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Conference Paper · October 2021

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Evaluation of ECG based Recognition of Cardiac Abnormalities using Machine Learning and Deep Learning

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2021 International Conference on Robotics and Automation in Industry (ICRAI) | 978-1-6654-2343-4/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICRAI54018.2021.9651457

***Abstract*— Around the world, the most common cause of death is due to heart disease. To reduce the risk of death, it is critical to analyze and predict heart diseases. The proposed approach introduces a novel technique to detect anomalies in Electrocardiogram signals and classify cardiac conditions (17 – classes) from 1000 fragments of ECG signals from 45 patients in the MIT-BIH Arrhythmia database. The proposed approach utilizes two methods, one approach based on conventional Machine learning algorithm i.e., SVM (Support Vector Machine) and while the deep learning method uses CNN (Convolutional Neural Network) based architecture (ALEXNET). Spectral power density was detected using Welch's process, and Discrete Fourier Transform. The data was standardized and scaled to a standard deviation of unity. On the test set, CNN classification accuracy was reported to be 87-90%, while SVM classification accuracy was recorded to be 70-76%. According to the literature this is the simplest approach with state-of-the-art deep learning method to achieve accuracy up to 90%. The deep learning technique improves precision and can be used in clinical settings.**

Keywords*— ECG signal, Arrhythmia, SVM, CNN, ALEXNET, machine learning and deep learning

I. INTRODUCTION

Heart problems are the main source of death around the world. Early detection and investigation of ECG signs can help decrease and treat heart issues. According to the China Cardiovascular Diseases (CVD) Report, 2011, there are approximately 230 million CVD patients, of whom 200 million have high blood pressure, 7 million have a stroke, 2 million have dead myocardial tissue, and 4.2 million have it Cardiovascular disease. There are 3 million recorded cases of CVD death, accounting for 41% of all deaths [1]Arrhythmia is an irregular heartbeat caused by abnormal electrical pulses. Abnormal electrical pulses cause the heart rhythm to beat too fast (tachycardia), too slow (bradycardia), premature (premature beat), or too unstable (fibrillation) [2].

In recent years, classification and identification of ecg signals has gained significant attention. Different techniques and algorithms have been proposed to classify ECG signals and abnormalities. ECG beat detection, Deep learning techniques, Principal Component Analysis, Higher Order Statistics, Discrete Wavelet Transform, Independent Component Analysis, Ensemble Learning and Hybrid System are used for the detection and classification of ECG signals [3].

Based on the measurement of the morphology and dynamic characteristics (evolution of the heart) of a single QRS complex, the classification of heart diseases using existing methods is very complicated, and due to the heterogeneity of these characteristics in different patients, it is prone to error. Therefore, special software and methods are needed to diagnose heart disease before the event occurs, and to prevent heart disease with extremely high accuracy and accuracy. According to the current literature review [4] [5]. there are six steps

- Obtaining information from publicly accessible databases.
- Preprocessing of signal to remove any noises. (normalize and standardization of data).
- Signal Segmentation of ECG signals and detection of QRS complex most prominent feature of ECG signal.
- Signal features are extracted, and data outliers are removed and optimize the feature using algorithms such as genetic algorithm.
- Cross-validate the data, prepare, test and optimize the parameters of the classifier, namely the classification of the QRS complex (detection of heart disease).
- Analyze the results on the test set to obtain accuracy.

To identify anomalies in ECG signals using 1000 fragments, we analyzed and compared machine learning algorithms [6], [7] such as Support Vector Machine (SVM) and deep learning algorithms [8] [9] based on Convolutional Neural Network-based architecture ALEXNET in the proposed approach. (MIH-BIH Arrhythmia database for one

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lead, 45 patients). Support Vector Machine is the most popular and computationally inexpensive machine learning algorithm used to classify data, while 1D CNN can be used for time varying signal data like ECG. The paper is divided into three sections. Section I describes the methodology adopted for this research. Section II describes the results. Section III presents the discussion and draws important conclusion from discussion and suggests the future directions for the proposed work. .

II. METHODOLOGY

A. Dataset

Data was acquired from MIT- BIH Arrythmia database's Physionet [10] service that is available online [11]. 45 patient's data were gathered out of which 19 were females (ages 23 to 89) and remaining males (ages 32 to 89). 17 types of ECG signals were recorded which include Normal sinus rhythm, pacemaker rhythm and 15 forms of heart disease. For a period of 10 seconds and sampling frequency of 360 Hz. The signal from ML II one lead was used.

B. Data Preprocessing

In this step data was properly organized. Then we performed rescaling and standardization of data. Rescaling step ensures the data to be on the same scale of 0 and 1. Data standardization was done so that data can have zero mean and unit standard deviation. Data was filtered using low pass 4Hz Butterworth filter. The Butterworth filter minimizes noise by having a maximally flat response.

1) Normalization or Rescaling:

In when the data set comprises of numbers on different scales, so the data is normalized to retain homogeneity during the training.

formula for normalization,

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

x_{min}, x_{max} represents maximum and minimum of the data set points.

To center the data around mean to have unit standard deviation and zero mean, standardization technique for scaling is used,

$$x_{norm} = \frac{X - \mu}{\sigma}$$

Where μ is the mean and σ is the standard deviation of the feature.

C. Feature Extraction

Due to the periodic nature of the ECG signal the data was converted to the frequency domain using the Fast Fourier Transform, and the signal's power spectral density was extracted [1]. Using Welch's approach, Periodogram and Discrete Fourier Transform [12].

1) Power Spectral Desnity:

The signal's power spectral density (PSD) defines the signal's power as a function of frequency, per unit frequency. When the shape of the spectrum is fairly stable, this is useful because changes in the ASD would be equal to changes in the signal's voltage level.

2) Periodogram:

The periodogram is used to find the time series' dominant intervals (or frequencies). This can be a useful tool for recognizing the series' dominant cyclical behavior, particularly when the cycles aren't related to the more typical monthly or quarterly seasonality.

3) Discrete Fourier Transform:

The Discrete Fourier Transform is a beneficial technique in digital signal processing for figuring out the spectrum of a signal of finite duration. In some of cases, the frequency content of a time-domain signal needs to be calculated. This is wherein the discrete Fourier transform can support (DFT). The Discrete Fourier Transform is a useful tool for analyzing discrete time signals in the frequency domain, but the infinite range of time and frequency in the conversion formulas can make analysis difficult, particularly on a computer. The Discrete Fourier Transform is analogous to the DFT, but it uses a finite-time signal, causing its formulas to be finite sums which will be easily calculated by a computer.

D. Support vector Machine (SVM)

The Support Vector Machine is a machine learning classifier that can was initially used for binary classification but later used for multiclass classification problems. It creates hyperplanes to divide data into different classes [13]. Support vectors are created optimizing the margin distance and separating the data using hyper planes. Support vector machines have become a research subject of the machine learning community due to their its simplicity and higher accuracy [14]. It is commonly used for decision making in machine learning tasks due to its simplicity and computational performance.

The hyperplane equation for 2-Dimensional feature space is [15]

$$f(x) = (a)(x) + b \tag{1}$$

Where a and x belong to $\underline{R}^2$. The following cost function is used to measure the ideal distance that divides the groups by a maximum margin:

$$J(a, \gamma) = \frac{1}{2}(a^2) + c(\sum_{m=1}^{n} \gamma^n) \tag{2}$$

Where 'C' stands for the regularization concept, a hyper-parameter that the user can experiment with to find the best value for the experiment.

E. Convolutional Neural Network

Traditional machine learning algorithms necessitate a significant amount of human effort to manually pick features in order to prepare data for use in a classifier. It involves intelligent selection of appropriate features from training data and classification of high dimensional data, in contrast to deep learning-based approaches.

Convolutional Neural Networks are a form of deep learning algorithm that keeps data's spatial characteristics and can be used to solve problems like signal and image

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processing. As seen, a typical CNN has convolutional layers with filters that are processed via an activation mechanism, followed by a pooling layer to restrict input data dimensions fully connected layer.

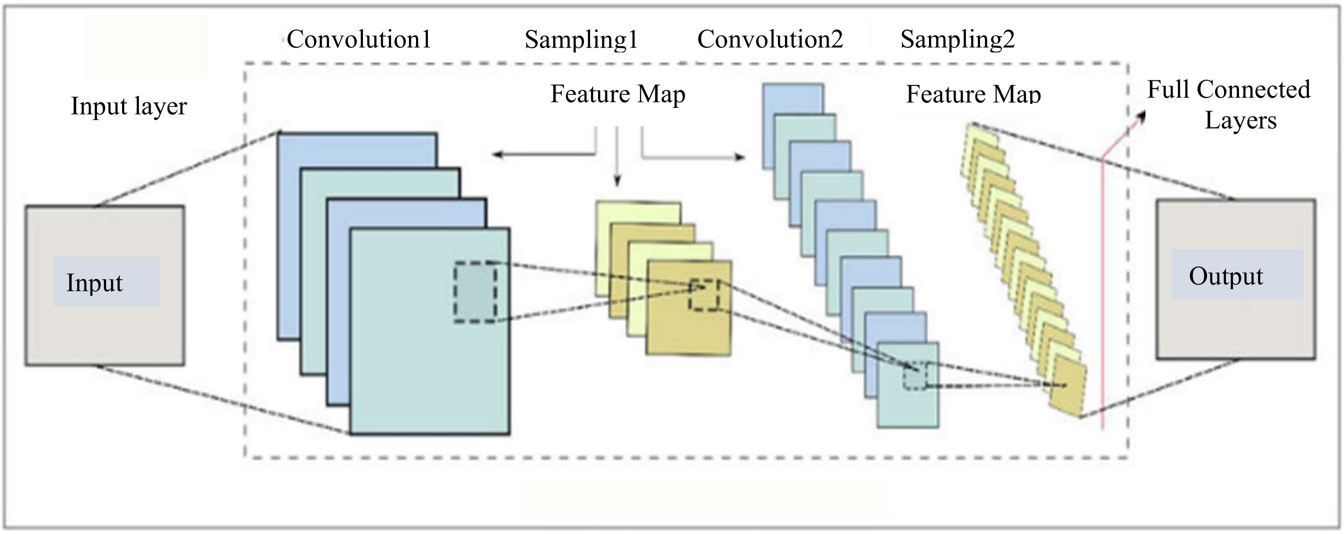

Fig. 1. CNN Architecture with two convolution layers

ALEXNET architecture [16] of CNN is used in this paper as it is the simplest architecture, Furthermore, it is robust and easily trainable using Google Colab GPU.

F. Methodology Block Diagram

In this section we present a complete summary of the proposed methodology in the form of a block diagram.

Raw data was gathered and preprocessed using normalization and standardization technique. Low pass Butterworth filter was passed with a cutoff frequency of 4 Hz.

Preprocessed data was shifted to frequency domain by using Fourier transform. Features were extracted by Welch's method, periodogram and Hamming Window. All the features were concatenated along with labels and test train split was performed. Training set of 80% and Test set of 20% was used and cross validation technique was used. Two models were prepared first was machine learning based SVM classifier and second was CNN architecture of AlexNet.

AlexNet was trained on 100 epochs with a 0.0005 learning rate and Adam optimizer was used. Experiments were performed using different hyperparameters, but different types of glitches and random behavior was observed. Above set of hyper parameters gave the best results for our testing set.

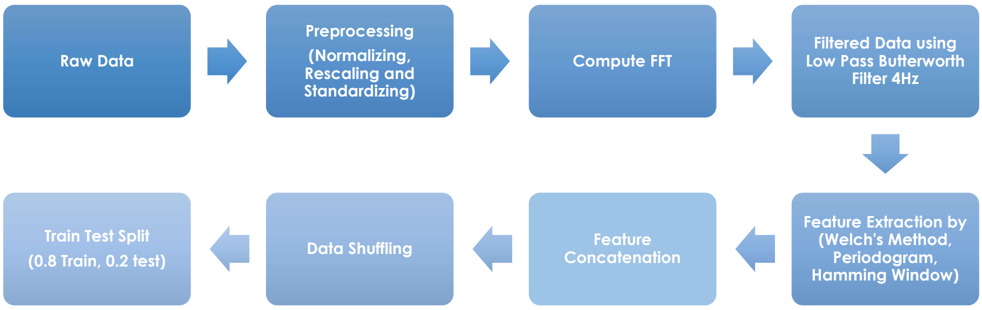

Fig. 2. Overall Process Diagram

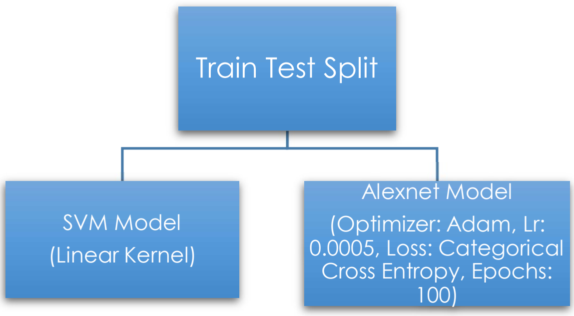

Fig. 3. Classifiers

III. Results and Disussion

The accuracy for abnormal cardiac rhythms using machine learning and deep learning techniques is reported on ECG 1000 fragments MIT-BIH dataset.

For classification model validation and generalization, the 10-fold cross validation is applied to avoid overfitting and a test set is used for the prediction. AlexNet was trained using Google Colab at 100 epochs and the time taken for the training was 11.66 minutes. The average accuracy achieved by the SVM classifier is 72.3% with the maximum accuracy of 75.69%. CNN based architecture was trained for 100 epochs and average classification accuracy of 87.2% was achieved

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with the highest accuracy of 90%. The accuracy metrics for SVM was confusion metrics.

Better results can be achieved for more number epochs as the model is still converging.

In the graph below it can be clearly seen that the loss is gradually decreasing, and accuracy is increasing.

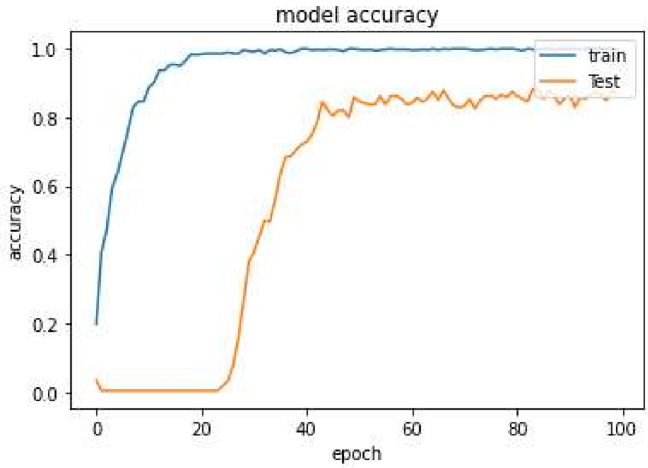

Fig. 4. AlexNet Accuracy Graph

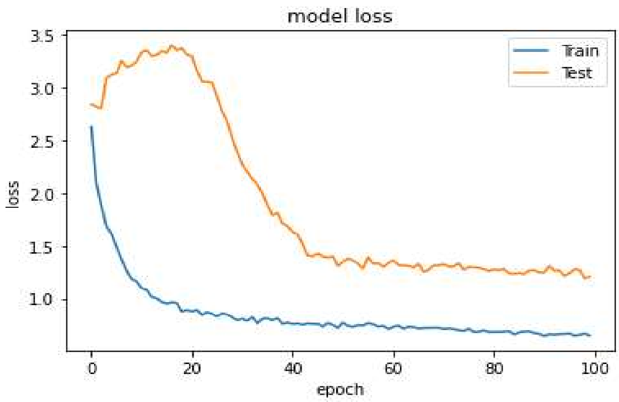

Fig. 5. AlexNet Loss Graph

IV. Conclusion

This research proposes a comparison of Machine learning based conventional classifier SVM with Deep learning-based CNN architecture AlexNet on MIT-BIH 17 classes arrythmia dataset for one lead from 45 patients. Raw data was preprocessed, and features were extracted and cleaned data was divided into train and test set and was given to SVM and CNN models and predictions were made on the test set.

In conclusion it is observed that deep learning-based approach of CNN outperforms and classifies the ECG signal abnormalities with a great margin as compared to traditional machine learning with an average classification accuracy of 87.2%. CNN architecture of ALEXNET is simple and can automatically extract features.

For future work it is recommended to use different deep learning-based approach and different architectures of CNN like VGG-NET or RESNET with more data and different hyperparameters for ECG signal classification as it can lead to more accurate results and can be clinically useful. Future studies can also additionally even consist of the development of a prototype of a cell tool for recording ECG indicators with implemented algorithms for diagnosing coronary heart problems. this could permit the usage of the proposed solution in medical trials. The final purpose of the studies can also be to fashion a telemedicine tool for affected person self-discipline and prevention packages.

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