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Classification of Noise-Induced Hearing Loss UsingBayesian Optimization Support Vector Machine

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ABSTRACT – Noise Induced Hearing Loss (NIHL) is an occupational disease is becoming leading cause of Occupational Noise Related Hearing Disorder (ONRHD) among Malaysian workers. To lower the number of reported NIHL cases, it is important to detect NIHL at an early stage. The primary goal of this study is to identify the key factors contributing to diagnosis of NIHL while developing an enhanced Support Vector Machine (SVM) prediction model using Bayesian Optimization to produce high precision classification results. The study examined 355 secondary datasets consisting of 24 variables divided into four segments which are 100, 200, 300 and 355.This data were analyzed to determine the best percentage of the sample size to be classified. Using the MATLAB application, the Support Vector Machine was used to classify the data based on the five prediction outputs based on the severity level of the NIHL. Using the Bayesian Optimization SVM using linear kernel the training accuracy exceeded 85.00%. This improved prediction model using kernel gaussian was recorded outperformed and achieved 100% prediction accuracy during testing. Because this improved prediction model produced high accuracy prediction results, it has the potential to reduce misinterpretations in ingratiating cases, thereby lowering the number of unconfirmed NIHL cases reported.

KEYWORDS: Support vector machine, Noise induced hearing loss, Bayesian optimization, Artificial Intelligence

1.0 INTRODUCTION

In Malaysia, Occupational Noise-Induced Hearing Loss (NIHL) falls under the category of Occupational Noise-Related Hearing Disorder (ONRHD). NIHL is defined as a function of exposure and duration of continuous or intermittent noise, which normally develops slowly over several years [1]. Excessive workplace noise adversely damages the cochlear hair cells [2]. Excessive noise exposure at the workplace leads to an increase in hearing loss cases and is now terrorizing the workers.

According to Y. Chen et al. (2019) prolonged exposure to excessive noise often causes NIHL, an irreversible disease [3]. Guidelines on Management of Occupational Noise-Related Hearing Disorders define excessive noise as a daily noise exposure level of more than 85 dB (A) for a daily personal noise dose. Exposure to noise with sufficient intensity and duration may distort cochlea hair cells [1]. The primary nerves, known as cochlea hair cells, convert the movement into nerve impulses and send signals to the brain via the auditory nerve. The brain then translates these signals into sound which humans can interpret.

The rise of NIHL cases has been recognized as a serious and global public health issue. In February 2024, a new article from the World Health Organization (WHO) reported that the projection is expected to cause nearly 700 million people by 2050 compared to the 2018 forecast stating that 630 million people in the world will live with disabling hearing in 2030 based on projected data in 2008. This number confirms the existence of NIHL, which has now become the second most common type of sensorineural hearing loss [4,5] after conduction and mixed hearing loss, both of which can result in permanent hearing damage for workers.

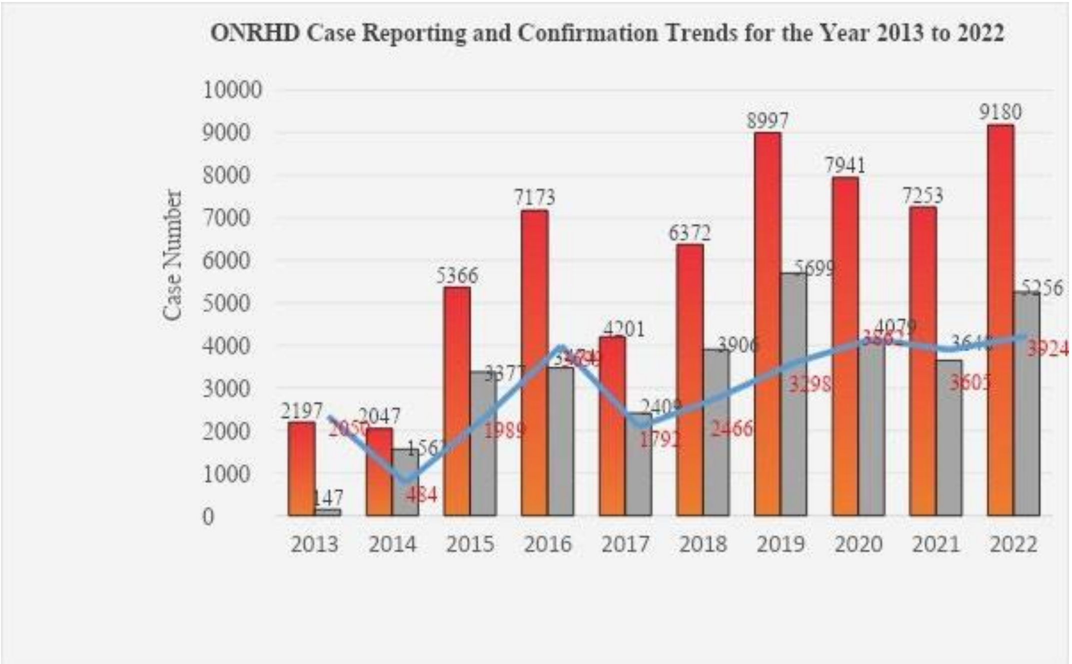

Figure 1. ONRHD Case reporting and confirmation trends for the year 2013 to 2022

Growing trends of NIHL cases were increasingly high after new guidelines and the Occupational Safety and Health Act (OSHA 2022) were introduced in 2019 and 2022 respectively. Figure 1 illustrates the recent trends of NIHL in Malaysia from 2013 to 2022. This trend shows the prevalence of NIHL is now widespread among workers in Malaysia. The 2022 annual report from the Department of Occupational Safety and Health (DOSH) Malaysia shows that 8997, 7941,7253, and 9180 cases of ONRHD were reported in Malaysia for the years 2019, 2020, 2021, and2022, respectively. There has been an upward trend with an increment 1927 of cases reported in 2022 throughout the year. The number of confirmed NIHL cases also was found to increase up to 1508 cases and 2022 recorded the highest number of cases with 5256 compared to the previous year. This trend has led to a proliferation of studies demonstrating NIHL as one of the occupational hearing diseases now experiencing a growing trend that leading to ONRHD cases in Malaysia. This would imply that there are issues in investigating and detecting confirmed cases from the reported ones. Furthermore, this would have undesirable consequences, such as time,money, and expertise needed.

From Figure 1, we identified the unfavorable outcomes in the interval between the reported and confirmed cases, which we referred to as unconfirmed cases. We classified unconfirmed cases as instances of unrelated occupational NIHL. Unconfirmed cases were recorded by experts during the investigation when they found an inaccurate understanding among medical practitioners about the definition of NIHL, symptoms, associated risk factors leading to NIHL, classification type of hearing impairment, and the complexity in establishing the work-related hearing disease [6].

Risk factors are an important component that plays a major role in predicting NIHL. The investigation of NIHL cases began with the initiative to develop the relationship of NIHL with other risk factors. This problem in developing the relationship has been a continuing concern among medical practitioners and researchers to provide an accurate diagnosis [7-10]. There is a large volume of published studies about NIHL, starting from 1985 to describe the definition of NIHL [11] until now the identification of the role of age, duration of noise exposure, and exposure level has become the significant risk factor in predicting NIHL [2]. Due to this issue, there has been growing interest among researchers in recent years in discovering the exact risk factors that lead to NIHL. In addition, sociodemographic and work history information such as age, gender, and occupational history encompasses details of job description, workplace, factory, length of employment [12,13], and the history of using hearing protection devices also found to correlate with the wide spread of NIHL [14-17].

Additional evidence suggests that NIHL may be caused by exposure to a variety of complex industrial noises that frequently arise from machinery used in construction and mining industries. Besides that, the impact of industrial noise on environmental factors that influence NIHL has also been explored [18-20]. Apart from the construction and mining sectors, the manufacturing sectors also play a role in contributing to the increment of NIHL cases. Previous researchers found that manufacturing sectors that are involved in industrial work and activities such as metal cutting, surface treatment, stamping, welding, milling, assembly, plastic molding, and forging contribute to the prevalence of NIHL [21,13, 22].

Furthermore, research has shown a strong correlation between clinical factors such as age, gender, BMI, diabetes, smoking, audiometric notches [23,24,13], noise exposure level and duration of exposure strongly correlated with hearing [25]. Meanwhile, the audiometric notches from the audiometric testing normally is a one-sheet report called an audiogram report. A diagnostic examination, known as an audiometric test, assesses an individual's hearing capacity due to exposure to noise hazards [26].To diagnose NIHL, audiometric testing employs a variety of practical methods to identify the four (4) potential outcomes, which are;

(i) Normal audiogram
(ii) Hearing loss without temporary Standard Threshold Shift (STS)
(iii) Hearing loss with temporary STS
(iv) Temporary STS only. STS is defined as an average displacement of more than 10 dB at frequencies of 2000, 3000, and 4000 Hz relative to the baseline in both ears.

Recently, researchers have developed automated auditory technology to concisely describe audiograms, thereby alleviating the burden among on medical practitioners. The development of new technologies to identify NIHL, such as a prediction model in mobile applications, primarily aims to align with WHO predictions and curb the spread of the disease. Additionally, the goal is to facilitate accurate diagnosis and treatment, which can lead to immediate treatment initiation and prevent the progression and complications of NIHL.

Since 2011, a group of researchers from Malaysia has developed the NIHL prediction model using Artificial Intelligence (AI), with the aim of identifying the key factors influencing workers' hearing ability through the use of an Artificial Neural Network (ANN). The methods used include Gradient Descent Back Propagation Neural Network, Gradient Descent with Adaptive Momentum algorithm, and Hybrid BAT Back Propagation [27-29]. This research aims to scrutinize overlooked, crucial factors and incorporate them into predictive models for prediction accuracy. Meanwhile, Rehmanl et al. (2012) conducted similar research in an effort to explain the prediction output by using the same variables; age, work duration, and noise exposure as input for two (2) different models and managed to achieve a prediction accuracy 98.21 to 99.37% [29].

SVM classifiers are the primary method for classifying NIHL [2]. Furthermore, SVM performed better than adaptive boosting, random forest, and ANN in making accurate predictions using associated risks such as age, duration, and noise exposure level. Research has continuously tested the SVM using PTA results, revealing that it can accurately and robustly predict hearing impairment [20]. Another study has initiated a new development using random forest classifiers in the mobile application to address the limited involvement of qualified personnel, which leads to NIHL misinterpretations. This study has shown increasing interest among researchers in NIHL prediction models and identifying high-accuracy results and performance. Given all that has been mentioned so far, it seems that researchers have extensively used SVM to determine NIHL based on associated risk factors. However, Zhao et al (2019) study does not fully address the NIHL risk in audiogram classification [20]. Therefore, this research introduces a NIHL prediction model using twelve (12) risk factors and 12 audiogram results as input variables using a Support Vector Machine (SVM) with an adaptation of Bayesian optimization. The 12 risk factors that were introduced include:

i. Age
ii. Race
iii. Citizenship
iv. Hobbies
v. Employment duration
vi. Employment History
vii. Sectors
viii. Subsectors
ix. Laterality
x. Tinnitus
xi. Symptoms
xii. Medications

Meanwhile, 12 audiogram results were obtained from the following frequencies: 500 kHz, 1000 kHz, 2000 kHz, 3000 kHz, 4000 kHz, and 6000 kHz for each ear. In addition, we refined this analysisby evaluating the effectiveness and precision of the prediction model through the application of four (4) different kernel methods:

i. Linear
ii. Gaussian
iii. Quadratic
iv. Cubic

This analysis also applies Principal Component Analysis (PCA) as a feature selector to eliminate the independent variables not associated with NIHL. The application of SVM was selected based on the capability of this prediction model to produce high-accuracy results [2,20] including the idea of improvising the classification methods and variable inputs to be used.

This research aims to identify the main contributing factors in diagnosing NIHL while formulating an improvised Support Vector Machine (SVM) model using Bayesian optimization to produce a high-accuracy classification result using NIHL-confirmed cases among Selangor workers. The study utilized data from 2010 to 2018 to provide fresh insights derived from workers in Malaysia. This research also aims to implement the optimal classifier using the SVM model, which can provide the most accurate predictive model for NIHL. This research encompasses all pertinent studies and outlines the limitations and constraints involved in extracting information from secondary data gathered from the DOSH Selangor record between 2011 to 2018. Random sampling is used during the collection of data on NIHL-confirmed cases that comply with audiogram results. However, this research has excluded unconfirmed cases, incomplete audiogram results, employees over 60 years of age, misinformation, and improper recording methods to avoid misinterpretation errors that can reduce prediction accuracy.

2.0 METHODOLOGY

This section describes the flow of in SVM prediction model starting from dataset arrangement to be analyzed, enabling the Principal Component Analysis (PCA) and operating procedure of the SVM classifier using four different types of kernels: Linear, Gaussian, Quadratic and Cubic with arrangement 5-fold Cross Validation in predicting NIHL. The secondary data that was used in the SVM classifier application using MATLAB R2022b software was applied as a platform that provides an SVM classifier and other features to classify the data based on the targeted output.

SVM with Bayesian Optimization is a method that classifies the training data using different kernels. The primary focus of SVM with Bayesian Optimization is to create the optimal separating hyperplane to correctly classify the NIHL training data based on five (5) severity classes which are normal, mild, moderate, severe, and profound. This test also uses four (4) kernel functions that are provided in the MATLAB SVM Toolbox: linear, gaussian, quadratic, and cubic. Principal Component Analysis (PCA) is a feature selection method used to identify and select highly associated risk factors that lead to NIHL. Before the classification process, 355 pieces of data were divided into four (4) groups: 100, 200, 300, and 355 respectively. The groups of data were used during the training and testing processes. Meanwhile, the prediction model was created using the PCA+SVM model as illustrated in Figure 2.

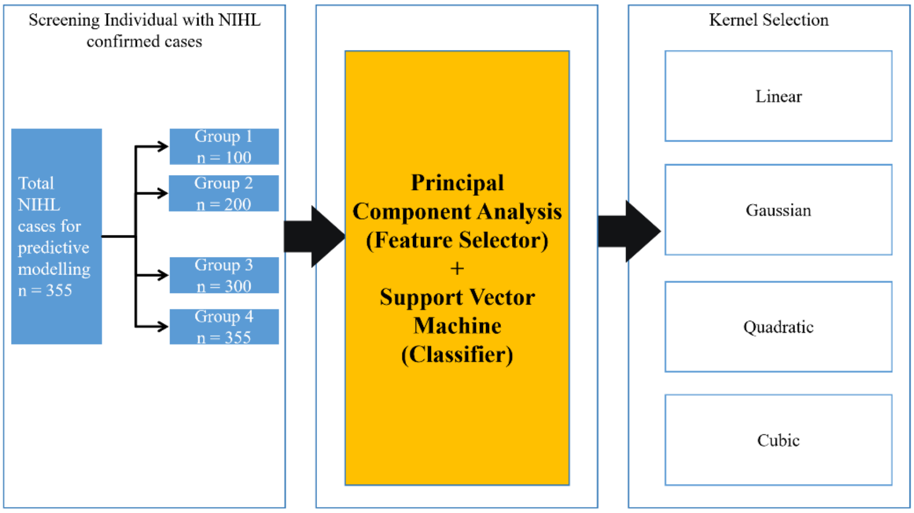

Figure 2. Diagram allocation of screening NIHL datasets

3.0 RESULT AND DISCUSSIONS

This section contains the results of two (2) processes of prediction modeling which are training and testing using SVM with Bayesian Optimization and PCA. According to Table 1, 14 out of 24 variables were selected to be included in the SVM classification for training and testing. The features undergo a selection process using a PCA features selector to enhance the classification performance by removing the unrelated associated risk variables. Four (4) different types of kernels were utilized in this work to identify multiple-ranging outputs and check the capability of t he SVM prediction model. These kernels were set in each SVM training process after enabling the PCA and SVM prediction Gaussian model. This method is repeatedly set using four types of datasets 100, 200, 300 and 355. According to Table 1, the linear kernel model demonstrated outstanding training performance with accuracy ranging between 82 to 85% surpassing the quadratic, cubic, and Gaussian models. The prediction model achieved the maximum accuracy in the linear, quadratic, cubic and Gaussian kernel test with 85%, 81%, 76.67% and 75.67% from 73.75% to 79.93% for 100, 200, 300, and 355 data samples. This implies that the 300 dataset has a significant impact on improving the prediction accuracy.

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Table 1. Training performance of SVM model using Linear, Quadratic and Cubic prediction method

Sample No	Support Vector Machine (SVM) 14 over 24 variables selected during PCA			
	Linear	Gaussian	Quadratic	Cubic
100	82.00	66.00	75.00	72.00
200	85.00	70.00	77.50	77.50
300	85.00	75.67	81.00	76.67
355	84.51	75.77	80.85	78.59

Nevertheless, the accuracy of prediction during testing has significantly increased in c omparison to the training phase. The prediction made during the testing phase is the final phase to determine the capability of the model. In the training, the application of variables has remained consistent 14 variables are continuation from the training process. Table 2 demonstrates the findings from the simultaneous testing of four SVM kernels that were tested concurrently using the same number of samples. Referring to the testing output in sample sizes of 100, 200, 300 and 355 has accurately generated 100% as recorded in Table 2 for Gaussian, quadratic and cubic kernels. By examining the type of kernel, it has been determined that the Gaussian model is the most optimal, achieving 100% accuracy across all studied data sample sizes. Meanwhile, a performance produced by quadratic, cubic, and linear kernels produces an accuracy of 98.44%, 93.73%, and 93.72% respectively. Figure 3 shows the illustration of SVM resulting in confusion matric.

Table 2. Testing performance of SVM model using Linear, Gaussian, Quadratic and Cubic prediction method

Sample No	**Support Vector Machine (SVM)**			
	Linear	Gaussian	Quadratic	Cubic
100	97.00	100.00	100.00	100.00
200	92.50	100.00	100.00	100.00
300	93.00	100.00	96.33	100.00
355	92.39	100.00	97.46	74.93

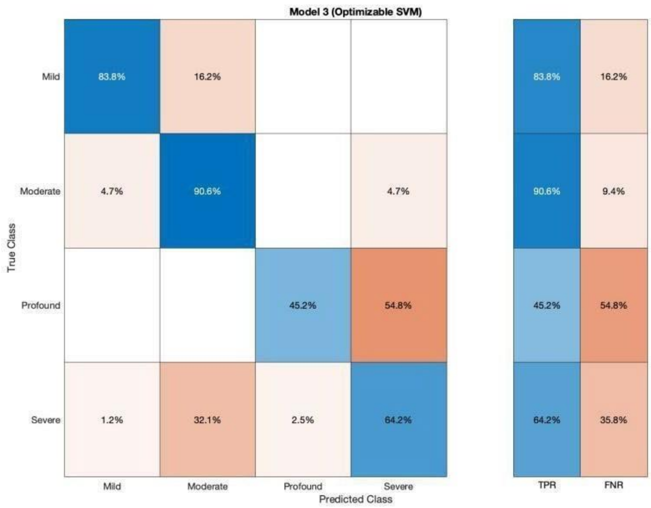

Figure 3. Illustration of SVM results in confusion in matric

This result was compared with Artificial Neural Network (ANN) using the 355 data that comprise 70% for training and 30 data for testing. This prediction model achieved 99.00% during training and 75.6% during the testing with an overall performance reaching 93.3% which is lower than SVM prediction accuracy as illustrated in Figure 4. This comparison has proven SVM as an effective machine learning in predicting NIHL among workers that exposed to diverse complex industrial noise.

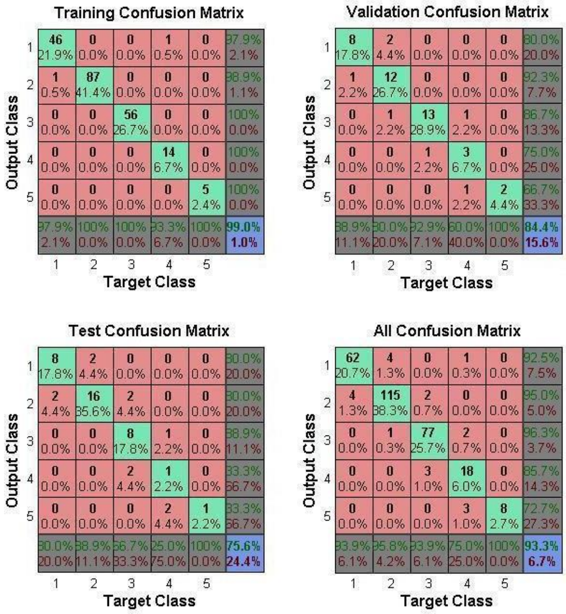

Figure 4. ANN Prediction Model in Confusion Matrix Result

4.0 CONCLUSION

Artificial Intelligence has become a medium that is widely applied to medical automation systems that can replace several human resources in order and reduce the effort of medical officers and legal enforcement bodies to capture and cattle NIHL cases among workers. As the NIHL number of unconfirmed cases keeps increasing annually, the SVM model was found to be the best approach due to the capability to provide the highest accuracy in the SVM prediction model using 12 risk factors and 12-octave frequencies from the audiogram. This study has successfully identified two (2) main objectives. The research has successfully identified the main contributing factors in diagnosing NIHL, with high accuracy. The research has also successfully formulated and improvised an SVM model with high degree of accuracy. This was a major issue among the NIHL cases in Malaysia. This will be a great help to the local agency in reducing the number unconfirmed cases among workers by applying this audiology technology to the public. Currently, researchers are implementing the SVM model into a mobile application to be used by Occupational Health Doctors. There has been a collaboration between the researchers and the Department of Occupational Safety and Health (DOSH) for future use.

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