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Cardiac Abnormality Prediction using Logsig-Based MLP Network

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Abstract—**Regardless of gender, age, or ethnicity, anyone can get cardiac illness. However, the likelihood of intermediate heart failure is very well predicted by family history. Cardiovascular abnormalities, which rarely show early symptoms, cause patients to die suddenly. The electrical activity or surge that makes up the heartbeat is usually erratic. The Multilayer Perceptron (MLP) network is used in this study as an early detection method for cardiac issues. Using a number of training techniques using Logsig as the MLP network's activation function, the cardiac anomaly dataset from the MIT-BIH database is used to train the chosen MLP network. According to the study, the MLP network's BR training strategy outperformed other strategies with mean square errors (MSE) of 0.0212 and regression performance of 0.9867.**

Keywords- ***cardiac abnromality; Logsig; MIT-BIH; MLP network.***

I. INTRODUCTION

A specific type of irregular cardiac activity or heartbeat that affects people and frequently results in unexpected heartbeats is referred to as an arrhythmia. Among these aberrations are activity-triggered, re-entry, and induced fibrillation. A broad category of disorders where the electrical activity in the heart is aberrant is referred to as cardiac rhythm abnormalities. Regular or irregular, quick or slow, or mixtures of these can all be considered abnormal rhythms [1-2]. The spectrum of abnormality of rhythm ranges from asymptomatic innocent criteria such as isolated irregular beats, to conditions causing major symptoms such as breathlessness, blackouts, and even sudden death. Arrhythmias are categorised using bradycardia, tachycardia, and typical heart rhythms [1-2]. These conditions that affect the electrical activity of the heart may be an early warning sign or an indicator of heart disease. Cardiac irregularity occurs when blood clots form in the body and block the flow of blood through the heart [3]. Blood flow throughout the body is hampered by constricted arteries surrounding the heart. As a result of improper blood distribution throughout the body, the cells, on the other hand, struggled with the low oxygen concentration in the blood. As a result, nerve damage to the human body is conceivable.

An effective method for finding heart problems is the electrocardiogram (ECG). Cardiovascular electrical activity is identified via an ECG test by contracting and expanding (or repolarizing and depolarizing) core muscles [3]. The patient's body is covered with electrodes in order to record the ECG output. This electrode can detect even the tiniest changes in the electrical signal of the nucleus. The heart rate of an ECG can be determined by adjusting the electrical voltage in two electrodes and observing the electrical current associated to cardiac activity [4]. Through the use of digital techniques and MLP networks, these confirmed instances will foresee cardiac problems. The nodes of the MLP network, which are formed of layer numbers, are used to connect layers to the edge. The P, QRS, and T waves of the ECG signal should always be used as the reference vector for the MLP network [4].

The remaining content in the essay is formatted as follows. In part II, the research on ANNs and MLP networks is reviewed, and an explanation of ECG signals is also provided. The suggested approach is fully described in Section III. Section V offers the conclusion after Section IV shows the results and addresses certain issues of debate.

II. LITERATURE REVIEW

In this section, we will go into greater detail on the operation of our hearts and how electrical signals or pulses are generated within the heart. Additionally, a full explanation of how to recognise heart issues using an ECG will be provided. These ECG parameters will be supplied as inputs to the artificial neural network (ANN). Normally, type and application numbers are used in conjunction with the ANN. Multilayer Perceptron (MLP) networks are among the most well-liked methods. The neurobiological comparison, input-output mapping, and nonlinear properties of this MLP network are useful. The MLP network has been successfully used in a variety of other disciplines, including technology, mathematics, economics, and others [5-8]. In this study, MLP networks are utilised to first identify patterns and then classify the data. The MLP network prepares by combining a few selected learning algorithms before optimising the mesh and Logsig's activation function to enable the MLP network.

A. Human Heart

The heart plays a more important role in the human body since it works nonstop throughout the day. The heart pumps blood while supplying nutrients and oxygen to tissues during the blood circulation cycle [9]. The left side of the heart contains thicker cardiac muscle in comparison to a healthier portion. The only muscles to receive non-oxygenated blood will be those on the right while the left muscles continue to pump blood throughout the trunk [10–11]. Wastes like carbon dioxide are routinely expelled through the blood circulation system.

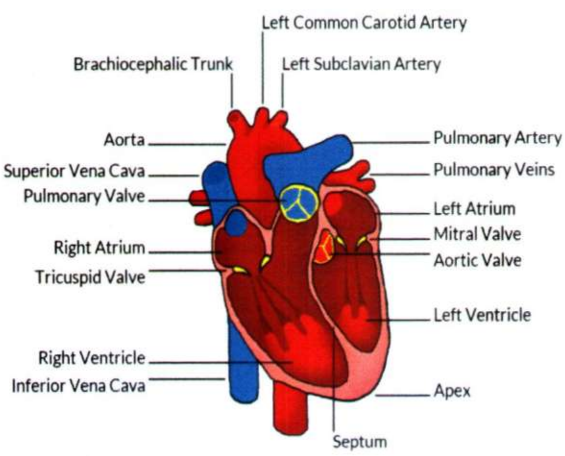

Figure 1. Human heart [5].

The heart channel and the lung channel are the two channels that make up the circulatory system of the human body. The aorta transports the oxygenated blood throughout the body after receiving it from the pulmonary vein. To supply tissue bodies with oxygen, this oxygen-rich blood enters the capillaries and arteries. Deoxygenated blood from the body is delivered into the lungs by the pulmonary artery, which is situated in the right ventricle and connects to the vena cava. Deoxygenated blood is given oxygen by the lungs before being sent to the left atrium via the pulmonary veins. The electrical system of the heart can fluctuate, which can result in arrhythmias, which alter the rhythm of the heartbeat. Various types of arrhythmia exist, including bradycardia, regular, and tachycardia [12–13]. Table 1 lists the various cardiac abnormalities' types and behaviours.

TABLE I. HEAART ACTIVITY AND CARDIAC ACTIVITY

Heartbeat Activity	Cardiac Condition
60 < beats per minutes < 100	Normal
beats per minutes < 60	Bradycardia
beats per minutes > 100	Tachycardia

B. Electrocardiogram (ECG)

The sinoatrial (SA) node is where electrical impulses in the heart first appear before moving on to both atria. The atrioventricular (AV) node receives the electrical impulses next. The Bundle of His directs the AV node's electrical impulses to the ventricles. The myocardium's individual cells can only contract in unison when an electrical signal reaches them; as a result, the ventricles can contract, creating a systemic circulation through the left ventricle and a pulmonary circulation through the right. An ECG connects to and represents the electrical activity or electrical signal in the heart since it is a continuous recording of the electrical signal. In order to assess electrical activity as well as electrical impulses produced during atrial and ventricular contraction and rest, several electrodes are positioned on the limbs and chest. A wave can visually or numerically indicate the difference in current and voltage between any two electrodes [14]. ECG waves consist of P, QRS, and T waves. U waves, which are ECG waves, can occasionally be seen. Table 2 shows the P, QRS, and T waves as a representation of the electrical activity of the heart. The electrical changes that occur in the heart are visible on the ECG monitor's waveform. The heart undergoes both depolarization and repolarization in response to stimulation. Depolarization occurs as a result of an electrical boost to the heart.

TABLE II. ELRCTRICAL ACTVITY PATTERN AND ITS ELECTRICAL ACTIVITY

Electrical Activity Wave Pattern	Electrical Activity in the Heart
P wave	Depolarization of Atrial
PR segment	Delay at AV node
QRS complex	Depolarization of Ventricular
T wave	Repolarization of Ventricular

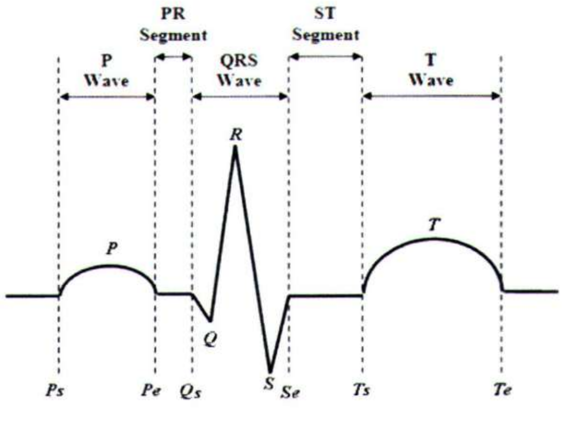

Figure 2. A cycle of ECG complex [15].

C. *Artificial Neural Network and Activation Function*

To replicate the biological structure of the human brain, a tool known as an Artificial Neural Network (ANN) was developed. In ANN, there are synthetic neurons (networks, sometimes known as "nodes"). This node links every other node to itself. The community of artificial intelligence recognises ANN as possessing functional human brain activity (AI). Algorithms are developed and set up to work like the human brain [5–6]. The MLP is one of the network topologies used by ANNs. It consists of layers connected between the input and output layers. Vectors are entered in a single direction from the input to the output of the layer. The nodes to which the input neurons are connected lack any such orientation, but the node to which the neuron's output is attached lacks any such position. Because the intended value provided in the training pattern affects the amount of neuron output, MLP does not merely concentrate on neuron output. The connections between a neuron's input and output are called hidden neurons.

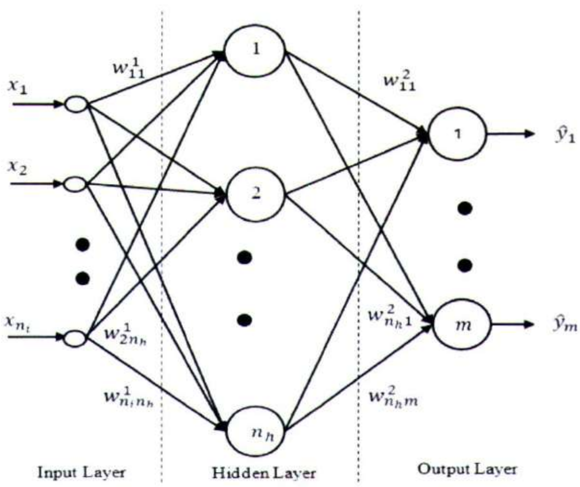

Figure 3. MLP structure.

There could be one or more layers between the layer of input and output in this network, and they were intended to be transparent layers. It is essential to choose the correct input-output variables since the nodes on the input-output layer of the MLP network depend on them. According to research by Hashim et al., a concealed layer must get close to the continuous feature before sufficient precision is reached [15]. The following strategies display the results of the MLP network prediction:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \, \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + w_{k0}^1 x_0^1\right) \quad (1)$$

$$for\ 1 \le j \le n_h \text{ and } 1 \le k \le m$$

where, respectively, n_i and n_h represent the number of input nodes and the number of hidden nodes. The MLP network has been turned on using the Logsig activation function $\partial(\cdot)$. The unknown variables are represented by the weights w_{ij}^1 , w_{jk}^2 and w_{k0}^1 , which are set at the minimum vectors. The network's objective is to reduce prediction error as it approaches the optimum, which is defined as:

$$e_k(t) = y_k(t) - \hat{y}_k(t) \quad (2)$$

utilising the actual output $\hat{y}_k(t)$ indicated or derived from the database in conjunction with the expected output $y_k(t)$ provided or generated by the algorithm. This transfer function of Logsig is coupled to a bipolar sigmoid. An activation function, Logsig's ranges from 0 to +1. As the reference, Figure 4 shows the activation function of Logsig for the MLP network. The threshold must be configurable at any point between 0 and +1.

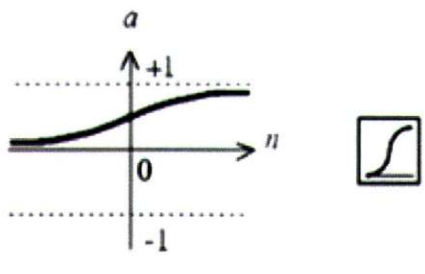

Figure 4. Logsig activation function [16].

III. METHODOLOGY

The issue arises when performing various activities like running quickly or ascending stairs; the heart rate changes depending on the patient's or participants' size and the speed of the activity. Most heart rate measurements are made while the individual is at rest or walking at a constant, controlled speed on a treadmill. However, by reducing the time between complexes, readings of the heart rate for nonstationary patients can also be analysed. Only complexes with a period of peak R to peak R will remain after this operation. A square pulse is used in this test to generate an ECG complex that can last up to ten pulses and begins at a pulse. A 2n-1 function, where n is the number of rectangular pulses, is used to create the intersections. Four rectangular pulses are all that are required to produce the most accurate simulation-based forecasts (seven crossings). Most ECG signals are variable in clinical settings, not only from subject to subject but also from procedure to procedure. Finding the ECG complex using morphological maximum R-R data is the primary goal of this investigation (RRI). A substantial number of ECG complexes may be found in the ECG signal that was utilised to create the RRI morphological data set. Following that, the created rectangular pulse covers the RRI morphological array. The neural network receives the discrete point of the ECG complex (amplitude reading and time between each intersection), as illustrated in Figure 5, as a vector input. From the figure, seven interceptions point will be set as the input parameter while the output is either normal or AF condition.

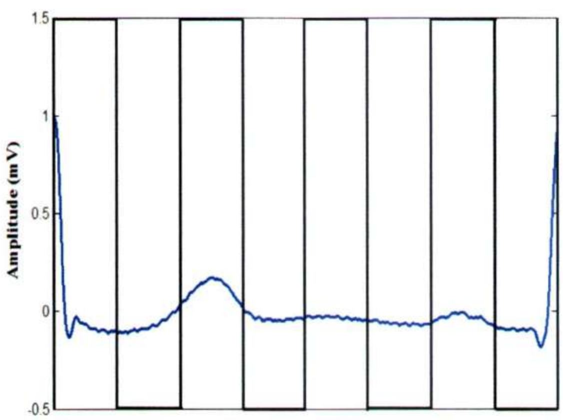

Figure 5. Feature extraction based on RRI [15].

IV. Results and Discussion

The table's four pulses (intersections) are more than enough to produce reliable results with excellent predictability. RRI data must be abundant for neural networks to make precise predictions. If the data set is too large, it will take the network longer to reach its optimal values, making the network more complex and difficult to correctly classify. The network was trained using 800 of the 1,000 data in the database for training and 200 for testing. Feed-Forward (FF), Cascade-Forward Reinforcement (CFR), and Multilayer Perceptron network topologies were used in this study (MLP). Using the Logsig activation function for RRI morphology, all network structures are activated [16-17]. This series makes use of the Bayesian Regularization (Bay), Resilient (Res), and Levenberg-Marquardt (Lev) learning techniques. To compare all network architectures and learning strategies, the results are illustrated using the least average readings (MSEs) and regression performance.

TABLE III. Comparison Performance Between MLP, FF and CFR Networks with Tansig Activation Function

Structure / Training Algorithm	Training Algorithm	MSE Performance	Regression Performance
CFR	Bay	0.2132	0.9217
	Res	0.5198	0.9134
	Lev	0.4187	0.9268
FF	Bay	0.0132	0.9246
	Res	0.4918	0.9142
	Lev	0.3556	0.9241
MLP	Bay	0.0212	0.9867
	Res	0.0419	0.9240
	Lev	0.0296	0.9802

MLP networks outperform RRI morphology CFR and FF networks in terms of prediction, as shown in Table III. The MLP network generates the lowest MSE reading for the RRI morphology dataset and he highest regression scores of 0.0212 and 0.9217, respectively. The MLP network was trained using the Bay learning technique. In spite of the fact that the Bay learning algorithm-trained MLP network can be solved, the Lev training algorithm-trained MLP network also exhibits high-precision prediction performance. Even while both the CFR and FF networks are capable of delivering trustworthy outcomes, the MLP network has greater capabilities than these networks.

V. Conclusion

Potentially capable of identifying structural defects in the human heart is the MLP network. Predicting the cardiac problems requires an efficient neural network design, learning algorithm, and feature activation. Using the Bay training method and Logsig activation feature, this study demonstrates that the MLP network performs better than other neural network combinations, learning algorithms, and function activation in terms of producing the best regression output and the lowest MSE reading.

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