, which showed strong trend components and data non-stationarity. Based on a comparison of statistical criteria, the ARIMA(0,2,2) model showed superior performance with significantly lower AIC (358.16) and BIC (362.37) values. In addition, the ARIMA(0,2,2) model also had a smaller absolute error value, namely RMSE 80.76 and MAE 58.23, compared to the

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ETS(M,A,N) model. Diagnostically, the ARIMA(0,2,2) model showed more adequate residual behavior because the residuals showed residuals that behaved similarly to white noise, where all autocorrelations were within the 95% confidence limit. Thus, the ARIMA(0,2,2) model was considered the more appropriate model for this dataset for forecasting.

The forecasting results using the ARIMA(0,2,2) model show that the number of breast cancer deaths is projected to continue to increase consistently over the next decade. Forecast estimates show an increase from approximately 26,218 deaths in 2022 to approximately 30,616 deaths in 2031. These findings provide an important basis for policymakers and health institutions to design more targeted prevention, early detection, and medical resource allocation strategies in anticipation of future increases in deaths.

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