2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)

ECG Cardiac Abnormality Signal Classification using HMLP Network

Shazreen Shaharuddin [1], Nur Izzani Mat Rozi [2], Maizatullifah Miskan [1], Fakroul Ridzuan Hashim [2,*]
Mohd Salman Mohd Sabri [2], Siti Noormiza Makhtar [2]

[1] Faculty of Medical & Defence Health
National Defence University of Malaysia,
Sg. Besi Camp, Kuala Lumpur, Malaysia

[2] Faculty of Engineering
National Defence University of Malaysia,
Sg. Besi Camp, Kuala Lumpur, Malaysia

*Email: fakroul@upnm.edu.my

***Abstract*—Since irregular heartbeat symptoms arise, it's critical to accurately diagnose the patient's heart problem. This research aims to use a training algorithm for disease detection. The amplitude and duration of P peaks, QRS waves and T peaks are among the data of ficidual detection points that the electrocardiogram (ECG) signal offers. These informational points serve as input parameters. To further develop the prediction model, the Hybrid Multilayer Perceptron (HMLP) network was employed to perform the prediction. To estimate the correctness of the ECG signal model more accurately, Bayesian regularization (BR) training algorithm is applied. HMLP network trained by BR training algorithm capable of performing with mean squared error (MSE) of 0.32 and a regression value of 0.96. The trained model uses Tansig activation function to activate the network.**

Keywords—mean square error, accuracy, electrocardiogram, cardiac abnormality, amplitude and duration.

I. Introduction

Heart disease, often known as cardiac pathology, is a prevalent global ailment, particularly prevalent in Malaysia. Cardiac abnormalitily, or heart disease can happen since blood clots obstruct blood flow to the heart [1]. Arterial blood clots are responsible for coronary artery blockages. The heart will ultimately experience cessation of blood circulation when a thrombus completely obstructs a significant artery. Due to the heart's requirement for oxygen to circulate blood throughout the body, there is a resultant deficiency of oxygen in the heart. Insufficient oxygen supply rapidly weakens the heart muscle, leading to decreased blood circulation throughout the body. This leads to a myocardial infarction. Cardiac problems can be effectively detected using an ECG. An ECG, a valuable diagnostic instrument, can detect anomalies and illnesses of the heart.

It serves as a sensor to detect any electrical impulses produced by the heart on the skin surface [2]. The process of taking an ECG involves positioning several electrodes at different points on the skin's surface. While there are acknowledged drawbacks to electrocardiography, [2] The ECG could seem normal even if there is a serious cardiac condition. A patient with a normal ECG may, however, exhibit notable alterations suggestive of a cardiac abnormality within ten minutes passed the exam. It happens since the ECG is essentially a visual picture of the heart. It is possible that the patient will not have cardiac symptoms during the current test, even though they may have existed in the past.

The test may yield normal results in people with serious cardiovascular issues because it cannot detect artery narrowing until it occurs during physical exercise or a heart attack. Comparably, for those with irregular cardiac rhythms, an ECG is the conclusive test. When a patient does not exhibit an arrhythmia during the examination, however, the findings could seem normal despite a significant underlying issue [3–4]. Consequently, a precise diagnosis of aberrant cardiac activity can be made by extracting elements in the ECG signal, such as the P peak's amplitude and length, the QRS wave's duration, and the T peak's duration, and using these data as input variables for prediction models [5].

II. Literature Review

A. *Electrocardiogram (ECG)*

An ECG is commonly used to assess and record the heart muscle's electrical activity and function. Despite the test's apparent simplicity, mastery in ECG tracing analysis necessitates extensive training [6]. The electrical activity of the heart is measured by electrodes inserted into the skin and by an implanted two-stage electric pump [6-7]. An ECG not only measures pulse rate and rhythm, but also indirectly evaluates blood flow to the heart muscle. The rhythm, which is another name for the heartbeat, varies greatly. A common cardiac rhythm known as the sinus rhythm is depicted in Figure 1. This rhythm is known as a normal ECG signal because each electrical impulse that originates at the sino-atrial (SA) node generates a ventricular contraction [8].

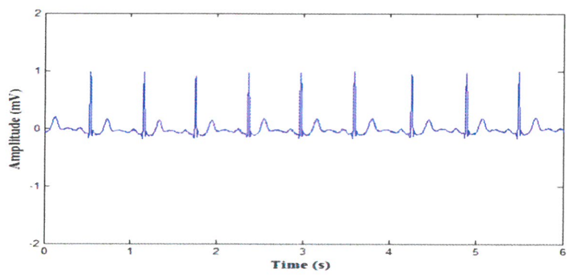

Fig. 1 ECG signal in the heart for normal patient.

Figure 2 shows a variety of irregular electrical rhythms. While certain specimens might not be dangerous, others might. Another cause of unexpected death is cardiac arrhythmias that do not result in a pulse. Figure 2 of the ECG depicts atrial fibrillation, an abnormal cardiac rhythm that can lead to sudden death [9–10].

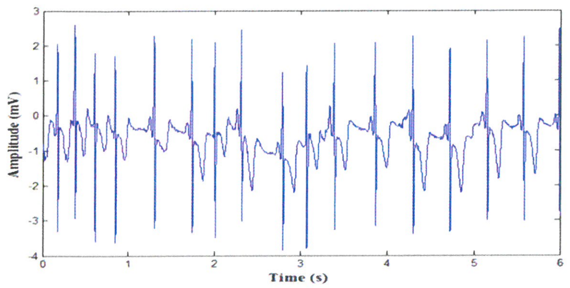

Fig. 2 ECG signal in the heart for AF patient.

B. Ficidual Detection Point

The highest point, or a specific location in the three main waves seen in the complex ECG, corresponds to a distinct and easily identifiable point known as a fiducial point. This is a crucial element to keep in mind when doing analysis and interpretation. At least nine distinct reference points can be distinguished using this incredibly effective technique. However, it is impossible to pinpoint the exact beginning and end of a fundamental wave because the human eye is unable to distinguish between the borders of each wave. Ahmad et al. [11–12] developed a method that precisely locates the three main waves in ECG data. This method requires the determination of the dimensions, duration, and velocity at which the signal changes. Khamis developed the idea of figuring out the local curvature radius, both minimum and maximum, in their research [13]. Combining these two methods can enhance the precision and accuracy of ECG waveform identification. Several ECG recording equipment manufacturers incorporate these methods into their products. Figure 3 displays the parameters of the complex ECG.

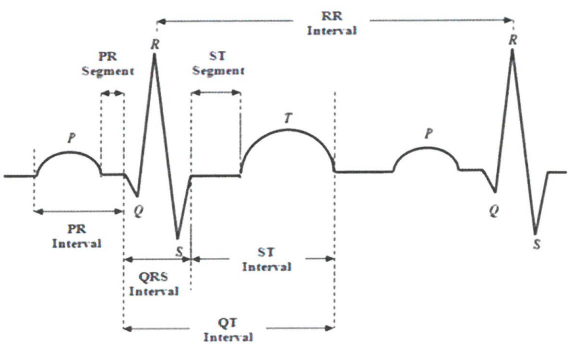

Fig. 3 The fiducial detection points in a complex ECG signal.

C. Hybrid Multilayer Perceptron (HMLP)

An MLP network, as defined in reference [14], is a type of feed-forward neural network that takes a specific set of inputs and produces a similar set of outputs. The network is composed of an input layer, one or more hidden layers, and an output layer. The number of nodes in the input and output layers is determined by the quantity of input and output variables [15]. Empirical evidence has demonstrated that, within an acceptable level of precision, a single hidden layer can approximate a continuous function effectively [16]. The input vector x_i is transformed into a vector of hidden variables u_j by applying an activation function φ_1. Equation (1) can be used to express the output u_j of the node j^{th} in the hidden layer

$$u_j = \varphi_1\left(\sum_{i=1}^{n} w_{ij}\, x_i + \theta_j\right) \quad (1)$$

The variables w_{ij} and θ_j denote the weight and bias of the link between the j^{th} node in the hidden layer and the i^{th} input node. The HMLP network, a modified version of MLP, was proposed as the best method for characterising both linear and nonlinear systems [17]. Figure 5 shows the standard configuration of an HMLP network.

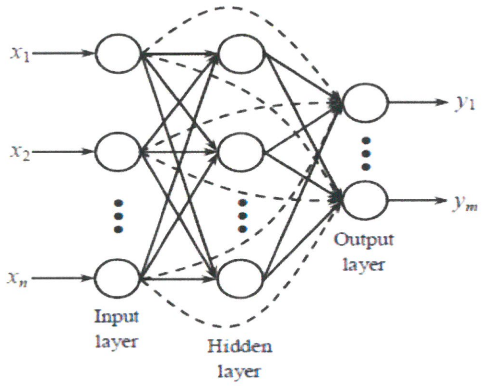

Fig. 4 Structure of HMLP network [12].

The network enables direct connections between inputs and k^{th} output nodes through weighted connections. This creates a linear model that functions simultaneously with the traditional non-linear MLP model [18]. Therefore, Equation (2) represents the outcome derived from the y_k HMLP network.

$$y_k = \varphi_2\left(\sum_{j=1}^{h} w_{ij}\, u_i + \sum_{i=1}^{n} w_{jk}\, x_i + \theta_k\right) \quad (2)$$

D. Training or Learning Algorithms

To guarantee that neural networks function properly, the learning phase is essential. The two most frequently used learning strategies are supervised and unsupervised learning [19–20]. In machine learning, supervised learning refers to the process of building a model that connects input and output variables. Using pre-existing training models with no predetermined output target is known as unsupervised learning. Unsupervised learning, based on prior knowledge, greatly benefits data compression [21]. The investigation began with the implementation of an experimental protocol, followed using neural network techniques for modelling. The extra dataset that was collected along with the main goal was used to train the ECG cardiac abnormality classification model using supervised learning methods such as backpropagation (BP) [22], Levenberg-Marquardt (LM) [23], and Bayesian regularisation (BR) [24].

Continuous evaluation of the performance and accuracy of MSE prediction during the training and testing stages determines the ideal number of training iterations [25–27].

When using regression analysis to assess the suitability of data or project outcomes, the goal is to lower the MSE to show better accuracy. Regression analysis, a statistical technique, estimates the response variable using one or more independent variables. Simple linear regression illustrates this concept by examining a single independent variable in relation to a dependent variable. However, to perform multiple linear regression, two or more explanatory variables must be included in addition to the response variable.

Continuous evaluation of the performance and accuracy of MSE prediction during the training and testing stages determines the ideal number of training iterations [25–27]. When using regression analysis to assess the suitability of data or project outcomes, the goal is to lower the MSE to show better accuracy. Regression analysis, a statistical technique, estimates the response variable using one or more independent variables. Simple linear regression illustrates this concept by examining a single independent variable in relation to a dependent variable. However, to perform multiple linear regression, two or more explanatory variables must be included in addition to the response variable.

III. METHODOLOGY

A. Collection of Data

The ECG information utilised in the research was taken from the Physionet database. The sample consisted of unprocessed signals for cardiomyopathy, along with various types of arrhythmias. In addition, data from normal ECGs is collected for comparison purposes. ECG signals are recorded at a frequency of 1 kHz. This study used MATLAB R2023b for all signal processing and categorization tasks, along with various statistical prediction models. Motion artefacts, electrical wires, and electromyogram (EMG) signals have the potential to interfere with the ECG. Therefore, it is necessary to perform preprocessing of the raw signal to modify the baseline and minimise the noise.

B. Pre Processing Dataset

The statistical prediction model will receive six (6) extracted features from the ECG data. The characteristics are the P wave's amplitude and duration, the QRS complex's amplitude and duration, and the T wave's amplitude and duration. Consequently, there will be six input nodes in the prediction model. Based on the difference between normal and abnormal ECG signals, one of the six traits is chosen. The prediction model incorporates 200 data points from each condition, including random data. To predict whether the heart is healthy or sick, the prediction model considers six distinct ECG signal properties as input parameters [28–30]. Figure 4 displays two output nodes that indicate the heart's status as either normal or dysfunctional. Every output node acts as a heart issue detector. The input parameters are shown in Figure 4 as Amplitude of P peaks (P_a), Amplitude of QRS waves (QRS_a), Amplitude of T peaks (T_a), Duration of P peaks (P_d), Duration of QRS waves (QRS_d), and Duration of T peaks (T_d).

The P_a parameter is calculated from the highest elevation of the P peak, while the P_a parameter is calculated from the sharpest elevation of the T peak. The duration of the P peak is calculated by following its course from inception to conclusion. The QRS duration begins when Q peaks transition into S peaks, whereas the T length is computed from the start of T peaks to their end. According to the research findings, all the factors are used as input parameters in supervised prediction models to classify cardiac anomalies as normal or aberrant signal circumstances.

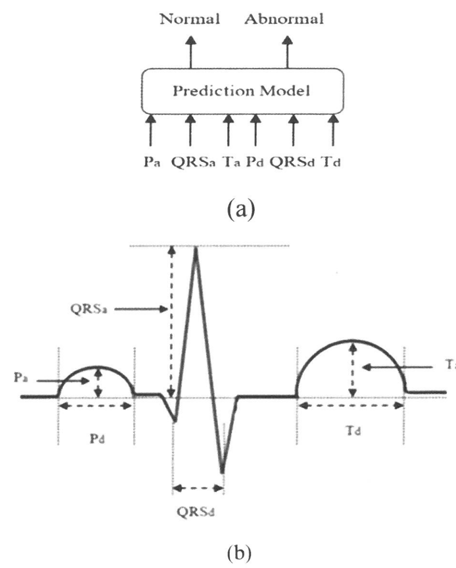

Fig. 5 (a) Prediction block of cardiac abnormality using supervised prediction model, (b) Extracted parameters in ECG complex.

IV. RESULT AND DISCUSSION

It is simpler to evaluate the MLP neural network's performance via prediction analysis by utilising MATLAB's neural network capabilities. This analysis demonstrates the accuracy of the network's prediction of explosion pressure. Three separate steps make up the evaluation technique. 70% of the data that is available is set aside for training in the first phase. In the subsequent phase, thirty percent of the data is reserved for testing purposes alone. Utilising a total of 200 ECG datasets further enhances the evaluation. The two methods used to assess performance to find the best match are MSE and regression analysis. The optimal regression performance and the minimum MSE are used to gauge how effective the training process was. A lower MSE in the prediction phase denotes greater predictive power and reduced relative error [31–33].

By calculating how close a measurement is to one, the regression performance of the network is evaluated. A measurement that is closer to zero (0) denotes poor performance, whereas a value that is closer to one (1) denotes superior performance. Using the MATLAB neural network tool, the MSE and regression values for several training procedures were calculated. The performance of the HMLP network is shown in Table 1. Two different training algorithms are used to evaluate the performance, and the Tansig activation function is used to activate it. Two criteria are used to establish the ranking: the highest regression results and the lowest MSE performance.

Table I presents the results, which include the regression and MSE values as performance measures. The results showed that applying the BR training algorithm to the MLP network yielded the most significant MSE performance and regression coefficients of 1.12 and 0.89, respectively. By contrast, the MLP network-based BP training algorithm did poorly, with regression MSE of 0.71 and 1.75. The subsequent investigation employed the BP, which contained the HMLP network structure, as a training method. The results of the regression study showed that the MSE and regression performance were, respectively, 0.32 and 0.96. Then, in terms of regression performance, the HMLP networks trained by the BR training algorithm fared better than those trained using the BP approaches. Using an HMLP network in with BP training algorithm yields a regression score of 0.86 and an MSE of 1.43.

TABLE I. PERFORMANCE OF SEVERAL PREDICTION MODEL

Structure & Training Algorithm	MSE Performance	Regression Performance
HMLP with BR	0.32	0.96
MLP with BR	1.12	0.89
HMLP with BP	1.43	0.86
MLP with BP	1.75	0.71

Data are displayed in Table I demonstrates an impressive disparity in the effectiveness of the models of training algorithms used. The stochastic model-based BR approach fared better than the deterministic model-based BP algorithm. The presence of random variables distinguishes stochastic models from deterministic models, which have received extensive study and are more prevalent in real-world applications. BP-based algorithms frequently run into local minima during training, which could lead to subpar performance. But several changes have been made to improve the algorithm's capacity to avoid local minima and converge to global ones, which has resulted in notable speed increases overall. The BP technique finds the ideal structure with good computational efficiency but a somewhat lower degree of precision than the BR algorithm. The standard MLP network performed better in predictions after adding a linear connection. Table I shows unequivocally that in terms of regression and MSE performance, the HMLP network performs better than the MLP network.

V. CONCLUSION

This study examines how well a training algorithm can categorize data about heart issues, and then compares the results to those from clinical monitoring techniques. This paper's data empirically supports the idea that training algorithms, which consider the amplitude and length of the P wave, QRS complex, and T wave in ECG signals, can accurately categorise heart issues. This study also examines different training algorithms that can yield the highest regression values and the lowest MSE readings. The BR training algorithm capable to reduce the MSE and optimise the regression results, better than BP training algorithm. On the other hand, the BP training algorithm capable to reduce time processing but unable to outperform BR training algorithm in regression performance. This study aims to identify the best technique to use as a foundation for monitoring heart problems. Several improvements could be made, such as classifying data using a more sophisticated version of a neural network. Implementing data enrichment techniques can enhance performance, but it is crucial to acknowledge that these projects have associated costs.

REFERENCES

[1] N. Fayyazifar, S. Ahderom, D. Suter, A. Maiorana and G. Dwivedi, "Impact of Neural Architecture Design on Cardiac Abnormality Classification Using 12-lead ECG Signals," 2020 Computing in Cardiology, Rimini, Italy, 2020, pp. 1-4.

[2] A. Srivastava et al., "Channel Self-Attention Deep Learning Framework for Multi-Cardiac Abnormality Diagnosis from Varied-Lead ECG Signals," 2021 Computing in Cardiology (CinC), Brno, Czech Republic, 2021, pp. 1-4,

[3] J. L. Costa, P. Couto and R. Rodrigues, "Multitask and Transfer Learning for Cardiac Abnormality Detections in Heart Sounds," 2022 Computing in Cardiology (CinC), Tampere, Finland, 2022, pp. 1-4,

[4] E. Ihsanto, K. Ramli and D. Sudiana, "Real-Time Classification for Cardiac Arrhythmia ECG Beat," 2019 16th International Conference on Quality in Research (QIR): International Symposium on Electrical and Computer Engineering, Padang, Indonesia, 2019, pp. 1-5.

[5] W. Wang, J. Guan, X. Che and W. Wang, "MS-MLP: Multi-scale Sampling MLP for ECG Classification," 2022 30th European Signal Processing Conference (EUSIPCO), Belgrade, Serbia, 2022, pp. 1288-1292.

[6] H. T. Tefai, H. Saleh, T. Tekeste, M. Alqutayri and B. Mohammad, "ASIC Implementation of a Pre-Trained Neural Network for ECG Feature Extraction," 2020 IEEE International Symposium on Circuits and Systems (ISCAS), Seville, Spain, 2020, pp. 1-5.

[7] B. S. Roopa and R. Manjunatha Prasad, "Concatenating framework in ASD analysis towards research progress," 2019 1st International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE), Bangalore, India, 2019, pp. 269-271.

[8] N. Zahia, O. Mohammed Assam, L. Mohamed and B. Hamza, "EMD Based Average Wavelet Coefficient Method for ECG Signal Denoising," 2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE), M'sila, Algeria, 2022, pp. 1-5.

[9] S. S. Salam and R. Rafi, "Deep Learning Approach for Sleep Apnea Detection Using Single Lead ECG: Comparative Analysis Between CNN and SNN," 2023 26th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2023, pp. 1-6.

[10] F. F. Ahmad Saad, S. Shaharuddin, M. N. Abdullah, R. Adawiyah, A. Tajuddin, A. D. Ahmad Shahrir, K. A. Khairumman, S. E. Syed Reyaz Uddin Shamim, "Artificial intelligence (AI) in the era of precision medicine," Human-Assisted Intelligent Computing: Modelling, Simulations and Applications, 2023, pp. 23.1-23.13.

[11] A. F. Ahmed, A. A. Al-Hamadani and M. K. Al-Obaidi, "Efficient and Real-Time Approach for PQRST and Atrial Fibrillation Detection of ECG Signal," 2023 46th International Conference on Telecommunications and Signal Processing (TSP), Prague, Czech Republic, 2023, pp. 91-96.

[12] H. Khamis, J. Chen, J. Stephen Redmond and N. H. Lovell, "Detection of Atrial Fibrillation from RR Intervals and PQRST Morphology using a Neural Network Ensemble," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 5998-6001.

[13] V. Singh, S. Tewary, V. Sardana and H. K. Sardana, "Arrhythmia Detection - A Machine Learning based Comparative Analysis with MIT-BIH ECG Data," 2019 IEEE 5th International Conference for Convergence in Technology (I2CT), Bombay, India, 2019, pp. 1-5.

[14] N. A. Azmi, A. H. Hilmi, M. A. Yusof, and A. Ismail, "Characteristic of Solid Metal using Underground Explosion Pressing," in IOP Conference Series: Materials Science and Engineering, 2018, pp. 012096.

[15] N. N. Umi, M. N. Norazman, N. M. Daud, M. A. Yusof, M. A. Yahya, and M. Othman. "Heat conductivity resistance of concrete wall panel by water flowing in different orientations of internal PVC pipe." IOP Conference Series: Earth and Environmental Science, vol. 140, no. 1, 2018, pp. 012111.

[16] M. Othman, M. Frost and N. Dixon, "Stability performance and interface shear strength of geocomposite drain/soil systems," AIP Conference Proceedings, vol. 1930, no. 1, 2018.

[17] F. N. A. Rahim, M. A. Yusof, N. M. Nor, A. Ismail, M. A. Yahya, V. Munikanan, "Investigation of PE-4 equivalence of spherical emulsion

explosive at different point of initiation," Journal of Advanced Research in Dynamical and Control Systems, vol. 12, 2020, pp. 8-19.

[18] M. M. Swisdak and L. D. Sadwin, "Airblast equivalent weights of various explosive charge shapes for testing structures," APT Research Huntsville AL2010, 2010.

[19] F. R. Bin Hashim, J. J. Soraghan, and L. Petropoulakis, "Multi-classify hybrid multilayered perceptron (HMLP) network for pattern recognition applications," in Artificial Intelligence Applications and Innovations: 8th IFIP WG 12.5 International Conference, AIAI 2012, Halkidiki, Greece, September 27-30, 2012, Proceedings, Part I 8, 2012, pp. 19-27.

[20] K. Thirunavukkarasu, A. S. Singh, P. Rai, and S. Gupta, "Classification of IRIS dataset using classification based KNN algorithm in supervised learning," in 2018 4th International Conference on Computing Communication and Automation (ICCCA), 2018, pp. 1-4.

[21] A. C. Idris, M. R. Saad, M. R. A. Rahman, F. R. Hashim, and K. Kontis, "Experimental validation of artificial neural network (ANN) model for scramjet inlet monitoring and control," International Journal of Recent Technology and Engineering, vol. 7, 2019, pp. 558-563.

[22] R. Dar and P. J. Winzer, "On the limits of digital back-propagation in fully loaded WDM systems," IEEE Photonics Technology Letters, vol. 28, 2016, pp. 1253-1256.

[23] S. Bari, S. S. Z. Hamdani, H. U. Khan, M. ur Rehman, and H. Khan, "Artificial neural network based self-tuned PID controller for flight control of quadcopter," in 2019 International conference on engineering and emerging technologies (ICEET), 2019, pp. 1-5.

[24] A. N. Handayani, N. Lathifah, H. W. Herwanto, R. A. Asmara, and K. Arai, "Neural network Bayesian regularization backpropagation to solve inverse kinematics on planar manipulator," in 2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR), 2018, pp. 99-104.

[25] F. M. Dekking, C. Kraaikamp, H. P. Lopuhaä, and L. E. Meester, A Modern Introduction to Probability and Statistics: Understanding why and how vol. 488: Springer, 2005.

[26] D. C. Montgomery, E. A. Peck, and G. G. Vining, Introduction to linear regression analysis: John Wiley & Sons, 2021.

[27] M. Othman, M. Frost, and N. Dixon. "Soil interface softening from capillary break formation in geocomposite drainage systems." 10th international conference on geosynthetics, 2014.

[28] J. Adnan, N. G. N. Daud, S. Ahmad, F. R. Hashim, M. M. Ibrahim. "Heart abnormality activity detection using multilayer perceptron (MLP) network," AIP Conference Proceedings, vol. 2016, 2018.

[29] S.H.-F.S.A. Jamil, J. A. Kadir, F. R. Hashim, N. S. Hasan, Y. Januar, "Optimization of ECG Peaks for Cardiac Abnormality Detection using Multilayer Perceptron," 10th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2020, 2020, pp. 169–173.

[30] F. R. Hashim, S. H-F. Syam Ahmad Jamil, J. A. Kadir, B. Mustapha, Y. Januar, "Tansig Based MLP Network Cardiac Abnormality," 9th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2019, 2019, pp. 199–203.

[31] M. H. Mat, P. Nagappan, F. R. Hashim, M. S. Saleh, K. Isa, K. Ahmad. "Hybrid multilayer perceptron network for explosion blast prediction," Journal of Advanced Research in Applied Sciences and Engineering Technology, vol. 30, no. 3, 2023, pp. 265-275.

[32] P. Nagappan, M. H. Mat, S. H.-F. S. A. Jamil, F. R. Hashim, M. A. Yusof, M. S. Saleh. "MLP Network Prediction for Blast Explosive based Training Algorithm." in 2023 IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE), 2023, pp. 17-21.

[33] M. H. Mat, P. Nagappan, S. H.-F. S. A. Jamil, F. R. Hashim, K. A. Ahmad, K. Kamal. "Explosive Blast Prediction using MLP Network based Training Algorithm." in 2023 IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE), 2023, pp. 12-16.