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Employing Convolutional Neural Network Model in Predicting Heart Diseases

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Abstract

Heart disease is a global health challenge and one of the leading causes of death worldwide. Early diagnosis of heart disease allows for appropriate therapeutic intervention and necessary measures to prevent disease progression and prevent serious complications. The significance of ECG lies in its ability to detect heart disease and accurately diagnose various conditions. Many research studies have been conducted in the field of artificial intelligence techniques to analyze cardiac signals. This study aims to create a one-dimensional convolutional neural network (CNN) to process these ECG signals utilizing MIT-BHI database that contains 87554 samples of ECG signals was used. The database contains different cardiac signal classes, including normal signals, regular atrial contraction, premature ventricular contraction, combined beat, which results from the superposition of several waves in the presence of a cardiac pacemaker, and a class labeled as "unknown signals". Data were divided after processing into 80% training data, 15% test data, and 5% validation data. We processed the data and trained the CNN neural network model accordingly, and the results showed that the diagnostic accuracy reached 99.52% for training and 99.45% for testing.

Keywords: Deep Learning, Covolutional Neural Network, Heart Disease Prediction, Healthcare.

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استخدام نموذج الشبكة العصبية التلافيفية في التنبؤ بأمراض القلب

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الملخص

أمراض القلب تمثل تحديًا صحيًا عالميًا وهي من الأسباب الرئيسية للوفاة في جميع أنحاء العالم. يسمح التشخيص المبكر لأمراض القلب بالتدخل العلاجي المناسب واتخاذ التدابير اللازمة لمنع تفاقم الحالة القلبية وتجنب المضاعفات الخطيرة. تكمن أهمية تخطيط القلب الكهربائي في قدرته على كشف أمراض القلب وتشخيص الحالات المختلفة بدقة. تم إجراء العديد من الدراسات البحثية في مجال تقنيات الذكاء الاصطناعي لتحليل الإشارات القلبية. تهدف هذه الدراسة إلى إنشاء شبكة عصبية تلافيفية أحادية البُعد (CNN) لمعالجة هذه الإشارات الكهربائية القلبية، حيث تم استخدام قاعدة بيانات MIT–BHI التي تحتوي على 87554 عينة من الإشارات القلبية. تحتوي قاعدة البيانات على فئات مختلفة من الإشارات القلبية، بما في ذلك الإشارة الطبيعية، والانقباض الأذيني المنتظم، والانقباض البطيني المبكر، والنبضة المركبة التي تنتج عن تداخل عدة موجات في وجود جهاز تنظيم ضربات القلب القاري، وفئة مصنفة على أنها إشارة غير معروفة. تم تقسيم البيانات بعد المعالجة إلى 80% بيانات تدريب، و15% بيانات اختبار، و5% بيانات تحقق. قمنا بمعالجة البيانات وتدريب نموذج شبكة CNN العصبية وفقًا لذلك، وأظهرت النتائج أن دقة التشخيص بلغت 99.52% للتدريب و99.45% للاختبار.

الكلمات المفتاحية :التعلم العميق، الشبكة العصبية التلافيفية، التنبؤ بأمراض القلب، الرعاية الصحية.

I. Introduction

The term "cardiovascular diseases" varies significantly, encompassing many conditions that affect the function of the heart and blood vessels[1], which include the pumping of blood and circulation throughout the body comprehensively[2-6]. These conditions can lead to various complications that may, in some cases, result in a deterioration of quality of life or even death, especially in developing countries [7, 8]. Arrhythmias can generally be classified as either life-threatening or non-life-threatening[9].

Rapid and early detection of heart diseases is vital for accurate diagnosis and appropriate treatment for each case, which can reduce the risk of serious complications and increase the chances of complete recovery[10]. Electrocardiography (ECG) is a fundamental medical test that measures the electrical activity of the heart and is used to diagnose many conditions associated with cardiovascular diseases. ECG can effectively reveal changes

in heart activity, such as arrhythmias, and record them as an electrical pattern, contributing to early detection of these changes and ensuring heart safety[11, 12].
The detection of arrhythmias is typically conducted through ECG recordings [13, 14], which reflect the heart's electrical activity over time via electrodes placed on the skin[15]. These leads can capture electrical signals from various angles, aiding in the identification of the condition through distortions in waveforms and heart rhythms[16, 17].
In recent years, deep learning technology has proven effective in analyzing ECGs using deep convolutional neural networks that automatically extract features from the raw signals. Deep learning is a branch of artificial intelligence that can be utilized for analyzing medical data and diagnosing various health conditions, including heart diseases[18].
Deep learning techniques can contribute to the analysis of electrical signals from ECGs by training computational models to extract vital information from these signals and analyze them to detect changes in heart activity and diagnose a variety of heart disease cases. Training these models requires large amounts of medical data [19] .
Modern deep learning technologies offer unique opportunities for developing computer-aided diagnostic systems and applying them in various fields. Developing intelligent systems in healthcare and processing vast amounts of raw data are vital tasks, and this has become essential in healthcare[20]. Reducing errors and increasing diagnostic accuracy is a primary goal for developing CAD systems to facilitate diagnosis using ECG[21]. Creating an effective CAD system requires precise pattern classification and the presence of feature extractors to extract critical information from medical data[22].
This study aims to develop a one-dimensional convolutional neural network (CNN) to improve the accuracy of heart disease diagnosis by analyzing heart signals using the MIT-BIH database. To achieve this goal, an advanced data processing methodology was implemented, which includes data augmentation by splitting each signal into 12 signals. This resulted in a ready-to-train database containing 50,000 samples for each category, totaling 250,000 samples across all categories. This enhances the model's ability to recognize patterns in the signals and improves diagnostic accuracy.

II. Normal Electrocardiogram

A normal electrocardiogram consists of the P wave, QRS complex, and T wave, as shown in Figure 1. The QRS complex typically consists of separate waves: Q, R, and S, although this is not always the case[23]. The P wave results from the electrical potentials generated by depolarization of the atria before the onset of atrial contraction, while the QRS complex arises from the potentials generated by depolarization of the ventricles just before their contraction[24], during the spread of the depolarization wave through the ventricles Accordingly, we refer to the P wave and the components of the QRS complex as depolarization waves[25]. The T wave results from the potentials generated by repolarization of the ventricles, occurring naturally in the ventricular muscle after

depolarization, within a time frame of 0.25 to 0.35 seconds[26]. The T wave is known as the repolarization wave[27].
Before muscular contraction occurs, depolarization must spread to initiate the chemical processes of contraction, as the P wave occurs at the beginning of atrial contraction and the waves of the QRS complex occur at the beginning of ventricular contraction. The ventricles remain contracted for a few tenths of a second after repolarization, which happens at the end of the T wave[28].
The atria repolarize approximately 0.15 to 0.20 seconds after the P wave, coinciding with the moment the QRS complex begins to be recorded on the ECG. Consequently, the atrial repolarization wave, defined as the atrial T wave, often becomes obscured by the much larger QRS complex, which is why the atrial T wave is rarely seen on the ECG[27].
The atrial repolarization wave is the T wave in a normal ECG, and typically, the ventricular muscle begins to repolarize in some fibers about 0.20 seconds after the onset of the QRS complex depolarization, and after 0.35 seconds in many other fibers[28]. Thus, the repolarization process extends over a long duration of about 0.15 seconds[26], which is why the T wave in a normal ECG is often prolonged and stretched, although its voltage is noticeably lower than that of the QRS complex, partly due to its extended duration[29, 30].

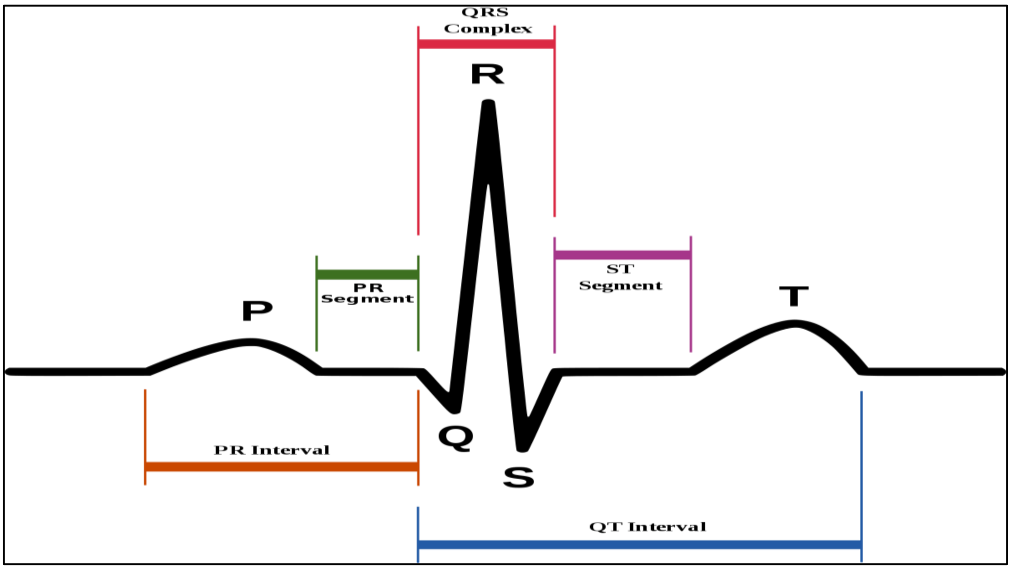

Figure1. Normal Electrocardiogram (ECG)

III. Methodology of the proposed model

The methodology of the proposed model is divided into two main parts: signal processing, and after completing that, we proceed to build and train the neural network, as shown in Figure (2).

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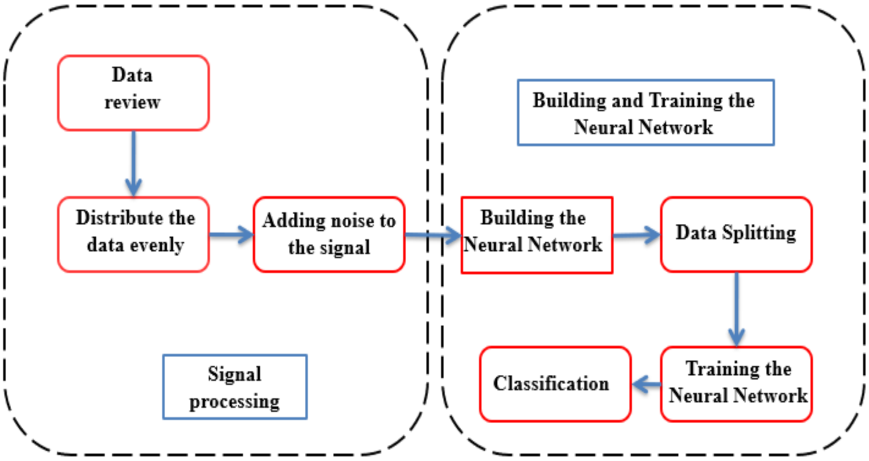

Figure2. Block diagram of the Proposed Model

1. Database

Artificial intelligence algorithms (deep learning and machine learning) fundamentally rely on data, which is used to train them on a specific task—in our case, classification. They are trained on a certain amount of data and tested on another, thereby gaining knowledge and the ability to make specific decisions. We utilized a portion of the "MIT-BHI" database, which contains 87,554 samples, as shown in Figure (3). Data are divided into five classes: normal signal, irregular atrial contraction, premature ventricular contraction, merged pulse, and a set of other signals classified as unknown signals [31]. The processed data was then divided into 80% training data, 15% testing data, and 5% validation data.

	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	18
0	0.977941	0.926471	0.681373	0.245098	0.154412	0.191176	0.151961	0.085784	0.058824	0.049020	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
1	0.960114	0.863248	0.461538	0.196581	0.094017	0.125356	0.099715	0.088319	0.074074	0.082621	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
2	1.000000	0.659459	0.186486	0.070270	0.070270	0.059459	0.056757	0.043243	0.054054	0.045946	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
3	0.925414	0.665746	0.541436	0.276243	0.196133	0.077348	0.071823	0.060773	0.066298	0.058011	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
4	0.967136	1.000000	0.830986	0.586854	0.356808	0.248826	0.145540	0.089202	0.117371	0.150235	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
87549	0.807018	0.494737	0.536842	0.529825	0.491228	0.484211	0.456140	0.396491	0.284211	0.136842	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
87550	0.718333	0.605000	0.486667	0.361667	0.231667	0.120000	0.051667	0.001667	0.000000	0.013333	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
87551	0.906122	0.624490	0.595918	0.575510	0.530612	0.481633	0.444898	0.387755	0.322449	0.191837	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
87552	0.858228	0.645570	0.845570	0.248101	0.167089	0.131646	0.121519	0.121519	0.118987	0.103797	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
87553	0.901506	0.845886	0.800695	0.748552	0.687138	0.599073	0.512167	0.427578	0.395133	0.402086	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0

87554 rows × 188 columns

Figure3. Database

Figure (4) shows the distribution of the number of samples in the database, where number 0 indicates the class of normal signals, which exceeds 70,000 samples, while no other class exceeds 10,000 samples.

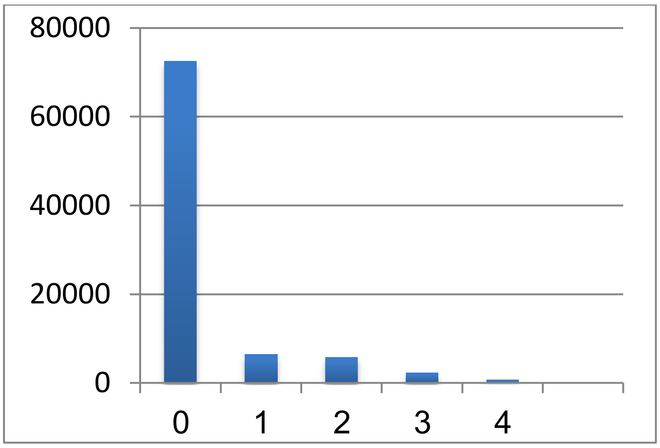

Figure 4. Distribution of Database Samples

Each sample of the data is a signal composed of 13 cycles with 3600 points within the complete signal, as shown in Figure (5).

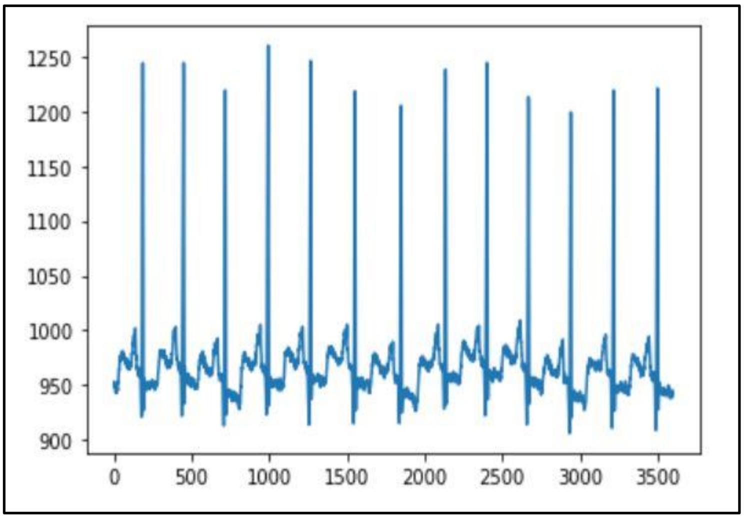

Figure 5. Digital Representation of the ECG Signal

2. Data Processing

Deep learning algorithms can read the data fully, but machine learning algorithms perform poorly with large amounts of data. Therefore, we will divide and process the data according to the following stages:

Due to the limited number of data points relative to the number of samples within each signal, we worked on data augmentation by splitting each signal into 12 signals. The division was carried out as follows.

A, the highest peak in the signal, which is the R wave peak in one of the cycles of the signal. This gives us the result shown in Figure(6) .

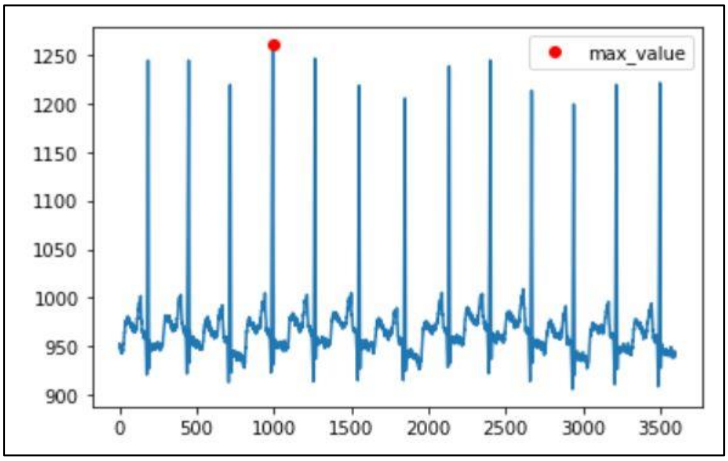

Figure 6. Peak Detection

B. The collection of all peaks that constitute 90% of the R peak detected in the previous step, as shown in Figure (7).

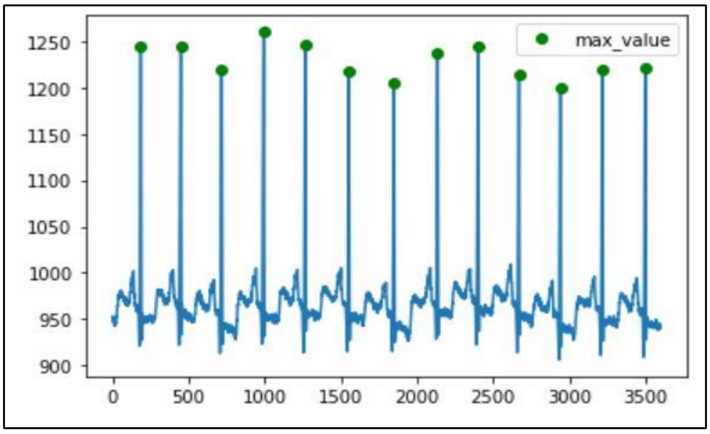

Figure 7. Detection of All R Peaks

C. We take 100 steps backward and 200 steps forward at each peak detected in the previous step. This results in one cycle of the signal, as shown in Figure(8) .

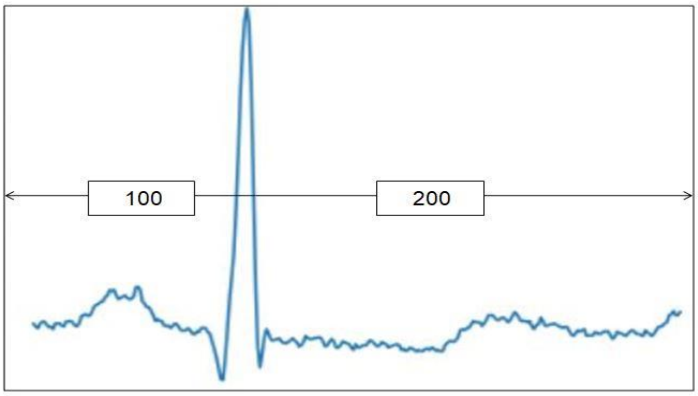

Figure 8. Dimensions of the Signal Sample

D. Adding Noise to the Signals: Since the signals in the database are noise- free, and to enhance the network's diagnostic capability, we add Gaussian noise to the signals, as shown in Figure (9). Gaussian noise is interference that has a probability density function equal to the probability density function of the normal distribution. It can be expressed in Eq. 1.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\sigma)^2}{2\sigma^2}} \qquad (1)$$

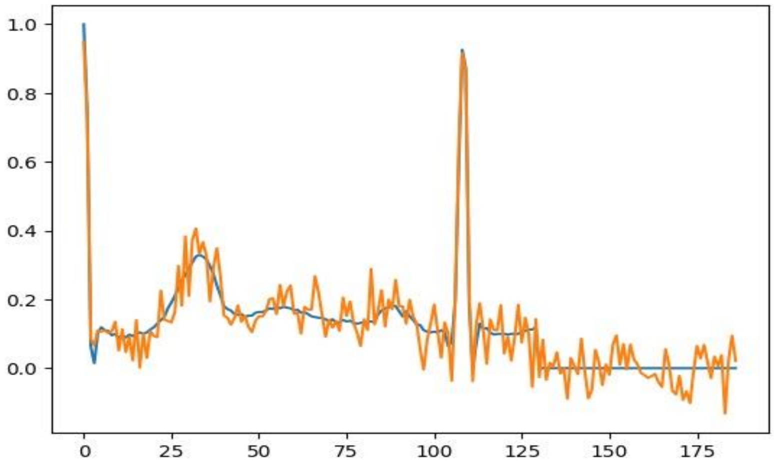

Figure 9. The Signal after Adding Noise

After completing the entire processing, we have obtained a ready-to-train database for the algorithms, consisting of 250,000 samples for each class, as shown in Figure(10) .

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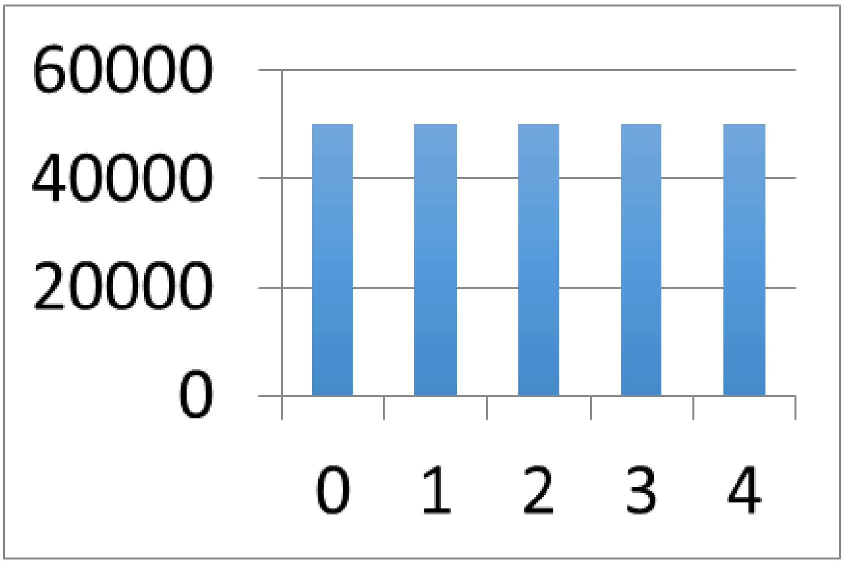

Figure10. Equal Distribution of Data

3. Model Training

We will begin with the training process of the neural network.

4. Building the Artificial Neural Network

Figure (11) shows that our neural network is a Convolutional Neural Network (CNN), specifically a one-dimensional (1D) network since we are dealing with signals represented as one-dimensional digital vectors.

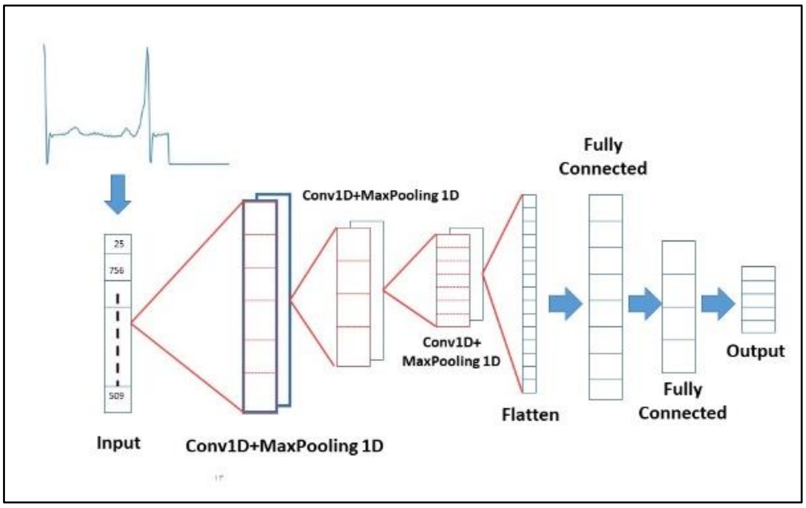

Figure 11. Neural Network Architecture

Figure (12) illustrates the input layer, which contains three one-dimensional convolutional layers (Conv1D), utilizing the activation function (ReLU), as expressed in Eq.2. Each layer is followed by a MaxPooling1D layer with a size of 2×3. Each convolutional layer contains 64 neurons and has a filter size of 6×1.

$$Relu(x) = \begin{cases} 0 \ \ for\ x\ < 0 \\ x\ \ for\ \ x \geq 1 \end{cases} \qquad (2)$$

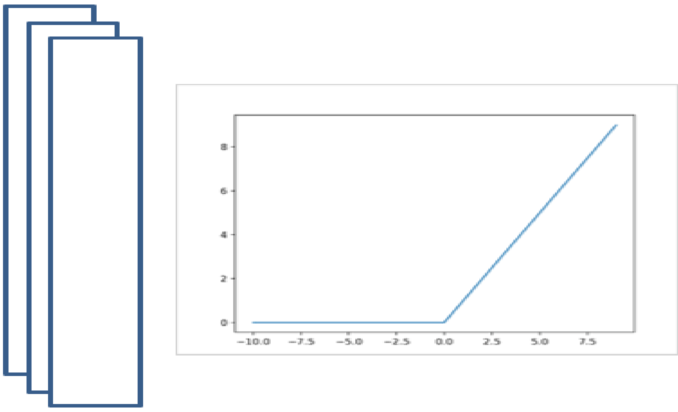

Figure12. Input Layer

Flatten Layer: This layer converts the features extracted from the previous layers into a one-dimensional vector .
Two Fully Connected Layers: The first has 64 neurons, and the second has 32 neurons. These layers process the extracted features and use the activation function (RELU).
Output Layer: it is composed of 5 neurons with a SoftMax activation function, as shown in Figure(13) .

$$S(y)_i = \frac{\exp(y_i)}{\sum_{i=1}^{n} \exp(y_i)} \qquad (3)$$

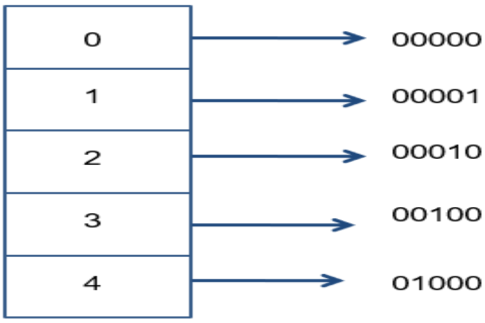

Figure13. Output Layer

We divided the processed data into 80% training data, 15% testing data, and 5% validation data.

IV. Results Discussion

After completing the training and testing process, Figures (14) and (15) present an overview and evaluation of the results obtained from our proposed model .

We achieved a classification accuracy of 99.52% for training and 99.45% for testing, while the error rates were 0.0172 for training and 0.0183 for testing. The blue curve indicates training accuracy, while the yellow curve indicates test accuracy.

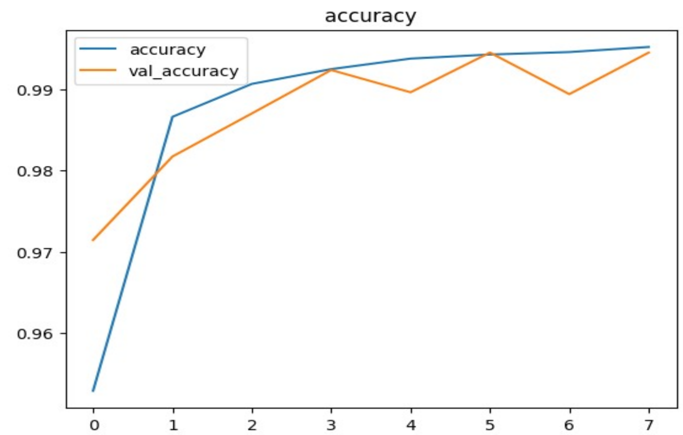

Figure14. Accuracy

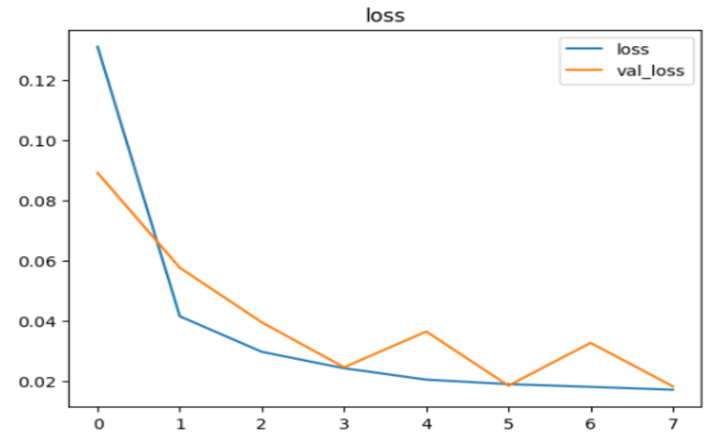

Figure15. Loss

To delve deeper into the model's accuracy, we discuss the confusion matrix shown in Figure (16) to assess the classification accuracy for each class individually.

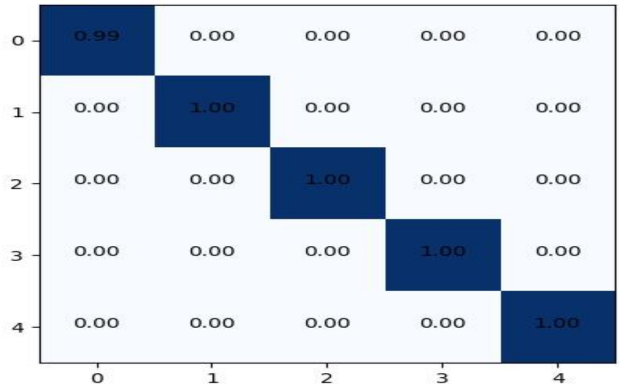

Figure16. Confusion Matrix of Neural Network Results

We observe that the classification accuracy is 99% for the normal signal class, 100% for the irregular atrial contraction class, 100% for the premature ventricular contraction class, 100% for the merged pulse class, and 100% for the unknown signals class, with an overall average accuracy of 99.8%.

V. Conclusion

In this paper, a CNN deep learning model was proposed, trained and tested to classify heart diseases in the "MIT-BHI" dataset. The performance of the models was evaluated using accuracy metrics, and the results showed a positive impact on diagnosing heart diseases, with high accuracy rates. Based on the project results, future development can be achieved through:

- Increasing the size and diversity of the data used to enhance system performance.
- Conducting clinical studies and practical experiments to evaluate the performance of deep learning detection systems in real-world settings.

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