ORIGINAL RESEARCH ARTICLE

Predicting Noise-Induced Hearing Loss among Elderly Residents Near Powerloom Industries Using Machine Learning

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ABSTRACT

Background: Environmental noise from small-scale industries, particularly powerloom clusters, is an under-recognized public health concern in India. Older adults in these settings are especially vulnerable due to age-related auditory decline compounded by chronic noise exposure. With expanding semi-urban industrialization and a growing elderly population, noise-induced hearing loss (NIHL) is emerging as a significant yet overlooked health burden. This study estimated the prevalence of NIHL among elderly residents near powerloom industries and evaluated key predictors and machine learning models for community-level screening.

Methodology: A community-based cross-sectional study was conducted in Kumarapalayam, Tamil Nadu, among 436 adults aged ≥60 years. Participants were categorized into an exposed group (n = 218; residing <500 m from powerloom units) and a control group (n = 218; residing >2 km away). Environmental noise levels were recorded using standardized sound level meter, showing substantially higher mean daytime noise exposure among the exposed group (77.6 ± 5.67 dB) compared to the control group (52.35 ± 3.95 dB). Hearing thresholds were assessed using validated mobile audiometry. Four ML classification models Random Forest, Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Logistic Regression were trained and evaluated to predict NIHL from demographic and exposure-related variables.

Results: Bilateral hearing loss was markedly higher in the exposed group (65.14%) than in the control group (35.18%). Random Forest demonstrated the strongest performance, achieving an accuracy of 93.4%, a precision of 93.0%, and a recall of 93.2%, outperforming the other models. Predictive variables such as age, proximity to powerloom units, duration of residence, and measured environmental noise levels played significant roles in model performance.

Conclusions: Elderly individuals residing near powerloom industries experience significantly greater noise exposure and a correspondingly higher prevalence of NIHL. Machine learning demonstrates strong potential as a practical, field-friendly tool for early identification of at-risk individuals in resource-limited settings.

Keywords: Hearing Loss, Elderly, Noise Exposure, Powerloom Industries, Machine Learning

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Introduction

Noise-induced hearing loss (NIHL) is a major but preventable public health concern, affecting approximately 430 million people worldwide, with chronic exposure to noise above 85 dB recognized as a primary cause.[1] Although extensively studied in occupational settings, particularly in textile and powerloom industries,[2] its impact on elderly residents living near these industrial zones who experience continuous environmental noise is largely unknown. Older adults are especially vulnerable due to age-related hearing decline (presbycusis) and common comorbidities, often resulting in speech comprehension difficulties, tinnitus, and hyperacusis.[3,4]

Machine learning (ML) is increasingly applied in healthcare for disease prediction, risk stratification, and patient monitoring,[5] yet it has not been used to predict NIHL in this population. By integrating factors such as age, noise exposure, duration of residence, and comorbidities, ML can identify high-risk individuals and support targeted community interventions. In audiology, artificial intelligence (AI) has already improved diagnostic accuracy, optimized hearing aid and cochlear implant performance, and expanded tele-audiology access.[6]

The study aimed to assess the prevalence of noise-induced hearing loss among elderly individuals residing near powerloom industries in comparison with those living in non-industrial areas, identify key demographic, clinical, and environmental factors associated with hearing loss, and develop and evaluate machine learning models using community-level variables to predict NIHL, with the objective of proposing a scalable, data-driven framework for early identification of high-risk elderly populations in industrially exposed communities.

Methodology

Study Design and Sample: A community-based cross-sectional study was conducted among 436 elderly adults (≥60 years). Participants were divided equally into an exposed group (n = 218) residing within 500 m of powerloom clusters and a control group (n = 218) residing >2 km away. The minimum required sample size was 218, calculated using power analysis with 80% power, 5% types I error, an effect size of 0.3, and a 95% confidence level. Equal recruitment of exposed and control participants was undertaken to enable epidemiological comparison between groups. Machine learning modeling was performed exclusively in the powerloom-exposed cohort (n = 218) to train and evaluate established machine learning algorithms for the prediction of hearing loss. Random sampling was employed within each stratum to minimize selection bias.

Inclusion criteria comprised ≥3 years residence in study area with documented noise exposure >70 dB (exposed) or <55 dB (control). Exclusion criteria included prior occupational noise exposure, documented hearing impairment, otological pathology, cranial trauma, ototoxic medication history, cognitive impairment and comorbid condition like hypertension, diabetes mellitus, cardiovascular conditions precluding informed consent.

Sampling Procedure: Systematic door-to-door sampling was employed. In each selected street, every 3rd household was approached based on a sampling interval calculated from the total number of households in the sampling frame divided by the required sample per cluster ($k = N/n \approx 3$). This ensured near-random household selection while maintaining feasibility. Only one eligible participant per household was randomly selected using a Kish grid method to avoid clustering bias.

Noise Exposure Assessment: Environmental noise levels were assessed using QAWACHH Digital Professional Sound Level Meters (Model 1351-EN-00; range: 30-130 dBA; accuracy: ±1.5 dB), compliant with IEC 651 Type 2 and ANSI S1.4 Type 2 standards. All instruments were laboratory-calibrated prior to deployment and underwent daily field calibration. Research personnel completed a standardized three-day training program in noise measurement procedures under the supervision of a certified acoustic engineer to ensure methodological consistency. Noise measurements were collected at four time points per day (08:00, 12:00, 16:00, 20:00) across three days, including one weekend day, to capture diurnal and weekday-weekend variability. For each household, six measurement locations were assessed three indoor (living room, bedroom, kitchen) and three outdoor (front entrance, backyard, and either the nearest point to the powerloom facility for the exposed group or the nearest major road for the control group). Each measurement session lasted 15 minutes, with sound levels logged every 5 seconds, and mean values were computed to derive representative exposure levels. The final aggregated exposure values showed substantially higher noise levels in the exposed group (77.66 ± 5.67 dB) compared with the control group (52.35 ± 3.95 dB), consistent with typical semi-urban residential environments and well below CPCB limits for the control area.

Hearing Assessment: Hearing function was evaluated using the Hearing Test Pro™ mobile audiometry application (version 2.4, e-audiologia.pl) installed on calibrated Samsung Galaxy A23 smartphones. The application has demonstrated high concordance with conventional pure-tone audiometry in prior studies,[7,8] with reported sensitivity of 93.3% and specificity of 94.2% for detecting hearing loss >25 dB HL. A local validation study conducted prior to the main survey (n = 60; age 60-85 years) showed substantial agreement with clinical audiometry (Cohen's κ = 0.84).

Frequency-specific validation revealed acceptable accuracy across audiometric ranges, consistent with published Bland-Altman limits of agreement: Low frequencies (250-1,000 Hz): ±4-6 dB; Speech frequencies (500-2,000 Hz): ±3-5 dB; and High frequencies (2,000-8,000 Hz): ±5-8 dB

Audiometric assessments were performed in quiet indoor environments with ambient noise maintained below 50 dBA. Daily calibration included verification with an acoustic calibrator and impedance checks of headphones. Tests exhibiting excessive intra-test variability (>10 dB threshold fluctuation) or high false-positive responses (>15%) were repeated to ensure reliability.

Prior to data collection, a two-week pilot study involving 30 participants (excluded from final analysis) was conducted to evaluate feasibility, refine data collection tools, and optimize procedural logistics. Based on pilot findings, adjustments were made to the questionnaire structure, testing environment setup, and participant scheduling protocols.

Hearing thresholds were classified based on World Health Organization criteria: Normal: ≤25 dB HL; Mild: 26-40 dB HL; Moderate: 41-60 dB HL; Severe: 61-80 dB HL; and Profound: >80 dB HL

Participants were categorized as having hearing loss if thresholds exceeded 25 dB HL in at least one ear. Pure-tone averages were calculated for low (250-1,000 Hz), speech (500-2,000 Hz), and high (2,000-8,000 Hz) frequency ranges.

Statistical Analysis and Machine Learning Implementation: Data normality was assessed using the Kolmogorov-Smirnov test, confirming non-normal distribution; therefore, continuous variables were summarized as medians with minimum-maximum values. Group comparisons were performed using the Kruskal-Wallis test, with statistical significance set at $p < 0.05$. The primary outcome for machine learning classification was the presence of hearing loss, defined using WHO criteria as >25 dB HL in one or both ears.

Four supervised ML algorithms Random Forest, Support Vector Machine (linear kernel), K-Nearest Neighbors (k = 5), and Logistic Regression were developed using 14 input features spanning demographic factors (age, sex, education), exposure parameters (residential duration, noise level), health variables (BMI, smoking, alcohol use, hypertension, diabetes, ototoxic medication use), and audiological symptoms (tinnitus, hyperacusis, speech perception difficulty). Data preprocessing included categorical encoding, missing value imputation (mean/mode), and feature scaling. The dataset was partitioned into an 80:20 training-testing split, and 5-fold cross-validation was applied for internal validation.

Feature importance was evaluated using two complementary methods: Gini importance (Mean Decrease in Impurity) within the Random Forest model and SHAP values to quantify marginal contributions of each predictor. Variables such as age, residential noise exposure, duration of residence, comorbidities, and tinnitus demonstrated the highest SHAP impact scores. Model performance was assessed using accuracy, precision, recall, F1-score, and area under receiver operating characteristic curve. All statistical and ML analyses were conducted using Python (scikit-learn).

Ethical Considerations: The study was approved by the Institutional Ethics Committee of JKKN College of Pharmacy (Approval No. JKKNCP/IEC-CER/0172I24/38, dated 17/02/2024) and adhered to the Declaration of Helsinki and ICMR guidelines. All participants received study information in Tamil, and written informed consent was obtained. A brief cognitive screening (Mini-Cog Tamil version) was performed to ensure capacity for consent; those with cognitive impairment were excluded. For participants >75 years or those with borderline comprehension, consent was reconfirmed through conversational assessment, and a legally authorised representative was involved when necessary. Privacy and confidentiality were ensured throughout data collection. No financial incentives were provided, but each participant received a free hearing assessment report and referral advice when hearing loss was identified. The study involved minimal risk, and all procedures were conducted in quiet indoor environments with noise levels maintained below 50 dB to ensure the validity of audiometric testing.

Results

Median age was comparable between exposed and control groups (64.0 vs 64.5 years), while residential noise levels were substantially higher among powerloom residents (77.7 dB vs 52.4 dB), along with a greater prevalence of tinnitus (23.9% vs 8.3%) and hyperacusis (14.2% vs 3.7%) (Table 1).

Bilateral hearing loss was markedly more common in the exposed group (65.1%) than in controls (35.8%), whereas normal hearing was less frequent among exposed participants (15.1% vs 42.2%) (Table 2).

Moderate-to-severe hearing loss in both ears was more prevalent among powerloom residents, while normal hearing predominated in non-powerloom residents (Table 3).

Among machine learning models, Random Forest demonstrated the highest accuracy (93.4%), followed by SVM (92.1%), outperforming logistic regression and KNN (Table 4).

The target variable for machine-learning classification was binary: hearing loss (>25 dB HL in one or both ears) versus normal hearing (≤25 dB HL bilaterally). In the exposed group (n = 218), 185 participants (84.86%) had hearing loss (43 unilateral; 142 bilateral), while 33 participants (15.14%) had normal hearing. This class distribution was considered during model evaluation, and precision, recall, F1-score, and accuracy were reported to account for class imbalance.

Table 1: Sociodemographic, Environmental, and Clinical Characteristics of Study Participants in Kumarapalayam, Tamil Nadu (N=218)

Characteristics	Exposed Group (n=218) (<500m from powerloom)	Control Group (n=218) (>2km from powerloom)	P Value
Sociodemographic Factors			
Age, years, median (min-max)	64.0 (60.0-90.0)	64.5 (60-90)	0.4815
Age categories, n (%)			0.6948
60-65 years	130 (59.6)	135 (61.9)	
66-70 years	30 (13.8)	39 (17.9)	
71-75 years	28 (12.8)	22 (10.1)	
>75 years	30 (13.8)	22 (10.1)	
Sex, n (%)			0.0534
Male	49 (22.5)	38 (17.4)	
Female	169 (77.5)	180 (82.6)	
Exposure Parameters			
Duration of residence, years	21.0 (3.0-48.0)	18 (3-41)	0.037
3-10 years, n (%)	78 (35.8)	30 (28.3)	
11-20 years, n (%)	47 (21.6)	34 (32.1)	
21-30 years, n (%)	32 (14.7)	29 (27.4)	
>30 years, n (%)	61 (28.0)	13 (12.2)	
Environmental Noise Measurements			
Average noise level at residence, dB	77.66 ± 5.67	52.35±3.95	
Health And Lifestyle Factors			
Current smoker, n (%)	49 (22.5)	38 (17.4)	0.0534
Alcohol use, n (%)	44 (20.2)	33 (15.1)	0.1162
Tinnitus, n (%)	52 (23.9)	18 (8.3)	<0.001
Hyperacusis, n (%)	31 (14.2)	8 (3.7)	<0.001

WHO: World Health Organization continuous variables presented as Mean±SD or median (min-max) based on distribution on P values; Independent t-test/Mann-Whitney U test for continuous; χ^2 test for categorical variables

Table 2: Hearing outcome distribution among study participants with 95% Confidence Intervals (CI)

Outcome	Exposed Group (n=218)		Control Group (n=218)	
	Cases (%)	Confidence Interval	Control (%)	Confidence Interval
Normal hearing (<25 dB HL)	33 (15.14)	10.99% to 20.50%	92 (42.2)	35.84% to 48.84%
Unilateral hearing loss	43 (19.72)	14.99% to 25.51%	48 (22.02)	17.03% to 27.98%
Bilateral hearing loss	142 (65.14)	58.60% to 71.15%	78 (35.78)	29.71% to 42.34%

Table 3: Distribution of grade of hearing loss in Powerloom and Non-Powerloom residents

WHO Grade of hearing loss	Powerloom residents (n=218)		Non-Powerloom residents (n=218)	
	Right ear (%)	Left ear (%)	Right ear (%)	Left ear (%)
Normal	61 (28)	48 (22)	118 (54)	113 (52)
Mild	74 (34)	74 (34)	66 (30)	73 (33)
Moderate	60 (27)	67 (31)	31 (14)	23 (11)
Severe	23 (11)	29 (13)	3 (2)	9 (4)

Table 4: Machine Learning Model Performance for Predicting Hearing Loss in Elderly Residents Exposed to Powerloom Noise

Model	Precision	Recall	F1-Score	Accuracy
Logistic Regression	81.3%	79.5%	79.9%	79.5%
Random Forest	93.0%	93.2%	93.0%	93.4%
SVM (Linear Kernel)	92.2%	92.2%	92.1%	92.1%
K-Nearest Neighbours	88.3%	88.6%	87.7%	88.6%

Receiver Operating Characteristic (ROC) (Figure 1) curves illustrating the discriminatory performance of the four supervised machine learning models Logistic Regression, Support Vector Machine (Linear Kernel), K-Nearest Neighbors (k = 5), and Random Forest in predicting hearing loss among elderly residents exposed to powerloom-associated environmental noise. The x-axis represents the False Positive Rate (1 - Specificity), and the y-axis represents the True Positive Rate (Sensitivity). The area under the ROC curve (AUC) quantifies model accuracy, with higher AUC values indicating superior classification performance. The Random Forest model demonstrated the highest AUC, consistent with its highest accuracy (93.4%), precision (93.0%), recall (93.2%), and F1-score (93.0%), followed by SVM and KNN.

The ROC curves highlight the strong predictive capability of ensemble methods for community-level hearing loss risk stratification. The curves were generated using the study dataset of powerloom-exposed elderly participants (n = 218).

Confusion matrix (figure 2) depicting the classification performance of the Random Forest model in predicting hearing loss (hearing threshold >25 dB HL in one or both ears) versus normal hearing among elderly participants. The x-axis denotes the predicted class (hearing loss vs normal hearing), and the y-axis denotes the actual observed class. The matrix displays the number of true positives (correctly identified hearing-loss cases), true negatives (correctly identified normal-hearing cases), false positives (normal individuals misclassified as hearing loss), and false negatives (hearing-loss individuals misclassified as normal). The high proportion of true positive and true negative classifications reflects the model's excellent discrimination ability, further supported by its overall accuracy of 93.4%. This figure supports the utility of Random Forest modeling as a reliable tool for early detection of noise-induced hearing loss in community settings. This matrix was derived from the study dataset of powerloom-exposed elderly residents (n = 218).

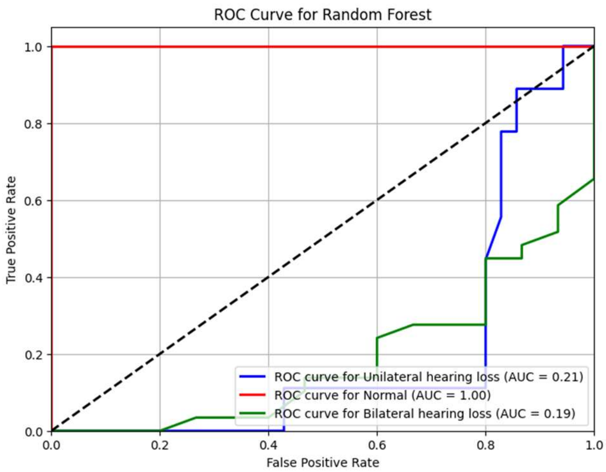

Figure 1: ROC Curve for Model Performance in Predicting Type of Hearing Loss

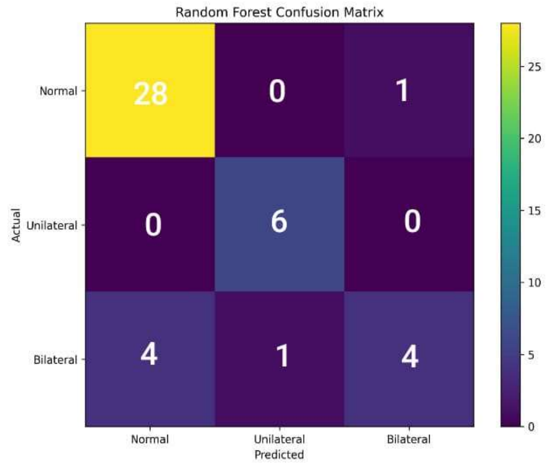

Figure 2: Confusion Matrix for Random Forest Model Performance

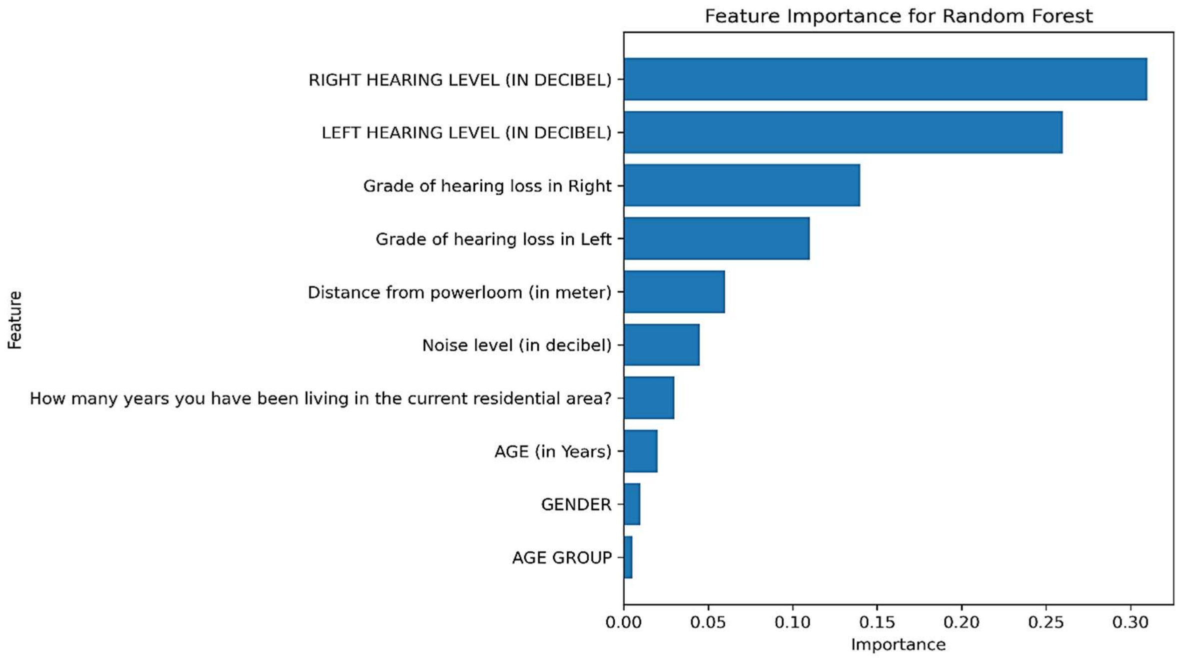

Figure 3: Feature importance derived from the Random Forest model for predicting hearing loss among elderly residents

Feature importance values represent the relative contribution of each predictor to the model's classification of hearing loss status (figure 3). The x-axis represents the relative feature importance score (mean decrease in impurity), and the y-axis lists the predictor variables included in the model. Higher importance scores indicate greater influence on model predictions. Importance estimates were calculated using the mean decrease in impurity across all decision trees in the Random Forest algorithm. These values reflect internal model behavior and should be interpreted as associative rather than causal relationships. Feature importance was computed using the study dataset of powerloom-exposed elderly participants (n = 218).

Discussion

The present study demonstrates a significantly higher prevalence of bilateral hearing loss among elderly residents living near powerloom industries (65.14%) compared to control populations (35.18%), with a Random Forest machine learning model achieving 93.0% accuracy in predicting hearing loss. These findings contribute to the growing body of evidence linking environmental noise exposure to accelerated hearing impairment in aging populations and highlight the potential of machine learning approaches for community-based hearing health surveillance.

Contextualization Within Environmental Noise Research: The exposed elderly group showed a higher bilateral hearing loss prevalence (65.14%) than community estimates such as the 38.3% reported by Chen X et al.[9] (2023), who also identified increased impairment risk near major roadways. The recorded noise levels, ranging from 101.6 to 109.8 dB(A), were evaluated in comparison with OSHA and WHO occupational noise exposure standards.[10]

The control group prevalence (35.18%) is consistent with age-related hearing loss patterns in developing regions, with Verma RR et al.[11] (2021) reported that hearing impairment prevalence was higher among elderly populations in India compared with younger age groups.

Machine Learning Performance in Context: Our Random Forest model achieved 88.6% accuracy, comparable to recent studies, despite using only demographic and exposure variables rather than complex audiometric data, similar to Machine learning models using NHANES data effectively predicted hearing loss and hearing thresholds, with Light Gradient Boosting showing the best performance (80.1% accuracy for mild hearing loss and >86% for higher thresholds); age, gender, blood pressure, and waist circumference emerged as key factors, highlighting the potential for early, risk-based hearing loss detection.[12]

Industrial Noise Exposure and Community Health: Textile mill weavers exposed to 101.3 ± 2.7 dBA show reduced hearing acuity.[13] Our community-based study extends this concern to nearby elderly residents, with 67% prevalence compared to 71.6% among workers,[14] highlighting cumulative health impacts from long-term residential exposure. Industrial noise often exceeds CPCB residential limits (55 dB day/45 dB night),[15] and inadequate buffer zones likely contribute to the elevated hearing loss observed.

Interaction Between Aging and Noise Exposure: Longitudinal research indicates that aging-related decline interacts with prior noise exposure. In the Framingham cohort, noise-affected ears showed faster threshold deterioration across frequencies, suggesting heightened vulnerability rather than a direct causal pathway.[16] Shared mechanisms such as oxidative stress, mitochondrial dysfunction, synaptopathy, and cochlear vascular compromise link presbycusis and NIHL. In C57BL/6 mice, early noise exposure intensified later oxidative stress and vascular dysregulation through pathways involving antioxidant imbalance and HIF-1α/VEGFC signaling.[4] Chronic noise also induces central auditory changes.[17] Early-life subclinical damage can prime delayed neural degeneration, accelerating age-related decline.[18]

Public Health Implications and Interventions: The hearing loss burden observed warrants coordinated public health action. The societal economic burden of age-related hearing loss is estimated at approximately $297,000 per affected individual over their lifetime. This substantial cost stems primarily from reduced employment opportunities, diminished workplace productivity, and elevated healthcare expenditures.[19] In 2019, the global economic burden of hearing loss exceeded $981 billion (PPP-adjusted), with 47% attributable to quality-of-life losses and 32% to additional health-related costs; 57% of total costs occurred in low- and middle-income countries, 6.5% were incurred among children aged 0-14 years, and a modelled 5% reduction in prevalence was associated with potential savings of approximately $49 billion worldwide. Even modest decreases in the prevalence or severity of hearing loss could prevent significant economic burdens on society.[20]

Mobile Audiometry Applications: Mobile audiometry supports community screening as a feasible option in resource-limited settings. Validation work from South Africa shows smartphone-based audiometry can perform reliably in untreated primary health-care clinics, with conventional thresholds exceeding 15 dB HL corresponding to smartphone thresholds within ≤10 dB in 92.9% of cases (average difference -1.0 dB ± 7.1 SD).[21] Yalamanchali S et al.[22] (2022) reported 89% sensitivity and 70% specificity in Indian populations. However, the lack of frequency-specific thresholds in our study limits distinguishing the NIHL 4 kHz notch from presbycusis' gradual slope.[23]

Comparison with Regional Studies: Regional studies show higher hearing loss in lower- and middle-income countries due to limited care and greater noise exposure;[24] our semi-urban industrial setting reflects this combined risk.

Comparison With Similar Indian NIHL Studies: Industrial and construction studies similarly report significant high-frequency loss, dose-response patterns, and modifiable workplace contributors.[25,26] Powerloom research further confirms the auditory impact of long-term loom noise.[14,27] Most Indian

NIHL research focuses on workers in transportation, industry, construction, or powerloom sectors, whereas our study examines non-workers community residents living near powerloom units. Evidence of gradual, bilateral loss in our sample indicates that community-level noise from powerlooms can approximate occupational intensity, underscoring the need to address residential noise regulation and screening.

Strengths and Limitations

Several limitations warrant consideration in interpreting our findings. The cross-sectional design precludes causal inference and cannot establish whether current hearing loss resulted from cumulative lifetime exposure or recent industrial noise. Longitudinal studies tracking hearing changes in relation to documented noise exposure would strengthen causality assessment.[28] The use of mobile audiometry, while enabling community-based screening, lacks the precision of clinical audiometry performed in sound-treated booths. This may have introduced misclassification bias, particularly in distinguishing mild degrees of impairment. The absence of frequency-specific audiometric data represents a significant limitation, as it prevented detailed characterization of audiometric notch patterns typically associated with noise-induced hearing loss. The study did not assess lifetime occupational or recreational noise exposure, which limits the ability to attribute observed hearing loss solely to current industrial noise sources. Individual noise dosimetry was not conducted, preventing quantification of dose-response relationships. Potential selection bias may also exist if healthier elderly individuals were more likely to participate.

The study's strengths include its community-based design, robust sample size, and use of validated mobile audiometry for real-world applicability. Additionally, integrating machine learning models enhanced predictive accuracy for early detection of hearing loss in vulnerable populations.

This study highlights several priorities for future research. Longitudinal cohort studies with baseline audiometry and regular follow-up would clarify the temporal relationship between industrial noise exposure and hearing loss progression. Environmental noise mapping combined with personal dosimetry would enable dose-response modeling. Inclusion of complete frequency-specific audiometric profiles would support more precise differentiation between presbycusis and noise-induced patterns. Incorporating biomarkers of oxidative stress and inflammation may elucidate mechanistic pathways underlying the interaction between noise and aging. Implementation research should evaluate culturally appropriate hearing conservation interventions for communities near industrial settings. The high accuracy of machine learning models suggests strong potential for risk-prediction tools that integrate environmental exposure data, demographic characteristics, and symptom-based screening.

Conclusion

The present study demonstrates a significantly higher prevalence of hearing loss among elderly residents living near powerloom industries, indicating that prolonged exposure to elevated environmental noise poses a substantial public health concern. Although the machine learning model showed encouraging predictive performance, these results should be interpreted as preliminary and require external validation before broader application. The findings highlight the need for targeted community screening programs for older adults in high-noise localities, stricter enforcement of residential noise regulations, and implementation of zoning strategies to mitigate industrial noise encroachment into living areas. Strengthening environmental noise surveillance and integrating periodic hearing assessment into geriatric care pathways may help reduce the long-term burden of preventable auditory impairment in industrially adjacent communities. Future research should prioritize longitudinal designs and detailed exposure assessments to better characterize the progression of noise-related hearing decline.

Individual Authors' Contributions: **VLK** conceptualized the study and was responsible for data collection, data entry, and drafting of the initial manuscript. **CTS** contributed to the literature review, provided methodological support, performed data analysis, prepared tables and figures, and critically revised the manuscript. **VN** guided the study design, supervised the research process, provided statistical guidance, coordinated the overall study, and gave final approval of the manuscript. **RJ** provided technical support in machine learning model development, validated the results, and contributed to manuscript editing and proofreading.

Availability of Data: The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Non-use of Generative AI Tools: This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

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