

Web Based Cardiac Arrhythmia Classification System Using ECG Data Analysis and Machine Learning

Dr. Meenakshi Thalor^{1*}, Dr. Mrunal Pathak², Dr. Amita Shinde³, Dr. Rakesh Dhumale⁴, Dr. Amrapali Chavan⁵, Dr. Sanjay Srivas⁶

Submitted: 25/04/2023

Revised: 24/06/2023

Accepted: 07/07/2023

Abstract: The leading reason of death worldwide is due to heart disease and late treatment. The detection and diagnosis of cardiac arrhythmia is tedious and time consuming from arranging expert to analyse a large amount of ECG data. Therefore, detection of cardiac arrhythmia by analysis of ECG characteristics using machine learning has become predominant. This paper proposed a web-based system which classify heart disease depending on the patient's ECG values using support vector machine and convolutional neural network. At the end, comparison in between support vector machine and convolutional neural network is also done using evaluation measures like precision, recall and f-measure. This work can be supporting automated tool to cardiologists for the preliminary screening of cardiac arrhythmia patients to know presence or absence of arrhythmia.

Keywords: Electrocardiogram, Cardiac arrhythmia, Convolutional Neural Network, Support Vector Machine

1. Introduction

Heart Disease diagnosis is based on Electrocardiogram (ECG) test. In this test, continuous recording of ECG is obtained through a sensor which provides actual view of patient's heart condition by keeping track of factors like diabetes, stress, depression, anxiety, and high blood pressure. The patient's data is stored on remote health monitoring system so that later this information can be used for clinical access to patient's physiological information by the healthcare applications. Cardiac arrhythmia describes an irregular heartbeat- heart may beat too slow, too fast, too early, or irregularly. It indicates the malfunctioning of the heart's electrical system. This condition, if not treated and diagnosed well can lead to severe arrhythmia and even death. Thus, early detection of heart disease is vital because it can simplify the treatment and save people's lives. ECG Interpretation includes assessment of waves, intervals, segments and one complex of ECG signal as defines below:

Waves: P, Q, R, S, T and U wave.

Interval: PR interval, QRS interval, QT interval and RR interval

Segment: PR segment, ST segment and TP segment.

Complex: QRS complex

1) Arrhythmias are broken down into various types such as tachycardia, bradycardia, supraventricular tachycardia, atrial flutter, atrial fibrillation, etc. Classification is done

based on beats per minute (BPM). It is broadly classified into three types.

These broad types are further classified into subtypes depending upon certain conditions.

1) Bradycardia- $BPM < 60$

2) Normal heart- BPM is between 60 to 100.

3) Tachycardia- $BPM > 100$.

Bradycardia is divided into two types.

1) 1° heart block- In this situation, the PR wave is prolonged i.e., $PR > 200ms$.

2) 2° heart block- In this situation, PR and QRS complex occur alternatively. i.e., when $PR > 0$, $QRS = 0$, and when $QRS > 0$, $PR = 0$.

Tachycardia is further classified based on narrow and broad QRS complex.

1) Narrow complex- $QRS < 120ms$.

2) Broad complex- $QRS > 120ms$.

Under narrow QRS complex, the following types are detected.

1) Normal sinus rhythm.

2) Supra ventricular tachycardia (SVT).

3) Atrial fibrillation.

Under broad QRS complex the following types are detected.

1) Monomorphic Ventricular Tachycardia (MVT).

2) Polymorphic Ventricular Tachycardia (PVT).

1,2,3,4,5 AISSMS Institute of Information Technology, Pune, Maharashtra, India

6 Software Technology Park of India, Pune, Maharashtra, India

* Corresponding Author Email: meenakshi.thalor@aiissmsioit.org

3) Ventricular Flutter. i.e., disorganized rhythm.

The medical data of the patients is necessary for detection of heart disease because it contains unknown patterns which are essential for data analysis which is done using many algorithms and mathematical models. The healthcare sector has the vast amount of medical data, which is not excavated.

Many researcher has proposed many Machine learning algorithms to classify the cardiac arrhythmia.

In [1] author used a neural network for expanding Heart Disease Prediction system. The possibility that a patient might suffer from a heart disease is predicted by the HDPS. Various medical parameters such as sex, blood pressure, cholesterol, heart rate, to name a few are the ones amongst the 13 parameters used for prediction. While two more parameters such as smoking habits and obesity are added in the above list to get better accuracy. In [2] author has opted for a method that uses feature selection for Heart Disease Prediction. She found that a good performance was resulted by using the fuzzy measure and the relevant nonlinear integral method. The none additively of the fuzzy measure reflects the prominent of the feature attributes as well as their interactions. Author used features like age, sex, blood sugar level as well as blood pressure to detect the likelihood of the patients getting heart disease. Because of this, accuracy is greatly improved thus leading to a decrease in the computational time. In [3] author makes use of decision tree model structure which in turn makes use of a reduced set consisting of 6 binary factors. Production of continuous data as well as generation of false alerts is done by many health monitoring systems that make use of wearable sensors. Thus, use of such kind of systems is not preferable in clinical practice. Some machine learning approaches are explained in [4] to provide the solution where wearable sensor data is used. This data is added with scientific observations to provide a primary warning of a severe physiological changes in the patients, if any. The staff can finally make important decisions about the patient by combining this data with the manual observations. In [5] author makes use of Artificial Neural Network (ANN) and Naive Bayes (NB). These techniques help to diagnose the heart disease. Use of AVR-328 microcontroller is made which is used as an interface to communicate to the several sensors. It includes ECG sensor, heartbeat sensor, the sensor for monitoring of drip levels and a sensor for monitoring of motion. Good efficiency is provided by the system since it has a low power consumption capability, easy setup technique and along with this it provides high performance as well as timely response. In [6] author developed an algorithm which is implemented on an IoT-based embedded system for analysis of ECG signals and classification for heartbeat diagnosis. Author proposed a wearable IOT based ECG diagnosis device suitable for 24 hour keeping track of heartbeat of patient using Discrete Wavelet Transform

(DWT) and a Support Vector Machine (SVM).In [7] author provides a survey of different DM techniques available involving Neural network (NN), the Genetic algorithm (GA), NB, Decision tree (DT) and Clustering algorithms like K nearest Neighbour (KNN), and Support Vector Machine (SVM).In [8] author gives detection of cardiac disease by applying data mining classification techniques. The classification technique used by this application provides decision tree for the detection of heart disease. Decision tree uses the factors like blood pressure, age, and blood sugar to get the probability of patients fallen in cardiac disease. In [9] author proposed a weighted fuzzy rule-based clinical decision support system (CDSS) for the diagnosis of heart disease, which obtains knowledge from the patient's clinical data. To define the weighted fuzzy rules mining techniques like attribute selection and attribute weighting methods are used and fuzzy system is prepared using these defined weighted fuzzy rules and the attributes which are selected using the above techniques. Finally, the experimentation is carried out and compared with the neural network-based system by performance metrics like accuracy, sensitivity, and specificity. In [10] author applied k-Nearest Neighbour on a Cleveland Heart Disease dataset in diagnosis of heart disease in patients. This paper enhanced the accuracy by integrating voting with KNN. Alfaras et.al in [11] came up with integration of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) approaches for automatic diagnosis of Cardiac Arrhythmia while Chen et. al in [12] proposed CNN-Based Model using ensemble approach for detection and classification of cardiac arrhythmia. In [13] Cubic Wavelet Transform for analysing the ECG signals used under deep learning model. In addition, a survey of classification and prediction of Cardiac Arrhythmia using Machine Learning is presented in [14]. Decision tree classifier is used to obtain multi-domain-based features in [15]. Recently many researchers are using CNN with different structure for detection of Cardiac Arrhythmia [16,17].

The objective of this work is to create web-based platform to classify the given ECG data as belonging to either normal or abnormal (arrhythmia) category. Section 2 explicates proposed system with system architecture. Section 3 depicts results and comparison. At end, Section 4 shows conclusion with future work.

2. Web Based Cardiac Arrhythmia Classification System

Cardiovascular disease causes most of the deaths today. This web-based system helps to predict heart disease which make use of patient's ECG values related to heart disease. Medical dataset of the patients is used to extract the ECG values. In this paper, cardiac arrhythmia type is classified and predicted using machine learning algorithms as shown in figure 1.

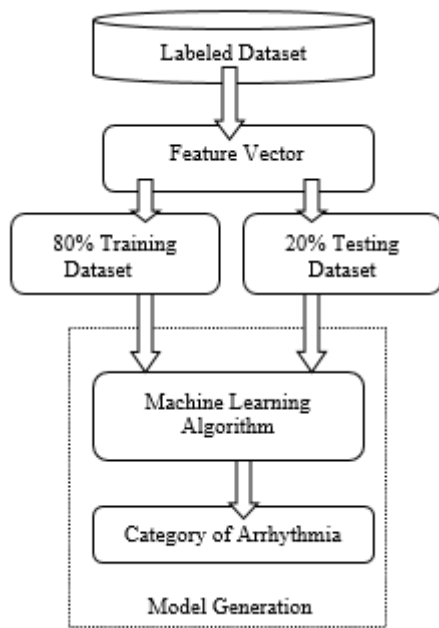


Fig. 1(a). Training phase of cardiac arrhythmia detection system

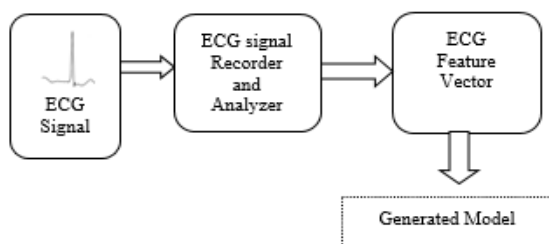


Fig. 1(b). Testing phase of cardiac arrhythmia detection system

In architecture of the proposed work where SVM classifier as well as CNN are used as machine learning algorithms to predict the type of cardiac arrhythmia. The proposed system, under machine learning algorithms, two classifiers named as SVM and CNN are used for analysis purpose. The purpose of both the classifier is to test the patient data and give prediction about presence or absence of arrhythmia and provide the category of arrhythmia. In web-based application, choice of machine learning algorithm selection is given to admin where he/she can select anyone of machine learning algorithm and can get the prediction about disease. As this system provide choice to select machine learning algorithm so admin/operator can compare the results of two techniques if any doubt arises. The modules of system are explained as follows: Submit your manuscript electronically for review.

2.1 ECG signal Recorder and Analysis

The main objective of ECG signal Recorder and Analysis module is to retrieve ECG data of patient and detect heartbeat signal parameters such P, Q, R, S as shown in figure 2. In ECG signal recorder and analyzer module,

admin can set sample size and frequency and capture the beat peak and other characteristics.

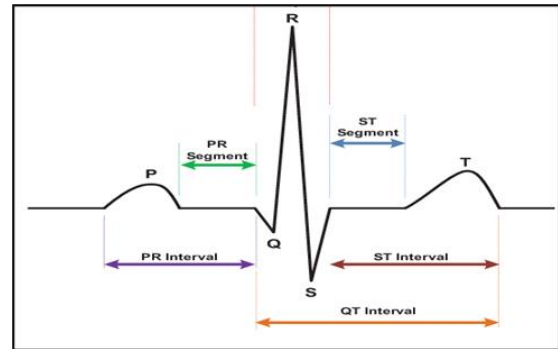


Fig. 2. ECG wave

Figure 3 shows ECG signal Recorder screen with the patient's data and device information which is controlled by admin. This will feed the data directly to the main page of the web-based application.

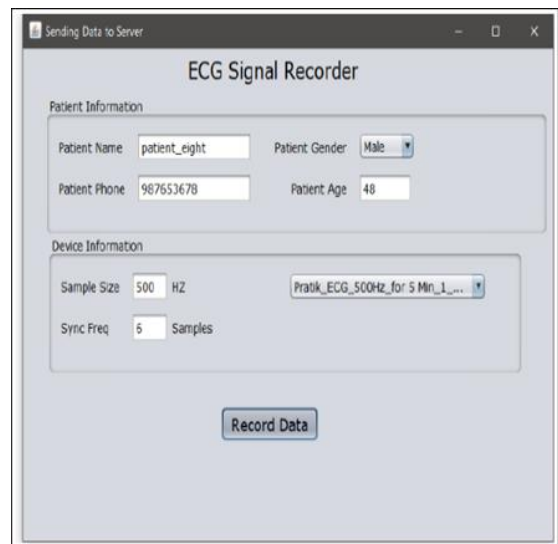


Fig. 3. ECG signal recorder

Once the parameters are derived, these are stored in database for future processing. Machine Learning algorithms can use it to detect patients state (Normal heart/ Abnormal Heart). Table 1 shows the normal ECG Parameters with phase duration amplitude. If ECG signals parameters don't follow these ranges, then considered as Abnormal heart.

Table 1. Normal range of ECG parameters[21]

| Signal | Normal range | Phase Duration Amplitude |
|-------------|-------------------|--------------------------|
| P Wave | 0.06sec - 0.11sec | < 0.25 PR |
| PR Interval | 0.12sec - 0.20sec | |
| PR Segment | 0.08sec | |

| | | |
|--------------|-----------------------|---------|
| QRS | <0.12 sec | 0.8-1.2 |
| Complex | | |
| ST Segment | 0.12sec | |
| QT Interval | 0.36sec - 0.44 sec | |
| T Wave | 0.16 sec | < 0.5 |
| R-R interval | 0.6sec -1 sec | |

2.2 Machine Learning Algorithms

During implementation of proposed system, SVM and CNN machine learning algorithms are used. Different evaluation measures like confusion matrix, recall, precision, and f-measure are plotted to show effect of classification algorithm on given dataset.

2.2.1 Support Vector Machine

A Support vector machine (SVM) is a linear classifier proposed by Vapnik and Cortes which gives the line or hyperplane with the aim to reduce the classification error of the hidden test data.

It is intrinsically a binary classifier that separate data into 2 classes or groups which is denoted by positive or negative. If an image as feature vector is given as input to SVM then it returns the class of image. Based on training data it gives a model which predict the class of test data. The SVM model-built fits itself according to given training data and preforms classification on samples stored in test data.

To work with SVM classifier, one need a vast amount of training data and need to bare a high computational cost. The support vector machine is a popular supervised learning algorithm for classification which tries to find the optimum separating hyperplane in such a way that the distance between the hyperplane and the data is greatest as shown in fig. 4.

In Proposed work, feature set of size 109446 by 187 is extracted has input data $X=\{X_1, X_2, \dots, X_n\}$ where $X_i=\{x_1, x_2, \dots, x_n\}$ with labels $y=\{y_1, y_2, \dots, y_n\}$. Each input data is a 1D-vector $[1 \times 187]$. SVM classifier is trained on training set to obtain hyperplane represented as $wX + b = 0$ where, w is normal vector and b is the intercept of hyperplane. Stochastic Gradient Descent (SGD) is implemented to avoid overfitting .

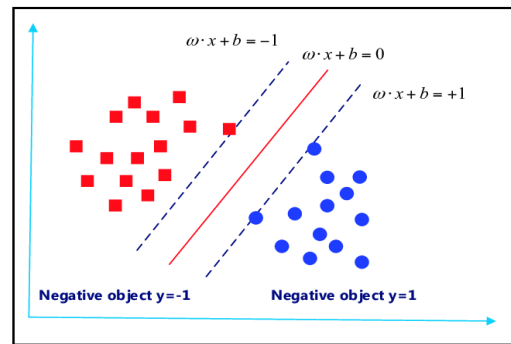


Fig. 4. Classification using SVM

2.2.2 Convolutional Neural Network

A convolutional neural network (CNN) is a kind of feed-forward artificial neural network where during training, data goes through forward pass, then loss function is computed and to reduce the loss, weights of neuron are updated in backward pass. Convolutional networks have its root from biology and mathematics. Convolutional networks are variations of multilayer perceptron (MLP). A CNN comprises of different layers like Convolutional Layer, Pooling layer, and Fully Connected Layer as shown in fig.5.

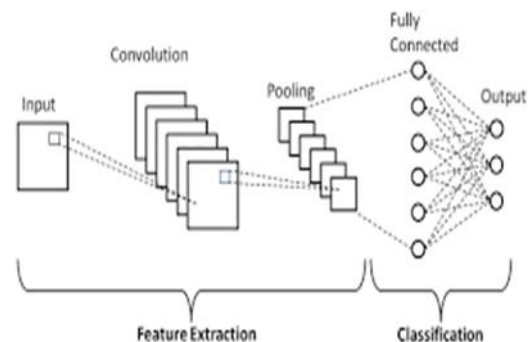


Fig. 5. Classification using CNN

In Convolution layer, a kernel/filter is used which defines weights for input image pixels. Convolution operation is performed in convolution layer where the dot product of input image pixel values and weight defined by filter is carried out. This operation is represented by one number. Over the entire input image, the filter is applied from left to right and top to bottom to cover each overlapping part. At end of this layer, a smaller convolution matrix is generated which represent the results of convolution operation.

The convolution matrix passed through activation function to introduce nonlinearity. In proposed system, Rectifier Linear Units (ReLU) is used as activation function which allows the network to train itself through backpropagation. The size of convolution matrix is further reduced by down sampling in Pooling layer. Here a filter is again passed over the previous matrix and one number is selected from each group of values. Pooling fastens the training process and provide focus on vital features of image.

A MLP come in picture at fully connected layer. MLP takes 1-d vector which is output of previous layer, and it provides list of probabilities of different possible classes. The class which gets highest probability is considered as final classification of input image.

In proposed work, a robust and efficient 5 layer one dimensional CNN model is trained on the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database. All trails of experiment are run for 500 epochs with learning rate in the range [0.01-0.5] using 32 filters, 5 kernel size and 1 strides value.

3. Results And Discussion

For implementation of web-based application Django framework is used with necessary python libraries. For experimental results, MIT-BIH arrhythmia database is used which consist of 109446 samples and 5 classes labeled as [N= 0, S=1, V=2, F=3, Q=4]. Table 2 shows the detail distribution of different categories of samples available in mentioned database.

Table 2: Original dataset detail

| Beat Type | Class Label | Group of Beats | Count | Percentage |
|----------------------------|-------------|------------------------------------|-------|------------|
| Normal | N | 1. Normal beats | 90589 | 0.8277 |
| | | 2. Left bundle branch block beats | 05 | 0.0005 |
| | | 3. Right bundle branch block beats | | |
| | | 4. Nodal (junctional) escape beat | | |
| | | 5. Atrial escape beat (e) | | |
| Fusion of paced and normal | S | 1. Atrial premature beats | 8039 | 0.0735 |
| | | 2. Aberrant atrial premature beat | | |

| | | | | |
|---|---|--|------|--------|
| Premature ventricular contraction label | V | 3. Nodal (junctional) premature beat | | |
| | | 4. Supraventricular premature | | |
| | | 1. Ventricular escape beat | 7236 | 0.0661 |
| | | 2. Premature ventricular contraction beats | | |
| Atrial Premature | F | 1. fusion of ventricular and normal beat | 2779 | 0.0253 |
| | | 2. Paced beats of normal and paced beat | 803 | 0.0073 |
| Fusion of ventricular and normal | Q | 3. Unclassified beat | | |
| | | | | |

MIT-BIH arrhythmia database is imbalanced so Synthetic Minority Over-sampling Technique (SMOTE) algorithm is used to oversample Q class labels and undersampling approach applied on over-represented classes(N). Table 3 shows the classification dataset detail after balancing. During testing , 10 FCV (fold Cross validation) is employed and performance is recoded after every fold and at the end overall performance is computed.

Table 3. Classification dataset detail

| Class Label | Unbalanced count | Balanced count |
|-------------|------------------|----------------|
| N | 90589 | 8682 |
| S | 8039 | 8039 |
| V | 7236 | 7236 |
| F | 2779 | 2779 |

| | | |
|---|-----|------|
| Q | 803 | 4563 |
|---|-----|------|

| | | | | | | | |
|---|-----|----|----|---|-----|-------|-------|
| Q | 328 | 50 | 14 | 9 | 451 | 91.84 | 98.93 |
| | | | | | 4 | % | % |

During testing, various evaluation measures are considered like confusion matrix, precision, recall and F-Score measures. The Performance of Proposed work is 99.34% during testing on MIT BIH database.

Here two machine learning algorithms SVM and CNN are taken into comparison. The performance of system is evaluated using confusion matrix as shown in fig. 6 and eq. 1 to 4 are computed from confusion matrix for all categories/classes.

| | | | | | | |
|--------|---|----------------|----------------|----------------|----------------|----------------|
| | | Predicted | | | | |
| | | n | s | v | f | q |
| Actual | N | N _n | N _s | N _v | N _f | N _q |
| | S | S _n | S _s | S _v | S _f | S _q |
| | V | V _n | V _s | V _v | V _f | V _q |
| | F | F _n | F _s | F _v | F _f | F _q |
| | Q | Q _n | Q _s | Q _v | Q _f | Q _q |

Fig. 6. Confusion Matrix for Evaluation

$$\text{True Negative (TN) of V class} = N_n + N_s + N_f + N_q + S_n + S_s + S_f + S_q + F_n + F_s + F_f + F_q + Q_n + Q_s + Q_f + Q_q \quad (1)$$

$$\text{False Negative (FN) of V class} = V_n + V_s + [V_f + V]_q \quad (2)$$

$$\text{True positive (TP) of V class} = V_v \quad (3)$$

$$\text{False Positive (FP) of V class} = N_v + S_v \quad (4)$$

Similarly for other classes (N, S, F, Q) the TN, FN, TP and FP are calculated and precision and recall is calculated. Fig. 7 shows confusion matrix for CNN.

| | | | | | | | | |
|--------|---|-----------|-----|-----|-----|----|-----------|--------|
| | | Predicted | | | | | Precision | Recall |
| | | n | s | v | f | q | | |
| Actual | N | 833 | 1 | 2 | 2 | 7 | 99.86% | 96.00% |
| | S | 5 | 789 | 8 | 58 | 19 | 98.87% | 98.15% |
| | V | 1 | 45 | 721 | 200 | 20 | 96.44% | 99.64% |
| | F | 13 | 53 | 2 | 211 | 3 | 96.74% | 88.69% |

Fig 7. Confusion matrix of CNN on classification dataset Table 4 shows the performance comparison of proposed work with existing work on MIT BIH database.

Table 4. Performance comparison with existing work

| Existin g work(y ear) | Clas s | Feature set | Classifier | Effecti veness |
|--------------------------|--------|---|------------------|----------------|
| Park et al.(2008)[18] | 4 | higher-order statistics and Hermite basis functions | Hierarchical SVM | 85% |
| Ye et al.(2012)[19] | 2 | Wavelet, Independent component analysis | SVM | 86.4% |
| Zhang et al.(2014)[20] | 4 | RR,Interval,Morphological, | Combined SVM | 86% |
| Swapn a et al.(2018)[21] | 2 | End to end | CNN(3 layer) | 78% |
| Wu et al.(2021)[22] | 5 | Wavelet | CNN(5 layer) | 97.20% |
| Propos ed work | 5 | Wavelet | CNN(5 layer) | 99.34% |

Fig. 8 shows the graph for model train accuracy, test accuracy, train loss, and test loss values.

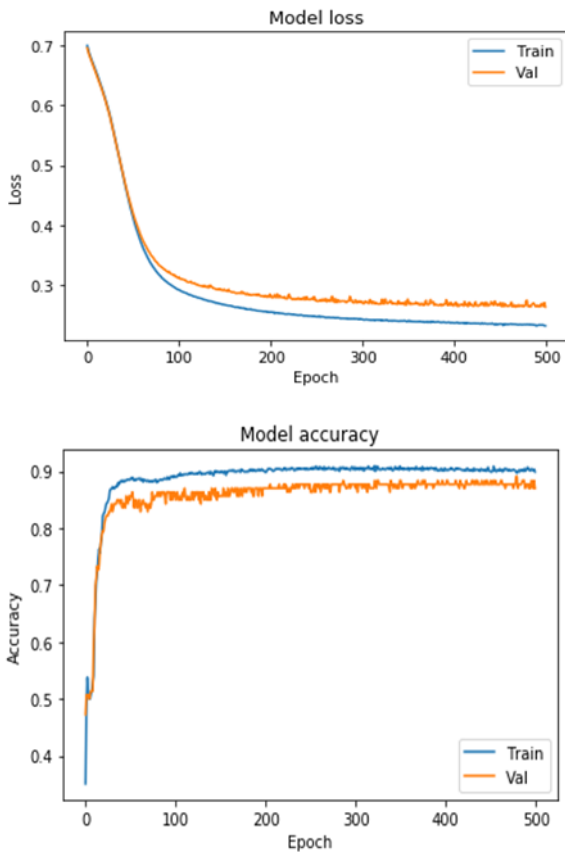


Fig. 8. Graph for model loss and model accuracy

Fig. 9 shows the graphical user interface of web-based system. The left side corner of the page will contain the admin credentials along with their photo. Moving on to the top center of the page, this section will contain the patients full name in yellow along with the type of disease mentioned to the right of the name. Normal will appear in green and any other type will be referred as abnormal and will appear in red. A live/offline switch is provided that will switch between live data and prerecorded data. Right below the patients name and disease case, the patients full name, phone number, their age and their gender will be displayed which will be entered in the ECG Recording software. A drop-down menu is provided to change the prerecorded patient data on the fly. A display is provided that will show ECG values plotted as the data is processed buy the machine learning algorithm along with to the right of the block, a real-time detector will display the status of the disease as per the machine learning algorithm and above it a logic-based procedure. Lastly, in black, a list will display intervals such as PR, RR, QR, QT and the Beats Per Minute of the patient. Just above it all the averages are displayed along with real-time results as the data is fed to the machine.

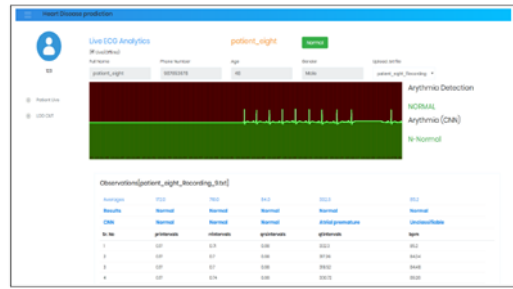


Fig. 9. Graphical user interface of cardiac arrhythmia detection system

During testing phase, five real time sample of patients are tested to prove the effectiveness of system where machine learning algorithm gives category as N shows absence of cardiac arrhythmia whereas detection of other categories shows presence of cardiac arrhythmia.

The result of comparison is CNN is more feasible, fast computation, more accuracy than SVM as shown in table 5 and table 6.

Table 5. Evaluation measures of SVM

| Sample | Class | Precision | Recall | F1-score |
|--------|-------|-----------|--------|----------|
| 1 | S | 0.92 | 1 | 0.96 |
| 2 | F | 0.85 | 0.99 | 0.92 |
| 3 | Q | 0.89 | 0.52 | 0.66 |
| 4 | V | 0.83 | 0.99 | 0.9 |
| 5 | N | 0.99 | 0.87 | 0.92 |
| Avg. | | 0.89 | 0.87 | 0.87 |

Table 6. Evaluation measures of CNN

| Sample | Class | Precision | Recall | F1-score |
|--------|-------|-----------|--------|----------|
| 1 | S | 0.73 | 1 | 0.85 |
| 2 | F | 0.99 | 0.73 | 0.84 |
| 3 | Q | 0.95 | 0.95 | 0.95 |
| 4 | V | 0.98 | 0.92 | 0.95 |
| 5 | N | 1 | 0.98 | 0.99 |
| Avg. | | 0.93 | 0.91 | 0.92 |

SVM and CNN implementation both provides the output of types of arrhythmias as a result. After comparison between the models which were created using the dataset and input text file (which contains sensor ECG numeric data), this paper can conclude that CNN provides better results as compared to SVM on real time patient dataset. CNN provides the average score of 92% on all evaluation measures considered whereas SVM can provide average of

87% on all evaluation measures.

4. Conclusion

This paper presents a web-based application system which predicts heart disease depending on the patient's ECG values using SVM and CNN machine learning algorithms. Based on experimental results CNN provides the average score of 92% on all evaluation measures considered whereas SVM can provide average of 87% on all evaluation measures. Further this system can be improved by considering hybrid approach or make use of ensemble of CNN. The key feature of this web-based application is giving choice of selection of machine learning algorithm to admin to compare the result of two classifiers rather than rely on classification result of one classifier. This work can be supporting automated tool to cardiologists for the preliminary screening of cardiac arrhythmia patients to know presence or absence of arrhythmia. In future, different variant of CNN can be integrated in application as CNN inherently support parallelization.

References

- [1] Dangare, C.S., and Apte, S.S., "A Data Mining Approach for Prediction of Heart Disease Using Neural Networks," *International Journal of Computer Engineering and Technology*, 3(3), pp. 30-40 ,2012.
- [2] Soni, S., Soni, J., Ansari, U., and Sharma, D., "Predictive Data Mining for Medical Diagnosis: An Overview of Heart Disease Prediction," *International Journal of Computer Applications* 17, pp. 43-48,2011.
- [3] Mendes, D., Paredes, S., Rocha, T., Carvalho, P., Henriques, J., Cabiddu, R., and Morais, J., "Assessment of cardiovascular risk based on a data-driven knowledge discovery approach," *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 6800-6803 ,2015
- [4] Collins, F, "Mobile Technology and Healthcare," Available at <http://www.nlm.nih.gov/medlineplus/magazine/issues/winter11>.
- [5] Aieshwarya, B., ChavanPatil, C., and Sonawane, S.S., "To Predict Heart Disease Risk and Medications Using Data Mining Techniques with an IoT Based Monitoring System for Post-Operative Heart Disease Patients," *Proceeding International Journal on Emerging Trends in Technology*, 4(2) ,2017.
- [6] Azariadi, D., Tsoutsouras, V., Xydis, S., and Soudris, D., "ECG signal analysis and arrhythmia detection on IoT wearable medical devices. 2016 5th International Conference on Modern Circuits and Systems Technologies (MOCAST)," 1-4,2016.
- [7] Banu, N., and Swamy, S., "Prediction of heart disease at early stage using data mining and big data analytics: A survey," *2016 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT)*, pp. 256-261,2016
- [8] Aziz, A., and Rehman, A.U., "Detection of Cardiac Disease using Data Mining Classification Techniques," *International Journal of Advanced Computer Science and Applications*, 8,2017
- [9] Anooj, P.K., "Clinical decision support system: risk level prediction of heart disease using weighted fuzzy rules and decision tree rules," *Central European Journal of Computer Science*, 1, pp. 482-498,2011.
- [10] Shouman, M., Turner, T., and Stocker, R., "Applying k-Nearest Neighbour in Diagnosing Heart Disease Patients," *International Journal of Information and Education Technology*, pp. 220-223,2012.
- [11] Alfaras, M., Soriano, M.C., and Ortin, S., "A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection," *Frontiers in Physics*, 7,2019.
- [12] Chen, T., Huang, C., Shih, E.S., Hu, Y., and Hwang, M., "Detection and Classification of Cardiac Arrhythmias by a Challenge-Best Deep Learning Neural Network Model," *iScience*, 23, 2020.
- [13] Sumathi, S. and Agalya, V., "Early Detection of Life-Threatening Cardiac Arrhythmias Using Deep Learning Techniques," *Current Signal Transduction Therapy* ,2019.
- [14] Thalor, M.A., "Classification and Prediction of Cardiac Arrhythmia using Machine Learning: A Survey," *International Journal for Research in Applied Science and Engineering Technology*, 7, pp. 1244-1246,2019.
- [15] Sahoo, S., Subudhi, A., Dash, M. et al., "Automatic Classification of Cardiac Arrhythmias Based on Hybrid Features and Decision Tree Algorithm," *International Journal. of Automation and Computing*, 17, pp. 551–561,2020.
- [16] R. Krishnamoorthy, B. S Liya, S. Arun, S Padmapriya, Gunasundari B, R Thiagarajan, "Categorizing the Heart Syndrome Condition by Predictive Analysis Using Machine Learning Approach", *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, pp.104-108, 2021.
- [17] M. Degirmenci, M.A. Ozdemir, E. Izci, A. Akan, "Arrhythmic Heartbeat Classification Using 2D Convolutional Neural Networks," *IRBM*, 2021,
- [18] K.S. Park, B.H. Cho, D.H. Lee, S.H. Song, J.S. Lee, Y.J.

Chee, I.Y.Kim, S.I. Kim, Hierarchical support vector machine based heartbeat classification using higher order statistics and hermite basis function, in: *Comput. Cardiol.*, 2008, pp.229–232.

- [19] Ye, B.V.K. Kumar, M.T. Coimbra, Combining general multi-class and specific two-class classifiers for improved customized ECG heartbeat classification, in: *International Conference on Pattern Recognition (ICPR)*, 2012, pp.2428–2431.
- [20] Z. Zhang, J. Dong, X. Luo, K.-S. Choi, X. Wu, Heart beat classification using disease-specific feature selection, *Comput. Biol. Med.* 46 (2014) 79–89.
- [21] Swapna G, Soman KP, Vinayakumar R, Automated detection of cardiac arrhythmia using deep learning techniques , *International Conference on Computational Intelligence and Data Science (ICCIDS 2018)*, *Procedia Computer Science* 132,1192-1201,1192–1201
- [22] Mengze Wu, Yongdi Lu, Wenli Yang and Shen Yuong Wong, A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network, *Frontiers in Computational Neuroscience*, volume 14, 2021
- [23] Roberto F. Automatic heartbeat monitoring system. *Arch Case Rep.* 2019; 3: 029-034. DOI: 10.29328/journal.acr.1001018
- [24] Dr. Govind Shah. (2017). An Efficient Traffic Control System and License Plate Detection Using Image Processing. *International Journal of New Practices in Management and Engineering*, 6(01), 20 - 25. Retrieved from <http://ijnpme.org/index.php/IJNPME/article/view/52>
- [25] Dasari, S. ., Reddy, A. R. M. ., & Reddy , B. E. . (2023). KC Two-Way Clustering Algorithms For Multi-Child Semantic Maps In Image Mining. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(2s), 01–11. <https://doi.org/10.17762/ijritcc.v11i2s.6023>
- [26] Kathole, A. B., Katti, J., Dhabliya, D., Deshpande, V., Rajawat, A. S., Goyal, S. B., . . . Suci, G. (2022). Energy-aware UAV based on blockchain model using IoE application in 6G network-driven cybertwin. *Energies*, 15(21) doi:10.3390/en15218304