Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, No. 1, April : 2023

CLASSIFICATION OF ARRHYTHMIA BEATS IN ECG SIGNALS USING DEEP LEARNING TECHNIQUES

Ch. Venkata Bangara Raju, Ch. Sai Varun, G. Hemanth, B. Bhargav Sai UG Students, Department of ECE, GMR Institute of Technology, Rajam, Andhra Pradesh, India
M. V. Nageswara Rao, Corresponding Author Department of ECE, GMR Institute of Technology, Rajam, Andhra Pradesh, India, nageswararao.mv@gmrit.edu.in

Abstract: *Cardiovascular diseases (CVDs) are among the leading causes of death worldwide. Arrhythmia, a type of CVD that refers to abnormal heart rhythms, can be difficult to detect early and can have fatal consequences if left untreated. Manual identification of arrhythmias is time-consuming and dependent on the experience of doctors. Many types of arrhythmias can be prevented if detected early, making it important to regularly monitor heart rhythms. Electrocardiogram (ECG) is a non-invasive medical tool that can display the rhythm and status of the heart, and automatic detection of irregular heart rhythms from ECG signals is crucial for preventing cardiac diseases. However, some machine learning algorithms may not detect arrhythmia beats. This thesis proposes a deep two-dimensional CNN model to classify ECG into six categories, including normal and five different types of arrhythmias. Pre-processing transforms each ECG beat into a grayscale image, which serves as input for the CNN model. The model employs deep-learning techniques such as Image normalization, data augmentation, and linear initialization to improve accuracy. The effectiveness of the classifier is evaluated using ECG recordings from the MIT-BIH arrhythmia disease database, resulting in an average accuracy of approximately 93.05%. The model also incorporates ADAM optimizer to enhance its speed of operation. Model efficiency is measured using Accuracy, Precision, Recall, and F1 score metrics, and the study results are recorded.*

Key words: *ECG, Cardiac arrhythmias, Convolution Neural Network.*

1. Introduction

As per the World Health Organization's findings, Cardio-vascular disease is responsible for the highest number of fatalities. Each year, this disease claims the lives of millions of people, accounting for approximately 30% of all deaths. Arrhythmia, a type of CVD, refers to any irregularities in the heartbeat from its usual pattern. There are different forms of arrhythmias, such as ventricular fibrillation, premature ventricular contraction, LBB, RBB, among others. Persistent irregular heartbeats can be fatal, even though a single arrhythmia beat may not pose a significant threat to life. Frequent premature ventricular contractions (PVC) can lead to cardiomyopathy, which can ultimately result in sudden cardiac arrest.

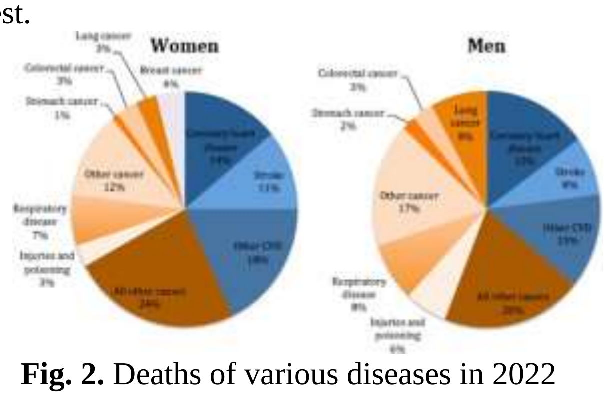

Fig. 2. Deaths of various diseases in 2022

Therefore, it is essential to monitor the heart's condition regularly to prevent and manage cardiovascular diseases. The electrocardiogram (ECG) is a medical tool that displays the heart's beats and is beneficial for monitoring its condition. As a result, the classification of arrhythmia beats through ECG signals is a critical task in the field of cardiology [1].

Several methods have been suggested for classifying ECG arrhythmias, including the use of feed-forward neural networks (FFNN) as a classifier. Linh et al and Guler et al both employed FFNN as the classifier, with Linh et al incorporating a fuzzy neural network model utilizing the Hermite function for feature extraction, and Guler et al using wavelet transform (WT) for feature extraction and training facilitated by the LavenbergMarquard algorithm. Additionally, Ceylan et al utilized FFNN as the classifier, along with principal component analysis (PCA) and WT for feature extraction, and fuzzy c-means clustering (FCM) for feature reduction.

To categorize ECG signal patterns as different types of arrhythmias, a Convolutional Neural Network (CNN) is used which incorporates both 1D and 2D CNN. However, the 2D CNN is more effective in accurately identifying arrhythmia types compared to 1D CNN. Our research proposes a new approach to the 2D CNN model, which can identify up to 6 classes of arrhythmia including NRML, APB, PVC, PB, FVCN, LBBB, and RBBB.

2. Arrhythmia

1. Bundle Branch Block: A condition known as bundle branch block occurs when the path that electrical impulses take to produce the heartbeat is delayed or obstructed. It is categorized into two types.
   I. Left Bundle Branch Block: Left bundle-branch block (LBBB) occurs when there is a hindrance in the conduction pathway of the left bundle branches. LBBB may be temporary, sporadic, or constant in nature.
   II. Right Bundle Branch Block: The ECG displays a relatively distinctive appearance for RBBB, but other conditions with similar ECG presentations must be ruled out before diagnosing RBBB.
2. Normal Beat: Normal function of the heart to give normal range between 60 and 100 beats per minute in a healthy adult is a normal beat.
3. Atrial Premature: Atrial Premature contractions (APCs) refer to heartbeats that originate in either of the atria, the upper chambers of the heart, and occur in addition to the regular heartbeats. These additional beats interfere with the normal heart rhythm and are classified as a type of heart arrhythmia.
4. Premature ventricular contraction: Premature ventricular contractions (PVCs) are extra heartbeats that come from the ventricles, which are the lower chambers of the heart responsible for pumping. These extra beats interfere with the heart's regular rhythm, occasionally resulting in a feeling of fluttering or skipped beat in the chest.
5. Ventricular Fibrillation: Ventricular fibrillation refers to a form of cardiac arrhythmia marked by an irregular heartbeat. In the event of this particular ailment, the lower chambers of the heart, also known as ventricles, undergo irregular and very swift contractions. This causes the heart to lose its ability to circulate blood effectively throughout the body. Fig. 2. shows different arrhythmia beats and abbreviated as shown below.
   APC: Atrial Premature Contractions
   LBB: Left Bundle Branch
   RBB: Right Bundle Branch
   PVC: Premature Ventricular Contractions
   VF: Ventricular Fibrillation

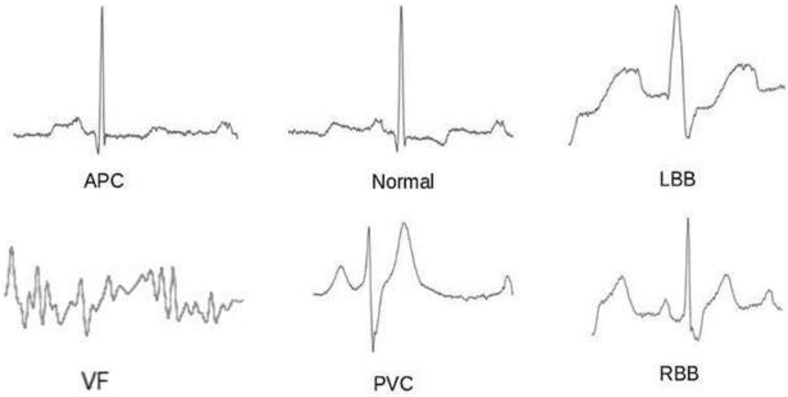

Fig. 2. Different classes of Arrhythmia beats

2.1. Existing Problem

Cardiovascular diseases are a major contributor to global mortality. In 2022, over 17.7 million people lost their lives due to CVDs, representing nearly 31% of all deaths. Unfortunately, low and middle-income nations are disproportionately affected, accounting for more than 75% of fatalities attributable to these diseases. Among the different types of CVDs, arrhythmia refers to any abnormal changes in the heart's rhythm from its normal pattern. Arrhythmias encompass several types of irregular heart rhythms, such as premature contractions, atrial fibrillation, ventricular fibrillation, and tachycardia.

3. Related Works

Robby Rohmantri et.al presented a novel approach for classifying arrhythmia disorders. Instead of using the state-of-the-art input size, they utilized a reduced input diversity to create a simple image classifier using 2D CNN. The researchers categorized the classes according to the modified ECG signal sourced from the MIT-BIH Arrhythmia database. As a result of the study, they achieved a 90.11% accuracy rate for 2 classes, an 89.10% accuracy rate for 7 classes, and an 87.45% accuracy rate for 8 classes [1].

Mohammad et.al presented a technique for categorizing heartbeats using deep convolutional neural networks. The method can identify five distinct arrhythmias following the AAMI EC57 protocol, and the authors proposed a way to apply the knowledge gained from this task to myocardial infarction classification. The authors tested the approach on the MIT-BIH and PTB Diagnostics datasets from Physio-Net and obtained an accuracy of 90.4% for arrhythmia classification [3].

Elif Izci et.al introduced a new 2-D convolutional neural network using neural networks techniques to accurately classify various types of arrhythmias. The model is designed to identify five specific types of arrhythmias and is tested on Electrocardiogram (ECG) signals obtained from the MIT-BIH arrhythmia database. To input the data, the ECG signals are segmented into individual heartbeats and transformed into 2-D grayscale images. The model achieved an accuracy of 90.42% during training, demonstrating the effectiveness of the 2-D CNN architecture for accurately classifying transformed 2-D ECG images [4].

Mengze et.al presents a technique for identifying ECG characteristics using machine learning. Nevertheless, there are certain drawbacks associated with this method, including the need for manual identification of features, employment of intricate models, and extensive training periods. To address these issues, the current study proposed a 12-layer deep 1-D CNN to classify five micro- class heartbeat types, using data from the MIT-BIH Arrhythmia Catalogue. According to [5], the proposed model outperforms the BP neural network, random forest, and other CNN networks in accurately classifying five types of heartbeat features. The model demonstrates better accuracy and sensitivity, as well as greater efficiency overall [5].

4. Methodology

The proposed CNN model-based ECG arrhythmia classifier, outlined in Figure 3, consists of two stages: ECG data filtering and the arrhythmia classification. The first stage involves a signal pre-processing procedure. During the process, ECG signals are converted into ECG images to be compatible with the CNN model's input, which is designed to handle two-dimensional images. To identify the arrhythmia type of a signal requires extracting ECG beats. To achieve this, the signal undergoes heartbeat segmentation to separate ECG signals into their respective heartbeats, followed by an image transformation to convert each beat into a 2-D image. In the second stage, a deep CNN model utilizes ECG images as the input dataset to extract features automatically, and performs classification of six ECG types in the CNN Classifier stage. The use of CNN offers the advantage of eliminating the need for hand-crafted feature abstraction, as it can automatically extract complex features. After validating the results, the hyperparameters of the model are adjusted to ensure that the proposed classifier achieves optimal performance during evaluation.

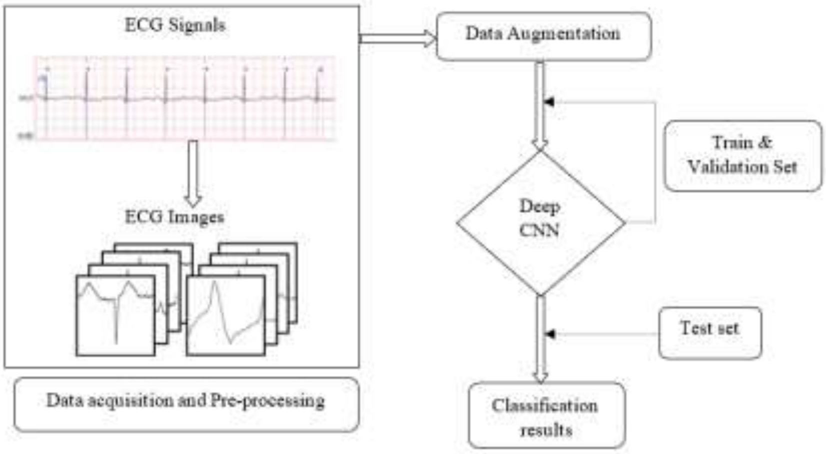

Fig. 3. General methods employed for the classification of ECG arrhythmias

4.1 Data acquisition and Pre-processing

Data collection: In this paper, the ECG dysrhythmias tracings are sourced from the MITBIH arrhythmia catalogue. The tracings are collected from 47 patients between 1975 and 1979, and the dataset includes 48 half-hour ECG recordings. The sampling rate of the ECG recording is 360 Hz, and it is bandpass filtered within the range of 0.1–100 Hz [1]. The data set comprises of a pair of channels, specifically, an adjusted limb II and one among the modified leads V1, V2, V4, or V5. For this study, the modified limb II (Single lead) has been chosen. The MIT-BIH database contains roughly 110,000 ECG beats, consisting of both normal beats and 15 different types of arrhythmias. From the MIT-BIH database, we opted to choose the normal beat (NOR) and five distinct forms of ECG irregularities, which include premature ventricular contraction (PVC), right bundle branch block beat (RBBB), left bundle branch block beat (LBBB), atrial premature contraction (APC), and ventricular fibrillation beat (VF). In Table 1, we have provided a breakdown of how we categorized the ECG waveforms obtained from the MITBIH arrhythmia catalogue.

Table 1. ECG Data Overview

Type of Beats	ECG Tracings	Beat Count
NOR	100,101,103,105,108,112,113,114,115,117,121,122,123, 202,205,219,230,234	75052
PVC	106,116,119,200,201,203,208,210,213,215,221,228,233	7130
PAB	102,104,107,217	7028
RBB	118,124,212,231	7259
LBB	109,111,207,213	8075
APC	209,220,222,223,232	2546
VFW	207	472
VEB	207	106
Total		106501

ECG waveform Segmentation: The 2D convolutional neural network (CNN) requires an image as input data, which led us to transform ECG signals into ECG images by creating grayscale images of each ECG heartbeat that are 64 x 64 in size. To accomplish this, we utilized the MIT-BIH arrhythmia database, which slices ECG beats based on the Q-wave peak time. The Pan-Tompkins algorithm is applied to detect R-peaks. Subsequently, the dataset is segmented and centered around these peaks. Each beat of the dataset contained signals ranging from the present R-peak to halfway towards the previous R-peak. The time information is used to define a range for a single ECG beat.

$$T\ (Qpeak\ (n-1)+20) \leq T(n) \leq T\ (Qpeak\ (n+1)-20)$$

Image Generation: In this paper, 2-D image formation is used to assess ECG data in contrast to conventional methods. After beat segmentation, 2-D images of each heartbeat are created. Filtering and feature extraction are dropped as a result of this conversion. To remove the effects of RGB colour, each image is additionally converted into 64×64 grayscale images. The study showed that colour is not a decisive factor in categorizing arrhythmia types from images. Converting the images to grayscale reduces their size and facilitates analysis. The classifier takes in the 2-D ECG beat images as input without any prior image processing.

Image Pre-processing: Since the images originate from diverse datasets, their dimensions vary, making classification tasks difficult. Therefore, to achieve uniformity, all images are resized to 64×64. Additionally, to ensure consistency in the RGB image's three channels, their intensities are normalized between 0 and 1. Normalizing images is a crucial step in preparing them for network training since it allows for faster convergence during training by ensuring that every pixel has a similar distribution.

$$N = \frac{p - MinC}{MaxC - MinC}$$

The terms MaxC and MinC are used to refer to the highest and lowest levels of intensity present in the original images respectively, where p refers to the original intensity, which ranges from 0 to 255, and N refers to the normalized intensity, which ranges from 0 to 1 of the respective images.

4.2 Image data augmentation

The use of images as input data offers a benefit in the form of data augmentation. However, in prior research on arrhythmia, incorporating augmented data into the training set manually posed a challenge. This is because distorting a single ECG image value had a detrimental effect on performance in the test set. Image data augmentation involves creating modified versions of images in the dataset to artificially expand the training dataset size. To reduce overfitting, four geometric transformations are applied to training samples: re-scaling, horizontal flip, vertical flip, and zooming. A total of 22,116 images are collected from the MIT-BIH arrhythmia database, where every image represents one of the six classifications of ECG beats. We see that for training there are 15341 images belonging to 6 classes and for testing there are 6825 images belonging to 6 classes respectively. The six types of ECG beats are illustrated in Fig. 4 using 64x64 grayscale images which are acquired through the ECG data pre-processing method. Table 2 depicts the splitting of the dataset.

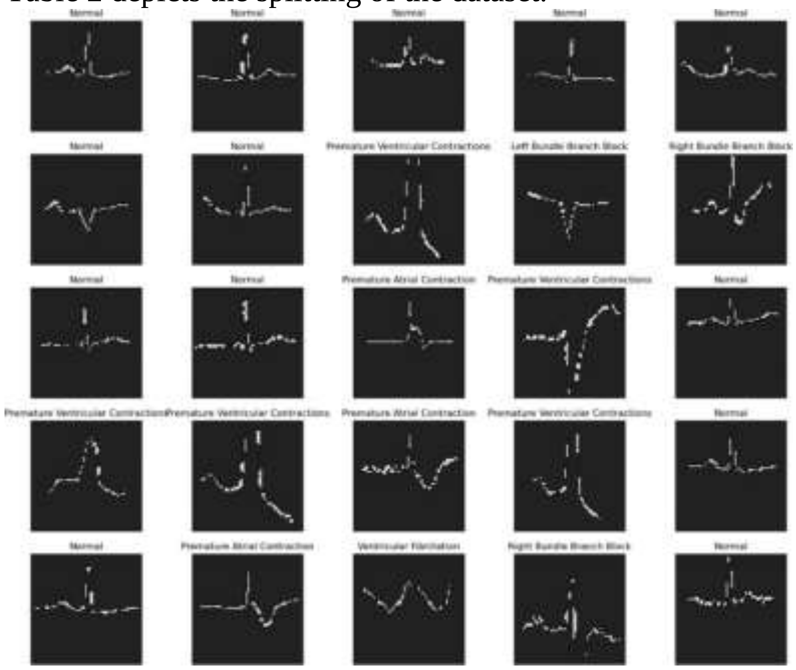

Fig. 4. Samples of Normal and Arrhythmia beats

Table 2. Dataset's depiction

Beat Name	Training Data	Testing Data	Total
Ventricular Fibrillation	450	250	700
Right Bundle Branch Block	2200	1600	3800
Premature Ventricular Contraction	2700	900	3600
Premature Atrial Contraction	2100	1500	3600
Normal	7300	2200	9500
Left Bundle Branch Block	500	350	850

4.3 Building the CNN model Framework

Convolutional neural networks (CNNs) are a particular kind of neural network that make use of a number of different methods, including convolutional layers, pooling, non-linear activation functions, and normalization etc. to extract complicated characteristics from images and this feature of CNN makes it a popular model to deal with images. We proposed a new model to identify and classify into six classes one being normal and other five kinds of arrhythmia beat from given ECG beats which consists of regular and irregular patterns from a particular ECG signal. Figure 5 illustrates the structure of the model that has been suggested. The model is capable of processing a 64x64 greyscale image without the need for any filtering such as removing noise or feature extraction. In Keras, there are two methods to define a network: the sequential method and the Function API. The sequential approach initializes the model using linear layer initializations, which together make up the model. The Sequential constructor builds the model by adding layers using the add () method. The proposed CNN design has 10 weight layers and is a 2D CNN network with two convolution layers with filter sizes of 3 and 32 filters, followed by two pooling layers with filter sizes of 3 and 32 filters. After that, the network comprises five fully connected layers with 128 output neurons each and a softmax layer for

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, No. 1, April : 2023

forecasting output class probabilities Max pooling is utilized by the pooling layers to reduce the input size, and prior to the pooling layers, ReLU activation functions are executed. The convolution and pooling layers function as a feature extraction step, while the fully connected layers function as a classification step. Lastly, the input is flattened after passing through the max pool layer.

Fig. 5. Architecture of 2D CNN Classifier

Deep learning is an artificial neural network technique that varies from typical machine learning approaches. It involves the use of more layers, with an addition of hidden layers known as dense layers. Dense layers are neural network layers that are deeply connected, and they are utilized more frequently. In this model, there are five fully connected layers, each with 128 output neurons. Following the completely linked layers, a softmax function is used to classify the output into six arrhythmia types: left bundle branch, right bundle branch, premature atrial contraction, ventricular fibrillation, and normal. The model predicts the probability of each class, and the output is determined by the class with the highest probability. The softmax activation function is used in the output dense layer. The proposed model's architecture is presented in Table 3.

Table 3. Proposed CNN model and its Architecture

Layer	Type	Size of Kernal	Stride	Filter	Size of Image
1	Conv2D	3 x 3	1	32	64 x 64 x 1
2	MaxPooling	2 x 2	2		62 x 62 x 32
3	Conv2D	3 x 3	1	32	31 x 31 x 32
4	MaxPooling	2 x 2	2		29 x 29 x 32
5	Fully-connceted			128	14 x 14 x 32
6	Fully-connceted			128	128
7	Fully-connceted			128	128
8	Fully-connceted			128	128
9	Fully-connceted			128	128
10	Softmax (Out)			6	128

4.4 Configuring the Learning Process

The next step in the model after compilation is the training phase, where a loss function is employed to identify errors or deviations in the learning process. To ensure greater accuracy of the Keras model, a loss function is necessary. Optimization is a crucial process that involves comparing the prediction to the loss function in order to optimize the input weights. During the learning process of the model, there are 8,79,910 parameters that need to be set as trainable. After that, the model is built using the

Adam optimizer with a learning rate of 0.001, categorical cross entropy as the loss function, and conventional back propagation with a batch size of 32. After trying different numbers of epochs, it is determined that 10 epochs are the optimal number.
Once the training stage is completed, the model accuracy will be evaluated. The dataset is split such that 70% (15,341) of total are used for training, while the remaining 30% (6,825) are used for testing as outlined in Table 2. The model is trained using the training dataset during the training phase. The model is tested on the validation dataset during the validation phase, and the hyperparameters are adjusted based on the findings. Finally, during the testing phase, the model's performance is assessed based on its accuracy, precision, recall, f1score, and loss.

4.5 Evaluation Metrics
In order to make a more precise assessment and comparison of the model's classification performance, relying only on accuracy is insufficient. As a result, additional metrics such as precision (P), recall (R), F1-score (F1), and the confusion matrix are utilized. Out of these, the accuracy rate signifies the capability to identify the actual situation of the sample. Accuracy and F1-Score are successful measures produced by averaging the performance verification findings. The correctness indicates how exact the numbers are anticipated to be. Precision determines how well a measurement can be reproduced or anticipated. Recall determines the correct outcome. Because there is an exchange between accuracy and recall, a corresponding harmonic mean, known as the F1-score, is employed. The criteria used in the assessment of specificity, sensitivity, and accuracy in Confusion Matrix are performance measurement TP, TN, FP, and FN.
True Positive (TP): It is the arrhythmia detected correctly
True Negative (TN): It is the arrhythmia correctly identified as normal
False Positive (FP): It detected incorrectly as arrhythmia
False Negative (FN): It detected incorrectly as normal

5. Results and Discussions
The performance of the suggested and implemented two-dimensional CNN Model is discussed in this section. The experimental results are compared to cutting-edge approaches to normal and arrhythmia classes. In Table 4, the effectiveness of our anticipated model is processed in terms of Accuracy, Precision, Recall, and F1-Score in comparison to all classes one being normal class and all other five arrhythmia classes. The best performance is highlighted in bold. In all evaluation metrics, our model achieves good classification results. The proposed model achieves a higher accuracy rate of 92.95% when applied to new data, surpassing previous results.
214/214 [==============================] - 8s 36ms/step - loss: 0.2958 - accuracy: 0.9295
Accuracy = 92.95238256454468 %
Fig 6 shows the result of comparison of scores for 6 classes of normal and abnormal class, input size 64 x 64. Table 4 displays the precision and accuracy scores for the classification of 6 classes. The RBBB class achieves the highest precision score of 99.90% and an accuracy score of 98.65%. According to the results, the PVC class has the highest recall score, which is 99.78%. Alternatively, the Normal class is having highest F1 score, indicating that the RBBB class is predicted more accurately than any other class.

Scores	Accuracy	Precision	Recall	F1-Score
Normal	92.69	95.22	97.74	**96.09**
LBBB	97.56	93.13	92.31	93.90
RBBB	**99.90**	**98.65**	87.91	92.70
PAC	87.02	91.77	92.55	91.46

PVC	92.15	89.89	**99.78**	94.67
PAB	96.77	97.17	96.32	97.32
Macro Average	94.67	94.99	94.76	94.67
Weighted Average	93.78	93.34	93.98	93.56
Accuracy	**93.57**			

Table 4. Average score for six classes

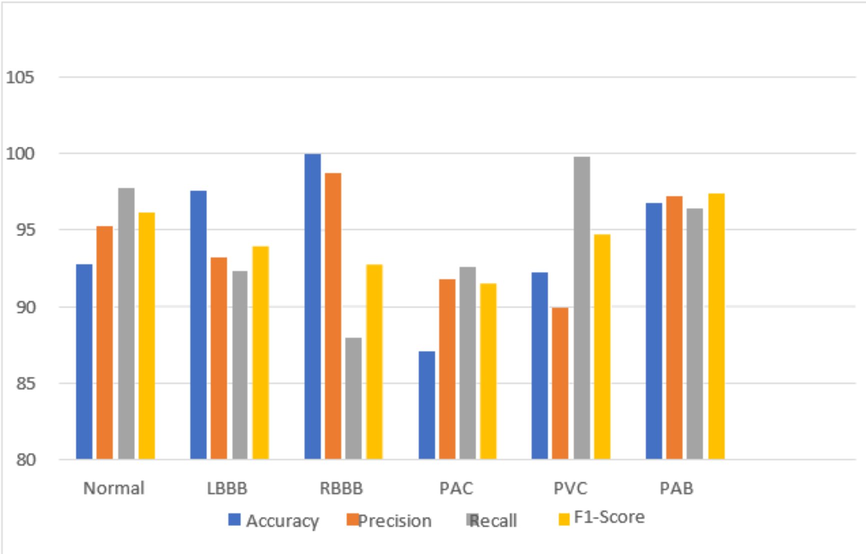

Fig. 6. Comparison of scores for six classes

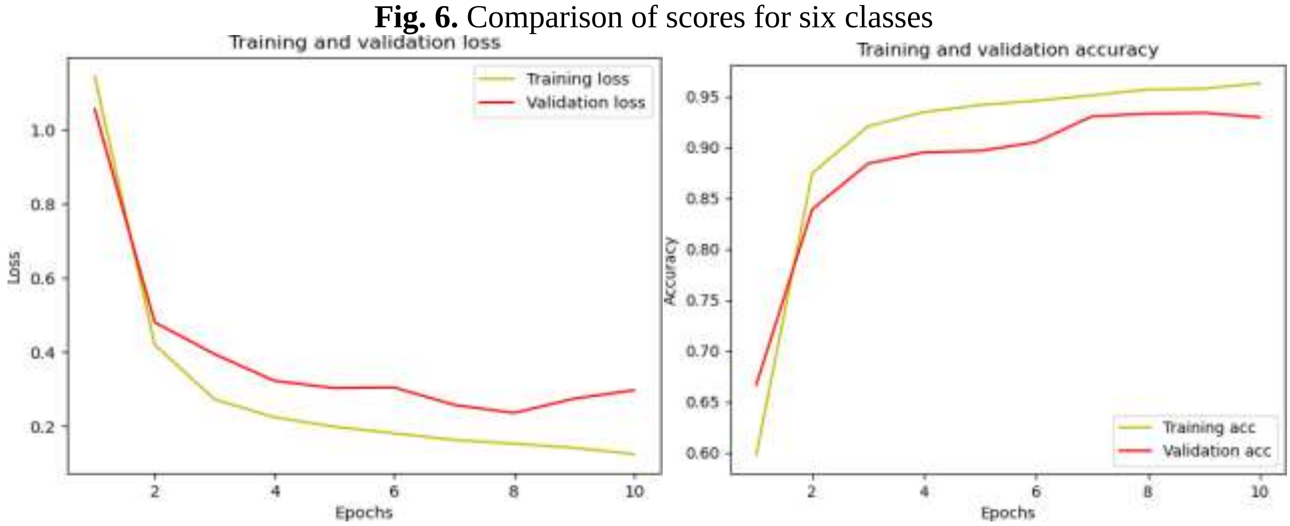

Fig. 7. Performance Metrics of ECG Arrhythmia Classifier (a) Training and Validation Loss (b) Training and Validation Accuracy

During the training phase, images of beats are divided into training and validation sets, with 70% of the data allocated to training and 30% to testing. The resulting model produced a training loss of 0.1238, training accuracy of 0.9742, validation loss of 0.2958, and validation accuracy of 0.9295, as shown in Figure 7, which presents the performance metrics of the proposed architecture. The X-axis represents the no of epochs, while the Y- axis represents the loss and accuracy values. The fig 7 demonstrate that the validation and training curves loss and accuracy merged after the second epoch and became parallel after the sixth epoch.

The proposed arrhythmia classifier's confusion matrix is depicted in Fig. 8. The matrix shows that the light shade signifies the accurate classification of the arrhythmia type. A predicted label and an actual

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, No. 1, April : 2023

label, respectively, are assigned to each row and column of the table. Out of 6825 valid images 481 are wrongly classified and 6344 are correctly classified. From fig. 8 we can see 11 LBBB beats are wrongly classified as normal, PVC and RBBB, 171 normal beats are wrongly classified as LBBB, PVC, RBBB and VF, 195 PAC beats are wrongly classified as PVC, RBBB, VF and normal, 76 PVC beats are wrongly classified as LBBB, PAC, RBBB, VF and normal, 18 RBBB beats are wrongly classified as PAC and PVC and 242 VF beats are wrongly classified as LBBB, PAC, RBBB, PVC and normal. By analyzing both figure 7 and figure 8, it can be shown that the model is suitable for distinguishing the various types of arrhythmias in an ECG signal. The confusion matrix from the simulation results is shown below without normalization.

```
214/214 [==============================] - 7s 33ms/step
confusion matrix
[[ 330    3    0    7    1    0]
 [   4 2008    4   12  150    1]
 [   0  120 1308   57   15    3]
 [  13    8   15  839   38    2]
 [   0    6   10    2 1627    0]
 [   0    4    2    3    1  232]]
```

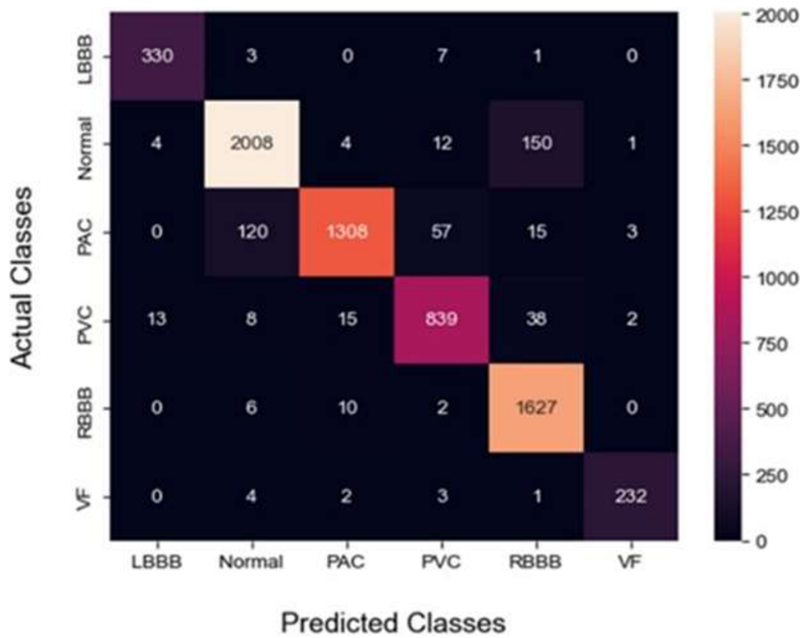

Fig. 8. Confusion matrix of CNN model

Fig 9 shows the Normalized confusion matrix. From this, we can observe that the sloping values of the normalized confusion matrix are the individual accuracy scores of each predict class. According this, light colour represents correct individual classification accuracy of each arrhythmia type and other normalized values represents incorrect individual classification accuracy of the predicted class. Now, the normalized confusion matrix from the simulation results is shown below.

```
214/214 [==============================] - 7s 33ms/step
Normalized confusion matrix
[[9.68e-01 8.80e-03 0.00e+00 2.05e-02 2.93e-03 0.00e+00]
 [1.84e-03 9.22e-01 1.84e-03 5.51e-03 6.88e-02 4.59e-04]
 [0.00e+00 7.98e-02 8.70e-01 3.79e-02 9.98e-03 2.00e-03]
 [1.42e-02 8.74e-03 1.64e-02 9.17e-01 4.15e-02 2.19e-03]
 [0.00e+00 3.65e-03 6.08e-03 1.22e-03 9.89e-01 0.00e+00]
 [0.00e+00 1.65e-02 8.26e-03 1.24e-02 4.13e-03 9.59e-01]]

Diagonal values
array ([0.96774194, 0.92152363, 0.87025948, 0.91693989, 0.98905775, 0.95867769])
```

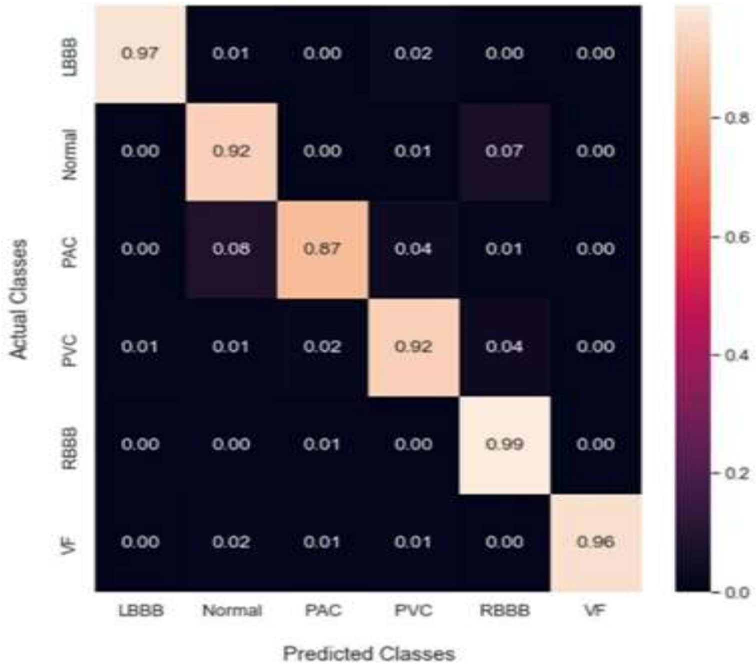

Fig. 9. Normalized confusion matrix of proposed architecture

Fig 11 summarizes, classification report on deep learning-based 2-D CNN classifier to classify cataract all six classes including normal and provides accuracy, precision, recall, and f1-score. Our model is performing poorly on premature atrial contractions and has less accuracy when compared to the other arrhythmia beats. The newly proposed model exhibits superior performance than the latest test data when considering metrics such as precision, recall, and f1-score metrics. Figure 10 demonstrates the predicted results from the model by analyzing multiple input images and categorizing them into six different classes. Additionally, Table 5 provides a summary of the predictions made by the suggested model on the test data, highlighting its accuracy and f1-score.

```
1/1 [==============================] - 1s 516ms/step
1/1 [==============================] - 0s 63ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 67ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 80ms/step
```

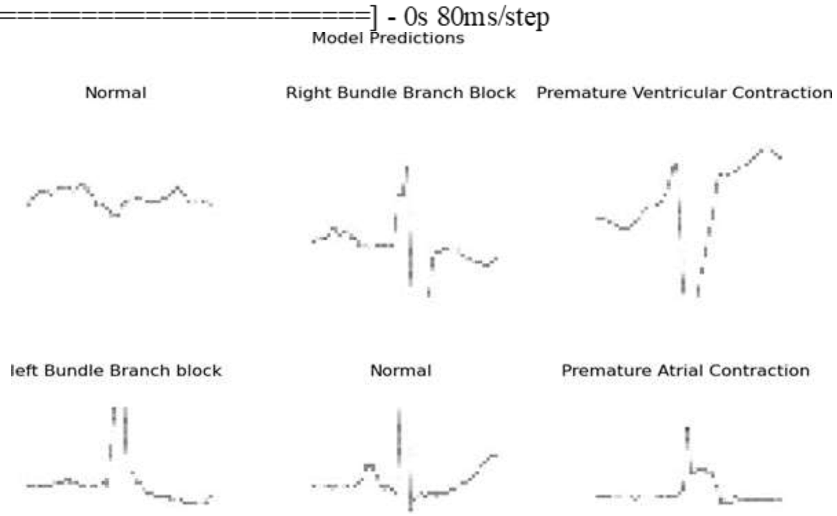

Fig. 10. Predicted classes

classification Report

	precision	recall	f1-score	support
left Bundle Branch block	0.95	0.97	0.96	341
Normal	0.93	0.92	0.93	2179
Premature Atrial Contraction	0.98	0.87	0.92	1503
Premature Ventricular Contraction	0.91	0.92	0.91	915
Right Bundle Branch Block	0.89	0.99	0.94	1645
Ventricular Fibrillation	0.97	0.96	0.97	242
accuracy			0.93	6825
macro avg	0.94	0.94	0.94	6825
weighted avg	0.93	0.93	0.93	6825

Fig. 11. Classification report

Table 5. Predictions on test data

Approaches	Dataset used	Accuracy	F1-score
This Work	MITDB	93.05	93.84

5. Conclusion and Future Scope

Through this, we have introduced an effective CNN model for the categorization of six different arrhythmia conditions. The data used to feed the deep network is initially an ECG signal and is improved to images by pre-processing, and augmentation. The algorithm used here, designed with the primary purpose of classifying various arrhythmia diseases and used precision, accuracy, recall and f1-score as metrics. In terms of accuracy (93.50%), precision (95.69%). The cardiologists could quickly and more accurately diagnose different arrhythmia diseases using this efficient CNN model because of its excellence in accuracy, cost and time-efficiency. There are other arrhythmia diseases apart from the six diseases we have taken. Those diseases cannot be detected by our model. Our model can detect the six mentioned arrhythmia diseases. The field of disease detection offers immense potential for deep learning algorithms. As the database is fed with more data, the system becomes more intelligent. In the future, there is a possibility of creating an integrated ECG arrhythmia classification system that uses a medical robot's camera to scan the patient's ECG monitor and diagnose arrhythmia, thereby informing the physician. Hence in the future there is a need to build a more generalize that algorithm which can detect different types of diseases more accurately.

6. Acknowledgment

It gives us an immense pleasure to express deep sense of gratitude to our guide Dr. M. V. Nageswara Rao, Associate Dean (Academics), GMRIT for his valuable guidance and help in this work.

7. References

[1] Rohmantri, Robby, and Nico Surantha. "Arrhythmia classification using 2d convolutional neural network." International Journal of Advanced Computer Science and Applications 11.4 (2020).

[2] Kachuee, Mohammad, Shayan Fazeli, and Majid Sarrafzadeh. "ECG heartbeat classification: A deep transferable representation." 2018 IEEE international conference on healthcare informatics (ICHI). IEEE, 2018.

[3] Izci, Elif, et al. "Cardiac arrhythmia detection from 2d ECG images by using deep learning technique." 2019 medical technologies congress (TIPTEKNO). IEEE, 2019.

[4] Wu, Mengze, et al. "A study on arrhythmia via ECG signal classification using the convolutional neural network." Frontiers in computational neuroscience 14 (2021): 564015.

[5] Hammad, Mohamed, et al. "Automated detection of Shockable ECG signals: A Review." Information Sciences 571 (2021): 580-604.

[6] Zemouri, Ryad, Noureddine Zerhouni, and Daniel Racoceanu. "Deep learning in the biomedical applications: Recent and future status." Applied Sciences 9.8 (2019): 1526.
[7] Jun, Tae Joon, et al. "ECG arrhythmia classification using a 2-D convolutional neural network." arXiv preprint arXiv:1804.06812 (2018).
[8] Luz, Eduardo José da S., et al. "ECG-based heartbeat classification for arrhythmia detection: A survey." Computer methods and programs in biomedicine 127 (2016): 144-164.
[9] Ebrahimi, Zahra, et al. "A review on deep learning methods for ECG arrhythmia classification." Expert Systems with Applications: X 7 (2020): 100033.
[10] Rajkumar, A., M. Ganesan, and R. Lavanya. "Arrhythmia classification on ECG using Deep Learning." 2019 5th international conference on advanced computing & communication systems (ICACCS). IEEE, 2019.
[11] Desai, Usha, C. Gurudas Nayak, and G. Seshikala. "An efficient technique for automated diagnosis of cardiac rhythms using electrocardiogram." 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT). IEEE, 2016.
[12] Lai, Dakun, et al. "Intelligent and efficient detection of life-threatening ventricular arrhythmias in short segments of surface ECG signals." IEEE Sensors Journal 21.13 (2020): 14110-14120.
[13] Osowski, Stanislaw, Linh Tran Hoai, and Tomasz Markiewicz. "Support vector machine-based expert system for reliable heartbeat recognition." IEEE transactions on biomedical engineering 51.4 (2004): 582-589.
[14] Obasi, Thankgod, and M. Omair Shafiq. "Towards comparing and using Machine Learning techniques for detecting and predicting Heart Attack and Diseases." 2019 IEEE international conference on big data (big data). IEEE, 2019.
[15] Mohanty, Monalisa, et al. "Classification of ventricular arrhythmias using empirical mode decomposition and machine learning algorithms." Progress in Artificial Intelligence 10 (2021): 489-504.
[16] https://physionet.org/content/mitdb/1.0.0/