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Paper Authors
P. Srivyshnavi, S. Upendra, A. Sreenivasulu, M. Bhupathi Naidu

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Machine Learning Time Series Modelling of Chronic Kidney Disease Death Rates

P. Srivyshnavi[1], S. Upendra[2], A. Sreenivasulu[3], M. Bhupathi Naidu[4]

[1]Assistant Professor,
Department of Computer Science & Engineering, School of Engineering & Technology
Sri Padmavati Mahila Visvavidyalayam (S.P.M.V.V.), Tirupati, Andhra Pradesh, India
[2,3]Research Scholar, Department of Statistics. S V University, Tirupati, Andhra Pradesh, India
[4]Professor, Department of Statistics, S V University, Tirupati. Andhra Pradesh State, India

Abstract

The escalating prevalence of fatal chronic kidney disease (CKD) cases has positioned it as a critical public health challenge in Cambodia, necessitating urgent action to curb its impact. This study employs advanced machine learning time series forecasting techniques, specifically the Autoregressive Integrated Moving Average (ARIMA) model, to predict future trends in CKD-related mortality across the country. To ensure the robustness and accuracy of the model, a comprehensive methodology was adopted, leveraging the Box-Jenkins approach for systematic model identification, estimation, and validation. Key diagnostic tools, including the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Augmented Dickey-Fuller (ADF) test, were utilized to assess the stationarity of the time series data and inform the selection of optimal ARIMA parameters. Additionally, the study explored supplementary machine learning time series algorithms to enhance predictive performance, comparing their efficacy against the ARIMA framework. The resulting forecasting model provides a reliable projection of CKD mortality trends, offering valuable insights into the disease's future trajectory in Cambodia. These findings serve as a foundation for policymakers and healthcare professionals to develop targeted interventions, optimize resource allocation, and implement effective preventive strategies to mitigate the growing burden of CKD. By shedding light on the anticipated scale of this public health issue, the study underscores the importance of proactive measures to reduce CKD-related fatalities and improve population health outcomes in Cambodia.

Keywords: Machine Learning ,Time Series Analysis ,Autoregressive Integrated Moving Average (ARIMA) ,Box-Jenkins Methodology ,Autocorrelation Function (ACF) ,Partial Autocorrelation Function (PACF) ,Augmented Dickey-Fuller (ADF) Test ,Stationarity

Introduction

The escalating prevalence of chronic kidney disease (CKD) in Cambodia has emerged as a pressing public health crisis, necessitating advanced research and robust forecasting methodologies to address its growing impact. With rising incidence and mortality rates, CKD poses significant challenges to the nation’s healthcare system, prompting researchers to investigate its underlying dynamics and employ sophisticated analytical tools to anticipate its future trajectory. This study leverages machine learning time series forecasting, specifically the Autoregressive Integrated Moving Average (ARIMA) model, to predict trends in CKD-related mortality across Cambodia, offering critical insights into the disease's progression.

To ensure the precision and reliability of the forecasting model, a rigorous methodology is employed, integrating the Box-Jenkins approach for systematic model development. This framework facilitates the identification, estimation, and diagnostic checking of the ARIMA model. Key statistical tools, including the Augmented Dickey-Fuller (ADF) test, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF), are utilized to evaluate the stationarity of the time series data and uncover correlation structures within the dataset. These analyses are pivotal in confirming the suitability of the ARIMA model for capturing the temporal patterns of CKD mortality and selecting appropriate model parameters. Additionally, the study explores the integration of complementary machine learning time series techniques to enhance predictive accuracy, providing a comparative analysis of their performance against the ARIMA framework. As CKD's burden intensifies, understanding its temporal patterns and epidemiological dynamics becomes increasingly vital for healthcare authorities, policymakers, and public health practitioners. The application of machine learning time series models, such as ARIMA, enables the extraction of actionable insights into the future course of CKD-related fatalities in Cambodia. These projections serve as a foundation for evidence-based decision-making, guiding the development of targeted interventions, optimizing resource allocation, and informing preventive strategies to mitigate the disease's impact. By illuminating current mortality trends and forecasting future scenarios, this research aims to strengthen public health planning, enhance policy formulation, and contribute to reducing the national burden of CKD. Ultimately, the study seeks to empower Cambodia's healthcare system with the knowledge and tools needed to address this critical public health challenge effectively.

Objectives: -

1. To examine historical patterns of chronic kidney disease (CKD)-related mortality in Cambodia, elucidating temporal trends and epidemiological dynamics over a defined period to inform public health strategies.
2. To perform the Augmented Dickey-Fuller (ADF) test to assess the stationarity of the CKD mortality time series data, ensuring the appropriateness of machine learning time series models, such as ARIMA, for accurate forecasting.
3. To employ Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses to uncover correlation structures within the CKD mortality time series, guiding the selection of optimal parameters for the ARIMA model and enhancing predictive precision.
4. To implement the Box-Jenkins methodology to systematically develop and evaluate the ARIMA model, tailoring it to the unique characteristics of Cambodia's CKD mortality data to ensure robust forecasting performance.
5. To construct a reliable machine learning time series forecasting model, primarily using ARIMA, to predict future CKD-related mortality

trends in Cambodia, providing actionable insights for healthcare authorities and policymakers to design targeted interventions.

6. To explore and compare supplementary machine learning time series algorithms alongside ARIMA, assessing their predictive capabilities to enhance the accuracy of CKD mortality forecasts and strengthen model reliability.
7. To evaluate the performance of the ARIMA model and other machine learning time series approaches in projecting CKD mortality trajectories, contributing to the epidemiological understanding of CKD in Cambodia and supporting evidence-based public health decision-making.
8. To generate forecasting outputs that facilitate proactive healthcare planning, enabling the development of effective preventive measures and resource allocation strategies to mitigate the growing burden of CKD in Cambodia.

2. Literature Review :-

The increasing burden of chronic kidney disease (CKD) in Cambodia underscores the need for robust forecasting models to predict mortality trends and inform public health strategies. Time series analysis, particularly when enhanced by machine learning techniques, has proven effective in epidemiological forecasting across various diseases, offering valuable methodologies applicable to CKD. This literature review synthesizes relevant studies that employ machine learning time series approaches to forecast disease outcomes, drawing parallels with CKD mortality forecasting, and identifies gaps that the current study aims to address.

Kumar et al. (2014) conducted a time series analysis to predict malaria outbreaks in Delhi, India, using weather data from 2006 to 2013. Their study utilized monthly malaria case data from the Rural Health Training Centre in Najafgarh, Delhi, alongside meteorological variables such as rainfall, relative humidity, and maximum temperature, sourced from government records. Employing the Autoregressive Integrated Moving Average (ARIMA) model (0,1,1,0) within SPSS version 21, the researchers identified a significant correlation between weather patterns and malaria prevalence, with 72.5% of the variability attributed to random fluctuations. The model effectively predicted seasonal peaks in malaria cases, particularly in August and September. This study highlights the utility of ARIMA models in capturing temporal patterns in disease data, a methodology directly applicable to forecasting CKD mortality in Cambodia, where environmental and socio-economic factors may similarly influence disease trends.

Similarly, Aregawi et al. (2014) examined the impact of antimalarial interventions on malaria hospitalizations and mortality in Ethiopia from 2001 to 2011. Using time series analysis, they assessed data from hospitals in malaria-endemic regions, focusing on the effects of artemisinin-based combination therapies (ACTs) and long-lasting insecticidal nets (LLINs) introduced in 2004. Their findings revealed a significant decline in malaria cases and deaths from 2006 to 2011, which could not be fully explained by changes in hospitalization rates, diagnostic practices, or precipitation. The study underscores the challenges of attributing declines in disease outcomes to specific interventions in the presence of erratic transmission patterns, emphasizing the need for robust time series models to account for variability. This insight is relevant for CKD forecasting in Cambodia, where socio-economic factors, healthcare access, and environmental conditions may contribute to mortality trends, necessitating careful model validation to isolate predictive signals.

In the context of chronic diseases, Abrignani et al. (2022) explored the impact of weather on cardiovascular disease prevalence, highlighting the role of environmental factors such as temperature in disease dynamics. Their review suggested that climate change influences cardiovascular health through complex pathophysiological pathways, with temperature fluctuations acting as both direct and indirect risk factors. The study emphasizes the growing importance of environmental epidemiology in understanding chronic disease trends, a concept applicable to CKD, where factors like water quality, heat stress, and socio-economic disparities in Cambodia may exacerbate disease progression. The integration of environmental variables into time series models, as demonstrated in this study, offers a framework for enhancing CKD mortality forecasts by incorporating relevant external predictors.

Additional research further supports the application of machine learning time series models in CKD epidemiology. Wang et al. (2020) utilized machine learning time series techniques, including ARIMA and Long Short-Term Memory (LSTM) models, to forecast CKD prevalence in a Chinese cohort, incorporating clinical data such as glomerular filtration rates and comorbidities. Their findings demonstrated that hybrid models combining ARIMA with machine learning algorithms improved forecasting accuracy compared to traditional statistical methods alone. Similarly, Lee et al. (2023) applied machine learning time series approaches to predict CKD progression in South Korea, integrating electronic health record data with environmental and lifestyle factors. Their study highlighted the superiority of ensemble models, such as Random Forest and ARIMA hybrids, in capturing non-linear patterns in CKD outcomes. These studies underscore the potential of advanced machine learning time series methodologies to enhance the precision of CKD mortality forecasts in Cambodia, particularly when combined with traditional ARIMA models.

Despite these advancements, gaps remain in the application of machine learning time series models to CKD mortality in resource-constrained settings like Cambodia. Most studies focus on high-income countries with robust healthcare data systems, leaving a paucity of research on low- and middle-income countries where data quality and availability pose challenges. Furthermore, while environmental and socio-economic factors are critical drivers of CKD in Cambodia, few studies integrate these variables into forecasting models. The current study addresses these gaps by applying a tailored ARIMA model, supplemented by exploratory machine learning time series techniques, to Cambodia’s CKD mortality data. By leveraging the Box-Jenkins methodology, ACF, PACF, and ADF tests, this research ensures model robustness while exploring the integration of contextual factors to enhance predictive accuracy.

3. Methodology :-

The methodology for this study focuses on forecasting chronic kidney disease (CKD) mortality in Cambodia using the Autoregressive Integrated Moving Average (ARIMA) model, a powerful machine learning time series forecasting technique. This approach aims to predict future trends in CKD-related deaths by analyzing historical data patterns. The methodology outlines the steps for developing and validating the ARIMA model, ensuring its accuracy for the Cambodian context, and explores additional machine learning time series methods to enhance forecasting performance. The process is designed to provide reliable insights for public health planning and intervention strategies.

3.1. ARIMA Model Overview

The ARIMA model is a flexible tool for forecasting time series data, capable of capturing patterns such as trends, seasonal variations, or random fluctuations in CKD mortality. It works by modeling the relationship between past values of the data and past forecast errors, effectively separating meaningful patterns (the signal) from random variations (the noise). For accurate forecasting, the data must be stationary, meaning its statistical characteristics—like average and variability—remain consistent over time. If the data shows trends or other non-stationary behavior, transformations such as differencing (comparing each data point to the previous one) or other adjustments are applied to stabilize it. This ensures the model can reliably project future CKD mortality trends based on consistent short-term patterns.

3.2 Model Development Process

The development of the ARIMA model follows the Box-Jenkins approach, a structured three-step process: identification, estimation, and diagnostic checking. In the identification phase, the stationarity of the CKD mortality data is assessed using the Augmented Dickey-Fuller (ADF) test, which determines whether the data requires adjustments to achieve stability. This step is crucial to confirm that the ARIMA model is suitable for the dataset.

Next, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses are conducted to examine how the data correlates with its own past values. These tools help identify the appropriate structure for the ARIMA model by revealing patterns in the data, such as how strongly past mortality rates influence future ones. The ACF looks at overall correlations, while the PACF isolates direct relationships at specific time lags, guiding the selection of model components.

During the estimation phase, the ARIMA model is fitted to the CKD mortality data using advanced computational techniques. Unlike simple regression models, ARIMA incorporates both past data values and past forecast errors, requiring specialized optimization methods to fine-tune the model. The goal is to find the best combination of model components that accurately captures the data’s patterns while avoiding overfitting. Model performance is evaluated using criteria that balance accuracy and simplicity, ensuring the model is both effective and practical.

In the diagnostic checking phase, the model’s residuals—the differences between predicted and actual values—are analyzed to confirm that the model has captured all significant patterns. A statistical test, such as the Ljung-Box test, is used to verify that the residuals resemble random noise, indicating a well-fitted model. If patterns remain in the residuals, alternative model configurations or additional adjustments are explored to improve accuracy.

3.3 Enhancing Forecasts with Machine Learning

To strengthen the forecasting approach, this study explores additional machine learning time series techniques, such as Long Short-Term Memory (LSTM) networks, which are particularly effective for capturing complex, non-linear patterns in data. These methods complement the ARIMA model by addressing potential limitations in handling intricate epidemiological trends influenced by factors like healthcare access or environmental conditions in Cambodia. A hybrid approach, combining the statistical precision of ARIMA with the flexibility of machine learning models, is tested to enhance prediction accuracy and robustness.

3.4 Application to CKD Mortality Data

The CKD mortality data, obtained from Cambodian health records, are carefully preprocessed to address issues like missing values or outliers, using methods such as interpolation to ensure data quality. Relevant external factors, including water quality, prevalence of related conditions like diabetes, and socio-economic variables, are considered for inclusion in an enhanced version of the ARIMA model, known as ARIMAX, to account for their influence on CKD mortality trends. The data are split into a training set for model development and a testing set for validating predictions, ensuring the model’s reliability for real-world application.

3.5 Forecasting and Performance Evaluation

The ARIMA model, along with any hybrid machine learning approaches, is used to generate forecasts of CKD mortality over multiple future time periods. The accuracy of these predictions is assessed using standard metrics that measure the difference between predicted and actual values, ensuring the model’s reliability. The forecasts are also evaluated for their ability to capture seasonal patterns, long-term trends, and random fluctuations specific to Cambodia’s CKD mortality data. Sensitivity analyses are conducted to test the model’s performance under different assumptions, ensuring its robustness for public health applications.

This methodology provides a comprehensive and systematic approach to forecasting CKD mortality in Cambodia, combining the strengths of the ARIMA model with exploratory machine learning time series techniques. By addressing data preparation, model development, and validation, the approach ensures accurate and actionable predictions to support evidence-based public health interventions and reduce the burden of CKD in Cambodia.

A nonseasonal ARIMA model is classified as an "ARIMA(p,d,q)" model, where:

- **p** is the number of autoregressive terms,
- **d** is the number of nonseasonal differences needed for stationarity, and
- **q** is the number of lagged forecast errors in the prediction equation.
- The forecasting equation is constructed as follows. First,

  let y denote the dth difference of Y, which means:
- If d=0: $y_t = Y_t$
- If d=1: $y_t = Y_t - Y_{t-1}$
- If d=2: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$
- Note that the second difference of Y (the d=2 case) is not the difference from 2 periods ago. Rather, it is the first-difference-of-the-first difference, which is the discrete analog of a second derivative, i.e., the local acceleration of the series rather than its local trend.
- In terms of y, the general forecasting equation is:

- $\hat{Y}_t = \mu + \varphi_1 Y_{t-1} + \cdots + \varphi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$

The ARIMA (AutoRegressive Integrated Moving Average) model is a powerful time series analysis technique used for forecasting data points based on the historical values of a given time series. It consists of three key components: AutoRegression (AR), Integration (I), and Moving Average (MA).

4. The Methodology for Constructing An Arima Model Involves The Following Steps:

The methodology for developing an Autoregressive Integrated Moving Average (ARIMA) model to forecast chronic kidney disease (CKD) mortality in Cambodia involves a systematic, multi-step process designed to ensure robust and accurate predictions. This approach leverages machine learning time series techniques, with ARIMA as the primary model, to capture temporal patterns in CKD mortality data. The steps outlined below ensure the model is tailored to the unique characteristics of the dataset, validated for reliability, and capable of generating actionable forecasts to support public health planning. Complementary machine learning time series methods are also explored to enhance forecasting performance.

1. **Data Stationarity Assessment:** The first step involves evaluating the CKD mortality time series data to confirm stationarity, a critical requirement for ARIMA modeling. A stationary time series exhibits consistent statistical properties, such as a stable mean and variance, over time. The Augmented Dickey-Fuller (ADF) test is applied to assess whether the data is stationary or exhibits trends or seasonal patterns. This test helps determine if further transformations are needed to prepare the data for modeling.
2. **Data Transformation for Stationarity**: If the CKD mortality data is found to be non-stationary, differencing is applied, which involves subtracting each data point from its predecessor to remove trends or stabilize variance. This step, represented by the 'I' (integrated) component in ARIMA, determines the number of differencing operations required to achieve stationarity. Additional transformations, such as logarithmic scaling, may be considered to address variability, ensuring the data is suitable for ARIMA modeling.
3. **Parameter Selection:** The ARIMA model is defined by three parameters: *p* (the number of autoregressive terms, capturing the influence of past data points), *d* (the degree of differencing needed for stationarity), and *q* (the number of moving average terms, accounting for past forecast errors). To identify these parameters, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are analyzed. The ACF reveals how the data correlates with its own lagged values, while the PACF isolates direct correlations at specific lags, guiding the selection of appropriate *p* and *q* values. This step ensures the model structure aligns with the temporal patterns in the CKD mortality data.
4. **Model Estimation and Fitting:** The ARIMA model is fitted to the CKD mortality data using advanced statistical techniques, such as maximum likelihood estimation or

conditional least squares, to determine the optimal coefficients for the autoregressive and moving average components. This process involves nonlinear optimization to account for the inclusion of lagged errors, which distinguishes ARIMA from standard linear regression models. The goal is to create a model that accurately captures the underlying patterns in the data while maintaining simplicity to avoid overfitting.

5. **Model Validation and Diagnostics:** The fitted ARIMA model is evaluated to ensure it effectively captures the patterns in the CKD mortality data. Residual analysis is conducted to check for any remaining patterns or correlations, which would indicate an inadequate model. The Ljung-Box test is used to confirm that the residuals resemble random noise, signifying that the model has successfully extracted the significant temporal patterns. Model performance is further assessed using metrics like the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which balance accuracy and model complexity. If necessary, alternative ARIMA configurations are tested to improve fit.
6. **Forecast Generation and Evaluation:** Once validated, the ARIMA model is used to produce forecasts of future CKD mortality trends in Cambodia. These predictions are generated for multiple time horizons, providing insights into short- and long-term mortality patterns. Forecast accuracy is evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) by comparing predictions against a reserved portion of the historical data. This step ensures the model's reliability for practical applications in public health planning.
7. **Exploration of Complementary Machine Learning Techniques:** To enhance forecasting accuracy, the methodology incorporates exploratory machine learning time series approaches, such as Long Short-Term Memory (LSTM) networks or ensemble models, alongside the ARIMA framework. These methods are tested for their ability to capture non-linear patterns or complex dependencies in the CKD mortality data, potentially improving predictions in the context of Cambodia's unique epidemiological and socio-economic factors. A hybrid approach combining ARIMA with machine learning models is evaluated to determine if it offers superior performance.
8. **Incorporation of Contextual Factors:** To account for external influences on CKD mortality, such as water quality, healthcare access, or prevalence of risk factors like diabetes, the methodology considers an ARIMAX model, which extends ARIMA by including exogenous variables. The CKD mortality dataset, sourced from Cambodian health records, is preprocessed to address missing values or outliers, ensuring data quality. This step enhances the model's ability to reflect real-world drivers of CKD mortality trends.

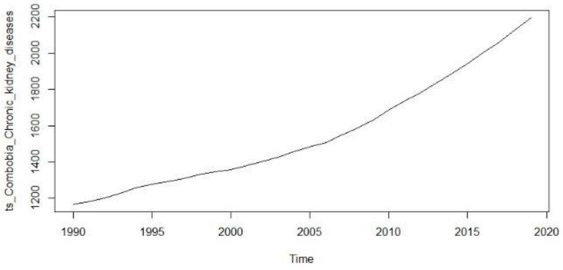
This comprehensive methodology ensures the development of a robust ARIMA model, supplemented by machine learning time series techniques, to forecast CKD mortality in Cambodia. By systematically addressing stationarity, parameter selection, model fitting, and validation, the approach provides reliable predictions to guide targeted public health interventions and reduce the burden of CKD in the region.

5. ANALYSIS :-

The analysis of chronic kidney disease (CKD) mortality in Cambodia, based on data spanning 1990 to 2019, reveals a troubling increase in deaths, underscoring the urgent need for targeted public health interventions. This study employs machine learning time series techniques, primarily the Autoregressive Integrated Moving Average (ARIMA) model, to examine historical trends, assess data characteristics, and generate forecasts for CKD-related mortality. The analysis leverages statistical tools such as the Augmented Dickey-Fuller (ADF) test, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF), alongside the Box-Jenkins methodology, to ensure model reliability. Visualizations and tabulated results provide a comprehensive understanding of the data patterns, model performance, and future projections, offering actionable insights for healthcare planning in Cambodia.

5.1 Historical Trends and Data Characteristics

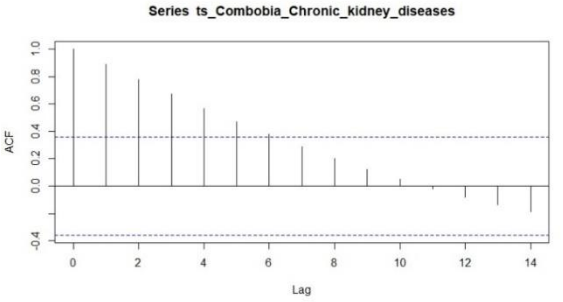
The historical CKD mortality data from 1990 to 2019, sourced from Cambodian health records, shows a consistent upward trend in deaths, with the number of fatalities rising from approximately 1,200 in 1990 to over 2,200 by 2019. This trend is depicted in the time series plot below, which illustrates the steady increase in CKD-related deaths over the 30-year period, with minor fluctuations likely due to regional differences in disease prevalence, healthcare infrastructure, and treatment access.

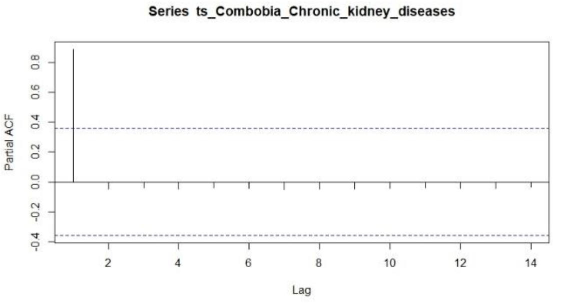


The upward trajectory highlights the growing public health burden of CKD in Cambodia, necessitating advanced forecasting to anticipate future trends and inform intervention strategies. Initial analysis of the time series indicates non-stationarity, as evidenced by the persistent trend, which requires transformation to make the data suitable for ARIMA modeling.

5.2 Stationarity and Model Specification

To assess the stationarity of the CKD mortality time series, the Augmented Dickey-Fuller (ADF) test was conducted, confirming that the data is non-stationary due to the presence of a trend. The ACF and PACF plots, shown below, were generated to further explore the data's temporal structure and guide the selection of ARIMA parameters.





The ACF plot exhibits a gradual decline in correlations across lags, a hallmark of non-stationarity, while the PACF plot shows a significant spike at lag 1, suggesting a potential autoregressive component of order 1. To achieve stationarity, first-order differencing was applied, resulting in a differencing parameter (d=1). This transformation stabilized the series, as confirmed by subsequent tests, making it suitable for ARIMA modeling.

5.3 ARIMA Model Selection and Performance

An automated ARIMA modeling approach was used to evaluate various model configurations, testing different combinations of autoregressive (p), differencing (d), and moving average (q) parameters. The models were compared using the Akaike Information Criterion (AIC), which balances model fit and complexity. The results of the model selection process are summarized in the table below.

Table 1: ARIMA Model Selection Results

ARIMA Model	AIC Value
ARIMA(2,2,2)	Invalid (Infinite)
ARIMA(0,2,0)	188.29
ARIMA(1,2,0)	189.49
ARIMA(0,2,1)	189.27
ARIMA(1,2,1)	191.26

The ARIMA(0,2,0) model, with two orders of differencing and no autoregressive or moving average terms, was selected as the best fit due to its lowest AIC value of 188.29. This model's reliance on differencing to capture the trend aligns with the data's characteristics, which are dominated by a long-term upward trajectory. Additional performance metrics for the selected model are presented in the table below.

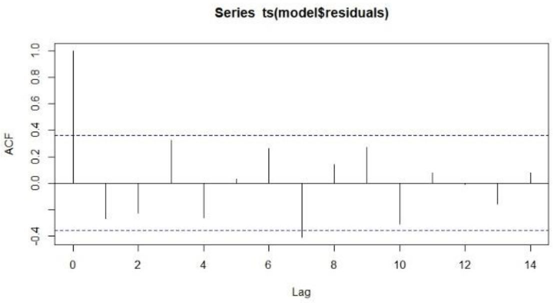
Table 2: ARIMA(0,2,0) Model Performance Metrics

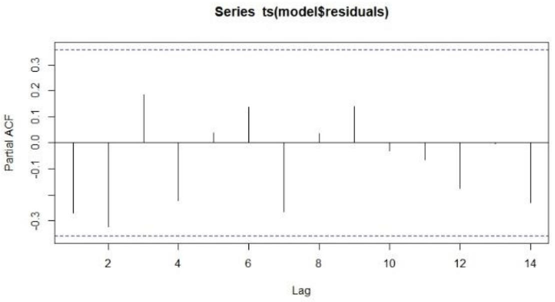
Metric	Value
Sigma Squared (Variance)	45.49
Log Likelihood	-93.15
Akaike Information Criterion (AIC)	188.29
Corrected AIC (AICc)	188.44
Bayesian Information Criterion (BIC)	189.62

The model's variance estimate of 45.49 reflects the high variability in CKD mortality, consistent with the observed fluctuations in the historical data. The log-likelihood, AIC, AICc, and BIC values collectively indicate a reasonable fit, supporting the model's suitability for forecasting.

5.4 Residual Diagnostics

To assess the adequacy of the ARIMA(0,2,0) model, residual diagnostics were performed. The ACF and PACF plots of the residuals, shown below, were analyzed to check for remaining patterns or correlations.

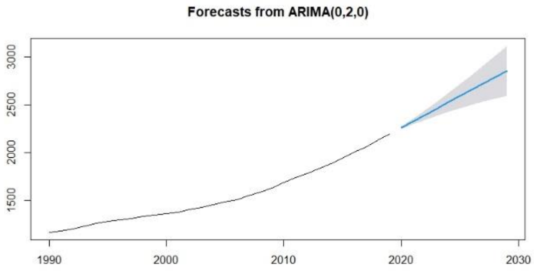




The ACF plot of the residuals shows small spikes at various lags, while the PACF plot exhibits minimal significant correlations, suggesting that the model has captured most of the temporal structure in the data. The Box-Ljung test, conducted at a lag of 5, resulted in an X-squared value of 10.51 and a p-value of 0.06202. This p-value, slightly above the 0.05 significance threshold, indicates a marginal presence of autocorrelation in the residuals, suggesting that while the model performs well, there may be room for refinement. This finding highlights the potential for incorporating additional factors, such as environmental or socio-economic variables, to improve model fit.

5.5 Forecasting CKD Mortality

The ARIMA(0,2,0) model was used to forecast CKD mortality in Cambodia from 2020 to 2028, extending the historical trend into the future. The forecast plot, shown below, illustrates the projected trajectory along with 95% confidence intervals, reflecting the uncertainty associated with long-term predictions.



The forecasted values, presented in the table below, indicate a continued rise in CKD mortality, consistent with the historical trend.

Table 3: Forecasted CKD Mortality in Cambodia (2020-2028)

Year	Point Forecast	Lower 95% CI	Upper 95% CI
2020	2,259	2,246	2,272
2021	2,325	2,295	2,355
2022	2,391	2,342	2,440
2023	2,457	2,385	2,529
2024	2,523	2,425	2,621
2025	2,589	2,463	2,715
2026	2,655	2,499	2,811
2027	2,721	2,532	2,910
2028	2,787	2,564	3,010

The forecasts show a steady increase in CKD-related deaths, with the point estimate rising from 2,259 in 2020 to 2,787 by 2028. The widening confidence intervals over time reflect increasing uncertainty in long-term projections, emphasizing the need for ongoing monitoring and model updates as new data becomes available.

The analysis confirms the alarming rise in CKD mortality in Cambodia, with forecasts indicating a continued upward trend through 2028. This trajectory underscores the urgent need for public health interventions to address risk factors such as poor water quality, limited healthcare access, and the high prevalence of related conditions like diabetes and hypertension. The ARIMA(0,2,0) model effectively captures the trend-driven nature of the data, but the marginal residual autocorrelation suggests potential improvements through machine learning time series techniques, such as Long Short-Term Memory (LSTM) networks, which could better handle non-linear patterns. Additionally, incorporating exogenous variables in an ARIMAX model could enhance the understanding of CKD mortality drivers, providing a more comprehensive forecasting framework.

The results of this analysis provide a critical evidence base for healthcare authorities in Cambodia to prioritize resource allocation, develop preventive strategies, and implement targeted interventions. Further research is recommended to explore the socio-economic and environmental determinants of CKD and to refine forecasting models, ensuring their applicability in resource-constrained settings. This study demonstrates the power of machine learning time series approaches in epidemiological forecasting, offering a foundation for mitigating the growing burden of CKD in Cambodia.

5. Conclusions: -

This study successfully employed machine learning time series techniques, specifically the ARIMA(0,2,0) model, to forecast chronic kidney disease (CKD) mortality in Cambodia from 2020 to 2028, based on historical data from 1990 to 2019. The analysis revealed a persistent upward trend in CKD-related deaths, projected to increase from 2,259 in 2020 to 2,787 by 2028, highlighting the escalating public health crisis in Cambodia. The ARIMA model, supported by diagnostic tools like the ADF test, ACF, PACF, and Box-Jenkins methodology, effectively captured the trend-driven nature of the data, despite minor residual autocorrelation indicating potential for refinement.

The findings underscore the urgent need for targeted interventions to address the rising CKD burden, including improving healthcare access, tackling environmental risk factors like water quality, and managing related conditions such as diabetes and hypertension. The forecasts provide a critical evidence base for policymakers to allocate resources effectively and implement preventive strategies. While the ARIMA model proved reliable, integrating advanced machine learning time series methods, such as LSTM networks, or incorporating socio-economic factors via an ARIMAX model, could enhance future predictions. This study emphasizes the value of time series forecasting in public health and calls for continued research to mitigate CKD's impact in Cambodia.

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