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Prediction of Noise-Induced Hearing Loss in the Forest Sector Using Machine Learning Techniques

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ABSTRACT

In this study, the effects of gender, age, total working time (years), working time in the sector (years), working time in a noisy environment (months), smoking, having a noisy hobby and inadequate use of ear protection equipment on noise-induced hearing loss (NIHL) were evaluated in the forest sector. The study included 1477 workers, consisting of 1247 (84.4%) males and 230 (15.6%) females. The population was aged between 18 and 60. The initial phase of the study focused on comparing regression algorithms to determine if eight independent variables contribute to NIHL in workers. The multiple linear regression algorithm was deemed the most effective in this category, yielding an R^2 value of 0.3079 when tested with a data size of 25%. The second phase of the study aimed to compare classification algorithms, exploring the degree of hearing loss, measured in dB, attributed to the same eight independent variables. The dependent variable for these algorithms was categorized as "NIHL present" or "NIHL absent". The random forest algorithm emerged as the most effective classification method, yielding an accuracy of 75% when tested with a data size of 20%. The findings of this study can guide the implementation of engineering controls to reduce noise levels, administrative controls such as limiting exposure time, and the use of personal protective equipment like hearing protection devices.

Keywords: Noise measurement, Machine learning, Noise-induced hearing loss (NIHL), Prediction

INTRODUCTION

Noise is defined as an unwanted sound that can have various negative effects on our physical and mental well-being. Excessive noise exposure can lead to hearing damage and can also cause stress, anxiety, and sleep disturbances. It is important to minimize exposure to excessive noise to protect our health. The sensitivity to noise and the level of hearing loss can vary from person to person, even when exposed to the same noise intensity and duration. Personal characteristics such as age, genetics, overall health, and previous noise exposure can influence an individual's susceptibility to noise-induced hearing loss. Noise-induced hearing loss (NIHL) is a type of hearing loss that is caused by exposure to loud sounds over an extended period of time. Many machines and tools used in the forest sector, which is one of the noisiest sectors, cause noise. Noise has a variety of mental and physical impacts that are related to health issues, such as hearing loss, sleeplessness, and psychological

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degradation (Çakıt, 2019). NIHL cannot be attributed only to the noise level in the environment. Since noise is a subjective concept, not only the noise level of the environment but also personal characteristics affect the degree of hearing loss.

Machine learning (ML) has revolutionized the way we analyze data by enabling us to automatically uncover complex correlations, patterns, and insights that may not be readily apparent through manual analysis. This has made it possible to extract valuable information from large and diverse datasets, ultimately leading to more informed decision-making in various fields (McKearney and MacKinnon, 2019). ML has indeed shown promise in the field of Audiology. By leveraging sophisticated algorithms, ML can effectively model and analyze the nonlinear relationships between various risk factors and patients' hearing thresholds. This enables audiology professionals to make more accurate predictions and informed decisions when assessing and managing patients' hearing health (Chang et al., 2019). Abdollahi et al. (2018) built eight ML models to predict sensorineural hearing loss (SNHL) after chemoradiotherapy, five of which had over 70% accuracy and precision. Other studies found similarly high accuracy with ML models predicting sudden sensorineural hearing loss (SSNHL) and hearing loss induced by ototoxicity. Different studies using various ML algorithms and inputs to predict risk factors for NIHL reported accuracies ranging from 64% to 99% (Aliabadi et al., 2015; Farhadian et al., 2015; Kim et al., 2011; Mohd Nawi et al., 2011; Yin et al., 2019; Zhao et al., 2019; Fan et al., 2022).

The main purpose of this study is to apply machine learning algorithms for estimating NIHL. The initial phase of the study aimed to compare regression algorithms, exploring the degree of hearing loss, measured in dB, attributed to the same eight independent variables. The second phase of the study focused on comparing classification algorithms to determine if eight independent variables contribute to NIHL in workers.

MATERIALS AND METHODOLOGY

Study Variables

The study included 1477 workers, consisting of 1247 (84.4%) males and 230 (15.6%) females. The population was aged between 18 and 60. The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Gazi University (June 5, 2023) for studies involving humans. Table 1 displays the description and categories of variables that are part of the data collection that was utilized for the investigation. In this study, the effects of gender, age, total working time (years), working time in the sector (years), working time in a noisy environment (months), smoking, having a noisy hobby and inadequate use of ear protection equipment on noise-induced hearing loss (NIHL) were evaluated in the forest sector.

Table 1. Variables in the data set.

Variable Name	Definition	Variable Type
Gender	Gender of the employee (Female/Male)	Categorical
Age	Employee's age	Nominal
Total working time (years)	The employee's total working hours until the date of hearing test	Nominal
Working time in the sector (years)	The employee's total working hours in the sector until the date of the hearing test.	Nominal
Working time in a noisy environment (months)	The total number of months the employee has worked in a noisy workplace.	Nominal
Smoking	Whether the employee smokes or not	Categorical
Noisy hobbies	If the employee possesses a hobby beyond their professional life that can be characterized as producing a significant amount of noise.	Categorical
Personal protective equipment use	Does the employee utilize ear protection equipment during their work?	Categorical
Noise – induced hearing loss (NIHL) (dB)	The employee's audiometry test result in dB	Nominal

Noise-Induced Hearing Loss (NIHL) and Audiogram Test

The audiometry test involves transmitting sounds at frequencies of 500, 1000, 3000, 4000, 6000, and 8000 Hz to both ears of the employee in a quiet cabin. The sounds are sent sequentially with increasing intensity. The employee is instructed to press a button whenever they hear a sound. The intensity of the sound that the employee cannot hear is recorded in the evaluation of the audiogram (Ozdemir, 2016). This evaluation provides information about the degrees of hearing loss, which can be seen in Table 2. Hearing loss is considered to be present when values exceed 20 dB.

Table 2. Hearing loss degrees (adapted from ANSI, 2018).

Hearing Threshold Level	Degree of Hearing Loss
−10 to 20 dB	Normal hearing
20 to 40 dB	Mild hearing loss
40 to 70 dB	Moderate hearing loss
70 to 90 dB	Severe hearing loss
90 dB or more	Profound loss

For classification algorithms, such as decision trees, support vector machines, or neural networks, it is indeed common to categorize the dependent variable (NIHL status) into two classes: "NIHL present" for values above 20 dB and "NIHL absent" for values of 20 dB and below. These algorithms can then be used to identify the factors that contribute to the presence or absence of NIHL among employees, and to develop predictive models for early detection and prevention.

On the other hand, regression algorithms, such as linear regression or random forest regression, can be applied to analyze the quantitative relationship between independent variables and the degree of hearing loss in decibels (dB) at specific frequencies, such as 4000 Hz. This approach helps in understanding the impact of workplace factors on the severity of hearing loss and can inform targeted interventions and control measures to mitigate NIHL risk.

RESULTS AND DISCUSSION

A total of twenty-four models were performed using eight distinct regression algorithms from the Python/Jupyter Notebook Scikit-Learn library. These models were trained with three different test data sizes (20%, 25%, and 30%) and underwent 10-fold cross-validation. Similarly, twenty-four models were established using eight different classification algorithms from the same library, following the same test data sizes and cross-validation process.

Performance Comparison of Regression Models

By utilizing a variety of performance measures, the model accurately determined the disparity between the actual and estimated values (Çakıt and Karwowski, 2015; Çakıt and Karwowski, 2017; Çakıt et al., 2020; Çakıt and Dağdeviren, 2022; Çakıt and Dağdeviren, 2023). The evaluation of regression models involves comparing various metrics such as root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and r-squared (R^2) values. The regression algorithm that exhibits the lowest RMSE, MSE, and MAE values, along with the highest R^2 score, is considered to be the best performed model. The performance analysis of these regression models is tabulated in Table 3.

Table 3. Performance comparison of machine learning algorithms for prediction.

	Algorithms	RMSE	MSE	MAE	MAPE	R^2
Test size = 20 %	Multiple linear regression	0.2715	0.0737	0.2232	0.1952	0.2679
	Ridge regression	0.2715	0.0737	0.2232	0.1952	0.2679
	Lasso regression	0.2695	0.0727	0.2211	0.1937	0.2785
	Elastic-net regression	0.2686	0.0722	0.2207	0.1932	0.2833
	Decision tree algorithm	0.2835	0.0804	0.2270	0.1961	0.2018
	Random forests algorithm	0.2752	0.0757	0.2263	0.1988	0.2478
	K-NN algorithm	0.2788	0.0778	0.2305	0.2004	0.2277
	Support vector regression	0.2730	0.0745	0.2242	0.1960	0.2598
Test size = 25 %	**Multiple linear regression**	**0.2637**	**0.0696**	**0.2159**	**0.1876**	**0.3079**
	Ridge regression	0.2687	0.0722	0.2211	0.1920	0.2814
	Lasso regression	0.2694	0.0726	0.2204	0.1921	0.2777
	Elastic-net regression	0.2680	0.0718	0.2197	0.1912	0.2851
	Decision tree algorithm	0.2881	0.0830	0.2353	0.2030	0.1739
	Random forests algorithm	0.2739	0.0750	0.2256	0.1964	0.2532
	K-NN algorithm	0.2820	0.0795	0.2315	0.2013	0.2088
	Support vector regression	0.2692	0.0725	0.2218	0.1928	0.2785
Test size = 30 %	Multiple linear regression	0.2729	0.0745	0.2227	0.1953	0.2848
	Ridge regression	0.2774	0.0769	0.2276	0.1988	0.2614
	Lasso regression	0.2782	0.0774	0.2270	0.1989	0.2567
	Elastic-net regression	0.2769	0.0767	0.2264	0.1981	0.2641
	Decision tree algorithm	0.2996	0.0898	0.2418	0.2123	0.1382
	Random forests algorithm	0.2818	0.0794	0.2294	0.2015	0.2376
	K-NN algorithm	0.2887	0.0833	0.2368	0.2074	0.2000
	Support vector regression	0.2779	0.0772	0.2281	0.1990	0.2584

The regression analysis of this study yielded the most favorable outcomes in terms of RMSE, MSE, MAE, and R^2 values when employing multiple linear regression with a test size of 25%, as indicated in Table 3.

Performance Comparison of Classification Models

Classification models using various performance metrics derived from a confusion matrix, such as accuracy, recall, precision, F-1 score and ROC score. The ROC score is particularly important for assessing a model's ability to distinguish between positive and negative classes, with higher values indicating better performance in this regard. Performance comparisons of classification models are shown in Table 4.

Table 4. Performance comparison of machine learning algorithms for classification.

	Algorithms	Accuracy	Recall	Precision	F1 score	ROC Score
Test size = 20 %	Binary logistic regression	0.7432	0.53	0.67	0.59	0.6941
	K-NN algorithm	0.7230	0.48	0.64	0.55	0.6675
	SVM	0.7399	0.39	0.75	0.52	0.6607
	Decision trees	0.7331	0.46	0.68	0.55	0.6709
	Random Forests	**0.7500**	**0.53**	**0.69**	**0.60**	**0.750**
	Naïve Bayes (Gauss)	0.7162	0.66	0.58	0.62	0.7041
	Naïve Bayes (Bernoulli)	0.7399	0.71	0.61	0.66	0.7334
	Stochastic Gradient Descent Classifier	0.7331	0.58	0.63	0.60	0.6973
Test size = 25%	Binary logistic regression	0.7054	0.46	0.61	0.52	0.6495
	K-NN algorithm	0.7027	0.38	0.62	0.48	0.6298
	SVM	0.7108	0.34	0.68	0.45	0.6255
	Decision trees	0.6432	0.49	0.49	0.49	0.6087
	Random Forests	0.7108	0.47	0.62	0.53	0.6554
	Naïve Bayes (Gauss)	0.7000	0.61	0.57	0.59	0.6788
	Naïve Bayes (Bernoulli)	0.7135	0.66	0.58	0.62	0.7016
	Stochastic Gradient Descent Classifier	0.6622	0.31	0.53	0.39	0.5809
Test size = 30 %	Binary logistic regression	0.7072	0.44	0.62	0.52	0.6481
	K-NN algorithm	0.6982	0.36	0.63	0.46	0.6227
	SVM	0.6982	0.33	0.65	0.44	0.6156
	Decision trees	0.7005	0.42	0.61	0.50	0.6386
	Random Forests	0.6982	0.44	0.61	0.51	0.6397
	Naïve Bayes (Gauss)	0.6892	0.59	0.56	0.57	0.6667
	Naïve Bayes (Bernoulli)	0.6914	0.63	0.56	0.59	0.6769
	Stochastic Gradient Descent Classifier	0.6621	0.42	0.53	0.47	0.6075

As shown in Table 4, the random forest algorithm provided the best results when tested with a data size of 20%, considering these metrics, suggests that it achieved a good balance between correctly identifying positive instances, minimizing false positives, and achieving high overall accuracy. Additionally, the cross-validation with 10 folds helps ensure that the results are more robust and less prone to overfitting or random variability. Corresponding confusion matrix is tabulated in Table 5.

Table 5. Confusion matrix of the random forest algorithm.

	Predicted negative	Predicted positive
Actual negative	167 (True negative)	25 (False positive)
Actual positive	49 (False negative)	55 (True positive)

Based on the ROC curve plot in Figure 1, it was determined that there was a "acceptable distinction" between individuals with NIHL and those without, as indicated by the ROC score of 75 % obtained using the random forest algorithm.

This score suggests that the algorithm is effectively identifying the presence of NIHL in the data with a reasonable level of accuracy. An ROC score of 75% is generally considered to be a good performance, as it demonstrates that the algorithm can differentiate between the two groups with a balance of true positive and false positive results.

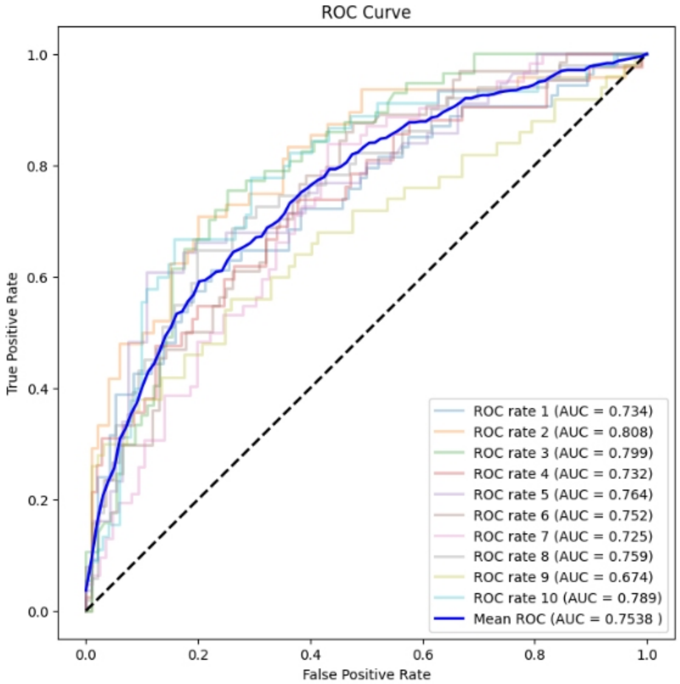

Figure 1: ROC curve graph of the random forest algorithm.

The random forest algorithm emerged as the most effective classification method, yielding an accuracy of 75% when tested with a data size of 20%.

Sensitivity analysis of the random forest algorithm revealed that the "working time in a noisy environment" was the most influential parameter, affecting outcomes at a rate of 35 % (Figure 2). This finding could be valuable for organizations and businesses to understand the importance of providing suitable working conditions for their employees, as it may significantly affect the accuracy of their classifications.

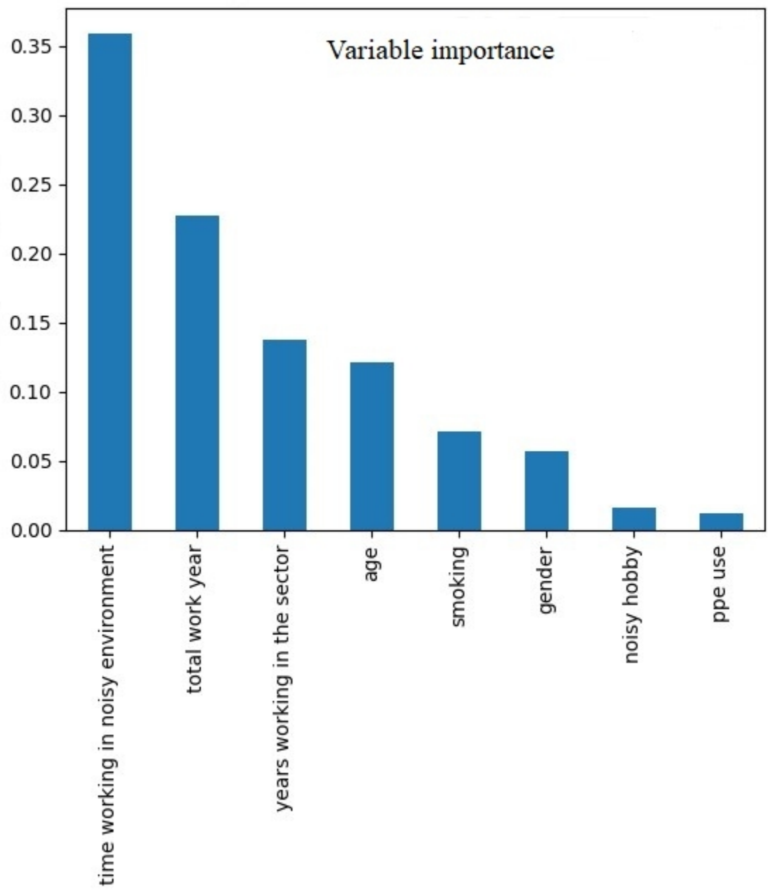

Figure 2: Sensitivity of input variables versus output variable for random forest algorithm.

CONCLUSION

Regression and classification algorithms are therefore useful methods for assessing NIHL in forest sector workers who are subjected to noise. The findings of this study can guide the implementation of engineering controls to reduce noise levels, administrative controls such as limiting exposure time, and the use of personal protective equipment like hearing protection devices. It also helps in monitoring and evaluating the effectiveness of the hearing conservation program over time. By leveraging machine learning techniques, researchers and occupational health professionals can gain valuable insights to improve workplace conditions and protect employees from the adverse effects of noise exposure. Additional research is anticipated to enlist a greater number of participants and incorporate additional predictors that are pertinent to noise-induced hearing loss. This will allow for a comprehensive exploration of the underlying causes of noise-induced hearing loss or related issues, including hidden hearing loss, noise-induced tinnitus, and hyperacusis. In conclusion, by sharing the collected data among researchers and increasing the sample sizes, the field of NIHL research and occupational health can benefit from the development and implementation of more advanced and robust machine learning techniques, such as deep learning. This collaborative approach will likely result in improved models for identifying and preventing NIHL, ultimately benefiting the affected individuals and society as a whole.

REFERENCES

ASA/ANSI S3.6–2018 (R2023): Specification For Audiometers. https://blog.ansi.org/asa-ansi-s3-6-2018-r2023-audiometers-specification/ Accessed 15 Jan 2024.

Aliabadi, M., Farhadian, M., & Darvishi, E. (2015). Prediction of hearing loss among the noise-exposed workers in a steel factory using artificial intelligence approach. International archives of occupational and environmental health, 88, 779–787.

Abdollahi, H., Mostafaei, S., Cheraghi, S., Shiri, I., Mahdavi, S. R., & Kazemnejad, A. (2018). Cochlea CT radiomics predicts chemoradiotherapy induced sensorineural hearing loss in head and neck cancer patients: a machine learning and multi-variable modelling study. Physica Medica, 45, 192–197.

Chang, Y. S., Park, H., Hong, S. H., Chung, W. H., Cho, Y. S., & Moon, I. J. (2019). Predicting cochlear dead regions in patients with hearing loss through a machine learning-based approach: A preliminary study. PLoS One, 14(6), e0217790.

Çakıt, E. (2019). Analysis of Noise Level in a Campus Area: Case Study for Gazi University Maltepe Campus. Ergonomics International Journal, 3(4), 1–8.

Çakıt, E., & Karwowski, W. (2015). Fuzzy inference modeling with the help of fuzzy clustering for predicting the occurrence of adverse events in an active theater of war. Applied Artificial Intelligence, 29(10), 945–961.

Çakıt, E., & Karwowski, W. (2017). Predicting the occurrence of adverse events using an adaptive neuro-fuzzy inference system (ANFIS) approach with the help of ANFIS input selection. Artificial Intelligence Review, 48(2), 139–155.

Çakıt, E., Karwowski, W., & Servi, L. (2020). Application of soft computing techniques for estimating emotional states expressed in Twitter® time series data. Neural Computing and Applications, 32, 3535–3548.

Çakıt, E., & Dağdeviren, M. (2023). Comparative analysis of machine learning algorithms for predicting standard time in a manufacturing environment. AI EDAM, 37, e2.

Çakıt, E., & Dağdeviren, M. (2022). Predicting the percentage of student placement: A comparative study of machine learning algorithms. Education and Information Technologies, 27(1), 997–1022.

Fan, B., Wang, G., Han, H., Li, B., Wang, L., Qu, C., Zhang, X., Liu, H., Sun, Z., Zhou, Y., Zhang, Y. and Wu, W. (2022). Machine Learning Model Identifies Genomic Variation in Noise-Induced Hearing Loss via Wholeexome Sequencing. Research Square, Vol. 2. Website: https://www.researchsquare.com/article/rs-1829497/v2.

Farhadian, M., Aliabadi, M., & Darvishi, E. (2015). Empirical estimation of the grades of hearing impairment among industrial workers based on new artificial neural networks and classical regression methods. Indian journal of occupational and environmental medicine, 19(2), 84.

Kim, Y. S., Cho, Y. H., Kwon, O. J., Choi, S. W., & Rhee, K. Y. (2011). The risk rating system for noise-induced hearing loss in Korean manufacturing sites based on the 2009 survey on work environments. Safety and health at work, 2(4), 336–347.

McKearney, R. M., & MacKinnon, R. C. (2019). Objective auditory brainstem response classification using machine learning. International journal of audiology, 58(4), 224–230.

Nawi, N. M., Rehman, M. Z., & Ghazali, M. I. (2011). Noise-induced hearing loss prediction in Malaysian industrial workers using gradient descent with adaptive momentum algorithm. International Review on Computers and Software, 6(5), 740–748.

Ozdemir, M. (2016). "Investigation of Noise-Induced Hearing Loss in Employees in Small-Scale Body Works", Occupational Health and Safety Specialization Thesis, The Republic of Türkiye Ministry of Labor and Social Security, Ankara.

Yin S., Wang H., Jiang Z. and Huang S. (2019). Noise-Induced Hearing Loss and It's Individual Susceptibility Laryngo-Rhino-Otologie 2019; 98(S02): p. 159.

Zhao, Y., Li, J., Zhang, M., Lou, Y., Xie, H., Tian, Y. and Qui, W. (2019). Machine Learning Models for the Hearing Impairment Prediction in Workers Exposed to Complex Industrial Noise: A Pilot Study. Ear and Hearing, 40(3). pp. 690–699.