A Machine Learning Model to Uncover the Impact of Traffic Noise Annoyance in the Inhabitants of Ranchi, Jharkhand

Abhishek Kumar[1], Deepak Kumar Singh[1], Kumar Amrendra[2], Ravi Kumar Burman[1], Dinesh Kumar Prabhakar[3], Rajan Kumar Tiwari[1]

[1]Computer Sciences & Engineering, Jharkhand University of Technology, Ranchi, India
[2]Faculty of CSE & IT, Jharkhand Rai University, Ranchi, Jharkhand, India

[3]Computer Sciences & Engineering, NIAMT, Ranchi, Jharkhand, India

abhishek28mca@gmail.com

Abstract. In rapidly urbanizing areas like Ranchi, the capital city of Jharkhand, traffic noise has emerged as a serious health concern. This study explores the impact of traffic noise irritation on Ranchi's residents using machine learning models. A dataset, including traffic noise levels, psychological responses (noise irritation), and physiological health markers, was collected from a representative sample of the population. Supervised learning techniques, such as Random Forest and Artificial Neural Networks (ANN), were employed to predict the likelihood of noise-related health issues like hypertension, sleep disturbances, and cardiovascular problems. Feature importance analysis highlighted key factors contributing to noise irritation, such as traffic density, proximity to major roads, and exposure duration. The model's performance, validated through confusion matrices and classification metrics, showed a strong association between prolonged noise exposure and health risks. These findings provide valuable insights for policymakers to implement noise control measures and urban planning strategies to safeguard public health in Ranchi.

Keywords: Traffic noise, Noise annoyance, Machine learning, Health impacts of noise, Noise control measures, public health, Ranchi, Jharkhand

1 Introduction

The negative effects of environmental stress on health are widely known. Research has shown that excessive or continuous amounts of background noise, such as noise from traffic, may be one of these stressors that negatively affects things like sleep quality and cardiovascular health. Extensive exposure to road traffic noise has been shown to dramatically increase the risk of a number of health problems, such as heart attacks, strokes, cardiovascular disorders, hypertension, depression, and even higher

P. Ranjan et al. (eds.), *Proceedings of the International Conference on Recent Advances in Artificial Intelligence for Sustainable Development (RAISD 2025)*, Advances in Intelligent Systems Research 196,
https://doi.org/10.2991/978-94-6463-787-8_4

mortality. There is substantial evidence linking transportation noise to poor health outcomes, especially heart disease and stroke. One unfavorable consequence of urbanization and industrial expansion is environmental noise. In addition to having a harmful impact on the environment, this unwanted sound has major negative impacts on people, such as hearing loss, hypertension, and trouble sleeping. One of nature's most pervasive poisons is noise. Though it was once thought to be a problem exclusive to the military and large business, it is now seen as almost universal. India's transportation sector is growing at a rate of around 7.50% year, and the number of cars on Indian roads is also increasing rapidly. This has resulted in congested roads and the emergence of another aspect of urban life: noise pollution, which has been increasing over time. Numerous factors are found to be involved, such as traffic volume, speed, and number of vehicles; whether the road is elevated or in a cutting; the angle of the road; and the state of the road surface.

1.1 Impact of the noise on human health

There are many different ways that noise can negatively affect a person's mental health. Here are a few crucial elemenst: Noise pollution has a detrimental effect on people's physical and mental health by causing hearing loss, social isolation, stress, anxiety, sleep difficulties, cognitive decline, and cardiovascular issues. Prolonged exposure to noise levels higher than 85 decibels can lead to irreversible hearing impairment and interfere with hormone balance, raising the risk of chronic illnesses and impacting the endocrine and respiratory systems.

1.2 Study area

The most populous district of Jharkhand, Ranchi, is situated in the southern Chota Nagpur Plateau. It is an important urban center with a high population and intricate transit infrastructure. Noise pollution needs to be investigated since the city's zones for industrial, commerce, residential life, and recreation create complex noise and traffic flow dynamics.

1.3 Motivation for the Present Study

As shown in Fig 1, the volume of vehicles using Indian roads has been steadily and significantly rising with every day. The trajectory of vehicle expansion in Ranchi city, India—the research area for this study—is shown in Figure 1. Figure 1clearly shows that the number of automobiles has more than tripled between 2000 and 2023. The escalating issues brought on by traffic congestion and its after effects, particularly noise pollution, are highlighted by this brief expansion. The clear growth in vehicle traffic and the growing public awareness of the detrimental effects of noise pollution on the environment and human health make it imperative to develop a robust prediction model capable of accurately predicting future trends, requiring such a paradigm for effective urban.

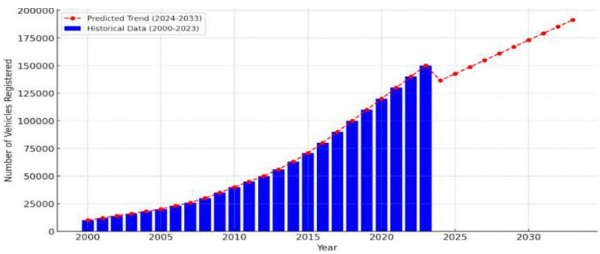

Fig.1: Vehicular Growth and Prediction Trends in Ranchi, Jharkhand (2000-2033 Source: - from Regional Transport Office, Ranchi Jharkhand)

2 Literature Review

The study by Patel et al. (2024) focuses on traffic noise modelling in mid-sized Indian cities using Neural Network and Linear Regression techniques, revealing that ANN outperforms Multiple Linear Regression [1].

The effects of constant high-intensity traffic noise on mental function are investigated in this study using noise sensitivity tests and cancelation exercises. The results of the study, which tested participants in both quiet and noisy settings, showed that high-intensity noise significantly impacted cognitive function, underscoring the need for noise mitigation in urban areas [6]. The study "Noise Prediction Using Machine Learning with Measurements Analysis" by Po-Jiun Wen and Chihpin Huang focuses on noise prediction in high-noise situations. The noise equivalent levels from the National Synchrotron Radiation Research Centre are examined in order to create a gradient boosting model for sensor 8 (125 Hz), which is necessary for workers in high-noise environments to prevent long-term exposure and forecast future pollution [7]. The study by Vasava et al. [2019] highlights the global health risks of traffic noise, its impact on disease, and its impact on adolescents, providing valuable insights for environmental and welfare planning [8]. Machine learning models were developed to predict an individual's level of annoyance caused by traffic noise, taking into account factors such as exposure levels, noise perception, and demographics. Artificial neural networks (ANN), support vector machines (SVM), and multiple linear regressions (MLR) were used to develop the models. In terms of error reduction, ANN outperformed MRL and SVM models, with error reductions of 42% and 35%, respectively, in training and testing subsets. The technique provides a reliable way to assess traffic noise's effects in cities [9]. Based on research conducted by N. Manojkumar, Khadar Basha, and B. Sri Muruganandam, the most reduced noise limitations in India are 45 dB(A). The study was titled "Assessment, Prediction and Mapping of Noise Levels in Vellore City, India, Noise Map." Nevertheless, recent study from the WHO indicated that noise levels more than 40 dB (A) may have deleterious impacts on health. The Central Pollution Control body of India approved the noise regulation in 2000, and the body hasn't updated it since. The investigation has brought to light the pressing necessity to reform India's noise rules and laws in order to enhance living conditions in the nation's cities [10]. In 2018, Saba Ismail and Shahid Ahmed conducted a study on noise pollution among Delhi university students. The results showed that educated adolescents knew the causes and effects of noise pollution, with young women being more sensitive. However, they consider noise pollution as a small problem, with loud music being the second most significant source [11]. For the purpose of this study, 120 persons were questioned about their perceptions of noise pollution in various contexts. Even in cases when they were able to pinpoint the sources of the noise, a significant number of participants did nothing to limit their exposure to it. The differences between proactive actions and knowledge regarding noise pollution in urban environments are clarified by this study [12]. Goswami S, Swain BK, and Panda SK (2013) conducted a study on road traffic noise pollution in Rourkela, India, assessing, analyzing, and appraising the issue.Their findings showed that the biggest source of pollution was traffic noise. Based on their responses to the survey, half of the subjects reported having high blood pressure, headaches, and difficulty sleeping [13]. Research on the topic of "Environmental noise assessment and its effect on human health in an urban area of Burdwan" was submitted by Srimanta Gupta and Chitralekha Ghatak in 2011. The current study focuses on the assessment of traffic noise and its detrimental effects on the health of those who live near roads. A total of five distinct locations with daytime Leq levels ranging from 60 to 89.5 dBA were chosen to be situated along Burdwan National Highway. The research area's residents experienced a range of noise-related discomforts, from mild discomfort to aggravation, according to an evaluation of several noise descriptors including L10, L50, L90, Leq, LNP, and TNI [14].

This work employs deep learning algorithms for noise exposure forecasting in highly populated metropolitan areas. Singh and Bhardwaj focus on predicting related health risks and assessing noise levels using state-of-the-art algorithms. Their findings are particularly useful in Ranchi, where heavy traffic congestion and inadequate noise control measures are contributing to a rise in health issues. Regional authorities can benefit from the accuracy with which the system predicts noise annoyance [2]. Traffic noise pollution in developing cities is the main topic of Xie's research. The research draws comparisons between Ranchi's urban noise problems and traffic patterns, noise exposure, and public health outcomes in a mid-sized Chinese city. The study suggests ways for regulating the noise-health link, including green spaces and noise barriers. It also underlines the importance of effective urban design [3].

This research proposes a machine learning method to forecast noise irritation caused by vehicles. The study finds important variables like traffic volume and road closeness, which are pertinent for comprehending noise irritation in developing cities by utilizing Random Forest and Artificial Neural Networks (ANN). This study is important for urban planners who want to reduce traffic noise in growing cities since Gupta et al. show how machine learning can improve the accuracy of noise pollution projections [4]. This research employs machine learning algorithms to evaluate the threats that traffic noise poses to the public's health. Zhao's research shows how predictive models can assess the long-term health effects of noise exposure, including stress and hypertension, which are major issues for the urban population of metro cities. The study emphasizes how critical it is to include machine learning into public health initiatives to counteract the negative impacts of traffic noise [5].

3 Objective

The project's objective is to develop a machine learning model that will examine the impact of traffic noise on the physical and mental health of Ranchi residents. The model will shed light on the threshold noise levels that result in impairments by spotting patterns and links between noise levels and health issues. The goal of the study is to teach legislators, health professionals, and urban planners about the dual effects of noise pollution on mental and physical health.

4 Methodology

This section details the input variables for a machine learning model to categorize Ranchi's traffic-induced noise discomfort. Data was collected from socio-acoustic surveys and environmental measurements. The model was created by analyzing noise nuisance data from Ranchi, India, and classified using Random Forest and Artificial Neural Network approaches. Cross-validation training methods were used to avoid overfitting.

Data table to evaluate the impact of traffic noise annoyance

Table1: Attribute to analyze the impact of traffic noise annoyance

Traffic noise level	Psychological level	Physiological level
Low	Poor	Poor
Moderate	Average	Average
High	Good	Good

Now applying neural network methodology to evaluate the impact of noise annoyance on above cases

Table 2: Analysis of impact of traffic noise annoyance

Traffic Noise Level			**Psychological Level**			**Physiological Level**			**Impact on Noise Annoyance**		
L	M	H	P	A	G	P	A	G	H	M	L

Legend:
H = High A = Average M = Moderate G = Good L = Low

Table 3: Effects of annoying traffic noise on routine activity performance in various age groups

Noise annoyance	Age group	Performance
High	0-20	Normal
Moderate	0-20	Normal
Low	0-20	Normal
High	20-40	Poor
Moderate	20-40	Poor
Low	20-40	Average
High	40-60	Poor
Moderate	40-60	Poor

Low	40-60	Average

4.1 Modeling Approaches

Overview of model
Building decision trees on random data improves accuracy and decreases overfitting, whereas ANNs use layers and back propagation to maximize performance for complicated, non-linear data.

Data collection approach
Using an urban noise monitoring system, a traffic noise forecast model, and a health effect assessment tool, the study use machine learning to forecast how Ranchi, Jharkhand, inhabitants will perceive traffic noise.

Test Dataset
Traffic Noise Exposure Dataset (Containing following parameter)

Person ID: Person ID: An individual's specific ID given to them in the dataset
Noise Level dB: This variable represents the traffic noise levels measured in decibels (dB).
Exposure Duration Hours: The number of hours per day that the individual is exposed to traffic noise.
Age: The age of the individual. This demographic attribute is used to analyze how traffic noise impacts individuals across different age groups.
Gender: The gender of the individual (e.g., Male, Female)
Residence Proximity: The proximity of the individual's residence to high-traffic areas.
Noise Sensitivity: A self-reported measure of the individual's sensitivity to noise. This variable is categorized into low, moderate, and high sensitivity, and helps in understanding individual variations in response to noise exposure.
Annoyance Level: A binary variable indicating whether the individual reports being annoyed by traffic noise (Yes/No)

Physiological disease dataset due to traffic noise (Containing following parameter)

Person ID: Person ID: An individual's specific ID given to them in the dataset
Noise Level dB: This represents the intensity of traffic noise exposure in decibels (dB).
Exposure Duration Hours: The number of hours per day that the individual is exposed to traffic noise.
Age: The age of the individual in years.
Gender: The gender of the participant (Male/Female).
Blood Pressure Level: The measured blood pressure of the individual

Cardiovascular Risk: An assessment of the risk level (categorized) for cardiovascular disease
Hearing Loss Level: A categorical measure representing the degree of hearing loss (if any) caused by prolonged exposure to traffic noise.
Sleep Disruption: A binary variable (Yes/No) that indicates if exposure to traffic noise disturbs the person's sleep.
Physiological Diagnosis: The final medical diagnosis for physiological health issues such as cardiovascular problems, hypertension, or hearing loss attributed to traffic noise

Psychological disease dataset due to traffic noise (containing following parameter)
Person ID: Person ID: An individual's specific ID given to them in the dataset
Noise Level dB: The decibel (dB) level of traffic noise exposure experienced by the individual
Exposure Duration Hours: The duration (in hours) of traffic noise exposure per day for each individual
Age: The age of the individual
Gender: The gender of the participant, categorized as Male or Female.
Stress Level: This variable is key to assessing how traffic noise contributes to increased stress levels
Anxiety Level: A self-reported measure of anxiety, categorized or scaled
Depression Level: A self-reported measure of depression severity, typically recorded on a scale
Sleep Disruption: A binary measure (Yes/No) indicating whether traffic noise disrupts the individual's sleep patterns.
Psychological Diagnosis: A formal diagnosis related to psychological conditions such as stress, anxiety, or depression, directly linked to traffic noise exposure

4.2 Model built using Random Forest Machine (RFM)

By creating a variety of decision trees on random data subsets, Random Forest Machine (RFM) is a potent ensemble learning technique that performs exceptionally well in classification and regression. Through bagging, it lessens overfitting, efficiently manages missing data, and offers insights into the significance of features. For intricate, real-world datasets in a variety of domains, RFM is dependable.

Fig. 2: Flowchart of RFM

Pseudo code of RFM

Import Libraries: Pandas handles data, train-test split separates training and testing data, Random Forest Classifier trains models, confusion matrix predicts outcomes, and Label Encoder turns category data into numerical form.

Load Datasets: The developer reads the physiological, psychological, and traffic noise exposure datasets using pd. read__csv().

Merge Datasets: They merge the physiological and psychological datasets on the Person ID column and then merge the result with the traffic noise exposure dataset on the same column.

Drop Duplicates: The developer removes any duplicate columns from the merged dataset using the drop () method.

Prepare Features and Target: They select relevant columns for the features (X) and designate the Annoyance Level column as the target variable (y).

Encode Data: They apply one-hot encoding to the feature set to convert categorical variables and map annoyance level to binary values (Yes=1, No=0).

Split Dataset: Pandas handles data, labels categorical data into numerical form, the Random Forest Classifier trains models, the confusion matrix predicts outcomes, and the train-test split separates data into training and testing.

Train Classifier: The developer initializes a Random Forest Classifier with a random state and fits it on the training data.

Make Predictions: They use the trained classifier to predict the target variable on the test data.

Generate Confusion Matrix: They calculate the confusion matrix to evaluate the model's performance.

Display Results: A printout of the confusion matrix is made for scoring analysis.

4.3 Model built using of ANN

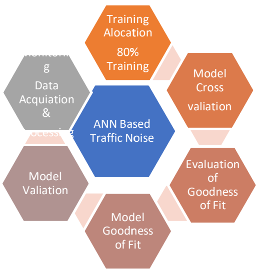

Fig.3: Flow diagram for ANN approach

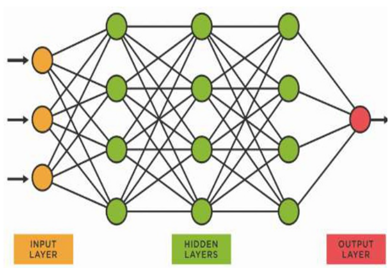

Fig.4: Architecture of neural network

Artificial Neural Networks (ANNs) represent intricate, non-linear data interactions by simulating the human brain. They are made up of weighted connections between input, hidden, and output layers. ANNs learn patterns using activation functions and back propagation. For efficient training and optimization, they modify weights using gradient descent techniques like SGD, Adam, and RMS prop.

Pseudo code of ANN:

The developer imports necessary libraries for data processing, model building, and evaluation

Load and Merge Datasets: The developer reads the physiological, psychological, and traffic noise datasets, then merges them on Person ID.

Drop Duplicates: Duplicate columns resulting from the merge are removed.

Prepare Features and Target: The developer selects the feature columns and encodes the target variable (Annoyance Level).

Split the Data: Both the training and test data sets are separated out of the data set.

Scale Features: The developer standardizes the feature values using a scaler.

Build ANN Model: An ANN model is built with two hidden layers and an output layer for binary classification.

Compile and Train Model: The developer constructs the model, which is then trained using the training data set.

Make Predictions: The developer uses the model to predict the test data.

Evaluate Model: The confusion matrix, classification report, and accuracy are generated and printed.

4.4 An Assessment of the Model

Using cross-validation approaches, the machine learning model's performance is verified by classification metrics. The model is viewed as a classification problem since the goal is to predict whether traffic noise nuisance is present (Yes/No). We use a confusion matrix and a classification performance score to evaluate its efficacy.

Analysis

A confusion matrix and cross-validation are used to assess the model's performance as a classification task. Accuracy is evaluated using key metrics such as True Positives, True Negatives, False Positives, and False Negatives, which show the percentage of accurate predictions in identifying traffic noise nuisance.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{F1-Score} = 2 * \frac{Precision \times Recall}{Precision + Rec} \quad (4)$$

The machine learning method successfully predicts traffic noise irritation using the confusion matrix and parameters including accuracy, precision, recall, and F1-score. These observations help make well-informed decisions on noise management and urban development.

5 Result and Discussion

5.1 Performance Evaluation of the RFM Model

The Random Forest Machine (RFM) model was evaluated using significant classification metrics such as accuracy, precision, recall, and F1-score. These metrics, which are based on demographic and traffic parameters, provide helpful information about how effectively the model predicts noise irritation (Yes/No).

Table 4: Classification report of RFM

Metric	Precision	Recall	f1-score	Support
0	0.632353	0.530864	0.577181	81
1	0.536585	0.67681	0.582781	69
Accuracy	0.58	0.58	0.58	0.58
Macro average	0.584469	0.584273	0.579981	150
Weighted average	0.5883	0.58	0.579757	150

The RFM model accurately predicts noise annoyance levels in 58% of situations, while the Random Forest Machine mode has moderate accuracy, precision (63%), and recall (53%).

Performance Interpretation

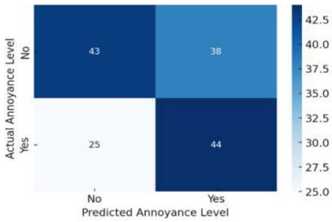

Fig.5: Confusion matrix of RFM

Based on the value given in Fig 5, the parameters are stated below
44 True Positives (noise discomfort) and 43 True Negatives (noise absence) were accurately predicted by the model. However, it missed 25 real cases (False Negatives), highlighting opportunities for improvement in sensitivity, and produced 38 False Positives, exaggerating displeasure.

5.2 Performance Evaluation of the ANN Model

Important classification metrics were utilized to evaluate an Artificial Neural Network (ANN) model, including F1-score, recall, accuracy, and precision. The model's ability to forecast noise discomfort (Yes/No) based on traffic and demographic data is usefully illustrated by these metrics. Using the ANN's ability to describe complex, non-linear interactions, these measures give a comprehensive picture of the model's success in forecasting noise annoyance. This helps identify areas that require further improvement and development.

Table 5: Classification report of ANN

Metric	Precision	Recall	f1-score	Support
0	0.58	0.44	0.5	81
1	0.49	0.62	0.55	69
Accuracy	0.53	0.53	0.53	150
Macro average	0.53	0.53	0.53	150
Weighted average	0.54	0.53	0.52	150

The ANN model's overall accuracy is 0.53, with 53% of predictions being accurate. However, it has moderate competence in predicting noise annoyance and no animosity, producing false positives despite a robust 62% recall. Improvements could be achieved through feature refinement and model tuning.

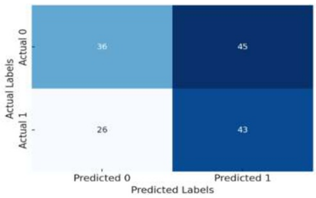

Fig.6: Confusion matrix of ANN

Performance Interpretation

As shown in fig 6, the model correctly predicted "Annoyance" in 43 instances, and "No annoyance" in 36 instances. However, it overestimated noise annoyance in 45 instances, leading to false alarms. In 26 instances, it predicted "No annoyance" but failed to detect actual noise irritation, indicating a missed detection of noise annoyance.

5.3 Comparison of Artificial Neural Networks (ANN) and Random Forest Machines (RFM) Using Classification Report and Accuracy as Measures

The Random Forest Machine (RFM) demonstrated superior accuracy, precision, and recall for predicting traffic noise irritation compared to the Artificial Neural Network (ANN). RFM was the more practical option for this work since it demonstrated greater reliability, even though both models performed similarly for "Annoyance" situations.

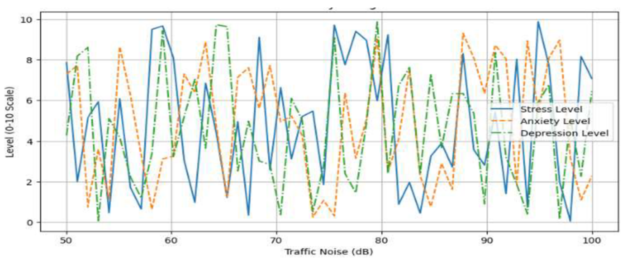

Fig. 7: Traffic Noise(dB) vs psychological level

- X-axis: Traffic Noise Levels (dB)
- Y-axis: Stress, Anxiety, and Depression Levels (Scale 0-10)
- Findings: As noise levels rise, the trends for stress, anxiety, and depression change, suggesting differing degrees of psychological impact. Increases in stress and anxiety seem to be correlated with noise levels higher than 70 dB. Depression levels fluctuate as well, albeit in slightly different ways.
- Fig 7 illustrates the intricate connection between noise and psychological health, demonstrating how exposure to noise can eventually worsen mental health issues. As shown in Fig 7

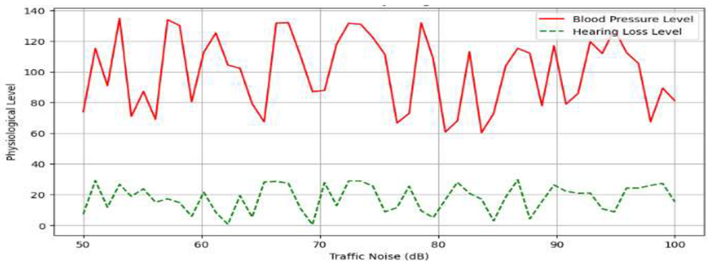

Fig.8: Traffic noise vs physiological level

- X-axis: Traffic Noise Levels (dB)
- Y-axis: Blood Pressure and Hearing Loss Levels
- Findings: Blood pressure rises noticeably in response to increasing traffic noise levels, suggesting that exposure to loud noises may cause hypertension or cardiovascular stress.
- A cumulative effect on auditory health is suggested by the pattern of increased Hearing Loss, especially at greater noise levels.
- The physiological hazards of prolonged exposure to traffic noise, such as high blood pressure and possible hearing impairment, are shown in Fig 8.

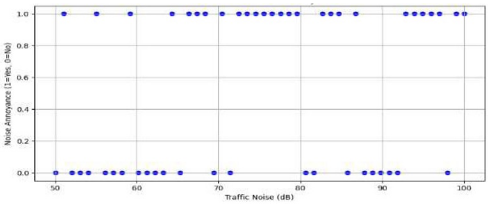

Fig.9: Traffic Noise vs Noise Annoyance level

- X-axis: Traffic Noise Levels (dB)
- Y-axis: Noise Annoyance (Binary: 1 = Yes, 0 = No)
- Findings: The scatter plot in Fig 9 reveals that traffic noise levels significantly increase the frequency of noise annoyance, with reports of irritation more correlated with higher noise levels.
- It would appear from this that traffic noise is a major source of discomfort for the public after a certain point.
- All of these graphs show that increased traffic noise levels may be quantified in terms of noise irritation as well as physical and mental wellbeing. Patterns show that:
- A particular level of noise (about 60–80 dB) greatly increases annoyance.
- Long-term noise exposure has an impact on mental health, increasing stress, anxiety, and grief.
- Noise levels are linked to hearing loss and high blood pressure, emphasizing the need for noise mitigation strategies in urban planning to protect public health.

6 Conclusion

Traffic noise levels have a substantial effect on both physiological and psychological health consequences, as this research has shown in Fig 10. Higher degrees of noise irritation, psychological stress, anxiety, and depression, as well as physiological disorders like blood pressure and hearing loss, are clearly correlated with increasing traffic noise levels (measured in dB).

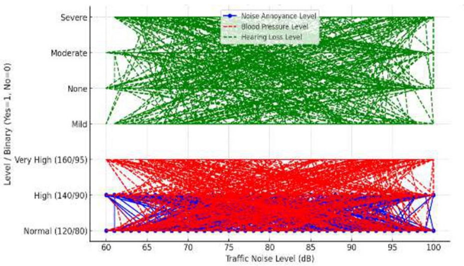

Fig.10: Trends of traffic noise(dB) vs Noise annoyance with psychological and physiological effect

7 Constraints and Room for Additional Work

The study's shortcomings include its reliance on publicly accessible statistics, its lack of high-resolution data, and its generalizability to other contexts regarding traffic noise and health outcomes in Ranchi, Jharkhand. Additionally, it ignores things like air pollution and socioeconomic conditions. Because of their intricacy, the study's Random Forest Machine and Artificial Neural Network models require more optimization. Subsequent investigations ought to encompass ecological concerns, juxtapose consequences with those of other emerging urban areas, augment data collection, and concentrate on feasible measures and regulations. Cutting-edge machine learning techniques could improve our understanding of how traffic noise affects urban populations and have an impact on public health and urban development strategies.

Disclosure of Interests:-The authors declare that they have no conflict of interest.

References

1. Sadique, R.: Assessing Effect of High Intensity of Continuous Traffic Noise on Mental Performance. Acta Neurophysiologica **4**(3), 1-9(2023)
2. Singh,G. P., and Bhardwaj,K. A.: Journal of Building Engineering, **67**, 105785 (2023) doi: 10.1016/j.jobe.2023.105785
3. Patel, R., Singh, P.K. and Saw, S.:A modeling approach for suitability evaluation of traffic noise prediction under mixed traffic situation in mid-sized Indian cities. Innovative Infrastructure Solutions, **9**(6), 183(2024)
4. Xie, W., Yu, Q., Fang, W., Zhang, X., Geng, J., Tang, J., Jing, W., Liu, M., Ma, Z., Yang, J. and Bi, J.:Data-driven approaches linking wastewater and source estimation hazardous waste for environmental management. Nature Communications **15**(1), 5432 (2024)
5. Patel, S.K. and Raj, A.K.: Traffic Noise Measurement and Mapping at Different Intersections of Ranchi City. 1-39(2025).Available at SSRN 5096780.
6. Wen, P.J. and Huang, C.: Noise prediction using machine learning with measurements analysis. Applied Sciences, 10(18), 6619 (2020)
7. Bravo-Moncayo, L., Lucio-Naranjo, J., Chávez, M., Pavón-García, I. and Garzón, C., 2019. A machine learning approach for traffic-noise annoyance assessment. Applied Acoustics, **156**, 262-270 (2019)
8. Vasava,N. V., et al.:Traffic Noise – A Health Stressor for Mankind. International Journal of Scientific Research and Engineering Development **2**(6), 188-193 (2019)
9. Manojkumar, N., Basha, K., and Srimuruganandam B.: Assessment, Prediction, and Mapping of Noise Levels in Vellore City, India. Noise Mapp. **6**, 38–51 (2019)
10. Borges Filho, O., Ribas, A., Gonçalves, C.G.D.O., Lacerda, A.B.M., Riesemberg, R. and Klagenberg, K.: Perception of noise pollution in a youth and adults school in Curitiba-PR. International archives of otorhinolaryngology, 21(04), 313-317 (2017)
11. Goswami, S., Swain, B.K. and Panda, S.K.: Assessment, analysis and appraisal of road traffic noise pollution in Rourkela city, India. Journal of Environmental Biology, **34**(5), pp.891-895(2013).

12. Gupta, S., Ghatak, C.: Environmental noise assessment and its effect on human health in an urban area. Int. J. Env. Sciences **1**(7), 1954-1964 (2011)
13. Kumar, K. and Jain, V.K.: Autoregressive integrated moving averages (ARIMA) modelling of a traffic noise time series. Applied Acoustics, 58(3), 283-294(1999)
14. Kumar, A., Prasad, U. and kumar Tiwari, R.: Analysing the Impact of Exogenous Determinants on Booking Cancellations With the GNN. In AI and Green Technology Applications in Society. pp. 313-352, IGI Global Scientific Publishing (2025)
15. Kumar, A., Kumari, A., Burman, R.K., Pandey, M., Kumar, N. and Kamaldeep, K.: November. Reservation Systems Cancellation Determination Using Machine Learning. In 2024 First International Conference for Women in Computing (InCoWoCo) (pp. 1-5). IEEE (2024).
16. Kumar, A., Prasad, U., Tiwari, R.K. and Pandey, V.: April. Research Study: Data Preprocessing Using Machine Learning for Prediction of Booking Cancellations. In International Conference on Recent Trends in Artificial Intelligence and IoT, pp. 164-182, Cham: Springer Nature Switzerland (2023).