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Novel Techniques of Detecting Arrhythmia using Artificial Intelligence Techniques

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Abstract: The study shows that many computer programs using AI have been made to look at the ECG signal and find heart problems. We need to find and treat cardiac diseases early these days if we don't want them to happen. With the help of new technology in health informatics that gathers, sorts, and finds data, there may be new ways to avoid CVDs. Using AI-based methods, it is possible to correctly sort ECG data to find tachycardia. There are several steps in the process of classifying. It is easier for a convolutional neural network to find rhythms. But the health care system still needs to use smart tech to always check on people's heart health. The experts have found some issues in this area. You need better tools to do a great job of analysing ECG data. Sometimes these computer methods don't work right, but they are becoming very helpful for making medical progress. In the field of heart electrophysiology (EP), simple AI have been used for many years. Deep learning techniques are becoming more common once more. This has led to new discoveries in electrocardiography research, like being able to tell when someone is sick by looking at their signature. AI is getting better, and computers, devices, and websites are getting better quickly. This has led to the fast growth of AI-enhanced apps and big data studies. New ways of living, the rise of the internet of things, and better phone systems have made it easier to find people in a community who have atrial fibrillation than it was before. AI has made it possible to get better 3D images of the heart, which led to the idea of virtual hearts and models of heart beats.
Keywords: AI, healthcare, arrhythmia, IoMT, algorithms, efficiency.

1. Introduction:

The UN said in 2015 that the world's population is, on average, getting older [1]. By 2030, there will be 1.4 billion more people over 60 than there are now, and by 2050, that number is expected to have twice to 2.1 billion [1]. The heart and blood vessels get weaker with age, making people more likely to get sick [2]. Also, the arteries get stiffer and the muscle wall of the left ventricle gets thicker [3], which makes the muscles less flexible and hurts their ability to do their job. Arrhythmia is more likely to happen because of the anatomical and electrical alterations that happen in the heart at the same time [3]. In this way, arrhythmias are pulse patterns that don't work normally. Several of these strange beats are very dangerous, while others are not. AFIB is the most common type of arrhythmia. It is marked by disorganised atrial activity because of the growth of a certain number of abnormal sites that send electrical signals without the SAN [4]. The AVN gets electrical signals from the atria at random times and sends them to the ventricles. This causes the QRS complex and pulse to be uneven. Re-entry happens when a desire doesn't go away after the heart has normally beat and keeps stimulating the heart. The chance of return goes up with the number of abnormal foci, which is what makes it possible for AFIB episodes to turn into chronic AFIB [5,6]. With AFIB, the ECG rate is crazy and fast, at 150 to 220 beats per minute. AFIB is defined by an uneven RR interval, uneven fast heart rate, and the lack of a P wave on an ECG. AFL happens in a macroreentrant circuitry and works in a normal way electrically and physiologically [7]. The electric system in the atrium is round and moves electricity quickly. This causes the atrium to constrict at a rate of 240 to 360 beats per minute, showing up on an ECG as a sawtooth pattern that repeats itself. This waveform is called a flutter wave. The AVN can send signals to the ventricles on a regular or irregular basis. This means that the pulse in AFL can be regular or irregular [8]. There is a lot of agreement within AFIB and AFL [5, 6]. There is no link between the two diseases and their effects on illness and death. At the moment, ECG measures are the usual way to gather data that supports a finding of AFIB or AFL. The ECG readings may be checked as a component of a program of prevention for people who have had a stroke, as well as could be monitored to look into symptoms, like to learn more about heartbeat. So, the heart polarisation vector is recorded by an ECG to show the electric action of the heart [9]. Standardised testing methods are used to put electrodes on a person's body and pick up the signal. The signal-to-noise ratio will generally be higher when there exist more electrodes, which means the data quality will be stronger [10]. To look at heart function, you need a good ECG reading. To get information that is useful for diagnosing a disease, clear signal traits that explain the heartbeat must be found. These are the T wave, the QRS complex, and the P wave. Since ECG traits are often the same, it is hard to tell the difference between AFIB and AFL. Unexpected artefacts and weak symptoms could cause the beat to be mislabelled or important parts to be missed. That causes diversity both within and between observers. It's possible that CAD could be a way to lower that unpredictability and cut down on the time-consuming signal analysis. It might also make it easier to choose signal patterns that people can understand. In addition, collecting and analysing ECG readings needs a lot of space to store data. We will be able to record longer signal traces for automatic rhythm analysis once we can tell the difference between AFIB and AFL using RR interval analysis. This will improve both the rate of discovery and the accuracy of the evaluation. This current work identifies the current trends and gives a detailed review.

2. Comparative study

This section provides various techniques that are used in the detection of Arrhythmia using various AI techniques

2.1. Deep Learning on ECG Data

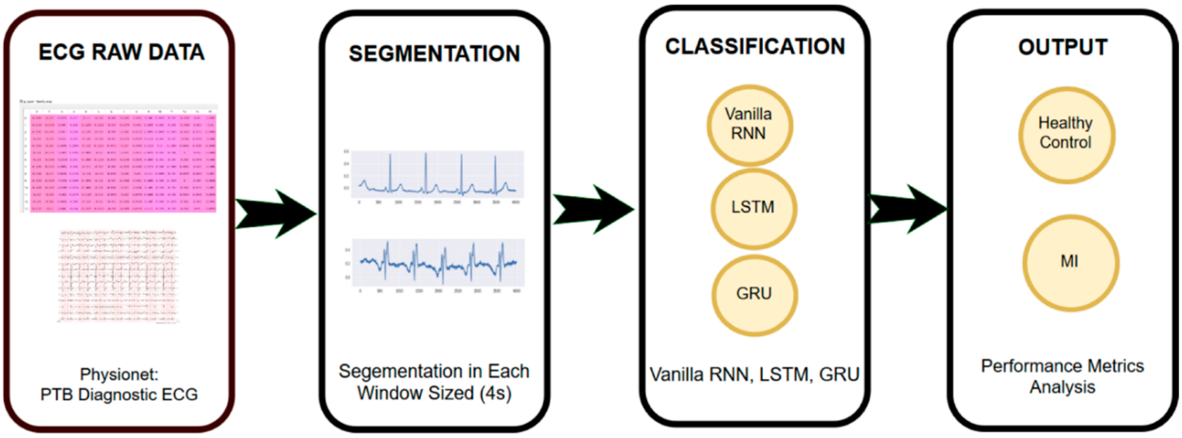

Figure 1: ECG Processing [12]

The work in [12] got the ECG signal sequence data from the free database Physionet: PTB Diagnostic ECG, which is run by the National Metrology Institute of Germany [27]. The PTB Diagnostic ECG database has 549 records from 290 patients, with 209 men and 81 women making up the patients. There were between one and five ECG records for each subject. This library has ECG signs for nine heart problems and nine good heart states. One of these is a MI. The ECG processing is shown in Figure 1. The first step in pre-processing an ECG signal is to divide the area into sections of the same size. This is done because the duration of the test of signal data changes from one ECG record to the next. For MI, the ECG signal lasts between 480000 and 1800180 samples, or 480 to 1800 seconds. As the ECG signal time in the group of healthy controls, the span was from 1455,000 to 1800180 specimens, or 1455 to 1800 seconds. There are four seconds of data examples in each window, that is enough time for at least three average heartbeats. At 1000 samples per second, each input has been turned into a digital output. A total of 12,359 pieces of data for signals from each 4-s window have been separated (see Figure 2). There are 10.144 data points for the MI class and 2.215 genomic data for the normally fit comparison class. Another name for an ANN is an RNN. It processes raw data by using links that happen over and over again. RNN is a deep learning method because it automatically figures out traits without having to choose the right ones ahead of time. RNN has "memory," which is made up of state (st) that stores data regarding all the input parts (xt) to output $\hat{y}\,t$. Original RNN, also called "vanilla RNN," works in a way that is similar to other ANNs in terms of its forward- and reversed-pass processes. The only thing that is different is the backpropagation process, where the word "backpropagation" is described over time (BPTT).

2.2. Transfer Learning

You can find ECGs online in datasets such as ECGVIEW [27] and physionet [13]. These databases can be used for study reasons. They couldn't find any ECG records for people who had fallen, so they took the ECG data as part of the study. The system for collecting data had two parts: a hardware part that came from and a software part. The hardware part was an ECG monitor on a belt that was connected to an Arduino board. The portable version was made by taking a number of factors into account. The gadget ought to be able to keep track of the signs all the time and be capable of to handle the routine of the test, which calls for a lot of moving and falls. Because of this, a 3-lead ECG was chosen because it is common for emergencies (like in an ambulance) and it also needs less wires, which makes it easier for the patient to use. In our test, the results of a 3-lead ECG are the same as those of a 12-lead ECG.

From many kinds of falls, rolling-out-bed was picked as the main and most important one for this study. When you roll out, you get up from sitting down, roll out of bed, and hit the floor. The trial set-up was either a bed or a table. The person wore the monitor and the Arduino thing. The ECG sensors were placed on the person's chest. Then a Bluetooth low energy (BLE) link was made between the secondary device and the main device. The ECG was taken three times: while the person was lying down, when they fell by moving over in bed, and when they were doing normal things like jogging or running. The fall is shown in Figure 3 as three steps. The first one, on the far left, is the resting pose. The next step is to start the fall, and the last step is to lay still on the floor.

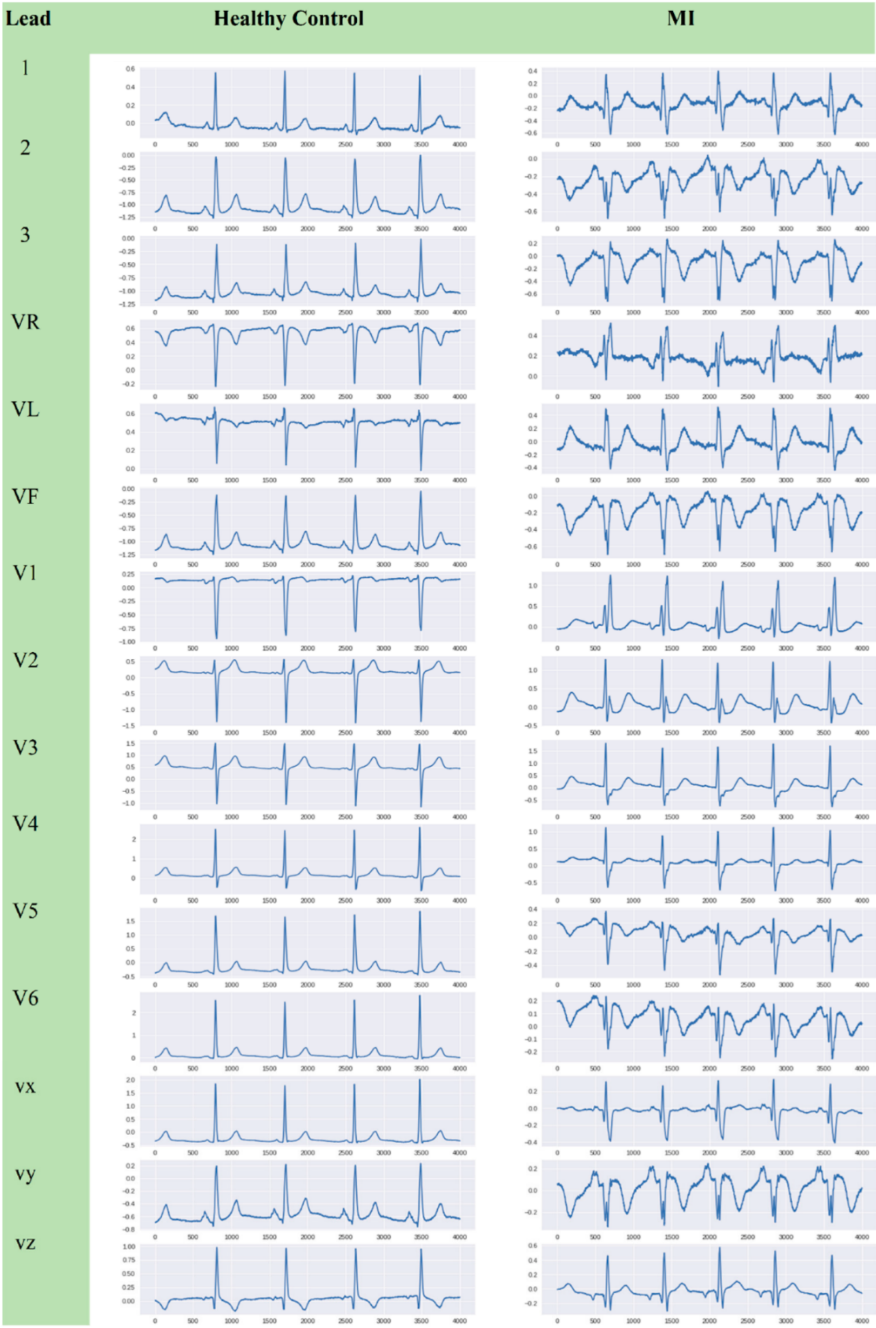

Figure 2: The ECG window's division happened every 4 seconds [12]

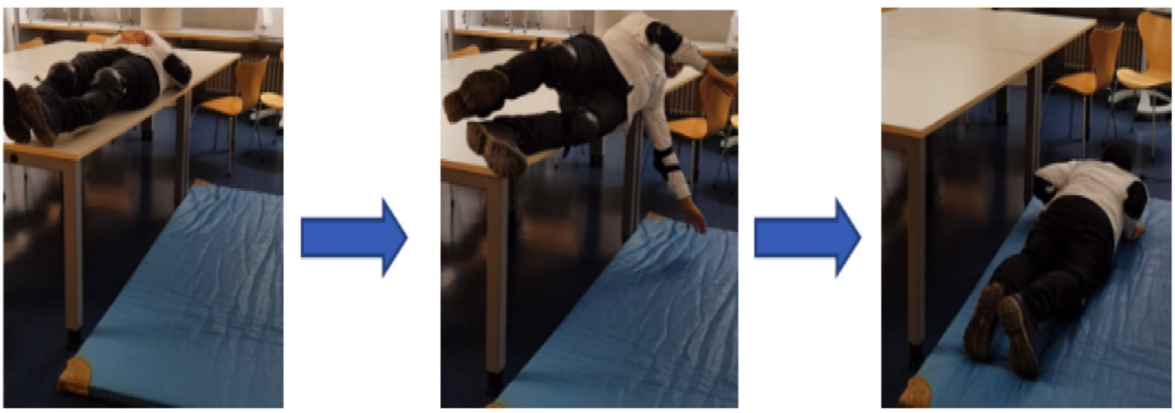

Figure 3: The procedure of rolling fall [13]

Each trial had several 30-second readings spread out over a total of 40 to 45 minutes. In one reading, there were an aggregate of three falls. As demonstrated in Figure 3, the model was at rest for the first 10 seconds of each fall. In the next 10 seconds, the subjects were to roll off the edge of the table or bed and hit the ground. They would stay there for 30 seconds. The person is going to come back and say it again. They used an identical method, a well-known collection for falls and daily tasks. The time spent lying down or sleeping after a fall may be a sign of unconsciousness after a fall, so it needs to be included when making a fall procedure for the old. Some old people don't move after they fall. A study with 110 people found that 60% of them fell and couldn't get back up. Following no less than one fall, 80% of them felt unwilling to get up, and 30% had been on the ground for a minimum of an hour. There are studies that says that inaction after an exercise is a typical way to tell if someone has fallen. Each reading was 90 seconds long and had a 30 second drop every 30 seconds. In general, 10 books to each topic were gathered. In order to get a good rest ECG, the person had to lie prostrate on a flat surface and not move or talk. It delivered the log information to the main unit via BLE. It had 90 seconds for "fall" and 30 seconds for "resting." As part of their daily lives, the subjects did things like swiftly strolling, seated and waiting for 10 to 15 seconds on average, without following a set plan.

In [14], authors use a model that has already been trained (ResNet-18) that was developed on a large dataset called ImageNet. The model's learnt information is then moved to a smaller dataset called MIT-BIH and INCART. First, data various Datasets are analysed and marked up. Then, in the initial processing phase, each example of a normal or PVC beat to those files is turned into a matching 2D beat picture. The pre-trained model is fed the pictures that have already been changed. The inside levels of ResNet were used to get the retrieved general descriptions, which show that there are different types of picture patterns. The way the suggested method to find PVCs from regular beat images uses what ResNet has learnt from learning on the ImageNet dataset. The ResNet classification layer is swapped out for a fully connected (FC) layer and a Softmax classification is added for fine-tuning. The FC layer's weights are set at random at the start. The class numbers, on the other hand, stay the same as the target groups. Figure 4 shows how the suggested way with learning transferred works. When PVCs are found by hand from heart beats, how decisions are made still faces a big problem. It requires quite a while and isn't safe to do things by hand. For this reason, using deep learning to automatically find PVCs shows a lot of potential. A lot of study has been done on structural methods for automatic PVC identification, but these methods have trouble scaling up, especially as the amount of data they need to handle grows. Deep learning methods can fix the issue with morphological-based methods, as shown by our study. There is a lot of variation between patients, noise in the real world, and not sufficient evidence for deep model building in practical situations. This means that tailored to patients and transfer learning methods have a lot of potential. In contrast, turning historical data into the matching pictures makes it easier to sync the time when pulling highlights and can also improve how things look in some situations. Because of this, 2D-based identification methods look better than 1D CNN these days. So, we came up with a deep learning method using 2D CNN that uses both patient-specific and transfer learning on two unbalanced datasets that are open to the public. So, the results show that the proposed method works better than the most recent methods for finding PVCs in ECGs. The results also show that the suggested approach [14] works almost the same even when distinct approaches are used in many tests with two distinct data sets that are mixed (have different traits). This shows that the method can be used on a large scale and in many situations. Because of this, it could be a useful tool for cardiac specialists' systems for clinical decision-support, whether they use them online or off. The study used a heart rate measurement (ECG) from a single lead, but data from more than one lead could be added to the signal to make it stronger. In the future, researchers will look at signs from more than one lead to make the trial cases even better. The work also planned on working on an assortment of unique areas, such as making the suggested method more flexible so that it can be used with EEG and EMG datasets to find other types of human diseases, like Alzheimer's, sleep apnoea, and epilepsy. It is good to know that a thin and deep model works well in real-world situations. Because of this, we also want to make a light-weight tweaked ResNet model that can be used in the real world and will use the micro-attention process.

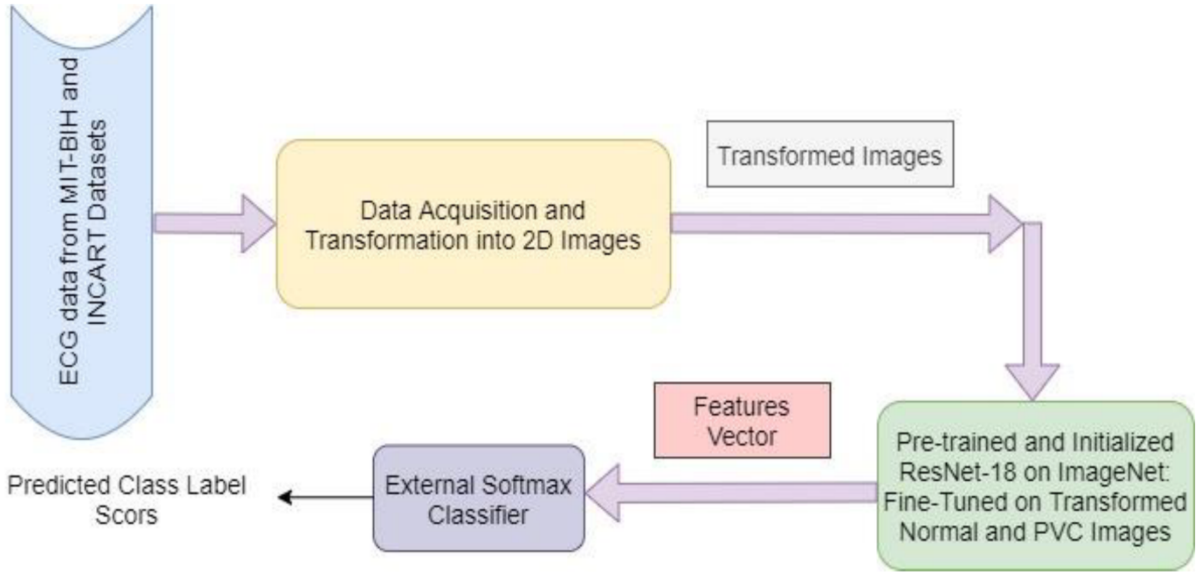

Figure 4: Model in [14]

By mixing novel innovations and AI systems, the Pneulytics platform is meant to keep an eye on people with COPD. COPD is a common, avoidable, and manageable disease that causes chronic respiratory symptoms like shortness of breath, coughing, and trouble breathing. It can also block airways because of lung damage caused by things like cigarette smoke and pollution in the environment. People with COPD are usually treated with medicines that are put on the skin, like patches that are transdermal or small sticky strips, to keep their symptoms from getting worse, to ease their symptoms, and to improve their lung function. These days, it's hard to tell how constant patient results are between clinical study and real life. This is mostly because people don't stick to their treatments and abuse drug inhalers. The risk of relapses and progression of COPD goes up when people don't use their inhalers, and the risk of fatal outcomes goes up even more when people don't follow through and abuse their inhalers. In the past few years, advances in technology have made it possible to watch patients from afar and let patients talk directly to medical workers. Inhalers that are smart can record and digitise important parts of patient tracking, like how much medicine is used and how the inhaler should be used (for example, peak inspiratory flow, length of the inspiratory phase, and direction of the inhaler). With those sophisticated inhalers, medics can find out if the patient is following their treatment plan and if they are using the inhaler correctly. They can then keep a close eye on the patient. You can look at data from smart inhalers, IoMT patient tracking data, and diagnostic information from follow-up visits all at the same time with the Pneulytics system. Even though technology is getting better, web-based tracking of patients' health is still not a good way to get a complete picture of their health. The Pneulytics framework wants to help doctors and health organisations keep an eye on patients' vital signs by combining IoMT devices with new AI algorithms. The goal is to avoid and manage diseases, like COPD, with the help of remote monitoring by doctors and health organisations. The Pneulytics prototype is made up of gadgets that collect information about the patient using IoMT devices and software parts that accurately process the data from the sensors using algorithms that use machine learning, especially explainable AI [27], along with data from the past. In the previous study, data were only about a smart inhaler. Figure 5 shows the picture of the suggested tech platform [27].

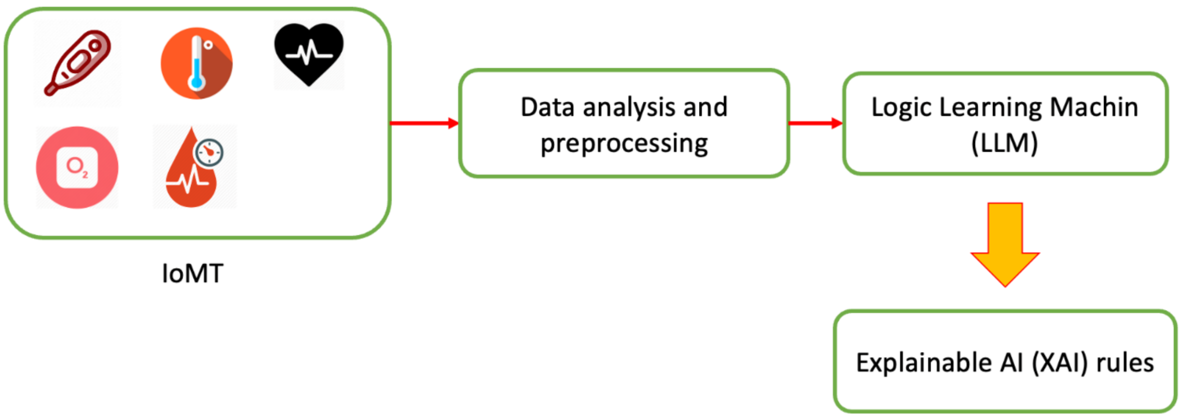

Figure 5: Model in [27]

In more specific terms, patients wear devices that track data related to the sickness being studied all day. At the moment, all devices are linked to a smartphone. The smartphone transmits information to the cloud on a regular basis, in which the information is kept. Along with sensors for the patient, sensors for the surroundings will be added to see how the living conditions can impact the illness. Then, after getting information from patients, ad hoc AI algorithms are used to make forecasting models that may be utilised to find, describe, and stop likely diseases. Doctors can also make medical plans and changes to treatments because they have full possession of the findings and findings of AI programs. The goal of [27] is to look into how smart buildings and health gadgets can be used for tracking, especially to measure the quality of life and overall health [28-29]. Take Indoor Environmental Quality (IEQ) as an example. It is a group of different data that show how good an indoor setting is. To do this, we set up a smart tracking system that can look at, record, and process measures of both the body and its surroundings. The devices that are part of the IoT make it easy to get and share this kind of data because they are linked to a central data store tool. With the IoT sensors that were used for the software, we worked on how to get to the raw data that the detectors collected. We paid special attention to both wearable devices that patients can connect to and actively handle and ecological devices that will be directly placed at the patients' homes and are going to be featured in an upcoming version of the software. For the first demonstrations of concept study on wearable IoMT devices, we used the H&S cloud platform HealthPlatform v3 (CompuGroupMedical), which can access gathered tracking data and give the end user authorised access [28].

3. Discussions and Future Scope:

The study reveals that many AI-based computer methods have been created to examine the ECG signal and find heart disease. To keep circulatory diseases from happening, we need to find and treat them early these days. There may be new ways to avoid CVDs with the help of new technology in health informatics that deals with collecting, processing, and finding data. It is possible to accurately classify ECG data to find tachycardia using AI-based methods. The process of classification is made up of several steps. A convolutional neural network is more accurate at finding arrhythmias. Even so, the healthcare system needs to use smart tech to keep an eye on people's heart health all the time. Some problems have been found in this area by the experts. In order to do a great job of analysing ECG data, you need better tools. Even though there are some problems, these computer methods are growing into very useful tools for making medical progress. For decades, simple on AI have been used in the area of heart electrophysiology (EP). Deep learning methods are becoming more popular again, and this has led to new developments in electrocardiography research, such as the ability to identify sick states by their signatures. Improvements in AI along with fast growth in computing resources, advances in sensors, and websites have led to the quick growth of AI-enhanced applications and big data study. Lifestyle changes, the growth of the internet of things, and improvements in telecommunications technology have made it possible to find atrial fibrillation in a community in ways that were not possible before. Improvements in 3D cardiac imaging made possible by AI opened the door to the idea of virtual hearts and the modelling of heart rhythms.

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