Iran J Public Health, Vol. 53, No.7, Jul 2024, pp.1537-1548

Original Article

Application of Machine Learning Algorithms to Analyze the Clinical Characteristics of NIHL Caused by Impulse Noise and Steady Noise

Boya Fan [1,2,3], Gang Wang [2], Wei Wu [1,2]

1. *Department of Otorhinolaryngology Head and Neck Surgery, The 306th Hospital of PLA-Peking University Teaching Hospital, Beijing, 100101, China*
2. *Department of Otorhinolaryngology Head and Neck Surgery, PLA Strategic Support Force Characteristic Medical Center, Beijing,100101, China*
3. *Peking University Health Science Center, Beijing, 100191, China*

***Corresponding Author:** Email: ent306ww@126.com

(Received 12 Jun 2023; accepted 14 Aug 2023)

Abstract

Background: Occupational hearing loss of workers exposed to impulse noise and workers exposed to steady noise for a long time may have different clinical characteristics.

Methods: As of May 2019, all 92 servicemen working in a weapon experimental field exposed to impulse noise for over 1 year were collected as the impulse noise group. As of Dec 2019, all 78 servicemen working in an engine working experimental field exposed to steady noise for over 1 year were collected as the steady noise group. The propensity score matching (PSM) model was used to eliminate the imbalance of age and working time between the two groups of subjects. After propensity score matching, 51 subjects in each group were finally included in the study. The machine learning model is constructed according to pure tone auditory threshold, and the performance of the machine learning model is evaluated by accuracy, sensitivity, specificity, and AUC.

Results: Subjects in the impulse noise group and the steady noise group had significant hearing loss at high frequencies. The hearing of the steady noise group was worse than that of the impulse noise group at speech frequency especially at the frequency of 1 kHz. Among machine learning models, XGBoost has the best prediction and classification performance.

Conclusion: The pure tone auditory threshold of subjects in both groups decreased and at high frequency. The hearing of the steady noise group at 1 kHz was significantly worse than that of the impulse noise group. XGBoost is the best model to predict the classification of our two groups. Our research can guide the prevention of damage caused by different types of noises.

Keywords: Noise-induced hearing loss; Impulse noise; Steady noise; Machine learning

Introduction

Military operators are easily exposed to various noises. These noise environments are more complex than those exposed to factory personnel, such as impulse noise from weapons and explosions, and steady noise from engines of vehicles, aircraft, and ships(1). Unlike the usual steady noise, impulse noise is defined as a single burst of noise with a duration of less than 1 second and a peak value of 15 dB higher than the background noise. In previous studies, multiple shipborne, ground, air transport, and weapon platforms created a noise environment of 110 dBA during operations (1, 2). Noise-induced hearing loss (NIHL) is a major health risk among military personnel due to excessive noise exposure throughout their military career (3). The standards for permissible occupational noise exposure, according to National Institute for Occupational Safety and Health, is for an 8-hour workday not to exceed 85 to 90 dBA. However, the output of military weapons and machinery can easily exceed these permissible levels (4). The analysis of different types of military noise will help us to better protect the hearing of servicemen.

In special operation posts that may be exposed to different noises for a long time, hearing loss and tinnitus are common consequences of workers exposed to high-intensity noise(5). The main impact of hearing loss among adults, especially noise-induced hearing loss, is high-frequency hearing loss and may cause communication barriers to some extent, which may adversely affect the relationship with family and friends and cause difficulties in the workplace. Untreated hearing loss also has indirect health, psychosocial and economic effects, and has adverse effects on social isolation and quality of life decline of hearing-impaired individuals (6). Impulse noise is discontinuous and consists of irregular pulses or noise spikes with short duration and large amplitude. In the military environment, the impulse noise generated by weapons is the most common. Hazards are associated with high levels of noise in military environments, which may physically damage fragile cells and structures in the inner ear, leading to tinnitus and temporary and possibly permanent hearing loss. For steady noise, these effects may appear after long-term repeated exposure. For impulse noise, a single unprotected exposure may cause irreversible damage. If the servicemen are exposed to impulse noise for a long time, the chances of hearing loss will be greatly increased. Although theoretically, NIHL can be prevented with sufficient protective measures. So far, NIHL is still the main health burden for soldiers. An ideal prediction model can reduce the hearing loss of servicemen.

Occupational NIHL mainly occurs in mining, construction, manufacturing plants, and the military (7). In past studies, there were many investigations on the hearing of veterans, mainly focusing on the research on the damage of high-frequency hearing threshold. The hearing loss of personnel exposed to military noise would be aggravated by environmental noise, which was more serious than the age factor (8-10). Many studies have shown that military noise exposure causes the greatest hearing loss at 4, 6, and 8 kHz. Moreover, NIHL may cause tinnitus (8, 11). In the past, machine-learning methods were also used to distinguish different exposure environments through listening situations (12, 13). However, the method of machine learning is single, and it is impossible to find an optimal algorithm. In addition, they only distinguish the sound pressure level for industrial noise, and cannot distinguish different types of noise.

In previous studies, the classification of impulse and steady noise was not detailed, and the investigation and classification of environmental noise were relatively general. Although some studies have classified military noise to some extent, in the previous NIHL study, the noise exposure of the included population may be complex (11, 14-15). It is impossible to distinguish the different impacts of different military noises, especially the possible impacts of steady noise and impulse noise. In our study, military operators were engaged in a more specific and consistent position, and the noise exposure was characterized by long daily duration.

For a long time, the research on the damage of steady noise and impulse noise to hearing has been controversial and little research has been done. Therefore, it is particularly important to select appropriate research objects to carry out the hearing loss caused by military steady noise and impulse noise and build a classification model to better identify the exposed environment.

Materials and Methods

Participants

As of May 2019, all 92 servicemen working in a weapon experimental field exposed to impulse noise for over 1 year were collected as the impulse noise group. As of Dec 2019, all 78 servicemen working in an engine working experimental field exposed to steady noise for over 1 year were collected as the steady noise group. All subjects in the two groups were asked to have no family history of hearing loss, ototoxic drug use, or nervous system disease. They were no abnormal symptoms of the hearing system such as conscious hearing loss, tinnitus, and ear tightness before work, and successfully passed the routine specialized physical examination for enlistment. They were also asked to be generally healthy and had never experienced traumatic brain injury. The subjects of this study stated that they did not use ear plugs or other protective devices in their previous work. Among them, servicemen from the weapon experimental field are 20 to 59 yr old and have worked for 1 to 36 yr. Servicemen from the engine working experimental field are 21 to 55 yr old and have worked for 1 to 30 yr. Due to the particularity of the working environment and military operations, the subjects in both groups were all males.

Data Collection Methods

In the steady noise group, the steady noise test was carried out according to the different working environments of the subjects, and 20 tests were completed to test the noise conditions of different engine workshops at the test sites. In the impulse noise group, the impulse noise test was carried out for different weapons. Overall, 18 tests were completed to test the impulse noise exposure of different posts at the test site. Using a handheld acoustic analyzer (Danish B&K, BK2250), on-site detection of noise acoustic parameters in the subject's work positions was conducted. For impulse noise, we calculate the average peak sound pressure level of the noise. For steady noise, we calculate the average A-weighted sound pressure level of the noise.

Hearing test method: We used pure tone audiometry (Danish Otometrics, Astera) to test the hearing function in both ears of the subjects. In May 2019, we conducted pure tone audiometry on subjects in the impulse noise group. In Dec 2019, we conducted pure tone audiometry on subjects in the steady noise group. Then compare the hearing loss in the results of pure tone audiometry at 0.25 kHz, 0.5 kHz, 1 kHz, 2 kHz, 3 kHz, 4 kHz, 6 kHz, and 8 kHz of the steady noise group and the impulse noise group. Speech frequency is the average value of the hearing threshold at 0.25, 0.5, 1, and 2 kHz, while high frequency is the average value of the hearing threshold at 3, 4, and 6 kHz.

According to the working years exposed to noise, subjects are divided into two groups: the ≤ 10 yr group and the>10 yr group. Regarding the grouping, the hearing impairment of the subjects caused by impulse noise and steady noise during the working years exposed to noise is analyzed.

Statistics

R (4.2.1) was used for statistical analysis. Quantitative data are expressed as mean ± standard deviation (SD). Age, working hours, and hearing threshold, which are consistent with the continuous measurement data of normal distribution, were tested by *Student t*. $P < 0.05$ was considered statistically significant. The propensity score matching (PSM) method was adopted with a ratio of 1:1, to overcome the data imbalance in the grouping analysis process. Boxplot and line charts were used to show the visualization of the hearing condition of the two groups of subjects.

Machine learning

To distinguish different military operating environments from the differences in hearing thresholds of the two groups of personnel, to predict different hearing loss that may occur in different military operating environments. Four machine learning methods were tested, including logistic regression (LR), random forest (RF), XGBoost (XGB), and support vector machine (SVM). A detailed description of the above algorithms can be found in other studies (16, 17). In the two groups of subjects, 60% of the subjects were randomly selected as the training set and 40% as the test set. Use 10-fold cross validation to train four machine learning models in the training set, and put the trained models in the test set to see the performance.

Model performance evaluation adopts accuracy, sensitivity, and specificity, where accuracy=(TP+TN)/(TP+FP+FN+TN),sensitivity=TP/(TP+FN), specificity=TN/(TN+FP), T=true, F=false, P=positive, N=negative. The ROC curve is generated by comparing the true positive rate (TPR) and false positive rate (FPR) under various threshold settings, while AUC represents the area under the ROC curve. The AUC of a model with good predictability is close to 1. We use the possibility of the prediction made by the four machine learning methods to visualize the actual grouping and the predicted grouping according to the hearing of the subjects in different groups.

Ethics approval and consent to participate

The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by the ethical committee of PLA Strategic Support Force Characteristic Medical Center (No. K2019 (03) and informed consent was taken from all individual participants.

Results

Groups' characteristics

Ninety-two servicemen were recruited from a weapon experimental field as the impulse noise group. They were generally exposed to the impulse noise generated by weapons and worked more than 6 h a day. Overall, 78 servicemen were recruited from the engine experimental field as the steady noise group. They were generally exposed to the steady noise generated by the engine for a long time, and their daily working hours were more than 6 hours.

Table 1 shows the age of the steady noise group is significantly greater than that of the impulse noise group. Through the PSM method, age and working time are included in the logistic regression model, and age and working time are matched to eliminate the differences between groups. After matching, 51 subjects were finally included in each group. Finally, age and working time, which may have a significant impact on the hearing condition, were controlled. Table 2 shows the baseline of age and work time of 51 subjects in each group after matching.

Table 1: Comparison of age and working time between the impulse noise group and the steady noise group before PSM

Group	*Impulse Noise Group（*N=92）*	*Steady Noise Group（*N=78）*	*T*	*P*
Age(yr)	31.23±8.98	34.15±8.42	3.080	0.002
Work Time (Years)	9.81±8.4	8.81±8.04	1.114	0.266

*n: Number of subjects in each group.

Table 2: Comparison of age and working time between the impulse noise group and the steady noise group after PSM.

Group	*Impulse noise group (*n=51)*	*Steady noise group (*n=51)*	*t*	*P*
Age(yr)	33.75±8.35	33.75±8.12	0.000	1.000
Work time (years)	10.28±8.39	10.22±8.54	0.051	0.959

*n: Number of subjects in each group.

Hearing condition

According to the noise measured at several points, the average peak sound pressure level of impulse noise in the weapon experimental field is 145 dB, and the average A-weighted sound pressure level of steady noise in the engine working experimental field is 81 dB. Table 3 shows the hearing threshold of the two groups of military operators increases with the increase in frequency. It is the highest at 6 kHz and the average value exceeds 25 dB. This is also similar to the previous study of noise-induced hearing loss. At the speech frequency of pure tone audiometry, especially at 1 kHz, the hearing of people in the steady noise group was significantly worse than that in the impulse noise group, with statistical significance ($P < 0.05$). As two groups of subjects were exposed to noise, the impulse noise group and the steady noise group suffered from hearing loss at high frequencies and the damaging effect was similar. However, at the speech frequency, the hearing of the subjects in the engine experimental field is significantly worse than that in the weapon experimental field. Figures 1 and 2 show the hearing condition of two groups of subjects at each frequency by visualizing way.

In the impulse noise group, 33 people worked for less than or equal to 10 yr and 18 people worked for more than 10 yr. In the steady noise group, 34 people worked for less than or equal to 10 yr and 17 people worked for more than 10 yr. According to the results in Table 4 and Fig. 3, when working for a short period, steady noise will cause more damage to hearing than impulse noise at the speech frequency (P is 0.001), especially at the frequency of 1 kHz (P is 0.002). There is also a slight difference in the frequency of 250 Hz (P=0.081). With the increase of working years, the damage of steady noise and impulse noise to hearing is aggravated, but the difference is not obvious.

Table 3: Comparison of pure tone audiometry thresholds between impulse noise group and steady noise group (mean±SD)

Frequency (khz)	*Impulse noise group (N=102)*	*Steady noise group (N=102)*	*t*	*P*
Speech frequency	14.71±4.87	16.94±4.99	2.028	0.001
High frequency	24.02±12.87	22.29±13.07	0.953	NS
0.25	15.25±5.94	16.13±6.45	1.078	NS
0.5	16.96±6.30	16.18±6.86	0.030	NS
1	14.17±6.06	17.21±7.63	5.216	0.002
2	16.32±7.74	15.88±7.43	0.728	NS
3	18.28±11.64	18.24±10.52	0.897	NS
4	22.79±15.39	23.09±16.71	0.407	NS
6	28.92±17.54	29.85±19.27	1.384	NS
8	24.02±15.67	23.33±18.99	0.282	NS

N: Number of ears in each group.

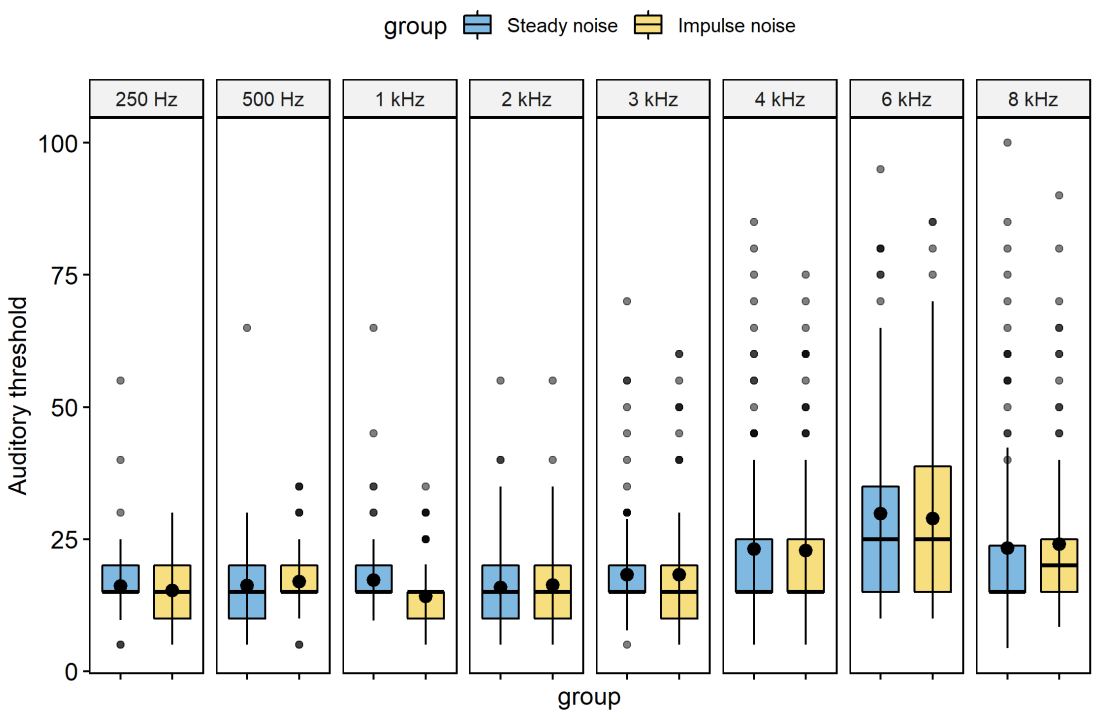

Fig. 1: Boxplot of pure tone auditory threshold results in impulse noise group and steady noise group

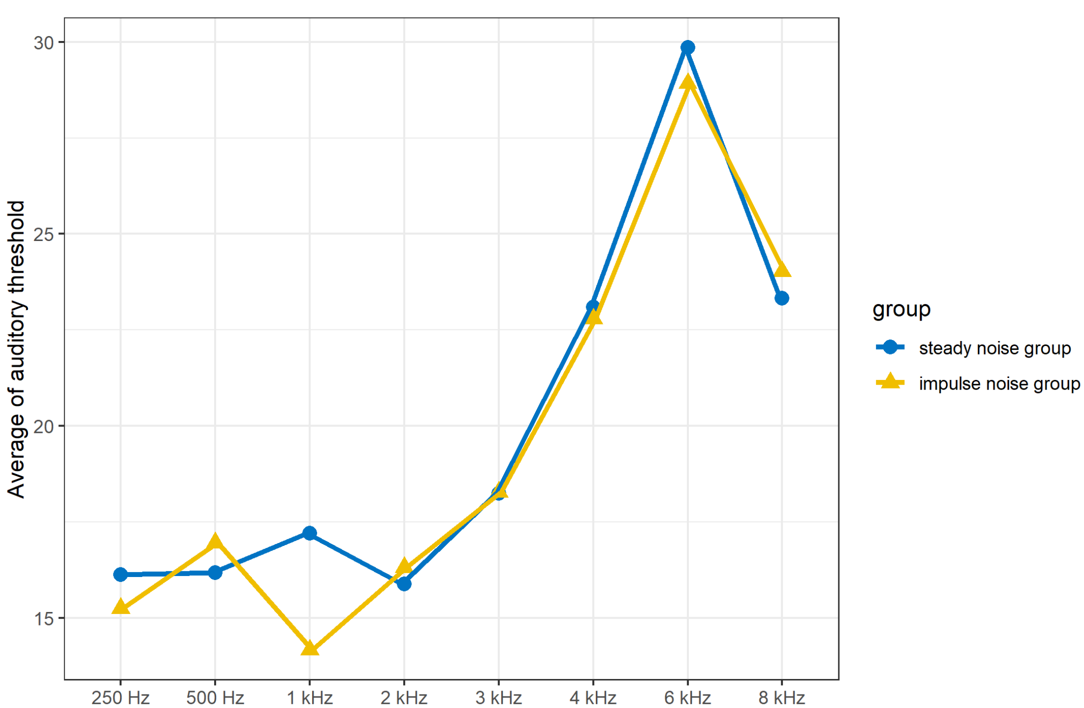

Fig. 2: Line Chart of the average of pure tone auditory threshold in impulse noise group and steady noise group

Table 4: Pure tone audiometry thresholds of the two groups grouped by work time (mean±SD)

Worktime group	***≤10 year***			***>10 year***		
Frequency（khz）	Impulse noise group (N=102)	Steady noise group (N=102)	*P*	Impulse noise group (N=102)	Steady noise group (N=102)	*P*
Speech frequency	12.88±3.45	16.18±4.30	<0.001	18.06±5.35	18.46±5.93	NS
High frequency	20.81±10.47	20.59±11.40	NS	29.91±14.82	25.69±15.54	NS
0.25	13.64±4.69	15.07±4.77	0.081	18.19±6.88	18.24±8.61	NS
0.5	14.92±5.00	15.51±4.97	NS	20.69±6.78	17.50±9.55	NS
1	12.27±4.49	16.32±5.44	<0.001	17.64±7.02	18.97±10.64	NS
2	15.00±6.20	14.78±5.82	NS	18.75±9.59	18.09±9.61	NS
3	15.23±7.91	17.06±8.47	NS	23.89±14.98	20.59±13.58	NS
4	19.47±12.74	21.40±16.70	NS	28.89±17.97	26.47±16.45	NS
6	25.98±16.37	27.13±19.19	NS	34.31±18.56	35.29±18.54	NS
8	21.21±14.17	21.1±17.19	NS	29.17±17.13	27.79±21.75	NS

N: Number of ears in each group.

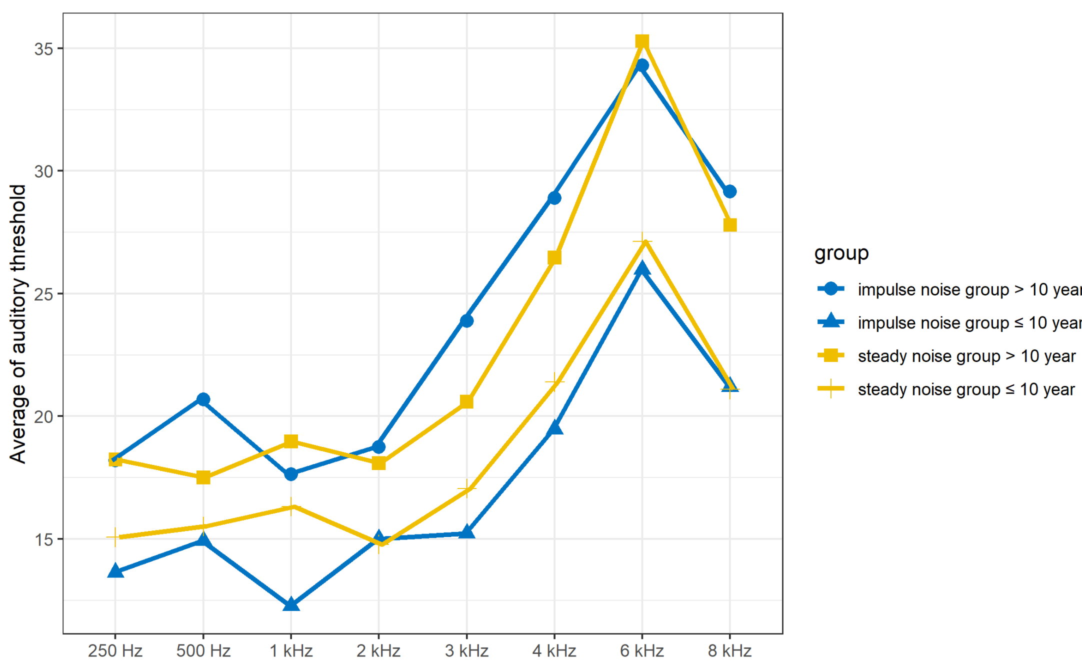

Fig. 3: Line Chart of the average of auditory threshold in impulse noise group and steady noise group

Machine learning predicts the working environment of different subjects according to hearing loss

According to hearing loss, we regard impulse noise and steady noise as two types and take the hearing of each frequency as a feature. After 10-fold cross validation in the training set, the trained model was used in the test set. For the noise exposure of subjects, compared with XGB and RF: 0.716(0.605, 0.811), the accuracy of LR and SVM is reduced. Table 5 shows the performance of the classifier used, and shows that random forests are significantly better than the results of logical regression and decision trees, which show more or less similar results in accuracy, sensitivity, specificity, and ROC area. In AUC (Fig. 4), XGB performs best (0.807). Overall, XGB is the best model in our dataset. Figure 5 shows the confusion matrix of the four machine learning algorithms, which shows the classification prediction of the four machine learning algorithms in the test set.

Table 5: The performance for LR, RF, SVM, and XGB in the testing samples

Model	*Accuracy (95%CI)*	*Sensitivity*	*Specificity*	*AUC*
LR	0.654(0.540, 0.757)	0.600	0.707	0.740
RF	0.716(0.605, 0.811)	0.650	0.781	0.762
SVM	0.642(0.528, 0.746)	0.575	0.707	0.641
XGB	0.716(0.605, 0.811)	0.650	0.781	0.807

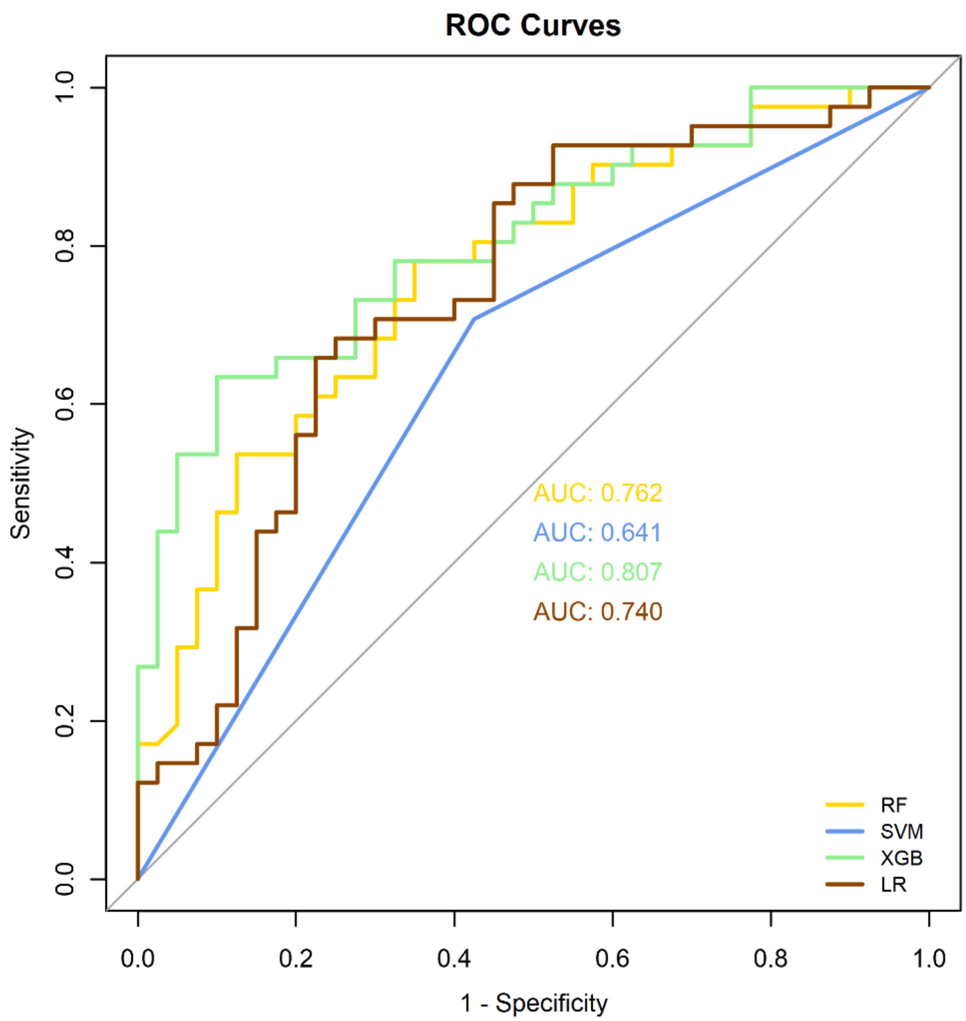

Fig. 4: ROC for machine learning algorithms

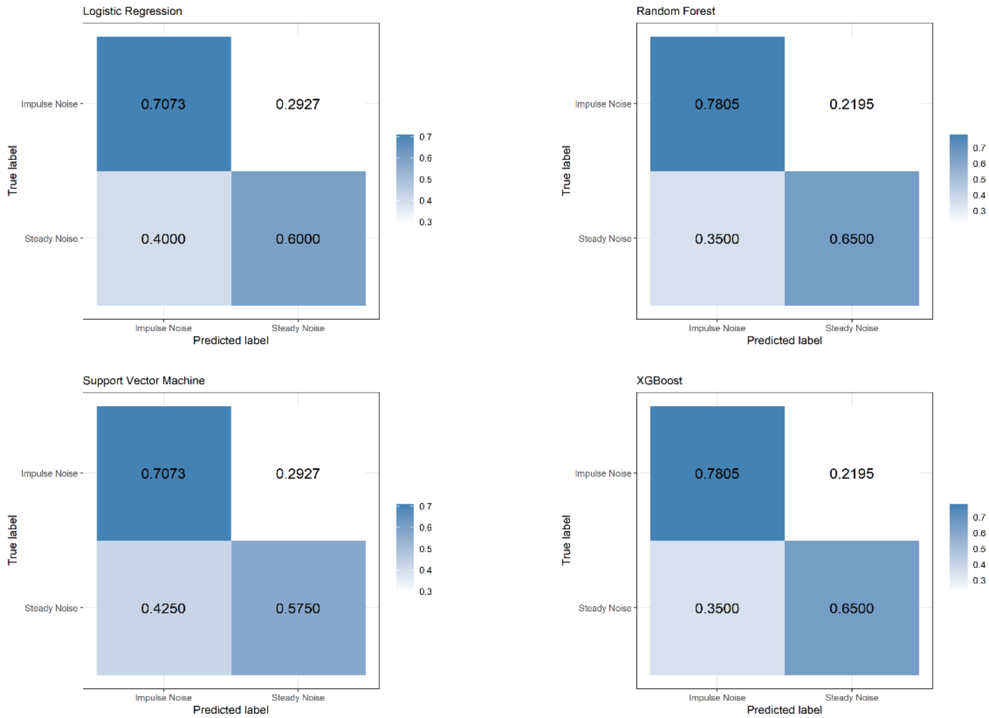

Fig. 5: Confusion matrix of four machine-learning algorithms

Discussion

As an unspecified physiological and psychological stressor, the potential impact of environmental noise is universal, numerous, lasting, and cumulative, and has corresponding actual and intangible losses. In a long time of chronic exposure, noise pollution is related to various auditory and non-auditory health effects, such as metabolic disorder, cardiovascular disease, and cognitive dysfunction (18, 19). Moreover, especially impulse noise can also affect hearing, nerves, cognition, and so on (9, 10, 20). NIHL is a complex disease caused by exposure to strong impulse noise or long-term exposure to steady noise of over 85 decibels (18). These high noise levels (85 dB) can cause hair cells in the cochlea to die after apoptosis (21). Many military servicemen may be exposed to noise for a long time and have hearing loss (22), it is necessary to carefully analyze different hearing loss caused by different noise environments in military operations. Even though there have been some studies to analyze the hearing of subjects exposed to a variety of steady noise or impulse noise environments, few studies are comparing steady noise and impulse noise to our knowledge.

This is the first retrospective study in China, which compares the clinical hearing loss results of subjects exposed to steady noise and impulse noise for a long time, stably and regularly. In addition, we used four machine learning methods to predict the classification of the two groups of subjects. In the past, some machine learning models about hearing loss have been used to classify and predict. Bing et al. made machine learning predictions on sensorineural deafness (23), and Tomiazzi et al. made predictions on the classification of hearing loss caused by smoke and pesticides among Brazilian farmers (24).

The focus of our research is to analyze the pure tone audiometry of subjects exposed to noise in two different noise environments and to build a machine learning model to achieve the role of prediction and classification. First of all, we need to exclude the influence of age and working hours on the hearing of the two groups of different subjects, so we used the PSM method to balance age and working time. The hearing condition of the two groups of subjects exposed to steady noise and impulse noise decreased significantly at high frequencies such as 4,6,8 kHz, which is similar to the characteristics of previous research on noise-induced hearing loss(25-27). The subjects exposed to steady noise were significantly worse than those exposed to impulse noise in terms of average speech frequency and 1 kHz frequency. In our subjects, no matter what kind of noise environment they were exposed to, the average hearing threshold at 6 kHz was the worst, and the average value exceeded 25 dB. 29.85 ± 19.27 dB at 6 kHz for the steady noise group and 28.92 ± 17.54 dB at 6 kHz for the impulse noise group. After grouping the working time of the two groups of subjects, we can see that the damage of steady noise to speech frequency is mainly reflected in the early working time. After working for more than 10 years, the difference in hearing loss between the two groups was not significant. As we all know, the impact of noise exposure is cumulative. Before the threshold sensitivity is affected, about 20% - 40% of the outer hair cells may be lost (23, 28). In addition, there may be temporary threshold shifts (TTS) in the early stage of work (29), so there may be some differences between the two groups. Therefore, it may be possible to reflect the difference in the damage caused by different environments of impulse noise and steady noise in the early stage, while in the late stage of work, due to the accumulation of noise damage, the difference in hearing loss between the impulse noise group and the steady noise group is not very obvious.

Pattern recognition is one of the most important functions of artificial intelligence (30). The efficiency of machine classification programs in the medical and biological fields (31, 32). In the machine learning models, we first randomly divide the listening situation of our subjects into the training set and test set. In the training set, we train our model through 10-fold cross validation. Accuracy, sensitivity, specificity, and AUC were used to evaluate the performance of our four machine learning algorithms. Random forests and XGBoost have the same accuracy: 0.716(0.605, 0.811). However, the XGBoost algorithm has the best performance. XGBoost is the abbreviation of eXtreme Gradient Boosting. It illustrates the Gradient Boosting Machine (GBM), which is a technology mainly used to build regression and classification predictive modeling problems. XGBoost is an integration method in which a new model is generated to correct the residuals or errors of previous models. This machine-learning algorithm can minimize errors, maximize the performance of the model, and effectively prevent overfitting (33).

The innovation points of this study are listed below. First of all, this is the first study on the hearing loss of military operators exposed to impulse noise and steady noise in different military noise environments, and the hearing loss of two groups of different working time is compared. Then we developed a machine learning model to predict the grouping of subjects in different hearing loss situations, and used different indicators to explore the performance of different machine learning algorithms.,

Our research still has some limitations. First, the data of noise and hearing of servicemen from two different military operating environments were selected retrospectively. This may lead to selection bias. A prospective cohort can be designed to improve the reliability of future results. Secondly, we can increase the number of people to improve the reliability of the model.

Conclusion

We creatively selected subjects in different military noise environments, summarized, and evaluated noise-induced hearing loss between groups. Subjects in the steady noise group and the impulse noise group had significant hearing loss at high frequencies, while the hearing condition of the steady noise group is worse than the impulse noise group in speech frequency, especially in the frequency of 1 kHz. Several prediction models based on machine learning are comprehensively evaluated, and the XGBoost algorithm may be the best model to predict the classification of patients with noise-induced hearing loss in our situation.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

Funding

This research received no external funding.

Conflict of interest

The authors declare that there is no conflict of interests.

References

1. Jokel C, Yankaskas K, Robinette MB (2019). Noise of military weapons, ground vehicles, planes and ships. *J Acoust Soc Am,* 146 (5):3832.
2. Tufts JB, Weathersby PK, Marshall L (2009). Estimation of Equivalent Noise Exposure Level Using Hearing Threshold Levels of a Population. *Ear Hear,* 30 (2):287-290.
3. Yuan BC, Su FM, Wu WT, et al (2012). A predictive model of the association between gene polymorphism and the risk of noise-induced hearing loss caused by gunfire noise. *J Chin Med Assoc,* 75 (1):36-9.
4. Theodoroff SM, Konrad-Martin D (2020). Noise: Acoustic Trauma and Tinnitus, the US Military Experience. *Otolaryngol Clin North Am,* 53 (4):543-553.
5. Bramhall NF, Konrad-Martin D, McMillan GP, Griest SE (2017). Auditory Brainstem Response Altered in Humans With Noise Exposure Despite Normal Outer Hair Cell Function. *Ear Hear,* 38 (1):e1-e12.
6. Bainbridge KE, Wallhagen MI (2014). Hearing Loss in an Aging American Population: Extent, Impact, and Management. *Annu Rev Public Health,* 35:139-152.
7. Themann CL, Masterson EA (2019). Occupational noise exposure: A review of its effects, epidemiology, and impact with recommendations for reducing its burden. *J Acoust Soc Am,* 146 (5):3879.
8. Clifford RE, Ryan AF, Program VMV (2022). The Interrelationship of Tinnitus and Hearing Loss Secondary to Age, Noise Exposure, and Traumatic Brain Injury. *Ear Hear,* 43 (4):1114-1124.
9. Xiong M, Yang CH, Lai HW, Wang J (2014). Impulse noise exposure in early adulthood accelerates age-related hearing loss. *Eur Arch Otorhinolaryngol,* 271 (6):1351-1354.
10. Kim S, Lim EJ, Kim TH, Park JH (2017). Long-term effect of noise exposure during military service in South Korea. *Int J Audiol,* 56 (2):130-136.
11. Lewis MS, Reavis KM, Griest S, et al(2023). The influence of tinnitus and hearing loss on the functional status of military Service members and Veterans. *Int J Audiol*, 62(1):44-52.
12. Zare S, Ghotbi-Ravandi MR, ElahiShirvan H, et al (2019). Predicting and Weighting the Factors Affecting Workers' Hearing Loss Based on Audiometric Data Using C5 Algorithm. *Ann Glob Health,* 85 (1):88.
13. ElahiShirvan H, Ghotbi-Ravandi M, Zare S, Ahsaee MG (2020). Using Audiometric Data to Weigh and Prioritize Factors that Affect Workers' Hearing Loss through Support Vector Machine (SVM) Algorithm. *Sound and Vibration,* 54 (2):99-112.
14. Chen SM, Fan YT, Martinez RM, Chen CY (2023). Noise-induced hearing loss profile among Taiwan Airforce on duty pilots. *Am J Otolaryngol,* 44(3):103802.
15. Servi AT, Davis SK, Murphy SA, et al (2022). Prospective measurements of hearing threshold during military rifle training with in-ear, protected, noise exposure monitoring. *J Acoust Soc Am,* 152 (4):2257.
16. Doupe P, Faghmous J, Basu S (2019). Machine Learning for Health Services Researchers. *Value Health,* 22 (7):808-815.
17. Guan X, Zhang B, Fu M, et al (2021). Clinical and inflammatory features based machine learning model for fatal risk prediction of

hospitalized COVID-19 patients: results from a retrospective cohort study. *Ann Med,* 53 (1):257-266.
18. Basner M, Babisch W, Davis A, et al (2014). Auditory and non-auditory effects of noise on health. *Lancet,* 383 (9925):1325-1332.
19. Zaman M, Muslim M, Jehangir A (2022). Environmental noise-induced cardiovascular, metabolic and mental health disorders: a brief review. *Environ Sci Pollut Res Int,* 29(51):76485-76500.
20. Cui B, Wu MG, She XJ, et al (2012). Impulse noise exposure in rats causes cognitive deficits and changes in hippocampal neurotransmitter signaling and tau phosphorylation. *Brain Res,* 1427:35-43.
21. Miguel V, Cui JY, Daimiel L, et al (2018). The Role of MicroRNAs in Environmental Risk Factors, Noise-Induced Hearing Loss, and Mental Stress. *Antioxid Redox Signal,* 28 (9):773-796.
22. Malowski KS, Gollihugh LH, Malyuk H, et al (2022). Auditory changes following firearm noise exposure, a review. *J Acoust Soc Am,* 151 (3):1769.
23. Bing D, Ying J, Miao J, et al (2018). Predicting the hearing outcome in sudden sensorineural hearing loss via machine learning models. *Clin Otolaryngol,* 43 (3):868-874.
24. Tomiazzi JS, Pereira DR, Judai MA, et al (2019). Performance of machine-learning algorithms to pattern recognition and classification of hearing impairment in Brazilian farmers exposed to pesticide and/or cigarette smoke. *Environ Sci Pollut Res Int,* 26(7):6481-6491.
25. McBride DI, Williams S (2001). Audiometric notch as a sign of noise induced hearing loss. *Occup Environ Med,* 58 (1):46-51.
26. Narasimhan S, Rajagopalan R, Margret JJ, et al (2022). Audiometric notch as a sign of noise induced hearing loss (NIHL) among the rice and market flour mill workers in Tamil Nadu, South India. *Hearing Balance and Communication,* 20 (1):21-31.
27. Moon IS, Park SY, Park HJ, et al (2011). Clinical Characteristics of Acoustic Trauma Caused by Gunshot Noise in Mass Rifle Drills without Ear Protection. *J Occup Environ Hyg,* 8 (10):618-623.
28. Bajin MD, Dahm V, Lin VYW (2022). Hidden hearing loss: current concepts. *Curr Opin Otolaryngol Head Neck Surg,* 30 (5):321-325.
29. Ryan AF, Kujawa SG, Hammill T, et al (2016). Temporary and Permanent Noise-induced Threshold Shifts: A Review of Basic and Clinical Observations. *Otol Neurotol,* 37 (8):e271-e275.
30. Papa JP, Falcao AX, de Albuquerque VHC, Tavares JMRS (2012). Efficient supervised optimum-path forest classification for large datasets. *Pattern Recognition,* 45 (1):512-520.
31. Chen H, Hu L, Li H, et al (2017). An Effective Machine Learning Approach for Prognosis of Paraquat Poisoning Patients Using Blood Routine Indexes. *Basic Clin Pharmacol Toxicol,* 120 (1):86-96.
32. Wang XM, Chen XH, Wang QG, Chen GN (2022). Early Diagnosis of Parkinson's Disease with Speech Pronunciation Features Based on XGBoost Model. *2022 2nd Ieee International Conference on Software Engineering and Artificial Intelligence (Seai 2022)*:209-213.
33. Mo XL, Chen XJ, Leong CF, et al(2020). Early Prediction of Clinical Response to Etanercept Treatment in Juvenile Idiopathic Arthritis Using Machine Learning. *Front Pharmacol,* 11: 1164.