© April 2024 | IJIRT | Volume 10 Issue 11 | ISSN: 2349-6002

Advanced Diagnostic Approaches for the Cardiac Arrythmia

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Abstract—One important category of cardiovascular disorders is arrhythmias, and early identification and diagnosis are essential to averting high-risk incidents like sudden cardiac death. Even while automatic arrhythmia identification based on electrocardiogram (ECG) patches ,heart-beat sensor and body temperature sensors has garnered interest, Many heart patients in rural areas are unable to get the appropriate emergency treatment on time due to the limitations of the IoT wearable sensor connections with a reliable and accurate network. This paper provides a review that aimed to analyze Connectivity, Scheduling and Backup (CSB) components of IoT wearable sensors for smart healthcare. The IoT technology helps to connect the remote patients reliably by establishing the best network connection. This study compares important techniques with different IoT sensors used to detect the vital situations for remote cardiac health monitoring. In IoT health monitoring, The stored data in cloud will be of capable classifying the collected data from the sensors and generate two different signals as emergency and normal for the accurate data transmission. Moreover, WI-Fi is used to connect to the health caregivers with reliable connections. Finally, suitable algorithms will be taken for filtering the data before forwarding to a health center database. This provides appropriate analysis for network connection, data accuracy with scheduling and backup module for IoT health monitoring..

Index Terms—- Deep learning (DL), Random forest (RF), Support Vector Machine (SVM), K-nearest Neighbor (KNN), Electrophysiological, CSB .

I. INTRODUCTION

Cardiac arrhythmia refers to a variety of heart rhythm disorders in which the heartbeat is irregular, rapid, or sluggish. Arrhythmias come in a variety of forms, experienced when symptoms are present noticeable.
The integration of mobile communications with wearable sensors has facilitated the shift of healthcare services from clinic-centric to patient-centric and is termed as “Telemedicine”. In more extreme instances, light headache,fainting, Breathing, difficulties or pain in the chest might appear. While the majority of arrhythmias are unharmful, some can have catastrophic side effects including cardiac failure or stroke. Some of them might cause cardiac arrest. Arrhythmia affects millions of individuals throughout the world. Cardiovascular disease causes around 15% of all fatalities worldwide, or close to half of all deaths, are caused by sudden cardiac death. Ventricular arrhythmias account for approximately 80% of sudden cardiac death. Arrhythmias can affect people of any age, although they are more frequent as they get older. Arrhythmia affects millions of individuals throughout the world. Cardiovascular disease causes around 15% of all fatalities worldwide, or close to half of all deaths, are caused by sudden cardiac death. Further, although wearable technology has contributed heavily in the advancement of healthcare monitoring systems, concerns are there that may affect performance of the healthcare monitoring systems. These concerns include (1) failing to use real-time data in the monitoring systems during testing of application, (2) battery issues, (3) security and privacy of the data collected from patients, (4) requirement of medical professional’s recommendations at each step of the development, (5) clinical validation or experts’ acceptability, and (6) user friendliness for the patients and for healthcare professionals. The integration of wearable technologies with mobile networks can offer new potentials of rapid, reliable, and secure information transfer from patient to the doctor.

II. LITERATURE REVIEW

[1]Smart-IoT Business Process Management: A Case Study on Remote Digital Early Cardiac Arrhythmia Detection and Diagnosis
Author : Patricia Gómez-Valiente; Jennifer Pérez Benedí
In this study, we proposed an arrhythmic classification framework that combines ResNet with

SE block and biLSTM using the single-lead ECG data. The proposed architecture uses an augmentation method, in particular SMOTE, to solve the problem of imbalance between classification categories. The experimental results showed that the model with augmentation outperformed the model without augmentation on all overall classification metrics in all classification categories. In addition, an ablation study was performed to evaluate the effects of the architecture. SMOTE has the disadvantage that the augmentation effect can be minimized because baseline wander and noise could be added to the rhythm data. We used SMOTE as one of the data augmentation methods of the proposed framework. SMOTE obtained statistically higher performance when SMOTE was compared with ADASYN, ROS, and GAN. Nevertheless, there are still limitations; thus, further studies about effective augmentation methods of ECG data are needed in the future.

Methodology: Case study, Smart-IoT integration

Observation : Efficient early detection and diagnosis of cardiac arrhythmias remotely.

Limitation : SMOTE has the disadvantage that the augmentation effect can be minimized because baseline wander and noise could be added to the rhythm data.

[2]SRECG: ECG Signal Super-Resolution Framework for Portable/Wearable Devices in Cardiac Arrhythmias Classification

Author : Tsai-Min Chen; Yuan-Hong Tsai; Huan-Hsin Tseng

To support automatic clinical diagnosis and long-term smart healthcare services on P/W devices while incorporated with CE, this work develops a novel DL-based SRECG as a cloud processor to enhance low-resolution ECG signals sampled from low frequency for CAs classification of HMC to achieve better accuracy. In future work, we will not only further investigate the effect of training SRECG with compound loss using different lead sources and their combinations but also explore different preprocessing methods for SRECG. Since DL-based diagnosis of ECG signals has great potential in deciphering other physiological conditions, it is worth applying SRECG for P/W devices in other diagnostic criteria of healthcare, such as mortality and heart failure, in addition to CAs.

Methodology : Signal super-resolution, portable/wearable devices .

Observation : Proposed SRECG for enhanced ECG signal quality on portable/wearable devices for arrhythmia classification.

Limitation : In the absence of a systematic evaluation approach and the lack of standardized datasets, it is difficult to address these limitations at the present stage

[3] Three-Heartbeat Multilead ECG Recognition Method for Arrhythmia Classification

Author : Liang-Hung Wang; Yan-Ting Yu; Wei Liu; Lu Xu,2022

The study innovatively proposed a THML ECG recognition method for arrhythmia classification based on the dual-channel one-dimensional convolutional neural network (1D-CNN) model and the priority model integrated voting method. Under the inter-patient experiments, the results show that the overall average accuracy of the integrated model is 94.4%. Compared with the existing literature, this method can improve the classification accuracy in arrhythmia categories, proving the practicability and theoretical feasibility of the THML ECG signal that contains the important spatial and temporal characteristics of ECG signal.

Methodology : Multi-lead ECG Recognition.

Observation : Efficient arrhythmia classification with a recognition method based on three heartbeats in multilead ECG.

Limitation : The lack of ECG data samples is an important factor limiting the development of ECG recognition.

[4]The simulation was carried out on the 12-channel PhysioNet/Computing in Cardiology Challenge database. Such low rates are due to the lack of personalization of signals. In the PhysioNet/Computing in Cardiology Challenge database was also used for modeling.

Author : Basab Bijoy Purkayastha; Shovan Barma,2023

In this work, we have verified that the multifractal singularity spectrum derived from the embedded attractor of the ECG signal provides a quantitative measure of the complexities associated with cardiac dynamics. A nonlinear dynamical study is an efficient tool for extracting multifractal signatures from the ECG signal. We have demonstrated a classification technique capable of learning multivariate multifractal singularity spectra. The idea is derived from the ESN-

based model, a variant of the RC technique used for studying time series problems.
Methodology : Multifractal Analysis, Reservoir Computing
Observation: Successful discrimination of cardiac abnormalities using multifractal analysis in a reservoir computing framework. Developed high-speed and accurate CNNs for ICD and smart ECG devices
Limitation : There is no such significant groupwise clustering of data points for the different parameter planes. Memory limitations in hardware implementation should be examined because complex networks have a large number of parameters and will create hardware limitations, and a lot of memory should be considered for them.

By synthesizing findings from existing literature, a comprehensive review of cardiac arrest can contribute to our understanding of this critical medical emergency and inform clinical practice and research efforts aimed at improving patient outcomes.

III. PROPOSED SYSTEM

The current study addresses the issue of integrating a wearable sensor with mobile technology by developing a remote monitoring system for heart patients. In this study, we propose a location based real-time monitoring system comprising a wearable sensor, mobile application, and a web interface to overcome some of the issues, as mentioned in the literature. The wearable sensor has been used to generate patient's diagnostic information which is then transferred to a smartphone wirelessly via Bluetooth low energy technology. Further, the collected information on the smartphone is transferred to a web interface via Wi-Fi. The proposed system has the ability to generate emergency alerts on the basis of predefined values by comparing patient's data to inform the doctor if there is a requirement of checkup or investigation. Furthermore, various types of sensors have been used and results are compared to identify the most promising sensor providing most accurate results close to the systems. The developed system has been evaluated under the supervision of the experts The real-time monitoring system is compatible to use various wearable sensors to extract medical information which helps finding out multiple parameters such as heart rate, ECG rate , and body and skin temperature at the same time. These wearable sensors are becoming promising due to the fact that these sensors are low cost, easily available, user friendly, accurate, and reliable These cardiac parameters help early detection of diseases such as arrhythmia, sinus tarchardyia , left and right bundle block and hyperthermia through front end based system based.

IV. MATERIALAND METHODS

This study develops a remote monitoring diagnostic frame-work to detect underlying heart conditions in real-time which helps avoiding potential heart diseases and rehabilitation of the patients recovering from cardiac diseases. The proposed real-time monitoring system is compatible to use various wearable sensors to extract information which helps finding out multiple parameters such as heart rate, ECG rate and body and skin temperature at the same time. These cardiac parameters help early detection of cardiac abnormalities such as sinus , left bundle block, right bundle block , and hyperthermia through system based on values. Similar to the existing monitoring systems, the developed system has two interfaces, one for patients and other for the doctor. The patient interface is comprised of wearable sensors which extract medical information of the patients and transmit to an Android based listening port via WiFi. The listening port transfers this information to web server which processes data to show reports on doctor interface. Designing a real-time monitoring system for remote cardiac patients involves several key components, including sensors, data transmission protocols, data processing algorithms, and user interfaces. Here's a general outline of the materials and methods you might consider:

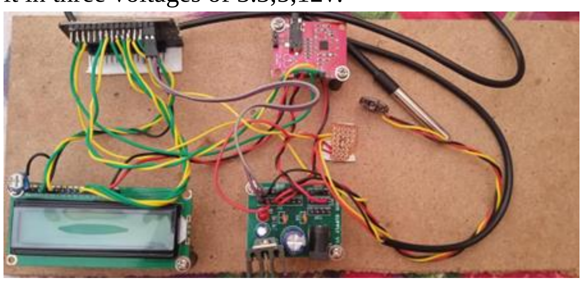
1. Sensors:
Electrocardiogram (ECG) Sensor: Measures the electrical activity of the heart. This sensor is a cost-effective board used to measure the electrical activity of the heart. This electrical activity can be charted as an ECG or Electrocardiogram and output as an analog reading.

Heart Rate sensor: The principle behind the working of the Heartbeat Sensor is Photoplethysmography. According to this principle, the changes in the volume of blood in an organ is measured by the changes in the intensity of the light passing through that organ Could be based on ECG or photoplethysmography (PPG) sensors.

1 -wired Temperature Sensor: Monitors the patient's body temperature. This is a pre-wired and waterproofed version of the DS18B20 sensor. Handy for when you need to measure something far away, or in wet conditions. While the sensor is good up to 125°C the cable is jacketed in PVC so we suggest keeping it under 100°C. Because they are digital, you don't get any signal degradation even over long distances

A.ESP32- Microprocessor with integrated Wi-Fi and Bluetooth. The good thing about ESP32, like ESP8266 is its integrated RF components like Power Amplifier, Low-Noise Receive Amplifier, Antenna Switch and Filters

B. Power Supply: It is used to provide power to all components. It will take 12v input voltage and convert it in three voltages of 3.3,5,12v.



2. Data Transmission:
Wireless Communication Modules: Such as Bluetooth, Wi-Fi, or cellular networks for transmitting data from sensors to a cloud monitoring system.
Encryption Protocols: Ensure data security and privacy during transmission in cloud.

3. Data Processing and Analysis:
Signal Processing Algorithms: To filter and analyze the sensor data, extracting relevant parameters such as heart rate variability, ST-segment changes, etc.
Machine Learning Models: Can be used for anomaly detection, prediction of cardiac events, and personalization of patient care based on historical data.

Real-time Monitoring Software: Develop software to process and display the data in a user-friendly interface for healthcare providers.

4. Cloud Monitoring System:
Server Infrastructure: Backend servers for storing patient data securely.
Database Management System: To store and manage patient records.

Web Application: Interface for healthcare providers to monitor patients' vital signs in real-time and receive display message on lcd display for any abnormalities in the patients.

By integrating these materials and methods, you can create a robust real-time monitoring system for remote cardiac patients, enabling timely intervention and improving patient outcomes.

V. IMPLEMENTION

5.1. System Architecture.
The system architect is three-tier comprising (1) a patient interface, that is, wearable biosensors (2) a web portal and (3) cloud monitoring the data as shown in Figure 1. The first tier of the system is patient's interface which consists of multiple wearable sensors used to collect medical information of the patient. This tier transmits real-time data wirelessly from wearable devices worn by the patient to second tier of the system via WiFi connection. The second tier consists of an Android smartphone used to extract patient's information from wearable sensors .Wireless networking has the ability to communicate with web portal or Wi-Fi networks. In third tier, Web portal is a platform that acquires the data of multiple patients wearing wearable sensors and displays them on web interface, also known as doctor's interface, along with personal information for identification. In this study, three types of wearable sensors are used to extract heart rate, ecg rate ,and body and skin temperature .

The proposed system has the ability to use multiple sensors which enables simultaneous monitoring of several heart parameters from multiple patients. The facility of using multiple sensors at same time to obtain required data increases applicability of the developed system and assists in comparing the accuracy of various sensors. The focus of this study is to develop a real-time diagnostic system for remotely located heart prone patients by measuring heart rate, blood pressure, and body temperature using wearable sensors. The measuring accuracy of the sensor has direct impact on accuracy of the heart rate measurement in real-time monitoring systems. Therefore, the selection of an accurate heart rate monitoring device is of prime importance in early detection of underlying heart diseases.

5.2. Web Interface: Web interface enables several physicians, doctors, and medical centers to view and diagnose patients' medical status simultaneously. However, to ensure data visibility only to authorized doctor/physician, web portal requires user ID and password.

Web interface is implemented using Larval PHP framework. The data from the listening port is presented to the doctor on web portal in order to check medical status of the patient. Web portal is an interface between doctor and patient .

5.2.1. Modules of Web Interface

Patient Data storing: This module consists of the patient's personal and medical records. Real-time data acquired by wearable sensors has been shown with respect to time. It contains the medical history of individual patient after getting registered at Android listening port device.

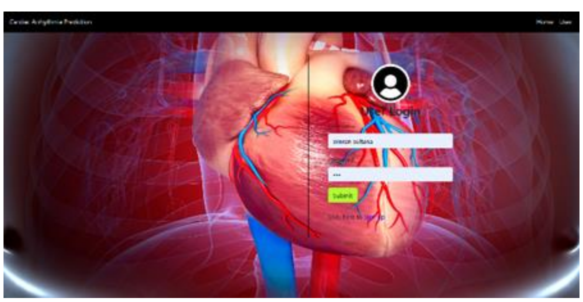


Fig 5.2 user login of patients

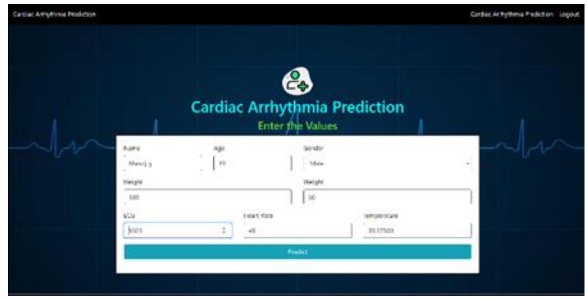
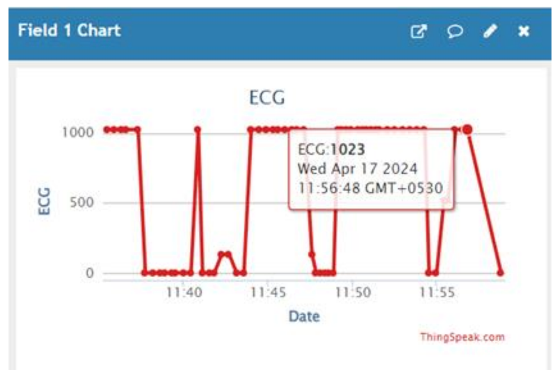
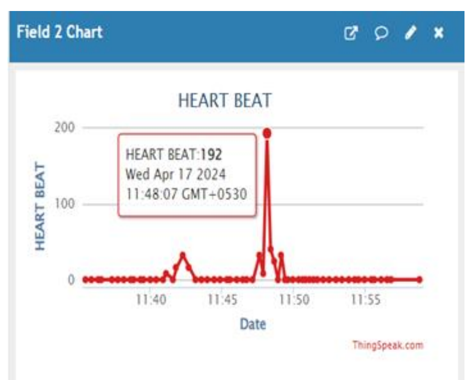


Fig 5.3 Input of patients data storing

Messages: This module contains notify messages generated at web based portal handheld listening port. Extracted physiological parameters give the signals after comparison with assigned threshold values. These notification signals indicate abnormalities like arrhythmia, sinus tarchardyia etc.





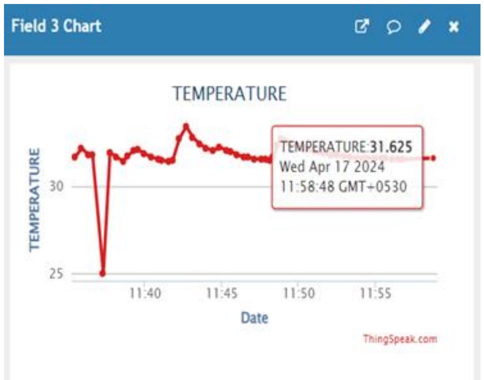


Fig 5.4 describes the monitoring of the ecg and heart beat and temperature system

- Cloud Monitoring System:

Cloud Monitoring System allows the involvement of the web application for diagnosing patients in as early as possible In case of large data from multiple patients, several doctors can get involved in monitoring and diagnosing processes. Here we are having the data of three sensors such as heart rate sensor ,ECG patches and the 1-wired temperature ,where it record the data instantly along with the particular values of individual data of the patients

The above fig shows the various variation of individual patients in all the three field.

- Body Mass Index:

BMI is a measurement of a person's leanness or corpulence based on their height and weight, and is

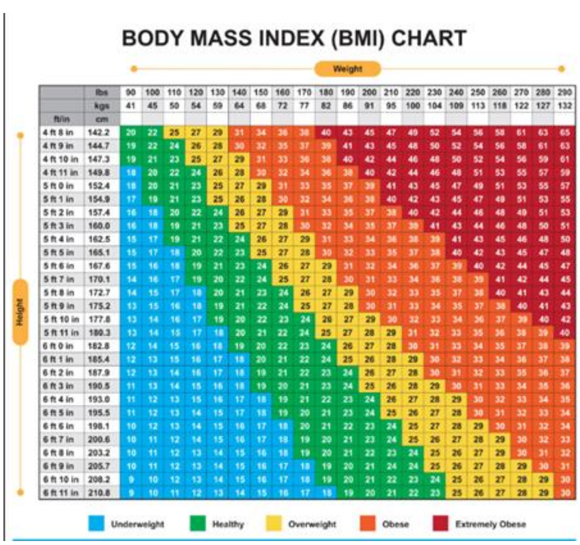


Fig 5.5 Body Mass Index Chart

intended to quantify tissue mass. It is widely used as a general indicator of whether a person has a healthy body weight for their height. Specifically, the value obtained from the calculation of BMI is used to categorize whether a person is underweight, normal weight, overweight, or obese depending on what range the value falls between. These ranges of BMI vary based on factors such as region and age, and are sometimes further divided into subcategories such as severely underweight or very severely obese. Being overweight or underweight can have significant health effects, so while BMI is an imperfect measure of healthy body weight, it is a useful indicator of whether any additional testing or action is required. By using this BMI Chart we can analysis the persons height and weight by there age .

VI. EVALUATION MATRIX

In the realm of attention value classification, ML algorithms assume a significant role. The evaluation matrix serves as a critical tool in assessing the performance of the entire model. Beyond merely predicting and monitoring seizures, the objective is to achieve optimal performance, elucidated through a Confusion Matrix.

This matrix offers a comprehensive overview of the model's effectiveness. Here is some of the definitions of confusion matrix:

[1] Accuracy: It measure the overall correctness of the model's predictions, calculated as the ratio of correctly predicted instances to the total number of instances. A higher accuracy indicates that the model is making more correct predictions

$$\text{Accuracy} = \frac{TCP+TNC}{TPCC+TNC+FPCC+FNC}$$

[2]. Precision: Precision measures the proportion of true positive predictions among all positive predictions made by the model. It indicates the model's ability to avoid false positives, meaning instances that were incorrectly classified as positive.

$$\text{Precision} = \frac{T\,P\,C}{TPC+ FPC}$$

[3]. Recall: Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive instances in the dataset.

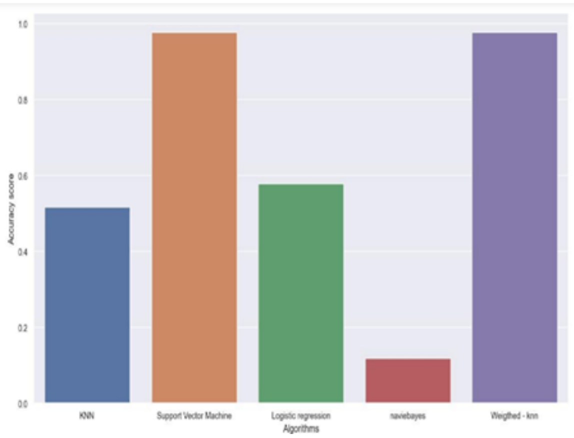
It indicates the model's ability to capture all positive instances without missing any.

$$\text{Recall} = \frac{TPC}{TPC + FNC}$$

[4]. F1-score: F1-score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is particularly useful when there is an imbalance between the number of positive and negative instances in the dataset.

$$\text{F1-score} = = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Recall} + \text{Precision}}$$

A. Performance Analysis:



These metrics provide different perspectives on the model's performance, with accuracy giving an overall measure, precision and recall focusing on specific aspects of prediction correctness, and F1-score providing a balanced measure of precision and recall. In this study, we introduce a novel approach to classify heartbeats, termed "heartbeat dynamics." This feature offers a comprehensive analysis of heartbeats, particularly sensitive to subtle variations. We assess its efficacy in heartbeat classification using three conventional classifiers: KNN, SVM, and RF. Our results demonstrate exceptional performance, achieving 99.41% accuracy, 99.10% precision, 98.84% recall, and a 0.9897 F1-score with KNN on the original dataset. Importantly, experiments on both original and balanced datasets reveal that heartbeat dynamics effectively discerns between different heartbeat classes, irrespective of data balance. This suggests that the proposed feature has promising implications for enhancing the generalization capacity of heartbeat classification systems

CONCLUSION

Increasing rate of Cardiac-diseases in aging population is becoming a serious concern due to lack of sufficient facilities and extremely high cost of lab test. The situation is even worse for the people residing in remote areas far from medical facilities as delay in diagnosis and treatment may lead to death. Timely diagnosis and treatment can solve these issues to a great extent. In this study a real-time heart monitoring system for heart patients located in remote areas has been proposed. The developed system is comprised of wearable sensors, Android handheld device, and web interface. The system is adaptable and has the ability to extract several cardiac parameters such as heart rate, blood pressure, and temperature of multiple patients simultaneously. The extracted data is being transmitted to Android handheld device using Bluetooth low energy which is then transmitted to web application for further processing. Web application processes received data to show medical status of the patient along with personal information such as age, gender, address, and location on web interface. To evaluate its efficiency for arrhythmia classification, we conducted experiments on the public peoples, using three classical classifiers: k-nearest neighbor (KNN), random forest (RF), and support vector machine (SVM). These results indicate that heartbeat dynamics has a strong ability to discriminate between different classes of heartbeats and detect the heart problem based on the sensors

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