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Detection of Heart Diseases Using Deep Learning Techniques

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Abstract

Electrocardiography is an effective tool for detecting heart diseases or predicting heart diseases, and previous researchers have approved it as an effective tool in diagnosis. This early diagnosis's essential benefit is reducing deaths due to heart disease because the heart is the most critical part of the human body. From this Starting point, this paper used electrocardiography to diagnose and predict heart disease. A system that supports deep learning by using Convolutional Neural Network and the use of the most critical global data set approved by previous researchers was proposed to diagnose or predict the four most critical pathological conditions, namely (ST-T abnormalities, myocardial infarction (MI), arrhythmias, and Conduction disturbances and abnormalities) The proposed system goes through three primary stages (processing, classification, and prediction), where CNN deep learning algorithms of the design the proposed system. The data set was used. PTB-XL for calculating healthy and infected samples for complete system training, testing, and prediction. The proposed system achieved good results with a sensitivity of 72.3%, a specificity of 73.90%, an accuracy of 91.33%, an accuracy of 88.69%, and an f1 score of 92.51%.

Keywords: Electrocardiography, Diseases, PTB-XL, CNN.

الكشف عن أمراض القلب باستخدام تقنيات التعلم العميق

مرفت رزاق الجبوري و جمال مصطفى التويجري

قسم علوم الحاسبات - كلية العلوم - جامعة ديالى

الخلاصة

يعد تخطيط القلب الكهربائي أداة فعالة في الكشف عن أمراض القلب أو التنبؤ بأمراض القلب ، وقد وافق عليه باحثون سابقون كأداة فعالة في التشخيص. تتمثل الفائدة المهمة لهذا التشخيص المبكر في تقليل الوفيات بسبب أمراض القلب لأن القلب هو أهم

جزء في جسم الإنسان. من نقطة البداية هذه ، استخدمت هذه الورقة تخطيط القلب لتشخيص أمراض القلب والتنبؤ بها. حيث تم اقتراح نظام يدعم التعلم العميق واستخدام مجموعة البيانات العالمية الأكثر أهمية المعتمدة من قبل الباحثين السابقين لتشخيص أو التنبؤ بأهم أربع حالات مرضية وهي (شذوذ ST-T ، احتشاء عضلة القلب (MI) ، عدم انتظام ضربات القلب ، و اضطرابات التوصيل والشذوذ) يمر النظام المقترح بثلاث مراحل أساسية (المعالجة والتصنيف والتنبؤ) ، حيث خوارزميات التعلم العميق لتصميم النظام المقترح. تم استخدام مجموعة البيانات PTB-XL .لحساب العينات السليمة والمصابة لتدريب النظام الكامل والاختبار والتنبؤ. حقق النظام المقترح نتائج جيدة بحساسية 72.3٪ ، وخصوصية 73.90٪ ، ودقة 91.33٪ ، ودقة 88.69٪ ، ودرجة f1 92.51 ٪.

الكلمات المفتاحية: تخطيط القلب ، الأمراض ، CNN، PTB-XL .

Introduction

Heart disease kills about 17.9 million people yearly, 31% of all deaths worldwide. Cardiovascular disease is now the top cause of death and a severe threat to people's health. Electrocardiograms, or ECGs, are the most common way to determine if someone has heart problems [1]. Surface electrodes can record the ECG data, which shows how the heart's electrical activity changes during each heartbeat. By analyzing ECG signals, doctors can get important information about a patient's health and quickly spot cardiac problems, saving lives and improving the quality of life with the right care[2]. Electrocardiogram (ECG) classification is the most effective and straightforward way to detect heart disease, which helps diagnose most of the symptoms [3]. Medical staff are overburdened and may make mistakes due to work pressure, and ECG diagnosis depends on their judgment. ECG automatic analysis will help medical professionals [4]. ECG detection is the most effective and straightforward method. Doctors use manual detection and ECG analysis to diagnose heart disorders. Medical personnel can improve diagnostic efficiency by using automated ECG analysis techniques [5]. This paper will discuss the process of creating a system for diagnosing diseases based on electrocardiography, and the most critical work done by previous researchers will also be discussed.

Electrocardiography

Research on the human heart is considered among this field's most vitally significant aspects. The electrocardiogram (ECG) is the method most frequently used to locate and measure the heart's electrical activity. The electrocardiogram is a tool that can assist medical professionals in diagnosing heart conditions such as arrhythmia, coronary artery disease, and heart attack [6].

Traditional ECG analysis methods depend on trained specialists manually interpreting the data, which can take time and vary from person to person. In recent years, deep learning has become a potential way to diagnose heart conditions from ECG signals. It has shown promising results in accuracy and speed [7]. Twelve leads or nodes attached to the body record an electrocardiogram (ECG). An electrocardiogram captures the heart's electrical activity. It transmits it to graph paper or an electronic vault in an electronic form that can be used for medical and security purposes by constructing a diverse dataset and presenting it to researchers for biometric systems [8]. Twelve-lead ECGs detect arrhythmia. Ten electrodes—six in the thorax and four in the extremities—measure electrical potential in these examinations. Early diagnosis is essential for treating arrhythmias [9].

Related Work

Various studies on diagnosing heart diseases are based on the electrocardiogram. The following are the most important studies close to the proposed system within three time periods 2021-2023. **In (S. Clement Virgeniya & E. Ramaraj .2021)**[10]**:** In the CIGRU-ELM paradigm, the DL-based Gated Recurrent Unit (GRU) and Extreme Learning Machine (ELM) that were proposed are responsible for recognising ECG signals. Preprocessing, data sampling, feature extraction, and classification are all aspects that are covered by CIGRU-ELM. The report on the electrocardiogram is then prepared for processing. The class imbalance can be rectified with ADASYN's data sampling. GRUs extract meaningful feature vectors. In conclusion, the ELM model assigns a category to the test ECG signal and the PTB-XL is being tested. **In (F.Yang et al .2021)**[11]**:** suggests the use of electrocardiograms as a method for diagnosing cardiovascular illness. A poorly supervised pre-training method based on the Siamese neural network provides relevant feature representations of the ECG data. The goal of this method is to improve ECG anomaly detection algorithms with less expert annotations. The diagnostic information used in this method is authored by physicians. The results of weekly supervised pre-training indicated that ECG abnormality detection algorithms trained with 1/8 annotated ECG data performed better than traditional models trained with full annotation, hence preserving annotation resources. The proposed method can be utilised for a variety of other tasks provided that the text similarity metric is modified. **In (S. Karthik et al .2022)**[9]**:** proposed a system to create automated deep learning-based 1D biological ECG signal detection for cardiovascular disease diagnosis (DLECG-CVD). DLECG-CVD model preprocessing, feature extraction, hyperparameter adjustment, and classification. Data pretreatment prepares ECG data for further processing. DBN generates feature vectors. ISSO improves DBN model hyperparameter tuning. XGBoost classifies test ECG signals last. DLECGCVD model simulations show improved diagnostic performance on the benchmark PTB-XL dataset. **In(J. Qiu et al .2022)**[12]**: the** proposed system focuses on a new data augmentation method to improve heart disease detection robustness and accuracy in imbalanced ECG datasets. Optimal Transport balances ECG sickness and regular beats. Multi-Feature Transformer (MF-Transformer) categorization employs temporal and frequency data to diagnose heart issues. The 12-lead ECG can detect five cardiac disorders. Classification algorithms can predict five ECG types competitively, and our data augmentation technique enhances accuracy and resilience. **In (Q.Geng, et al .2023)**[2]**:** It is time to introduce a multitask deep neural network with SE-ResNet-based low-level feature extraction and task-specific categorization. Contextual Transformer (CoT) blocks are utilised by the categorization module in order to dynamically express local and global information pertaining to ECG feature sequences. The following Table 1 shows the summary of related work.

Table 1: summary of related work.

RF& YEAR	Method	Dataset	Aim	Result
2021 [6]	-(Siamese neural network) -(Ordinary Differential Equations net) **ODENet**	PTB-XL	Proposed a weakly supervised training method based on the Siamese neural network, which relies on the basic diagnostic information of the ECG signal to calculate the semantic match ratio between the ECG signals without classifying the ECG signal class, and as another basic step, use the semantic similarity as the label while training the network. Neuron to extract a representation of ECG signals. In the final stage, the Light GBM model was used for supervised training on a small portion of manually annotated ECG data to obtain a classifier about ECG signal abnormalities.	**Total** Accuracy= 0.9070 F-Score= 0.8081
2021 [7]	(CIGRU-ELM) from GRU&ELM	PTB-XL	The CIGRU-ELM model handles class imbalance using a DL-based tabbed repetition unit (GRU) and maximal learning machine (ELM) for ECG signal recognition. Use preprocessing for data preparation. Convert the ECG report into useful data and format it for post-processing. A GRU-based feature extractor extracts usable feature	**Total** Accuracy=0.89 F-Score= 0.900

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			vectors. Finally, an ELM model-based classification model categorizes the ECG test signal.	
2022 [5]	DLECG-CVD	PTB-XL	A 1-D structural ECG signal recognition model named DLECG-CVD was designed, and the model includes preprocessing, DBN-based feature extraction, ISSSO-based parameter tuning, and XGBoost-based classification. A new technique for ISSO-based feature selection is introduced by incorporating Levy concepts into the SSO algorithm to avoid the problem of local optimization.	**Total** Accuracy=0.88 F-Score= 0.9082
2022 [8]	**-(MF-Transformer)** Pipeline Augmentation wfdb library perform Fast Fourier transform (FFT)	PTB-XL	offered an ECG data imbalance solution. Optimal Transport was used to balance the data and prevent overfitting. To classify ECG data into cardiac ailments, we presented an MF-Transformer. Data augmentation improves classification accuracy and robustness across five ECG categories.	Average Accuracy= 75.82 % F1-score= 0.757
2023 [1]	SE-ResNet	PTB-XL CPSC2018	present a multitask deep neural network with a SE-ResNet-based low-level feature extraction module and a task-specific classification module. The categorization module uses a Contextual Transformer (CoT) block to represent ECG feature sequence local and global information dynamically.	**PTB-XL** **Total** Accuracy= 0.887 F-Score= 0.833

Proposed System

The proposed system goes through three main stages: preprocessing, training, and finally, evaluation and testing. System designed for diagnosing heart diseases by heart (ECG) using deep learning techniques, with Graphical User Interface (GUI) to assist the user, even if they are not specialists. The system goes through three stages. The first is the preprocessing stage, which is the data processing and splitting of the data according to what is recommended in the dataset for the training, validation, and testing parts. The third stage is the operations performed with deep learning by using CNN, where appropriate layers have been developed to extract high accuracy in addition to testing to evaluate the system's performance, efficiency, and accuracy, and how accurate the system is in disease classification and diagnosis, whether it is normal or has one of the four selected heart diseases. Figure (1) shows the proposed system's general structure applied to the global data set PTB-XL.

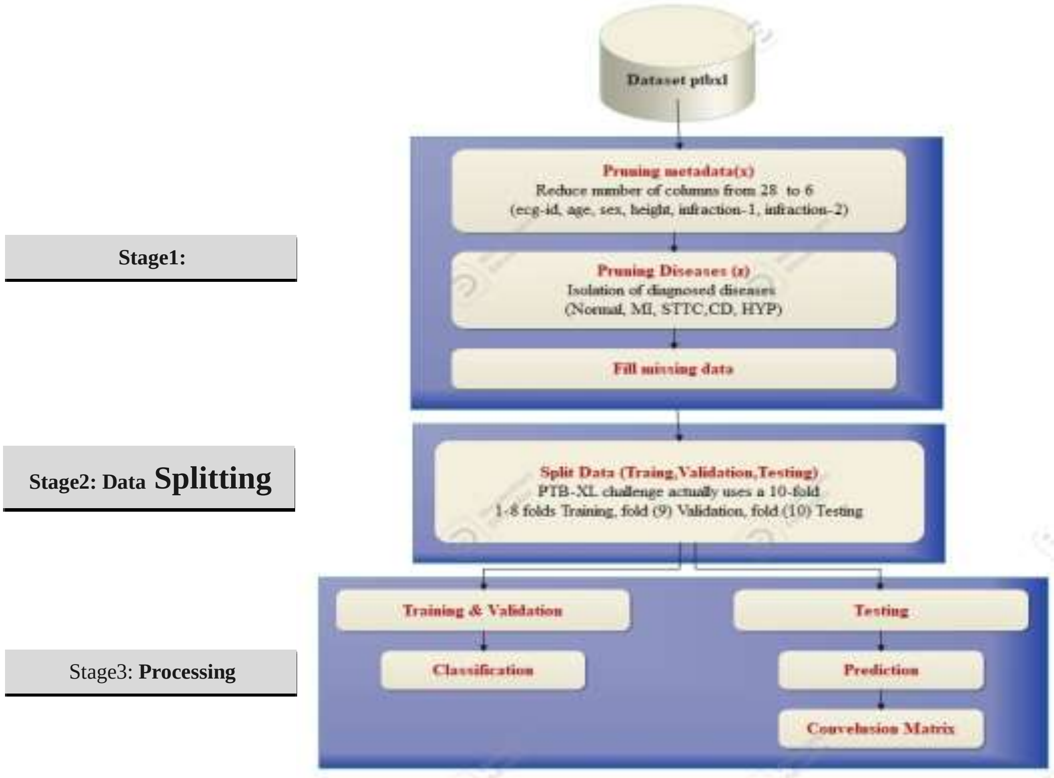

Figure 1: The proposed system structure.

Dataset

A PTB-XL data set, which was part of the PhysioNet/Computing in Cardiology Challenge 2021, was used to both train and test the system [2]. It is a significant electrocardiogram dataset that is accessible to the public. Developed for use in studies pertaining to machine learning and deep learning by PhysioNet and Computing in Cardiology. Each of the ECG records in the PTB-XL database lasts for ten seconds and consists of twelve leads. These records come from a total of more than 18885 patients. The recordings were obtained from a variety of resources, some of which include the PTB Diagnostic ECG Database, the PTB Stress ECG Database, and other public ECG databases. In addition, the dataset contains clinical information for each individual patient, such as their age, gender, and illness. The dataset has an equal number of males and females, with 52% males and 48% females, and it includes people of all ages, from 0 to 95 years old, with the median age being 62 and the interquartile range being 22. The ECG records have been annotated by up to two cardiologists, each of whom might have contributed multiple ECG statements from a list of

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71 distinct statements that comply with the SCP-ECG standard. Researchers now have a centralized resource with which to create and test novel machine learning and deep learning algorithms, thanks to the dataset. This makes the process of automating ECG analysis more straightforward, with a particular focus on identifying and categorizing arrhythmias. The following are some of the several ECG abnormalities or lesions that are included in this dataset:

1. ST-T abnormalities are changes in the ST segment and T wave of the ECG, which can indicate ischemia or injury to the heart muscle.
2. Myocardial infarction (MI): MI is a serious condition that occurs when the blood flow to a part of the heart is blocked, leading to damage to the heart muscle.
3. Arrhythmias: Arrhythmias are abnormalities in the heart's rhythm, including bradycardia (slow heart rate), tachycardia (fast heart rate), and various irregular heartbeats.
4. Conduction disturbances: These are abnormalities in the way electrical signals travel through the heart, including bundle branch blocks, AV blocks, and other conduction abnormalities.
5. Other abnormalities: The dataset contains other ECG abnormalities, including ventricular hypertrophy, left axis deviation, and more.

Figure (2) will explain PTB – XL in more detail

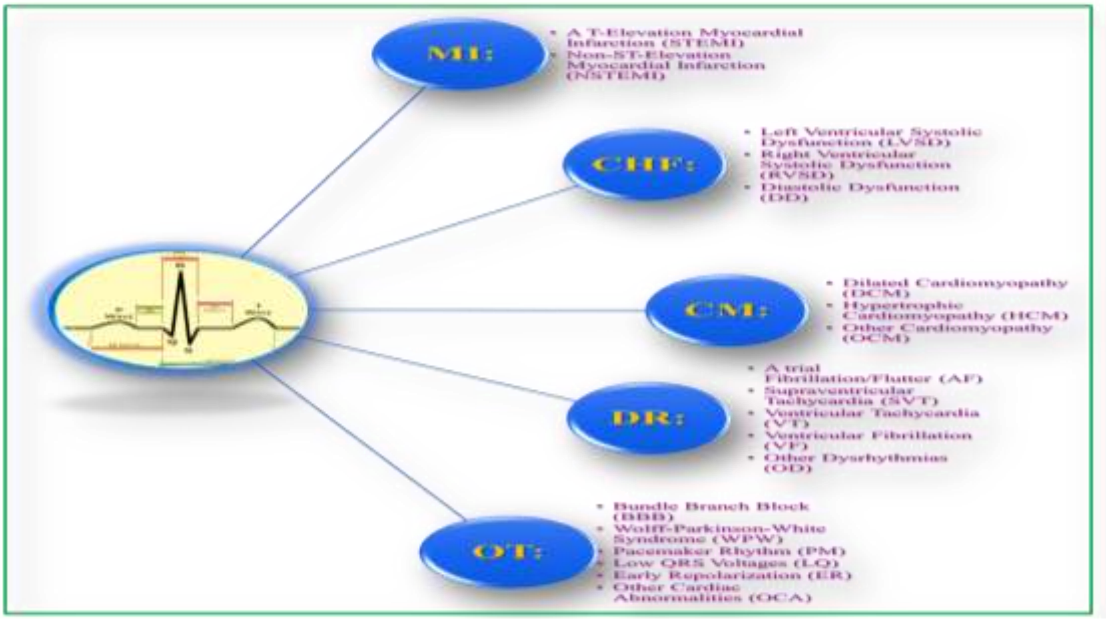

Figure 1: PTB-XL diseases in detail

The accompanying table lists five different sorts of diseases that the system predicts will occur.

Table 2: **Diseases Classes Description**

Records	Superclass	Description
9517	NORM	Normal ECG
5473	MI	Myocardial Infarction
5237	STTC	ST/T Change
4901	CD	Conduction Disturbance
2649	HYP	Hypertrophy

The table refers to the PTB-XL electrocardiogram (ECG) recording data set. The column "#Records" refers to the number of ECG recordings (or samples) in the dataset under each superclass category. It indicates the count of ECG recordings in the dataset classified into each superclass category mentioned in the table. The dataset includes a total of 21,837 ECG records, each classified into one of five superclasses, as described below:

1. NORM: Normal ECG recordings are free of any significant abnormalities or abnormalities.
2. MI: ECG recordings indicating a previous or current myocardial infarction (heart attack).
3. STTC: ECG recordings that show ST/T changes, which can indicate ischemia or other heart conditions.
4. CD: ECG recordings that indicate conduction disorders, such as bundle branch blocks or atrioventricular blocks.
5. HYP: ECG recordings that indicate an enlarged or enlarged heart muscle, usually due to chronic high blood pressure or other underlying conditions

The proposed system used this data set to classify heart diseases by reading the ECG using the CNN algorithm. The CNN algorithm classified heart diseases into four disease categories (MI, CD, STTC, HYP) in addition to the normal condition, which was considered the fifth category (NORM). Table (2) shows the categories classified under the proposed system. Table 3 explain the dataset PTB_XL in more detail.

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Table 3 :PTB-XL dataset in detail

Dataset Name:	**PTB-XL**
Data Type:	Electrocardiography (ECG) recordings
Recording Length:	10 seconds
Number of Recordings:	21,837
Number of Subjects:	5,388
Age Range:	0-95 years
Median Age:	62 years
Sex Balance:	52% male, 48% female
Several Diagnostic Superclasses:	5
Diagnostic Superclasses:	Myocardial Infarction, Congestive Heart Failure, Cardiomyopathy, Dysrhythmia, and Other Cardiac Abnormalities
Several Diagnostic Subclasses:	27
Diagnostic Subclasses Examples:	STEMI, NSTEMI, LVSD, RVSD, DCM, HCM, AF, SVT, VT, VF, BBB, WPW, PM, LQ, ER, OCA
ECG Sampling Frequency:	1,000 Hz
ECG Signal Resolution:	16-bit
Annotated by Cardiologists:	Yes, up to two cardiologists per recording
Annotations Based on:	Standard for the SCP-ECG, which includes a collection of 71 different statements

Ptbxl_database.csv is where the information that is specific to each record and may be distinguished by its own unique ecg_id is stored. This document has a total of 28 columns, all of which can be placed into one of two categories:

1. Identifiers: The patient_id and ecg_id identify each entry. Filename_hr and filename_lr contain the paths to the 500 Hz and 100 Hz recordings.
2. General Metadata: Age, gender, height, weight, nurse, site, device, and recording_date are stored.
3. ECG statements: consist of scp_codes, dictionary statements with likelihood entries. Unknown likelihood is zero. Report strings accompany scp_codes. Other parameters include heart_axis, infarction_stadium1, 2, validated_by, second_opinion, initial_autogenerated_report, and validated_by_human.
4. Signal metadata contains static_noise, burst_noise, baseline_drift, and electrode_problems. Extra beats count extrasystoles, and a pacemaker detects active pacemaker signal patterns.
5. Cross-Validation Folds: 10-fold train-test splits (strat_fold) were proposed to respect patient assignments using stratified sampling. All patient records were placed on one fold. Folds nine and ten had at least one human assessment, ensuring high label quality.

Thus, we recommend training on folds 1-8, validating on fold nine, and testing on fold 10.

Preprocessing Stage

A preprocessing process was conducted to prepare the data for the training, evaluation, and testing process. This stage consists of four steps are:

1. Collecting useful patient information in the training and classification process, excluding unnecessary information, storing it under the name (Metadata (X)), and putting it in the ECG Data Frame. Thus, a partial set of data frame columns was used, reducing from 28 columns to 6. For example, ECG_ID, age, sex, high, fraction 1, and fraction 2.
2. During *data frame* creation, any missing data in metadata have been handled, and categorical columns have been mapped to numerical representations to make them suitable for input into the CNN model.
3. The ECG (Y) curve is used as input as a split from the source without repartition. Because any change in the ECG will affect the outcome of the patient's examination and diagnosis, Figure (**3**) shows a sample of ECG curves of one patient **,**illustrating that each patient has 12 leads.
4. The Target (Z) separates the diseases that have been diagnosed from those that have not been diagnosed. This is based on the data set's recommendations and five classification cases, including the normal case.

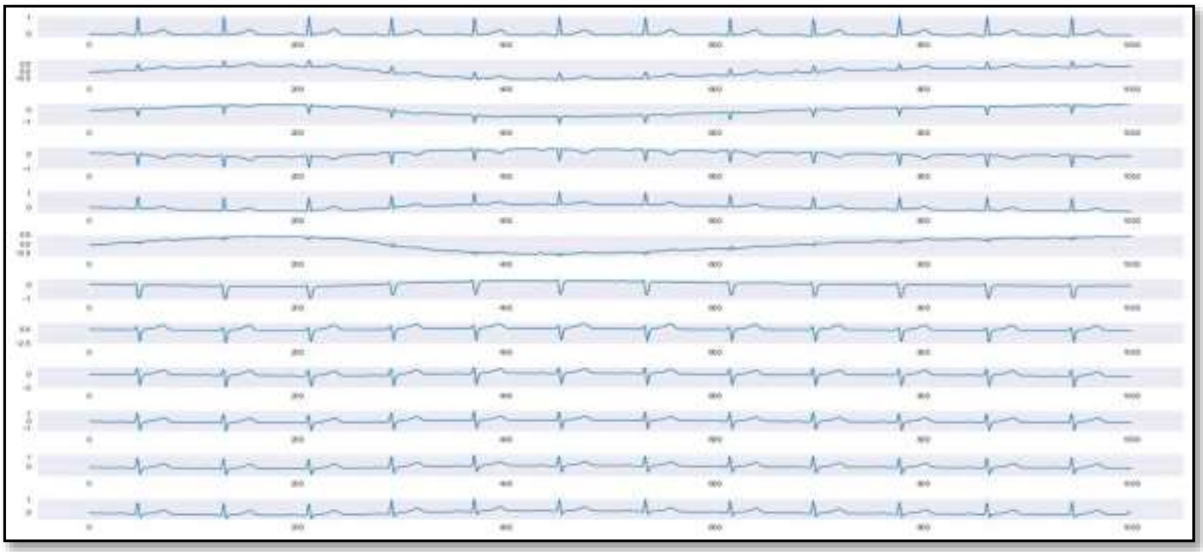

Figure 3: ECG curve sample.

Training and Validation

Usage in the training section CNNs (Convolutional Neural Networks) are commonly used in disease detection and classification because they can identify distinctive traits and attributes associated with diseases: CNNs are capable of spotting tiny visual features, patterns, and internal structural changes, medical images include millions of data points, and therefore they can handle high-dimensional data. In high-dimensional data management and image information extraction, CNNs are effective; They are compatible with deep learning because CNNs may be thoroughly trained on a sizable dataset of medical images, enhancing the accuracy of the identification of disease-related features, They are compatible with current performance-improving tools: It is possible to employ tools like semi-automatic processes to improve how well CNNs identify diseases, The accuracy of the models that are produced may benefit from this, Overall, CNNs have shown promise in a range of computer vision and deep learning applications, including the identification and classification of heart diseases imaging. The performance of a machine learning model on a validation set as a function of various hyperparameters or training parameters is represented graphically by a model accuracy curve. The model accuracy curve is useful for machine learning model selection and hyperparameter tuning. It aids in preventing overfitting and enhances the model's ability to generalize to fresh, untested data. The hyperparameter or training parameter values are plotted on the x-axis of the model accuracy graph along with the model accuracy on the y-axis. Examples of hyperparameters, or training parameters, include learning rate, regularization intensity, number of hidden layers, and number of neurons in a layer. The purpose of the model accuracy curve is to help the designer choose the best hyperparameter or training parameter values that improve the model's accuracy on the validation set. By testing the model on a different validation set at different hyperparameters or training parameter values, the modeler can determine which values lead to the highest accuracy. The 4. figure shows the training curve:

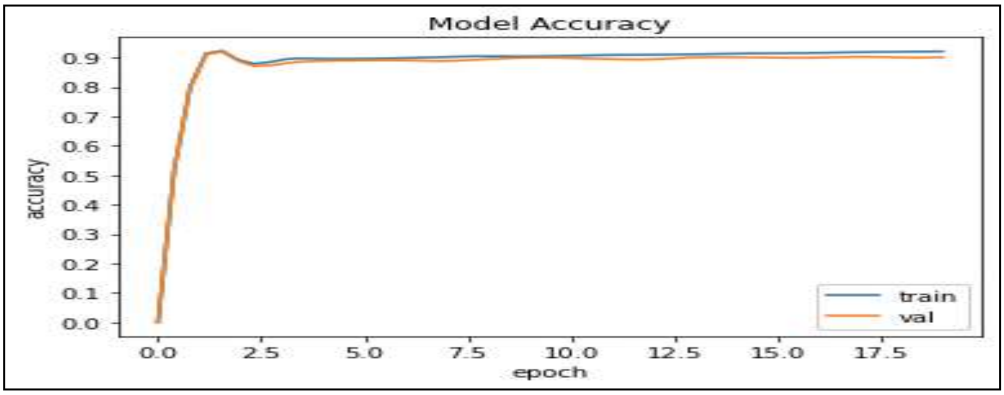

Figure 4: Model Accuracy curve

It is made up of several layers that were configured in our system and chosen based on prior outcomes to achieve high accuracy. Table (4) displays this layer.

Table 4: Neural Network layers description.

Layer Name	No. Layers Used	Description
Input	2	Disseminates fundamental information.
Convolution	5	Have multiple filters, each of which extracts different features from the input. The output of the convolution layer is a stack of feature maps, where each map corresponds to one filter.
Max_Pooling	4	Reducing the spatial dimensions (width and height) of the feature map works by partitioning the input feature map into non-overlapping rectangles and, for each rectangle, taking the maximum value over the elements in that rectangle.
Global Average Pooling	1	Calculates the average of all the values in each feature map. The resulting output is a single number for each feature map, representing the average activation of that feature over the entire spatial dimensions.
Batch Normalization	2	Normalizing the previous layer's output by subtracting the mean and dividing by the standard deviation of the batch. This centers the distribution of the activations, and the network can more easily learn the weights for the subsequent layers.
ReLU	3	ReLU sets all negative values in the input to zero, which results in a sparse output.
Dense	5	Each neuron is connected to every neuron in the previous layer, and every connection has a corresponding weight. The output of a dense layer is computed by taking a weighted sum of the inputs and passing the result through an activation function.

The CNN network was designed consisting of 23 layers divided as follows:

1. The variable Y, which consists of 16 layers, represents the ECG Curve, which consists of one input layer, five convolutional layers, and four Max Pooling layers. The fully

connected layer was three layers, Batch normalization, two of which were used, and one global average pooling. These layers were used to extract features from the ECG test. Several filters depend on the stride equation as a basis for their work. The number of filters increases as the depth of the network increases in layers to obtain higher accuracy in identifying the required features.

2. Metadata consists of 3 layers. Which is represented by the variable X, is reduced information, and does not need filters. Therefore, two dense layers were used in addition to the input layer.
3. As for the classification of the disease, which is the target, represented by the variable Z, it consists of a layer of concatenate and three layers of dense.

To address the problem of overfitting in deep neural networks, dropout has been applied. It is a simple and effective regulating method that helps prevent overfitting. By cutting out some neurons randomly during training, dropout forces the network to learn more powerful features and to generalize better on unseen data; in general, it can be observed that during the training of the convolutional neural network (CNN), a stride value of 1 was employed. This value was selected through trial and error which illustrates the stride. Additionally, Adam optimization was used, a powerful optimization algorithm that controls the model's learning speed. The use of batch normalization is an integral part of the CNN structure, whereby normalization is applied to the batch during training. The batch size used in this study was 8, and 100 epochs were executed. Early stopping was implemented to halt the training process if changes ceased, indicating that the model had been sufficiently trained. This ensured the iteration was stopped and the model was not over-trained. Early stopping was implemented to halt the training process if changes ceased, indicating that the model had been sufficiently trained. This ensured the iteration was stopped and the model was not over-trained. The following figure 5 shows the summary of layer that used in proposed system.

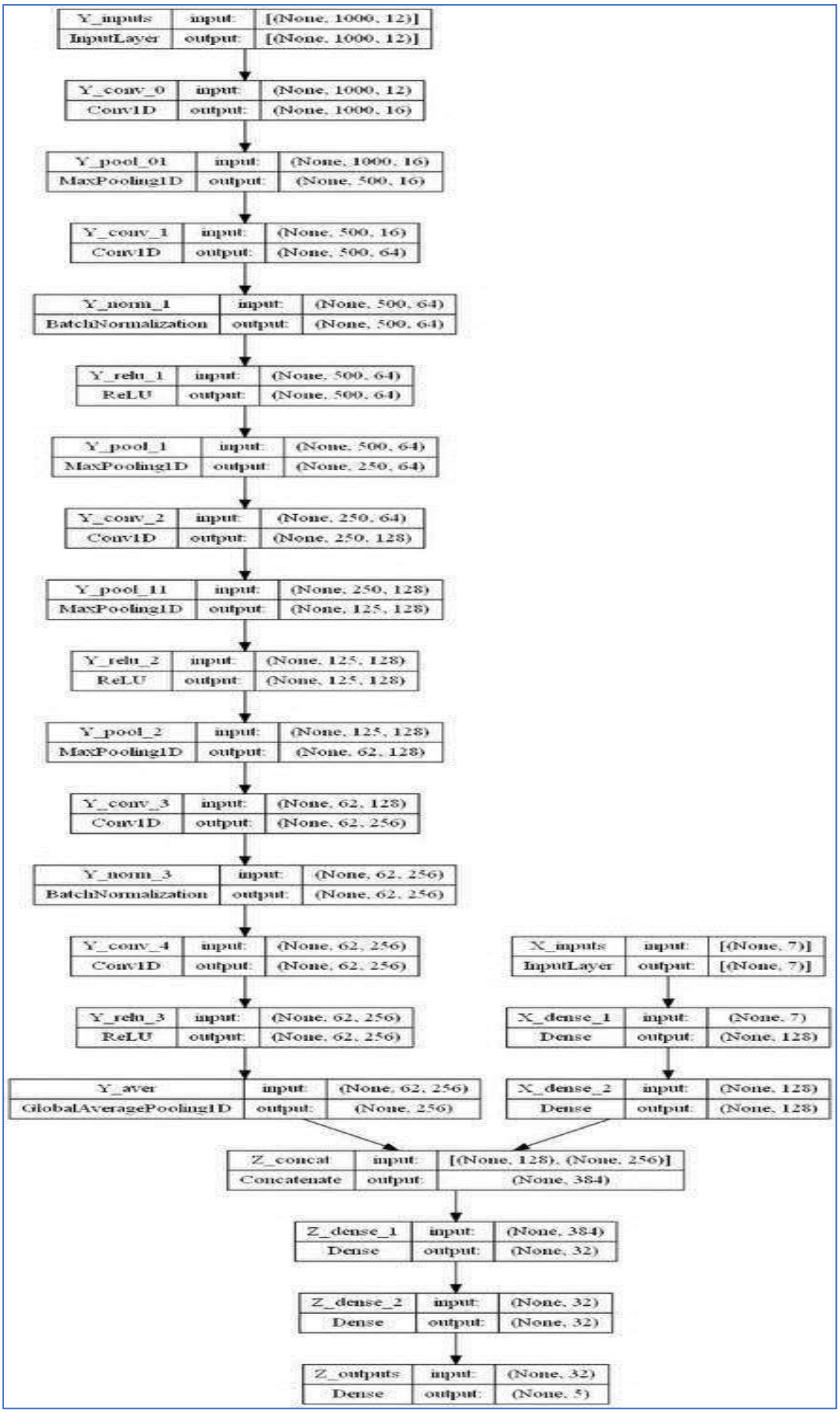

Figure 5: Proposed CNN layers in more details.

Result and Desiccation

In a classification task, the goal is to train an algorithm to predict which class or category a given input belongs to a set of classified training data. In the proposed system, the input value is an integer, and the output is the expected category for that value, an ECG reading such as NORM, CD, STTC, MI, and HYP. The proposed system trained 100 epochs. The results will explain in Table 5. Then, Table 6 explain the proposed system results for the testing stage.

Table 5: Proposed system training results for each Epoch.

Epoch No.	Batch	Time (s)	Loss %	Accuracy %	Precision %	Recall %
1/100	1091/1091	23	33.56	85.84	76.60	63.99
2/100	1091/1091	18	28.62	88.20	80.72	70.54
3/100	1091/1091	19	27.30	88.80	81.70	72.25
4/100	1091/1091	18	26.42	89.24	82.44	73.40
5/100	1091/1091	19	25.69	89.58	83.19	74.51
6/100	1091/1091	19	25.11	89.61	82.98	74.51
7/100	1091/1091	19	24.68	89.82	83.32	75.07
8/100	1091/1091	19	24.08	90.22	84.34	75.65
9/100	1091/1091	19	23.64	90.42	84.44	76.49
10/100	1091/1091	19	23.55	90.38	84.31	76.46
11/100	1091/1091	19	22.92	90.62	84.80	76.97
12/100	1091/1091	19	22.41	90.85	85.18	77.58
13/100	1091/1091	19	22.16	90.95	85.02	78.27
14/100	1091/1091	19	21.69	91.11	85.63	78.73
15/100	1091/1091	18	21.38	91.31	86.00	78.73
16/100	1091/1091	19	20.65	91.45	86.00	79.35
17/100	1091/1091	19	20.65	91.59	86.19	79.79
18/100	1091/1091	19	20.22	91.80	86.70	80.11
19/100	1091/1091	19	19.89	92.96	86.88	80.61
20/100	1091/1091	21	19.38	93.10	87.02	81.07

Table 6: proposed system results (Testing) for each Epoch.

Epoch No.	Batch	Time (s)	Val-loss %	Val-accuracy %	Val-precision %	Val-recall %
1/100	1091/1091	23	31.45	86.94	77.63	68.71
2/100	1091/1091	18	31.50	87.62	78.99	70.28
3/100	1091/1091	19	29.37	88.10	81.50	69.14
4/100	1091/1091	18	29.97	87.51	78.36	70.67
5/100	1091/1091	19	28.72	88.38	82.66	69.03
6/100	1091/1091	19	28.42	88.43	79.82	73.24
7/100	1091/1091	19	30.41	88.34	79.07	73.99
8/100	1091/1091	19	28.95	88.08	78.68	73.21
9/100	1091/1091	19	28.37	88.60	82.50	70.32
10/100	1091/1091	19	27.53	88.99	80.69	74.85
11/100	1091/1091	19	27.72	88.76	80.58	73.85
12/100	1091/1091	19	28.81	88.31	77.81	75.92

13/100	1091/1091	19	29.14	88.17	78.48	74.03
14/100	1091/1091	19	29.98	88.68	82.35	70.92
15/100	1091/1091	18	27.74	88.69	80.33	73.85
16/100	1091/1091	19	29.31	88.42	80.07	72.81
17/100	1091/1091	19	29.48	88.34	80.90	71.17
18/100	1091/1091	19	29.61	88.56	7992	73.81
19/100	1091/1091	19	28.83	88.24	78.03	75.13

- X_train: (17441, 7) Y_train : (17441, 1000, 12) Z_train : (17441, 5)
- X_valid: (2193, 7) Y_valid : (2193, 1000, 12) Z_valid : (2193, 5)
- X_test: (2203, 7) Y_test (2203, 1000, 12) Z_test : (2203, 5)
    - X_train: This variable contains training data for the model in the form (17441, 7). This means the training data has 17,441 samples (rows) and seven features (columns).
    - Y_train: This variable contains the corresponding training labels (17441, 1000, 12). The first dimension (17441) corresponds to the number of samples in the X train. The second and third dimensions (1000 and 12) correspond to the length of each ECG recording and the number of possible diagnoses, respectively. This indicates that the model is trained to predict one of 12 different diagnoses per 1000 sample ECG recordings.
    - Z_train: This variable contains additional training data in the form of (17441, 5). This data's exact nature is unclear from the information provided, but it likely contains some additional features not found in X_train.
    - X_valid, Y_valid, and Z_valid: These variables contain the validation data in the forms (2193, 7), (2193, 1000, 12), and (2193, 5), respectively. The sizes of these variables are smaller than the corresponding training data, which is expected since some of the data is usually kept for validation purposes
    - X_test, Y_test, and Z_test: These variants contain test data in the forms (2203, 7), (2203, 1000, 12), and (2203, 5), respectively. This is additional data that is not used for training or validation but instead is held back to test the performance of the trained model

Results of a Proposed System Based on the confusion matrix To evaluate the performance of the proposed classification model, a confusion matrix was used by presenting the expected and actual class labels for a set of test data. Provides a clear visual representation of model performance by showing the correct and incorrect predictions for each class label. By analyzing the confusion matrix, we can identify in which categories the model performs well and in which it suffers. The confusion matrix consists of four cells, each of which represents a possible outcome of the classification model prediction.

The main purpose of the confusion matrix is to assess the accuracy of the classification model. The confusion matrix calculates performance measures, such as accuracy, recall, sensitivity, specificity, and F1 score. These metrics provide more detailed insights into the model's performance, especially in cases where classes are not balanced. All in all, the confusion matrix is an important tool for evaluating the performance of a classification model in deep learning. With it, can identify areas where the model needs improvement and adjust its parameters to achieve better results.

Table 7: confusion matrix for each class

Confusion matrix Class type	TP	FN	FP	TN
NORM	1107	132	166	798
MI	1616	34	186	367
STTC	1510	170	98	425
CD	1618	87	168	330
HYP	1847	93	113	150
total results	7698	516	731	2070

The following figure explains the Confusion Matrix results for each class.

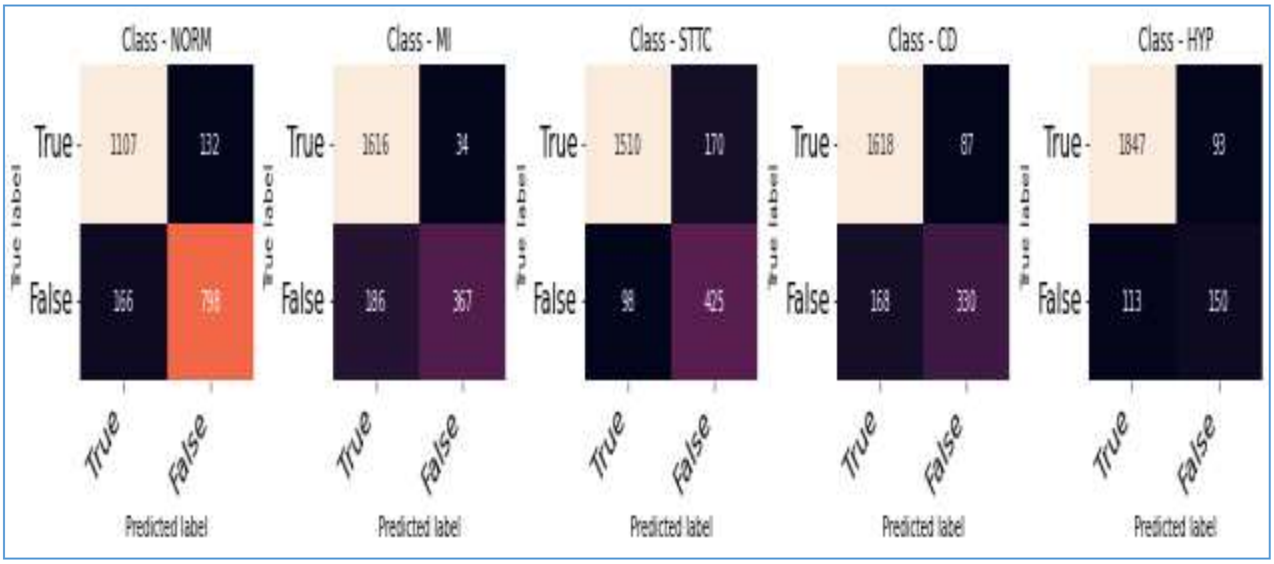

Figure 6: confusion matrix results

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Below we will show a table that shows the percentages of the measures achieved by the proposed system, which were extracted based on the values of the confusion matrix.

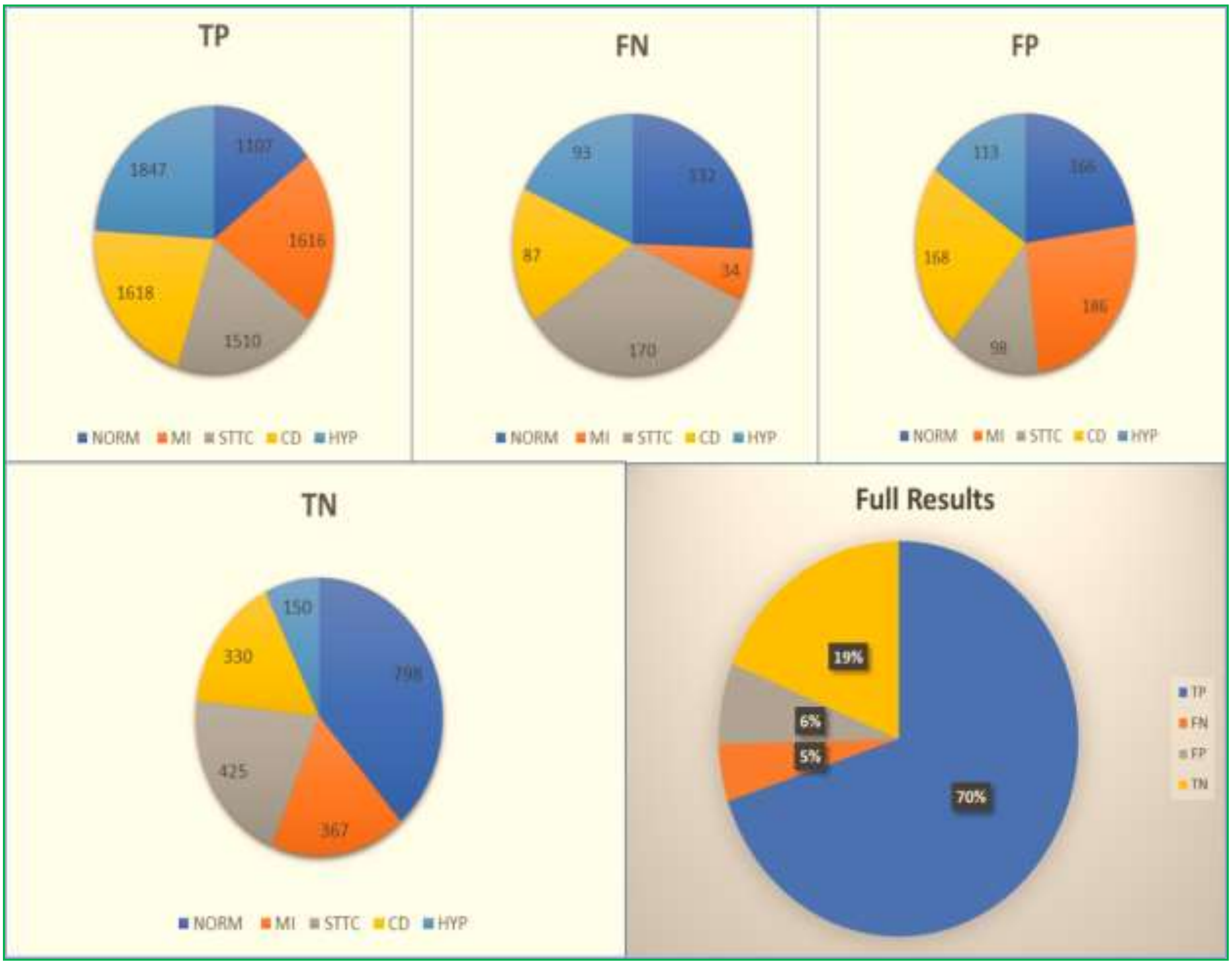

Figure 7**:** Confusion Matrix results for each class

Table 8: .Results table based on the confusion matrix

Measure	Value
Sensitivity	93.72%
Specificity	73.90%
Precision	91.33%
Accuracy	88.68%
F1 Score	92.51%

Figure 8 shows the histogram of the percentages achieved by the confusion matrix measures through the application of the proposed system.

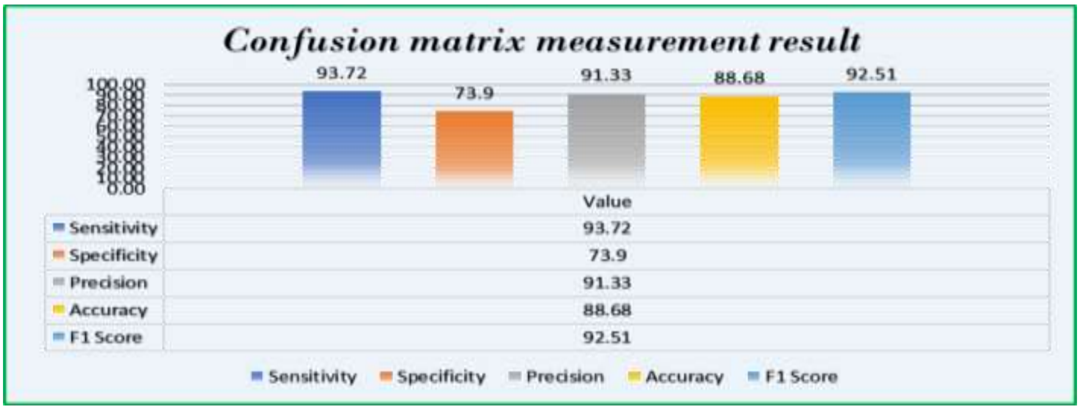

Figure 8: Confusion Matrix Measures Results

Conclusion

The main step was to choose a global data set that contains a sufficient number of patients, that is, a sufficient number of records that help conduct a good training process. Because the proposed system depends on deep learning technology, its main component is data, which is available in a data set (PTB-XL). The treatment process in the proposed system was somewhat different because the subject is medical. Still, the signal was dealt with in its original form because this fluctuation in the signal is possible evidence of the presence of a disease. Therefore, the treatment was. It is about pruning the data by removing unnecessary columns in the original data that doctors disapprove of in the diagnosis. The result is six columns out of 28. The other part of the processing process is dealing with the missing data, which was discovered during the work that the data contains a substantial lack of information. The data set's founders impose the data segmentation stage into training, testing, and evaluation. It is considered a challenge for researchers to work on this division; therefore, it has been approved and worked on. The proposed system is based on deep learning using CNN in the classification stage, configured based on the experiments and the extracted results. In this paper, the system is equipped with a user interface that enables the user to deal with it even if he does not have computer knowledge. This idea of the proposed system is to facilitate the work of the technical user.

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