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Classification of Cardiac Arrhythmias based on Deep Learning and Neural Networks-1

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Abstract: The greatest technique to track the functionality and health of the cardiovascular system and spot diseases associated with it is to use ECG signals. The ECG pattern reflects irregular heartbeats, and these abnormal signals are referred to as ARRHYTHMIAS. The need of the hour is growing for automated ECG arrhythmia signal categorization and identification that delivers faster and more precise results .Different machine learning techniques have been used to improve the models speed and durability as well as the accuracy of the findings. The architectures and datasets used have received a lot of attention, but preparing the data is also crucial. In this study, a pre-processing method that greatly increases the ECG classification accuracy of deep learning models is proposed alone with a modified deep learning architecture that increases training stability. The system can achieve accuracy levels of more than 99% with this pre-processing method and deep learning model without over fitting the model.

Keywords: Electrocardiogram (ECG), Deep learning (or deep neural network), Convolutional Neural Network (CNN) model, ARRHYTHMIAS, Activation techniques, epoch, validation accuracy.

I. INTRODUCTION

The rhythmic pumping system of the heart needs electricity to contract which is regulated by a specialized conduction pathway. The conduction pathway consists of five essentials components i.e. the sino-atrial (SA) node, the atrio-ventricular (AV) node, the bundle of Purkinje fibers which is shown in figure 1. The cardiac action potential (AP) is generated due to the brief change in tissue potential over the plasma tissue of the heart is shown in Fig. 1.1. Voltage is generated due to the movement of charged ions through ionic channels that connect the cell both internally and externally. [1-3]

The action potentials also vary within the heart because of the presence of different ion channels in various cells. The resting membrane potential of ventricular cells is around- 90 millivolts. At rest state, the sodium (Na+) and chloride (Cl−) ions are found outside the cell, whereas the potassium (K+) ions found inside the cell [9]. The action potential starts with depolarization because of sodium channels opening that allow Na+ to flow into the cell. The repolarization begins after a brief retard, when K+ to leave the cell due to opening of potassium channels, creates a negative membrane potential. The calcium (Ca2+) ion found to be inside- outside of the cell to make sarcoplasmic reticulum (SR). [4]

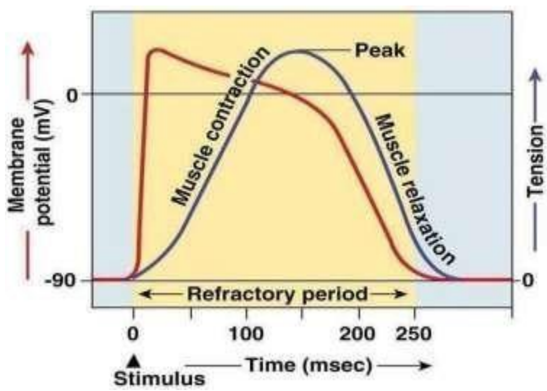

Figure 1 shows the action potential of the cardiac muscle.

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The SA node also called natural pacemaker of the heart. It is a specialized tissue located in the atria and under normal condition of the heart produces an electrical motivation of sixty to hundred times per minute at a regular interval of time. Each generated stimulus spreads rapidly through both atria in the form of a wave of contraction that passes through the myocardial cells. The electrical impulse moves from the SA node to atrio- ventricular (AV) node and then impulses are decreases slowly with in a less time period.

The electrical motivation flows in the conduction pathways to ventricles, which cause to contract and pumps out the blood. The two atrial chambers of the heart are stimulated first, then two ventricular chambers to contracts over a short period of time. The stimulus current travels through the conduction pathway via the bundle of His into the ventricles. The bundle of HIS then separates into two bundle branches one going right and the other left and impel both ventricles on each side. The pace making signal stimulates the right and left atrium to contract first, and then the right and left ventricles to allow the flow of blood with in the body.[5]

II. ELECTROCARDIOGRAM (ECG)

According to WHO, worldwide occurrence of CVD is greater than 60% and seen in developing countries due to lack of prompt diagnosis, medical assistance, and necessary lively amenities. (WHO, 2004).The numbers derived indicate that there is an immediate need globally for novel techniques to prevent, detect and treat these CVDs. The initial measures to keep CVDs at bay area to control or preclude depression, cholesterol and stress. This is totally governed by individual and clinical staff has got no role in that. A major stress however is laid on the usage of ECG for detection of CVD during the last decades for clinical support to the individual. The coherence of both the mechanical and electrical movements in the heart helps diagnose with the help of electric pulses the health of the heart muscles. Generally the ECG pattern in a cardiac sequence constitutes a series of rhythmically occurring waves and peaks.[6]

Customarily in a hospital the cardiologist prescribes an ECG test to be conducted on the patient complaining of chest pain. The Cardiologist diagnoses the patient by examining the ECG for irregularities in the waves and the peaks and with his expertise and experience in the field. In this day and age and form of CVD can be treated effectively with affordable medical treatment. Medical advancements have given way for superior quality medical devices like pacemakers and prosthetic valves and enhancement in operational procedures like bypass surgery substitute and revive defective portions of the heart. Several other medical progressions in other fields have replaced the need for surgery with a diverse number of implementations. A normal heart beats with the rate of 70 times per minute and thus 70*60*24=1,00,800 beats are available for a 24- hour ECG recording. Furthermore the abnormal heartbeats may appear randomly and this brings out the tedium in the task involved with analyzing these long-term ECG recordings. This warrants a system that can automatically and speedily analyze the ECG recordings and preferably classify the heartbeats according to the disease causing it. In other words a healthcare system is desirable that will intelligently analyze the long term ECG recording and generate an accurate diagnostic report for further study by the cardiac expert. Another aspect of designing such a system is more justified in developing countries like India, where the constraints like economy and remoteness of majority of the populace simply do not allow for consultation by a cardiac specialist. In such cases a healthcare system would certainly play an important role by proving as a diagnostic tool that can be easily deployed in remote and demanding areas under the supervision of a general medical practitioner.
[3-4]

The foremost aim of the present-day healthcare system is to provide everybody in need with all the necessary standard healthcare services. In order to ensure this, timely diagnosis of the ailments has to performed so as to suitable intervention assistance can be provides to the patients for effective treatment and recovery.

Present day medical sciences have pioneered aspiring to render first-rate health care services to the society. Many significant applications to support the above cause have been discovered using artificial intelligence and intelligent systems, Bio medical approaches adapting neural networks have proved to be resourceful in both diagnosing and examining infections and disorders. They also aid in supervising the course of treatment for ailments.

Implementation of neural network tools has been impactful in the processing and investigation of biomedical signals. A few of the popular areas of implementation are the analysis of electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG), and gait and movement biomechanics data. In additionthe productivity of neural networks can be seen in several healthcare domains like medical image investigation, speech/auditory signal identification and processing, somnipathy detection and others. [7]

The bio-electrical activity in the pumping action of the heart is outlined by the electrocardiogram signals. An electrode placed on the heart of the patient detects these signals and records it. A comprehensive examination of a person's heart condition is diagnosed and analysed by examining the routine ECG schedule-past plots and the other typical

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components of the P, Q, R, S, and T waveforms. Divergence in these waveforms can be connect to many heart disorders and ailments confirming a notable role the neural network plays in aiding the course of ECG diagnosis. [8]

III. HEART ARRHYTHMIA

Changes in the generation of electrical impulses or contraction in the heart lead to cardiac disorders. Heart arrhythmia is a condition of the irregular heartbeat either too fast, or too slow. The abnormal heart rhythms called arrhythmia occur due to changes in the normal sequence of electrical impulses of heart. The different organs of the body may be damaged or may not work properly if the heart doesn't pump blood effectively. Arrhythmias can occur in the upper and lower heart chambers, however arrhythmias of ventricles can be life- threatening events.

The factors like disease in coronary artery, changes in myocardium, damage from a heart attack, or healing process after heart surgery may cause arrhythmia. It may occur with a normal heart rate, brady arrhythmias (slow heart rates below 60 bpm) or tachyarrhythmia (rapid heart rates above 100 bpm). Many arrhythmias have no symptoms and if symptoms persist the person may feel a gap between heartbeats, shortness of breath, or chest pain. Most of arrhythmias are not dangerous, but some may complain of stroke, others may have cardiac arrest result. An ECG analysis and Holter monitor could be helpful in the diagnosis of cardiac disorders as shown in Fig 2.

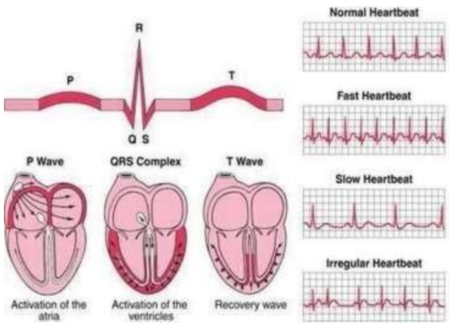

Figure 2 shows the typical ECG classification

The existing traditional system consist of various leads and electrodes attached to the body. The real time ECG wave is obtained on the CRO and includes paper work. The ECG pattern have to be shown to the medical experts or cardiologists. ECG technology has been used by doctors for gather vital information on the health of their patients. In the past this technology had to be used in control environments (in the Doctor's offices, Clinic or Hospital) In order to obtain best results and while nothing will never replace the advice and information provided by a train physician, that hasn't stopped the use of ECG from expanding well beyond the walls of Doctor's offices this is due in part to the rise of variable devices enable by ECG biosensors.

IV. PROPOSED SYSTEM

A two dimensional method of converting multichannel time series signals is proposed. The original 12 lead ECG is spliced into a 2D plane like a grace scale picture, where each column represents the time series of single lead and each 'pixel' represents the voltage value of ECG.A two dimensional CNN module is proposed for processing multichannel time series indication existing Heart Cardiovascular Diseases one such being arrhythmia. The existing data set acquired from real time Lab test are given cognitive ability there by plotting a real time replica of the existing ECG signal there by predicting the underlying diseases. Figure 3 shows the pre-processed loaded dataset.


```
DATABASE,RECORD,#BEATS,N,L,R,B,A,a,J,S,V,r,F,e,j,n,E,/,f,Q,?,SUM,_N,_S,_V,_F,_Q,CSUM,NN_ALL,NN_TRUE,NN_SEMI,NN_ABS,AA_ALL,SS
_ALL,VV_ALL,FF_ALL,QQ_ALL,XX_ALL
mitdb,100,2273,2239,0,0,0,33,0,0,0,1,0,0,0,0,0,0,0,0,0,2273,2239,33,1,0,0,2273,2237,2169,68,1914,34,33,1,0,0,0
mitdb,101,1865,1860,0,0,0,3,0,0,0,0,0,0,0,0,0,0,0,2,0,1865,1860,3,0,0,2,1865,1858,1848,10,1327,5,3,0,0,2,0
mitdb,103,2084,2082,0,0,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,2084,2082,2,0,0,0,2084,2080,2076,4,1694,2,2,0,0,0,0
mitdb,105,2572,2526,0,0,0,0,0,0,0,41,0,0,0,0,0,0,0,5,0,2572,2526,0,41,0,5,2572,2524,2432,92,2338,46,0,41,0,5,0
mitdb,106,2027,1507,0,0,0,0,0,0,0,520,0,0,0,0,0,0,0,0,0,2027,1507,0,520,0,0,2027,1505,987,518,569,520,0,520,0,0,0
mitdb,107,2137,0,0,0,0,0,0,0,0,59,0,0,0,0,0,0,2078,0,0,0,2137,0,0,59,0,0,59,0,0,0,0,2135,0,59,0,0,2076
mitdb,108,1763,1739,0,0,0,4,0,0,0,17,0,2,0,1,0,0,0,0,0,0,1763,1739,5,17,2,0,1763,1737,1694,43,885,24,5,17,2,0,0
mitdb,109,2532,0,2492,0,0,0,0,0,0,38,0,2,0,0,0,0,0,0,0,0,2532,2492,0,38,2,0,2532,2490,2410,80,2203,40,0,38,2,0,0
mitdb,111,2124,0,2123,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,2124,2123,0,1,0,0,2124,2121,2119,2,1705,1,0,1,0,0,0
mitdb,112,2539,2537,0,0,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,2539,2537,2,0,0,0,2539,2535,2531,4,2498,2,2,0,0,0,0
mitdb,113,1795,1789,0,0,0,0,6,0,0,0,0,0,0,0,0,0,0,0,0,0,1795,1789,6,0,0,0,1795,1787,1775,12,681,6,6,0,0,0,0
mitdb,114,1879,1820,0,0,0,10,0,2,0,43,0,4,0,0,0,0,0,0,0,0,1879,1820,12,43,4,0,1879,1818,1718,100,1125,59,12,43,4,0,0
mitdb,115,1953,1953,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1953,1953,0,0,0,0,1953,1951,1951,0,918,0,0,0,0,0,0
mitdb,116,2412,2302,0,0,0,1,0,0,0,109,0,0,0,0,0,0,0,0,0,0,2412,2302,1,109,0,0,2412,2300,2085,215,2063,110,1,109,0,0,0
mitdb,117,1535,1534,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1535,1534,1,0,0,0,1535,1532,1530,2,1166,1,1,0,0,0,0
mitdb,118,2278,0,0,2166,0,96,0,0,0,16,0,0,0,0,0,0,0,0,0,0,2278,2166,96,16,0,0,2278,2164,1957,207,1866,112,96,16,0,0,0
mitdb,119,1987,1543,0,0,0,0,0,0,0,444,0,0,0,0,0,0,0,0,0,0,1987,1543,0,444,0,0,1987,1541,823,718,618,444,0,444,0,0,0
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Figure 3 shows the pre-processed loaded dataset.

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Evaluation index the evaluation index of arrhythmia classification refers to the recommendations of AAMI and the practices of similar studies. We use the confusion matrix shown in Table 1 to represent the classification effect of the model, and count the accuracy, precision, and recall rates. The direction of the matrix row represents the true type of ECG beat and the direction of the column represents the type of ECG beat predicted by the model. For each of the heart rhythm types, the number of correct predicted values of the statistical model is TP, and the number of incorrect predictions is FP; the actual total amount of the other three types of heart rhythm is recorded as TN, and the total number of heart rhythm type incorrectly classified as the other three types by the model is recorded as FN. The calculation formulas of precision rate precious, recall rate, and false positive rate (FPR) are as Equation (1)-(3).

		Model to predict heart rhythm				Sum
		N	S	V	F	
True heart rhythm type	N	Nn	Ns	Nv	Nf	$\sum N$
	S	Sn	Ss	Sv	Sf	$\sum S$
	V	Vn	Vs	Vv	Vf	$\sum V$
	F	Fn	Fs	Fv	Ff	$\sum F$
Sum						$\sum$

Equation 1-3

```
Standard Labels::
N       b       Normal beat
L       b       Left bundle branch block beat
R       b       Right bundle branch block beat
B       b       Bundle branch block beat (unspecified)
A       b       Atrial premature beat
a       b       Aberrated atrial premature beat
J       b       Nodal (junctional) premature beat
S       b       Supraventricular premature or ectopic beat (atrial or nodal)
V       b       Premature ventricular contraction
r       b       R-on-T premature ventricular contraction
F       b       Fusion of ventricular and normal beat
e       b       Atrial escape beat
j       b       Nodal (junctional) escape beat
n       b       Supraventricular escape beat (atrial or nodal)
E       b       Ventricular escape beat
/       b       Paced beat
f       b       Fusion of paced and normal beat
Q       b       Unclassifiable
?       b       Beat not classified during learning
[       n       Start of ventricular flutter/fibrillation
!       n       Ventricular flutter wave
]       n       End of ventricular flutter/fibrillation
x       n       Non-conducted P-wave (blocked APC)
(       n       Waveform onset
)       n       Waveform end
p       n       Peak of P-wave
t       n       Peak of T-wave
u       n       Peak of U-wave
`       n       PQ junction
'       n       J-point
^       n       (Non-captured) pacemaker artifact
|       n       Isolated QRS-like artifact [1]
~       n       Change in signal quality [1]
+       n       Rhythm change [2]
s       n       ST segment change [2]
T       n       T-wave change [2]
*       n       Systole
D       n       Diastole
=       n       Measurement annotation [2]
"       n       Comment annotation [2]
@       n       Link to external data [3]
```

Figure 4 shows the prediction type labelling of various condition

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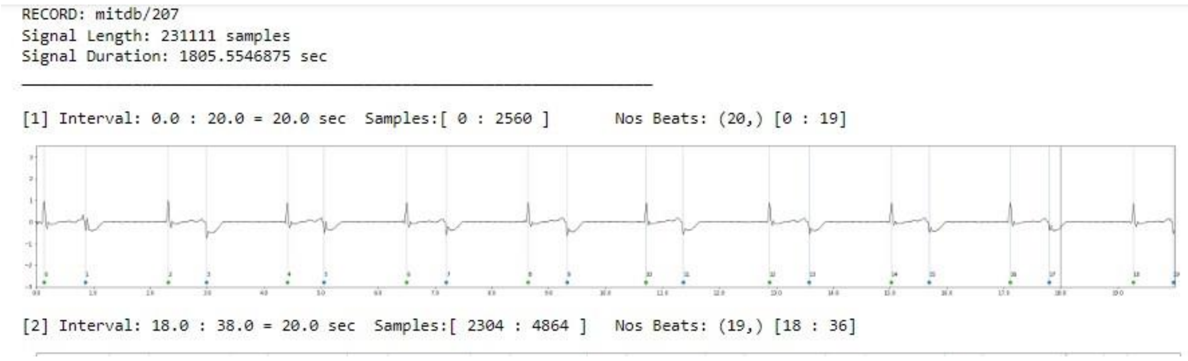

Figure 5 shows the process of AI computation for a particular interval [18:36]

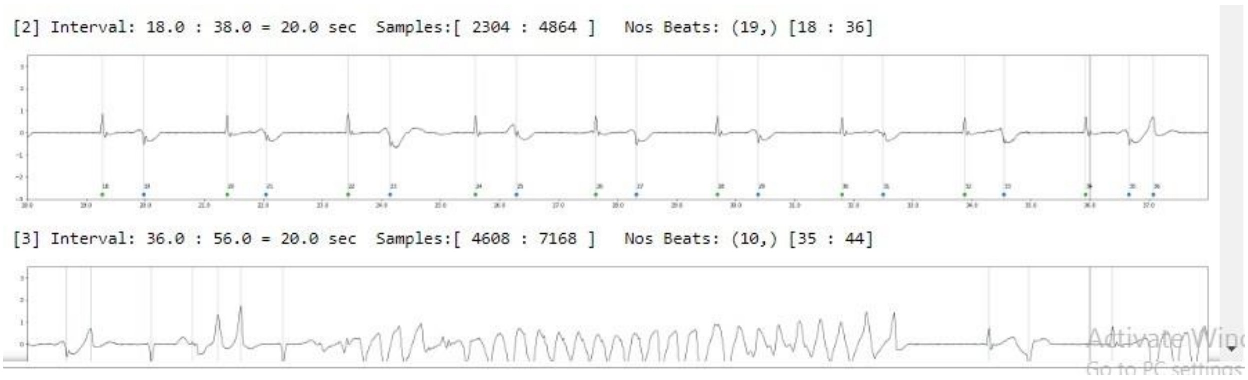

Figure 6 shows the process of AI computation for a particular interval [35:44]

V. CONCLUSIONS AND FUTURE ENHANCEMENTS

The proposed system aims to improve ECG arrhythmia prediction accuracy using the Time Series algorithm considering the health care data set which classifies the patients whether they are having Arrhythmia or not according to the information in the record. The amount of Heart diseases can exceed the current scenario to reach the maximum point. Heart disease are complicated and each and every year lots of people are dying with this disease. 21st century is the era of data explosion and manual analysis of such huge data is almost impossible. The model uses data analysis and Machine Learning algorithms to make predictions in seconds. Also, the accuracy of these data can be verified. Data analysis and visualization was carried out for statistical and graphical analysis of the acquired data. Accuracy score of the model was measured.

Upon extensive study and research, recommendations for improvement and enhancement of the ECG Cardiac Arrhythima Predictor system program are concluded as follows: More data can be extracted by considering a larger number of hospital data over a longer time frame to improve the model and other deep architectures can also be implemented. Another promising approach is to generalize the existing model for use in various domains in health care and management. A GUI can be implemented for ease of usage of the model.

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