Journal of Electrical & Electronics Engineering Research and Reviews

Academixs Open Access Publishers

Research Article

A Smart Traffic Noise Prediction Model for Nairobi City, Kenya

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Received Date: 02.10.2025 **Accepted Date:** 13.10.2025 **Published Date:** 16.10.2025

Abstract

Road traffic flow produces an undesirable externality since it distorts the ambient environmental noise, especially in cities. Such nuisance noise poses a risk to the health of the inhabitants. Globally, the combined concert of the forces of urbanization and road transport motorization has intensified the noise pollution challenge, yet, locally adapted predictive tools remain limited. In Nairobi, the capital city of Kenya, Road Traffic Noise (RTN) remains a less understood environmental nuisance. To date, no predictive RTN models have been developed, while established models such as CoRTN and RLS-90 lack applicability to Nairobi's traffic and environmental conditions. This study aimed to develop an accurate smart model leveraging artificial neural networks (ANNs) to forecast RTN levels using traffic information data.

Traffic data, including audio recordings using a Samsung Galaxy A12 Model SM-A127F/DS Android Smartphone, equivalent noise levels (Leq) using a Lutron SL-4033SD Class 1 Sound Level Meter (SLM), vehicular volume using a manual tally form, and speed using a speed gun, was collected across 42 locations within Nairobi. Using this data, an Artificial Neural Network (ANN), Multi-Layer Perceptron (MLP) model, was developed with two hidden layers.

Hyperparameter tuning via grid search was done to optimize model performance. The model achieved a Mean Absolute Error (MAE) of 0.97 dBA and an R2 value of 0.90, outperforming traditional statistical models like CoRTN with a MAE of 5.0 dBA and RLS-90 with a MAE of 11.0 dBA. These results highlight the model's high accuracy in predicting Nairobi's RTN. The model's deployment on a web-based dashboard enables real-time noise monitoring and stakeholder engagement. This pioneering smart predictive model for Nairobi offers a scalable solution for urban noise management, with potential applications in traffic planning and policy implementation.

Key Words: Road Traffic Noise, Machine Learning, Smart Prediction Model

Introduction

Road traffic noise (RTN) is a pressing environmental and public health concern in urban areas, particularly in rapidly urbanizing cities worldwide. As a byproduct of vehicular traffic, RTN contributes to adverse health outcomes, including stress, sleep disturbances, and cardiovascular diseases, as documented by the World Health Organization [1].

Studies by Clark et al. (2020) and Stansfeld & Clark (2024) highlight noise's auditory and non-auditory effects, such as anxiety and cognitive impairment, necessitating robust noise management. In Europe and North America, long-term monitoring has linked RTN to reduced well-being, with studies like Thacher et al. (2020), Dzhambov et al. (2021), and Roscoe et al. (2024) showing increased mortality, mental health issues, and cardiovascular risks.

In developing regions like Asia and Africa, dense traffic and heterogeneous vehicle compositions exacerbate RTN challenges. For instance, studies in Delhi, India, have reported noise levels consistently exceeding permissible limits across major traffic corridors [2]. In Africa, research in Lagos, Nigeria, documented chronic noise exposure surpassing WHO guidelines, posing significant health risks [3]. Similarly, Clark et al. (2022) applied spatial modeling to map environmental noise in Accra, Ghana, revealing exposure inequalities in urban settings [4]. Earlier work by Tétreault et al. (2013) further confirmed that traffic-related noise contributes to cardiovascular disease risk, highlighting the global relevance of RTN as a public health issue.

While measurement-based studies provide critical insights, their high costs and logistical complexity make them impractical for large-scale urban applications, driving demand for predictive models tailored to local conditions. Traditional statistical models, such as CoRTN and RLS-90, rely on traffic volume, speed, and road conditions but often underperform in non-European contexts due to differing traffic patterns [5]. Recent advancements in machine learning, particularly Artificial Neural Networks (ANNs) and ensemble methods, have demonstrated superior performance in capturing complex, non-linear relationships in traffic noise data. For example, Nourani et al. (2020) developed an emotional ANN model for vehicular traffic noise in Tehran, achieving high accuracy by modeling non-linear traffic dynamics [6].

Similarly, Acosta et al. (2024) employed an ANN with grid search hyperparameter tuning to predict RTN in Bogotá, optimizing for urban-specific variables [7]. Sharma et al. (2022) applied ensemble methods, such as random forests, to predict road traffic noise, emphasizing their robustness in handling diverse traffic datasets [8]. Lee et al. (2023) leveraged deep learning with convolutional layers to forecast urban noise in real time, incorporating spatial-temporal features [9]. Kumar et al. (2021) used ANNs to model highway noise in India, while Debnath et al. (2022) integrated ANN with contouring techniques for spatial noise mapping [10,11]. Umar et al. (2023) combined ensemble machine learning with GIS to predict campus traffic noise, highlighting the role of spatial variables in enhancing model accuracy [12].

These studies collectively demonstrate that machine learning approaches, when adapted to local conditions, outperform traditional statistical models by leveraging advanced mathematical frameworks to model complex urban noise patterns.

In Eastern Africa, smart predictive models for RTN remain scarce, with most studies relying on outdated statistical methods. Nairobi, Kenya's capital, presents unique challenges due to its diverse vehicle fleet, including bicycles, motorcycles, cars, buses, and trucks, operating within constrained road networks (Appendix 4). This heterogeneity, coupled with frequent congestion, results in irregular traffic flow and elevated noise levels. Existing models like CoRTN and RLS-90 are not calibrated for Nairobi's conditions, highlighting a critical gap in localized RTN prediction frameworks. This study addresses this gap by developing the first ANN-based RTN prediction model tailored to Nairobi's traffic and environmental context. Its novelty lies in using a Multi-Layer Perceptron (MLP) ANN, optimized for Nairobi's heterogeneous traffic patterns via grid search hyperparameter tuning, and deploying it on a web-based dashboard for real-time monitoring. The study contributes: (1) a high-accuracy MLP model for RTN prediction, (2) a scalable framework for noise management in African cities, and (3) a public platform for stakeholder engagement and urban noise policy formulation. These advancements aim to support urban planning, mitigate health impacts, and enhance liveability in Nairobi and similar contexts.

The source code for the MLP ANN model, including data preprocessing, model training, hyperparameter tuning, and web-based dashboard deployment, is available on GitHub at https://github.com/ElishaAkech/SOUNDAI. This repository includes Python scripts for implementing the model using libraries such as PyTorch, along with real datasets and instructions for reproducing the results.

Methodology

Study Area

The study was conducted in Nairobi City, Kenya, a bustling metropolis with a diverse vehicle fleet.

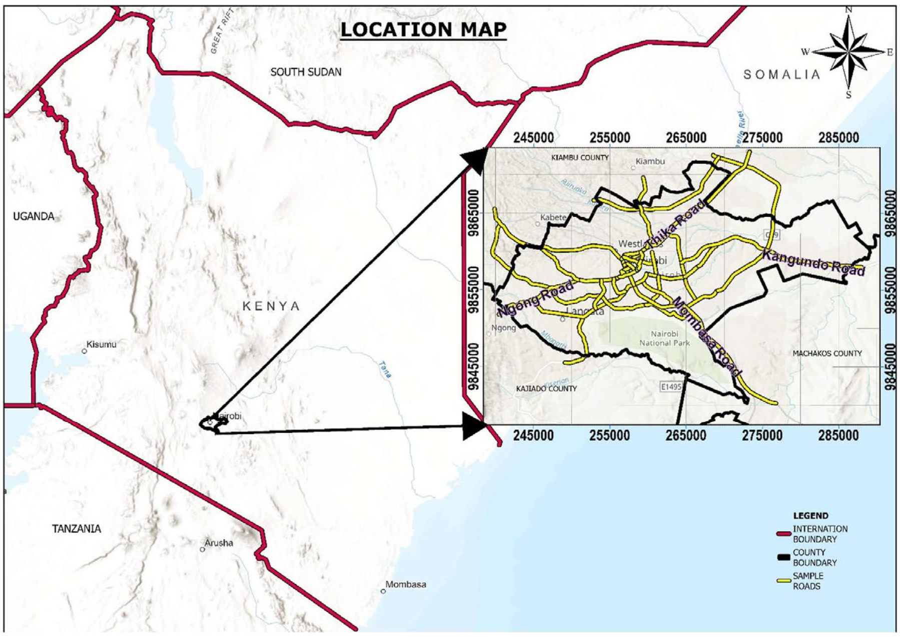


Figure 1: Map of Nairobi City, Kenya (Source: Author)

42 sampling points were selected across the city, spanning diverse land use types connected by diverse road corridors that have different traffic volumes, all representing varied urban traffic conditions, see Figure 2.

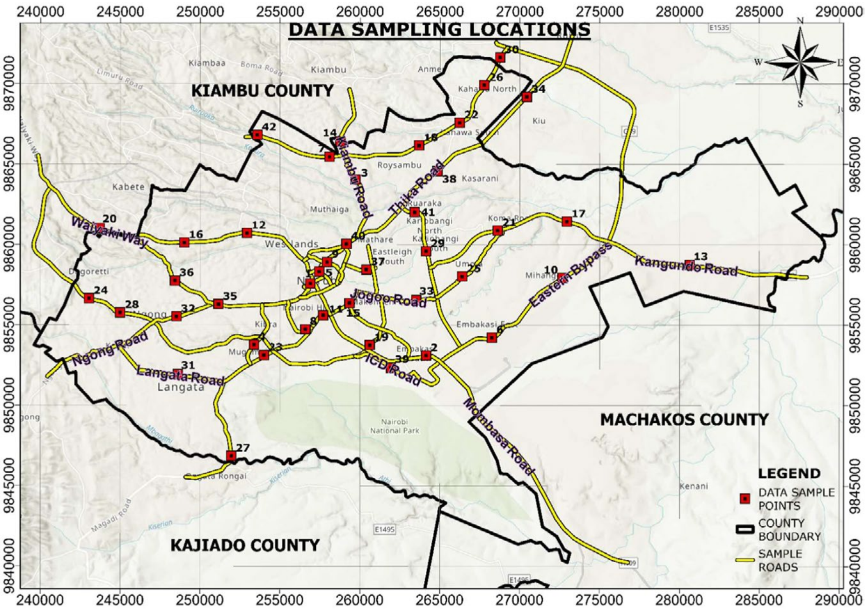


Figure 2: 42 Sampling locations selected across Nairobi (Source: Author)

Data Collection

Data were collected for seven days, across 42 Nairobi locations from 6 AM to 6 PM. Noise levels (Leq) were measured using a Lutron SL-4033SD Class 1 calibrated Sound Level Meter (SLM). A handheld Samsung Galaxy A12 Model SM-A127F/DS, Android smartphone was also used to capture audio recordings of RTN. Vehicle count spanning bicycles, motorcycles, private cars, SUVs, Pick-ups, Public Service Vehicles (PSVs), buses, light, medium, and heavy-duty trucks, and others such as tractors were manually tallied on a form shown in Appendix 1. Traffic speed was also captured using a calibrated Binar Radar speed gun and documented manually on a form shown in Appendix 1. From the data, a total of 504 samples of data were obtained.

Data Preprocessing

Noise levels were calculated in MS Excel from the logged SLM data. Vehicle counts were converted to Passenger Car Units (PCU) using standard conversion factors shown in Appendix 3. Average speeds were also calculated from the speed gun data, and the flow type was categorized as congested (<20 km/h), periodic (20–35 km/h), or fluid (>35 km/h). The smartphone audio recordings were preprocessed using Python to extract the Leq. They were compared with the SLM measurements to ensure consistency.

Framework Overview

The modelling process followed a structured pipeline, as shown in Figure 3, from data sources to evaluation, with shared preprocessing and diverse modelling approaches. The framework as presented in Figure 3, includes: (a) Data Sources: Three Excel sheets with the Noise Leq, Speed, and Vehicle Counts in PCU, per location and at different hour bands, providing the raw data,

Common Preprocessing

Shared steps across all models, including feature en- gineering (motorcycles, light/medium/heavy vehicles, speed, lanes, flow type), data processing and cleaning, and an 80/20 train/test split, (c) Model Section: Divided into three categories:

Traditional Machine Learning Models, that is, Random Forest, XGBoost, SVR, Custom ANN that is the 3-layer network implemented in this study, and Research-Based ANNs, that is, models from literature (Cammarata, Bogotá, Tehran, UAE, Genaro, and Torija), and Evaluation: Common performance metrics (Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2)) for comparing all models. This pipeline emphasizes that while preprocessing is identical, providing a standardized feature set to all models, the modelling approaches differ, utilizing distinct architectures and algorithms to predict the Leq.

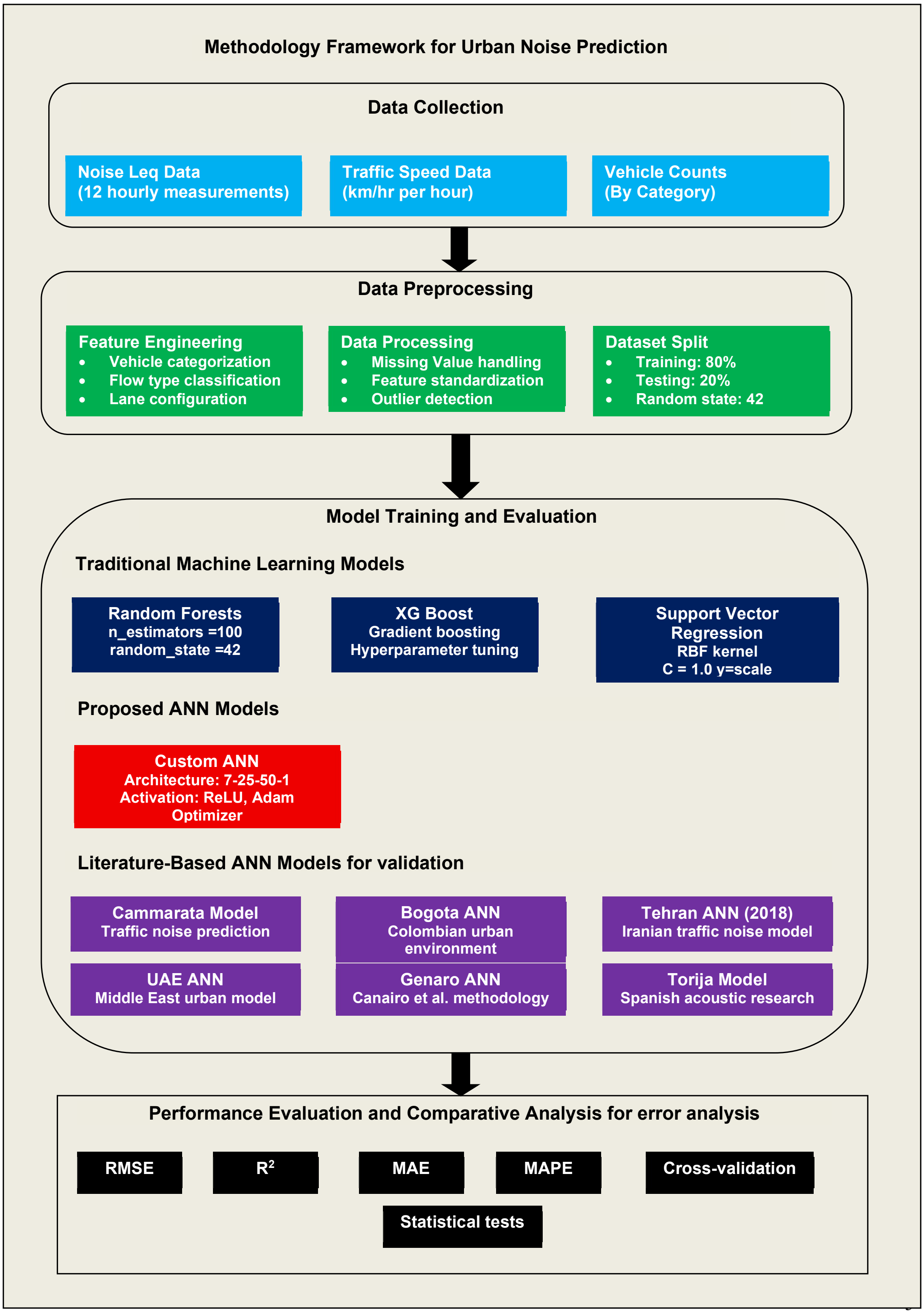


Figure 3: Visual pipeline diagram illustrating the modelling framework.

Smart Prediction Model

A Multi-Layer Perceptron (MLP) ANN was selected due to its superior handling of non-linear relationships, after comparing different algorithms such as Random Forest, XGBoost, SVR, and Linear Regression, see Figure 3 above.

Steps of Modelling

Input Vector Definition: The input to the neural network is formalized as a vector x, each component representing a key traffic or environmental feature contributing to RTN. x is defined as:

$$x = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8]^T$$

The superscript ^{T} means transpose, that is, turning a row into a column for math purposes. x_1 denotes the count of motor cycles, the high-frequency noise contributors; x_2 is the count of light vehicles, that is, cars, which are the primary volume drivers; x_3 medium vehicles that is, vans, which produce moderate noise; x_4 represents heavy vehicles, that is, trucks, which are low-frequency dominant; x_5 is average vehicle speed in kilometers per hour, influencing Doppler effects and tire-road interactions; x_6 represents the number of lanes, affecting noise propagation; x_7 represents the passenger car units (PCU), which is a standardized measure of traffic volume, and x_8 represents the flow type (categorical: 0 for congested, 1 for periodic, 2 for fluid), impacting noise variability. These features were selected based on correlation analysis and domain knowledge to capture the stochastic nature of urban RTN in Nairobi.

Forward Propagation: The network processes the input through a series of linear transformations and non-linear activations to model complex RTN patterns. The computations are:

The first hidden layer: $h_1 = \max(0, W_1x + b_1)$ Equation 1

Where $W_1 \in R^{25\times8}$ represents the weight matrix. It is a table of numbers that adjusts how much each input affects the layer. $R^{25\times8}$ means 25 rows by 8 columns of real numbers.

x is the input vector, and $b_1 \in R^{25}$ is the bias vector, which adds a constant to shift the output. max (0,) is the Rectified Linear Unit (ReLU) activation function, which introduces non-linearity (allows modeling curves, not just straight lines) to handle heteroscedastic noise data (varying error) and prevents vanishing gradients (a training problem where updates become too small)

The second hidden layer: $h_2 = \max(0, W_2 h_1 + b_2)$ Equation 2

Where $W_2 \in R^{50\times25}$, $b_2 \in R^{50}$ represents the weight matrix and the bias vector that expand feature representations for deeper pattern recognition.

The output layer (the Nairobi's Smart RTN Prediction Model): $y = W_3 h_2 + b_3$ Equation 3

Where $W_3 \in R^{1\times50}$, and $b_3 \in R$, yielding the predicted equivalent noise level, y, in dBA. This architecture allows the model to learn hierarchical features, from raw traffic counts to aggregated noise predictions, optimizing for the non-stationary characteristics of RTN.

Data Splitting and Cross-Validation: The dataset of 504 samples was partitioned into a training set (80%, 404 samples) and a testing set (20%, 100 samples) using stratified sampling to maintain distribution balance across noise hotspots. This split ensures robust generalization while allocating sufficient data for learning. To mitigate overfitting and assess model stability, 5-fold cross-validation was employed on the training set: the data is divided into 5 subsets, with each fold used once as validation while training on the remaining four. This process yields averaged performance metrics, providing a scientifically rigorous estimate of out-of-sample errors in the context of variable Nairobi traffic conditions.

Hyperparameter Optimization and Evaluation: Hyperparameters, including learning rate (range: [0.0001, 0.01]), batch size (range: [16, 64]), and number of epochs (up to 500 with early stopping), were tuned using grid search, exhaustively evaluating combinations to minimize validation loss. Model performance was quantified using:

Mean Absolute Error (MAE): $MAE = \frac{1}{N}\sum_{i=1}^{N}|(y_i - \hat{y}_i|$ Equation 4

Where N is the number of samples, for example, 100 in the test set, y_i is the observed Leq at sample *i*, and $\hat{y}_i$ is the predicted Leq at sample *i*. MAE measures average deviation in dBA and is crucial for practical noise forecasting.

Root Mean Squared Error (RMSE): RMSE= $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$ Equation 5

Where N is the number of samples, y_i is the observed Leq at sample *i*, and $\hat{y}_i$ is the predicted Leq at sample *i*. The RMSE emphasizes larger errors in high-noise scenarios.

The Coefficient of Determination (R^2): $R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$ Equation 6

Where $\bar{y}$ is the mean of the observed Leqs, y_i is the observed Leq at sample *i*, and $\hat{y}_i$ is the predicted Leq at sample *i*.

The coefficient of determination indicates an explained variance; a value closer to 1 is better, meaning that the model will account for most differences in the data.

$$\text{Pearson correlation coefficient: } r = \frac{\sum(y_i-\bar{y})(y_i-\bar{\hat{y}})}{\sqrt{\sum(y_i-\bar{y})^2 \sum(y_i-\bar{\hat{y}})^2}} \quad \text{Equation 7}$$

Where y_i is the observed Leq at sample i, $\hat{y}_i$ is the predicted Leq at sample i, $\bar{y}$ is the mean of the observed Leqs, and $\bar{\hat{y}}$ is the mean of predicted Leqs.

It assesses linear agreement between predicted and actual Leq, ensuring scientific validity.

Loss Function: The Mean Squared Error (MSE) was selected as the objective function for optimization, where:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad \text{Equation 8}$$

Where N is the number of samples, y_i is the observed Leq at sample i, and $\hat{y}_i$ Is the predicted Leq at sample i.

The MSE is quadratic, penalizing larger deviations more severely, which is appropriate for regression tasks like RTN prediction, where minimizing variance in noise estimates is critical for public health applications. It aligns with the Gaussian assumption of noise residuals in environmental modeling.

Optimizer: The Adam (Adaptive Moment Estimation) optimizer was utilized for efficient gradient descent, updating the weights as:

$$w_{t+1} = w_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad \text{Equation 9}$$

where wt is the weight at step t (current), w_{t+1} is the updated weight, η is the learning rate (step size), $\hat{m}_t$ is the bias-corrected first moment estimate (smoothed gradient, like momentum), $\hat{v}_t$ is the bias-corrected second moment estimate (smoothed squared gradient for adaptive rates), and $\epsilon = 10^{-8}$, for numerical stability (prevents division by zero). Adam combines momentum and RMSprop (adapts rates per parameter) advantages, adapting per-parameter learning rates, which accelerates convergence on the non-convex loss landscape of ANN training for RTN data with inherent multicollinearity.

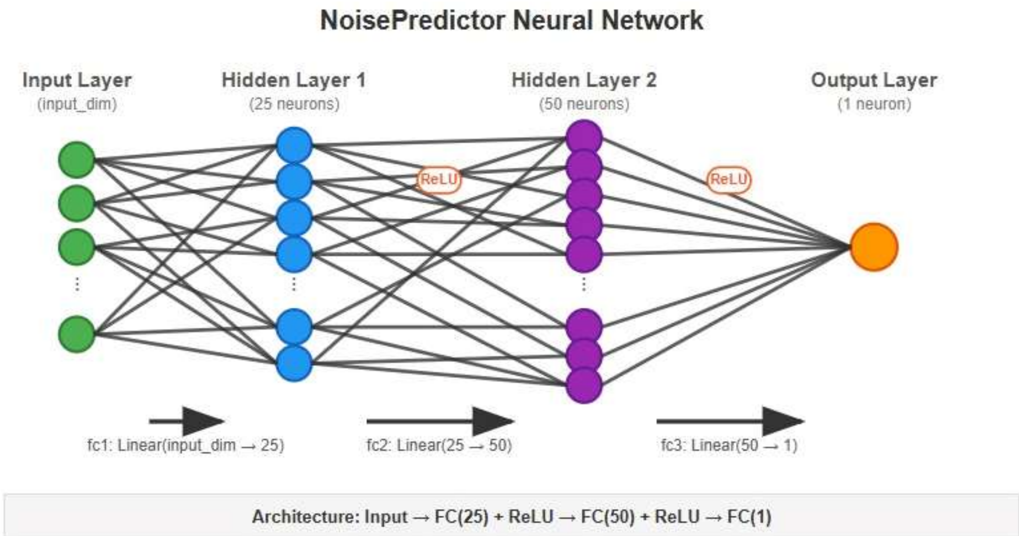


Figure 4: MLP Architecture for RTN Prediction

Detailed Explanation of Forward Propagation and Optimization

Forward Propagation Components

Forward propagation is the process by which the input data flows through the network layers to produce an output prediction. Imagine it as a factory assembly line where raw materials (inputs) are transformed step by step.

The key Variables are

- Weight Matrices (W): These are like adjustable knobs in the network. The weight matrices $W_1 \in R^{25\times 8}$ (25 by 8 grid of numbers), $W_2 \in R^{50\times 25}$, and $W_3 \in R_{1\times 50}$ contain learnable parameters that connect neurons (processing units) between layers. For instance, W1 weights the 8 input features, for example, motorcycle counts as x_1, and speed as x_5, to the 25 neurons in the first hidden layer, scaling each feature's contribution to capture its influence on noise. These weights are changed during training to make better predictions. A high weight on x_1 might mean motorcycles are very important for noise in Nairobi.
- Hidden Layer Outputs (h): These are intermediate results. The vectors $h_1 \in R^{25}$ (list of 25 numbers) and $h_2 \in R^{50}$ represent the activations (outputs) of the first and second hidden layers, respectively. Computed as in Equation 1, multiply weights by inputs, add bias, then set negatives to zero. Similarly, for h2 as in Equation 2, they apply the ReLU activation to introduce non-linearity, enabling the model to learn complex patterns, like how motorcycle counts and traffic flow together affect noise.

- Bias Vectors (b): These are constants added to adjust the output. The bias terms $b_1 \in R^{25}$ (25 numbers), $b_2 \in R^{50}$, and $b_3 \in R$ (single number) shift the linear transformations in each layer, allowing the network to fit data better. For example, b_3 adjusts the final prediction $\hat{y}$ to account for baseline noise, even if all inputs are zero.
- Observed Leq (y_i): This is the real, measured noise level (Leq, in dBA) for the i-th data sample (where i goes from 1 to N, the total number of samples). It is collected from actual measurements taken and is the "correct answer" the model tries to match.
- Predicted Leq ($\hat{y}_i$): This is the model's guess for the noise level for the i-th sample, calculated as in Equation 3. It is compared to y_i to see how wrong the model is, and is shown on the dashboard for users.

Adam Optimizer Components

The optimizer is like a teacher that corrects the model's mistakes by adjusting weights. The Adam optimizer updates the weights and biases to make the loss (error) smaller, using Equation 8. Think of it as taking small steps downhill to find the lowest error.

The Components are

- w_t and w_{t+1}: A single weight (one number in W) at the current step t (like time step in training), and its new value after update. This happens for every weight and bias to improve the model.
- Learning Rate (η): This is how big each step is (tuned between 0.0001 and 0.01). Too big, and you might overshoot; too small, and learning is slow. It is like the stride length when walking downhill.
- Bias-Corrected First Moment ($\widehat{mt}$): This is a smoothed version of the gradient (direction of steepest descent, calculated as change in loss (∂L) per change in weight (∂W):

$$g_t = \frac{\partial L}{\partial W} \qquad \text{Equation 10}$$

$$\widehat{m}_t = \frac{mt}{1-\beta t} \qquad \text{Equation 11}$$

Where:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \qquad \text{Equation 12}$$

and $\beta_1 = 0.9$ (a decay factor).

It adds momentum, like pushing a ball to keep it rolling in the same direction.

- Bias-Corrected Second Moment ($\hat{v}_t$): This smoothens the squared gradient for adaptive steps:

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \qquad \text{Equation 13}$$

with

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \qquad \text{Equation 14}$$

and $\beta_2 = 0.999$.

It makes steps smaller for noisy directions (high variance) and larger for consistent ones.

- Numerical Stability Term (ϵ): A tiny number (10^{-8}) added to avoid dividing by zero if $\hat{v}_t$ is very small, thus keeping calculations safe. This setup helps the model learn efficiently from Nairobi's traffic data, handling complexities like varying vehicle noise.

Statistical Descriptors for Input Data

Table in Appendix 4 presents statistical descriptors for the input data with a significance value α = 5% for the Kolmogorov-Smirnov (K-S) test. Statistical descriptors summarize data. $\bar{x}$ is the mean (average value), σ is the standard deviation (how it is spread out), Min and Max are the smallest and largest, Range is the Maximum minus the Minimum, IQR is the interquartile range (middle 50% spread), C.V. is the coefficient of variation (relative spread in %), Kurtosis measures tail heaviness (high means more extremes), Asy. Coe. is asymmetry (skewness, positive means tail to the right), Kol. Smi. is the K-S test p-value (low means not normal distribution), Proportion is % of vehicle types.

Evaluation

Performance was evaluated using MAE, RMSE, and R^2, with Pearson correlation analysis between predicted and actual Leq, obtained from SLM data. The performance metrics were compared to those of traditional machine learning models and literature-based models.

Model Deployment

The model is deployed on a web-based dashboard, accessible to the public. Users input parameters such as the location, time, speed, and vehicle count, and the dashboard outputs predicted Leq in real-time, visualized via interactive charts. The platform supports noise monitoring, public education, and integration with traffic management systems.

Results

The table in Appendix 5 shows the equivalent sound levels measured at different time intervals using the SLM for the 42 sampling locations

Nairobi Road Traffic Noise Prediction Model

The Nairobi's Smart RTN Prediction Model (MLP) $\mathbf{Leq}_{\mathbf{predicted}} = \mathbf{W}_3\, \mathbf{h}_2 + \mathbf{b}_3$ Equation 15

Where h2 is defined as in Equation 2 and $W_3 \in R^{1\times 50}$, and $b_3 \in R$ represents the weight matrix and bias for the output layer (single prediction).

Model Evaluation and Validation

The MLP model achieved a MAE of 0.97 dBA, RMSE of 1.38 dBA, and R^2 of 0.90 with a Pearson Correlation coefficient of 0.9476 between the predicted and the measured Leq values, indicating strong predictive accuracy. Table 2 compares the MLP with other models, showing superior performance over CoRTN, which has a MAE of 5.0 dBA and an R^2 of 0.80, and RLS-90, which has a MAE of 11.0 dBA and an R^2 of 0.50, attributed to its ability to capture Nairobi's unique traffic patterns. The UAE ANN and Torija ANN performed similarly well; however, the Current MLP is optimized for Nairobi's context [13,14].

Model	MAE (dBA)	RMSE (dBA)	R^2
Current MLP	0.97	1.38	0.90
Bogotá MLP [14] [14]	1.19	1.56	0.87
ANN (Torija) [8] [8]	0.87	1.08	0.94
ANN (UAE) [11] [11]	0.79	0.97	0.95
XGBoost	1.14	1.39	0.89
SVR	2.67	3.59	0.30
Random Forest	1.09	1.43	0.89
Linear Regression	3.74	4.44	-0.07
CoRTN	5.00	–	0.80
RLS-90	11.00	–	0.50

Table 1: Model evaluation and validation with existing predictive models

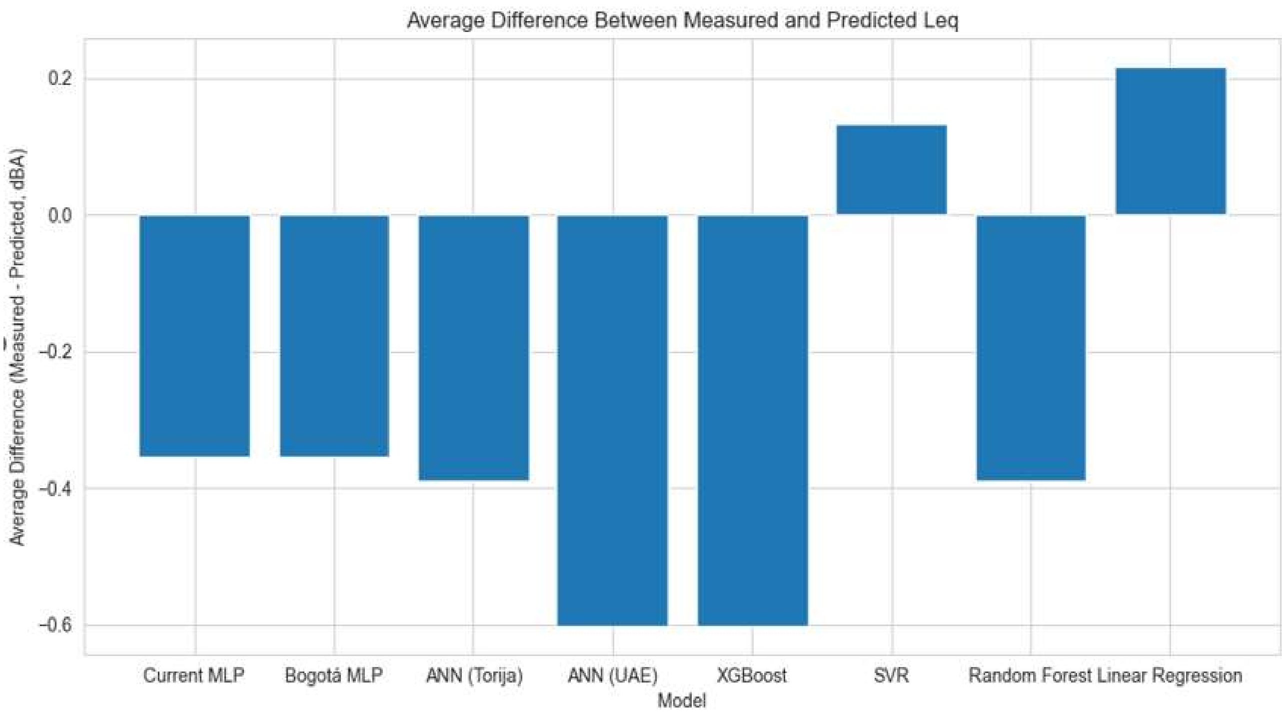


Figure 5: Average Difference Between Measured and Predicted Leq.

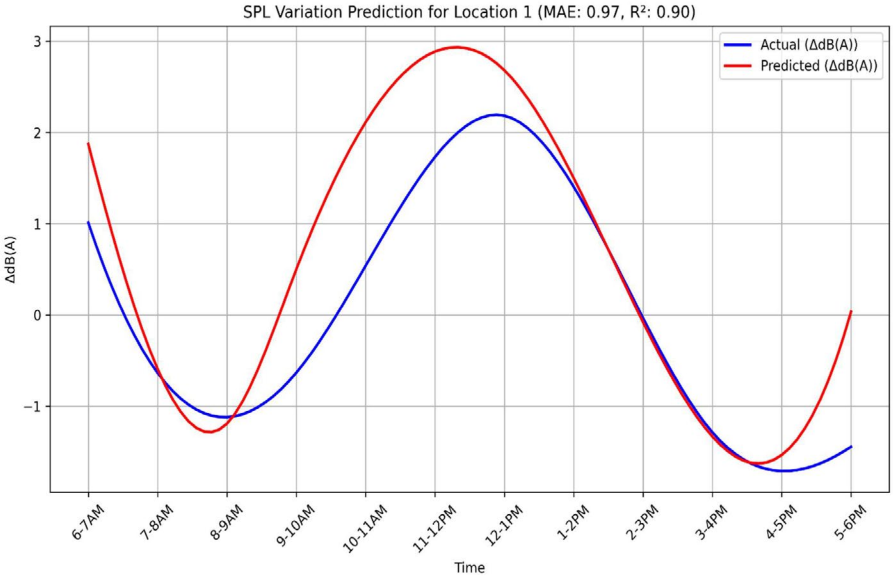


Figure 6: An example of a day SPL variation prediction for Location 1

The plot in Figure 6 above shows the actual and predicted change in Leq over time, illustrating the differences between measured and model-predicted noise levels per hourly interval from 6 AM to 6 PM. The close alignment, especially during peak hours, demonstrates the model's capability to capture temporal variations in RTN, with minor deviations reflecting real-world complexities like unmodeled variables.

Discussion

The MLP model developed in this study effectively captures Nairobi's complex traffic dynamics, including the high prevalence of motorcycles and variable flow types, which contribute significantly to road traffic noise (RTN) variability. As shown in Table 1, the model outperforms traditional models like CoRTN and RLS-90, primarily due to its ability to adapt to Nairobi's heterogeneous vehicle fleet and congested road networks, which these conventional models fail to address. This adaptability stems from the model's use of a Multi-Layer Perceptron (MLP) ANN, optimized through grid search hyperparameter tuning to handle non-linear relationships in traffic data. The model's predictive accuracy supports cost-effective noise monitoring, offering a scalable solution for urban planning in rapidly growing African cities like Nairobi.

By deploying the model on a web-based dashboard, it enables real-time noise prediction, facilitates stakeholder engagement, and supports public education on noise pollution. The platform's integration with traffic management systems can inform urban noise policies and mitigate health impacts, such as stress and subjective annoyance. However, the model's reliance on data from this study limits its ability to account for seasonal traffic variations or unmodeled variables like road surface type and weather conditions, which future research should address to enhance robustness.

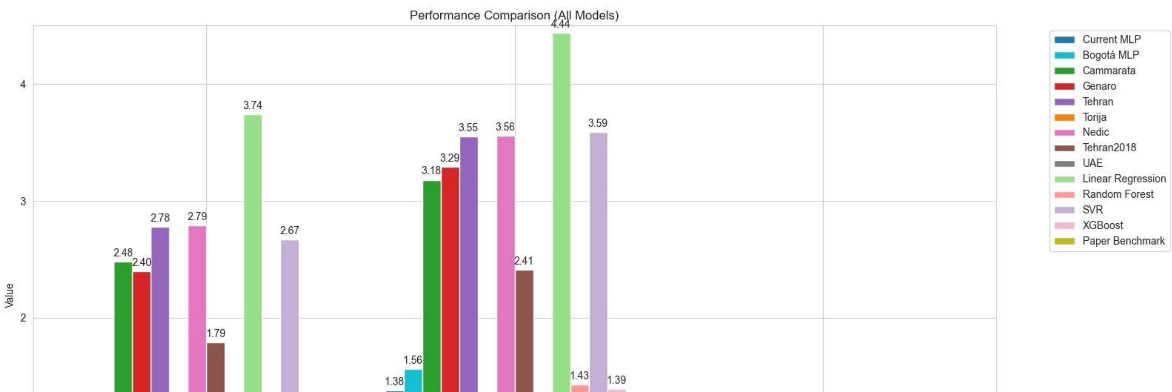


Figure 7: Performance Comparison (All Models) bar chart showing MAE, RMSE, and R^2 for each model

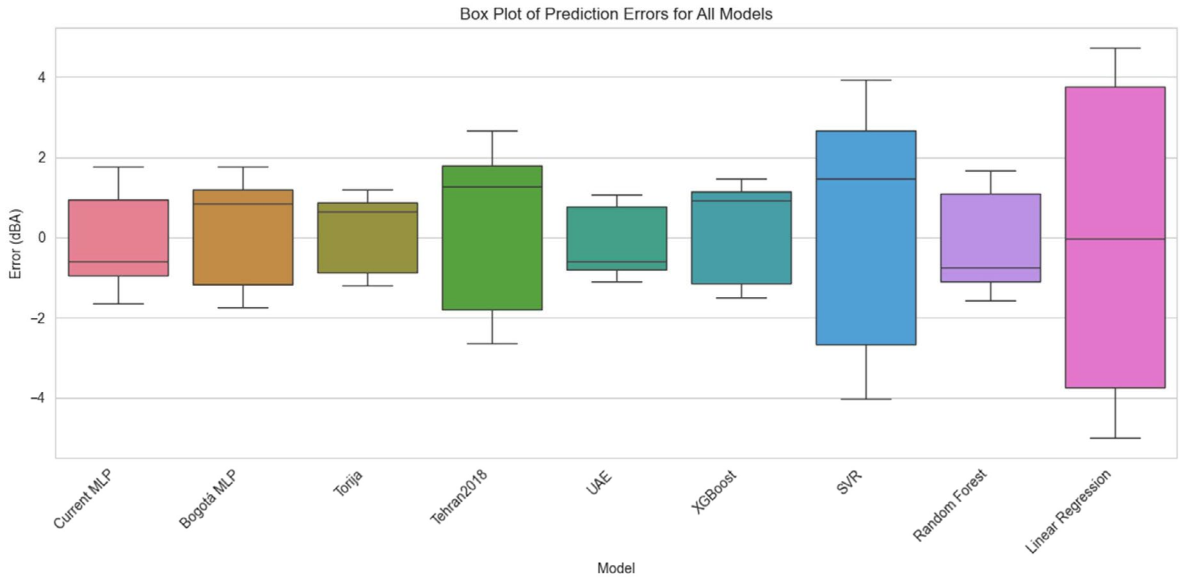


Figure 8: Box Plot of Prediction Errors for All Models

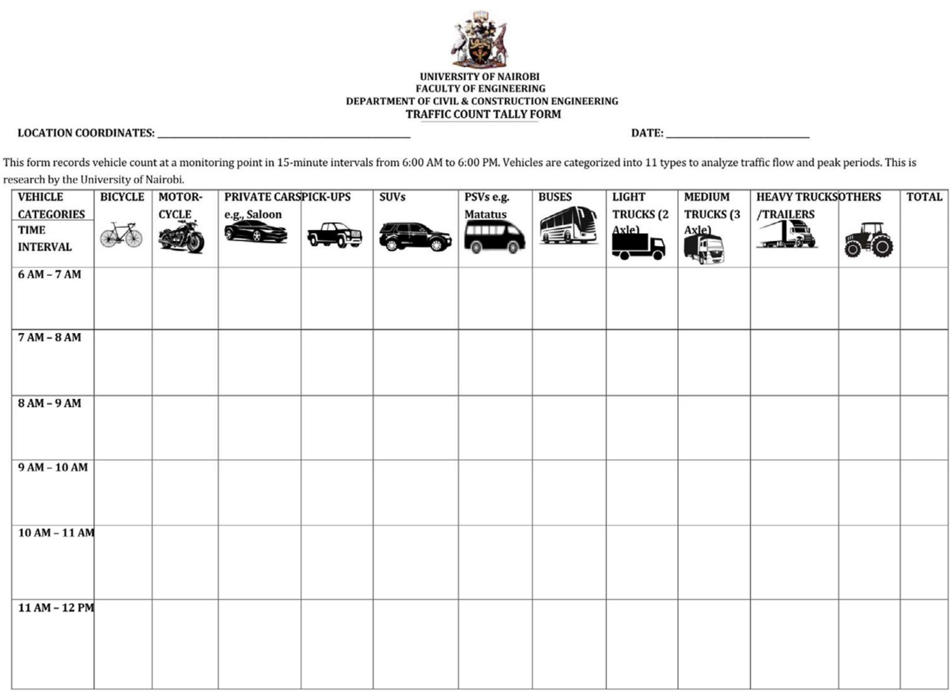
Predictive modeling offers significant advantages, including cost-effective noise monitoring and scalability, which are particularly beneficial for urban planning in rapidly growing cities like Nairobi. The deployment of the model on a web-based dashboard facilitates real-time noise prediction, enables stakeholder engagement, allows for public education on noise pollution, and integrates with traffic management systems to mitigate noise at major hotspots. Practical implications include informing urban noise policies and reducing health impacts like stress and subjective annoyance. However, its limitations lie in the model's reliance on this study's data, which may not account for seasonal traffic variations, and the absence of variables like road surface type or weather conditions.

Conclusion

This study developed the first smart RTN prediction model for Nairobi, leveraging an MLP ANN with high accuracy and surpassing traditional models like CoRTN and RLS-90. The model, tailored to Nairobi's traffic dynamics, is deployed public web dashboard, enabling real-time noise monitoring and prediction and citizen engagement. The study recommends including real-time data integration, expanding input variablesroad surface and weather, and collaboration with traffic authorities to enhance urban noise management. This pioneering model sets a baseline for smart noise prediction in African cities, with the potential for broader application [15-22].

Appendix 1

Manual Tally form used for traffic count



UNIVERSITY OF NAIROBI
FACULTY OF ENGINEERING
DEPARTMENT OF CIVIL & CONSTRUCTION ENGINEERING
TRAFFIC COUNT TALLY FORM

LOCATION COORDINATES: ____________________ DATE: ____________

This form records vehicle count at a monitoring point in 15-minute intervals from 6:00 AM to 6:00 PM. Vehicles are categorized into 11 types to analyze traffic flow and peak periods. This is research by the University of Nairobi.

VEHICLE CATEGORIES / TIME INTERVAL	BICYCLE	MOTOR-CYCLE	PRIVATE CARS e.g., Saloon	PICK-UPS	SUVs	PSVs e.g. Matatus	BUSES	LIGHT TRUCKS (2 Axle)	MEDIUM TRUCKS (3 Axle)	HEAVY TRUCKS /TRAILERS	OTHERS	TOTAL
6 AM – 7 AM												
7 AM – 8 AM												
8 AM – 9 AM												
9 AM – 10 AM												
10 AM – 11 AM												
11 AM – 12 PM												

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TRAFFICCOUNT TALLYFORM

VEHICLE CATEGORIES / TIME INTERVAL	BICYCLE	MOTOR-CYCLE	PRIVATE CARS e.g., Saloon	PICK-UPS	SUVs	PSVs e.g. Matatus	BUSES	LIGHT TRUCKS (2 Axle)	MEDIUM TRUCKS (3 Axle)	HEAVY TRUCKS /TRAILERS	OTHERS	TOTAL
12 PM – 1 PM												
1 PM – 2 PM												
2 PM – 3 PM												
3 PM – 4 PM												
4 PM – 5 PM												
5 PM – 6 PM												

Appendix 2

Manual Tally form used for recording speed

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VEHICLE SPEED FORM

LOCATION COORDINATES: ____________________ DATE: ____________

This form records vehicle count at a monitoring point in 15-minute intervals from 6:00 AM to 6:00 PM. Vehicles are categorized into 11 types to analyze traffic flow and peak periods. This is research by the University of Nairobi.

VEHICLE CATEGORIES / TIME INTERVAL	BICYCLE	MOTOR-CYCLE	PRIVATE CARS e.g., Saloon	PICK-UPS	SUVs	PSVs e.g. Matatus	BUSES	LIGHT TRUCKS (2 Axle)	MEDIUM TRUCKS (3 Axle)	HEAVY TRUCKS /TRAILERS	OTHERS	TOTAL
6 AM – 7 AM												
7 AM – 8 AM												
8 AM – 9 AM												
9 AM – 10 AM												
10 AM – 11 AM												
11 AM – 12 PM												

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VEHICLESPEED FORM

VEHICLE CATEGORIES / TIME INTERVAL	BICYCLE	MOTOR-CYCLE	PRIVATE CARS e.g., Saloon	PICK-UPS	SUVs	PSVs e.g. Matatus	BUSES	LIGHT TRUCKS (2 Axle)	MEDIUM TRUCKS (3 Axle)	HEAVY TRUCKS /TRAILERS	OTHERS	TOTAL
12 PM – 1 PM												
1 PM – 2 PM												
2 PM – 3 PM												
3 PM – 4 PM												
4 PM – 5 PM												
5 PM – 6 PM												

Appendix 3
PCU conversion factors

Bicycle	Motorcycle	Private car	Pickup	SUV	PSVs	Buses	Light trucks	Medium trucks	Heavy trucks	Others
0.5	1	1	1	1	1.5	4	1.5	5	8	8

Appendix 4
Table showing the Statistical descriptors for input data (significance value α = 5% for K-S).

Stat. Flow	Motorcycles	Light	Medium	Heavy	q (PCU)	Speed	Lanes
$\bar{x}$	11.65	58.24	12.83	5.71	1838.07	50.19	3.07
0.87 σ	15.23	38.76	7.45	6.12	580.34	14.82	0.98
0.34 Min.	0.00	5.00	0.00	0.00	409.00	25.00	2.00
0.00 Max.	63.00	210.00	42.00	21.00	6965.00	85.21	4.00
1.00 Range	63.00	205.00	42.00	21.00	6556.00	60.21	2.00
1.00 IQR	20.00	50.00	15.00	8.00	1200.00	20.00	2.00
1.00 C.V. (%)	130.69	66.55	58.06	107.18	31.57	29.53	31.92
39.08 Kurtosis	5.12	4.89	3.45	4.23	3.12	2.89	1.45
1.23 Asy. Coe.	2.34	2.10	1.87	2.01	1.65	1.23	0.67
0.45 Kol. Smi.	$p < 0.001$	$p < 0.01$	$p < 0.05$	$p < 0.01$	$p < 0.001$	$p < 0.05$	$p < 0.1$
$p < 0.05$							
Proportion 100.00%	24.37%	49.84%	14.84%	9.94%	100.00%	100.00%	100.00%

Appendix 5

Table showing the measured/observed RTN levels in Nairobi, Kenya.

LOCATION	6 AM-7 AM	7 AM-8 AM	8 AM-9 AM	9 AM-10 AM	10 AM-11 AM	11 AM-12 PM	12 PM-1 PM	1 PM-2 PM	2 PM-3 PM	3 PM-4 PM	4 PM-5 PM	5 PM-6 PM
1	73.52	72.12	71.32	71.92	73.02	74.32	74.92	74.22	72.02	71.32	71.12	71.02
2	82.89	81.39	80.69	81.29	82.39	83.69	84.29	83.29	81.39	80.59	80.39	80.29
3	75.99	74.39	73.79	74.39	75.49	76.79	77.39	76.29	75.09	74.39	73.59	73.39
4	72.2	70.8	71	71.6	72.7	74	74.6	73.5	71.7	71	70.7	70.6
5	75.35	74.45	74.85	75.45	75.95	77.85	78.45	77.35	75.55	74.85	74.65	74.55
6	82.92	81.22	81.72	82.32	83.42	84.72	85.32	84.22	82.42	81.72	81.52	81.42
7	79.46	76.96	78.26	78.86	79.96	81.26	81.86	80.76	78.96	78.26	78.06	77.96
8	78.9	76.4	77.7	78.3	79.4	80.7	81.3	80.2	78.4	77.6	77.5	77.2
9	74.22	72.62	73.02	73.62	74.72	76.02	76.62	75.52	73.72	72.92	72.82	72.72
10	78.69	76.69	76.49	77.09	78.19	79.49	80.09	78.99	77.19	76.39	76.29	76.19
11	77.71	75.91	75.51	76.11	77.21	78.51	79.11	78.01	76.21	75.41	75.31	75.21
12	80.69	78.59	78.49	79.09	80.19	81.49	82.09	80.99	79.19	78.49	78.29	78.19
13	81.07	78.97	78.87	79.47	80.57	81.87	82.47	81.37	79.57	78.87	78.67	78.57
14	76.1	74	73.9	74.5	75.6	76.9	77.5	76.4	74.6	73.9	73.7	73.6
15	75.25	73.15	73.05	73.65	74.75	76.05	76.65	75.55	73.75	73.05	72.85	72.55
16	75.74	73.64	73.54	74.14	75.24	76.54	77.14	76.04	74.24	73.44	73.34	73.24
17	70.89	69.89	68.19	67.79	70.19	76.39	77.79	76.69	72.89	71.09	70.69	70.39
18	75.19	74.09	73.99	74.19	74.89	76.39	77.19	76.59	74.79	74.09	73.79	73.49
19	72.58	71.08	70.38	70.98	73.38	74.98	76.08	74.78	72.18	71.38	70.88	70.68
20	68.86	66.76	66.36	67.46	69.66	72.76	74.26	73.16	70.36	68.66	67.96	67.16
21	68.71	67.71	66.51	67.11	69.61	73.91	75.81	74.71	70.91	69.21	68.11	67.71
22	73.03	71.73	71.43	71.83	74.03	75.23	75.93	74.83	73.03	72.33	71.73	71.53
23	80.86	78.96	78.66	79.26	81.66	84.56	85.46	84.36	82.56	80.86	80.26	80.06
24	73	70.9	70.8	71.4	73.9	76.5	77.7	76.6	74.8	73	72.5	72.3
25	74.44	72.34	72.24	72.84	75.34	77.74	79.14	78.11	76.24	74.84	74.54	74.34
26	70.37	68.27	68.17	68.77	71.27	73.57	75.07	73.97	72.17	70.97	70.17	69.97
27	72.7	71.1	70.5	71.1	73.6	76.1	77.4	76.3	74.5	73.9	71.9	71.7
28	71.36	69.86	69.16	69.76	72.16	74.46	75.96	74.86	73.06	72.06	70.66	70.36
29	76.94	74.84	74.74	75.34	77.74	79.64	81.54	80.44	78.94	77.64	76.54	76.24
30	74.48	72.38	72.28	72.88	75.28	77.18	79.08	77.98	75.76	75.18	74.58	74.38
31	75.48	73.38	73.28	73.88	76.28	78.18	80.08	78.98	76.3	75.68	75.18	74.88
32	69.78	67.68	67.58	68.18	70.58	72.48	74.38	73.28	71.48	70.48	69.68	69.38
33	80.7	78.6	78.5	79.1	81.5	83.9	85.3	84.2	82.4	81.37	80.5	80.3
34	74	73.2	72.5	73.1	74.5	77.4	78.3	77.2	75.4	73.55	73.2	73
35	83.33	81.93	81.13	82.23	84.13	86.03	87.93	86.83	84.03	82.33	82.03	81.83
36	76.54	74.44	74.34	74.94	77.44	79.24	81.24	80.14	77.34	75.64	75.44	75.24
37	77.18	75.08	74.98	75.58	78.08	79.88	81.88	80.78	77.08	76.58	75.88	75.68
38	81.64	79.54	79.44	80.04	82.54	85.04	86.34	85.24	83.44	82.34	81.54	81.24
39	83.3	82	81.1	81.7	84.2	86	88	86.9	85.1	84	83.6	83.3
40	77.61	76.21	75.41	76.01	78.41	80.31	82.21	81.11	79.31	77.61	77.11	76.99
41	78.41	76.31	76.21	76.81	79.21	81.61	83.01	81.91	79.11	77.91	77.31	77.01
42	77.07	74.97	74.87	75.47	77.87	79.77	81.67	80.57	78.77	76.07	75.67	77.77

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Citation: Ochungo Akech Elisha, Osano Simpson Nyambane, Gichaga John Francis, et al. (2025). A Smart Traffic Noise Prediction Model for Nairobi City, Kenya. *J. Electr. Electron. Eng. Res. Rev. 1*(1), 1-14.