MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert

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Abstract

Smart healthcare which is built as healthcare Cyber-Physical System (H-CPS) from Internet-of-Medical-Things (IoMT) is becoming more important than before. Medical devices and their connectivity through Internet with alongwith the electronics health record (EHR) and AI analytics making H-CPS possible. IoMT-end devices like wearables and implantables are key for H-CPS based smart healthcare. Smart garment is a specific wearable which can be used for smart healthcare. There are various smart garments that help users to monitor their body vitals in real-time. Many commercially available garments collect the vital data and transmit it to the mobile application for visualization. However, these don't perform real-time analysis for the user to comprehend their health conditions. Also, such garments are not included with an alert system to alert users and contacts in case of emergency. In MyWear, we propose a wearable body vital monitoring garment that captures physiological data and automatically analyses such heart rate, stress level, muscle activity to detect abnormalities. A copy of the physiological data is transmitted to the cloud for detecting any abnormalities in heart beats and predict any potential heart failure in future. We also propose a deep neural network (DNN) model that automatically classifies abnormal heart beat and potential heart failure. For immediate assistance in such a situation, we propose an alert system that sends an alert message to nearby medical officials. The proposed MyWear has an average accuracy of 96.9% and precision of 97.3% for detection of the abnormalities.

Index Terms

Smart Healthcare, Healthcare Cyber-Physical System (H-CPS), Internet-of-Medical-Things (IoMT), Smart Garment, Smart Home, Heart Condition, Stress, Medical Data Security.

I. Introduction

The Internet-of-Medical-Things (IoMT) based healthcare Cyber-Physical System (H-CPS) has made smart healthcare possible with enhanced quality of care and faster diagnosis [1]–[3]. Smart healthcare is now omnipresent, in the form wearables and implantabale devices with connectivity to have perpetual and continuous body vital monitoring, as it has significant capability to improve quality human life [4]–[6]. It is well understood that IoMT based H-CPS that makes smart healthcare is more important with the current pandemic scenario. With the introduction of the IoMT, integration of multiple sensors has enabled applications and devices to work efficiently and effectively. IoMT devices are usually connected to the network either by wired or wireless communication means. Smart healthcare is already being effective in fitness tracking and has potentials to revolutionize many aspects, from continuous body health monitoring to performing automatic analysis of electrocardiogram (ECG/EKG) and computed tomography (CT) scan.

Smart healthcare can allow doctors to remotely monitor patients based on their fitness tracker data [7]–[9]. Wearable such as smartwatches allow users to record ECG/EKG from the wrist and share a copy of the report to doctors for assistance and opinion. Most of the hospitals around the globe use body vital systems that backup the data in real-time in the cloud for doctors to monitor by sitting at home. IoMT-based H-CPS helps in collecting several vitals that describe the health of the person and transmit them to the cloud for post processing. The introduction of IoMT in wearable devices has unlocked various applications in areas such as self healthcare, fitness and yoga.

In the world of wearable technology, fitness trackers have been the part of our lives. Millions of people around the globe use wrist-worn fitness trackers [10]. People are using fitness trackers to keep track of their daily activities and fitness routine. Millions use wearable IoMT technology that keeps track of both physical and mental health [11]–[13]. In many cases the use of home based healthcare monitoring devices require the user to be rested and the devices used to record vitals. With the upcoming technologies such as bio-medical textiles and devices that can be worn by the user, making him/her free to move around. Many such wearable garments are being used by sports teams and athletes to improve their performance by analyzing body musculoskeletal data recorded by the garment [14].
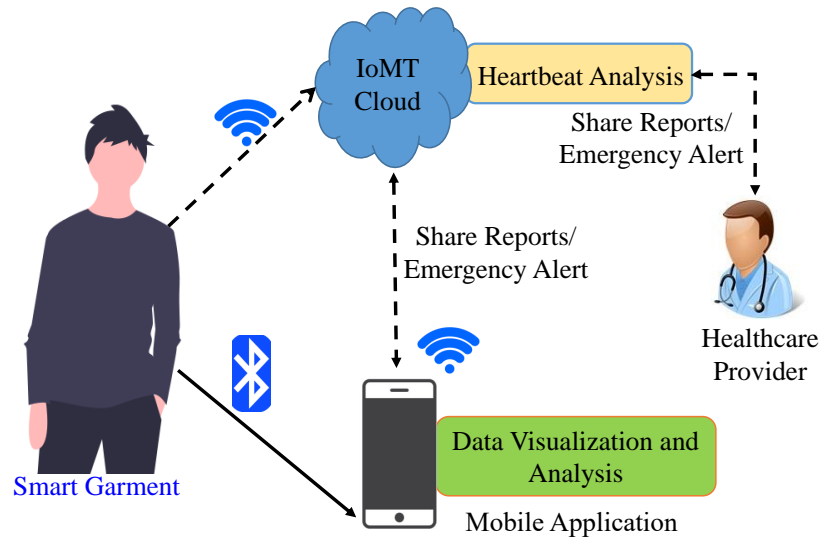

Figure 1. A thematic overview of the proposed MyWear.

Many fitness enthusiasts are using garments that have embedded sensors to suggest whether the workouts or yoga is performed efficiently. These garments also analyze physiological data with equipped GPS modules that track the user's location [15], [16]. With body vital data, fitness trainers, yoga instructors and doctors can modify the workout plan to favor a particular individual. The same data can be used for nutritionists and dietitians to analyze the body metabolism and accordingly plan the diet. Wearable garments are being developed not only to monitor ECG but also the activity the user is performing while wearing them [17]. Law enforcement personnel and armed forces are using wearable medical devices to analyze the stress and health of the soldiers and policemen throughout the day. The data collected provides insights on the lifestyle of the person. In the current work, we envision an wearable called MyWear which is depicted in Fig. 1 that can continuously monitor stress, heart conditions, muscle activities, and fall. With detailed analysis of the body and its muscle activity, analysts are helping athletes and teams perform and build better.

Rest of the paper is organized as follows: Section III explains the contributions made in this paper. Section II discusses about the existing related research. Section IV provides the system level architecture. Section V discusses the method proposed for automatic heart rate and stress. Section VI presents our

method for detecting heart arrhythmia. Section VII presents our method for automatic detection of fall. Section VIII explains the specific design of the proposed MyWear system along with the its validation through the results of the proposed MyWear system and also provides a comparative analysis with the state of the art similar wearables. Finally, the paper concludes in Section IX with brief discussions on future directions.

II. RELATED PRIOR RESEARCH

Consumer electronics to build smart healthcare is an active research area as evident from the fact that we see increasing more healthcare features are available in wearable and smart phones. The research on consumer electronics for smart healthcare has been undertaken in many fronts including stress management [18], diet management [19], assisting visually impaired individuals [20] and wearables focusing on women's health [21], hearing aids [22], and garments [23]. A consumer electronic device that can automatically quantify calorie intake as well as stress of an user is available [19]. Heart rate estimation using a photoplethysmography (PPG) based device was presented in [24] that deployed neural networks. A framework that can automatically monitor stress level from the physical activities was proposed in [18]. A smart watch for continuous monitoring of data in a privacy-assured manner was presented in [25]. A ECG signal analysis method using discrete cosine transformation (DCT) has been presented in [26]. A semi-automated IoMT-enabled diet management was discussed in [27]. A framework for detection of elderly fall and ECG abormality detection was presented in [28].

Table I
MYWEAR AS COMPARED TO SIMILAR WORKS IN CONSUMER ELECTRONICS.

Consumer Electronics	Real-Time HRV	Muscle Activity Detection	Abnormal Heartbeat Detection	Stress Level Detection	Fall Detection	Fall Prediction	Built-in Alert	Data Security
Puranik et al. [24]	Yes	No	No	No	No	No	No	No
Garment in [29]	Yes	No	No	Yes	Yes	No	No	No
Raj et al. [26]	Yes	No	Yes	No	No	No	No	No
Garment in [30]	No	Yes	No	Yes	Yes	No	No	No
Wang et al. [28]	Yes	No	Yes	No	Yes	No	No	No
Farjadian et al. [31]	No	Yes	No	No	No	No	No	No
Pandian et al. [14]	No	No	No	No	No	No	No	No
MyWear (Current Paper)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table I presents a comparative perspective of similar consumer electronics as the proposed MyWear of the current work. There are few smart wearable garments that can monitoring human body vitals in real-time [23]. Smart wearable garment in [30] uses surface electromyography (sEMG) to analyze the intensity of muscle activity of athletes. However, there is no HRV analysis observed in the training system to detect stress levels of the user. A consumer products [29] analyzes sleep activity and ECG for heart rate variability (HRV) analysis. However, it does not examine the muscle activity of the user. Garment in [31] use electromyography (EMG) to detect muscle activity and assist the user in physical therapy. There are few proposed solutions that use accelerometer data to analyze the intensity of exercises, however, it cannot be used in calculating individual muscle activity in comparison to using sEMG. Moreover, no accurate

measurement of the body orientation of the user is observed in the above mentioned wearables. There was no alert system observed in the above-mentioned garments, that notifies users contacts, paramedic forces in case of emergency after detecting any abnormalities.

III. Contributions of Current Paper

To the knowledge of the authors MyWear is the first smart garment to introduce an integrated mechanism for automatic HRV analysis, stress analysis, muscular activity analysis, and alert system to seek assistance in emergencies while providing data security.

A. Problem Formulation

We intend to address the following health conditions through the research and development of MyWear:

- How can health condition be automatically monitored and healthcare provider be notified?
- How can heart abnormalities be automatically detected from the ECG signal?
- How can stress be automatically detected from the ECG signal?
- How can muscle activity be automatically detected?
- How can fall of an individual be automatically detected?

B. Proposed Solution of the Current Paper

MyWear provides following novel solutions to the research objective stated above:

- An automated continuous health monitoring system by collecting body vitals in regular intervals of time, store it in a secured fashion and alert healthcare providers.
- A cloud based platform for user and healthcare providers to monitor previous logs and current routine in real-time.
- A novel automatic method to automatically analyze stress levels using Electrocardiogram (ECG) signal in real-time.
- A novel method to detect heart abnormality arrhythmia using Electrocardiogram (ECG) signal in real-time.
- A novel automatic method to determine fall of the user.

C. Novelty and Significance of the Proposed Solution

The novelty and significance of the proposed solutions include the following:

- A novel wearable that can automatically perform heart rate monitoring, heart arrhythmia, stress monitoring, and fall detection for a complete healthcare solution.
- A secured smart garment with an automated body vital data logging system to the cloud and mobile application.
- ECG signal analysis using deep learning model to detect different types of abnormalities in heartbeat that is not observed in any of the smart garments.
- Real-time stress detection using Heart Rate Variability (HRV) from ECG which is not present in most of the smart garments.

IV. System Level Architecture of the Proposed Framework

We present our vision of Internet-of-Medical-Things (IoMT) based healthcare Cyber-Physical System (H-CPS) with the proposed smart garment MyWear integrated in it. MyWear can be with 3 different options depending on where the computation happens and where the intelligence is built in [19], [32], [33]: (1) IoT-end device in-sensor computing, (2) IoMT-edge/fog computing, and (3) IoMT-cloud computing

paradigm. In option-1, IoMT-end device with all the sensors and models integrated in it, while IoMT-cloud stores data and diagnostic results [34]. In this option, IoMT-end device need to have a bit higher level of computational capability and battery life than the usual sensors to present results instantaneously to the user. Also, with the use of light-duty machine learning models (i.e. TinyML) it can be possible with limited computational and battery resources at the IoMT-end device [35]. In Option-2, the ML models are part of IoMT-edge devices like edge routers and edge datacenters (EDC) for faster response to the users [36]. In Option-3, heavy-duty accurate ML models can run in IoMT-cloud to detect the health conditions. Thus, Option-2 with IoMT-edge is a good trade-off accuracy and fast response. A more effective option is to have TinyML models in IoMT-sensor for fast response and at the same time have another health condition evaluation at IoMT-cloud before sending alarm to healthcare providers.

A. Proposed Healthcare Cyber-Physical System (H-CPS) using our Smart Garment

The complete overview of the proposed system in H-CPS framework is depicted in Fig. 2. The garment acts as the IoMT-End device and the input point for the mobile application and cloud service. Surface dry electrodes are embedded in the garment keeping in mind the optimal position to obtain stable signals. The dry electrodes are connected to the respective ECG and EMG sensors. These sensors extract, amplify and filter the raw signals therefore removing noise and unwanted artifacts. The filtered data is sampled by sampling unit along with the data received from the temperature and Inertial Measurement Unit (IMU) sensors. The temperature sensor measures the body temperature whereas IMU sensors measure the change in body orientation. Collectively, data is transmitted to the mobile application and cloud for further analysis using the embedded Bluetooth and Wi-Fi module, respectively. The vital data is AES128 encrypted and can only be decrypted or accessed in the user's mobile application. Thus, keep the body vital data safe and secure, only readable by the owner/user. The mobile device displays ECG in real-time along with the stress level of the user. The mobile application visualizes muscle activity in different muscle regions on the human map pertaining to the individual along with the body orientation and body temperature. The application allows the user to share Data with medical officials for further analysis and assistance. Meanwhile, the ECG data transmitted to the cloud is analysed to detect any abnormal Heartbeats. The proposed Deep Learning model deployed in the cloud checks for any abnormalities and detects the kind of abnormality that occurred. In case of emergency, an alert is sent to medical officials for immediate assistance. Moreover, the body vital data received in the cloud can be monitored by medical officials in real-time.

MyWear gathers body vitals such as Heart Rate, body temperature, muscle activity and sends it to IoMT-edge and IoMT-cloud through Internet. The smartphone acts as an interface to visualize data post analysis for users information. The deep learning (DL) model in the cloud analyzes the user's ECG and stress level. It also returns a report to the user's smartphone for the user to access. The *main objectives of MyWear* are the following:

- To create an automated health monitoring wearable that analyzes the user's body vitals regularly.
- To provide a solution that analyzes a user's stress level based on Electrocardiogram.
- To bridge the communication between User and medical officials, real-time user monitoring system to allow doctors, therapists to analyze the user's routines.
- To create an alert system to call for help in case of emergency.

B. Architecture of the Proposed Smart Garment

Fig. 3 shows the architecture of the proposed smart garment. The garment (called MyWear) is embedded with dry electrodes that are connected to ECG and EMG sensors. The sensors extract, amplify and filter the raw signals captured by the dry electrodes. The filtered data is sampled by sampling unit along with the data received from Temperature and IMU sensors. The data is then transmitted to the smartphone and
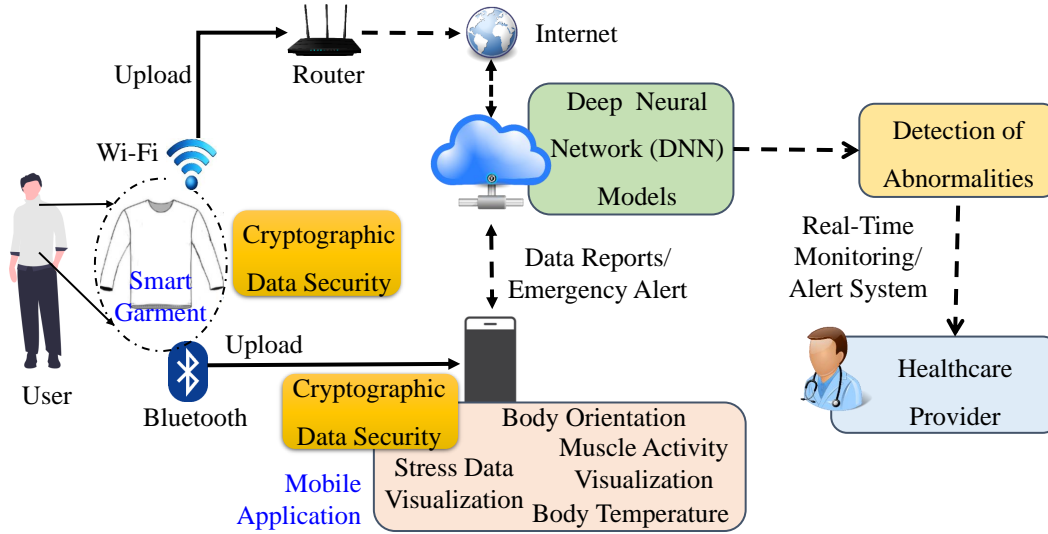
Figure 2. A detailed architecture of the proposed MyWear in a Healthcare Cyber-Physical System (H-CPS) framework.

cloud server for storage and analysis. The received ECG data is used to analyze user stress levels and heart rate as discussed later. The analyzed outcome along with a report is sent to the smartphone application for the user to comprehend. The filtered muscle data received at the smartphone application end is used to visualize on the human map. The application also displays the body orientation and temperature of the user. The user can also grant access to cloud data for doctors, therapists and anyone to monitor on a real-time basis. In case of emergency, an alert message is sent to contacts and paramedic forces for immediate assistance.
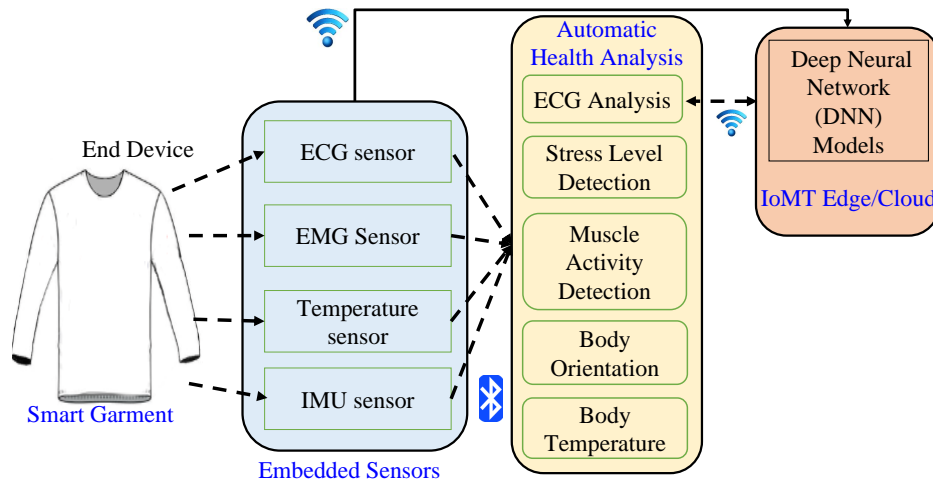

Figure 3. Architecture of the proposed Smart Garment (MyWear).

C. Electrocardiogram (ECG) Acquisition Unit for Heart Rate

Electrocardiogram (ECG) is a technique used to measure the electrical activity produced by the heart during a diastole and systole (relaxation and contraction). ECG is a reliable method to measure the heart rate variability and beats per minute (BPM) [37]. For convenient use, a 3 electrode system is used. The

electrodes are placed following the Einthoven's triangle (refer Fig. 4(a)), which depicts the placement of electrodes to obtain stable ECG [38], [39].
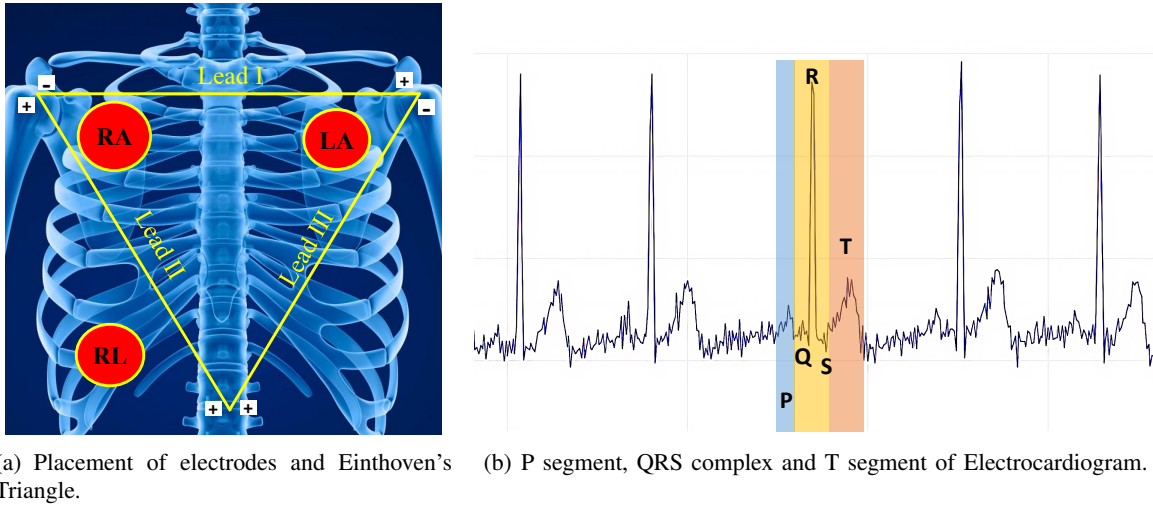

(a) Placement of electrodes and Einthoven's Triangle.

(b) P segment, QRS complex and T segment of Electrocardiogram.

Figure 4. Einthoven's Triangle based electrode placement and P segment, QRS complex and T- segment of ECG.

D. Eulers Angle Unit Using Inertial Measurement Unit (IMU) Sensor

MyWear is embedded with an Inertial Measurement Unit (IMU) sensor. It measures and provides details on orientation and velocity of a particular entity with the use of accelerometers and gyroscopes. IMU detects rotational movements and acceleration of the Euler angles, also known as yaw, pitch and roll. The gyroscope measures angular velocity which defines the rate of change of angle with respect to x, y and z axes. The accelerometer defines the velocity at which the entity is rotating in a particular axis.

E. Electromyography (EMG) Unit

Electromyography (EMG) is used to measure the change in electric potential that depicts the force exerted by the muscle. For ease of use, a three-electrode system is used to measure the muscle activity at a particular muscle region. Two electrodes are used to measure the muscle signal and the third electrode acts as a ground. Initially, the sensor is tuned by changing the gain. The gain helps in adjusting the sensitivity of signal acquisition to capture stable signals with low noise. EMG helps in understanding the muscle activity and its intensity in a muscle region. EMG is used to measure the change in electric potential generated at neuromuscular junctions as electric signals or action potential pass through. Clinical settings of EMG use a needle that is inserted into the muscle. For measuring ECG on the go and better ease of use, surface EMG is chosen [40], [41]. Surface EMG uses electrodes that measure overall activity of a large portion of the muscle. The activity is measured in voltage and represents the amount of force exerted by the muscle in real-time. MyWear records muscle activity at the biceps or biceps brachii and at the chest or pectoralis major.

F. Body Orientation Detection Unit

Upon Calibration of the Euler's angle to the initial position of the user, the change in angles is recorded and defined for a few positions such as bending is four directions: right, left and forward, back. The user is prompted with the text in the application that shows the orientation of the user as shown in Fig. 8(b). Body orientation provides insights into a person's activity.

G. Emergency Alert Unit

The ECG data is sent to the model to detect any abnormalities. The proposed deep Learning model detects any abnormalities if any. Detected abnormalities are sent as an alert to the users mobile application and the medical official. Regular intervals of Abnormalities are usually considered to cause a potential heart failure and hence, a prompt is sent to the users smartphone application and triggers an alarm. Another alert is sent to Medical officials and doctors for immediate assistance.

H. Data Security Unit

Privacy and Security play a major role when handling Body vital or Health Data. Health data when misused can pose serious privacy and security violations and eavesdropping. In order to keep user's data safe and secure, the body vitals data is AES128 encryption enabled. Advanced Encryption Standards (AES) is an encryption method which uses a 128-bit block with key size of 128bits. It functions on a symmetric algorithm wherein the key is used to encrypt and decrypt data. Before transmitting data from Arduino to Application. The collected data from all sensors is encrypted using AES128 with the predefined key. The key is unique to a particular garment, mobile device and is assigned by the mobile application when pairing and registering initially. Any other device with installed application will not be able to access and receive the sensors data. Once the encrypted data is transferred to assigned application, the data is decrypted with the pre-defined key.

V. PROPOSED METHODS FOR AUTOMATIC HEART RATE AND STRESS MONITORING FROM ECG

A. Proposed Method to Obtain Heart Rate from ECG

Fig. 4(b) shows what an ECG graph would look like and its features. Every beat of the heart corresponds to a P-QRS-T waveform in the graph and collection of multiple waveforms depicts the successive beats in a period of time. As seen in Fig. 4(b), the 'P' wave or bump that precedes the QRS complex represents the depolarization of the atria which tends to brief isoelectric period or state of near zero voltage.

The P wave lasts no more than 0.10 seconds and 2.4 mm tall. P wave is followed by the QRS complex. QRS complex consists the rapid succession of three waves i.e. 'Q' wave, 'R' wave and 'S' wave. The QRS complex represents the activation of ventricular muscles that contract the heart. The normal duration of the QRS complex is between 90 milliseconds and 100 milliseconds. The R wave is usually a peak and positive unlike Q and R wave. The 'T' wave follows the QRS complex and indicates ventricular repolarization that leads to relaxation of the heart. This repeats for every single beat of the heart. The heart rate is measured in beats per minute as the following:

$$\text{Heart Rate } (bpm) = \left(\frac{60}{T_r}\right), \tag{1}$$

where T_r = time between two successive R peaks.

To calculate the time between two successive 'R' peaks, the time at which first and second peaks occurred is saved. Subtracting the first peak time from second peak time results in RR-interval time. Beats per minute are obtained as follows:

$$\text{Heart Rate } (bpm) = \left(\frac{1.0}{RRinterval}\right) \times 60.0 \times 1000, \tag{2}$$

where RR intervals are used for Heart Rate Variability (HRV) analysis to detect the stress levels of the user.

B. Metrics for obtaining Heart Rate Variability (HRV) score

1) Time-domain metrics: HRV score can be calculated by measuring the time between two successive RR intervals using Time domain metrics as shown below:

a) MeanRR: Average of all RR intervals (distance between two 'R' peaks) is calculated using the following expression:

$$MeanRR = \left(\frac{\sum\limits_{i=1}^{n} R_i}{n} \right).$$ (3)

b) Standard Deviation of RR intervals (SDNN): The standard deviation of RR intervals (also known as NN-interval) is calculated by using the following expression:

$$SDNN = \sqrt{\frac{\sum\limits_{i=1}^{n} (R_i - mean)^2}{n}}.$$ (4)

c) Root Mean Square of Successive Differences (RMSSD): The root mean square of two RR intervals' differences is calculated using the following expression:

$$RMSSD = \sqrt{\frac{\sum\limits_{i=1}^{n-1} (R_i - R_{i+1})^2}{n - 1}}.$$ (5)

2) Frequency-domain metrics: HRV score can be calculated by measuring the low and high frequency heart beats. Poincare plot is a reliable frequency domain metric among other metrics to visualize HRV. The algorithm plots two successive RR intervals and depicts how well each RR interval predicts the consecutive RR interval.

C. Proposed Method to Automatically Monitor Stress from ECG

Fig. 5 shows the algorithm to calculate stress level using Heart rate. RMSSD is usually obtained from ECG and is considered as the HRV score [42]. Studies have shown that an increase in HRV depicts a reduction in stress levels [43] and vice versa. High HRV score was found in users performing optimal levels of fitness routine. However, sometimes, during strenuous exercise, low HRV scores were noted because of the body trying to increase the user's heart rate for the activity. A user achieves a high HRV score during sleep as the result of state of relaxation and low stress levels. HRV score changes depending on the user's activity. Apart from HRV, ECG can also be used to detect Heart Arrhythmia. Table II shows the relation between HRV score and stress levels [44].

Table II
RELATION BETWEEN HRV SCORE AND STRESS LEVELS [44].

HRV Score	Stress Level
90+	Very low
80-90	Low
71-80	Moderate
61-70	Average
<60	High

VI. PROPOSED DEEP NEURAL NETWORK (DNN) MODEL FOR AUTOMATIC DETECTION OF HEART ARRHYTHMIA

An arrhythmia is a disorder of the heart that affects the rate or rhythm at which the heart beats. This takes place when electrical impulses that direct and regulate heartbeats don't function properly. As a
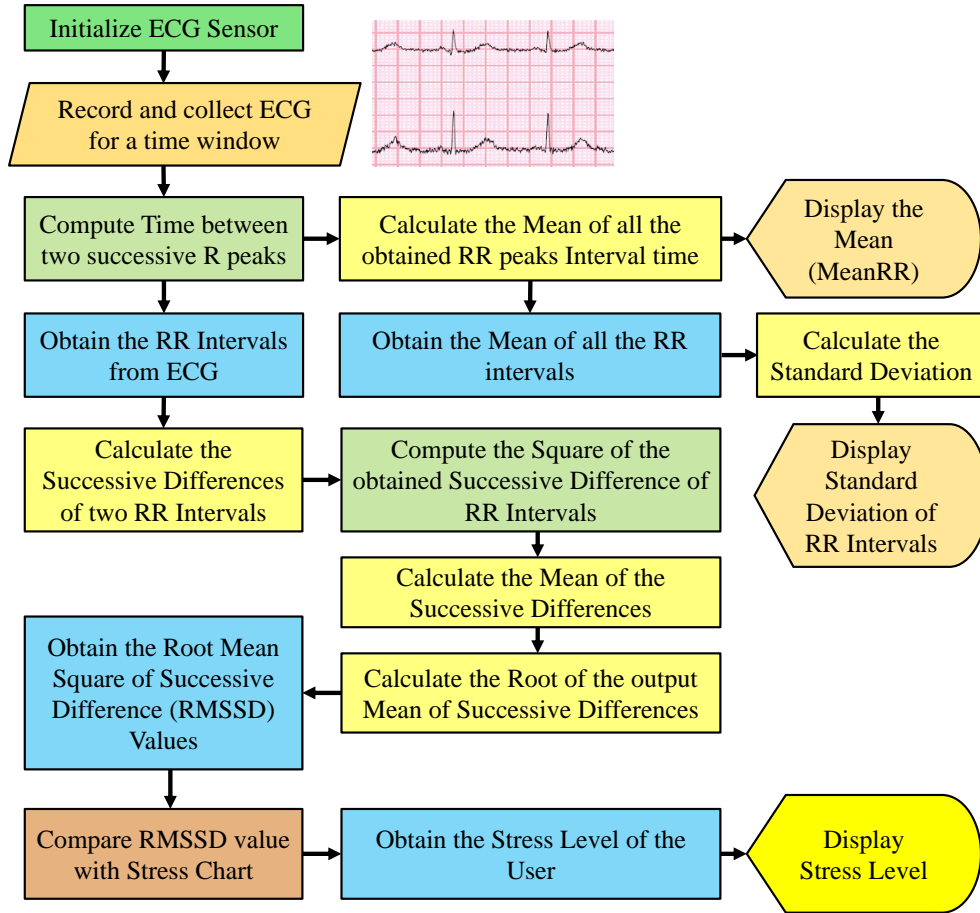
Figure 5. Proposed approach for calculating stress level from the heart rate.

result the heart may be too fast (tachycardia), too slow (bradycardia), too early (premature contraction), or too erratically (fibrillation). Thus, it is of critical importance to determine such conditions automatically and in real-time. We present a Deep Neural Network (DNN) model based method that is integrated in MyWear for the automatic determination of arrhythmia and corresponding automatic warning to healthcare provider.

A. Proposed DNN Model for Heart Arrhythmia

Fig. 6 shows the architecture of the proposed deep learning model. The proposed learning model consists of 6 one-dimensional convolutional layers with 64 filters each and input stride length of 2 and uses Rectified Linear Unit function (ReLU) activation function. Every convolutional layer is succeeded by the Maxpool layer of pool size 2 and stride size 2. The set of Convolutional layers is connected to 3 Fully Connected Layers. Finally, a softmax function is used in the output layer to predict probabilities of individual classes. The model is used to classify the dataset into four categories based on the heart beat rhythm and predict whether the input heart beat is normal or consisting of abnormalities. The activation function used in every layer is ReLU which is represented as follows:

$$f(x) = \begin{cases} 1 & x > 1 \\ x & x = 1 \text{ and } 0 \\ 0 & x < 0 \end{cases} \tag{6}$$

The output layer connected to the fully connected layer of n neuron. The predicted classification of heartbeats for a sample x is denoted by the Softmax function [45] defined as the following expression:

$$f_n\left(x\right) = \left(\frac{e^{(W_n h_x \, + \, b_k)}}{\sum\limits_{j=1}^{K} e^{(W_j h_x \, + \, b_j)}} \right)(n \;=\; 0, ..., n-1),\tag{7}$$

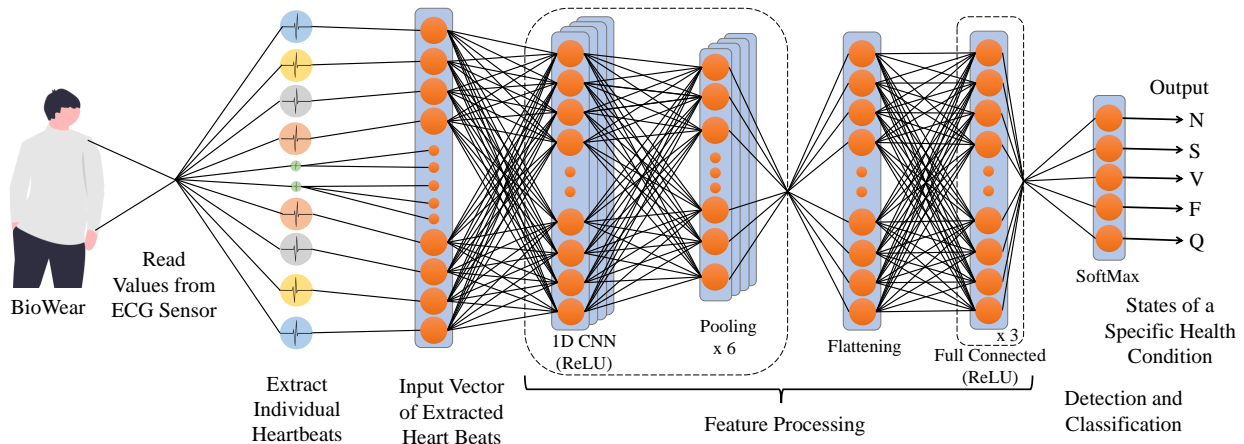where h_x is the feature representation of x extracted from the previous convolutional layer, W_k and b_k from nth neuron in the output layer.

Figure 6. Deep Neural Network (DNN) Model model explored for our MyWear.

B. Metrics for evaluating the DNN Model

The metrics used for evaluating the proposed DNN model are precision, recall, accuracy and loss [19]. In order to evaluate these metrics, there are four basic errors that describe the metrics which are to be defined. The errors are calculated as follows:

- *True Positive (TP)*: Heart beats that belong to the truth class and predicted as belonging to the same class
- *True Negative (TN)*: Heart beats that do not belong to the truth class and predicted as not belonging to the same class.
- *False Positive (FP)*: Heart beats that do not belong to the truth class and predicted to not belonging to the same class
- *False Negative (FN)*: Heart beats that belong to the truth class and predicted as not belonging to the same class.

These metrics that are used to evaluate the DNN model are the following:

- *Precision*: The ability of the model to identify the possible heart beats from the input:

$$P \;=\; \left[\frac{TP}{TP + FP} \;*\; 100\% \right].\tag{8}$$

- *Recall*: The ability of the model to identify all the relevant heartbeats from the predicted possible heartbeats:

$$R \;=\; \left[\frac{TP}{TP + FN} \;*\; 100\% \right].\tag{9}$$

- *Accuracy*: The ratio of correct predictions made by the model to the total number of predictions by the model:

$$\alpha = \left[\frac{TP \ + \ TN}{TP + TN \ + \ FP \ + FN} \ * \ 100\% \right].$$

(10)

C. Preparation of Dataset

In order to detect abnormalities in ECG, a dataset with classification of heartbeats into normal beats, Ventricular and Supraventricular beats along with Fusion beats and Unknown beats is considered. The MIT-BIH Arrhythmia Dataset [46] is used that contains 48 half an hour excerpts of two channel ECG with over 150,000 samples. The proposed model is trained on 100,000 and tested on approximately 22,000 samples. The sample information that is being considered in MyWear is described in Table III.

Table III
DIFFERENT HEARTBEAT INFORMATION CONSIDERED FOR CLASSIFICATION.

Characteristics	Specifics
Number of samples	100,000
Sampling frequency	125Hz
Classes	Normal, Supraventricular, Ventricular, Fusion, Unknown

VII. PROPOSED METHODS FOR AUTOMATIC MUSCLE ACTIVITY DETECTION, AND FALL DETECTION AND PREDICTION

Electromyography (EMG) helps in understanding the muscle activity and its intensity in a muscle region. EMG is used to measure the change in electric potential generated at neuromuscular junctions as electric signals or action potential pass through. Clinical settings of EMG use a needle that is inserted into the muscle. For measuring ECG on the go and better ease of use, surface EMG is chosen [40], [41]. Surface EMG uses electrodes that measure overall activity of a large portion of the muscle. The activity is measured in voltage and represents the amount of force exerted by the muscle in real-time. MyWear records muscle activity at the biceps or biceps brachii and at the chest or pectoralis major.

A. Proposed Method for Muscle Activity Automatic Detection from Electromyography (EMG)

EMG is used to measure the change in electric potential that depicts the force exerted by the muscle. For ease of use, a three-electrode system is used to measure the muscle activity at a particular muscle region. Initially, to capture stable signals with low noise, the sensor is tuned by changing the gain. The gain helps in adjusting the sensitivity of signal acquisition. EMG helps in understanding the muscle activity and its intensity in a muscle region. EMG is used to measure the change in electric potential generated at neuromuscular junctions as electric signals or action potential pass through. Clinical settings of EMG use a needle that is inserted into the muscle. For measuring ECG on the go and better ease of use, surface EMG is chosen [40], [41]. Surface EMG uses electrodes that measure overall activity of a large portion of the muscle. The activity is measured in voltage and represents the amount of force exerted by the muscle in real-time. MyWear records muscle activity at the biceps or biceps brachii and at the chest or pectoralis major.

B. Proposed Method to Calculate Body Orientation

In order to determine the body orientation. The sensor is calibrated with the user's initial position and orientation. The increase or decrease in the Euler's angle determines the change in body orientation of the user. Upon initializing the sensor, it provides the X, Y and Z values, however, these values depend on

the sensitivity. The default sensitivity is -2g to +2g. To calibrate the sensor, offset values are initialized. Initial position or offset values are recorded when the person is stood up straight and still. These values are written in X, Y and Z axis offset registers. After calibration, the user's movements are measured as X_{out}, Y_{out} and Z_{out}. Roll, Pitch and Yaw values are calculated using the following expressions [47]:

$$Roll, \rho = arctan \left(\frac{Y_{out}}{\sqrt{(X_{out})^2 + (Z_{out})^2}} \right) \tag{11}$$

$$Pitch, \phi = arctan \left(\frac{X_{out}}{\sqrt{(Y_{out})^2 + (Z_{out})^2}} \right) \tag{12}$$

$$Yaw, \theta = arctan \left(\frac{\sqrt{(Y_{out})^2 + (X_{out})^2}}{Z_{out}} \right) \tag{13}$$

These values define the change in the X, Y and Z values from the calibrated values. The orientation of the user is provided as simple text showing whether the person is bending towards right, forward or diagonally towards left feet. The above expressions form the basis of calculating any movement recorded by the IMU as well as computing these would be helpful to detect action such as fall and body orientation.

C. Proposed Method for Fall Prediction

In order to detect sudden fall of the person triggered by involuntary force, simple three-layer CNN followed by two MaxPooling layers and an output Softmax function is used to predict a probable fall [48]. The model predicts whether the person is about to fall by the change in resultant acceleration obtained from the garment's Accelerometer. The resultant acceleration is calculated using the following expression [49]:

$$g_i = \sqrt{\frac{x_i^2 + y_i^2 + z_i^2}{g}}, \tag{14}$$

where g is the acceleration due to gravity which is 9.8. g_i is the resultant acceleration at instance i, x_i, y_i, z_i are the values of accelerations at instance i along x, y and z axis, respectively [49]. g_i is calculated at every instance of time that accelerometer is received.

D. Proposed Method for Fall Detection

After a fall is predicted, if it found that the resultant acceleration swiftly decreases below the maximum threshold of +0.90g from +1g in less and quickly increases over +1g in less than 0.3 seconds [50], [51], it can be concluded that the predicted fall occurred and is detected as seen in the Fig. 7. Table IV shows the change in body vitals during fall.

Table IV
BODY VITALS DURING FALL.

Characteristics	Specifics
Fall Prediction	Swift decrease in Resultant Acceleration(g) below the calibrated threshold
Muscle Activity	Quick activation in bicep and Chest Muscle forces
Beats/min	A sudden fall triggers quick increase in Heart Rate
Fall Detection	Increase in g to above +1g within 0.3 seconds

VIII. EXPERIMENTAL VALIDATION OF MYWEAR

We prototyped NyWear using off the shelf components. The prototype was validated using various datasets. This Section discusses all the details.
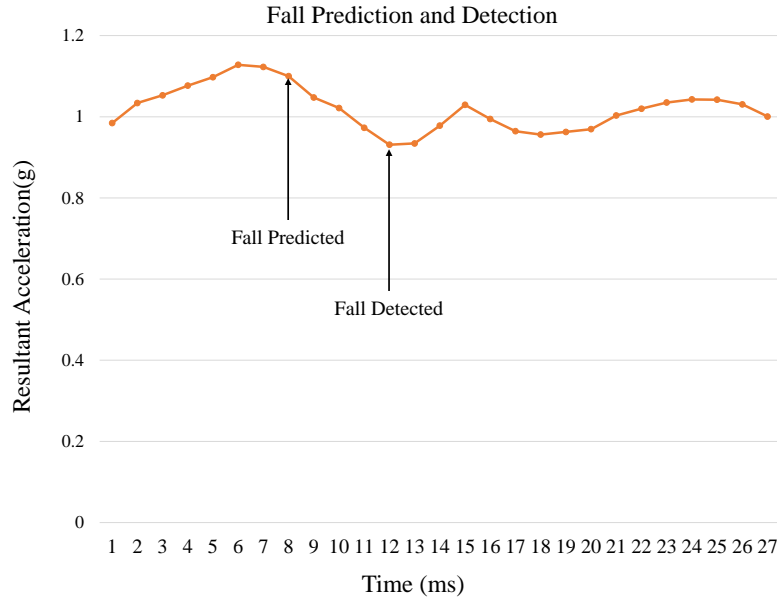
Figure 7. Fall detection and Prediction.

A. A Specific Design of Proposed MyWear

Fig. 8(a) shows the photograph of the experimental prototype. The characterization table of the MyWear system is given in Table V. The sensors acquire the body vital data upon initialization. The filtered data is sent to the smartphone application using bluetooth. A copy of data is sent to the cloud for analysis and backup through Wi-Fi connectivity.The application displays vitals data as shown in the Fig. 8(b). The temperature and body orientation is displayed. ECG samples of 4 minute time duration are recorded every 20 minutes. In case, no heartbeat is detected, the user is prompted to check whether the electrodes are in contact or not. The HRV score is calculated from ECG as discussed later which helps in determining the stress level of the user. The muscle activity and its intensity is visualized on the human map in forms of colors. The darker the color is, the larger the exerted muscle force is for the particular muscle.

Table V
CHARACTERIZATION OF MYWEAR SYSTEM.

Characteristics	Specifics
Sensor System	EMG, ECG, IMU, Temperature Sensor
Classifier	Deep Neural Network: C25
Input Dataset	MIT-BIH Arrythmia Dataset
Data Acquisition	Mobile Application and Cloud Service
Connectivity	Bluetooth and Wi-Fi
DNN Accuracy	98.2% (worst case)

The vital data is stored in a Firebase database (cloud platform) that is also capable of running a deep learning model. The model detects whether the heartbeat is normal or irregular. The same is repeated for two samples. If an abnormal or irregular beat is detected, a prompt is then sent to the user's application and an alert is sent to the prescribed doctor and medical officials for immediate assistance.
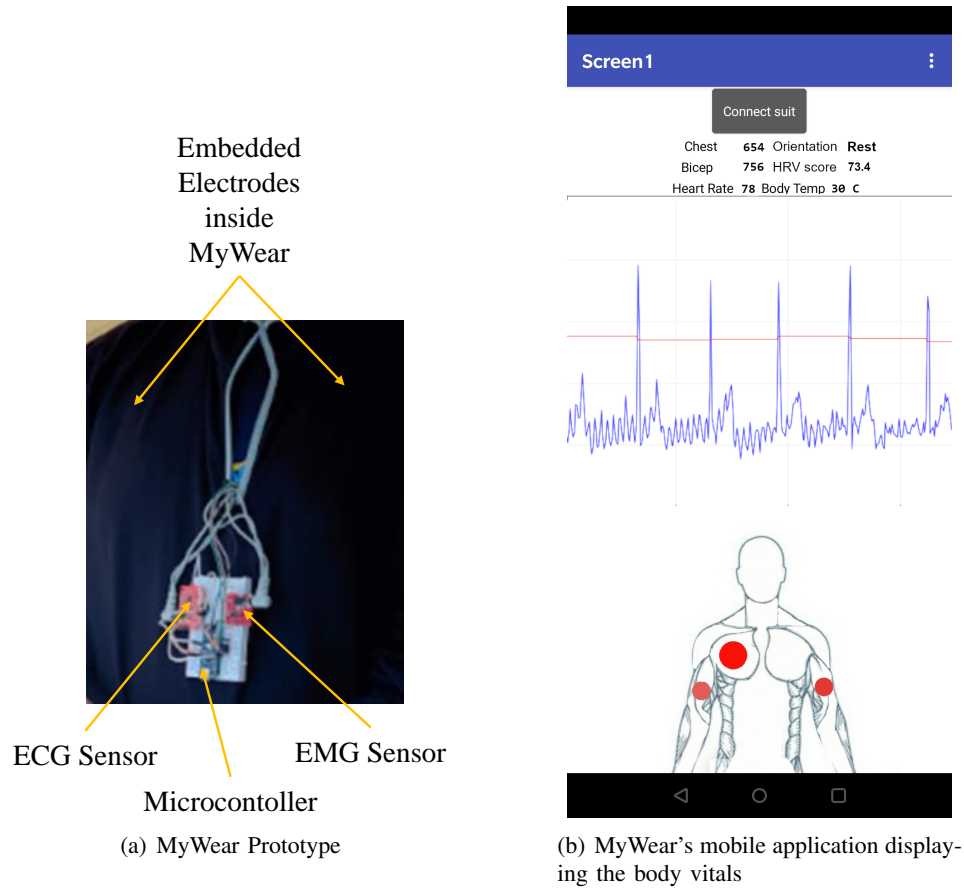
(a) MyWear Prototype

(b) MyWear's mobile application displaying the body vitals

Figure 8. Prototyping of the MyWear using off-the-shelf components.

## B. Validation of Detecting Muscle Activity

Overall, 5 tests of 20 minutes were carried out to study the relation of flexing of muscle on the intensity of activity recorded. And the recorded electrical activity was plotted with respect to time. It was noted that while flexing, there was an increase in muscle activity depicted by peaks in the graph. The peaks were sharper and taller when the subject flexed a muscle with greater effort, hence conveying high intensity of muscle force. It was concluded that the higher the intensity the taller the peaks in the graph, suggesting that a greater exert force exerted by the muscle. Fig. 9(a) and Fig. 9(b) shows the plotted graph depicting instances of increase in muscle intensity in left bicep brachii (bicep) and pectoralis major (chest), respectively.

C. Validating ECG Classification

Electrocardiogram was collected from three different subjects wearing the garment. ECG was plotted at three different time frames. Fig. 10(a) shows the Electrocardiogram value of a healthy subject.

The healthy subject showed a HRV score of 71.87. The HRV score is equal to the RMSSD value as discussed in the existing literature. Fig. 10(b) depicts a normal heartbeat and Fig. 11 shows different type abnormal heartbeats extracted from MIT-BIH Arrhythmia Dataset [46]. Fig. 11 shows the different abnormal heartbeat visualized into the following:

1) Supraventricular
2) Unknown
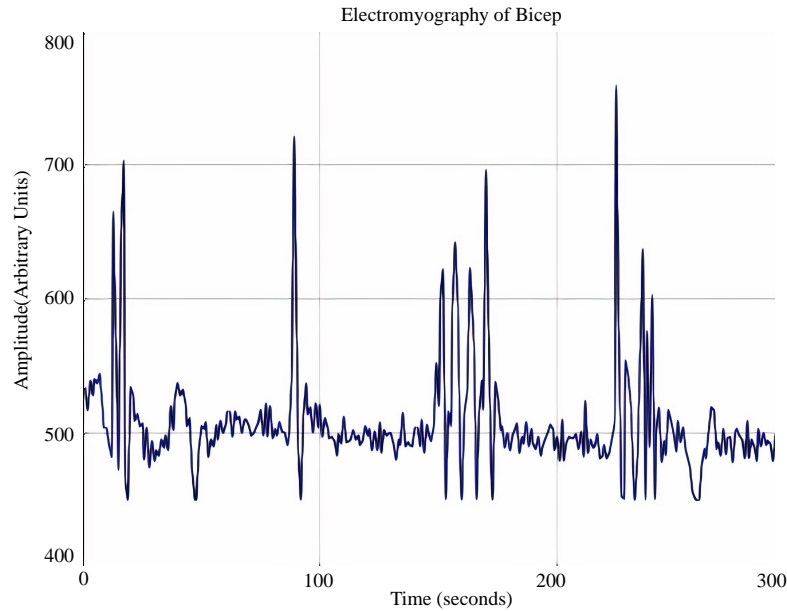
(a) Muscle Activity - Bicep
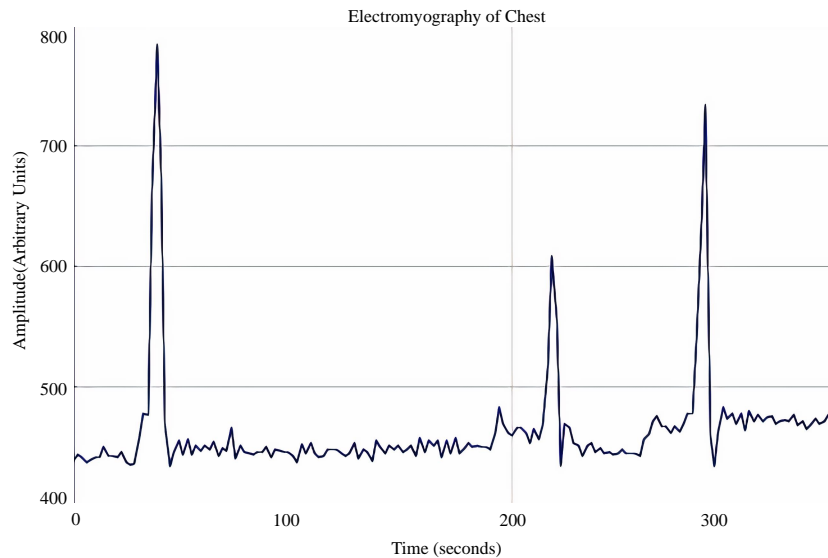
(b) Muscle Activity - Chest

Figure 9. Muscle Activity detection using EMG with highlighted peaks taken from Bicep and Chest.

    3) Ventricular
    4) Fusion

The proposed DNN model classifies ECG on the basis of the mentioned type of abnormal heartbeats

D. Validation of Stress (HRV) Detection - Time-Domain Metrics

    Table VI shows the time domain metrics obtained after analyzing a 5 minute ECG sample. Fig. 12 shows frequency domain metric Poincare plot. The greater the distance between values in plot, the higher the HRV and lower are the stress levels of the user. Poincare plot is a frequency domain metric or analysis
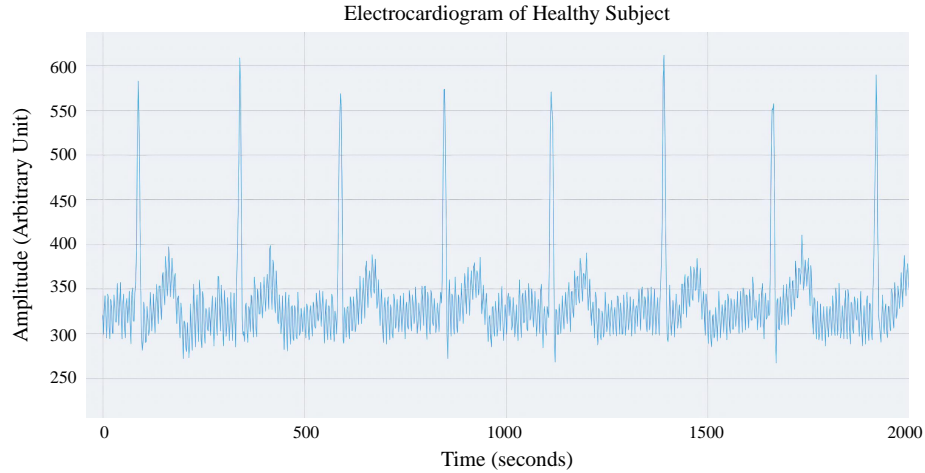
(a) ECG of a healthy subject
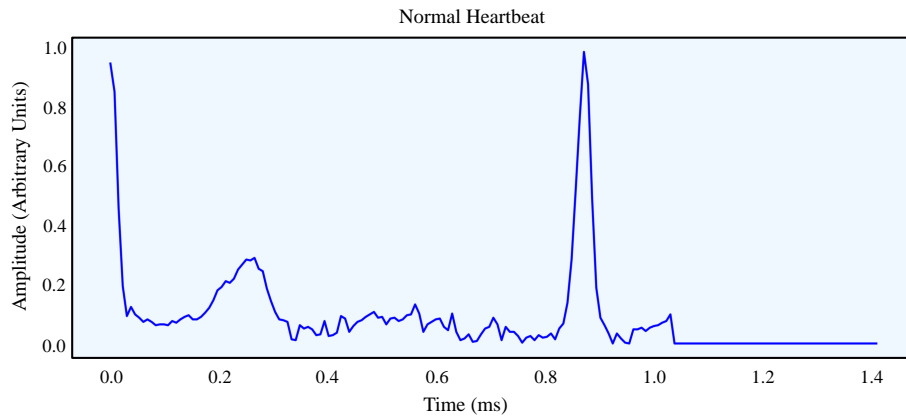
(b) Normal heartbeat of a healthy subject

Figure 10. ECG and Normal Heartbeat of a healthy subject.

wherein R-R intervals are plotted as a function of the previous RR-interval. The values of each pair of consecutive RR intervals represent a point in the plot. The plot consists of Standard Deviation SD1 and SD2 that correspond to the Standard Deviation of RR interval and Standard Deviation of Successive Difference of RR interval, respectively.

Table VI
TIME DOMAIN METRIC AND VALUES

Time Domain Metric	Values
Mean RR (ms)	865.41
STD RR/SDNN (ms)	66.51
Mean HR (beats/min)	69.81
STD HR (beats/min)	6.40
Min HR (beats/min)	58.42
Max HR (beats/min)	122.95
RMSSD (ms)	71.87
NNxx	123.00
pNNxx (%)	35.04

(a) Supraventricular

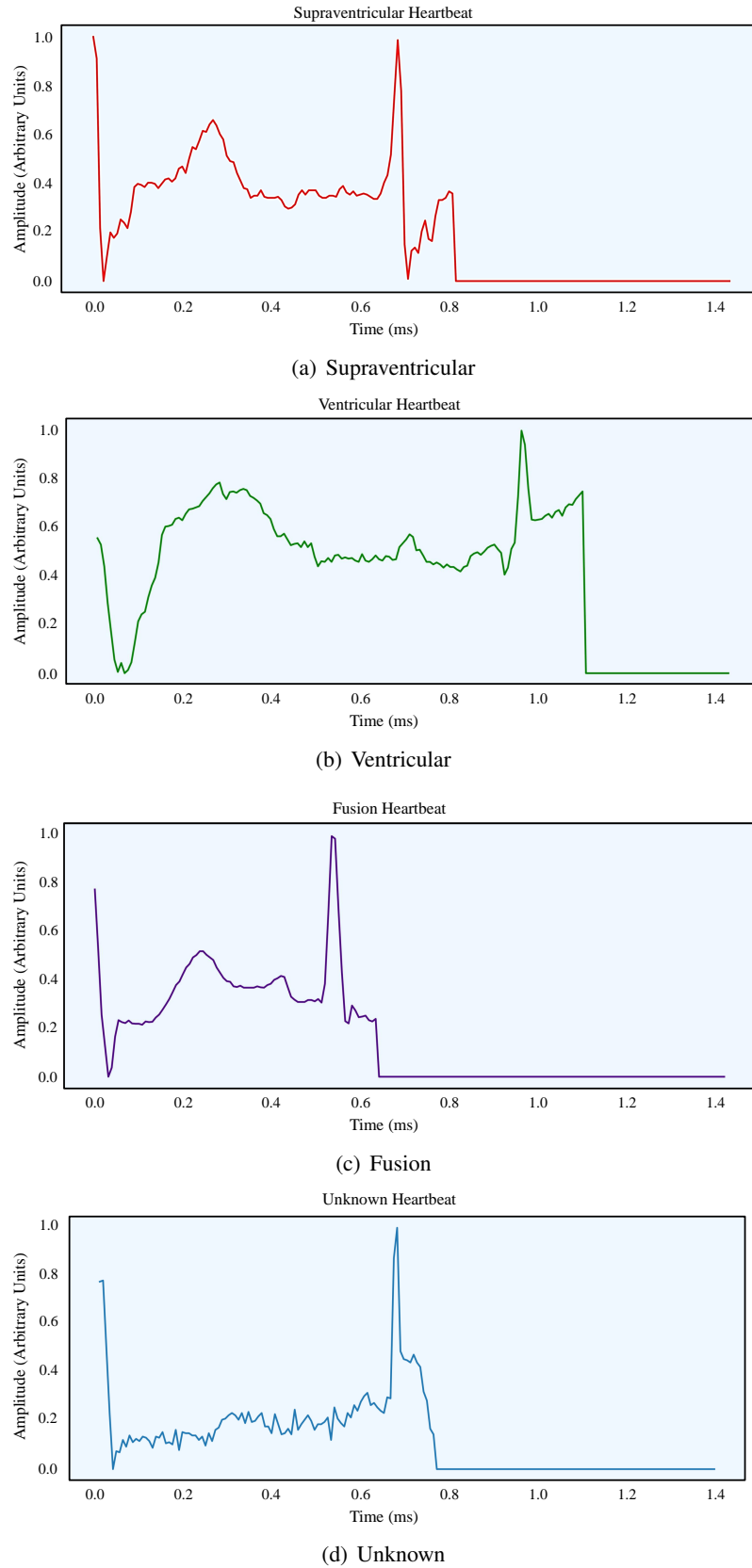
(b) Ventricular

(c) Fusion

(d) Unknown

Figure 11. Abnormal heartbeats in various forms: a. Supraventricular b. Ventricular c. Fusion d. Unknown.
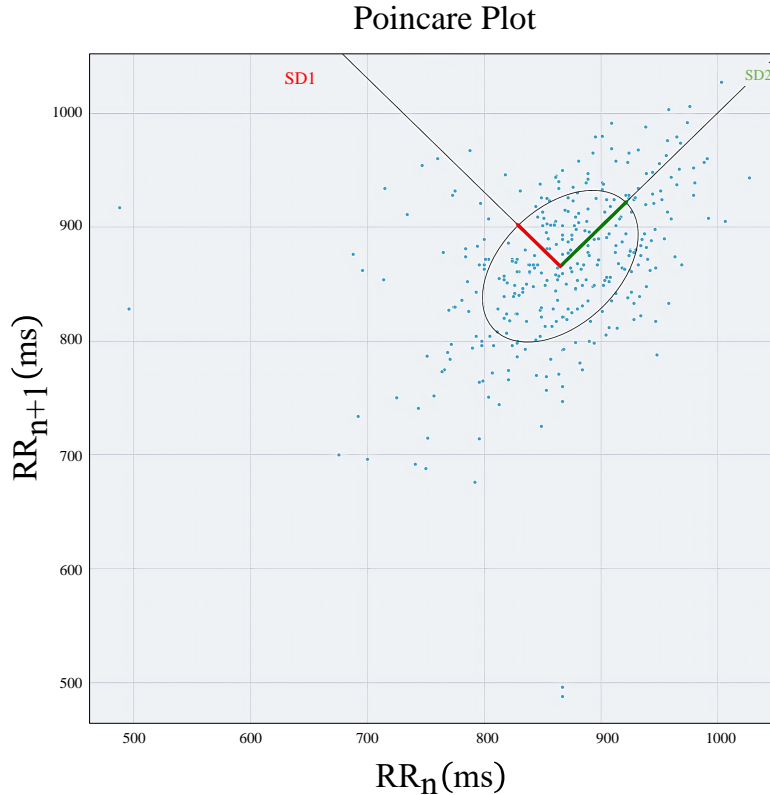
Figure 12. Poincare plot of heart rate variability (HRV).

E. Validation of the DNN Model for for Heart Arrhythmia

The accuracy obtained for the proposed model is 98.2%. The rate of learning of the model was 0.001. The pattern of maintaining accuracy and tracking loss in classifying heartbeats on the basis of defined categories is shown Fig. 13(b) and Fig. 13(a), respectively. Loss represents the rate at which the model is optimized with respect to the number of epochs the model is trained. The accuracy curve represents the rate at which the system is trained and has reached the maximum level of predicting the heartbeats.

Fig. 13(c) shows a plot depicting the relation of performance of recall and precision metric with the number of epochs trained with. The average accuracy of the model is 96.9% while the precision 97.3% and recall 97.1%. Table VII shows the comparison of the heartbeat classification results with other state of the art models [52]–[54]. Fig. 14 shows the confusion matrix depicting the predicted and truth label after classification of target variables.

Table VII
COMPARISON OF HEARTBEAT CLASSIFICATION RESULTS.

Methodology	Approach	Average Accuracy (%)
Raj et al. [26]	DCST + ABC-SVM	96.1
Wang et al. [28]	H-Box	95
Acharya et al. [52]	Augmentation + CNN	93.5
Martis et al. [53]	DWT + SWM	93.8
Li et al. [54]	DWT + random forest	94.6
MyWear (Current Paper)	DNN	96.9
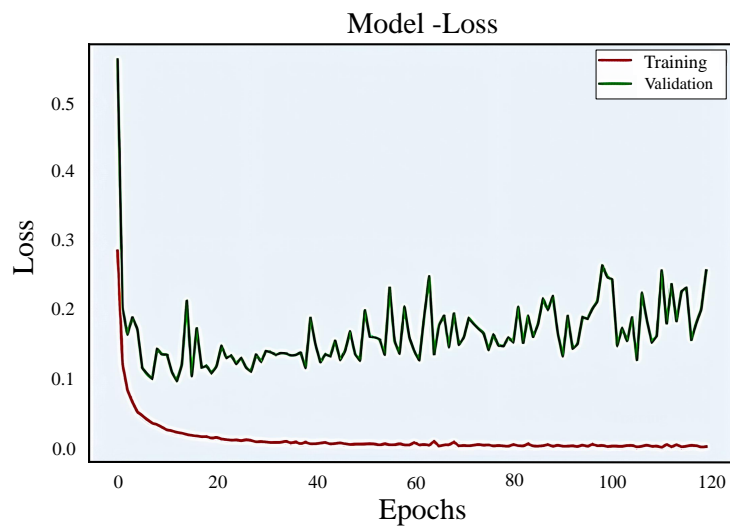
(a) Loss
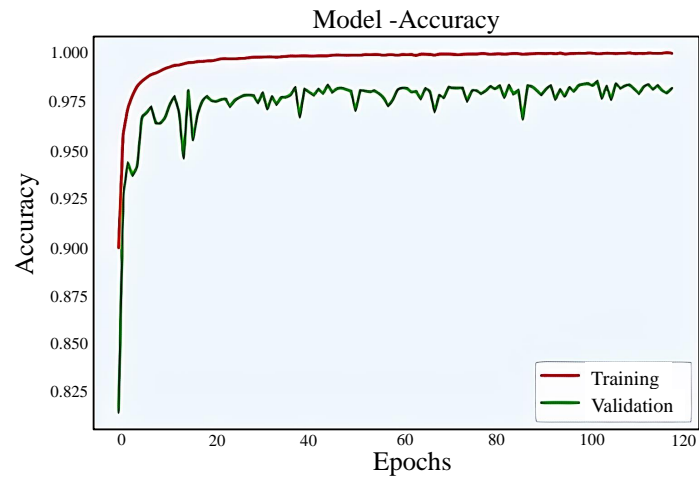
(b) Accuracy
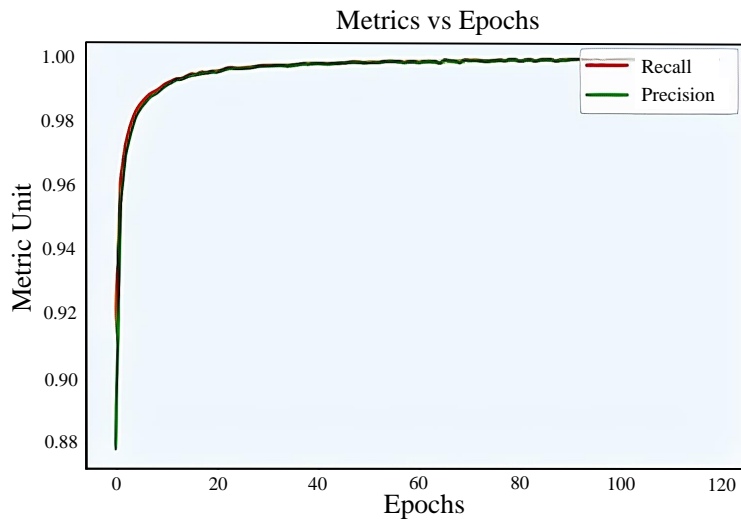
(c) Recall and Precision

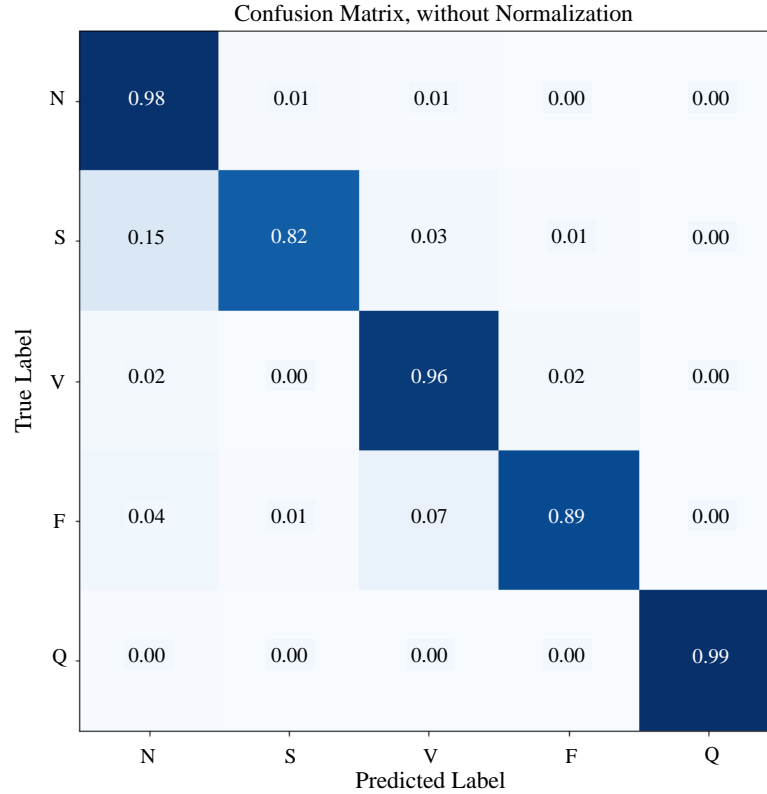Figure 13. Performance measures of the proposed DNN model.

Figure 14. Confusion matrix for DNN heartbeat classification model validation.

Table VIII
COMPARISON OF CLASSIFYING MYOCARDIAL INFARCTION RESULTS.

Methodology	Accuracy (%)	Precision (%)	Recall (%)
Raj et al. [26]	96.1	NA	NA
Acharya et al. [55]	93.5	92.8	93.7
Kojuri et al. [56]	95.6	97.9	93.7
Sharma et al. [57]	96	99	93
MyWear (Current Paper)	98.2	97.3	97.1

Table VIII shows the comparison of classifying myocardial infarction results with other models [52], [56], [57]. Fig. 8(b) shows the MyWear's mobile application displaying the body vitals such as Heart rate, body temperature, body orientation and HRV score along with plotting ECG data in real-time. The application visualizes the muscle activity on the human map.

Table IX
COMPARISON OF FALL DETECTION RESULTS.

Methodology	Accuracy (%)	Sensitivity (%)	Specificity (%)
Hemalatha et al. [51]	92	NA	NA
Mezghani et al. [50]	98	97.5	98.5
Wang et al. [28]	95	NA	NA
MyWear (Current Paper)	98.5	98	99.5

F. Validation of Fall Prediction and Detection

Fig. 7 depicts the instance at which the model predicts when the person/user is about to experience a fall by recognizing a sudden and quick drop in the resultant acceleration. And a drop is detected when the resultant acceleration drops below $1g$ and quickly increases over $+1g$. Table IX shows the comparison of Fall detection results with other models [28], [50], [51].

IX. Conclusion and Future Research

Body vital provides insights into the life and lifestyle of the user. Analyzing them provides the user information to improve the health of individuals on a daily basis. Approach presented in this paper helps to enhance the mental and physical state of the user based on analysis of ECG and EMG data, respectively. The proposed garment is integrated with a deep learning model running in IoMT-cloud server that helps in detecting any abnormalities in the heart beat and classifies into the type of abnormality detected. The average accuracy and precision of the proposed deep learning model was 96.9% and 97.3%, respectively. MyWear can help in rehabilitation of athletes and sportsmen with the help of embedded sensors that detect Muscle activity and body movement to come up with help for overall body development.

Further, implementing the deep learning model on edge platforms would reduce computational time and resources hence giving results quicker. This can be an extension of the proposed garment and potentially future improvement. First this cane be integrated in IoMT-edge paradigm with TinyML models to rapidly detect the health conditions fast and at the user end [36], [58], [59]. It is a fact that various security and privacy related challenges arise in IoMT driven H-CPS that make smart healthcare. So, blockchain data and device management in of MyWear in IoMT or H-CPS needs serious research [60]–[62].

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