MyWear: A Novel Smart Garment for Automatic Continuous Vital Monitoring

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***Abstract*—Wearables are getting large acceptance in the continuous monitoring of health status and physiological data. Medical devices and their connectivity through Internet along with the electronics health record (EHR) and AI analytics making smart healthcare possible. Internet-of-Medical-Things (IoMT)-end devices like wearables and implantables are key for smart healthcare. Smart garment is a specific wearable which can be used for smart healthcare. This paper presents the design and development of a smart garment called MyWear that continuously monitors and collects physiological data. It can analyze muscle activity, stress levels, and heart rate variations and send all the data to the cloud. Through abnormal variations in vitals, it can also predict the risk of heart failure and with the in-built alert system, it can notify the associated medical officials if necessary. We also propose a deep neural network model that classifies heartbeat data into abnormalities with 96.9% accuracy and 97.3% precision.**

***Index Terms*—Smart Healthcare, Internet-of-Medical-Things (IoMT), Smart Garment, Smart Garment Security and Privacy.**

I. Introduction

The Internet of Medical Things (IoMT) based system has made smart healthcare possible with enhanced quality of care and faster diagnosis [1]–[3]. From acquiring blood samples to performing analysis on CT scan, Technology has revolutionized every aspect of Healthcare. Introduction of IoMT into multiple systems has made devices work efficiently. IoMT has allowed doctors to remotely monitor patients based on their fitness tracker data. Wearables such as smartwatches [4] allow users to record ECG 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 helps in collecting several vitals that describe the health of the person and transmit them to the cloud for post processing using wired or wireless communication means. IoMT in wearable devices has unlocked various applications in areas such as smart healthcare, fitness and yoga. Globally, over a half-billion people use wrist-worn fitness trackers alone. And millions use wearable IoMT technology that keeps track of both physical and mental health. This led to the use of home-based health monitoring equipment involving a bed-side monitor with sophisticated devices connected to the user through wires making them immobile. These devices often require the user to be rested while collecting and analyzing data. With the upcoming technologies such as bio-medical textiles, user's movement is not restricted. However, they are not cheap and user-friendly. Wearable garments are being used by sports teams and athletes to improve their performance by analyzing body musculoskeletal data recorded by the garment [5]. Wearable garments are being developed not only to monitor ECG but also the activity the user is performing while wearing them [5], [6]. With detailed analysis of the body and its muscle activity, analysts are helping athletes and teams perform and build better. The conceptual overview of MyWear is depicted in Fig. 1.

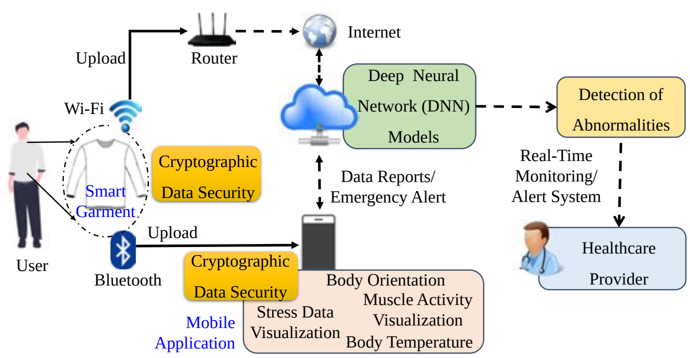

Figure 1. Conceptual overview of the proposed MyWear in a IoMT framework.

The significance of the proposed solutions:

- Technique to analyze stress levels in real-time from Heart Rate Variability using Electrocardiogram which is absent in most of the smart garments.
- A CNN model for Electrocardiogram analysis to detect different types of abnormalities in heartbeat that is not observed in any of the smart garments listed in Table I.

Rest of the paper is organized as follows: Section II explains the existing related research. Section III provides the system level architecture. Section IV outlines the novel methods proposed for automatic heart rate, stress and abnormality monitoring system. Section V presents a novel deep learning model for detecting heart arrhythmia. Section VI presents a prototype of the MyWear along with the validation of the results of the

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proposed MyWear and also provides a comparative analysis of MyWear with the state of the art wearables. Finally, the paper concludes in Section VII.

II. Existing Related Works and Advancement through the Current Paper

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 [11], [12] including stress management, diet management, assisting visually impaired individuals and wearables focusing on women's health [13], hearing aids [14], and garments [15]. A consumer electronic device that can automatically quantify calorie intake as well as stress of an user is available [11]. Heart rate estimation using a photoplethysmography (PPG) based device was presented in [7] that deployed neural network models.

A framework that can automatically monitor stress level from the physical activities was proposed in [12]. A study on the meta-analysis of stress and Heart Rate Variability showed that neuroimaging studies suggested HRV may be linked to cortical regions that are involved in stressful situation appraisal [16]. A review on the relationship between HRV and occupational stress provided an insight that lowered HRV specifically RMSSD value of the user indicated heightened occupational stress [17]. A framework to monitor different brain dynamics with HRV as the key factor, determining the relationship between RMSSD value as an indicator of change in stress levels was observed [18]. A wearable which considered RMSSD value as a contributing factor to assess the mental stress levels [19]. A framework for detection of elderly fall and ECG abnormality detection was presented in [9]. A smart phone based fall detection was presented in [20]. Table II shows the comparison of the existing fall detection implementations.

ECG signal analysis method using discrete cosine transformation (DCT) has been presented in [8]. Xu and Liu performed ECG classification using coupled-convolution layer structure with supporting group mechanism along with CNN trained on Holter data, achieving accuracy over 99% [21]. Niu et.al proposed MPCNN classifier to automatically learn and classifying the heartbeat [22]. Jin and Dong proposed a cloud computing framework with CNN and Bayesian Fusion to predict heartbeats with an accuracy of 98.26% [23]. Table I presents a comparative perspective of similar consumer electronics as MyWear.

A. Problem Formulation for the Current Paper

- Detection of abnormalities in heart beat and immediate medical assistance, if any.
- Continuous health monitoring system for medical officials to check patient vitals remotely.
- Stress level detection to understand user's physical and mental health status.
- Creating a portable and user friendly remote vital monitoring system.

B. Proposed Solution and Novelty of the Current Paper

It is evident from the above discussion that there are few smart wearable garments that can monitor human body vitals in real-time [26]. A smart wearable garment in the literature [6] used 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 [5] analyzes sleep activity and ECG for heart rate variability (HRV) analysis and it does not examine the muscle activity of the user. The mentioned wearables store data in the cloud and allow users to comprehend the data. The garments presented by Farjadian et al. [10] used electromyography (EMG) to detect muscle activity and assist the user in physical therapy. A few proposed solutions leverage accelerometer data to analyze exercises, however, it is not sufficient to indicate individual muscle activity. Moreover, accurate measurement of body orientation and built-in alert system to notify paramedics and users contacts in case of emergency is not observed in the above-mentioned solution. We believe that MyWear is the first 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.

III. Proposed IoMT-based System Level Architecture of MyWear

A. Proposed IoMT Architecture

The complete architecture of the proposed MyWear is shown in Fig. 2. The garment acts as the End device and the input point for the mobile application and cloud service. Surface 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 keeping the data safe and secure. 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. Meanwhile, the proposed Deep Learning model deployed in the cloud checks for any abnormalities and detects the kind of abnormality that occurred in the transmitted ECG data from the garment. In case of emergency, an alert is

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

Consumer Electronics	Real-Time HRV	Muscle Activity Detection	Abnormal Heart-beat Detection	Stress Level Detection	Fall Detection	Fall Prediction	Built-in Alert	Data Security
Puranik et al. [7]	Yes	No	No	No	No	No	No	No
Garment in [5]	Yes	No	No	Yes	Yes	No	No	No
Raj et al. [8]	Yes	No	Yes	No	No	No	No	No
Garment in [6]	No	Yes	No	Yes	Yes	No	No	No
Wang et al. [9]	Yes	No	Yes	No	Yes	No	No	No
Farjadian et al. [10]	No	Yes	No	No	No	No	No	No
MyWear (Current Paper)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table II
COMPARISON OF THE EXISTING FALL DETECTION IMPLEMENTATIONS.

Research	Sensors	Algorithm Used	Supported Fall Types	Supported Activities of Daily Life	Built-in Alert
Hemalatha et al. [24]	Accelerometer	CEP	3	8	No
Mezghani et al. [25]	Accelerometer, gyroscope	Non Linear SVM	4	11	No
Wang et al. [9]	GPS	H-Box	4	11	No
Lee et al. [20]	Accelerometer	Thresholding	4	11	No
MyWear (Current Paper)	Accelerometer	CNN	4	11	Yes

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 collects body vitals such as Heart Rate, Body temperature, Muscle activity and sends it to smartphone and cloud. The smartphone acts as an interface to visualize data post analysis for user's information. A report is sent to user to access post complete analysis.

The main objectives of MyWear are the following:

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

B. 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) [27]. For convenient use, a 3 electrode system is used. The electrodes are placed following the Einthoven's triangle to obtain stable ECG [28], [29].

C. EMG Unit

Electromyography is used to measure the change in electric potential that depicts the force exerted by the muscle. Two electrodes are used to measure the muscle signal and the third electrode acts as a ground. 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 [30], [31]. Muscle 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 and the chest region.

D. 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 user's 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 user's smartphone application and triggers an alarm. Another alert is sent to Medical officials and doctors for immediate assistance.

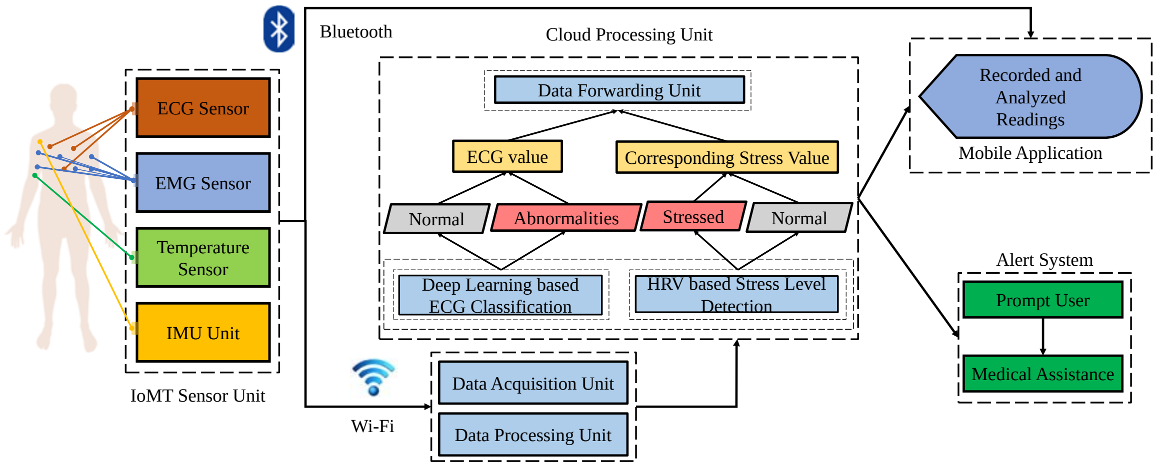


Figure 2. Architecture of the proposed MyWear.

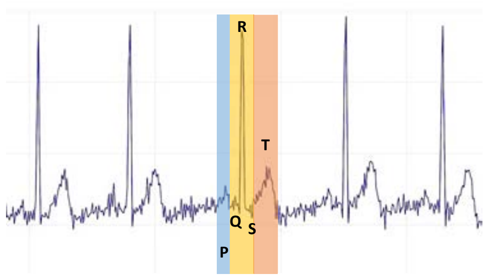


Figure 3. P segment, QRS complex and T- segment of ECG.

IV. Proposed Methods for Automatic Health Condition Monitoring through MyWear

A. Proposed Method to Obtain Heart Rate from ECG

Fig. 3 shows ECG graph along with 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 where the 'P' wave represents the depolarization of atria which results in brief isoelectric period or state of near zero voltage and lasts no more than 0.10 seconds. P wave is followed rapid succession of Q, R and S waves called the QRS complex, and lasts no more than 100 milliseconds representing the activation of ventricular muscles. QRS complex is followed by the T wave and indicates ventricular repolarization that depicts 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:

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

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:

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

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

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

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

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

C. Proposed Method to Automatically Monitor Stress from ECG

Fig. 4 shows the algorithm to calculate stress level using Heart rate. RMSSD is usually obtained from Electrocardiogram and is considered as the HRV score [32]. Studies have shown that an increase in HRV depicts a reduction in stress levels [33] and vice versa. High HRV score was found in users performing optimal levels of fitness routine.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. Table III shows the relation between HRV score and stress levels [34].

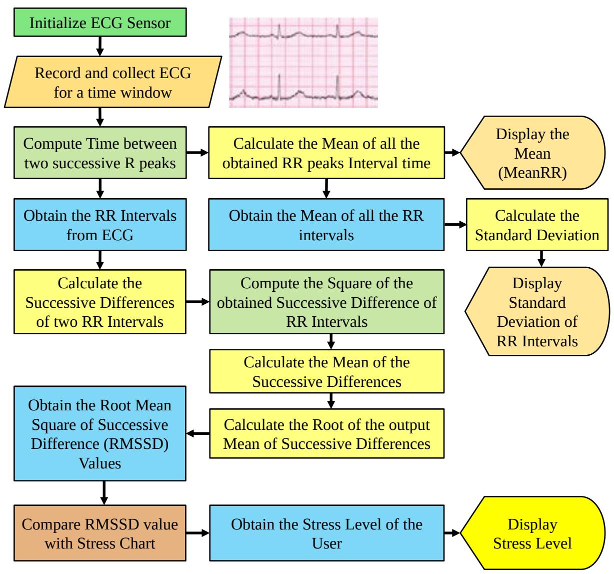


Figure 4. Proposed approach for calculating stress level from the heart rate.

Table III
RELATION BETWEEN HRV SCORE AND STRESS LEVELS [34].

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

D. 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 are calculated [35]. These values define the change in the X, Y and Z values from the calibrated values. The user is prompted with the text in the application that shows the orientation of the user as shown in Fig. 6(b).

E. Proposed Method for Fall Prediction and Detection

1) 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 [36]. The model predicts whether the person is about to fall by the change in resultant acceleration obtained from the garment's Accelerometer. Resultant acceleration is calculated using the expression:

$$g_i = \sqrt{\frac{x_i^2 + y_i^2 + \ z_i^2}{9.8}}, \tag{6}$$

where the acceleration of gravity value 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. g_i is calculated at every instance of time that accelerometer is received.

2) 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, it can be concluded that the predicted fall occurred and is detected as in Fig. 10.

V. THE PROPOSED DEEP NEURAL NETWORK (DNN) MODEL FOR DETECTING HEART ARRHYTHMIA

A. 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 [37] 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 22,000 samples.

B. Proposed DNN Model for Heart Arrhythmia

Fig. 5 depicts the architecture of the proposed deep learning model that consists of 6 one-dimensional convolutional layers with 64 filters each and input stride length of 2. Every convolutional layer is succeeded by the Maxpool layer of pool size 2 and stride size 2. These are connected to three Fully Connected Layers. 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 the following expression:

$$f(x) = \begin{cases} 1 & x{>}1 \\ x & x = 1 \text{ and } 0 \\ 0 & x{<}0 \end{cases} \tag{7}$$

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 [38] defined as:

$$f_n\ (x) = \frac{e^{(W_n h_x\ +\ b_k)}}{\sum_{j=1}^{K} e^{(W_j h_x\ +\ b_j)}}\ (n\ =\ 0, ..., n-1), \quad (8)$$

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.

C. Metrics for evaluating the DNN Model

The metrics used for evaluating the proposed DNN model are precision, recall, accuracy and Loss [11].

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

$$P\ = \left[\frac{TP}{TP+FP}\ *\ 100\%\right]. \quad (9)$$

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

$$R\ = \left[\frac{TP}{TP+FN}\ *\ 100\%\right]. \quad (10)$$

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

$$\alpha = \left[\frac{TP\ +\ TN}{TP+TN\ +\ FP\ +FN}\ *\ 100\%\right]. \quad (11)$$

VI. Experimental Validation of MyWear

A. A Specific Design of Proposed MyWear

Fig. 6(a) shows the photograph of the experimental prototype. The application displays vitals data as shown in the Fig. 6(b) being transmitted from the garment. The temperature and body orientation is updated and displayed time-to-time. Incase of a detected fall,an automatic alert along with the location is sent to the caregiver within the next 10-15 seconds. A notification appears on the user's app prompting the user that a fall has been detected, and the user can choose to cancel the transmission of the message if he/she chooses to.However, the fall is logged simultaneously to the cloud for future purposes .The HRV score is calculated from ECG which helps in determining the stress level of the user. The muscle activity and its intensity are 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. 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 users application and an alert is sent to the prescribed doctor and medical officials for immediate assistance if needed.

B. Validation of Detecting Muscle Activity

A total of 5 tests of 20 minutes each were carried out to study the relation of flexing of muscle on the intensity of activity was 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 is, the taller the peaks appear in the graph, stating greater exert force exerted by the muscle. Fig. 7 shows the plotted graph depicting instances of increase in muscle intensity in left bicep brachii (bicep).

C. Validation of Stress Detection using Heart Rate Variability

Electrocardiogram was collected from three different subjects wearing the garment. The healthy subject showed a HRV score of 71.87. The HRV score is equal to the RMSSD value as discussed earlier in the paper. Fig. 8 depicts the abnormal heartbeats extracted from MIT-BIH Arrhythmia Dataset [37]. A test subject showed a Mean RR of 865.41ms, STDNN of 66.51ms and a RMSSD value of 71.87.

D. Validation of the DNN Model for Heart Arrhythmia and Fall Prediction

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 is shown Fig. 9(b) and Fig. 9(a), respectively. Fig. 9(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% and the precision, recall was 97.3% and 97.1%. Table IV shows the comparison of the heartbeat classification results with other state of the art models [39]–[41]. Table V shows the comparison of classifying myocardial infarction results with other models [39], [42], [43]. Fig. 6(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.

Fig. 10 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 VI shows the comparison of Fall detection results with other models [9], [24], [25].

VII. Conclusion and Future Research

Body vital provides insights into the life and lifestyle of the user. They are an essential part of smart healthcare and analyzing them provides the user information to improve his/her health on a daily basis. Approach presented in this paper helps prevent Heart Arrhythmia and Fall Prediction of the user based on analysis of ECG and EMG data, respectively.

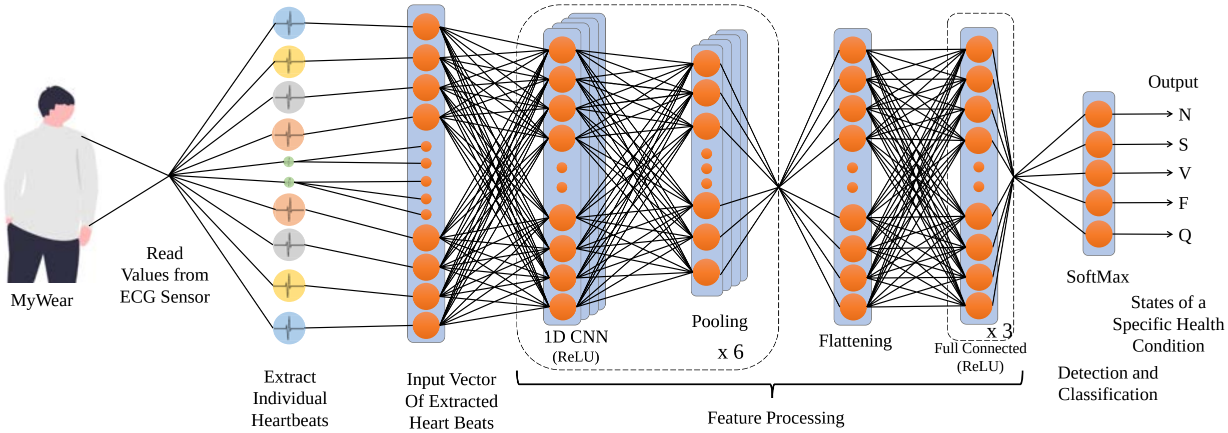
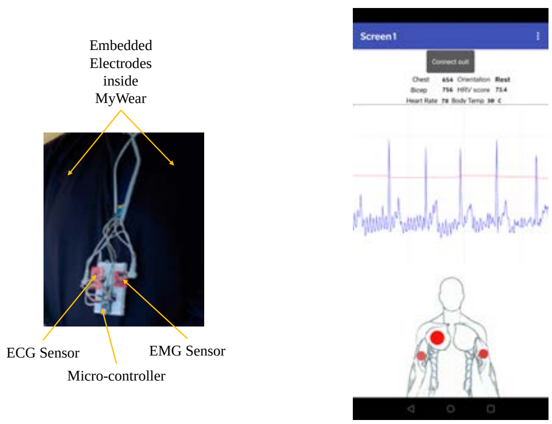


Figure 5. Deep Neural Network (DNN) Model model explored for our MyWear.



(a) MyWear Prototype

(b) MyWear user application

Figure 6. Prototyping of the MyWear using off-the-shelf components.

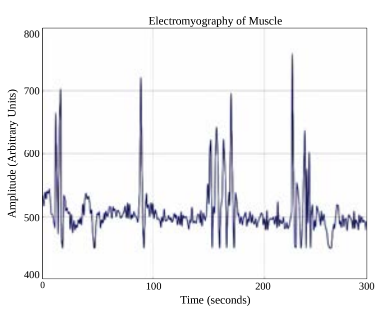


Figure 7. Muscle Activity detection using EMG with peaks taken from Bicep.

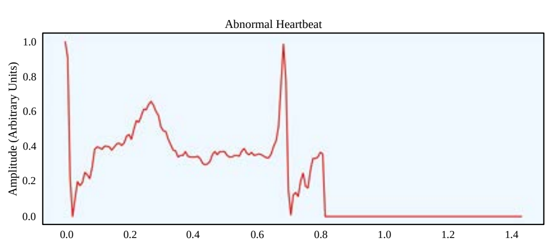


Figure 8. Abnormal Heartbeat from ECG.

Table IV
COMPARISON OF HEARTBEAT CLASSIFICATION RESULTS

Methodology	Approach	Average Accuracy (%)
Raj et al. [8]	DCST + ABC-SVM	96.1
Wang et al. [9]	H-Box	95
Acharya et al. [39]	Augmentation + CNN	93.5
Martis et al. [40]	DWT + SWM	93.8
Li et al. [41]	DWT + random forest	94.6
MyWear (Current Paper)	DNN	96.9

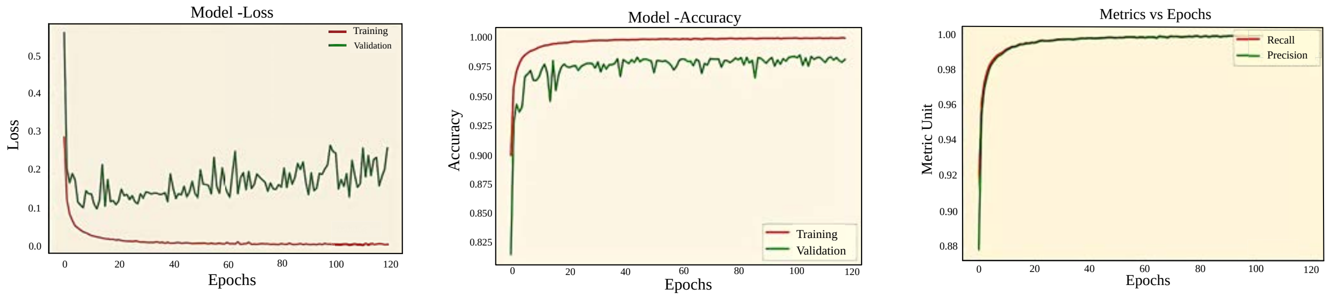
Table V
COMPARISON OF CLASSIFYING MYOCARDIAL INFARCTION RESULTS

Methodology	Accuracy(%)	Precision(%)	Recall(%)
Raj et al. [8]	96.1	-	-
Acharya et al. [44]	93.5	92.8	93.7
Kojuri et al. [42]	95.6	97.9	93.7
Sharma et al. [43]	96	99	93
MyWear (Current Paper)	98.2	97.3	97.1

The proposed garment is integrated with a deep learning model in 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 could also potentially 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

Table VI
COMPARISON OF FALL DETECTION RESULTS

Methodology	Accuracy(%)	Sensitivity(%)	Specificity(%)
Hemalatha et al. [24]	92	-	-
Mezghani et al. [25]	98	97.5	98.5
Wang et al. [9]	95	-	-
MyWear (Current Paper)	98.5	98	99.5



(a) Loss (b) Accuracy (c) Recall and Precision

Figure 9. Performance measures of the proposed DNN model.

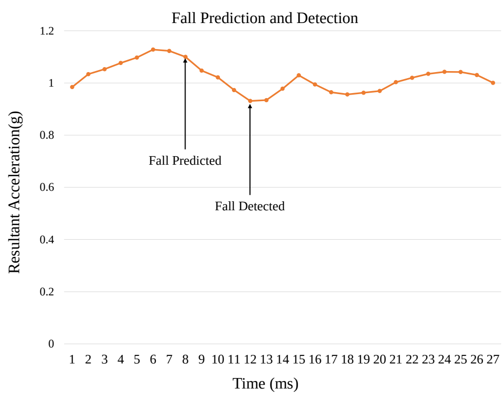


Figure 10. Fall detection and Prediction.

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.

Acknowledgments

The authors would like to thank the editors and reviewers. The authors Sibi Chakkaravarthy Sethuraman and Pranav Kompally would like to thank Dr. S. V. Kota Reddy, Vice Chancellor, VIT-AP University for his support. A special thanks to the team members of AIR Center, VIT-AP University. A different version of this work is archived as [45].

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