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Development of Noise Induced Hearing Loss Prediction Model Using Levenberg Marquardt

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***Abstract*—This research explores the creation of a noise-induced hearing loss (NIHL) prediction model. In the context of occupational health, NIHL is defined as hearing loss that occurs as a result of overexposure to noise hazards at work for a given noise level and time. Despite the high statistical instances that have been recorded over the course of a number of years, there have been very few, if any, efforts made to construct an appropriate prediction model using the combination of linked diagnostic occupational hazards. This study aims to show how an Artificial Neural Network Levenberg-Marquardt algorithm can be used to make a prediction model for NIHL. The goal is to find highly linked risk factors that increase the number of NIHL cases reported in Selangor, Malaysia. The study looked at 355 secondary data points taken from NIHL confirmed cases and given by the Department of Occupational Safety and Health (DOSH). The overall performance of the ANN prediction model was tested at a level of 90.46 percent average. Because of the great accuracy in predicting NIHL, it is inferred that the model may be employed as an intelligent system in the preliminary screening phase.**

***Index Terms*—Occupational Noise Induced Hearing Loss, Prediction Model, Artificial Neural Network, Levenberg-Marquardt**

I. INTRODUCTION

NOISE-INDUCED HEARING LOSS (NIHL) is a work-related illness that is on the rise among employees. It is known as heterogeneous that induced by intercourse between environmental factors and genetics. This condition is characterized by long-term exposure to excessive sound levels resulting from equipment or tool-generated noise.

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The Department of Occupational Safety and Health (DOSH) in Malaysia found that the number of suspected cases of NIHL diseases went from 2588 in 2013 to 6020 in 2016. This is an exponential increase of more than 3000 cases. There have been confirmed instances of NIHL ranging from 1821 all the way up to 3890. With an estimated 6.1% (466 million) of the global population suffering from hearing loss in 2018, this increase in cases reported is in line with WHO predictions [1]. According to 2008 projections, the number of individuals suffering from hearing loss would continue to rise, reaching 630 million in 2030 and 900 million in 2050, respectively. This alarming trend has prompted health authorities all over the world to enable and encourage further research aimed at reducing the risk of NIHL to employees. Certain occupations, such as those involving commercial fertilizer[2], fishermen[3], navy [4], and air force pilots [5], are particularly at risk for developing NIHL, which is classified as an occupational illness. Other risk variables include sociodemographic and age characteristics, chemical exposure, and hobbies [6] with high noise exposure, vibration, and diabetes mellitus[7-10] clinical factors that are utilized as indications of NIHL among employees.

Inadequate numbers of qualified professionals to investigate occupational NIHL cases is one of the primary obstacles that must be overcome in order to discover cases of NIHL. Occupational Health Doctors (OHD) are responsible for assessing occupational sickness reports in Malaysia. They are licensed medical doctors who have been granted the authorization to do assessments and investigations linked to occupational diseases by the Department of Occupational Safety and Health (DOSH). There are now 1084 OHD that have been registered in Malaysia, of which 891 are still active and 198 have become inactive due to having expired. Given the present number of OHD, it is an almost insurmountable obstacle for the Department of Occupational Safety and Health in Malaysia (DOSH) to examine all the NIHL instances among the 14,106,200 registered employees in Malaysia due to the lack of OHD. This problem is made more worse in Malaysia since there is a dearth of NIHL-related knowledge and research.

When compared to other nations, such as the United States and the United Kingdom, the amount of research that has been conducted on the potential risk factors of NIHL among Malaysians is still very low. The work culture, socioeconomic position, and general demographic factor are the only categories that may be included when evaluating the feasibility of implementing indicated risk factors discovered in research conducted in other nations. This is the only category that can be considered. In general, NIHL is largely caused by a variety of risk factors including clinical history, noise exposure, working environment, and socio-demographic risk variables. These risk factors all play a role in the development of the condition. In addition, other variables may include age, gender, Diabetes Mellitus (DM), inherited hearing loss, the noise intensity regardless of frequency, current smoking status, alcohol intake, excessive triglycerides, and chronic renal disease [7], [8], [11], [12].

Research on this topic in Malaysia has been restricted in scope and many prior studies did not provide an in-depth examination of risk variables and the strength level of each risk factor's contribution to the overall risk. The purpose of this study was to investigate a wide variety of risk variables that contribute to NIHL among employees in the state of Selangor. The purpose of this study is to construct an artificial neural network prediction model for NIHL that is based on a few comprehensive combinations of risk variables that contribute to the condition. Using this model, researchers expect to diagnose NIHL at an earlier stage.

II. LITERATURE REVIEW

A. Noise Induced Hearing Loss

The disorder known as NIHL is one that causes the ears to be unable to operate normally. Anatomically, the human ear has three peripheral auditory components: the outer ear, the middle ear, and the inner ear. In terms of physiology, sound waves go from the outer ear tunnel to the eardrum, which causes the eardrum to vibrate and initiate a chain reaction by turning the sound waves repeatedly. The malleus, incus, and stapes are the names of the three bones that make up the ossicles. Between the middle ear and the inner ear are these three (3) bones that link them. These three bones start to move and then send the vibrations on to a tiny layer of tissue known as the oval window, which is positioned at the entrance to the inner ear. The pressure exerted in the oval window then squashes the fluid in the inner ear, causing waves to form in the canals of the small-shaped cochlea. In the final step, the movement will be converted into nerve impulses by small hairs in the cochlea, which will then send a signal to the brain through the auditory nerve. In the end, the human brain is responsible for translating the impulses into sounds that are understandable to humans. The problem of NIHL manifests itself when the fine hairs in the cochlea get deformed as a direct result of exposure to excessive noise at a given level over an extended period. As a result, this condition has no outward manifestations, and the only way to detect it is via the manifestation of its symptoms, which include ringing in the ears, buzzing in the ears (tinnitus), and an inability to hear within one meter. During that period, the patient may receive a diagnosis of Temporary Threshold Shift [13], [14]or Permanent Threshold Shift[14-16].

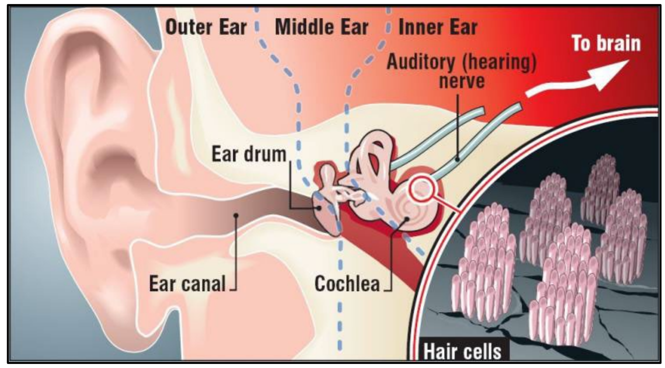

Fig. 1. Ear Anatomy

B. Artificial Neural Network

The use of ANN in medicine, particularly for NIHL illness, to forecast and categorize the NIHL disease has not been widely investigated among researchers. This is especially true for NIHL disease used this method in their study because ANN can deal with rapid changes in the effectiveness [17]. Due to the efficiency and precision that are comparable to the operation of the human brain, this technology has become a potential substantial contribution to the solving of medical issues. Network design, learning mechanisms, and training functions are what set ANN apart from other statistical methods in practice. A single layer feedforward network, a multilayer feedforward network, a recurrent network, and a mesh network are all included in the network design of an ANN. Unsupervised learning, supervised learning, and reinforcement learning are the three (3) primary basic learning mechanisms of an artificial neural network [18]. The efficiency of this learning mechanism should be evaluated using five (5) fundamental ANN phases, which are as follows:

(i) the choice of the network;
(ii) the initial weights and biases;
(iii) the pace at which the network learns;
(iv) the gain value of the activation function; and
(v) momentum.

The use of these five (5) fundamental methods has demonstrated that ANN is one of the prediction models that is able to cope with many data, the analysis of which would ordinarily call for the experience of humans. In addition, a recent study discovered that the development of the ANN could resolve an issue that occurred in the actual world when it attained the necessary level of maturity through its application [19]. This will immediately propel the technology to an unprecedented degree of success in preventing incorrect diagnosis[20] .

A recent study that was carried out by [21]has implied and supported the use and effectiveness of ANN in modelling the pathology process for the patients who have been diagnosed with otitis media by taking 19 variables into consideration. This study was carried out in the United Kingdom (such as gender, age, audiometric result, ear pathology and surgical procedures).

In addition to this, further research found that artificial neural network (ANN) prediction was more accurate than k-nearest neighbor (k-NN) prediction, as demonstrated by ANN's ability to achieve 89 percent correct prediction in the validation. In addition, a comparative study was carried out in order to examine the accuracy of the prediction when compared with regression methods. According to the findings of the study, artificial neural networks generate higher prediction accuracy than logistic regression techniques when it comes to determining the prevalence of hearing impairments among industrial employees. As a result, the ANN has been demonstrated to be capable of providing greater accuracy in prediction when compared with other standard statistical technique networks that have been designed to increase data mining and pattern recognition [22].

The researchers conducted literature reviews, which were then examined and compared to other prediction approaches in terms of gaps and differences. The use of artificial neural networks is one of the methods that comes highly suggested for offering a clear perspective of development and the implementation in NIHL forecasts (ANN). ANNs may be taught to make mathematical predictions and forecasts, a capability that could be helpful in the diagnosis of diseases in their earliest stages [23]. ANN does not always focus on the most prevalent statistical approach. Using ANN with Gradient Descent , Gradient Descent with Adaptive Momentum, and Hybrid, which is the mix of fuzzy and BAT backpropagation method, to improve the prediction model for NIHL necessitates continuing to measure the optimal performance and adapting this to the most recent risk. These kinds of precautions could, by accident, make it possible to improve the precision of NIHL predictions and forecasts. The classification performance in training using ANN backpropagation and multilayer perceptron was optimized by employing each of these three (3) different ways. [24-27].

The training function that was used in the hidden layers was, nevertheless, what distinguished any one of these three (3) distinct approaches from the others. In the backpropagation neural network, the learning convergence rate continues to be the primary difficulty, which has an influence on the convergence rate as well as the performance of the prediction models GD and GDAM.

In (Rehman, 2011), researchers effectively predicted NIHL among Malaysian workers with the goal of maximizing accuracy and accelerating the training process by employing Backpropagation (BP) with the adoption of Levenberg-Marquardt in training. This was made possible by the application of the Gradient Descent technique (GD). According to the findings, this tactic was able to reduce the amount of time required for training that was caused by local minima that were the result of an excessive gradient [27]. 1969 saw the creation of the Gradient Descent (GD) algorithm by Minsky and Paper. This was done with the intention of improving the effectiveness of the BP approach. The weight and biases for each variable were determined while the GD was being performed, and subsequently those values were modified in line with the GD method [18]. The adjustment was altered in such a way that it went in the opposite direction of the negative gradient that was displayed by the performance function. The most significant flaw of the GD algorithm was its propensity to deteriorate into an unstable state whenever the learning rate was either too high or too low, as well as whenever the process of convergence took too long to complete. This was the case whenever the learning rate was either too high or too low.

Gradient Descent with Adaptive Momentum Algorithm, or GDAM, is an upgrade to the GD algorithm. GDAM is an acronym that stands for Gradient Descent with Adaptive Momentum Algorithm. The change consisted of speeding up the gradient vectors so that they pointed in the right direction, which ultimately led to a faster convergence. When applied to the NIHL prediction technique, the training approach produced 98.21% more accuracy than the gradient descent method [24].

Gonz et. al, 2016 came up with the idea of the revolutionary swarm intelligence approach[28] known as the Hybrid BAT-BP to combat the difficulties associated with optimization. This method makes use of an artificial bee colony and is influenced by the concept of behavior forging. An additional innovation utilizing a meta-heuristic model based on the echolocation behavior of bats was the subject of research and development efforts, and comparison studies with previously developed algorithms were carried out. This effort was made in order to optimize the NIHL prediction system [25] by doing research on the echolocation properties shared by all species of bats as well as the association between those qualities and the hunting methods employed by each species. The ongoing development of the neural network was accomplished in 2014 with the implementation of a hybrid approach [29], which was a combination of the following three methods:

(i) BAT based metaheuristic optimization;
(ii) backpropagation neural network;
(iii) fuzzy logic in predicting and diagnosing NIHL.

By acknowledging other risk factors such as
(i) heat,
(ii) body mass index (BMI),
(iii) diabetes,
(iv) smoking,
(v) audiometric variables,
(vi) age,
(vii) frequency,
(viii) duration of exposure.

These aspects have contributed to a rise in the prediction's level of precision . The model has improved the accuracy of prediction and was able to bring the NIHL rate among employees in Malaysia down to a lower level. By utilizing the GDAM, the scope of forecasting was expanded such that it no longer just focused on NIHL but also considered the hearing degradation index (HDI) among workers.

In typical usage, the optimization of the bat algorithm of the ANN model is applied to the selection of the ANN model. The optimization was used to optimize the structure or weights connection in the ANN model in order to find the significant interaction between global divest exploration and local intensive exploitation, which affected the efficiency of the algorithm in data mining for the purposes of clustering [16]. This was done in order to find the significant interaction between global divest exploration and local intensive exploitation. For the purpose of improving prediction, a few improved methods in the training function for ANN have been devised. One example of this is the exponential adaptive skipping training technique. Because of this idea, the amount of time needed to train a multi-functional neural network (MFNN) was cut down [30].

During this time, (Siermala et al., 2007) presented several methods that have been used in order to establish the relevance of the input variables. These methods include scattering, spectrum analysis, and response analysis. These methods were utilized to convey the complexity of classification, particularly the overlap of output classes, by partitioning the input variables and output classes of a perceptron neural network [31]. Therefore, it is one of the solutions that may be used to lessen the problem of local minima in the gradient descent trajectory and raise the pace at which it converges.

III. METHODOLOGY

With Kelsey's technique, we were able to determine the size of the sample by applying confidence intervals that ranged from 95 to 100 percent and 36 percent of what was hypothesised based on the prior journal. This study determined that 355 NIHL confirmed cases were sufficient to reflect Malaysia's workforce population.

The data collection went exactly as planned for the study design and knowledge acquisition. The information collected was saved automatically in the database, which was built using web-based forms. The database information was converted to a Comma-Separated Values (CSV) file for use in the building of a prediction model and the machine learning application. The data was cleaned up so that unanticipated inaccurate, inconsistent, and missing data could be removed, and the data format was checked to make sure it was compatible with the prediction model. It was necessary to execute the descriptive analysis, which entailed processing and changing the raw data into the values, in order to guarantee that the data could be processed utilising the ANN prediction model method. After converting the data, the correlation approach was employed to quantify the linear connection between two variables by comparing the dependent and independent variables. In the 1880s, Karl Pearson and Francis Galton came up with this approach[1], which involves determining the link and importance of the correlation between these two groups of variables based on the value of R. In this particular investigation, 18 related risk factors and 12 octave frequencies were categorised as independent variables. The outcomes of the correlation were utilised as inputs for the artificial neural network (ANN).

Sample Size for Frequency in a Population

Population size(for finite population correction factor or fpc)(*N*):	14106200
Hypothesized % frequency of outcome factor in the population (*p*):	36%+/-5
Confidence limits as % of 100(absolute +/- %)(*d*):	5%
Design effect (for cluster surveys-*DEFF*):	1

Sample Size(*n*) for Various Confidence Levels

ConfidenceLevel(%)	Sample Size
95%	355
80%	152
90%	250
97%	435
99%	612
99.9%	998
99.99%	1396

Equation

Sample size n = $[DEFF*Np(1-p)]/ [(d^2/Z^2_{1-\alpha/2}*(N-1)+p*(1-p)]$

Results from OpenEpi, Version 3, open source calculator--SSPropor
Print from the browser with ctrl-P
or select text to copy and paste to other programs.

Fig. 2. Sample Size Calculation Using Open Epi

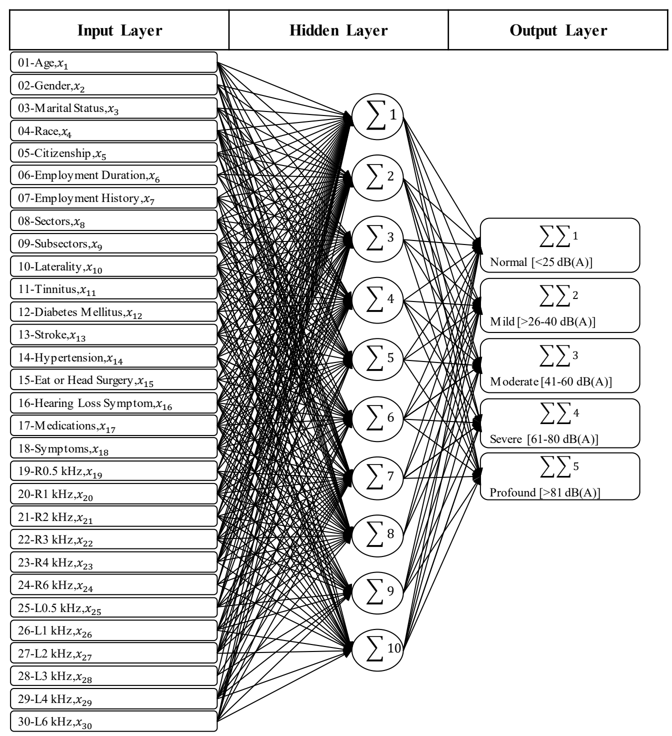

Fig. 3. Basic Architecture of ANN for NIHL

ANN is algorithm that categorised as Supervised Learning, where the 30 of input vectors was considers as target vectors. The main goal of ANN is to estimate five output vectors [32]which is Normal, Mid, Moderate, Severe and Profound for a specific input vector. ANN was consists of three (3) layers which is input, hidden and output layer. Using this method, the data was split into three stages—training, validation, and testing—prior to their being put through their respective execution procedures. The data was separated into 210 sets for training, 45 sets for validation, and 45 sets for testing, with the percentages of each separation being 70%, 15%, and 15%, respectively. The total number of data points used in MATLAB was 300. The objective of data separation is to guarantee that distinct data sets are utilised for each phase in order to safeguard the quality of the final product, particularly the accuracy and performance of the prediction model.

The ANN prediction model had three basic processes: training, validating, and testing. Each approach is utilised in a unique procedure. Testing is a process that provides self-measurement of the network after training without affecting the training process. This is done in accordance with the network setting of the training function. The training process was to train the input data with the output. Validation was to measure the generalisation and to pause the training when the process stopped improving. This network used Levenberg-Marquardt (LM) [33] as a training function for backward calculation to update the weight and bias values from the opposite direction. The Levenberg-Marquardt (LM) training function was used to evaluate how effective this optimization strategy was with regard to the 24 variables that were used as input and the 5 targets that were utilised as output for the NIHL data. The LM method is the one that doesn't use as much memory as other algorithms do, which is one reason why it's the quickest backpropagation algorithm. It was also highly suggested as an algorithm for supervised algorithms. This programme will focus on developing the skills necessary to formally formulate the minimization of a loss function that is formed of error and regularization.

The idea behind the LM training function was to construct it with the help of the Jacobian matrix, which is denoted by the letter J and consists of the first derivatives of network error with respect to the biases and network error that is denoted by the letter J. (e). The outputs of ANN were used in NIHL's inference engine, which was utilising the same method that had previously been transformed using the language Python. The Jupyter Notebook was one of the platforms that was utilised throughout the process of converting and configuring the NIHL inference engine. This platform allowed for the development and testing of the inference engine code that was written in the Python programming language. By configuring everything, the goal of this project is to construct an NIHL prediction model application with the lowest possible error value. It is hypothesised that this will result in contributed work delivering the maximum possible network performance.

IV. RESULTS AND DISCUSSION

This research concludes 30 identified variables include 18 risk factors and 12 octave frequencies; both were extracted from NIHL confirmed cases among Selangor workers. The variables include age, race, citizenship, marital status, hobbies, employment duration, employment history, sectors, subsectors, laterality, tinnitus, diabetes mellitus, stroke, hypertension, ear surgery, symptoms, ear trauma, medications, and 0.5, 1, 2, 3, 4, and 6 kHz for both respective ears.

TABLE 1
CORRELATION ANALYSIS OF NIHL RISK FACTORS

No	Risk Factors	Correlation Analysis, r			
		PTA Right Ear	p	PTA Left Ear	p
1	Age	0.186	<0.05	0.205	<0.05
2	Gender	0.058	n.s	0.012	n.s
3	Marital Status	0.006	n.s	0.055	n.s
4	Race	-0.062	n.s	-0.119	<0.05
5	Citizenship	0.023	n.s	0.071	n.s
6	Hobbies	0.175	<0.05	0.1	n.s
7	Employment duration	-0.078	n.s	-0.094	n.s
8	Employment history	-0.08	n.s	-0.027	n.s
9	Section	-0.136	<0.05	0.005	n.s
10	Subsection	0.041	n.s	0.094	n.s
11	Laterality	0.259	<0.05	0.273	<0.05
12	Tinnitus	0.129	<0.05	0.136	<0.05
13	Diabetes	-0.019	n.s	-0.011	n.s
14	Stroke	-0.061	n.s	-0.095	n.s
15	Hypertension	0.016	n.s	0.032	n.s
16	Surgery	-0.022	n.s	-0.04	n.s
17	Symptom	-0.165	<0.05	-0.153	<0.05
18	Medications	0.007	n.s	-0.088	n.s
19	R500	0.834	<0.05	0.326**	<0.05
20	R1000	0.867	<0.05	0.406**	<0.05
21	R2000	0.92	<0.05	0.458**	<0.05
22	R3000	0.821	<0.05	0.447**	<0.05
23	R4000	0.646	<0.05	0.388**	<0.05
24	R6000	0.54	<0.05	0.350**	<0.05
25	L500	0.399	<0.05	0.854**	<0.05
26	L1000	0.411	<0.05	0.883**	<0.05
27	L2000	0.463	<0.05	0.921**	<0.05
28	L3000	0.392	<0.05	0.813**	<0.05
29	L4000	0.311	<0.05	0.680**	<0.05
30	L6000	0.351	<0.05	0.691**	<0.05

n.s : not significant

P : Correlation is significant at the 0.05 level

The result of the Pearson correlation analysis was that 12 octave frequencies, age, hobbies, laterality, and tinnitus indicate strong positive associations with PTA. Meanwhile, race, section, and symptoms indicate weak negative relationships. Other factors, like gender, marital status, citizenship, length of employment, history of employment, section, diabetes, stroke, surgery, high blood pressure, and medications, show that there is no link.

NIHL common risk factors (i) age, (ii) citizenship, (iii) hobbies, (iv) employment duration, (v) employment history, (vi) sector, (vii) subsector, (viii) noise were used. The LM prediction model was able to achieve an accuracy of 97.64% during training, 79.89% during validation, and 85.87% during testing. The overall network accuracy is achieved at 93.33%.

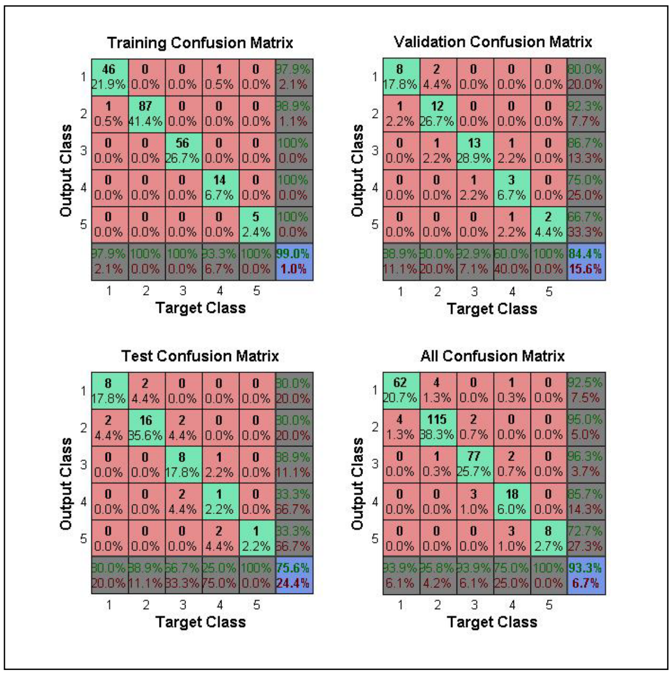

Fig. 4. NIHL Prediction Model Confusion Matrix Result

Figure 4 NIHL Prediction Model Confusion Matrix Result illustrates the confusion matrix results for all process includes training, validation, and testing. Confusion matrices were provided to show the number of processed data and an overall prediction percentage based on a comparison of target and output class. The correct response was shown in the green box, whereas the red box displayed incorrect responses, grey box illustrated the overall accuracies of each class, and the blue box illustrated the overall prediction accuracies of each phase.

The training matrix shows prediction using Levenberg-Marquardt has correctly classified 46 data in stage 1, 87 data in stage 2, 56 data in stage 3, 14 data in stage 4 and five data in stage 5. However, there were some classification errors for stage 2. The overall classification of data into stages during the training process has achieved 99.0% accuracy with 1% error in stage 2.

The validation process matrix shows the prediction has classified stage 1 as 8 data points, 12 data for stage 2, 13 data for stage 3, 3 data for stage 4 and 2 data for stage 5. Stages 1 and 2 involved 3 data points each, and one data point for each of stages 3, 4, and 5. The overall prediction in the validation process has achieved 84.4% with a 15.6% error.

The testing process was performed using 45 data points, which is similar to validation. According to the matrices, the prediction for stages 1 to 5 recorded 34 data points and was classified as correct, while 11 data points were classified as incorrect. The total percentage of predicted performance is 75.6%, with 24.4% of the data having been misclassified.

Overall, the total correct prediction is 93.3%, which is equivalent to 280 data points. While 20 records, which are equivalent to 6.7% of the total accumulated data used in ANN, were categorised incorrectly. This prediction model has achieved better compared to the previous study with its ability to predict using 24 variables with 93.3% accuracy.

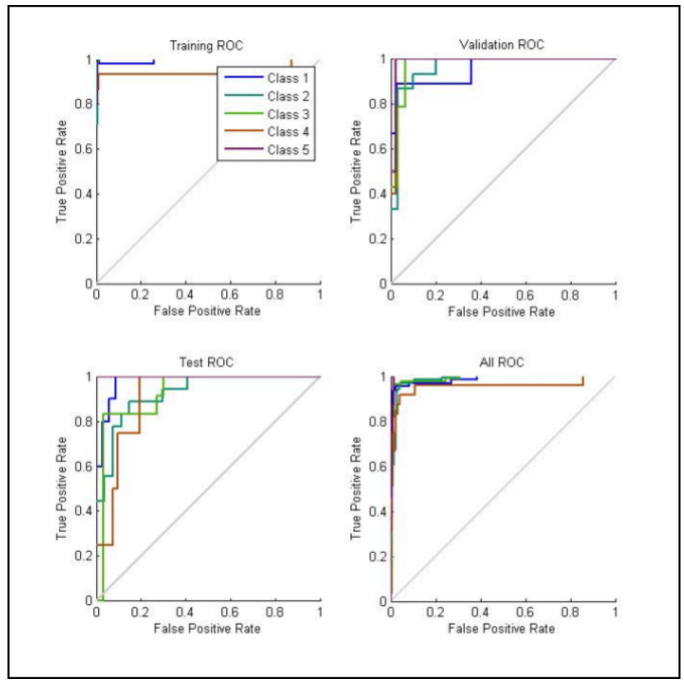

Fig. 5. R.O.C Graph from NIHL Prediction Model Result

Figure 5 illustrates the Receiver Operating Characteristic (ROC) graph result for the NIHL prediction model using ANN. The ROC curve was created as an illustration to analyze the sensitivity and specificity evaluation of a predictive model. The sensitivity graph in ROC was plotted in relation to the True Positive Rate (TPR) and specificity in relation to the False Positive Rate (FPR). The illustration filtered and classified the result into five class outputs: class 1 (blue) for normal, class 2 (cyan) for mild, class 3 (green) for moderate, class 4 (brown) for severe; and class 5 (purple) for profound. The ROC produced by MATLAB software was using a bootstrap confidence interval of 95% based on the corresponding Area Under Curve (AUC) that was originally set in nntool.

The result showed that the training sensitivity of class 4 slightly dropped to 95% and class 1 at 99%. While the other class showed a perfect value of 100% sensitivity and specificity. However, in the validation process, the sensitivity slightly dropped in classes 1 to 3, while specificity showed a decreasing value for all classes of less than 5%. The result from the training process was a bit worsening, where the specificity and the sensitivity for all classes were reduced by on average more than 3%.

V. CONCLUSION

Today, noise pollution is the main cause of a number of health problems at work in Malaysia. This is one of the diseases that has been linked to a condition or environment that is related to noise pollution. The ability of the ANN prediction model to produce accurate results has led to the widespread application of the model to forecast a broad variety of illnesses. Nevertheless, this technology is still in its infancy when it comes to the prediction of NIHL, and a great many transfer functions in the ANN prediction approaches have not yet been investigated in depth.

The most recent study has only proposed two transfer functions, which are denoted by the letters GD and GDM. In the meantime, other transfer functions, such as SCG, Resilient Backpropagation, and LM, which are methods introduced in this research, have never been used previously. The optimization in reaching high precision prediction results while simultaneously reducing the amount of time needed for the network to converge is something that still needs to be researched. As a result, this research is recognized as a pioneering study since it employs ANN and incorporates 24 factors to make predictions about NIHL. This work may be utilized as a reference by other research in the process of establishing a high accuracy prediction model, and it should be recognized as the most significant contribution in the process of commercializing this research product.

The advantage of this study over the earlier one is that it provides a mix of more sophisticated risk factors and variables than the earlier study did. The majority of the risk variables that were identified to lead to a contribution to the advancement of NIHL were found to be hobbies, sectors, and subsectors, and many of the prior studies did not take these aspects into consideration. However, if this work is successful in identifying the optimization approaches that can be used to achieve the minimal local minima and so lower the number of errors produced by the ANN prediction model, then it will be considered new.

Limitations of the Research and Suggestions for Future Work

Cost constraints in conducting the research are the limitation of this study. The cost considers not only the computer itself but also the software, internet connection, and transportation costs. The need for an Internet connection, as well as certain pieces of hardware and software, is directly connected to the development of the ANN prediction model and the NIHL online application. These are the key characteristics that a researcher must meet, particularly when constructing a prediction model with MATLAB.

On top of that, applications like MATLAB, Anaconda, Python libraries, and Jupyter Notebook that are used to design, produce, and analyze the code require a high-speed processor in order to avoid errors throughout the programming and installation process. To improve the accuracy of the NIHL prediction model, a few suggestions have been made for the further investigation and implementation of the NIHL investigation assessment standard. These suggestions may include important variables like the results of blood tests for disease checking, body mass index (BMI), smoking, and other factors related to risk. When it comes to ANN, the optimization process should be improved via the use of the activation function in order to lower the gradient and work toward reaching the local minimum.

VI. ACKNOWLEDGEMENT

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