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Improving Heart Disease Classification using Multimodal Fusion in Deep Learning

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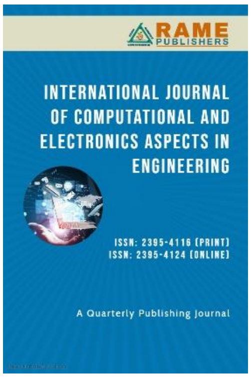

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Abstract: Heart disease is one of the causes of suffering for those affected and is also one of the leading causes of death. There are many studies that examine the diagnosis of diseases, and deep learning has emerged as a prominent tool in their diagnosis and differentiation. Previous studies relied on classifying heart diseases using deep learning techniques, either using clinical data or relying on electrocardiogram signals. This study focused on using the Multimodal Fusion in Deep Learning Neural Network MFDNN model to diagnose lung cancer through various types of data sets (imaging, genomic, clinical). In this research, a three-steps model was created. The first step extracts feature from images using the ResNet18 network, the second step extract features from clinical data by uses a neural network containing linear layers , and the final step combines the features extracted from the first and second steps and classifies them. The MFDNN model achieved a training accuracy of 99.69% and a testing accuracy of 99.93%. The proposed model also excelled in classifying each category of heart disease perfectly, with F1-score, Recall, and Precision values reaching 100% for each category. The proposed model was compared with previous studies and found to be superior in terms of reliance on clinical data as well as electrocardiography ECG tracings.

Keywords: Multimodal Fusion; Deep Learning; ResNet18; ECG; Image Classification.

1. Introduction

Heart disease is one of the leading causes of death [1][2][3]. The people with heart disease can be detected using electrocardiography signal [3]. Electrocardiography is used to diagnose heart disease along with other vital signs [4]. Analyzing ECGs and interpreting manually is a major challenge for doctors and medical staff [4]. digital transformation using artificial intelligence in order to improve medical care and diagnosis, has been used to help diagnose medical conditions, including heart disease [3] [4] [5]. In recent years, artificial intelligence technologies, especially machine learning and deep learning technologies, have donated to remarkable developments in the field of disease diagnosis through the analysis of medical data [4][5][7]. The medical data that deep learning deals with includes images, clinical data, and genomic data for the detection and classification of various diseases, as it is considered a diagnosis of diseases [7][8]. Thus, deep learning has become very effective in detecting and diagnosing diseases with high accuracy [5][7]. The use of multi-source data for disease diagnosis contributes greatly to the accuracy of deep learning models [8]. The multiple data consists of images, text data, and genomic data, and using all of them makes diagnosis easier in identifying diseases [7]. Deep learning models based on convolutional neural networks (CNN) rely on a large dataset to train and test the deep learning model [9].

Depending solely on medical images for diagnosis does not help in diagnosing the disease [10]. Relying on other clinical data about the patient helps to diagnose the condition more accurately [7] [10]. Using more and varied data leads to modifications in deep learning models, and these improved deep learning models become more accurate in their work [11] [12].

For the diagnosis of heart disease, we propose in this research a deep learning model inspired by the MFDNN model proposed for the diagnosis of lung cancer in [7], which has proven effective in diagnosing lung cancer through its analysis of imaging, clinical, and genomic data. This research also used PTB-XL data, a large publicly available electrocardiography dataset consisting of medical images and clinical data of patients for the diagnosis of heart disease. This is considered one of the challenges in designing deep learning models to integrate artificial intelligence with healthy living. The first section of the research provides an introduction and overview of the research, focusing on the importance of using deep learning in the field of disease diagnosis using multiple data (images with clinical data).

It also explains the idea behind the research. The second section explains Related Work in the field of disease diagnosis using artificial intelligence and deep learning models that use multiple data sets. It also provides an overview of some of the methods used to diagnose heart disease using artificial intelligence. The third section provides an overview of the dataset used in this research. The fourth section presents the methodology used in applying the MFDNN deep learning model to the PTB-XL dataset, a large publicly available electrocardiography dataset used to diagnose heart disease.

It provides a complete breakdown of how the model was transferred from diagnosing lung cancer to diagnosing heart disease, and what changes were made to the model to make it work for heart disease using the data set chosen for this deep learning model. The fifth section reviews the results of applying the MFDNN deep learning network or model to classify heart disease, mentioning details about data partitioning, confusion matrix, accuracy metrics, and model performance evaluation using F1. A comparison analysis of the model with other methods was also mentioned.

Finally, in the conclusions section, the final results and important findings of the study are presented. The importance of artificial intelligence and its dissemination and application in health fields is highlighted by clarifying future trends and improvements.

2. Related Work

This section reviews the role and impact of deep learning and artificial intelligence in healthcare and medical technology and how it has transformed them. This section work on reviews espitaly in the role and uses the approach of deep learning in disease diagnosis and its to diagnose diseases based on images or clinical data for patient in the medical field. It also focuses on the emerging uses of deep learning networks in terms their ability to achieve to accuracy to disease diagnosis to with greater than the ability of doctor's accuracy on disease diagnosis. All these reviews studies in this section of research shows the advantages have made the techniques of deep learning a significant donor to assisting and facilitating the ability of medical staff to verify and improve the quality of patient diagnostic results, enabling them to make therapeutic decisions and inform medical decisions. This section also explains the role of artificial intelligence particularly deep learning techniques in diagnosing heart diseases and diagnosing them early by depend on the images that results from convert ECG signal to image.

In the way of medicine healthcare, the previous studies on deep learning techniques in the medical field demonstrate firstly how deep learning is important in as it has brought significant advances in predicting and classification disease progression based on patient data. Then facilitates medical staff to taking therapeutic measures in diagnosing diseases, and guiding the patient's treatment path. Thus mean the artificial intelligence in the medical field could play a significant role in fundamental changes, both in terms of diagnostic accuracy and subsequent decision-making regarding the treatment path for patients, especially when combined with the human expertise of healthcare staff.

Firstly, this paragraph in this section talks about using deep learning techniques in disease diagnosis field that rely on multiple types of data no one type data like just clinical or just images. Where [07] suggest and work to design a model by using deep learning for lung cancer diagnosis by using multiple data (images, geonym, and clinical). The work on model relied on a multi-modal fusion of a dataset consisting of imaging, genomic, and clinical data for Cancer Imaging Archive (TCIA) and The Cancer Genome Atlas (TCGA) datasets. This two type of datasets were used by fusion it and extract features from it to train his suggested model in his study on lung cancer diagnosis by using multi types of data. The study achieved an overall accuracy value as a global measurement of 92.5%, a precision or sensitivity to true positive classification category value of 87.4%, finally a recall value for true e positive ratio was 84.4%%. These results demonstrate that this model is excellent at diagnosing the disease, and that the network is very good at predicting lung cancer and identifying lung cancer. The network is also very good at balancing diagnostic accuracy with reducing misdiagnoses, with an F1--score of 86.20. These result was the cause to propose the possibility of using the idea of using fusion multiple data in diagnose heart disease where available two types of data (ECG signals and clinical data for patients). Also in the field of using deep learning by uses the images to disease diagnosis, [08] worked on and in order to helps medical professionals and researchers by created a model that extract features from tissue images which contain colon cancer and classify them to identify or predict colorectal cancer. The images of tissue that used in his study was taken from 0" Lc25000 dataset", and used to train and test the proposed model. The researcher focused solely on colon cancer images from the dataset, as it contains 25,000 images of lung and colon cancer. Before training the proposed model in his study, he preprocessed the images to match the model proposed in his study. He then proposed dividing the data into a training set and a test set, with a ratio of 75% for training and 25% for testing. The model achieved an accuracy rate of 99.80%, which is higher than the models compared in his proposed study.

In the field of diagnosing heart disease using artificial intelligence and deep learning, [13] automated the process of predicting and diagnosing heart disease and identifying the best ranges in ECG images to distinguish between different heart diseases. The researchers relied on a publicly available online dataset of "ECG images," which is used to distinguish between different types of heart disease in individuals. Their method relied on the use of scanned images and prepared them for use in the model proposed in their study using simple preprocessing, meaning they did not require complex scanning of the scanned images. They then proposed dividing the data into three groups: training, validation, and testing. The first group accounted for 60% of the model's training, the second for 20% of the validation, and the third for 20% of the testing. The proposed model in their study achieved an accuracy of 91%% for diagnosing patients with or without heart disease, in addition to an accuracy of 80% for distinguishing between different types of heart disease. The researchers in [014] focused their study on developing a deep learning model that helps doctors in early detection or prediction of heart attacks in order to avoid them. They relied on the Convolutional Nural Network to build their model. The researchers used the "ECG Image dataset of cardiac patients." The researchers in their proposed method relied on the data preprocessing step to balance the data before splitting it to three groups first was to training set of 75% to training, second to a validation set of 15%, and the third set was a testing set model of 10%. In the training step, the learning InceptionV3 deep learning network was used after prosses simple modify on its layer except for the last three layers also adding a Global Average Pooling 2D layer and a Dense layer for final classification. By using this approach of model path, the proposed model in their study achieved an accuracy value of 93.27%, and the results of confusion matrix to classification between a person with cardiac disease and a normal person from disease was achieved an accuracy of 100%*.

As regards to investigate the diagnosis of heart disease and in field of using machine learning and deep learning techniques the researchers in [015], proposed a hybrid model. The researchers depend on used in their study relies on deleting the data from duplicate images and segmenting the ECG signal to create a clean ECG signal as a preprocessing step in order to draw the path way for the suggested model. This is achieved by isolating individual lines in the electrical signal. The researchers used to train and test the proposed model the "ECG image dataset of cardiac and COVID-19 patients," which is used to classify various heart diseases using ECG signal images. Also in preprocessing step the path way for proposed model depends on the data and extracting features from it. Then using the preprocessed data to using in pre--trained deep learning models, namely VGG16, VGG19, Resnet50, InceptionV2, and GoogleNet, combined with Support Vector Machine SVM to classify heart disease. The suggested hybrid models give different results but the hybrid model VGG19 and SVM was have better results in terms of accuracy was 100% for multiple diagnosis of heart disease on reconstructed data and 99.25% accuracy on the original data. But in binary classification of heart disease, the value of accuracy achieving 99% on the original data without preprocessing also in hybrid VGG19 and SVM model which mean outperformed other models, while its accuracy on the reconstructed data reached 97.95% for the same hybrid model.

The researchers in [016] also designed two hybrid models in order to heart disease classification. The idea that the two hybrid models based on use two deep learning networks, one of them was AlexNet and the other simpler CNN. This deep learning networks were used to extract features from images that are got it from convert the ECG signals to image of three channels as a preprocessing step. The MIT-BIH dataset and the publicly available PTB-XL dataset were used train and to test the efficiency of the hybrid models proposed in their study. The first model, and in more broadly in the data preprocessing step performs multi-image fusion by converting the ECG signal into three types: Gramian Angular Field (GAF), Recurrence Plot (RF), and Markov Transition Field (MTF) in grayscale, then combines them to produce three-channel images. The first hybrid model was named Multimodal Image Fusion (MFI), because it depends on images data as input to it. But the second proposed model is called Multimodal Transition Fusion (MFF), which depend on converting the electrical signals in the dataset used in their paper into an image during the data preprocessing step and This images is then converted into features, which are then fed into the model structure for classification, this was the cause of named it Multimodal Transition Fusion. The purpose of using a deep learning network, AlexNet, and a simpler CNN was to extract features from the data which was resulting from the data preprocessing step. Then for classification using SVM depend on data exit from deep learning networks and for two hybrid model. After testing the two hybrid models on the MIT-BIH and PTB-XL datasets, the proposed hybrid models achieved a high accuracy of 99.7% for arrhythmia classification when classify between heart disease category. The accuracy of myocardial infarction classification reached 99.2%. Comparing the two models, it was clear that the MFF model outperformed the MIF model after reviewing the results for both models.

There are many studies that have used deep learning techniques on ECG signals to diagnose and differentiate between heart diseases. However, this research relies on clinical data and ECG signals to diagnose multiple heart diseases, based on the ideas used in research [7] and [8] to create deep learning models that rely on more than one type of data for classification.

3. Dataset

The PTB-XL dataset [17] was used. This is a large, publicly available electrocardiogram dataset. It is used in research related to the diagnosis of heart disease. It was collected using PTB-XL waveform electrocardiogram devices and contains a set of descriptive or clinical data for patients. The heart diseases included in this dataset are: normal electrocardiogram, myocardial infarction (MI), cardiac hypertrophy, ST/T changes, and conduction disorders. The dataset consists of 12-lead ECG recordings, each lasting ten seconds. The number of recordings collected for patients is 21,799, collected from 18,869 patients, with 48% male and 52% female. The electrocardiogram frequencies are grouped into two versions, one recorded at 500 Hz for high quality and the other at 100 Hz for low quality.

The PTB-XL dataset provides important and abundant information that aids in the diagnosis of various heart diseases. In this study, we propose combining ECG signals with clinical data to provide multiple data for the proposed deep learning model.

4. Methodology

This section presents the steps involved in designing the proposed model for classifying heart diseases:

4.1 Data Pre-Processing

The pre-processing of the PTB-XL dataset for cardiac diagnosis, especially since it contains multiple data including ECG signals and patient clinical data, is an important step in verifying the data and preparing it for analysis. The data is considered complete because it is linked to the patient ID, which connects the ECG signals to the clinical data. Columns containing 70% missing data were removed, while the remaining columns were filled in with the mean value for missing numerical data and the value "unknown" for missing object data.). Numerical features were normalized, and in order to eliminate bias toward the largest category of the dataset, the few categories were balanced by expanding their data. The resulting clinical dataset was then saved after preprocessing.

As for the pre-processor for cardiac signals, in order to improve performance, a signal length of only 1000 was selected. The ECG signal was then converted to a GAF image and three copies were merged to form a three-channel image. The image was saved with a png extension and dimensions of $224\times 224 \times 3$.

After processing the clinical data and the electrical heart signal data for each record in the file generated by the preprocessor, the data is read in order to divide it into three groups: the first for training, which is 70%, the second for validation, which is 15%, and the third for testing, which is 10%. The data is then ready for training and testing the proposed deep learning model.

4.2 Proposed Deep Learning Model

To process multimodal data for cardiac diagnosis using deep learning, deep learning models must be built in a specific way to integrate, process, and classify data consisting of images and combined clinical data. This type of deep learning model can extract features from multiple data sets, with one part of its layers responsible for extracting features from images and the other part extracting features from clinical data, and finally combining them with a neural network model for classification using the extracted features. Figure 1 shows the details of the proposed model structure. Figure 2 shows the layers of the MFDNN model used for classifying heart diseases.

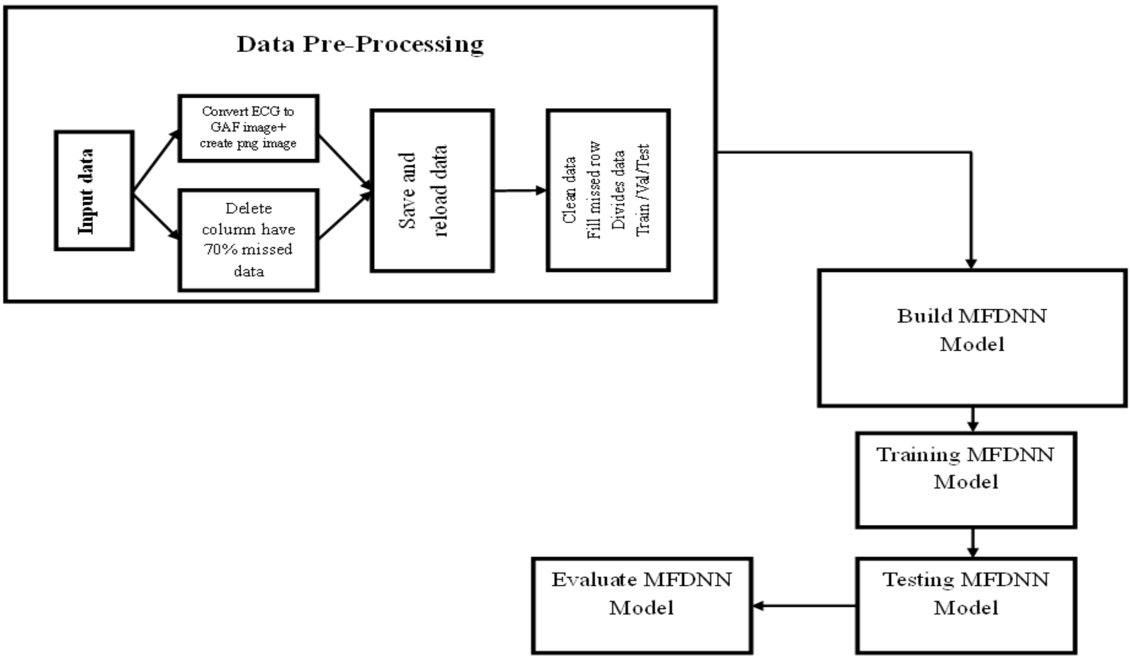

Figure 1. shows steps of implementation plan

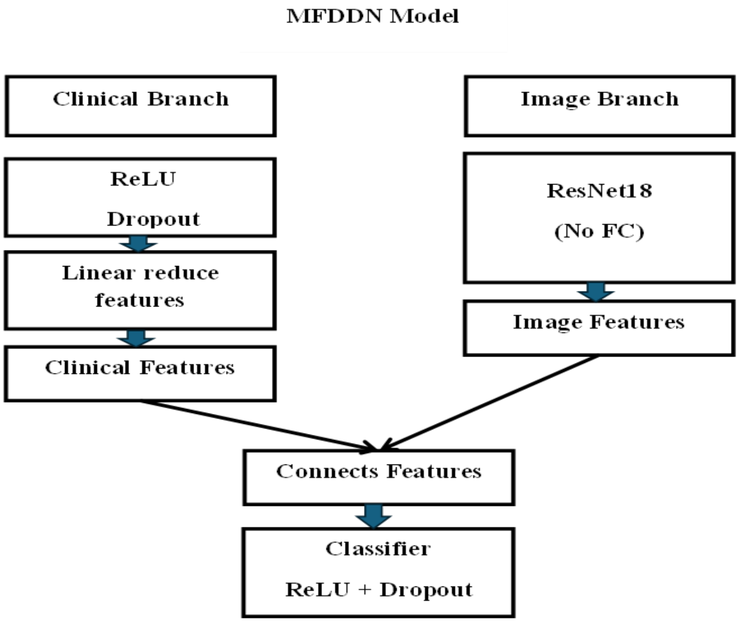

Figure 2. shows steps of suggested MFDNN Model

The first figure shows the program implementation plan. The second figure illustrates the proposed MFDNN layers. The figure above (MFDNN figure) illustrates the proposed model, whose layers are as follows:

4.2.1 ResNet18 for Image Feature Extraction

In this part of the proposed hybrid model, image data extracted from electrical signals of the heart is processed during the preprocessing stage to extract features from images for classifying heart disease types. The layers are the same as those in the pretrained ResNet18 model for feature extraction, but we only we replace the fully connected layer for classification with a layer where the features extracted from the images are saved for later use in the classification process after combining them with clinical data features. The ResNet18 network was chosen because it is commonly used in medical image analysis and classification.

4.2.2 DNN for Clinical Feature Extraction

This part of the proposed model for classifying heart diseases consists of two layers. The first layer converts the data into new dimensions and uses the ReLu function to detect the complex correlation between features. Dropout is also used in this layer to improve the model's generalization in recognizing data.

The second layer in this part of the model is responsible for reducing the representation of clinical data to match the data produced by the previous steps, and its output is also a data vector.

4.2.3 Classifier Layers

This stage is the most important and is considered the main research idea for classifying heart diseases using multiple data. It consists of two layers. The first layer uses Linear to reduce the inputs and ReLu to determine the correlation between the input features. Finally, Dropout is used to recognize the data well and does not rely on one side of the features. The second layer is Linear, which is used to extract the final classification of heart diseases based on the features extracted from the multiple data.

4.3 Training MFDNN Model

After preprocessing the data and building the proposed model, the model is trained using the data selected for training, which constitutes 75% of the total data, as well as the validation data, which constitutes 15% of the original data. Early stopping was used at this stage to avoid overfitting and obtain the best trained model after the last five cycles of model training without obtaining a better result. The number of training iterations for the model was also set to 30. The training process is verified for each iteration, and the accuracy, validation accuracy, and loss values are extracted for each iteration. These values indicate the model's learning ability at each iteration and evaluate the model's learning performance.

4.4 Testing MFDNN Model

At this stage, the data set for testing the best model after the training process was used. The confusion matrix was calculated for the entire testing process. The metrics (F1-score, Recall, Precision) for each of the classification categories available in the PTB-XL dataset used to diagnose heart disease and calculate the value (F1-score, Recall, Precision, loss value) for the overall performance of the model in diagnosing heart disease. Table 1 shows the equations used to calculate each metric. These metrics are important and necessary to ensure that the model has learned and recognized the data after learning.

Table 1. Equations used to calculate each metric

Evaluations Scales	Equation	Benefit
Accuracy	(TP+TN)/(TP+TN+FP+FN)	It expresses the accuracy of the model in general, i.e., the ratio of true positive and false values to the value of all predictions [18][19].
Precision	TP/(TP+FP)	It is the ratio of true positive samples to total positive identifications [20][21].
Recall	TP/(TP + FN)	It is the ratio of true positive sample recognition to total recognition of a single type [22].
F1-score	2TP / (2TP + FP + FN)	It works to reduce bias towards a particular category of the categories to be classified, as its principle is based on the balance between Precision and Recall [23][24].

5. Result and Experiments

This section presents the results obtained when testing the proposed model on the PTB-XL dataset to diagnose types of heart disease based on clinical data and electrocardiogram images in the form of signals, which are then converted into GAF images. The Python programming language was used to apply the proposed model for research. The program steps were implemented using a 16GB CPU with a frequency of 2.3GHz.

The results after the model training process indicated that the model works perfectly, with a training accuracy of 99.69% for the best model resulting from the training process, a train loss value of 0.0093, and a validation accuracy value of 99.94%. The validation loss value was 0.0013, indicating that the model learns with high accuracy and has the ability to generalize and overcome overfitting. It also indicates that the model is effective and stable in learning. Figure 3 shows the training and validation accuracy results for the proposed model.

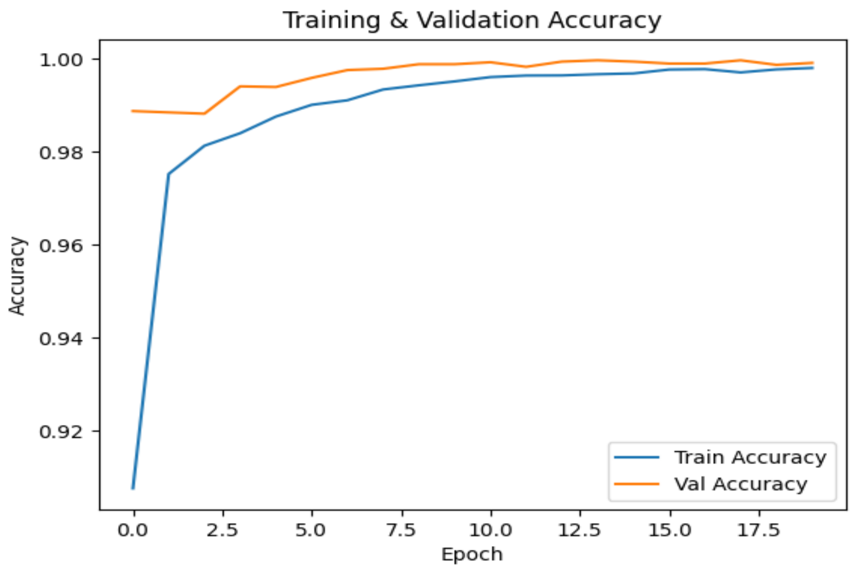

Figure 3. The training and validation accuracy

Figure 4 shows the classification result for each category of heart disease in the dataset used to test the model, coded from 0 to 4. Where 0 indicates a normal diagnosis, 1 indicates MI, 2 indicates STTC, 3 indicates CD, and finally 4 indicates HYP. The results show that the model classified all cases correctly, with a precision score of 100% and a recall score of 100% for all categories, indicating that it detected the true categories. The F1-score value is 100%, meaning that the model is ideal in terms of the balance between Precision and Recall for all categories.

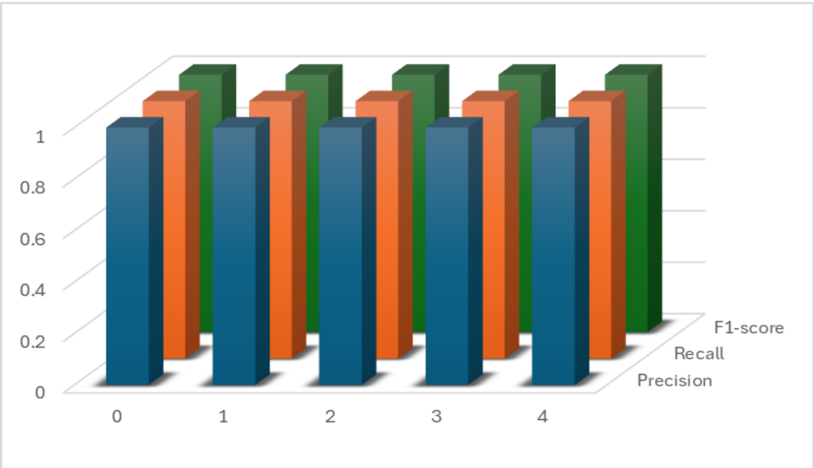

Figure 4. F1-score, Recall, Precision result for each category of heart disease

Figure 5 shows the confusion matrix, whose results indicate the number of true positive and true negative predictions, false positives, and false negatives for each category. The model predicted all values for healthy individuals, the second category representing MI, the third category representing STTC, and the fifth category representing HYP, and all were predicted correctly. As for the fourth category, two false values were predicted as belonging to category number one, i.e., MI, and one value as belonging to HYP. These false predictions resulted in the accuracy of the system being 99.69% instead of 100%.

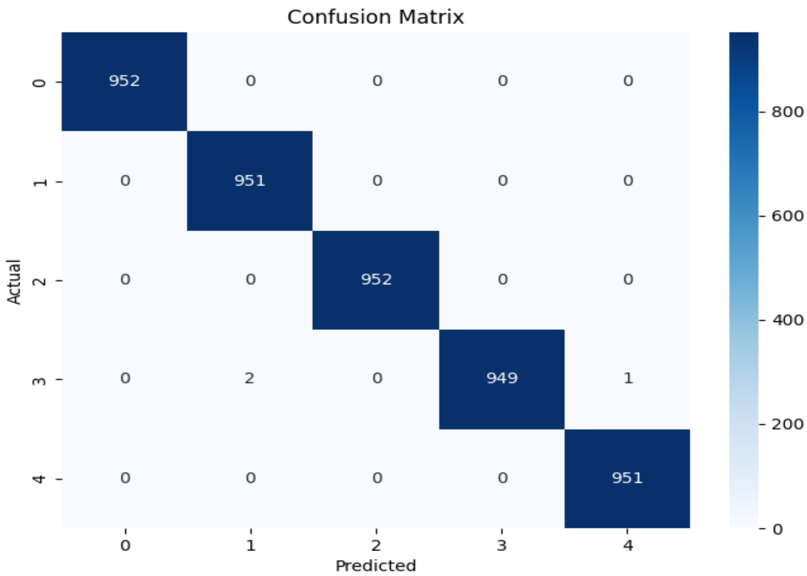

Figure 5. Confusion matrix for testing data

Figure 6 shows the values for evaluating the entire model at the testing stage, rather than for each category separately.

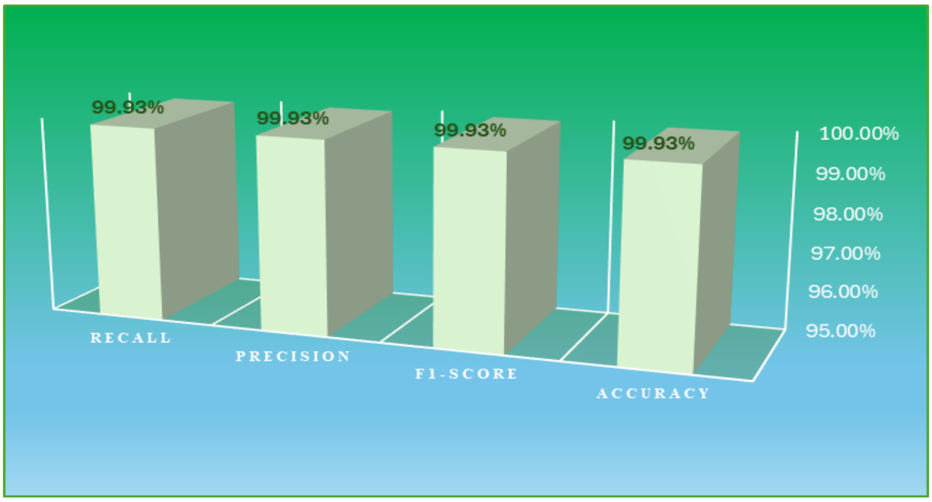

Figure 6. Results of model test metric values

These results were obtained by applying the stages of the MFDNN model to the PTB-XL dataset, even in the testing stage. However, predicting real values was not tested due to the difficulty of obtaining real data, which is due to ethical considerations in healthcare environments. Patient privacy is a priority in data collection, and patient data and privacy are very important.

Table (2) below compares the proposed model in terms of the data used and the accuracy value obtained in the studies discussed in paragraph 2 of the research for the multiple diagnosis of heart diseases, not the binary diagnosis. The table shows the superiority of the proposed model over other models, especially since it relies on two types of data: medical images and clinical data of patients. In doing so, it achieves a more realistic generalization and analysis of cases, as it learns from the context of imaging and clinical data, rather than just formal data, as in the model used by Ahmad, M., et al [15], which relied on converting electrical signals from the heart into three-channel images and training and testing the model on them. In comparison with Ahmad, Z., et al [16], it also relied on only one type of data by converting it into images and then classifying it, and the accuracy obtained from applying its model to the heart signals for the same data set used in this research is lower than what we obtained, in addition to the fact that testing the model by classifying each category separately reached 100%. Because the model achieved 99.93% accuracy for multiple classification, it was not tested on binary classification, and it also succeeded perfectly in recognizing every category in the data set.

Table 2. Compression the proposed MFDNN model with other studies.

Model	Dataset	Test Accuracy
Aversano, L., et al [13]	ECG Images of Cardiac Patients	80%
Sayin, I., et al [14]	ECG Images of Cardiac Patients	93%
Ahmad, M., et al [15]	ECG Images of Cardiac and COVID-19 Patients	100%
Ahmad, Z., et al [16] using AlexNet	MIT-BIH	99.7%
	PTB-XL	99.2%
Ahmad, Z., et al [16] simpler CNN	MIT-BIH	98.3%
	PTB-XL	96.5%
Proposed MFDNN Model	PTB-XL	99.93%

6. Conclusion

The challenge of detecting heart disease early requires continued research, development, and innovation, as heart disease is a common cause of death. Artificial intelligence, especially deep learning, has emerged as a key player with a direct impact on the analysis of medical data and images. This study reviewed several methods used to assist medical personnel in diagnosing and predicting diseases, where it focused on diagnosing various heart diseases using various deep learning networks and techniques, it also examined the nature and type of data used in diagnosis, using various types of data, including medical images and clinical data. The study relied on building a deep learning model used in the diagnosis of heart diseases by combining personals clinical data with images resulting from the conversion of the heart's electrical signals to them, which are the result of the data preprocessing phase. This is considered a new idea and step in the field of diagnosing various heart diseases, and we anticipate that it may help medical personnel diagnose various heart diseases and distinguish between them in the future. The accuracy of the proposed model, which relied on two types of data for diagnosis (ECG signals converted to images and clinical data), reached 99.69% in the training step and 99.93% in the testing step. The "F1--score for all categories of the dataset= used to diagnose heart diseases was 99.94%. That is, the model was not biased toward any category or type of disease in the dataset and was excellently balanced. The precision value of 99.94% means that the proposed model produced no false positives, correctly identifying all categories. We expect these results to be a promising sign in the field of diagnosing various heart diseases and to help identify the disease early. The idea of using more than one type of data to diagnose various heart diseases by combining clinical data and images resulting from converting ECG signals is a step closer to reducing late diagnosis of heart diseases. In the future, we propose to test the model on real, fully organized and structured data in order to subsequently work on the possibility of building an application that helps medical staff to quickly and reliably diagnose using electrocardiogram signals and clinical data.

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