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# Comparative Analysis of Heart Beat Abnormalities using Deep Learning Algorithm

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*Abstract:* An electrocardiogram (ECG) measures the electrical activity of the heart and has been widely used for detecting heart diseases. The ECG consists of waveforms P, QRS and T, the duration, shape of each waveform and the distance between different peaks are used to analyze heart beats. The current state of art methods of ECG based heartbeat abnormalities classification by presenting the ECG signal pre-processing, the heartbeat segmentation techniques, the feature description methods and the deep learning Convolutional Neural Network (CNN). The research of arrhythmia detection methods based on CNN algorithm can assist physicians in high precision arrhythmia diagnosis. In this work, we compared the ECG heartbeat classification systems performances such as Accuracy, Precision, Recall, F-1 score and Misclassification rate was corroborated from Physionet's MIT-BIH Arrhythmia Dataset using two deep learning CNN algorithm which is differ by means of number of convolutional layers, down sampling method and number of activation layer.

*KeyWords* - ELECTROCARDIGRAM **(ECG), SVP, PVC, FVN, FPN, MIT-BIH CONVOLUTIONAL NEURAL NETWORK (CNN).**

## I. INTRODUCTION

Globally, cardiovascular diseases (CVD) are the most common cause of death [1]. CVD can diagnosis by using auscultation methods, phonocardiogram and echocardiogram, through this we can record the heart beat [2]. The recorded heart beat sound may differentiate a normal heart sound and an abnormal sound. Practically, all of these heart masking procedures are expensive and highly require a lot of experience. Actually, in auscultation method to obtain an accurate result requires a field-tested cardiologist [3]. According to some research, medical students and primary care physicians can able to diagnosis only 20% to 40% of accuracy through the heart masking method and 80% of accuracy can be attain by expert cardiologist [4,5]. Due to this, there is a lack of dependable solution for earlier diagnosis of CVD [6]. According to the latest WHO report 17.3 million death per year causes due to CVD and it is evaluated to rise more than 23.6 million in 2030 [7].

Irregularity of heart beat is collectively known as Arrhythmia. Difference in the heart beat, arrhythmia is classified into two categories- Tachycardia, heart rate is more than 100 beat per minute and Bradycardia, less than 60 beats per minute [8]. In order to examine the activity of heart a preferred tool is Electrocardiogram (ECG). An ECG is one of the most common heart tests can be used to measure the electrical potential produce from the heart. ECG provide an information about heart rate, heart rhythm and displays if there is any changing in the heart functioning.

The five major heartbeats are classified as Normal heartbeat (N), Supra-Ventricular Premature (SVP), Premature Ventricular Contraction (PVC), Fusion of Ventricular and Normal (FVN) and Fusion of Paced and Normal (FPN). These mentioned heartbeats were grasped from MIT-BIH arrhythmia database and classified using machine learning and deep learning method [9, 10]. To identify the signals, there are several ML techniques such as K- nearest neighbours (K-NN), Decision tree (DT), Gradient boosting (GB), Random Forest (RF), Ada boost, Logistic regression (LR), Voting classifier, Support vector machine (SVM) and so on.

Ye et al [11] combined a general multi classifier with Wavelet transform (WT) and independent component analysis (ICA) were applied to the heartbeat. An incremental SVM was proposed to tackle memory constraint problem. This provides an accuracy of 86% for classification of the heartbeats. Jenish et al classified the approach to identify the disease accurately, by applying extra tree classification algorithm for feature extraction on pre-processed datasets and get a result with accuracy of 76.93% using KNN [12].

In Jovic et al. [13] proposed a classification model for the heart signals, their records were pulled out from an online database analysed by classifying algorithm with seven clusters and provide an accurate result of 99.6% by RF, 99.4% by Bayesian network, 98.4% by SVM. An efficient method was proposed to classify the ECG signals using algorithm like DT, RF, GB, etc. in Alarsan et al. [14] with an accuracy of 96.75% using GB, 98.92% using RF and 97.14% using DT. Atik et al. [15] suggested the ECG heartbeat classification using efficient Machine learning approaches on imbalanced datasets from MIT-BIH arrhythmia, they provide an efficient result using KNN, DT, ANN, SVM, LSTM and Ensemble approach from the mentioned algorithm ANN provides a maximum result of 98.06% accuracy.

Arrhythmia was classified based on Adaboost algorithm in Zhang et al. [15], grouped abnormal cardiac rhythm datasets are segmented by the non-crossover method and the result shows an accuracy of 94.15% for the categorized arrhythmia. For identifying the signals, several Machine learning algorithms are used to obtain an accurate output value. Deep learning algorithms can process the unstructured data and to estimate the feature extraction. Acharya et al demonstrated the five classes of heartbeats using CNN with nine layers each composed of 3 convolutional layers, one fully connected layer and single max-pooling layer give an accuracy of 94.03% without noise and for with noise it is 89.07% [17].

This paper is organized as follows: Section. I discuss the Introduction Section. II describes the five types of Heart beat classification. Section.III explains the Convolutional Neural Network Deep Learning Algorithm. Section.IV compares the classification metrics of model I and model II Section.V concludes the Heart beat classification using CNN.

## II. HEART BEAT CLASSIFICATION

A heartbeat is a pumping action of two-parts that takes about a second. In heart blood collects in the right and left atria, the SA node sends out an electrical signal that causes the atria to contract. This action pushes blood through the tricuspid and mitral valves into the right and left ventricles.

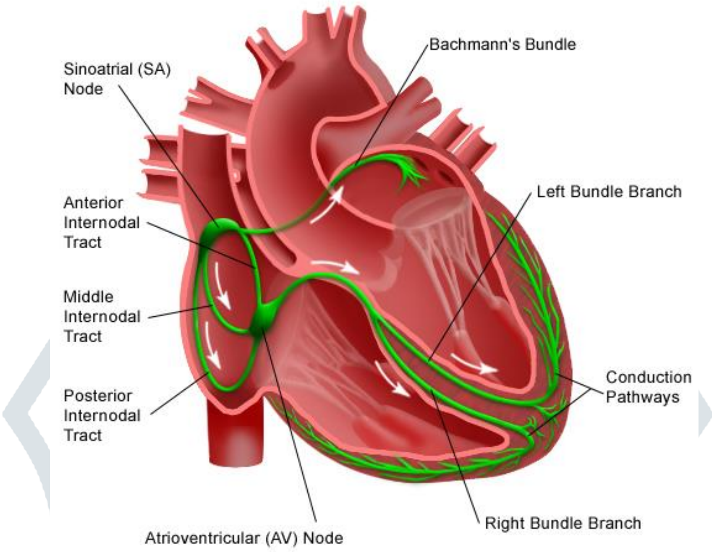


FIG.1. Electrical Conduction of Heart

### NORMAL HEART BEAT

The cardiac function is started in the Sinoatrial (SA) node which is in the right atrium (RA) near the superior venacava. Then it spreads through the RA and left atrium (LA). Next, it follows through the Atrioventricular (AV) node and then electrical impulse is passed to the Bundle of His. The stimulus passed into the left and right ventricles (LV and RV) by the way of the left and right bundle branches, which are the continuations of the bundle of His. Finally the cardiac signal spreads to the ventricular through the Purkinje fibers. The normal resting heart rate is between 60-100 beats per minute. The heart rate other than this range is treated as abnormal.

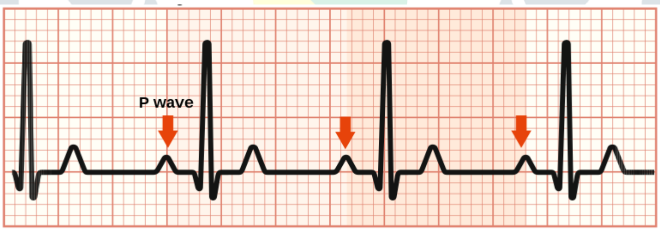


FIG.2. Normal Sinus Rhythm

### SUPRA VENTRICULAR PREMATURE

The premature activation of the atria from a site other than the sinus node is calling it as Supra ventricular premature beats. The SVP are extra heart beats that start in the upper chambers of your heart. The early signal tells the heart to contract, there may not be much blood in the heart at that moment. A pause and strong beat may follow the extra heartbeat, making it feel like a skipped beat.

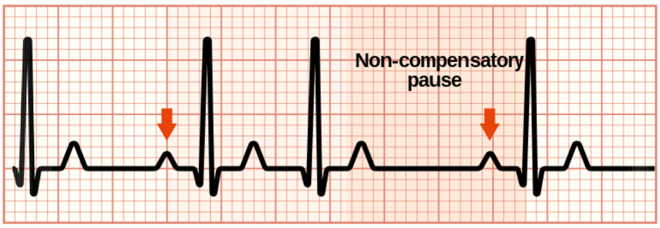


FIG.3. Supra Ventricular Premature

### PREMATURE VENTRICULAR CONTRACTION

Premature ventricular contractions (PVCs) are a type of abnormal heartbeat. The heartbeat initiated from Sinoatrial (SA) node but during a premature ventricular contraction, the heartbeat comes from one of the ventricles rather than SA node. This signal is premature, meaning it happens before the SA node has had a chance to fire. PVCs are also referred to as premature ventricular complexes, Ventricular extra systoles, and Ventricular premature beats. The symptoms of PVC s are dizziness, near-fainting, anxiety, pounding sensation in the neck and people may describe feeling a skipped or extra heartbeat.

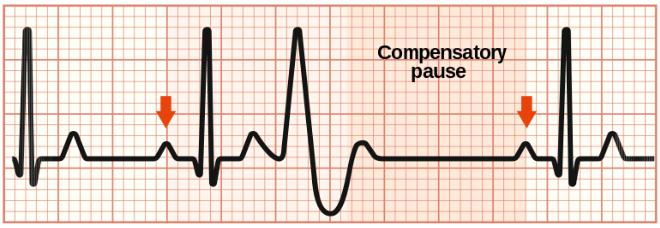


FIG.4. Premature Ventricular Contraction

### FUSION VENTRICULAR AND NORMAL

A fusion beat occurs when a supra ventricular and a ventricular impulse coincide to produce a hybrid complex. The usual pair of pacemakers is the sinoatrial node and an ectopic ventricular focus; but any pair of pacemakers, whose impulses occupy the ventricular myocardium more or less simultaneously but at different points, can produce fusion beats.

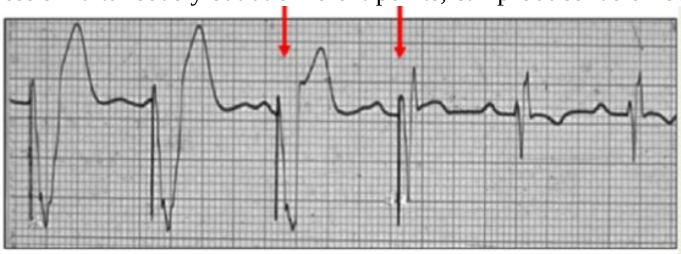

FIG.5. Ventricular Fusion

### FUSION OF PACED AND NORMAL

A pacemaker fusion beat occurs when the intrinsic beat and pacemaker stimulus beat partly depolarize the ventricles, causing a hybrid QRS complex. Patient with sinus rhythm and RBBB presented with symptomatic intermittent complete heart block. Following DDD pacemaker implant with RV lead placed in the lower septum, we were able to achieve fusion beats pacing by optimizing the AV delay. This resulted in narrow QRS complex morphology.


FIG.6.Ventricular Pacing

## III. DEEP LEARNING ALGORITHM

Deep learning is a branch of machine learning which is based on artificial neural networks. An artificial neural network or ANN uses layers of interconnected nodes called neurons that work together to process and learn from the input data. Deep learning algorithms train machines by learning from examples. Here the deep learning algorithm used for heartbeat classification to diagnose the cardio vascular disease.

### CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network (DNN) architecture commonly used in Computer Vision. Neural networks are used in various datasets like images, audio, and text. Different types of Neural networks are uses for different purposes for the image classification we use Convolutional Neutral Network. Convolutional Neural Network (CNN) is the extended version of artificial neural network (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. In a regular Neural Network there are three types of layer Input layer, Hidden layer, Output layer.

Convolutional Neural Network consists of multiple layers like the input layer, convolutional layer, pooling layer, and fully connected layer. The Convolutional layer applies filter to the input image to extract features, the Pooling layer down samples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through back propagation and gradient descent.

The CNN model I structure comprised of 4 convolutional layers, 3 pooling layers, one fully connected layer and a SoftMax are used to predict the deadly value for heartbeats which contained five different classifications [9]. The model II describe the Convolutional Neural Network with 3 convolutional layers, Max pooling and Rectified linear units (ReLU) for the same five heart beat classification from MIT-BIH arrhythmia database [10].

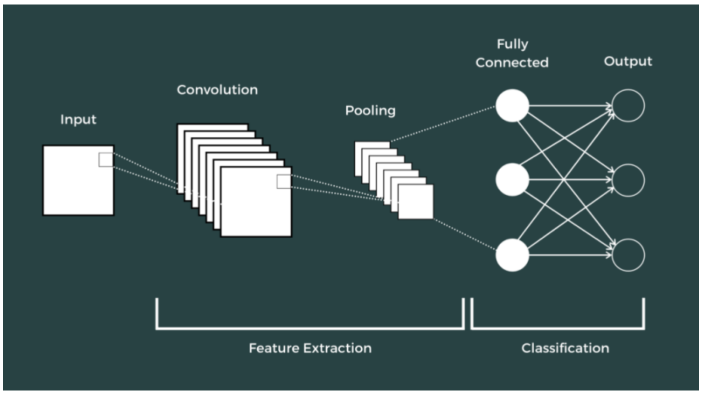


**FIG.7. CNN Architecture**

### CONFUSION MATRIX

A confusion matrix is a visual representation of the execution of a deep learning model. It summarizes the predicted values and actual values of a classification model to identify the misclassification. The confusion matrix helps data scientists to fine tune their models and improve their model achievement. Table.1 exhibits the block diagram of confusion matrix. It evaluates the performance of the classification models when they make prediction on test data and tells how good our model is. It also tells the type of errors such as type-I or type-II error.

Table.1 Confusion Matrix

| | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual Positive | True Positive (TP) | False Negative (FN) |
| Actual Negative | False Positive (FP) | True Negative (TN) |

**True Positive (TP):** TP denotes a true positive which is defined as the patient has normal heart beat and the classifier also predicts that the patient is normal.

**True Negative (TN):** TN indicate a true negative which is describe as the patient has abnormal heart beat and the classifier also forecast that the patient is abnormal.

**False Positive (FP):** FP signify false positive which is explain as the patient has abnormal and the classifier predicting that the patient is normal.

**False Negative (FN):** FN specifies false negative which is interpreted as the patient is normal and the classifier foretelling that the patient is abnormal.

## IV. CLASSIFICATION METRICS

The classification model is evaluated using various metrics, which are described below.

**Accuracy**: Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of dataset. The best accuracy is 1.0, whereas worst is 0.0.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

**Precision**: Precision refers to the number of true positives divided by the total number of positive predictions and it is also called positive predictive value (PPV).

$$\textbf{Precision} = \frac{TP}{TP+FP}$$

**Recall**: Recall or Sensitivity means, the percentage of data samples that a machine learning model correctly identifies as belonging to a class of interest out of total samples for that class. Also called as True Positive Rate (TPR).

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

**F1-Score:** F1-score (also Known as F-Measure or balanced F-score) is a metric used to measure the performance of classification machine learning models. It combines the precision and recall scores of a model.

$$\textbf{F1-Score} = 2 * \frac{Precision*Recall}{Precision+Recall} = \frac{2TP}{2TP+FP+FN}$$

| F1-Score | Interpretation |
|---|---|
| Greater than 90% | Very Good |
| Between 80% to 90% | Good |
| Between 50% to 80% | Ok |
| Less than 50% | Not Good |

**Misclassification:** The misclassification rate shows how often your classifier model is incorrect in predicting the actual positive and negative outputs.

$$\textbf{Misclassification} = \frac{FP+FN}{TP+TN+FP+FN}$$

**True Positive Rate (TPR):** The positive rate, also known as sensitivity or recall in machine learning, is a metric that measures the percentage of the actual positives that are accurately identified.

$$\textbf{TPR} = \frac{TP}{TP+FN}$$

**True Negative Rate (TNR):** The true negative rate, also known as specificity in machine learning, is a metric that measures the percentage of actual negatives that are accurately identified.

$$\textbf{TNR}=\frac{TN}{TN+FP}$$

**False Positive Rate (FPR):** It's the probability that a false alarm will be raised: that a positive result will be given when the true value is negative.

$$\textbf{FPR} = \frac{FP}{FP+TN}$$

**False Negative Rate (FNR):** The false negative rate-also called the miss rate-is the probability that a true positive will be missed by the test.

$$\textbf{FNR} = \frac{FN}{FN+TP}$$

**Positive Likelihood Ratio (LR+):** The probability that a positive test would be expected in a patient divided by the probability that positive test would be expected in a patient without a disease.

$$\textbf{LR+} = \frac{TPR}{FPR}$$

**Negative Likelihood Ratio (LR-):** The probability of a patient testing negative who has a disease divided by the probability of a patient testing negative who does not have a disease.

$$\textbf{LR-} = \frac{FNR}{TNR}$$

**Diagnostic Odds Ratio (DOR):** It describes the odds of a positive test in those with disease relative to the odds of a positive test in those without disease.

$$\textbf{DOR} = \frac{LR+}{LR-}$$

Table.2 Confusion Matrix 5x5 of Model-I

| ECG Beat | N | SVP | PVC | FVN | FPN | Precision | Recall | F1-Score |
|---|---|---|---|---|---|---|---|---|
| N | 779 | 4 | 15 | 0 | 2 | 0.90 | 0.97 | 0.93 |
| SVP | 33 | 751 | 7 | 3 | 6 | 0.97 | 0.94 | 0.95 |
| PVC | 3 | 0 | 791 | 4 | 2 | 0.94 | 0.99 | 0.96 |
| FVN | 46 | 13 | 29 | 694 | 18 | 0.99 | 0.87 | 0.93 |
| FPN | 2 | 3 | 0 | 1 | 794 | 0.97 | 0.99 | 0.98 |

Table.2 represents the confusion matrix of MIT-BIH arrhythmia database for the classification order 5 x 5. The accuracy and misclassification of the CNN model I was 95.23% and 4.77% respectively. The average precision, recall and F1 score were 95.4%, 95.2% and 95% respectively.

Table.3 Confusion Matrix 4x4 of Model-I

| ECG Beat | N | SVP | PVC | FVN+FPN |
|---|---|---|---|---|
| N | 779 | 4 | 15 | 2 |
| SVP | 33 | 751 | 7 | 9 |
| PVC | 3 | 0 | 791 | 6 |
| FVN+FPN | 48 | 16 | 29 | 1507 |

Table.3 Confusion Matrix 3x3 of Model-I

| ECG Beat | N | SVP | PVC+ FVN+FPN |
|---|---|---|---|
| N | 779 | 4 | 17 |
| SVP | 33 | 751 | 16 |
| PVC+ FVN+FPN | 51 | 16 | 2333 |

In the reduced classification of 4 x 4 confusion matrix shown in table.3, the accuracy and misclassification of the model-I was 95.7% and 4.3% respectively. The reduced classification order of 3 x 3 confusion matrix is displayed in Table 4. The exactness and misclassification of the model-I was 96.58% and 3.42% respectively.

Table.5 Confusion Matrix 2x2 of Model-I

| ECG Beat | Normal | Abnormal | |
|---|---|---|---|
| Normal | 779 | 21 | 800 |
| Abnormal | 84 | 3116 | 3200 |
| | 863 | 3137 | |
| TPR | TP/P | 779/800 | 0.97 |
| TNR | TN/N | 3116/3200 | 0.97 |
| FPR | FP/N | 84/3200 | 0.03 |
| FNR | FN/P | 21/800 | 0.03 |
| LR+ | TPR/FPR | 0.974/0.027 | 37.46 |

| | | | |
|---|---|---|---|
| LR- | FNR/TNR | 0.027/0.974 | 0.027 |
| DOR | LR+/LR- | 37.46/0.027 | 1403 |

Table.5 represents the binary classification of 2 x 2 confusion matrix. The accuracy and misclassification were 97.38% and 2.62% respectively. The precision, recall and F1 score averages were 94.8%, 97.4% and 96% respectively.

Table.6 Confusion Matrix 4x4 of Model-I

| ECG Beat | SVP | PVC | FVN | FPN | | Precision | Recall | F1-Score |
|---|---|---|---|---|---|---|---|---|
| SVP | 751 | 7 | 3 | 6 | 767 | 0.98 | 0.98 | 0.98 |
| PVC | 0 | 791 | 4 | 2 | 797 | 0.96 | 0.99 | 0.97 |
| FVN | 13 | 29 | 694 | 18 | 754 | 0.99 | 0.92 | 0.95 |
| FPN | 3 | 0 | 1 | 794 | 798 | 0.97 | 0.99 | 0.98 |
| | 767 | 827 | 702 | 820 | 3116 | 0.975 | 0.97 | 0.97 |

Table.6 represents the abnormal database classification for 4 x 4 confusion matrix. The accuracy and misclassification of the model I was 97.2% and 2.8% respectively. The precision, recall and F1 score average were 97.5%, 97% and 97% respectively.

Table.7 Confusion Matrix 5x5 of Model-II

| ECG Beat | N | SVP | PVC | FVN | FPN | Precision | Recall | F1-Score |
|---|---|---|---|---|---|---|---|---|
| N | 796 | 0 | 3 | 0 | 1 | 0.76 | 0.99 | 0.86 |
| SVP | 159 | 619 | 20 | 2 | 0 | 0.99 | 0.77 | 0.86 |
| PVC | 24 | 1 | 767 | 5 | 3 | 0.89 | 0.96 | 0.92 |
| FVN | 61 | 0 | 68 | 671 | 0 | 0.99 | 0.84 | 0.83 |
| FPN | 6 | 0 | 2 | 0 | 792 | 0.99 | 0.99 | 0.99 |

The performance of the model II is presented in Table 7. The correctness and misclassification of the model was 91.12% and 8.87% respectively. The precision, recall and F1 score averages were 92.4%, 91% and 89.2% respectively.

Table.8 Confusion Matrix 4x4 of Model-II

| ECG Beat | N | SVP | PVC | FVN+FPN |
|---|---|---|---|---|
| N | 796 | 0 | 3 | 1 |
| SVP | 159 | 619 | 20 | 2 |
| PVC | 24 | 1 | 767 | 8 |
| FVN+FPN | 67 | 0 | 70 | 1463 |

Table.9 Confusion Matrix 3x3 of Model-II

| ECG Beat | N | SVP | PVC +FVN+FPN |
|---|---|---|---|
| N | 796 | 0 | 4 |
| SVP | 159 | 619 | 22 |
| PVC+ FVN+FPN | 91 | 1 | 2308 |

The detailed classification information of the confusion matrix 4x4 is produced in Table 8. The accurateness and misclassification of the 1-D CNN model was 91.12% and 8.87% respectively. The classification performance of model II for the confusion matrix 3x3 information is exhibited in Table 9. The closeness and misclassification of the model was 93.07% and 6.93% respectively.

The detailed information of the classification metrics for CNN model II is showcased in Table.10. The truth and misclassification of 2 x 2 matrix were 93.65% and 6.35% respectively. The precision, recall and F1 score averages were 88%, 95.9% and 91% respectively.

Table.10 Confusion Matrix 2x2 of Model-II

| ECG Beat | Normal | Abnormal | |
|---|---|---|---|
| Normal | 796 | 4 | 800 |
| Abnormal | 250 | 2950 | 3200 |
| | 1046 | 2954 | |
| TPR | TP/P | 796/800 | 0.995 |
| TNR | TN/N | 2950/3200 | 0.922 |
| FPR | FP/N | 250/3200 | 0.078 |
| FNR | FN/P | 4/800 | 0.005 |
| LR+ | TPR/FPR | 0.995/0.078 | 12.756 |
| LR- | FNR/TNR | 0.005/0.922 | 0.005 |
| DOR | LR+/LR- | 0.005/12.756 | 2551.2 |

Table.11 represents the MIT-BIH arrhythmia abnormal database classification for 4 x 4 confusion matrix. The accuracy and misclassification of the 1-D CNN model was 96.58% and 3.42% respectively. The precision, recall and F1 score average were 97.25%, 96.75% and 97% respectively.

Table.11 Confusion Matrix 4x4 of Model-II

| ECG Beat | SVP | PVC | FVN | FPN | | Precision | Recall | F1-Score |
|---|---|---|---|---|---|---|---|---|
| SVP | 619 | 20 | 2 | 0 | 641 | 1 | 0.97 | 0.99 |
| PVC | 1 | 767 | 5 | 3 | 776 | 0.90 | 0.99 | 0.94 |
| FVN | 0 | 68 | 671 | 0 | 739 | 0.99 | 0.91 | 0.95 |
| FPN | 0 | 2 | 0 | 792 | 794 | 1 | 1 | 1 |
| | 620 | 857 | 678 | 795 | 2950 | | | |

## V. CONCLUSION

In this paper two deep learning CNN models are compared for the heart beat classification based on the performance metrics such as accuracy, misclassification rate, precision, recall and F1-score. The two CNN based arrthymia classification performance was substantiate from MIT-BIH data set.

Classification results demonstrate that model one achieved an overall accuracy of 95.2% with an average precision , recall and F1 score of 95.4%,95.2% and 95% and model two achieved an overall accuracy of 91.13% with an average precision, recall and F1 score of 97.5%,97% and 97%.

The two deep learning frameworks are analysed for different confusion matrix order and compared up to binary classification normal and abnormal heartbeat. If the number of classification is less the accuracy of the classifier is more. Further, the two ECG arrhythmia classifier model applied for abnormal heartbeat alone and the results exhibits that model one achieved the classification accuracy of 97.2 with an average precision, recall and F1 score of 97.5%, 97% and 97% and model two achieved an classification accuracy of 96.58% with an average precision, recall and F1 score of 97.25%, 96.75% and 97%.

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