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An Approach for Continuous and Simple Arrhythmia Monitoring

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Abstract : Due to the proliferation of the Internet of Things (IoT), the IoT devices are becoming utilized at the edge network at a much higher rate. Conventionally, the IoT devices lack the computation resources required for carrying out ultra-edge analytics. In this paper, we go beyond the typical edge analytics paradigm, which is mostly limited to user-smartphones, and investigate how to embed intelligence into the ultra-edge IoT sensors. To conceptualize the smart IoT sensors with enhanced intelligence, we select the arrhythmia detection task employing Electrocardiogram (ECG) trace as one of the mobile health (mHealth) cases. The existing approaches are not feasible for ultra-edge IoT sensors due to the extensive noise-filtering and manual feature extraction phase. Hence, in this paper, to facilitate the analytics, we propose a Deep Learning-based Lightweight Arrhythmia Classification (DL-LAC) method, which employs only single-lead ECG trace and does not require noise-filtering and manual feature extraction steps. As the proposed technique, we design a one-dimensional Convolutional Neural Network (CNN) architecture. Complying with the ANSI/AAMI EC57:1998 standard, four heartbeat types are taken into consideration as class labels. The efficiency and the generalization ability of the proposed model are evaluated, employing four different datasets from PhysioNet. The experimental results demonstrate that the proposed DL method outperforms traditional methods such as the Delay Differential Equation (DDE)-based optimization, K-Nearest Neighbor (KNN), and Random Forest (RF). The proposed DL-LAC illustrates encouraging performance in terms of time and memory requirement when the trained model is transferred to virtualized microcontrollers connected to IoT sensors.

Index Terms - Internet of Things (IoT), arrhythmia, electrocardiogram (ECG), deep learning (DL), convolutional neural network (CNN), smart health, smart sensor.

I. Introduction

Heartbeat irregularities, too-fast or too-slow heartbeats are all symptoms of cardiac arrhythmia. Many arrhythmias don't show any symptoms. When symptoms are present, there may be palpitations or a sensation of a stop between heartbeats. Chest pain, wooziness, shortness of breath, or light headedness may occur in more severe situations. A person may be at risk for heart failure or a stroke even if the majority of arrhythmias are not harmful. Others might bring on cardiac arrest. Arrhythmia has an effect on millions of people. Sudden cardiac death accounts for 15% of all deaths globally, or 50% of deaths from cardiovascular illness. Ventricular arrhythmias are responsible for about 80% of sudden cardiac fatalities. Arrhythmias can happen to anyone at any age, but the elderly are more likely to have them.

Arrhythmia can happen whenever the electrical impulses that drive the heart to contract are interrupted. When at rest, a person with a healthy heart should have a heart rate of 60 to 100 beats per minute. The lower a person's resting heart rate, the more fit they are. Because their hearts are so efficient, Olympic competitors, for instance, typically have a resting heart rate of under 60 beats per minute.

Some of the factors that can lead to the heart's improper functioning: Abuse of alcohol, Diabetes, using drugs, Drinking too much coffee, Heart disease, such as congestive heart failure, Hypertension (high blood pressure), Thyroid disease (an overactive thyroid gland). A healthy person almost never experiences long-term arrhythmia unless there is an exogenous cause, such as drug abuse or an electric shock. However, if there is an underlying problem, it may prevent the electrical impulses from properly passing through the heart, which would raise the chance of arrhythmia. When your heartbeat is normal, it has the ideal rhythm and rate. A cardiac arrhythmia is one of the most common heart conditions and is characterized by abnormally rapid, excessively slow, or irregular heartbeat. The majority of people do occasionally experience heart arrhythmias.Your heart's regular electrical system, which controls your heart rate and rhythm, becomes disrupted, leading to an arrhythmia. Cardiac arrhythmias can range greatly in severity. While certain arrhythmias are exceedingly serious and life-threatening, the majority are absolutely harmless and unimportant. Even while many of them are not extremely harmful, they often result in symptoms that can significantly disturb your life. The electrical circuitry of the heart causes the heartbeat. An electrocardiogram (EKG or ECG) uses a wave arm to represent each heartbeat. The regular sinus rhythm of the heart indicates that the electrical activity in the heart is proceeding normally. The node is normal but rhythm is erratic(about 50-100bmp). Tachycardias heart beat(greater than 100bpm),Bradycardias heart beat(less than 60bpm).

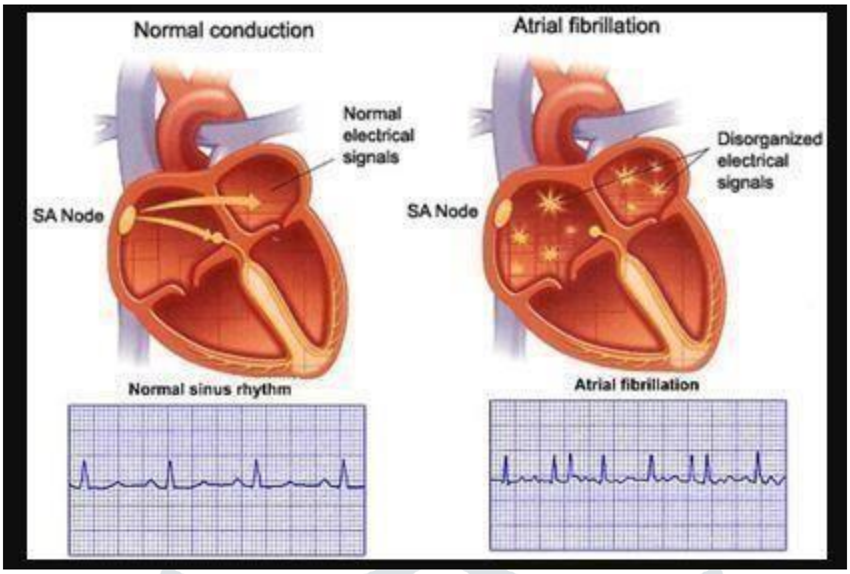

Figure 1. Rhythm of heartbeat

Multiple Diagnoses Normal electrical activity: The sinus node, sometimes referred to as the Sino-atrial node or SA node, is a small region of tissue in the right atrium of the heart. It is where every heartbeat begins as an electrical impulse. The atrioventricular (or AV) node, which is often the only electrical connection between the atria and the ventricles, is first activated by the impulse, causing both atria to contract (main pumping chambers). The impulse that causes the synchronized contraction of the heart's muscle travels through both ventricles with the help of the Bundle of His and Purkinje fibers, resulting in the pulse. Adults typically have a resting heart rate between 60 and 90 beats per minute.The resting heart rates of children are significantly greater. Athletes' resting heart rates, however, could be as low as 40 beats per minute while still being considered normal. With each inhale and exhale, the heart rate alternatively gently rises and slows, a condition known as "sinus arrhythmia." It gradually disappears with age but is typically highly noticeable in early children. When using deep breathing and breath retention techniques while meditating, this could also be present.

Bradycardias: The sinus rhythm is followed by a halt in sinus node activity, with solid black arrows pointing to typical P waves indicating normal sinus node function (resulting in a transient loss of heartbeats).The P wave that breaks up the pause is indicated by the dashed arrow. This P wave, which denotes an escape rhythm, differs from the preceding (normal) P waves in that it is emanating from a different area of the atrium. Bradycardia is a slow heartbeat (less than 60 beats per minute). The electrical impulse that travels from the atria to the ventricles is obstructed, the sinus node slows down its signal (sinus bradycardia), or the sinus node stops functioning normally (sinus arrest) (AV block or heart block). The degree and severity of heart block might differ. It may be caused by medications that momentarily impairment of conduction or irreversible damage to the AV node. In the healthy hearts of physically fit people and endurance athletes, bradycardias are also frequent. Bradycardia can also happen together with certain kinds of seizures.

Tychycardias: A resting heart rate of more than 100 beats per minute is referred to as tachycardia in adults and children over the age of 15, which is not usually an arrhythmia, can cause palpitations. A typical response to both physical and emotional stress is an increased heart rate. The sympathetic nerve system on the sinus node mediates what is known as sinus tachycardia. Other disorders that cause the sympathetic nervous system to become more active in the heart include anemia, an overactive thyroid (hyperthyroidism), and medicines that can be injected or consumed, such as caffeine or amphetamines.

Heart problems: Congenital heart defects are problems with the electrical function or structural integrity of the heart that exist from conception. This affects anyone since overall health is unimportant. Electrical problems in the heart can lead to highly rapid arrhythmias or even fatal ones. Wolff-Parkinson-White syndrome is brought on by a second channel the electrical muscular tissue that makes up the heart. The electrical impulse that starts the heartbeat can move exceedingly quickly because to this tissue. The most frequent type of ventricular tachycardia in otherwise healthy people is right ventricular outflow tract tachycardia. The right ventricle's electrical node, which is located immediately before the pulmonary artery, is the cause of this abnormality. The patient will have ventricular tachycardia when the node is activated, which prevents the heart from filling with blood before beginning to beat again. Long QT syndrome has been identified as a complex heart condition that a distinct cause of mortality. There are many ways to deal with this, including medicine, cardiac ablations, changing one's lifestyle to be less stressful and more active, among others.

II. PROBLEM STATEMENT

To create a system that can identify and categorize cardiac arrhythmia. As manifested in the previous section, the healthcare sector still needs accelerating improvement in establishing smart healthcare with embedded intelligent sensors. As our research focus in this paper is lightweight arrhythmia monitoring, we will discuss the drawbacks of the existing ECG/arrhythmia monitoring system and the hurdles associated with transferring the existing analytics to ultra-edge IoT. Traditionally, researchers have employed diverse heartbeat classification techniques that generally require a number of pre-processing steps such as noise filtering, manual feature extraction, and so forth. The steps needed by the conventional heartbeat classification employing ML methods are exhibited in . Diverse methods such as DWT, DDEs [24], and ML techniques are commonly utilized in the conventional feature extraction and classification tasks. Though these ECG analytics techniques overcome many drawbacks of the manual ECG monitoring, it still lacks the potential to be integrated with logic-in-sensors due to the extensive computational steps. These conventional ECG monitoring approaches mostly rely on multi-lead ECG signal and requires multiple preparatory steps (i.e., noise filtering), which is a significant issue for combining these models with the ultra-edge IoT logic-in-sensors.

III. LITERATURE SURVEY

[1] A. Mohsen, M. Al-Mahdawi, M. M. Fouda, M. Oogane, Y. Ando,and Z. M. Fadlullah, Now that we are about to enter the much anticipated "Society 5.0,"powered by the Internet of Things (IoT), it is challenging to use traditional methods of monitoring human heart signals for tracking cardio-vascular disorders, especially in remote healthcare settings. On the grounds of low power consumption, mobility, and non-intrusiveness, there are no viable Internet of Things solutions that can offer data comparable to the conventional Electrocardiography (ECG). In this study, it propose an Internet of Things (IoT) device that uses an ultra-sensitive Magnetic Tunnel Junction (MTJ) sensor based on spintronic technology to measure the magnetic fields created by cardio-vascular electromagnetic activity, or "Magnacardiography" (MCG). For the majority of other sensors that deal with low-frequency bio-magnetic signals, it deals with the sensor's low- frequency noise, which is a concern. We replace standard signal processing methods like moving average with deep learning training on bio-magnetic signals. A dataset of ECG records is used to create MCG signals. A unique deep learning model with a one-dimensional convolution layer, a gated recurrent unit (GRU) layer, and a fully connected neural layer is trained using labelled data that passes through a striding window. This model can efficiently identify and eliminate noise features. The simulation results that demonstrate the suggested strategy's encouraging performance are used to gauge its efficacy.

[2] Q. Yao, R. Wang, X. Fan, J. Liu, and Y. Li,Automatic arrhythmia identification using the electrocardiogram (ECG) is essential for the early diagnosis and treatment of cardiovascular problemsTo solve these issues, we proposed attention-based time-incremental neurallnetworks. Convolutional neural network (ATI-CNN), a deep neural network model, fuses spatial and temporal information from ECG data by combining CNN, recurrent cells, and the attention module. This method offers customizable input length, a parameter amount that is halved, and a real-time computation reduction of more than 90% in contrast to the CNN model. The results of the experiment showed that the classification accuracy of ATI-overall CNN was 81.2 percent.

When ATI- CNN was compared to the conventional 16-layer CNN known as VGGNet, accuracy improvements of 7.7% on average and up to 26.8% in identifying paroxysmal arrhythmias were seen. The ATI-CNN gave an example for a range of signal processing problems of varied lengths by combining all these excellent qualities.

[3] S. Sahoo, M. Dash, S. Behera, and S. Sabut,A condition known as cardiac arrhythmia causes an irregular heartbeat that can be either too slow or too fast. Faulty electrical impulses that control the heartbeats cause it to occur. Certain severe arrhythmia diseases can lead to sudden cardiac death. Because of this, the main objectiveof electrocardiogram (ECG) examination is to accurately identify arrhythmias as life- threatening in order to offer an appropriate therapy and save lives. Waveforms used to represent the electrical activity of the human heart are called ECG signals (P, QRS, and T). Each waveform's duration, organisation, and spacing between different peaks are used to determine whether there are any heart issues. The parameters of the AR signal model are then determined by doing an autoregressive (AR) analysis on the signals. The training dataset neatly separates the groups of recovered AR features for three different types of ECG, giving each ECG signalin the training dataset good connection classification and heart condition diagnosis. To more accurately assess ECG signals, a novel method based on fractional Fourier transform (FFT) algorithms and two-event-related moving averages (TERMAs) is proposed. This study may aid in the examination of the most recent cutting-edge techniques used in arrhythmia situation detection. Our proposed machine learning method features cross- database training and testing with enhanced properties.

[4] P. Kamble and A. Birajdar, Electrocardiogram (ECG) signal measurement is a crucial technique for detecting heart conditions. The ECG signal contains information about how well the heart is functioning. The loss of ECG data is caused by the inability of the current devices to save the data. In this study, we suggest a brand- new method for recording and monitoring ECGs utilising the Internet of Things (IoT).

The ECG data is collected by a wearable monitoring node, wirelessly sent to an IoT cloud, and then stored on an SD card for offline use. The local LCD and created web interface/mobile application both display the ECG wave. The cross-platform problem has decreased because it is easier to obtain ECG data using smart devices with a web browser.

[5] Z. Yang, Q. Zhou, L. Lei, K. Zheng, and W. Xiang,A growing amount of attention has been dedicated to public healthcare as a result of the exponential expansion in both the human population and medical costs. It is common knowledge that an efficient health monitoring system can diagnose conditions based on the gathered data and quickly identify irregularities of health conditions. ECG monitoring is a crucial method used to diagnose cardiac disorders that has been extensively researched and used. However, almost all portable ECG monitoring systems currently in use require a mobile application for data collection and display in order to function. In this study, we suggest a novel Internet-of-Things (IoT)-based ECG monitoring methodology. A wearable monitoring node is used to collect ECG data, which is then wirelessly sentto an IoT cloud. In order to give consumers visual and timely ECG data, the IoT cloud uses both the HTTP and MQTT protocols. Since almost all smart terminals with web browsers can easily acquire ECG data, the cross-platform problem has been considerably reduced. Healthy volunteers are used in experiments to test the system's dependability as a whole. The proposed system is reliable in gathering and showing real-time ECG data, according to experimental findings, which can help in the initial detection of several cardiac disorders.

IV. PROPOSED METHODOLOGY

In this section, we illustrate the proposed lightweight heartbeat classification technique for arrhythmia detection that can be deployed and integrated with AI-aided logic-in-sensor. A lightweight model for classification is an essential part of integrating the AI-aided model at the ultra-edge IoT sensors for faster analysis. Hence, we primarily focused on designing the deep learning-based model that only requires a single lead raw ECG signal so that the model can be sufficiently lightweight. Sensors with embedded intelligence can be utilized for long-term, accurate monitoring of a person's cardiac activity, which is demonstrated in one of the coauthors' previous works [1]. Keeping the concept of logic-in-sensor in focus, we developed a deep-learning-based lightweight model that can be integrated with these AI-aided sensors for analysis of ECG at the ultra-edge device. The acquired results of the ECG analytics can then be sent from the IoT nodes to the care-providers.

We propose an automated deep learning-based one dimensional (1-D) CNN that does not necessitate any noise-filtering and manual feature extraction. The CNN model detects unique patterns automatically from the raw single-lead ECG signal. The ECG signals are sampled at a frequency of fs before passing to CNN as input. The lightweight ECG analysis for arrhythmia detection task takes an ECG signal as input X = [x1,x2,x3,...xn], and outputs a sequence of labels Y = [y1,y2,y3,...yn]. Here each yi represents one of four different heartbeat classes and in terms of arrhythmia classification yi ∈ {F,N,V, S}. Table 1 exhibit of the summary of each of the classes. We consider a minimum length of ECG signal noted as δ to be passed as input to the model. Every output label corresponds to a portion of the input ECG signal, and collectively the output labels cover the full sequence of the ECG signal record of a subject.

As the deep learning-based solution, a 1-D CNN is designed and used because of its exceptional performance in automatically detecting patterns in the ECG signal. The proposed CNN model can be defined briefly as the combination of the convolution layers, max-pooling layer, and fully-connected layers. Fig. 2 represents the architecture of the proposed CNN model. Here the model receives raw ECG

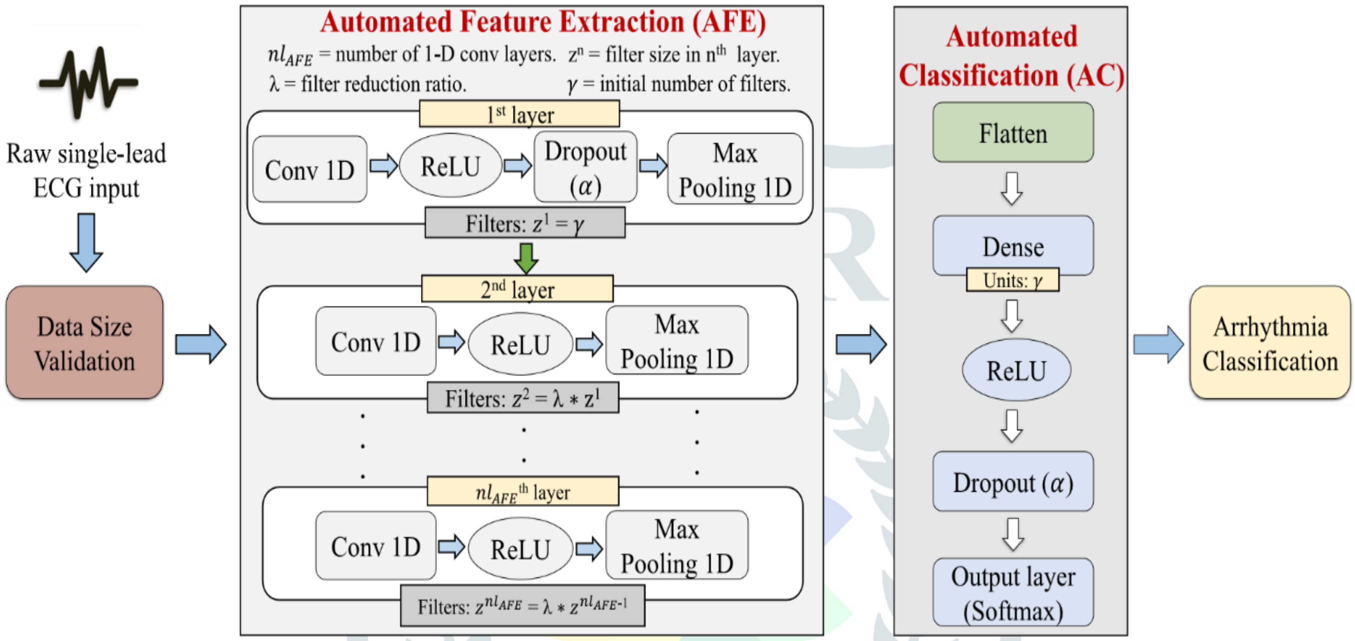

Fig 2. Proposed Methodology

V. RESULTS AND DISCUSSION

The figure 3 below display the sample UI developed for the project. The design allows the user to select the various inputs such as age, sex, height, QRS duration, QT interval and the T interval. Once these features are been entered and given for prediction the process is taken for next steps. The model further goes for training and prediction.

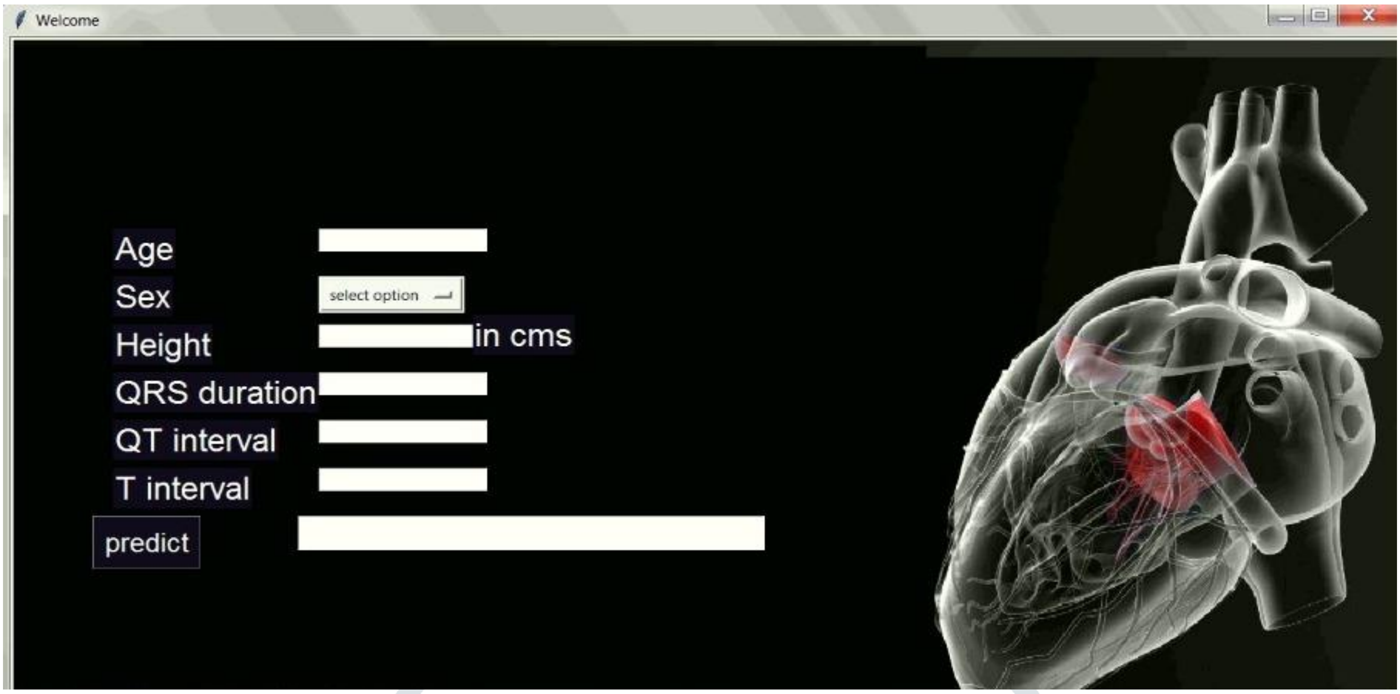

Figure 3 Sample User Interface designed for testing

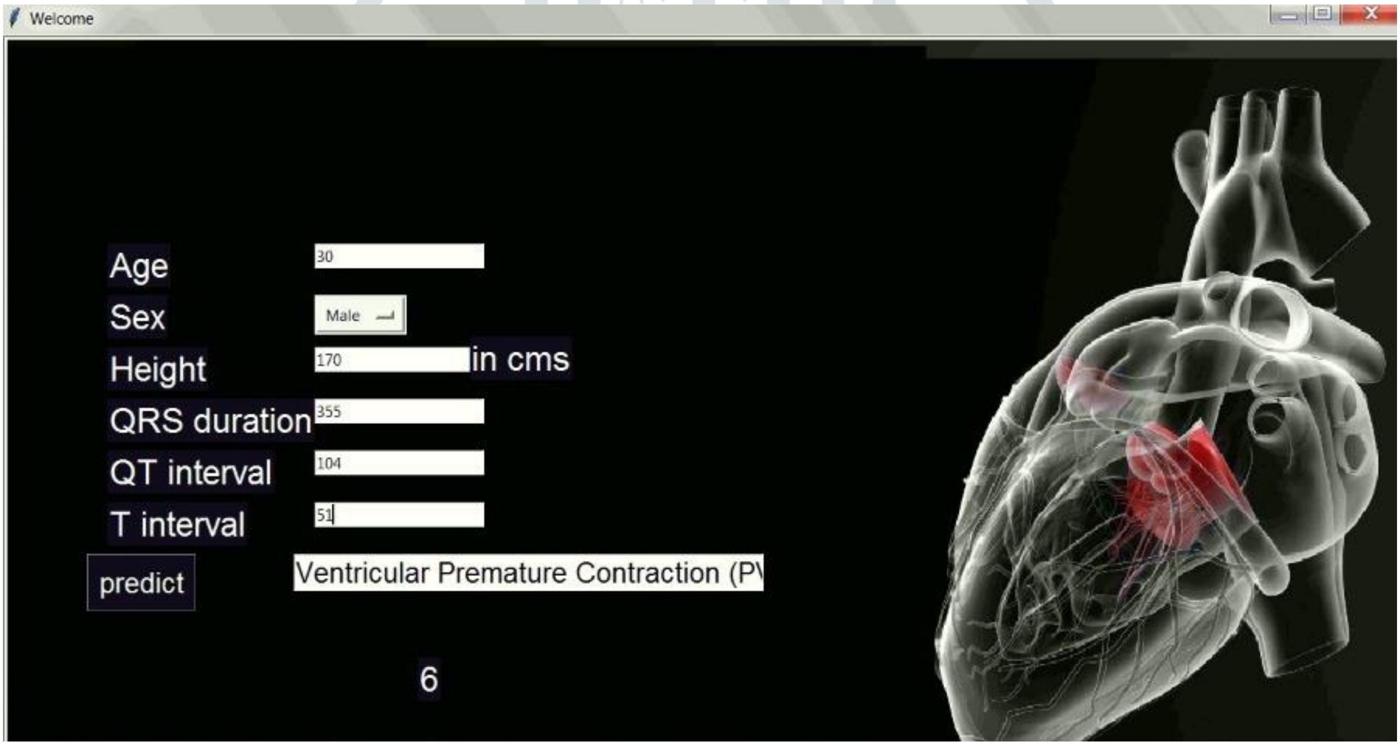

Figure 4 Sample User Interface Output after prediction

The figure 4, above display the outcome of the project after running with the training, prediction models of the process. The Output display the predicted output of the loaded sample as Ventricular Premature Contraction.

The figure 5, below shows the python code developed for the project. The code is developed in python 2.7 version and executed in the same.

final.py - C:\Users\Admin\Desktop\cardiac_final_reduced\final.py (3.7.0)

File Edit Format Run Options Window Help

```
import pandas as pd
from tkinter import *
from tkinter import ttk
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
import random
from PIL import ImageTk, Image

root = Tk()
root.title("Welcome")
img =Image.open('BC.png')
bg = ImageTk.PhotoImage(img)

##root.geometry("550x450")

# Add image
label = Label(root, image=bg)
label.place(x = 0,y = 0)

root.geometry("1350x850")

# Add image
label = Label(root, image=bg)
label.place(x = 0,y = 0)

df = pd.read_csv('test.csv')
x = df.iloc[:,:6]
y = df.iloc[:,-1]
X_train , X_test , y_train , y_test = train_test_split(x,y,test_size=0.2,random_state=100)

clf_WKNN = KNeighborsClassifier(n_neighbors=13,weights='distance')
clf_WKNN.fit(X_train, y_train)
```

Ln: 1 Col: 0

Figure 5 Python code sample written for the model

VI. CONCLUSION

The results strongly suggest that machine learning can aid in the identification of cardiac arrhythmias. It helps with early cardiac arrhythmia detection and forecasting.In order to prevent cardiac arrhythmias, early identification is necessary.

Centralized cloud-based analytics and edge analytics on smart-devices are the traditional health monitoring approaches. To make smart health even smarter, in this paper, we focus on the necessity to go beyond the realms of conventional methods and investigate how to incorporate intelligence into the ultra-edge IoT sensors. As an example of the smart ultra-edge health monitoring, we selected arrhythmia (a cardiovascular disease) classification by analyzing the ECG signal. As the sensors are resource-constrained, we designed a deep learning-based lightweight heartbeat classification model named DL-LAC, that utilizes raw single-lead ECG to classify arrhythmia with encouraging efficiency. We compared the proposed method with traditional machine learning (e.g., KNN, random forest) and the DDE-based optimization technique. The proposed method's generalization ability was evaluated using four different datasets. The promising experimental outcomes manifest that the proposed deep learning model has the potential to be coupled with smart IoT sensors for ultra-edge computing to enhance the existing ECG monitoring system. Therefore, this research can be considered as a pioneering footprint to encourage the sensor foundries to consider embedding intelligence into IoT devices, and if it can be produced in mass production, the fabrication cost of the intelligent sensors can be significantly reduced.

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