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Mathematical modelling of time series data for tuberculosis notified cases in India using neural networks models: CNN, NNAR, and ANFIS models integrated with wavelets

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Tuberculosis (TB) remains a persistent and critical public health challenge in India, contributing significantly to the global disease burden. Despite ongoing control measures, seasonal surges and underreporting continue to hinder timely intervention and resource allocation. There is an urgent need for accurate, data-driven forecasting tools to predict TB case trends and enable proactive healthcare planning. This study addresses this necessity by employing advanced Artificial Intelligence-based time series models, specifically NNAR, ANFIS, CNN, and their wavelet-integrated variants, to forecast TB notifications in India using data from the NIKSHAY database (2017–2022). By capturing the seasonal and trend dynamics inherent in TB cases, the study supports data-informed decision-making for public health authorities. The results demonstrate that wavelet-enhanced models significantly enhance predictive accuracy. Notably, the NNAR-Db8L2 model reduces forecasting errors by over 39%, while the CNN-D8L5 and ANFIS-Db8L6 models also show marked improvements, proving effective in modelling complex seasonal patterns. These findings emphasize the demand for hybrid AI models in disease surveillance and their potential to inform timely, evidence-based TB control strategies.

Keywords: Artificial intelligence, Db8 wavelet, Forecasting, MATLAB, Tuberculosis, Wavelet denoising

Tuberculosis (TB) has remained a major public health issue in India for decades[1]. India has the highest TB burden globally, accounting for approximately 26% of the world's TB cases by 2020[2]. The disease poses significant health, social, and economic challenges, especially in regions with limited access to healthcare and high population density[2]. Historically, India has made substantial efforts to control TB through initiatives such as the National Tuberculosis Program (NTP) launched in 1962, followed by the Revised National Tuberculosis Control Program (RNTCP) in 1997, which introduced the Directly Observed Treatment, Short-Course (DOTS) strategy to improve treatment compliance[3]. In 2018, the Indian government committed to eliminating TB by 2025, five years ahead of the global Sustainable Development Goals (SDGs) target of 2030[4]. To achieve this ambitious goal, the government implemented the National Strategic Plan (NSP) 2017-2025, which focuses on early diagnosis, universal drug susceptibility testing, and improved access to healthcare in rural and underserved areas[5].

Despite these efforts, challenges remain, including drug resistance and socioeconomic barriers to healthcare[2]. India has seen a growing prevalence of multidrug-resistant TB (MDR-TB), with approximately 135,000 cases reported annually, complicating treatment efforts and highlighting the need for continued surveillance and innovation in treatment and diagnostic approaches[2,6]. Given these challenges, improving the accuracy of TB case prediction is crucial for effective public health planning. Time-series forecasting techniques enable policymakers to anticipate disease patterns, optimize resource allocation, and implement timely interventions. Known statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ES) have been widely used for disease prediction due to their ability to capture temporal patterns and seasonality[7,8]. For instance, ARIMA models have been employed in forecasting influenza and tuberculosis cases by modelling past trends and projecting future values. However, they often struggle to capture the nonlinear patterns inherent in disease transmission[7,9-11].

Machine learning techniques, including Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, have gained popularity in

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epidemiology to address these limitations. ANNs, such as Neural Network Autoregressive (NNAR) models, can model complex relationships in disease data[8,12]. They can model the intricate nonlinear relationships between the target variable and its predictors. A neural network is structured with layers of "neurons." The input data occupies the first layer, whereas the output (forecast) is in the final layer. Between them, there may be one or more hidden layers with additional neurons[13-14]. The ability to model nonlinear patterns gives ANNs a strong capability to produce accurate forecasts[15]. Among these, the Nonlinear Autoregressive Neural Network (NARNN) has proven to be an effective approach owing to its robust fault tolerance in time-series prediction[16]. In some contexts, this model is referred to as the (NNAR) model[8].

Existing studies either rely on traditional models, which are limited in handling nonlinearity, or standalone deep learning models, which may struggle to effectively integrate linear and nonlinear components in time series forecasting, limiting their predictive versatility[7,17-19]. This study aims to bridge this gap by integrating wavelet decomposition with Convolutional Neural Networks (CNNs), Neural Network Autoregression (NNAR), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). By integrating wavelets, we aim to investigate their influence on model accuracy and determine whether this hybrid approach provides a significant improvement in forecasting performance. This combined methodology allows us to explore the synergies between neural networks and wavelet transformations, ultimately seeking to refine the predictions and better understand the dynamics of the underlying data (Fig. 1)

Materials and Methods

This study utilized secondary data on tuberculosis (TB) cases, sourced from the Ministry of Health and Family Welfare, Central TB Division, Government of India's open repository (https://tbcindia.gov.in), covering the period from January 2017 to December 2022. Monthly TB case notifications, recorded in the NIKSHAY repository (https://reports.nikshay.in/Reports/TBNotification), were extracted separately for each month, resulting in a total of 72 observations (Table 1). The collected data were systematically

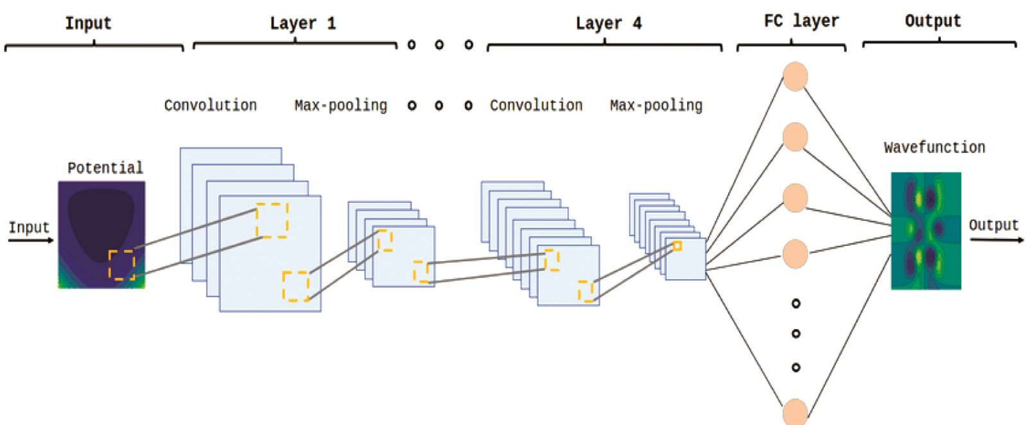

Fig. 1 — Architecture of Convolution Neural Network (CNN) for Wave function Mapping

Table 1 — Monthly Data of TB Cases in India from January 2017 to December 2022

Months	2017	2018	2019	2020	2021	2022
January	144781	149393	195596	196997	183398	161898
February	147133	152119	193142	213699	189377	188081
March	176283	177442	211868	169171	203648	228814
April	160671	193912	221100	83647	134825	220166
May	161146	206750	222455	120737	92827	222469
June	147705	190644	203098	157328	176007	223496
July	144041	184647	212255	140868	207751	207715
August	135239	169828	188278	121820	199885	195197
September	130291	169394	194154	140813	207685	200045
October	126237	179379	186196	150480	188803	159075
November	131882	160726	193955	141548	174757	191940
December	129434	166612	179260	174598	184173	185962
Total	1734843	2100846	2401357	1811706	2143136	2384858

compiled into a time series format using MS Excel 2019 for further processing. Time series analysis and forecasting were conducted using MATLAB, with statistical significance as data is non-stationary, tested by ADF (Augmented Dicky-Fuller Test) assessed at $P < 0.05$. This approach enabled precise evaluation and prediction of TB trends based on the structured dataset. A total of 6 models were used to evaluate the given time series data: three neural network-based models, *i.e.*, NNAR, CNN, and ANFIS, and three others by integrating them with wavelets (Fig. 2).

The additive decomposition of the time series of tuberculosis cases, showing the original case counts, a trend component with fluctuations before and after 2020, and a seasonal pattern with annual peaks. The residual component captures irregular variations. The above analysis helps to identify trends and seasonal effects in TB cases (Fig. 3).

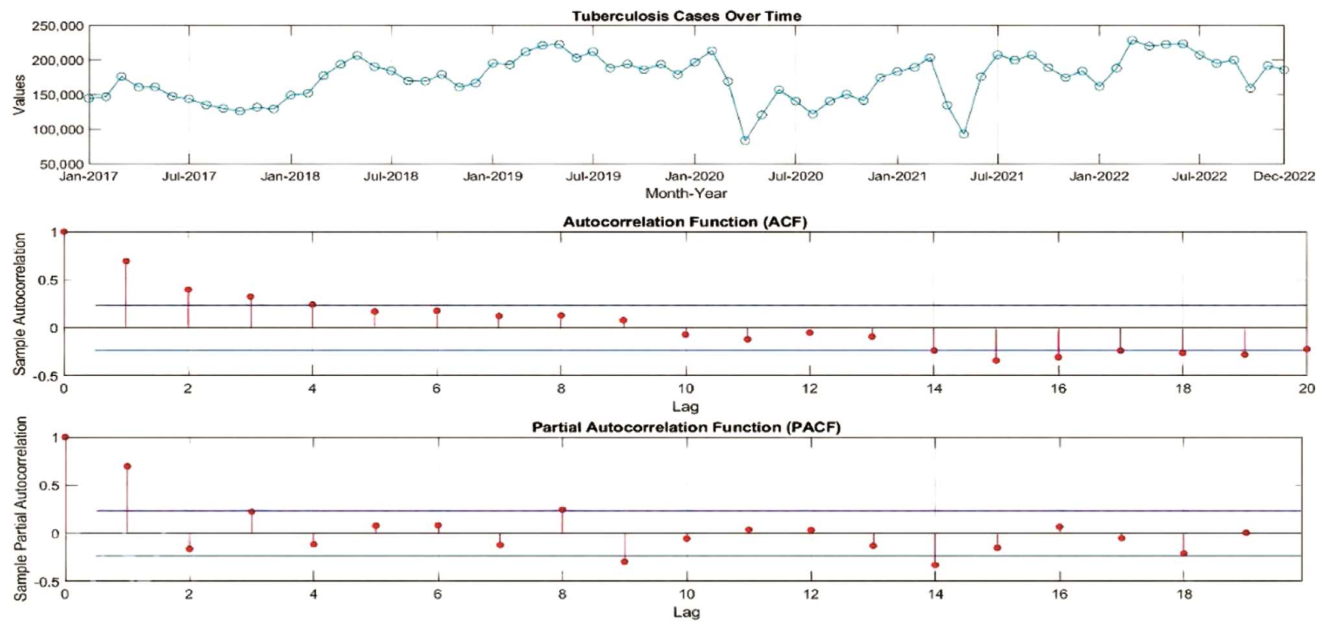

Fig. 2 — Time Series, ACF, and PACF Plot of TB Cases (2017–2022)

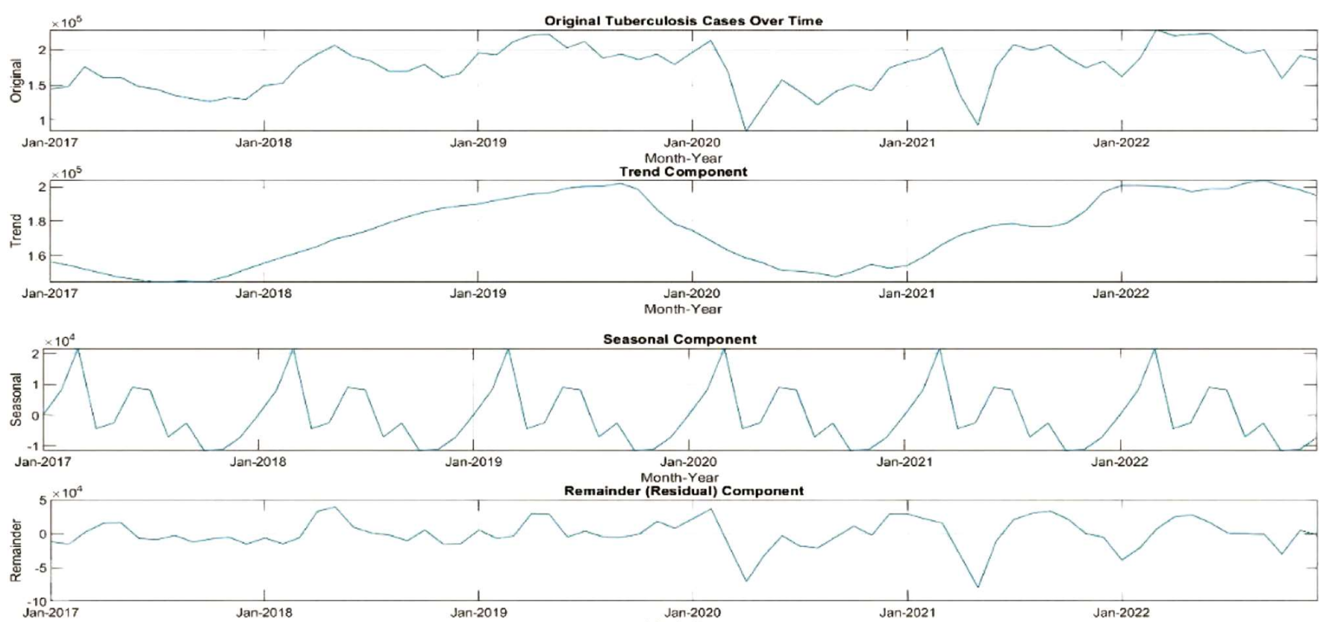

Fig. 3 — Additive Decomposition of Monthly TB Case Time Series

The time series graph of monthly TB cases, shown in (Fig. 4), indicates that peaks in TB case numbers typically occur in March, April, and May. An additive decomposition analysis revealed clear seasonal trends, with recurring cycles every 12 months, as presented in (Fig. 3).

NNAR (1,1,10) [12] Model

The model, known as a Neural Network Autoregressive (NNAR) model, takes lagged values from the time series data as inputs and is designated as NNAR (p, k), or for seasonal time series, as NNAR (p, P, k) m. In this nomenclature, p signifies the quantity of lagged inputs, P represents seasonal lagged inputs, k defines the number of neurons in the buried layer, and m indicates the seasonal period[8]. An NNAR (p,0) model is equivalent to an ARIMA(p,0,0) model, but without limitations on the parameters to maintain stationarity. More generally, a NNAR (p,P,k) m model contains inputs $(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, y_{t-p}, y_{t-m}, y_{t-2m}, \ldots, y_{t-Pm})$ and k neurons in the hidden layer[8,20]. An NNAR (p,P,0)m model is equal to an ARIMA (p,0,0)(P,0,0)m model but without limits on the parameters that assure stationarity. With seasonal data, it is useful to also add the latest observed values from the same season as inputs[8,20]. For example, a NNAR (1,1,10)12 model contains inputs $(y_{t-1}, y_{t-12})$and 10 neurons in the hidden layer, allowing it to capture both the immediate past values and the seasonal trends present in the data. By adding these seasonal lags, the model can enhance prediction accuracy and better adapt to the cyclical character of the time series being evaluated. The feed-forward neural network with a single hidden layer containing 10 neurons called NNAR (1,1,10)[12]. The hidden layer applies non-linear activation functions (e.g., sigmoid or tansig) to capture complex patterns in the data (Fig. 5). The model's output layer consists of a single neuron, providing one-step-ahead predictions.

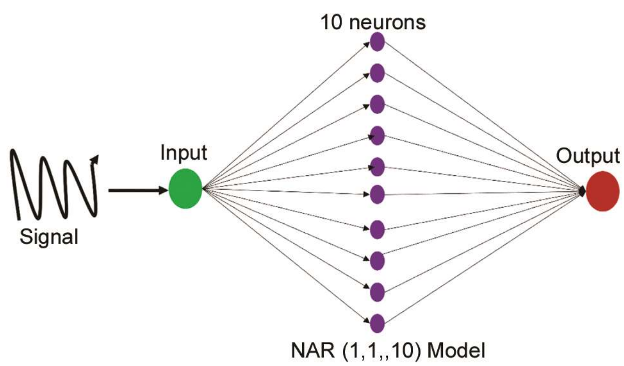

Fig. 4 —Feed-Forward Neural Network (NNAR (1,1,10)) Structure

The network is trained using the Levenberg-Marquardt backpropagation algorithm[21-22], optimizing the mean squared error between predicted and actual values. After training, the model forecasts future values iteratively by using the output of the previous step as input for the next prediction. This NNAR (1,1,10) [12]model is well-suited for capturing non-linear dependencies in time series data and provides reliable performance for both short-term and multi-step forecasts, as demonstrated by its ability to predict the next 12 values in the dataset.

CNN Model

Convolutional Neural Networks (CNNs), originally designed for image processing, have been adeptly repurposed for time series forecasting due to their proficiency in identifying localized patterns and

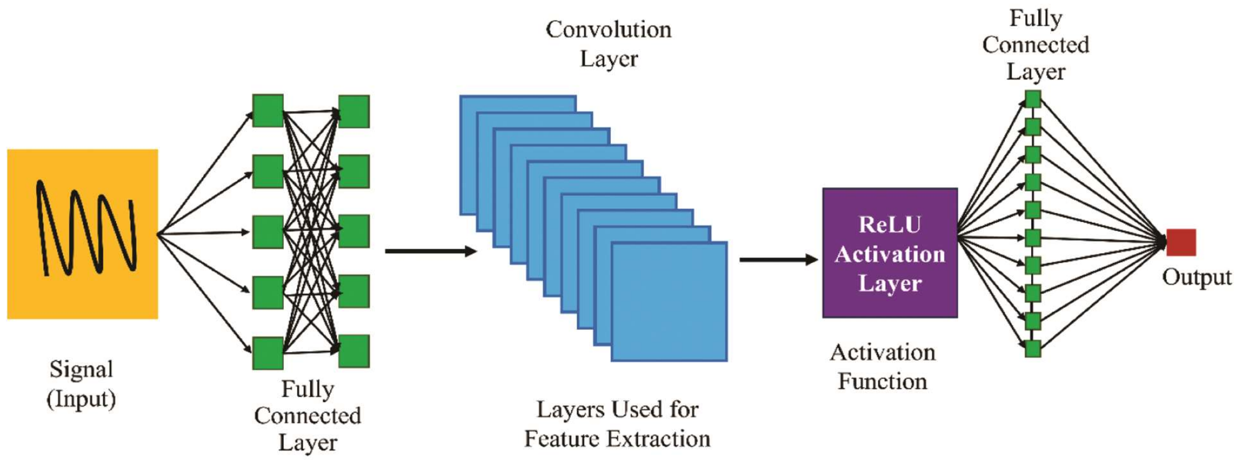

Fig. 5 — CNN Framework for Time Series Forecasting

intricate features[23]. CNNs operate by applying convolutional filters across input sequences, enabling the detection of trends and seasonal variations[24]. The natural behaviour of most time series is dynamic and nonlinear. Data normalization is used to deal with this problem. Because the main objective of data normalization is to ensure the quality of the data before it is fed to any model, it substantially influences the performance of any model.

Data normalization is essential for CNN because it can scale the attribute into a specific range required by the activation function. This study uses Min–Max normalization. The method assures that all features have the same scale, although it is inefficient in dealing with outliers[4,10]. The equation below shows the Min–Max formula, resulting in normalized data with smaller intervals within 0 to 1.

$$X_{t(norm)} = \frac{X_t - X_{min}}{X_{max} - X_{min}}$$

$X_{t(norm)}$ is the result of normalization, X_t is the data to be normalized, while X_{min} and X_{max} stand for the minimum and maximum value of the entire data[24-25]. Figure 6 illustrates the CNN model applied to time-series data utilizes convolutional layers to capture temporal dependencies and patterns in the data. It processes input data sequences through a sequence input layer, followed by a fully connected layer with 10 neurons to map complex relationships. A ReLU (Rectified Linear Unit) activation layer introduces non-linearity, and a final fully connected layer with 1 neuron produces the output. The model is trained using the Adam optimizer over 100 epochs with a mini-batch size of 32.

The CNN is adapted to one-dimensional data in this implementation, effectively capturing sequential patterns relevant to the forecasting task.

ANFIS Model

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the strengths of fuzzy logic and neural networks to model complex, non-linear relationships in data[26]. The ANFIS model is trained using 2000 epochs on tuberculosis case time-series data, where the input data (X) and target data (Y) are sequentially related. The model is initialized using MATLAB's genfis1 function, which generates a FIS structure based on training data. Training is performed to optimize both the membership function parameters and the consequent rules[20]. The model is then evaluated on training and testing datasets, providing predictions for both past and future values. A Sugeno-type fuzzy inference system (FIS) with three generalized bell-shaped membership functions (gbellmf) is used for each input variable (Fig. 7).

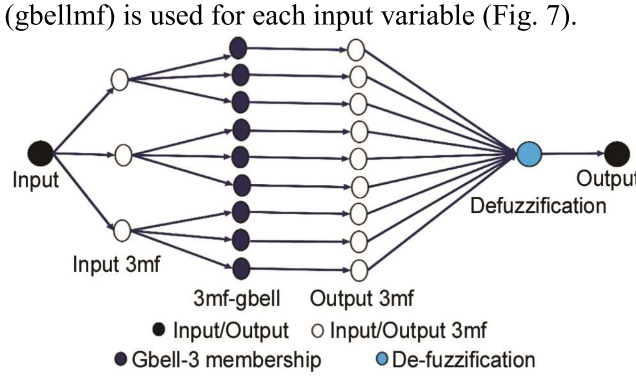

Fig. 6 — Architecture of ANFIS Using Bell-Shaped Membership Functions

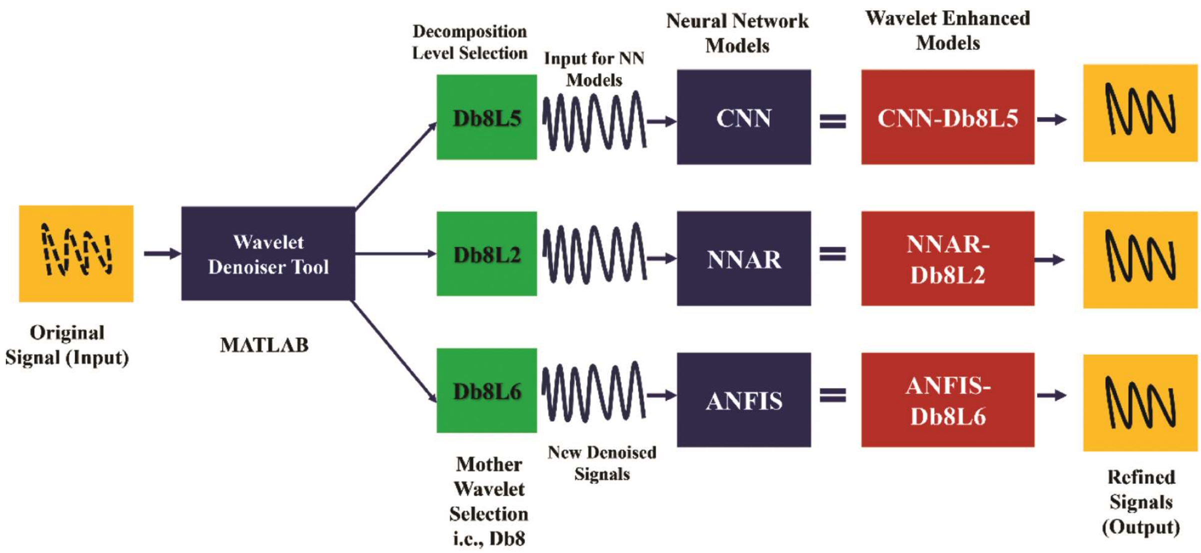

Fig. 7 — Wavelet Enhanced Neural Network Model Formation (CNN-Db8L5, NNAR-Db8L2 & ANFIS-Db8L6)

Here, the gbell membership function is given by:

$$f(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}}.$$

Wavelet Decomposition & Wavelet Enhanced Neural Network Models-CNN-Db8 Level 5, NNAR-Db8 Level 2, and ANFIS-Db8 Level 6

Wavelet decomposition is a valuable technique for breaking down time series data into its constituent components, i.e., approximation and detail coefficients, enabling the extraction of both high and low-frequency features[20,27-29]. The decomposition process was carried out in MATLAB, followed by wavelet denoising using the Bayesian method with the median rule and a Q-value of 0.05, assuming noise level independence. In this study, we explored various wavelet families, including Daubechies (Db), Fejér-Korovkin (Fk), Coiflet (Coif), and Symlet (Sym), to identify the most appropriate mother wavelet for our time series data. Using the wavelet denoising tool available in MATLAB, we tested our time series data with the above-mentioned wavelets in different orders at different levels, where Db8 (Daubechies at order 8) performed better than the rest, providing the most refined signal, resulting in the best performance for time series decomposition (Figs 8-11).

To enhance time series forecasting accuracy, models combining Convolutional Neural Networks (CNN), Nonlinear Autoregressive Neural Networks (NNAR), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with Daubechies wavelets were employed. Performance metrics, such as RMSE, MAE, MAPE, and R-square, are used to evaluate the models on training and testing datasets. Additionally, the models are extended to forecast 12 future values iteratively by using the last prediction as input for the next step (Table 2).

Forecasting evaluation criteria

All models were trained and tested using data from the past 72 months of TB notification. Specifically, 70% of the data (50 values) was used for training, while 30% (22 values) was used to evaluate model performance and accuracy. The forecasting accuracy of the CNN, NNAR, ANFIS, and wavelet-enhanced models was assessed using four critical performance metrics. These include the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the R-squared (r^2) value, which are standard indicators for evaluating the precision and robustness of time series forecasting models[30-32]. For the model evaluation, four indices are as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - f_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n} |y_i - f_i|}{n}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - f_i|}{y_i}$$

$$R - Square\ (R^2) = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{f_i})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

Where y_i's are the actual values, f_i's are the predicted values, $\bar{y}$ is the mean of actual values, and n is the total number of observations.

Results

The total number of reported TB cases in India from January 2017 to December 2022 reached 1,25,76,746 cases, as shown in (Table 1). Descriptive statistics were applied to the dataset, revealing an average incidence of 174,677.02 and a standard deviation of 31,906.84, as outlined in (Table 3). The data exhibited a slightly negative skewness of -0.15075, suggesting that the distribution is somewhat tilted to the left, and a kurtosis value of 0.2771, indicating the distribution has lighter tails than a normal distribution. This distribution pattern implies that while most cases cluster around the average, there are fewer extreme values on the higher end. Such data characteristics can influence public health strategies and resource allocation to effectively address the trends in disease incidence over the observed period. Table 4 presents evaluation metrics for different models, including CNN, NNAR, ANFIS, and wavelet-enhanced neural networks, on training and testing datasets. Metrics such as RMSE, MAE, MAPE, and R^2 indicate the performance of each model. Among the models, wavelet-enhanced versions (CNN-Db8L5, NNAR-Db8L2, ANFIS-Db8L6) show lower error values and higher R^2 scores, demonstrating improved predictive accuracy. The ANFIS-Db8L6 model has the lowest RMSE and MAE values on the testing set, suggesting better generalization. Standard CNN and NNAR models perform relatively worse, with lower R^2 values, especially on the testing set.

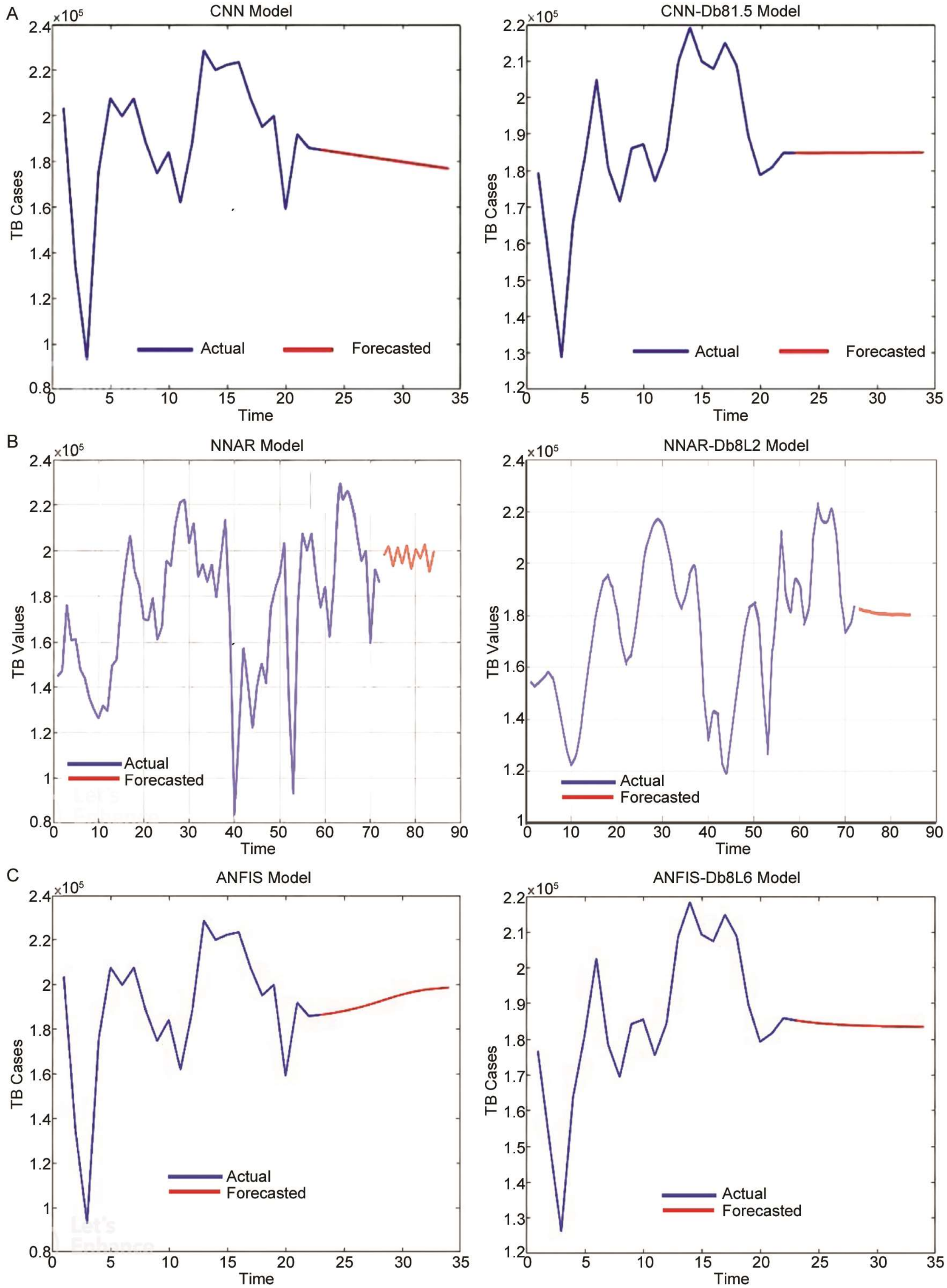

Fig. 8 — (A) Forecasting results with CNN and CNN-Db8L5 Wavelet Model; (B) Forecasting results with NNAR and NNAR-Db8L2 Wavelet Model; and (C) Forecasting results with ANFIS and ANFIS-Db8L6 Wavelet Model

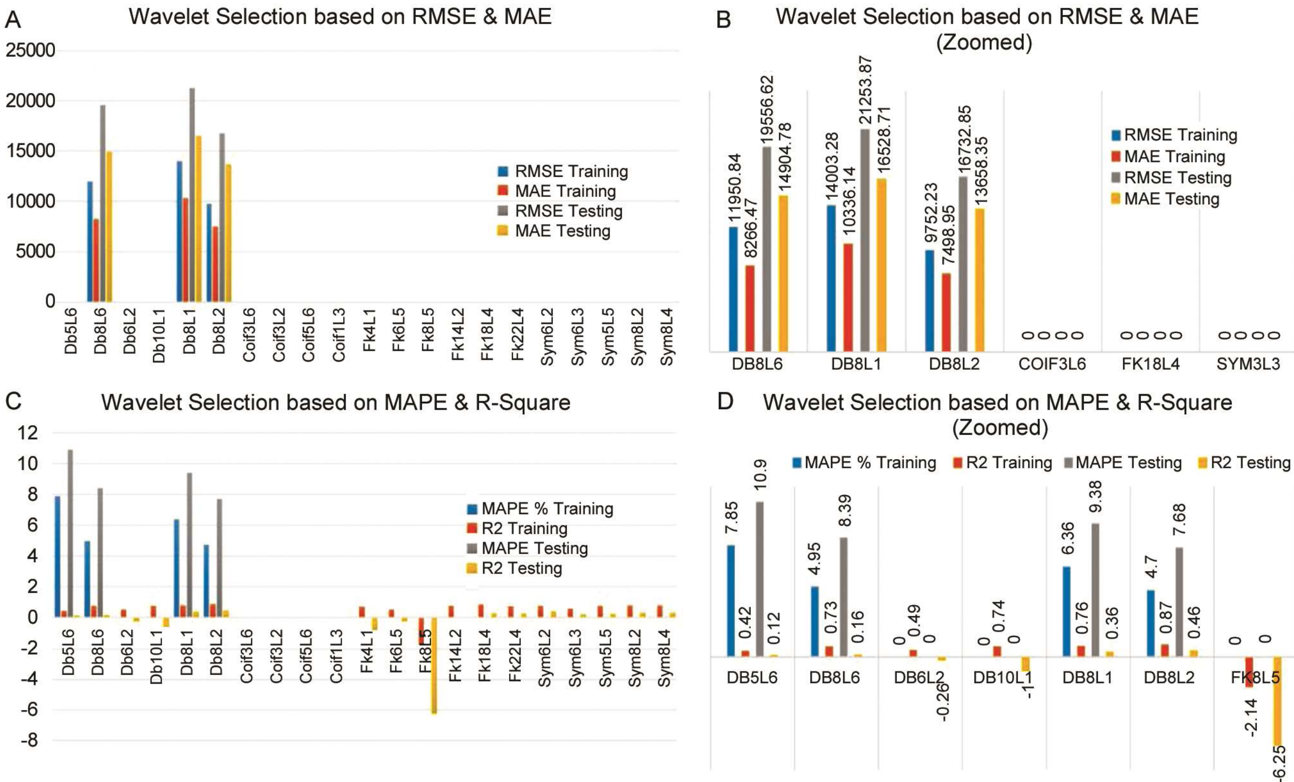

Fig. 9 — Wavelet comparison metrics for the NNAR model. Evaluation of multiple wavelet types based on RMSE, MAE, MAPE, and R² performance indicators. Daubechies-8 at level 2 (Db8L2) consistently shows superior forecasting accuracy across all metrics, supporting its selection for optimal NNAR model performance

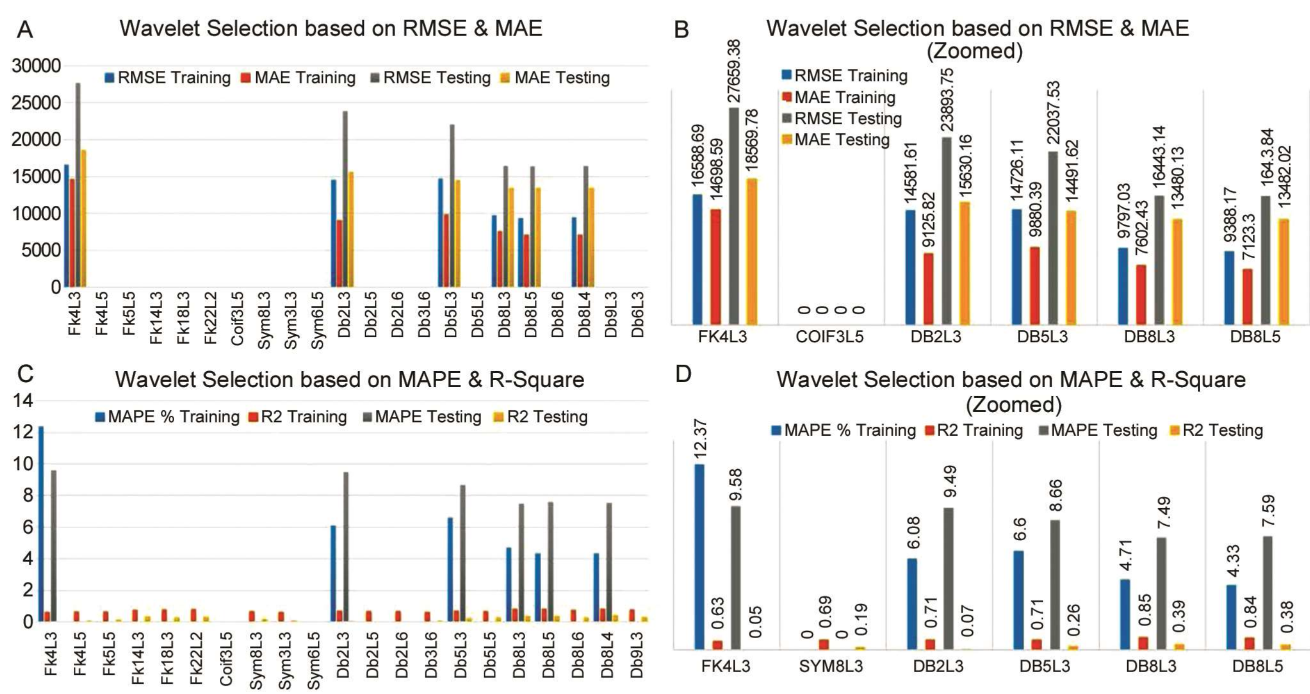

Fig. 10 — Wavelet comparison metrics for the CNN model. Performance assessment using RMSE, MAE, MAPE, and R² reveals that the Db8 wavelet at level 5 (Db8L5) offers the best trade-off between error minimization and model fit, justifying its use in the CNN-wavelet hybrid

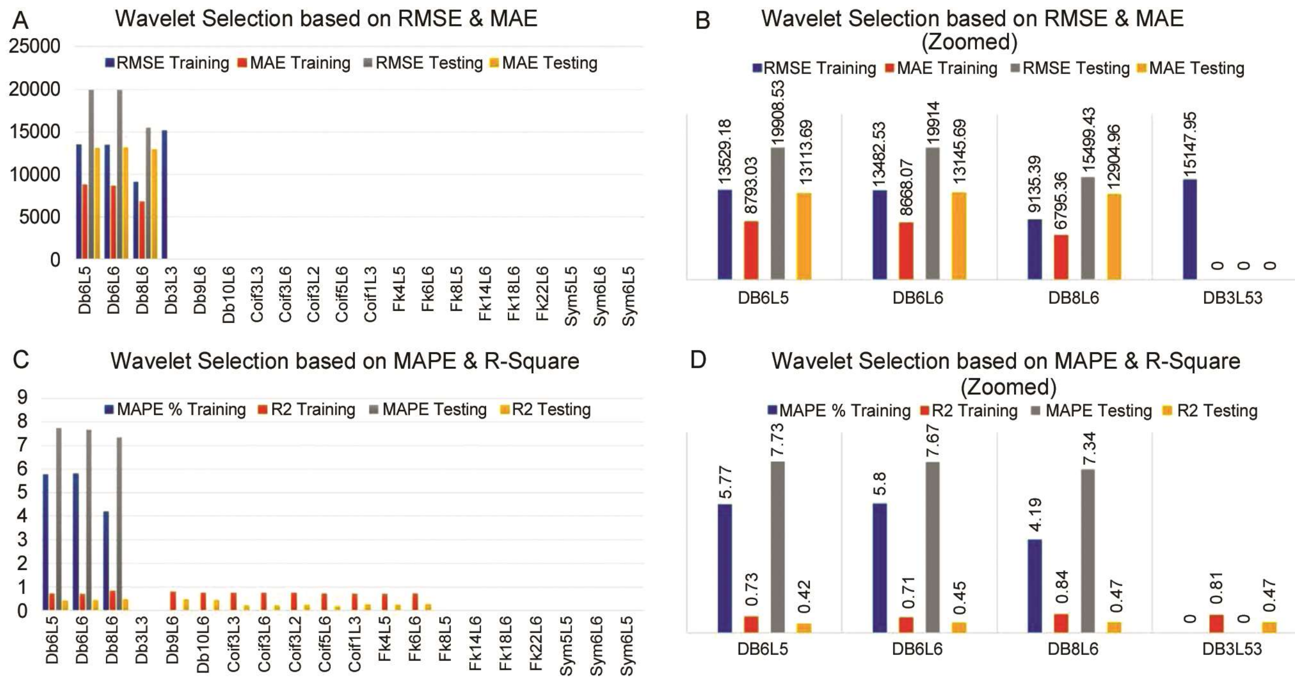

Fig. 11—Wavelet comparison metrics for the ANFIS model. Among various wavelets tested, Db8L6 demonstrates the lowest forecasting errors and highest R², confirming its effectiveness in enhancing the ANFIS model's ability to capture complex patterns in tuberculosis time series data

Table 2 — Model performance comparison for forecasting from January 2023 to December 2023

Forecast of Notified Tuberculosis Cases

Time	CNN	NNAR	ANFIS	CNN-Db8L5	NNAR-Db8L2	ANFIS-Db8L6
Jan-2023	185188.1094	197870.3762	186517.9039	184864.5781	182412.8151	185308.2058
Feb-2023	184417.4219	202014.5516	187246.3948	184874.2656	181945.2476	184856.1226
Mar-2023	183649.9688	192975.098	188186.0984	184883.9688	181467.0364	184516.1696
Apr-2023	182885.7031	201605.2894	189367.9832	184893.6563	181044.5145	184258.2024
May-2023	182124.6094	194151.5687	190796.0018	184903.3594	180722.628	184060.9322
Jun-2023	181366.7031	202407.5608	192418.1377	184913.0469	180506.9866	183909.1234
Jul-2023	180611.9219	191844.4318	194103.3427	184922.7344	180375.7427	183791.7072
Aug-2023	179860.2969	200745.7221	195660.4954	184932.4219	180300.7618	183700.5263
Sep-2023	179111.7969	196531.1489	196918.4243	184942.1406	180259.5251	183629.4936
Oct-2023	178366.4219	202898.9448	197809.622	184951.8281	180237.3313	183574.0179
Nov-2023	177624.1563	190456.6556	198375.9942	184961.5313	180225.5271	183530.6066
Dec-2023	176884.9844	199771.3331	198709.0777	184971.2344	180219.2886	183496.5829

Table 3 — Summary statistics for the dataset covering the period from 2017 to 2022 in India

Observation	Mean	Standard Deviation	Skewness	Kurtosis
2017	144570.25	15295.81	0.770409	-0.01812
2018	175070.50	17162.71	0.222839	-0.46957
2019	200113.08	13964.77	0.382131	-0.98476
2020	150975.50	35128.03	0.007909	0.367184
2021	178594.66	33500.67	-1.84962	3.453797
2022	198738.16	23136.01	-0.43817	-0.68566
2017 to 2022	174677.02	31906.84	-0.15075	0.2771459

Table 4 — Evaluation parameters of CNN, NNAR, ANFIS, and wavelet-enhanced NN models applied to training and testing datasets

Models	Training Set				Testing Set			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
CNN	20993.97	15337.31	10.22	0.516	31232.62	23242.07	14.03	-0.039
NNAR	20474.95	14440.32	9.72	0.540	26456.46	20558.44	12.70	0.253
ANFIS	18876.76	13949.09	9.21	0.609	28470.36	23007.49	13.90	0.136
CNN-Db8L5	9373.14	7144.47	4.35	0.843	16417.05	13494.93	7.61	0.382
NNAR-Db8L2	10651.69	7315.95	4.54	0.848	16032.40	13257.05	7.46	0.506
ANFIS-Db8L6	9135.39	6795.36	4.19	0.847	15499.43	12904.96	7.34	0.478

Discussion

In this study, we tested wavelet-based neural network models- CNN, NNAR, and ANFIS, to forecast TB cases in India, a method inspired by previous research demonstrating the effectiveness of wavelet pre-processing in improving neural network forecasts[33]. We found that the Daubechies-8 (Db8) wavelet, known for its good balance between time and frequency localization, consistently gave the most accurate results when applied at different decomposition levels in each model[34]. Specifically, the best outcomes were seen with Db8 at level 5 for CNN, level 2 for NNAR, and level 6 for ANFIS. These models performed better than others based on standard accuracy measures like RMSE, MAE, MAPE, and R-Square. Overall, the results highlight how well the Db8 wavelet captures both timing and frequency patterns, which helps in modelling the seasonal and non-linear nature of TB trends.

Compared with traditional neural network models, the wavelet-enhanced variants demonstrated substantial improvements. For instance, the ANFIS-Db8L6 model achieved the lowest RMSE (15,499.43) and MAPE (7.34%) on the testing phase, with a notable increase in R^2 (0.478), confirming enhanced predictive accuracy. These improvements are attributed to the denoising capability of wavelets, which mitigates the influence of irregular fluctuations and noise, allowing the neural networks to model the underlying patterns in a better way[35].

In comparison to previous studies, the present models provide significant advancements. In 2023, the SARIMA-NNAR hybrid model achieved a MAPE of 6.68% and RMSE of 13,738.97 on the tuberculosis time series data[36]. Although their model was effective but wavelet-enhanced ANFIS achieved greater performance in terms of both predictive error and explanatory power (R^2 = 0.478), despite the complexity of real-world data. Similarly, the CNN-Db8L5 model outperformed the previously developed ANN-based model in 2022, which reported an R^2 of 0.45[37]. A self-attention model for TB forecasting was employed and achieved MAPE = 7.58%, outperforming LSTM and ARIMA, where ANFIS-Db8L6 achieved MAPE 7.34%[38]. These comparisons confirm that incorporating wavelet decomposition enhances the performance of deep neural architectures in epidemiological forecasting tasks.

Despite the models showed improvement, there are still some limitations. They were trained only on reported TB cases from the NIKSHAY database and didn't take into account other important factors like age, weather, or economic conditions that could also affect TB trends. In the future, research could focus on combining these additional influences into the models, possibly using integrated modelling strategies or attention-based approaches, to get a complete and more accurate picture.

Overall, the use of wavelet-integrated neural networks presents a promising direction for public health forecasting. The models developed here can be potentially deployed in real-time surveillance systems, offering reliable short-term predictions to support targeted interventions and resource allocation.

Conclusion

The results of using CNN, NNAR, ANFIS, and their wavelet-enhanced versions demonstrate that wavelet-based models significantly improve forecasting accuracy. Integrating such forecasting techniques into India's NIKSHAY system could strengthen real-time surveillance and automated alerts. As India aims to eliminate TB by 2025, wavelet-enhanced models offer a more powerful, data-driven tool for disease management. To further refine the model performance, future research may focus on demographic and environmental factors.

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Conflict of interest

All authors declare that no conflict of interests.

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