Cardiac Diagnosis based ECG Images Classification System using Convolution Neural Network

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Abstract— **Electrocardiogram (ECG) is a widely-used for the diagnosis of heart disease and the cardiac arrhythmia classification for an efficient clinical approach. The ECG has the random signal nature. Thus, acquiring the accurate diagnosis of ECG becomes a challenging task. To analyze the ECG signal in the time domain, many machine learning approaches are used to analysis in ECG signals. However, these methods take the long calculation time because of its' preprocessing is complex and need to use the features extraction and selection methods to get the accurate heart diseases. ECG signals are one-dimensional signals to be processed while CNNs are better applied to multiple patterns of biomedical image recognition applications. Convolutional neural networks (CNNs) can use the arrhythmia images of ECG to find the cardiac diagnosis via automatic feature extraction of CNN. In this study, the morphology of ECG images is focused into a cardiac arrhythmia classification by processing the CNNs. The proposed CNN model demonstrates the results of accuracy that are efficient for irregular heartbeats or arrhythmias detection like atrial fibrillation and flutter. The proposed model is trained and tested on the arrhythmia database getting from the ECG library, the model achieved higher performance than the other machine learning method (SVM) for ten arrhythmia classification for cardiac diagnosis (the training and validation accuracy are 98.6% and 92% than 75% of SVM).**

Keywords— Electrocardiogram (ECG) signal images, Cardiovascular Arrhythmias, Convolution Neural Network (CNN), Support Vector Machine (SVM)

I. INTRODUCTION

The electrocardiogram (ECG) is an efficient tool to discover the diagnosis of cardiovascular diseases. Suddenly the 80% of cardiovascular death that are the irregular effect of ventricular arrhythmia or unpredictable heartbeats has been announced. Arrhythmias can be easily determined by a professional cardiologist using the perceptible morphological patterns of ECG signals, but a computerized approach effectively reduces time to diagnosis and cardiovascular disease by monitoring the health condition. However, the development of these approaches remains a challenge as the time-varying dynamics and diverse patterns of ECG signals because of classification accuracy varies from patient to patient, and signal morphological patterns are significant in ECG in a short period of time.

Many methods have been proposed to classify arrhythmias by automatically analyzing the ECG signals. Support Vector Machine (SVM), Least Squares Support Vector Machine (LS-SVM), Particle Swarm Optimization Support Vector Machine (PSO-SVM), Particle Swarm Optimization Radial Base Function (PSO-RBF), extreme and learning machines (ELMs) are machine learning methods which also been developed to accurately classify the arrhythmia.

However, these classification methods are still some weakness. For example, expert systems require an enormous enough data of prior knowledge, which may alter for different patients. Another issue is manual selection of heart rate functions in some machine learning methods. ECG feature extraction is the primary method for recognizing heart rhythm and is used to select representative subsets of features from raw ECG signals. Manual selection may cause the accuracy in the loss of information. Principal Component Analysis and Fourier Transform methods are caused the complexity raise and computational time need to recognize the classification results. As more and more patients have wide variations in the patterns of the ECG signals from different patients, the accuracy of the classification will decrease.

Therefore, the high performance in radiological image analysis can produced by developing the deep learning techniques. Convolutional neural networks (CNNs) are used in pattern recognition applications like the classification of handwriting and object detection in biomedical applications. CNNs have recently been shown to work with multidimensional (1-D, 2-D, and 3-D) inputs, but were originally designed for tasks involving images represented as two-dimensional inputs. Deep learning's CNNs extract features from images and help to recognize different classifications of ECG patterns.

This paper describes the 2D approach for ECG images classification with CNN for detecting the various Cardiovascular Diseases (CVDs) such as Myocardia Infraction, Ischemia and Hypertension. It uses the ECG arrhythmia images from ECG library arrhythmia database including many types of arrhythmia such as atrial fibrillation (AF), atrial flutter (AFL), right ventricular hypertrophy (RVH), left ventricular hypertrophy (LVH), right bundle branch block (RBBB) and left bundle branch block (LBBB), sinus tachycardia (ST), sinus bradycardia (SB), left main coronary artery (LMCA) and normal (N). It transforms to binary images which capture the morphology of ECG paper graph via the image segmentation and these images are used as the 2D input to a CNN. To accelerate the convergence speed of the learning, a predefined learning rate is added to dense 2D CNN method for classification which consists of data augmentation and dropout method are used to reduce the over-fitting of the network.

In this paper, Section 2 describes the related works, and Section 3 describes the cardiac diagnostic classification system which includes (1) pre-processing of ECG image segments (2) feature extraction and classification using CNN, and experimental results of the classification system in section (4), Section (5) explains the conclusion.

II. RELATED WORKS

Early identification of cardiovascular disease (CVD) can effectively reduce mortality by providing timely treatment. Arrhythmias show an irregular beating pattern in which the heart is too fast or too slow. The different subclasses and different types of cardiac arrhythmias are getting from the deviations. Accurate classification of these types can be useful in diagnosing and treating patients with heart disease. The automatic detection of such patterns is very important in clinical practice and provides expert clinical knowledge.

The paper [1] evaluated three different conditions of ECG waveform (normal, RBBB and paced beats) from MIT-BIH arrhythmia database by transferred deep convolutional neural network (namely AlexNet) used as a feature extractor and the extracted features are fed into a simple back propagation neural network to carry out the final classification. It removed the signal noise by using band stop filter and detected the QRS complex using Pan-Tompkins algorithms to extract the R-T intervals. ECG signals were converted to 256x256x3 images (214 total for training and 202 for testing) and sent to the pre-trained AlexNet for the 6th and 7th fully connected AlexNet. The output of the layer is retrieved as a feature of the RT segment images of three different heart beats.

Zahra Ebrahimi, Mohammad Loni reviewed the deep learning methods applied to the ECG signal for the arrhythmia types of classification over various types of the DL methods such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DBN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) in the paper [2]. It classified the twelve types of arrhythmia: normal and abnormal groups of rhythms to develop Compute Aided Diagnosis Systems (CADs).

The paper [3] described a two-dimensional convolutional neural network (CNN) model for classifying ECG signals into eight arrhythmic beats for accurate diagnosis of acute and chronic cardiac conditions in a patient. The 1D ECG signal was converted to a 2D spectrogram using a short-term Fourier transform. The 2-D CNN model, composed of four convolutional layers and a pooling layer, is designed to extract robust features from the input spectrograms available from the MIT-BIH arrhythmia dataset.

The paper [4] presented the detection of ECG classification problems between patients using a densely connected convolutional neural network (DenseNet) and a gated recurrence unit network (GRU), applying data from MIT-BIH arrhythmias and supraventricular databases. The results are displayed without pre-processing complex data or functional design. The two models showed the latest characteristics of arrhythmias in the ventricles (SVEB) and ventricles (VEB) to address the problem of ECG classification between patients.

Bahareh Pourbabaee, Mehrsan Javan Roshtkhari are focused on screening and identifying patients with paroxysmal atrial fibrillation (PAF), a life-threatening cardiac arrhythmia in paper [5]. The proposed approach worked with a large volume of raw ECG time-series data as inputs to a deep convolutional neural network (CNN). It autonomously investigated representative and key features of the PAF to be used in a classification module. The features are learned directly from the large time domain ECG signals using a CNN with one fully connected layer.

The paper [6] descried CNNs on the morphology and rhythm of the heart in two-dimensional information vectors, including gradient descent adaptive learning rates and bias drop-out method. It used one-hot encoding to convert the information fusion vector of signals to a binary image. The morphology of individual heartbeats in the temporal relationship between adjacent beats was captured by images used as 2D inputs to the CNN using the MIT-BIT arrhythmia database.

At the paper [7], it used integrated signal processing and machine learning to automatically classify ECG signals by heart rate type. It involved three stages: signal processing and transformation, feature extraction and classification. It classified beats into eight classes using the Fourier transform, principal component analysis, wavelet transform, and hidden Markov method. The characteristics are extracted from the time domain and frequency domain of the ECG signal obtained from the MIT / BIH arrhythmia database.

The paper [8] presented an ECG-based classification system for cardiac arrhythmia. The system divides the ECG signal into beats as the heart rate changes. The beats were converted to a dual-beat fusion matrix as 2D input to the CNN classifier, identifying both the morphology of ECG beats and the correlation between beats. The classification system was assessed for supraventricular ectopic beats (SVEB or S-beats) and VEB using the MIT-BIH arrhythmia database.

In the paper [9], image processing and artificial intelligence have been applied to the ECG classification system. Using haar-type descriptors based on the concept of integrated images, haar functions and multilayer classifiers were calculated as artificial neural networks. ANN is divided into two main types labeled data (normal ECG and sick ECG) and unlabeled data based another including a learning base for training and testing. The issues of deep learning architecture and its optimization used for segmentation and classification of medical images are described in paper [10]. As the data vary extensively from patient to patient, so traditional teaching methods like Support Vector Machine (SVM), Neural Network (NN), and KNN, etc. are not reliable. It described the explanation the differences between ML techniques without learning and why deep learning are used over machine learning.

The paper [11] showed a transfer learning perspective that transfers knowledge obtained from the image classification domain to features and feature maps are trained in deep neural networks. And in paper [12], which used image processing techniques as spatially oriented feature extraction to extract only important characteristics such as atrial (rate/min), ventricle, QRS, QT, QTc and PR interval/ sec and analyzed patients' cardiovascular activities. It applied root-mean-square-error (RMSE) and normalized root-mean-square-error (NRMSE) to assess the performance accuracy of extracted features. The paper [13] reviewed the findings of the posterior myocardial infarction (PMI) associated with inferior and lateral of MI from 12 leads ECG and used ECG images form the LITFL ECG library [14]. The paper [15] identified the STEMI equivalent ECG patterns in LBBB and RBBB on 12 lead ECG images using the LITFL ECG library.

This proposed system uses a convolution neural network for diagnosis the cardiac diseases applying the medical arrhythmia classification system to classify the image of ECG. Since ECG images are high dimensional data, it is difficult to obtain an accurate heart rate over time and normalize image pixel values to remove noise. Deep Learning's CNN provides scalable and efficient cardiac arrhythmia classification by training segmented binary ECG images and validating accuracy using a cross-entropy classification evaluator.

III. CARDIO DIAGNOSIS CLASSIFICATION SYSTEM

Cardio diagnosis image classification system includes three major stages: preprocessing, feature extraction, and classification. Although the patient ECG graph includes the twelve leads signals, ECG lead II, v1 and v5 are mostly used to analysis the arrhythmia and cardiac diagnosis. But this paper uses lead II of ECG for classification because lead II gives the good view of P wave, QRS complex, T wave to accurately assess the cardiac rhythm of diagnosis in heart diseases. Each ECG graph paper include twelve leads and it extremely show the lead II as a result The preprocessing includes denoised ECG images including gray-scale conversion, binarization and image segmentation, feature extraction is performed by the proposed CNNs. At last, a common classifier called SoftMax is used as a classifier to solve multiple classification problems like logistic regression. A classification system diagram is shown in figure 1.

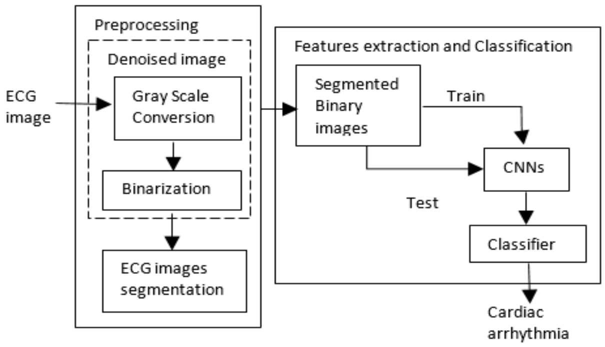

Fig.1. Cardiac Diagnosis Classification System

CNN is model used for training and testing. The training dataset of binary ECG image size (50×100×3) is firstly added to the CNN model. Each layer (convolution layer and full connection layer) of the trained CNN model produces weights and thresholds after 10 iterations. These weights and thresholds by automatic extracting are used as high-level features of the images. And then, the test set is added to the CNN model for testing and the classification results are obtained. After first time CNN, training accuracy and validation accuracy is slightly differed, So, CNN uses the data augmentation and drop out method to overcome the overfitting in second time. The system classifies the following ten different types of arrhythmia shown in figure 2.

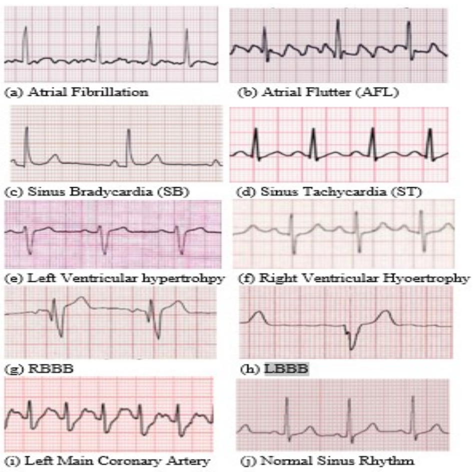

Fig.2. Ten Different Types of Arrhythmias

A. Preprocessing

ECG image preprocessing stage includes three processes: gray-scale conversion, binarization and ECG image segmentation. ECG denoising is used gray scale conversion to reduce the number of colors and binarization to remove the noises (gridlines). An ECG signal contains P, QRS, and T waves. The P wave is the contraction rate of the artery. The Q wave displaces downward just before the ventricles contract. The R wave is the peak of ventricular contraction. The S wave is the downward deviation immediately after ventricular contraction, and the T is the recovery of the ventricle.

1) Gray Scale Conversion

In this step, the system applies the lead II ECG signal images that extracted from twelve lead ECG images getting from ECG arrhythmia library database. It reads the twelve lead ECG image and transforms the RGB image in figure 3 to gray scale image in figure 4 using the MATLAB code; img=imread('./patient1.png'); and img1=rgb2gray(img);

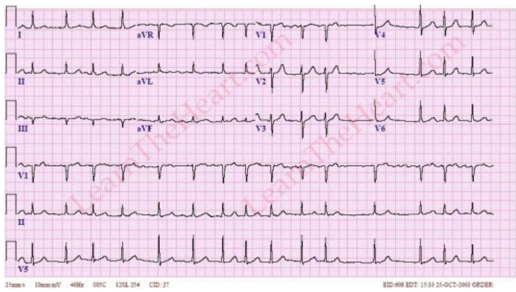

Fig.3. RGB image of Atrial Fibrillation

Fig.4. Gray scale image of Atrial Fibrillation

2) Binarization

In this system, the global binarization is used with a threshold comparing the gray level of the image by manually selected threshold value (0 to 1) and it determines which of the two classes will rise at this point clearing the noise. The goal of binarization is to remove the unwanted information (grid lines) in the image and extract only the corresponding ECG signal image as shown in figure 5. So, the system uses the threshold value 0.5 by manually selected using the global binarization and clears the noises (grid lines) at this point using the MATLAB code img3=im2bw (img1, 0.5).

Fig.5. Binary image of Atrial Fibrillation

3) Segmentation

In this paper, each binarized ECG signal image has twelve leads in 10 seconds but almost cardiac diagnosis is found in ECG lead II. Therefore, the system uses the lead II of ECG image with 700 pixels in Figure 6. Lead II ECG image is segmented into a one second segmented image having 50×100 pixels to get the morphology patterns of ECG. It segments the image automatically using the imcrop () method in MATLAB. Each segmented ECG image contains P wave, QRS wave, and T wave. As the range of ECG graph paper is 10 seconds, segmented morphological images are ten of one second images for each patient in Figure 7. This proposed system classifies the abnormal arrhythmia images to diagnose heart disease.

Fig.6. Lead II segmented image of Atrial Fibrillation

Fig.7. One second segmented images of Atrial Fibrillation

B. Features Extraction and Classification

CNNs can extract weight and thresholds value called high-level features automatically by training. In this paper, CNN is proposed for the classification of binary cardiac arrhythmia images. The CNN model stacks with 3 (convolution, 'relu', max-pooling) layers, one flatten layer, and one fully connected layer in first CNN.

The system encounters the overfitting in first CNN model, it constructs the second time of convolutional layer filtered into (16, 32, 64) each layer, a dropout layer, flatten layer and fully-connected layers 128 in dense network. Flatten layer is transformed the image data into feature vectors at the pooling layer. Each segmented image has (50×100) pixels but the CNN resizes the image size (180×180) pixels by defining the height, width in to get more accurate features and improve the performance of accuracy. The structure of proposed CNN model is illustrated in figure 8.

The proposed 2D CNN provides the data augmentation to benefit for the training. Data augmentation is useful in increase of the amount of data available. ECG images are imbalanced to represent the various patterns. When using small data in CNN based architectures, there causes the important issue called overfitting. Data augmentation is a way to deal with overfitting and allows for better training of a CNN model. For unbalanced data, data augmentation can help to maintain a balance between different classes.

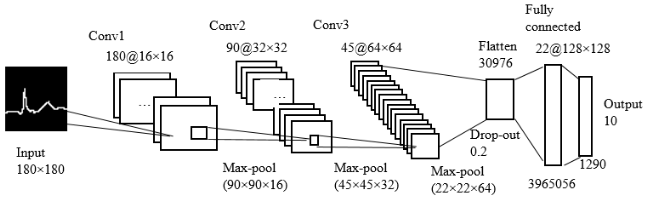

Fig.8. The structure of proposed Convolution Neural Network

The CNN model use 'relu' activation function in between layer and Softmax activation function in output layer. The accuracy of this model compile with the 'Adam' method and loss function evaluates with categorical cross-entropy loss method.

The rectifier linear unit (relu) activation function activated with learning rate 0.001. Softmax function is provided possible probabilities for each class in a multi-class classification model.

'Adam' optimization is a stochastic gradient descent method based on adaptive estimation of first-order and second-order moments.

'Categorical Cross Entropy' is used for two or more label classes that are floating point values per feature to calculate the loss function of training and validation. Because it is facing a ten-class classification problem, i.e. multiclass classification problem, ends with a sigmoid activation, so that the output of our network will be multi scalar between 0 and 9, encoding the probability that the current image is class 0 to 9 values.

IV. Experimental Results

This paper uses the database of arrhythmia from ECG library. It includes the various (A-Z) ECG arrhythmia and diagnosis of ECG images from the Life-In-The-Fastlane (LITFL) ECG database. The LITFL ECG library is over 100 ECG topics relevant to emergency medicine and critical care for educational purposes [14]. Dataset consists ten subclasses with the 686 samples of binary arrhythmia images for classification after segmentation. Each sample image size is (50×100) pixels but CNN uses the image size (180×180) pixels by resizing the height, width as following in figure 9.

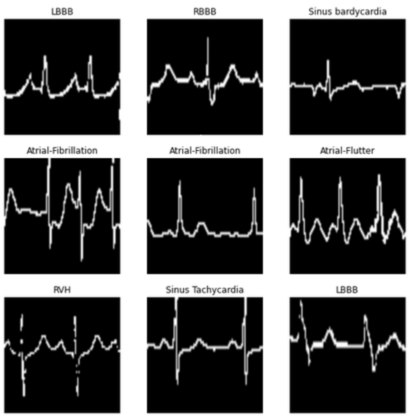

Fig.9. Types of Cardiac Arrhythmia images

A. Datasets

ECG arrhythmia dataset from ECG library includes the RGB images size (768*379) pixels that are twelve lead ECG in ten second. Images are transformed to binary images and extracted the ECG lead II for one second segmentation. After preprocessing, each image is segmented into one second images for lead II. The dataset includes 686 images for ten cardiac arrhythmias by segmented ECG lead II for classification.

B. Experiments I

This classification system was implemented in Python using Tensor-Flow, an open-source library developed by Google for deep learning. Training the CNN model required significant computing power and training time. The experimental setup includes an 8th Gen ASUS server with 32GB of onboard RAM, a 500GB external SSD hard drive with an optional internal hard drive, and an NVIDIA 1080 GPU with 11GB of storage.

1) Data Partition

Firstly, load the images of arrhythmia dataset to google drive and extracts the dataset. It defines 32 batch size and (180×180) height, width of images by resizing the image. The ECG images are divided for validation split that 80% of the data was used for training, 20% for validation. Therefore, the system uses 549 samples for the training and 137 samples for the testing. The system configures auto-tuning and rescaling for the performance of training.

2) CNN Model Training and Testing

The CNN’ convolutions operate on 3x3 windows and maxpooling layers operate on 2x2 windows. The 16 filters are used in first convolution, the 32 filters in second, the third extracts 64 filters and a fully layer is 128 filters. These filters are used in first experiment of CNN model.

The system experiments the CNN model in twice. The first time of the CNN model consists of three convolution blocks (16, 32, and 64), each with a max pool layer and a fully connected layer with 128 units. The first convolution of 16 filter includes 448 parameters in 180×180×16 and maxpooling in 90×90×16. The second convolution is 4640 parameters in 90×90×32 and maxpooling with 45×45×32. The third convolution is 18496 parameters in 45×45×64 and maxpooling in 22×22×64. The flatten layer is 30976 parameters, a fully connected layer in 128 filter with 3965056 parameters and the dense layer is 1290 parameters for ten classes. It trains epochs 10 times in the first CNN.

Each layer is used in same padding and ‘relu’ activation to extract features. The model compiles with the accuracy method in ‘Adam’ optimizer called stochastic gradient descent method and computes the loss using the categorical cross entropy method. The model produces training accuracy of 97% and validation accuracy of 87%. are showed by large margin in figure 10 (a). The model achieves only around 87% accuracy in the test set and validation loss is 0.75 in first CNN.

The system occurs the slightly difference in accuracy between training and validation in first CNN called over-fitting. So, the system uses the data augmentation with the training data for random transformation and adds (22, 22, 64) a drop out layer in second CNN. The CNN model uses the drop out method with 0.2 to reduce the overfitting. And then, the system trains the model in epochs 15 times with drop out layer with augmented images. The second CNN model produces training accuracy of 98.6% and the validation accuracy of testing is increasing 92% and validation of loss set is decreasing 0.3 showed in figure 10(b). The accuracy results of first and second CNN experiments are showed in table II.

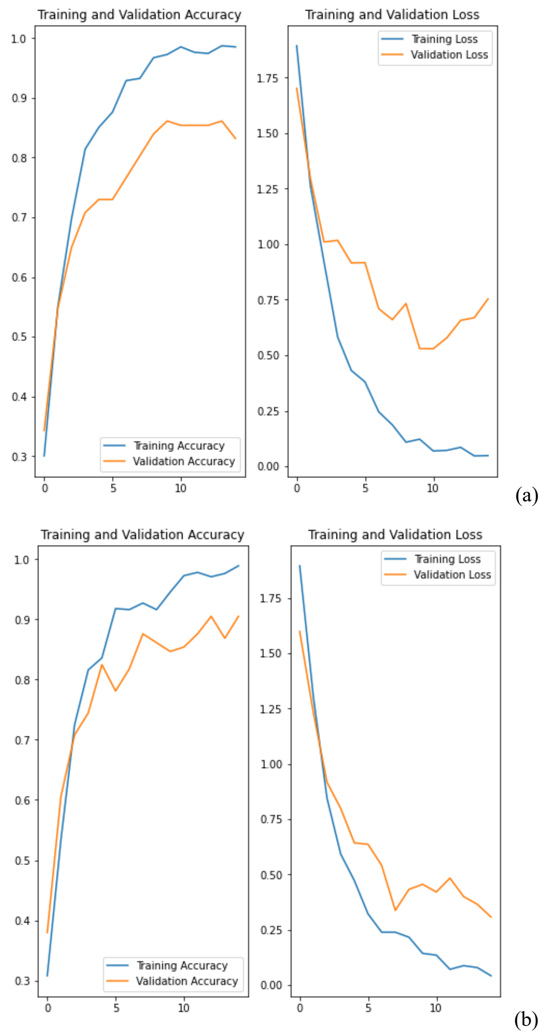

Fig.10. (a) Comparison of Training and Validation Accuracy & loss in 1st CNN (b) Comparison of increased Accuracy & decreased loss using data augmentation and drop out method in 2nd CNN

C. Experiment II

The system experiments the ten arrhythmia ECG images classification using the support vector machine in image classification of machine learning methods. The same arrhythmia dataset from ECG library database is used in that experiment. It firstly removes the noise of the images and extracts the meaningful features using the principle components analysis (PCA), and finally uses a grid search cross-validation to explore combinations of parameters. And then, it spliced into X-train, X-test, Y-train, and Y-test by train-test-split method. It trains SVM with the combination parameters: ‘C’ which controls the margin hardness and gamma which controls the size of the radial basis function kernel using the grid search cross validation. The SVM model predicts the class labels for test data using cross validation. At last, the system shows the training accuracy is 75%, testing accuracy is 69% for the classification and produces the metrics classification report with precision, recall, true f1-score. The diagram of metrics classification report for ten arrhythmia classification is showed in table I and the accuracy results of SVM is showed in table II.

TABLE I. CLASSIFICATION REPORT OF SVM

Types of Arrhythmia	*Precision*	*Recall*	*F1-score*
Atrial Flutter	1	0.73	0.85
Atrial Fibrillation	0.62	0.82	0.71
Sinus Bardycardia	0.85	0.77	0.81
Sinus Tachycardia	0.60	0.55	0.57
LBBB	0.65	0.79	0.71
RBBB	0.74	0.76	0.75
Left Ventricular Hypertropy	1	0.60	0.75
Right ventricular hypertrophy	1.00	1.00	1.00
Normal	1.00	1.00	1.00
Left Main Coronary Artery	1	0.60	0.75
Weighted Average	0.76	0.75	0.75
Macro Average	0.85	0.80	0.81
Training Accuray of Support Vector Machine = 75%			
Testing Accuray of Support Vector Machine = 69%			

Finally, the system shows the experimental results of accuracy comparison in three methods (typical CNN, CNN with dropout and SVM) as following in table II. The system experiments first CNN with 10 times epoch, second CNN with 15 times epoch using data augmentation and dropout method and Support Vector Machine (SVM). It compares the accuracy results of training and testing of two Convolution Neural Networks and Support Vector Machine methods using the same database using the ECG library database. The system shows the proposed CNN model with dropout method which get more accuracy than the typical CNN and SVM method.

TABLE II. ACCURACY RESULTS OF CNN AND SVM

Comparison Methods	*Convolution Neural Network with dropout method*	*Convolution Neural Network*	*Support Vector Machine*
Training Accuracy	98.6%	97%	75%
Testing Accuracy	92%	87%	69%

V. CONCLUSION

The cardiac arrhythmia classification system is classified the ten arrhythmias from ECG library database for the various diagnosis of heart diseases. To diagnosis the heart diseases like Myocardia Infraction, Ischemia and Hypertension, the system focuses on the lead II of ECG from twelve leads because irregulated arrhythmia and diagnosis are found in lead II. In preprocessing stage, it transforms the RGB images of ECG image to binary image for removing noise and grid lines using binarization with global thresholding. The system segments the lead II from the binary image and then divided into one second of each segmented image to get the morphology of ECG images. It proposes three convolution layers of CNN to extract the features and classify the arrhythmia classification. At first CNN classification with 10 epochs, it performs the accuracy 97% for training and 87% for validation. But the validation loss is 0.7 having the overfitting sign. Therefore, the system uses data augmentation and drop out value 0.2 to train the second CNN model with 15 epochs, then the validation loss decreases to 0.3 and get the accuracy 98.6% for the training and validation accuracy is 92%. The system get the higher accuracy in second CNN model than the first CNN model and the SVM of 75%. So, this system provides the high performance of arrhythmia classification using the ECG images for detecting the diagnosis of cardiac diseases.

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