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Original Research Article

Integrating statistical and machine-learning models to determine tuberculosis mortality rates in Malaysia

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ABSTRACT

Background: Tuberculosis (TB) mortality remains an important indicator of disease burden and health-system performance, reflecting the effectiveness of detection, treatment, and prevention efforts. In Malaysia, TB mortality rates based on temporal patterns remain insufficiently characterized, limiting understanding of mortality burden and forecasting performance; addressing this gap may strengthen public health planning. Thus, this study aimed to determine TB mortality rates and evaluate predicted mortality in 2024 alongside characterize temporal patterns from 2014 to 2024 using autoregressive integrated moving average (ARIMA), long short-term memory (LSTM), convolutional neural network (CNN), and hybrid CNN–LSTM models.
Methods: This time-series study analyzed monthly TB mortality data from 2014 to 2024 obtained from the National Tuberculosis Registry. The dataset comprised 132 monthly observations, with 80% used for model training and 20% for testing. Four forecasting models were applied: ARIMA, LSTM, CNN, and hybrid CNN–LSTM. Relative error (RE%) was used to evaluate deviation between observed and predicted mortality values.
Results: In 2024, observed monthly TB mortality rates ranged from 0.42 to 0.79 per 100,000 population, while age-standardized mortality rates ranged from 0.43 to 0.80 per 100,000 population. The hybrid CNN–LSTM model provided the best representation of Malaysia's TB mortality pattern, capturing the upward trend, mid-year peaks, early-year troughs, and cyclical fluctuations.
Conclusion: Observed TB mortality rates in Malaysia were slightly higher than ranges reported in other international studies. The hybrid CNN–LSTM model produced the most accurate estimates, suggesting that hybrid deep-learning methods can strengthen TB mortality monitoring and support timely public health decision-making.

Keywords: Machine learning, Tuberculosis mortality, Forecasting

INTRODUCTION

Despite advances in medicine and sustained global control efforts, tuberculosis (TB) remains a major public health threat worldwide, with approximately 10 million people developing TB and more than one million deaths each year, particularly in low- and middle-income countries.[1] In Malaya, pulmonary tuberculosis was first documented in the early 20th century and contributed substantially to morbidity and mortality.[2] TB mortality, defined by the World Health Organization as death occurring during TB treatment regardless of cause and similarly adopted in Malaysia's Clinical Practice Guidelines on tuberculosis, provides a harmonized measure for comparing datasets and

assessing treatment outcomes.[3] Therefore, continuous monitoring of TB mortality is essential for evaluating programme performance, identifying gaps in care, and guiding evidence-based interventions.[4]

Effective TB control and treatment can generate major health and economic benefits, including reduced disease burden, lower healthcare costs, and improved productivity, highlighting the need for robust surveillance and forecasting systems. Time-series analysis is useful in epidemiology for identifying seasonality, long-term trends, and random variation, as shown in studies from Brazil and Thailand where TB mortality and incidence varied over time due to pandemic-related disruption and seasonal factors.[6,7] Understanding these temporal dynamics is essential for TB prevention and control, while choosing an appropriate forecasting model is necessary to ensure both statistical accuracy and public health relevance.[8] The Box–Jenkins approach, particularly the autoregressive integrated moving average (ARIMA) model, is widely used for infectious-disease forecasting and has been applied in the WHO South-East Asia Region and China to project declining TB mortality trends.[9-11] However, because ARIMA is a linear model that relies heavily on historical patterns, it may be less responsive to complex non-linear influences, abrupt disruptions, and longer-term forecasting needs.[12]

In parallel with traditional approaches, the WHO recognises artificial intelligence (AI) as a transformative tool in healthcare.[13] Machine-learning models are increasingly used in disease modelling and forecasting because they can capture complex and non-linear patterns more effectively than conventional statistical methods.[14] Evidence from China showed that CNN–LSTM achieved better forecasting accuracy than traditional approaches, suggesting its potential value for dynamic TB mortality patterns.[15] However, the use of deep-learning and hybrid models in TB mortality research remains limited, particularly within national surveillance systems.[16]

In summary, TB remains a major global health challenge, yet TB mortality rates in Malaysia based on observed temporal patterns remain insufficiently characterized, limiting understanding of the mortality burden and forecasting performance. Addressing this gap is important to strengthen mortality prediction, improve surveillance, and support timely evidence-informed decision-making. Thus, this study aims to determine TB mortality rates and evaluate predicted mortality in 2024, alongside characterize temporal patterns from 2014 to 2024 using ARIMA, LSTM, CNN, and hybrid CNN–LSTM models to guide public health action in Malaysia.

METHODS

Study design

This time-series study examined TB mortality data in Malaysia over an eleven-year period, from 01 January 2014 to 31 December 2024. Mortality information, including the date of death for patients diagnosed with TB, was obtained from the Malaysian National Tuberculosis Registry (NTBR).

Study location

This study was carried out at the national level in Malaysia, a middle-income Southeast Asian country where TB remains a priority communicable disease. TB mortality is an important indicator for assessing the effectiveness of prevention, case detection, and treatment efforts. The Malaysian context is also shaped by epidemiological challenges such as comorbidities (including diabetes), population ageing, and the presence of migrant and mobile populations, all of which may influence TB mortality patterns.

Study population

The reference population for this study comprised the entire Malaysian population. The source population included all TB mortality cases recorded in the Malaysian NTBR between 01 January 2014, and 31 December 2024. The sampling frame consisted of all registered TB cases within the NTBR during the study period that met the inclusion criteria. The study sample included all TB mortality cases reported in the registry throughout this ten-year timeframe.

Inclusion and exclusion criteria

All tuberculosis mortality cases registered in the Malaysia National TB Registry between 2014 and 2024 were included in the study. No exclusion criteria were applied because all notified records met the operational definition of TB mortality.

Data preparation

The data preparation process began with a thorough assessment of data quality, completeness, and internal consistency. Prior to analysis, a standardized data proforma had been developed, and all data handlers were adequately trained to ensure accuracy and uniformity during data entry. This systematic approach contributed to the overall reliability of the dataset.

Within the dataset, 55 records (approximately 0.20%) were identified as having missing values for age. Although information on gender and end of treatment date was complete for these entries, they were classified as incomplete due to the absence of age data; a key analytical variable. As the study did not specify exclusion criteria, all available records were retained, except for those missing age information. Previous research indicates that when the proportion of missing data is less than 5%, the potential impact on bias or statistical efficiency is minimal, and the benefits of multiple imputation (MI) are negligible (Lee and Huber, 2021). Accordingly, these incomplete cases

were excluded, and no imputation procedures were applied, as their omission was unlikely to compromise the validity or generalizability of the study findings.

Data analysis

This study used time-series analysis to determine TB mortality rates in Malaysia using four modelling approaches: ARIMA, LSTM, CNN, and hybrid CNN–LSTM. Analyses were conducted in R software version 4.5.1 using the fpp3 framework for ARIMA and the keras and tensorflow libraries for deep-learning models. The outcomes were monthly crude TB mortality rate and age-standardized mortality rate (ASMR) from January 2014 to December 2024. Age, gender, and WHO standard population weights were used only to calculate ASMR. TB mortality was selected as the primary outcome because it reflects disease burden and the effectiveness of TB prevention and control strategies at the population level.

Monthly TB mortality data from January 2014 to December 2024 were used for model development and evaluation, comprising 132 monthly observations. The dataset was split chronologically into training and testing sets, with 80% of observations allocated to the training set (January 2014 to September 2022) and the remaining 20% allocated to the testing set (October 2022 to December 2024).

Data preparation

Data preparation was performed prior to modelling to ensure data quality and consistency. The monthly crude TB mortality rate and ASMR were calculated and organized in time-series format. The crude mortality rate was computed using the following formula.[17]

$$Crude\ mortality\ rate = \frac{Number\ of\ confirmed\ TB\ deaths}{Total\ number\ of\ Malaysian\ population\ in\ the\ same\ period} \times 100{,}00$$

For the ASMR, direct age standardization was applied using the World Health Organization (WHO) 2000–2025 World Standard Population as the reference. TB deaths were grouped into 5-year age intervals (0–4, 5–9, 10–14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 75–79, and 80+ years) for each study year. The age-specific mortality rate for each group was first calculated as the number of deaths in that age group divided by the population of the same age group, multiplied by 100,000. Subsequently, the ASMR was derived by multiplying each age-specific death rate by the corresponding weight of that age group in the WHO standard population. This direct standardization method was used to compute overall ASMR as well as gender-stratified ASMR (male and female).[18]

For machine-learning models, the input data were further prepared in sequential format, and preprocessing steps (including scaling/normalization, where applicable) were applied before model training.

Data visualization

Time-series visualization was conducted to examine the temporal behaviour of the monthly crude TB mortality rate and ASMR across the study period. Monthly time-series plots were generated to assess overall trend, variability, and potential cyclical patterns prior to model fitting. These graphical assessments informed subsequent modelling decisions and supported interpretation of the observed mortality patterns.

Model specification and estimation

ARIMA model

ARIMA model specification was guided by visual inspection of ACF and PACF plots, followed by automated model selection using the ARIMA function from the fable package within the fpp3 framework. This function applies the modified Hyndman–Khandakar algorithm to identify the optimal parameter combination based on the corrected Akaike Information Criterion (AICc), with parameters estimated using maximum likelihood estimation.[19] Model adequacy was assessed using residual diagnostics, including tests for normality, autocorrelation, homoskedasticity, and the Ljung–Box test. The final model was selected based on parsimony, lower AICc, and satisfactory residual performance.

Machine learning models

Model specification for the LSTM, CNN, and hybrid CNN–LSTM models involved defining the network architecture and training hyperparameters, including LSTM units, CNN filters, kernel size, dense units, optimizer, learning rate, dropout rate, batch size, and epochs.

All models used the same training and testing datasets to ensure comparability, with final configurations selected based on testing performance.

Table 1 summarizes the final hyperparameter settings and diagnostic results for all models for crude TB mortality rate and ASMR.[20,21]

Accuracy evaluation

Model performance was evaluated using the testing dataset from October 2022 to December 2024 to assess accuracy on unseen data. Predicted monthly values from each model were compared with observed values for both TB mortality rate and ASMR.

Predictive accuracy was assessed using relative error (RE%), allowing direct comparison across the ARIMA, LSTM, CNN, and CNN–LSTM models.

Table 1: final hyperparameter tuning and diagnostic results for forecasting models (crude TB mortality rate versus ASMR).

Model type	Forecasting model	Hyperparameter/diagnostic		
Statistical model	**Seasonal ARIMA**		**Crude TB mortality rate**	**ASMR**
			p, d, q (P, D, Q)$_m$	p, d, q (P, D, Q)$_m$
Deep-learning model	**LSTM**	LSTM units	32	32
		Optomizer	Adam	Adam
		Dropouts	0.1	0.1
		Learning rate	0.001	0.001
		Epochs	100	100
		Batch size	8	8
Convolutional model	**CNN**	Filters	32	32
		Kernel size	3	3
		Optomizer	Adam	Adam
		Dropouts	0.1	0.1
		Dense units	32	32
		Learning rate	0.001	0.001
		Epochs	100	100
		Batch size	8	8
Hybrid deep-learning model	**CNN-LSTM**	Filters	32	32
		Kernel size	3	3
		LSTM units	32	32
		Optomizer	Adam	Adam
		Dropouts	0.1	0.1
		Dense units	32	32
		Learning rate	0.001	0.001
		Epochs	100	100
		Batch size	8	8

Generate predicted mortality rates

Following training and evaluation, each model was used to generate monthly predicted TB mortality rates and ASMR, with observed and predicted values specifically compared for the year 2024.

RESULTS

Data visualization

Figures 1a and 1b show that the monthly TB mortality rate (2014–2024) demonstrates a clear upward long-term trend. A recurring within-year pattern is also observed, with repeated peaks and troughs across successive years, suggesting the presence of annual seasonality (period=12 months), indicating a non-stationary mean. In addition, the series exhibits cyclical fluctuations, as shown by rises and falls that occur at non-fixed intervals.

Figures 1c and 1d (subseries plots) further demonstrate a clear seasonal pattern in monthly TB mortality rates, with consistently lower rates in January (mean approximately 0.38 per 100,000) and progressively higher rates from mid-year onward, peaking in July and August (means approximately 0.72–0.73 per 100,000). Mortality rates remain relatively elevated through September to October before declining toward the end of the year, supporting the presence of a regular 12-month seasonal cycle. In addition, greater within-month variability indicating cyclical pattern.

Model specification and estimation

ARIMA

The series appears non-stationary, with pronounced seasonal variation and a non-linear trend. Therefore, a seasonal differencing step was applied first, and the resulting seasonally differenced series is presented in Figures 2a and 2b.

The ACF of the seasonally differenced series shows a dominant significant negative spike at lag 12, indicating the presence of a seasonal MA (1) component. At the non-seasonal lags, most autocorrelations are small, although an isolated significant positive spike is observed at lag 10, suggesting some remaining short-term dependence. The PACF of the seasonally differenced series shows that most non-seasonal lags remain within the confidence bounds, suggesting that the non-seasonal AR component may be minimal (approximately AR (0)).

However, a pronounced significant negative spike at lag 12 and another significant negative spike at lag 24 are observed, indicating persistent seasonal partial autocorrelation and supporting the inclusion of a seasonal AR (1) component. Automatic model selection was performed using the auto.arima() function in the forecast package in R. The optimal model was identified by including the automatically selected model and comparing candidate specifications, including a model fitted with stepwise=FALSE to allow a more exhaustive search. The final selected models were Seasonal ARIMA (1,0,1) (0,1,2) [12] with drift for the tb mortality rate and Seasonal ARIMA (1,0,1) (2,1,1) [12] with drift for the ASMR. The residual diagnostics for the selected models are presented in Figures 2c and d.

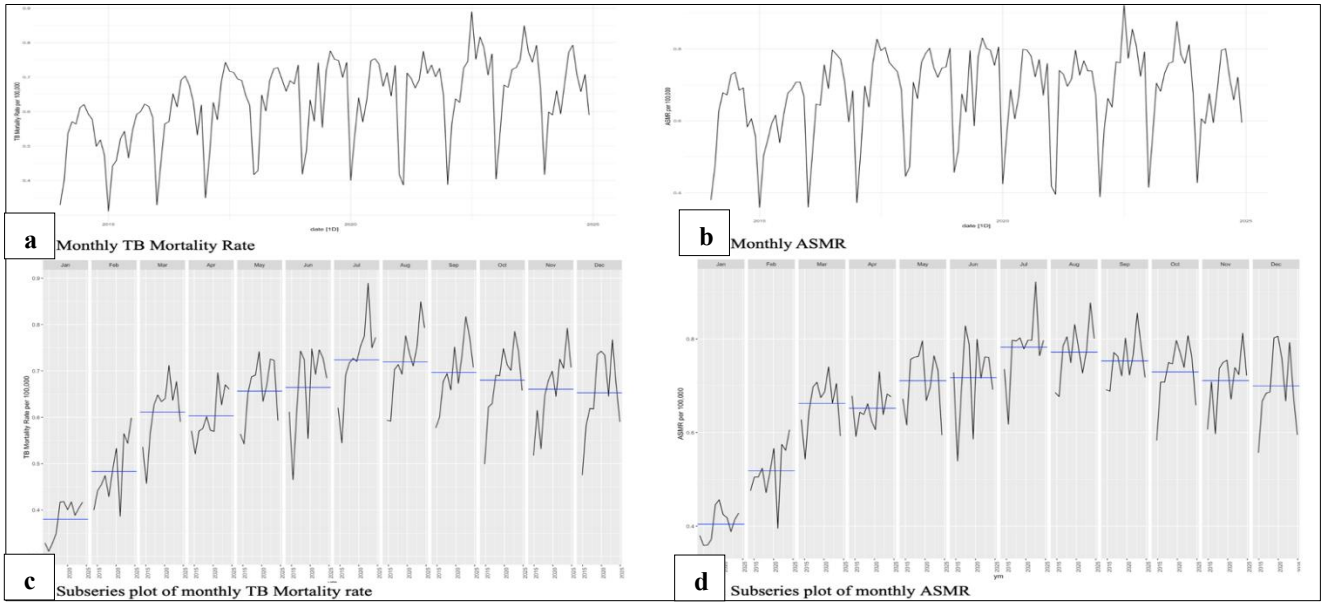

Figure 1 (a-d): Time series trend tuberculosis mortality in Malaysia, 2014–2024.

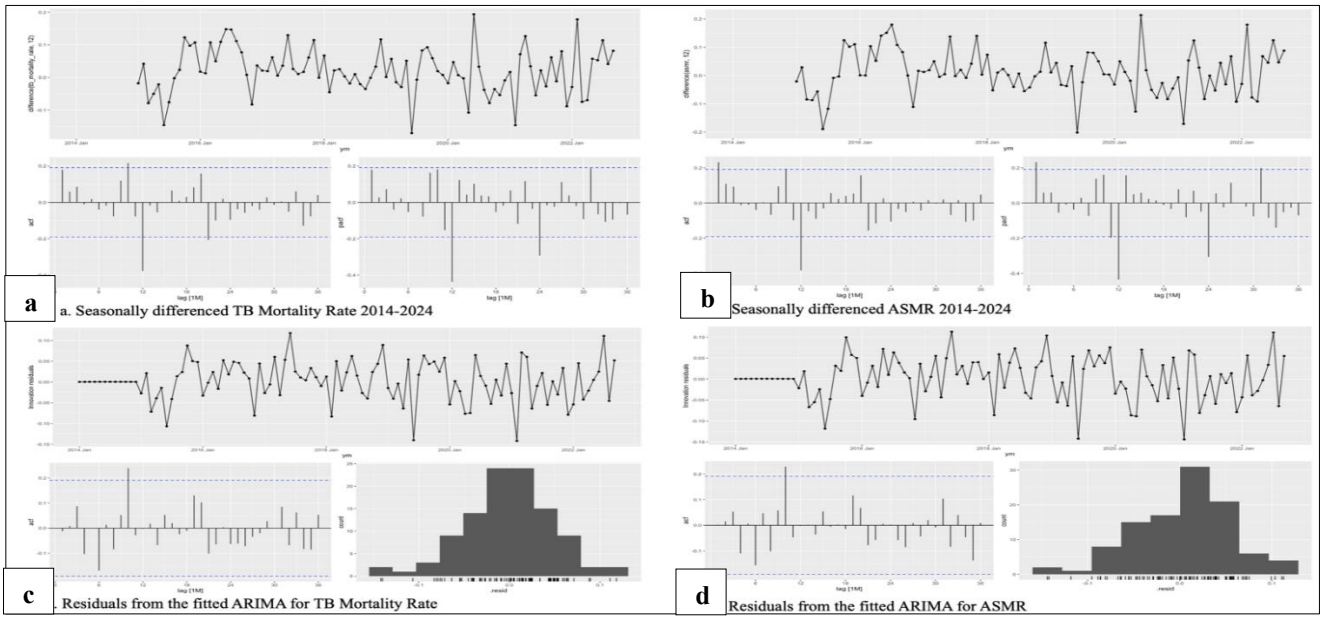

Figure 2 (a-d): Model specification and estimation for ARIMA.

Although the ACF shows a single significant spike at lag 10, this isolated exceedance among 36 lags is consistent with random variation expected under a white-noise process. Therefore, overall residual independence was evaluated using the Ljung–Box test, which assesses whether the residual autocorrelations up to the specified lag are jointly different from zero. For the TB mortality rate model, the Ljung–Box statistic was 27.31 with p=0.703, indicating no evidence of residual autocorrelation up to the tested lag. Similarly, for the ASMR model, the Ljung–Box statistic was 25.08 with p=0.764, also suggesting that the residuals are consistent with white

noise. These results support the adequacy of both fitted models in capturing the serial dependence in the data.

Machine learning models

The LSTM, CNN, and CNN–LSTM models are specified by their network architecture and hyperparameters, while estimation occurs during training where the model learns optimal weight parameters via backpropagation. Therefore, the "final model" for each deep learning approach refers to the tuned architecture together with the trained weights that minimize the validation loss.

Accuracy evaluation and predicted TB mortality rate

Observed versus predicted monthly TB mortality rates with relatives' error (RE) in 2024

The observed monthly TB mortality rates in 2024 ranged from 0.42 to 0.79 per 100,000 population, indicating moderate monthly variability throughout the year. Among the four models, the hybrid CNN-LSTM consistently produced the lowest absolute relative errors, typically within±10%, reflecting the closest alignment with observed mortality rates across the months. In contrast, the ARIMA model showed greater variability, with RE values ranging from 3.1% to as high as 32.9%, suggesting occasional overestimation of TB mortality, especially in the early (January–March) and late (November–December) months. The LSTM model tended to underpredict TB mortality for most months (negative RE%), with deviations exceeding −20% during the first quarter of the year. The CNN model also underpredicted several months but displayed slightly improved stability compared to the pure LSTM model. Overall, the CNN-LSTM hybrid model demonstrated superior predictive accuracy, balancing the CNN's ability to extract relevant temporal patterns with the LSTM's capacity to capture long-term dependencies in sequential data. Table 2 presents the comparison between observed and predicted monthly TB mortality rates for 2024, alongside the RE% as an indicator of predictive accuracy.

Observed versus predicted monthly ASMR with relatives' error (RE) in 2024

The observed monthly ASMR in 2024 ranged between 0.43 and 0.80 per 100,000 population, showing moderate month-to-month variation across the year. Among all models, the CNN–LSTM hybrid achieved the most consistent alignment with observed ASMR values, with RE% generally within ±10% across most months as shown in Table 3. The ARIMA model tended to overestimate ASMR in several months, particularly in March, May, and December, where RE% exceeded 25–30%, suggesting reduced precision during peak months. The LSTM model showed relatively close tracking but produced moderate positive deviations (10–18%) in mid-year, while the CNN model frequently underestimated mortality in the middle of the year (negative RE%), indicating a conservative tendency.

Figure 3a depicts observed versus predicted temporal pattern for TB mortality rate. The observed TB mortality rate shows a clear upward long-term trend from 2014 to 2024, together with annual seasonality characterized by recurring mid-year peaks around July–August and early-year troughs around January, while broader cyclical fluctuations are evident as multi-year rises and falls with no fixed frequency, most noticeably during 2020–2023.

Table 2: Observed versus predicted monthly TB mortality rates with relative error (%) in 2024.

Month	Observed TB mortality rate	Forecasted TB mortality rate cases using SARIMA		Forecasted TB mortality rate cases using LSTM		Forecasted TB mortality rate cases using CNN		Forecasted TB mortality rate cases using hybrid CNN-LSTM	
		Predicted	RE (%)	Predicted	RE (%)	Predicted	RE (%)	Predicted	RE (%)
January	0.42	0.49	17.72	0.33	−21.66	0.35	−16.33	0.4	−4.15
February	0.6	0.58	−3.34	0.43	−28.61	0.41	−30.96	0.47	−21.07
March	0.59	0.73	23.88	0.55	−7.09	0.53	−10.09	0.61	3.4
April	0.66	0.71	7.11	0.58	−12.54	0.51	−22.50	0.6	−9.05
May	0.59	0.78	30.76	0.63	6.13	0.71	20.19	0.65	9.75
June	0.68	0.78	13.91	0.67	−2.67	0.78	13.34	0.68	−1.05
July	0.77	0.85	9.92	0.7	−9.81	0.76	−2.05	0.71	−7.72
August	0.79	0.82	3.12	0.71	−10.26	0.76	−4.49	0.74	−7.25
September	0.71	0.81	14.93	0.71	0.76	0.68	−4.27	0.71	1.03
October	0.66	0.8	21.71	0.71	8.55	0.7	6.88	0.68	3.99
November	0.71	0.77	8.97	0.71	0.42	0.66	−6.77	0.66	−6.10
December	0.59	0.78	32.88	0.67	12.99	0.56	−5.78	0.67	13.03

Table 3: Observed versus predicted monthly ASMR with relative error (%) in 2024.

Month	Observed TB mortality rate	Forecasted ASMR cases using SARIMA		Forecasted ASMR cases using LSTM		Forecasted ASMR cases using CNN		Forecasted ASMR cases using hybrid CNN-LSTM	
		Predicted	RE (%)	Predicted	RE (%)	Predicted	RE (%)	Predicted	RE (%)
January	0.43	0.47	10.34	0.43	0.95	0.47	10.85	0.42	−1.91
February	0.61	0.55	−9.29	0.54	−10.72	0.49	−19.05	0.52	−14.43
March	0.59	0.75	25.84	0.65	10.03	0.6	2.01	0.64	8.63
April	0.68	0.71	5.47	0.68	0.32	0.62	−8.62	0.65	−3.82
May	0.59	0.78	30.94	0.71	18.79	0.77	29.33	0.73	22.43
June	0.69	0.78	12.81	0.73	5.68	0.83	19.24	0.76	9.51
July	0.8	0.85	6.39	0.75	−5.78	0.71	−11.16	0.79	−0.90
August	0.8	0.82	2.62	0.77	−4.36	0.77	−4.13	0.8	−0.20
September	0.72	0.81	13.43	0.77	7.04	0.74	3.41	0.78	8.77
October	0.66	0.81	22.5	0.76	14.81	0.78	18.42	0.75	14.31
November	0.72	0.77	7	0.74	2.81	0.7	−2.38	0.74	1.89
December	0.6	0.78	31.56	0.7	17.81	0.56	−5.71	0.73	22.93

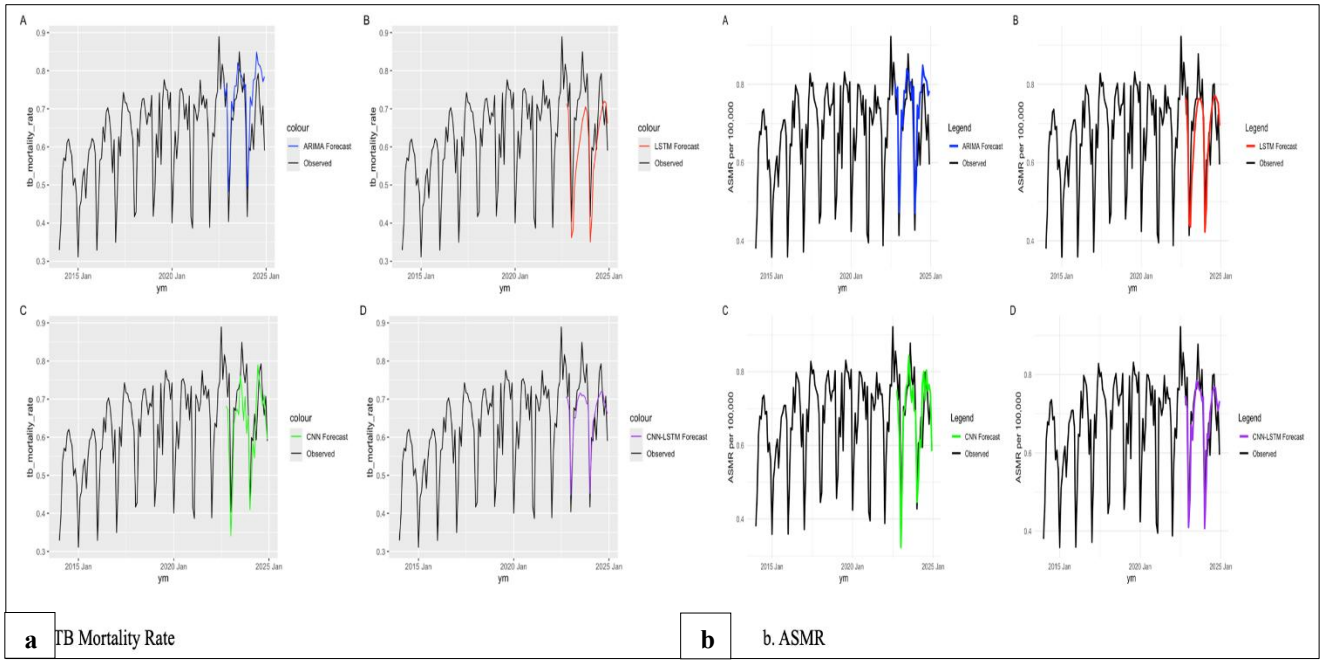

Figure 3 (a and b): Temporal pattern of observed monthly TB mortality in Malaysia from 2014-2024 and predicted values for 2024.

The seasonal ARIMA model captured the general increasing pattern but showed more noticeable short-term changes between months. The LSTM model produced a smoother pattern that closely followed the overall increase seen in the observed data. The CNN model also reflected the upward pattern but slightly underestimated months with higher mortality. In comparison, the CNN–LSTM hybrid model provided the closest match to the observed data, maintaining consistency in both the level and timing of changes across the study period.

Overall, the CNN–LSTM model most accurately represented the observed TB mortality pattern, effectively reflecting the long-term increase, seasonality and irregular multi-year fluctuations seen in the national data.

Figure 3b illustrates the observed vs predicted temporal pattern of ASMR across all four forecasting models. The observed TB mortality rate shows a clear upward long-term trend from 2014 to 2024, together with annual seasonality characterized by recurring mid-year peaks around July–August and early-year troughs around January, while broader cyclical fluctuations are evident as multi-year rises and falls with no fixed frequency, most noticeably during 2020–2023.

The seasonal ARIMA model successfully captures the long-term direction of the trend but shows more pronounced short-term variability, indicating limited responsiveness to irregular temporal changes. The LSTM model produces a smoother curve that follows the observed values more consistently, demonstrating better learning of temporal dependencies over time. The CNN model identifies the general cyclical progression but tends to slightly underrepresent mid-range variations, suggesting moderate sensitivity to finer temporal transitions. In contrast, the CNN–LSTM hybrid model aligns most closely with the observed ASMR, effectively combining CNN's strength in feature extraction with LSTM's capability to model temporal dependencies. Overall, the CNN–LSTM model emerged as the most reliable approach due to its superior ability to capture the increased trend, seasonality and cyclical patterns, resulting in forecasts that best reflected the real-world dynamics of ASMR in Malaysia.

DISCUSSION

Observed versus predicted monthly TB mortality rates and ASMR with relatives' error (RE)

The primary objective of this study was to quantify TB mortality in Malaysia and characterize its temporal dynamics using statistical and machine-learning forecasting models, namely Seasonal ARIMA, LSTM, CNN, and hybrid CNN–LSTM. In 2024, the observed monthly TB mortality rates ranged from 0.42 to 0.79 per 100,000 population, while monthly ASMR ranged from 0.43 to 0.80 per 100,000 population, indicating moderate variation over time. These values were broadly comparable to those reported in mainland China, where most regions recorded TB mortality levels between 0 and 0.5 per 100,000 population during 2004–2018, suggesting a similarly low mortality burden consistent with countries at intermediate stages of TB control progress.[22]

Across all models, the hybrid CNN–LSTM consistently showed the highest predictive accuracy, with lower RE% values than the other approaches, indicating a stronger ability to capture complex non-linear temporal patterns in TB mortality data. Lower absolute RE values suggest that the training data were sufficiently representative of the full dataset, supporting the reliability of the model forecasts.[23] This highlights the potential of CNN–LSTM for anticipating mortality changes before they become evident in surveillance reports. Similar findings have been reported elsewhere, including studies from Brazil and Yemen, where CNN–LSTM outperformed ARIMA in forecasting TB-related trends due to its ability to model nonlinear relationships and long-term dependencies more effectively.[20,24]

These findings support the need for rigorous model validation to ensure reliable epidemiological forecasting.[25] Models with smaller relative errors provide more precise forecasts and are generally more useful for public health planning, particularly for guiding the timing, location, and scale of response measures.[26,27] In this study, the hybrid CNN–LSTM model consistently recorded the lowest RE values, suggesting that it is a reliable approach for forecasting TB mortality trends and supporting earlier public health action. Accurate forecasting is crucial for guiding the timing, location, and scale of response measures, as seen in outbreaks such as SARS, Ebola, and Zika, where precise projections supported efficient resource allocation, while inaccurate estimates risked misdirected interventions and reduced public confidence (Eksin et al in 2019).

A clear upward long-term trend and cyclical fluctuations in TB mortality from 2014 to 2024 may reflect combined programmatic and epidemiological influences, including strengthened TB detection, wider screening of high-risk groups, improved electronic surveillance, and continuing implementation challenges. These efforts were aligned with Malaysia's National Strategic Plans for TB control, which emphasized case detection, programmatic management, high-risk groups, and supportive TB control environments.[28] However, COVID-19–related disruptions, resource reallocation, reduced service accessibility, delayed diagnosis, and interrupted follow-up may have contributed to poorer outcomes and fluctuations in TB mortality during the pandemic period.[29]

Epidemiologically, the upward trend may reflect increasing clinical vulnerability among TB patients. In Malaysia, comorbidities such as chronic kidney disease, HIV infection, active cancer, and liver disease are associated with higher all-cause mortality among TB patients.[30] The continued HIV burden, including 3,220 new infections in 2023 and a substantial proportion among people who inject drugs, may further contribute to poor TB outcomes, as TB–HIV co-infection increases diagnostic complexity, treatment challenges, and mortality risk.[31,32]

In Oyo State, Nigeria, TB mortality increased modestly from 2015 to 2019, partly attributed to improved surveillance and reporting rather than true seasonality.33 Similarly, Brazil recorded declining TB mortality until early 2020, followed by a sharp rise after 2021, likely due to COVID-19–related disruptions in TB detection, treatment continuity, and possible underreporting or misclassification of deaths.[34]

The recurring mid-year peaks in TB mortality in Malaysia, particularly around July to August, and early-year troughs around January suggest a seasonal component. Although TB seasonality is widely reported, most evidence focuses on incidence or notifications rather than mortality, limiting direct comparison.

A possible explanation is the lagged effect of monsoon-related conditions, where heavy rainfall, humidity, flooding, overcrowding, reduced ventilation, and disrupted healthcare access during the Northeast monsoon may delay diagnosis and treatment, contributing to higher mortality

several months later.[35,36] Similarly, a study in Thailand reported seasonal variation in TB incidence and mortality, with annual winter peaks possibly influenced by environmental factors such as air pollution during dry seasons.[6]

This study had several strengths, including the use of national surveillance data and comparison of statistical and machine-learning models, namely seasonal ARIMA, LSTM, CNN, and CNN–LSTM. This enabled assessment of long-term trends, cyclical fluctuations, and model performance in forecasting TB mortality. However, TB mortality before 2024 was estimated using the last treatment date as a proxy for the actual date of death, which may reduce temporal precision. The use of aggregate surveillance data also limited the inclusion of socioeconomic, clinical, and geographic covariates for more detailed subgroup interpretation.

CONCLUSION

The observed monthly TB mortality rates in Malaysia ranged from 0.42 to 0.79 per 100,000 population, while the observed monthly ASMR ranged from 0.43 to 0.80 per 100,000 population in 2014, indicating moderate monthly variation. Among the models evaluated, the hybrid CNN–LSTM provided the best fit for Malaysia's TB mortality prediction and temporal pattern, capturing the overall upward trend from 2014 to 2024, the annual seasonal pattern with mid-year peaks and early-year troughs, and the cyclical fluctuations over time. These findings deepen understanding of TB mortality patterns and support the integration of machine-learning forecasting into epidemiological surveillance to improve prediction and guide Malaysia's progress towards the End TB 2030 targets.

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