CHAPTER 3

METHODOLOGY

3.1 Introduction

Wearable technologies take new dimensions and have grown exponentially in the past few years in monitoring the marked changes of a player during his sports activity. Monitoring a player's performance on the field during a training session will help him analyze his performance and push him to the next level. To obtain the attributes and train the dataset, wearable devices with smart algorithms can be used. It can be put through more tests to ensure that it is accurate. As a result of technological advancements, smart devices will enable players to assess their activity levels better and coach themselves to attain the most significant results. This is the current demand in the modern sports field. For this reason, researchers are developing devices to be incorporated in training sessions to monitor the players health parameters and physical fitness. The system is designed for cricket game and the proposed system is given in Figure 3.1.

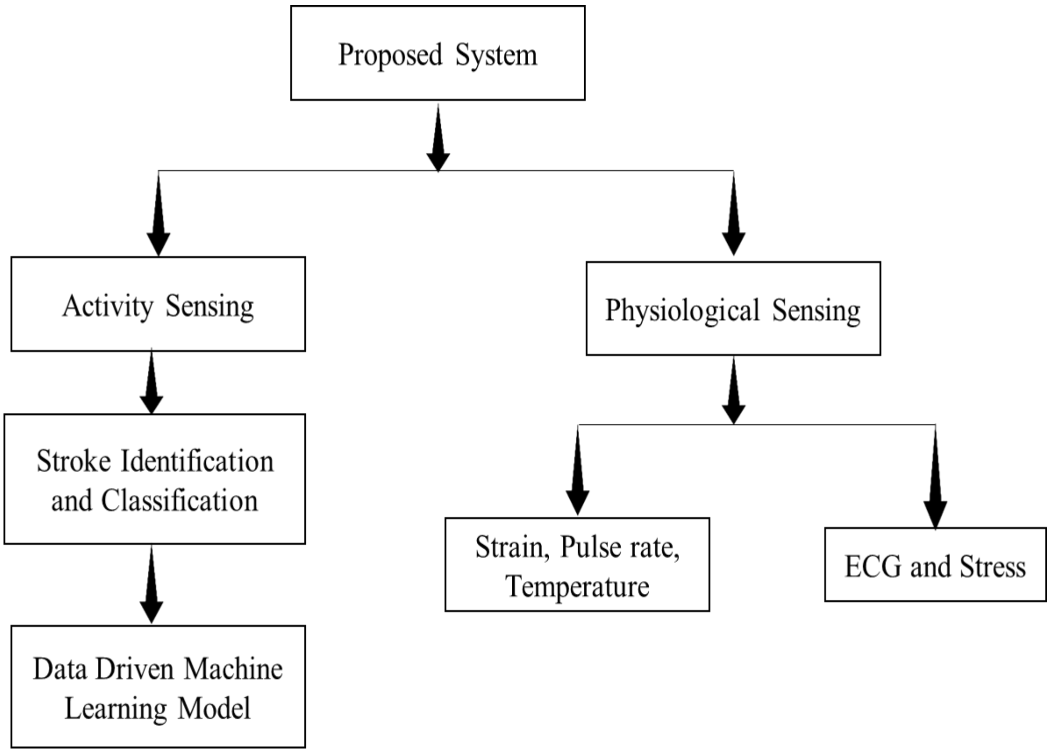


Figure 3.1 Proposed System

Low cost and miniaturization of devices led the embedded system to monitor the biometric parameters as well. The sensors are used to monitor physiological variables such as strain, force, vibration, muscle activity, temperature and heartbeat rate. Sometimes overstrain might lead injuries to the player. The injuries can be identified in the initial stage itself, which will help the players to take some remedial action before the injuries become severe.

Necessary feedback is provided to both the player and the coach. This acts as a virtual coach, and the actual coach can access the player's performance and it is not mandatory for the coach to be on the field.

The previously designed model works on a video-based approach to identify and classify the strokes. The proposed system works on collecting data using an inertial measurement unit (IMU) rather than images or videos using high definition cameras. The study focuses on building a wearable device that uses machine learning techniques to identify and classify shots.

3.2 Proposed System Architecture and Machine Learning Model for Classifying and Analyzing the Strokes

The proposed system comprises of three sections and is given below:

a. The Inertial Measurement Unit to identify the batting swing movement

b. A data processing unit that includes the main Processor and the Graphical processing unit

c. A dedicated user interface for getting the real-time inputs of the players

The processor performs all complex and advanced analyses. This system supports the real-time data processing by comparing the obtained values with the reference statistics. The forthcoming section discusses the individual parts in detail. The architecture of the wearable device is shown in figure 3.2. This shows the wearable system for the movement detection of the players and its classification.

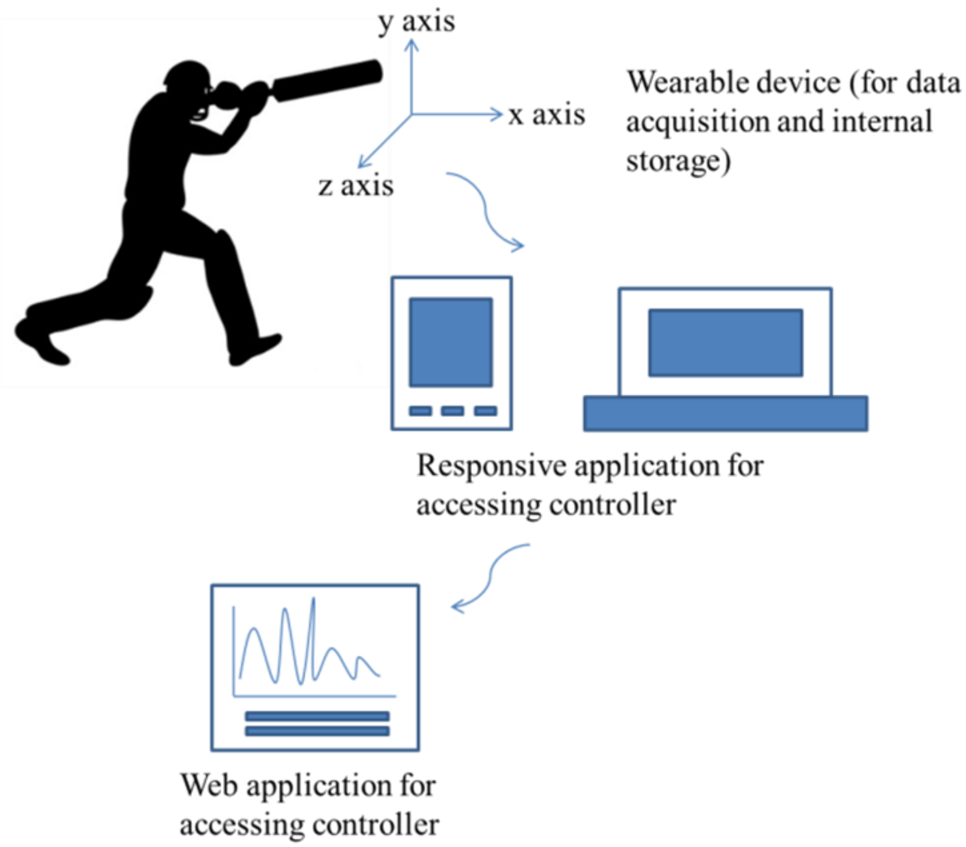


Figure 3.2 Architecture for the movement detection and classification

3.2.1 Hardware Design

A portable, lightweight data acquisition module is designed to record the bat movement. The whole body will be in motion while batting. The wearable can also be placed on the wrist, but since it is subjected to more rotation, the data accuracy will be less. So the best place would be on the player's arm for accurate results. The IMU records the translational and gyrational position of the bat. The placement is made on the tip of the handle of the bat. IMU placement does not disturb the player’s movement and performance. Figure 3.3 depicts the device position, the orientation of IMU and the way it’s attached to the players arm. The ARM cortex processor is the main processing unit. It is a RISC processor whose execution timing is less with simplified instruction set. It has a Broadcomm video core IV Graphics Processing Unit. The acceleration and the angular velocity is measured with MPU 6050. The accelerometer and the gyroscope are used to measure the bat's 3 D translational and rotational motion.

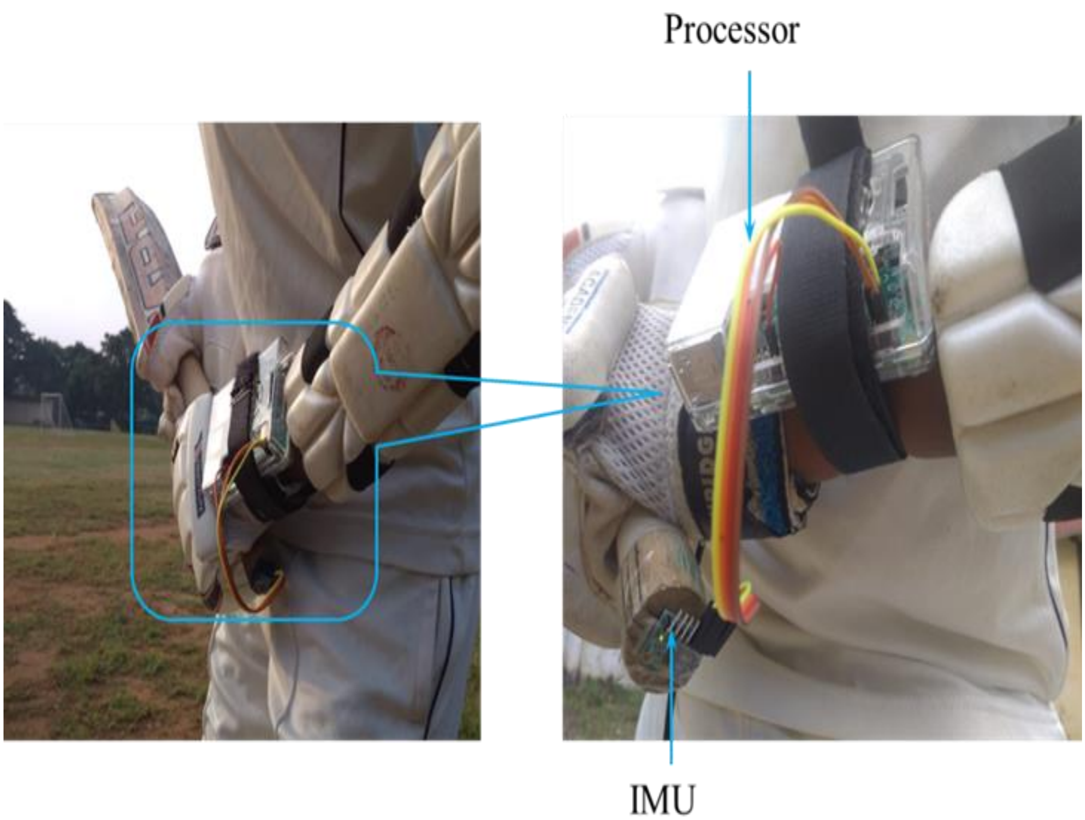


Figure 3.3 Data acquisition for movement – Device Position

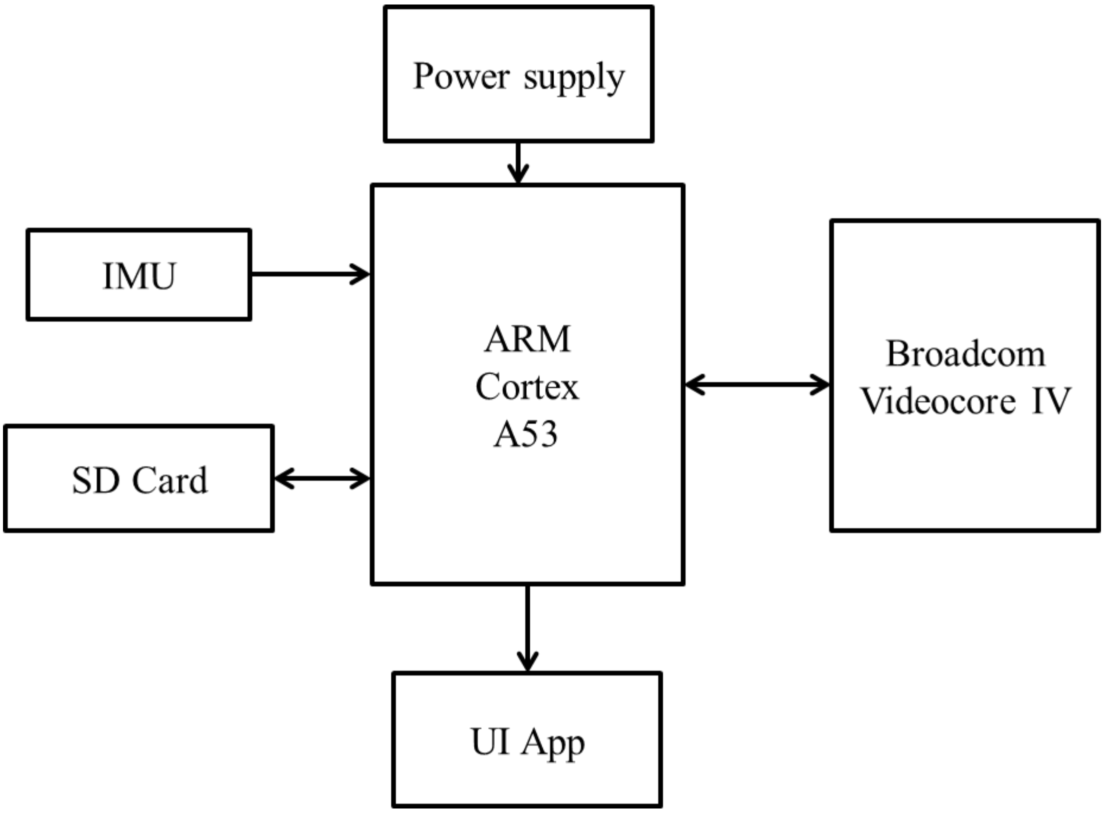


Figure 3.4 Proposed wearable device

The acquired data are recorded and then sampled at 50 different timeslots, which takes place in very few seconds. The processor has inbuilt wireless connectivity. So this feature helps to transfer the data between the device and the user interface. Since the memory requirements are high due to the large volume of data, the 16GB SD card is used as an external memory with the processor supporting with 1GB internal memory. The block diagram of the proposed system is given in figure 3.4. Figure 3.5 illustrates the hardware setup of the wearable module. The data processing unit is positioned on the forearm with the IMU sensor placed on the bat's tip. The battery can be conveniently placed in the arm guard or in the player's pocket so that the hardware does not interfere in his practice session. Either the laptop or the smartphone can be used along with the module to access the user interface. I2C bus is used to connect the IMU with the processor. The raw analog data is collected directly from the IMU as the player plays the shot. The data is sampled at 50 different time intervals by the processor, yielding 300 data points for each shot. The processor has SPI, USB, and I2C interfaces and runs at 1.4 GHz. A low-power, high-performance 64-bit RISC processor analyzes motion and biometric data. While playing, the IMU detects the position of the bat. It has 6 degrees of freedom and is composed of a 3-axis accelerometer and a 3-axis gyroscope (DOF).

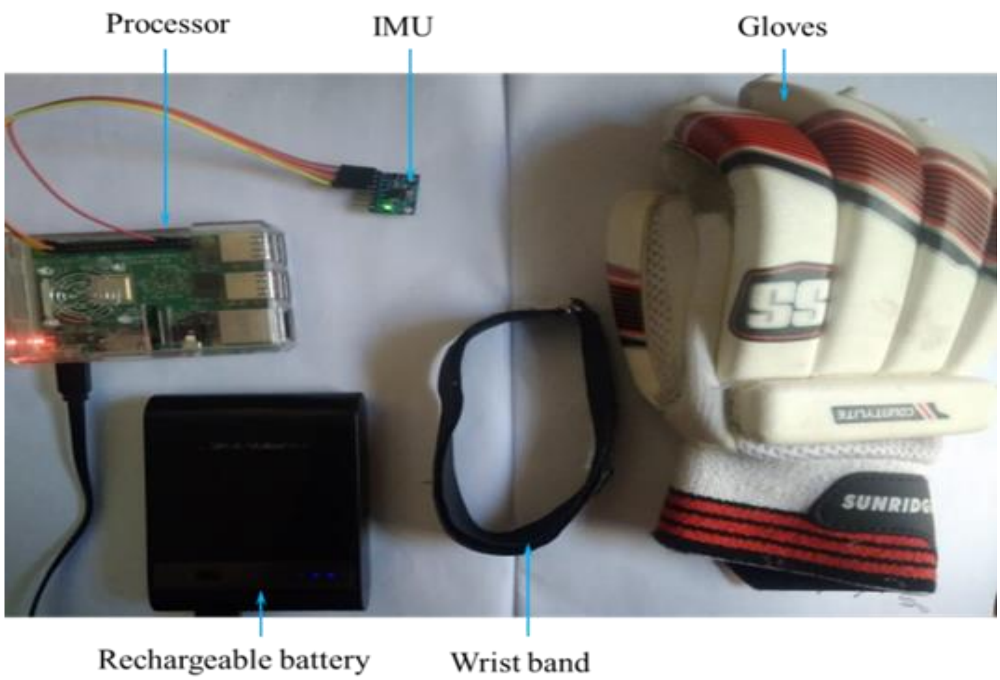


Figure 3.5 Wearable Device - Physical implementation

The processor has 1GB RAM for processing and classification. This system avoids the use of expensive online clouds and has the advantage of memory expansion up to 16/32GB for storage purposes. This memory is enough to publish the user interface details. Since the data are stored in comma separated format the memory occupied is less, and this data format is accessible by all types of processors. The module accumulates a total data of 18000 for 60 shots with 300 samples.

3.2.2 Software Design

In an embedded system we need software to control the hardware and compile the program. The system's software design is primarily centred on an interactive application for visualizing the data acquired. Tkinter and the Node-RED software application was used to create the user app. Python aid the application by providing excellent front-end and back-end functionality.

A remote desktop can be used to view the application. Multiple users can access the recorded data simultaneously because the processor allows wireless networking. The recorded information can be easily viewed and available for more extensive analysis after the motion, and biometric data is saved in CSV format. For example, the user can compare their current shot to the previously played reference shots saved in the module. As a result, the user can see his efficiency for the recent shot right away. With additional memory resources available, more advanced procedures and statistical approaches can be employed to analyze data within the device itself.

3.2.3 Movement Data Acquisition

This section describes the challenges faced in data acquisition, stroke detection and classification. The designed system is recommended for cricket players and is evaluated by testing the design with professional cricketers during their training sessions.

3.2.3.1 Cricket Stroke Detection and Classification

The shot played by the player has to be detected correctly. Only then the classification can be performed. The prototype is designed to detect and classify the three most commonly played shots. The Straight drive, Pull and Cut shot are considered for this study. After the bowler releases the ball, the following sequence of events takes place. Once the batsman attempts to hit the ball, the IMU starts recording the three axial positions and the angular displacement of the bat until the batsman completes his shot. It takes only a few seconds for the batting action to be completed, and within this time span a total of fifty distinct samples are acquired. Accelerometer data Ax, Ay and Az along with the Gyroscope data Gx, Gy and Gz are taken for every sample. The data obtained is preprocessed with Kalman filter to remove the unwanted signal variations caused by noise and vibrations. Fifty time samples with six raw data streams resulting in 300 spatial positions sampled at fifty distinct time intervals serve as the input for classification. To perform the classification of various strokes, a database is required. The data's are obtained from elite players and coaches. The database for the three strokes is generated to perform the classification. This becomes the training database for classifying the strokes. The model has to be trained with sufficient data, and the training database contains 44100(147*300) data's in the test situation. Support Vector Machine (SVM) is one of the popular supervised classification algorithms. The goal of SVM is to find a hyperplane that classifies the training vectors in the classes. Kernels are used to process the data and help plot the values in the hyperplane. Since there could be many hyperplanes to separate the instances of classes 300 dimension hyperplane is used for feature classification. Of the various kernels such as Linear, Polynomial and Gaussian, Polynomial gives better results with good accuracy, which allows the model to be nonlinear. The polynomial kernel is represented in equation 3.1.

$$K(X1,X2) = (a + X_1^T X_2)^b \qquad \text{-----------(3.1)}$$

where,

K(X1,X2)- kernel function

a – any constant

b – kernel order

X1,X2 – vectors

The polynomial kernel converts the obtained data, processes the information and then plots the value in the hyper planes of the machine learning model. The model is trained with the training data set fed to it, which helps in classifying the data and identifying the strokes with accuracy. The data obtained by the player in real-time are considered as the test data, and the shot played is detected by the machine learning model. The outputs are the classes that determines the kind of shot played by the batsman. Figure 3.6 shows the workflow model of the classification process.

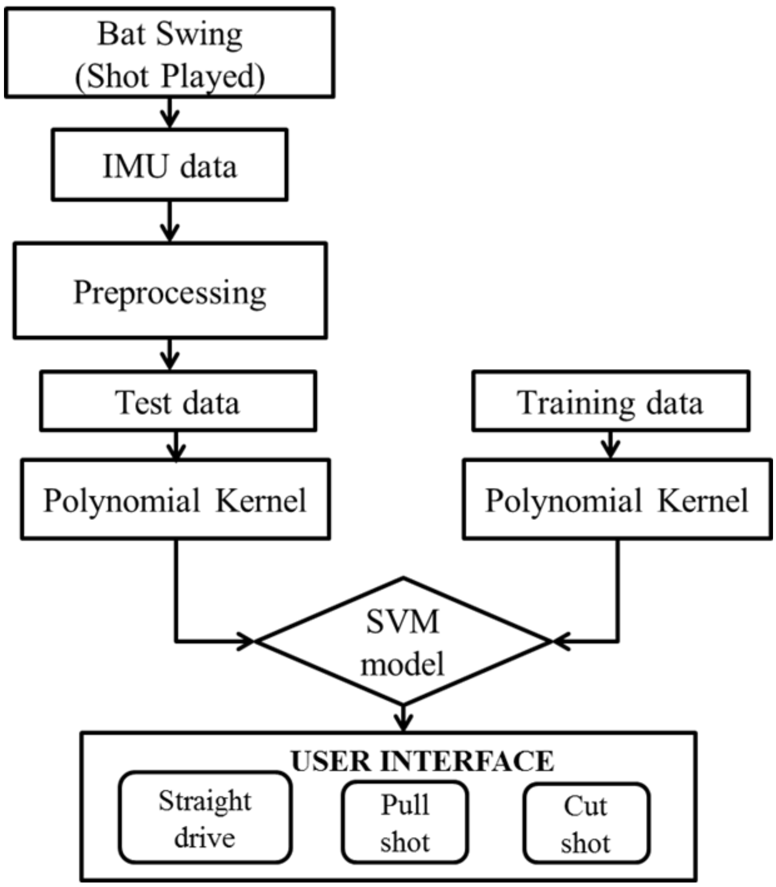


Figure 3.6 Cricket stroke classification - Work flow model

The batsman has to wear the module in his arm and establish the connection between the module and his user device. The interfacing application Tkinter is started. The IMU sensor fixed on the bat starts collecting the data and sends them to the processor as the player does his shot. The amplitude verses time data is the input from IMU. The data is sampled and stored in a temporary database as input csv files for classification. The data now obtained is the test data.

This data is the test data given to the model that is already trained with enough data collected from the elite players and the coaches. SVM processes data using the kernel trick and plots it on an N-dimensional graph, where N denotes the number of features. Here 300 features are provided to the model. Second, SVM classifier finds the perfect hyperplane to classify the data into classes. The ARM cortex A53 processor is internally performing the process. The end result can be visualized in the interactive user interface application. SVM with Polynomial kernel provides the model with best accuracy of 97%.

The common performance metrics for any machine learning classification problem are

a. Accuracy
b. Precision
c. Recall
d. F1 Score

These metrics are formulated from entries, namely False positive (FP), False Negative (FN), True Positive (TP) and True Negative (TN). True Positives are the instances that are true instances, and the machine learning model has predicted as true which means they are the correct prediction. True Negatives are those which are negative instances and the machine learning model has also predicted those instances as false. This is also the correct prediction by the model.

However, false negatives are those which are true instances and the model has predicted those instances as false, which is an incorrect prediction. False positives are false instances, but the model has predicted as true instances, which is again an incorrect prediction.

a. **Accuracy:** Accuracy is a metric that provides information on how accurate the machine learning models can classify the right outcomes. The accuracy is calculated by equation 3.2.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{-----------} \ (3.2)$$

Accuracy talks only about correct predictions. It is the ratio of the sum of true positive and true negative, which means the observations that are correctly predicted with the whole number of observations. But sometimes the accuracy alone might not be a perfect performance metric. For example, when the data is sensitive data like a prediction of some rare disease, it is good to know about the wrong predictions.

b. Precision: This metric is calculated as the ratio of the true positive to the total predicted positives, given by equation 3.3.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{----------- (3.3)}$$

Precision provides insight into how precise the model is from the total positive prediction.

c. Recall: This metric is calculated as the ratio of true positives to the total positives, given by equation 3.4.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{------------(3.4)}$$

Recall is a metric that finds out the number of true positives that the model captures of the total positives.

d. F1 Score: This metric provides a balance between the precision and recall. It is calculated by equation 3.5,

$$\text{F1 Score} = 2 * \frac{Precision*Recall}{Precision+Recall} \quad \text{----------- (3.5)}$$

When the dataset is highly uneven, it means the labels in the data belongs to the same category, then the accuracy alone will not be good enough to predict model performance. To attack this balance F1 score is calculated which is a perfect balance between the recall and precision values.

Previous stroke detection research relied on image frame classification from videos recorded while playing cricket, which necessitated the use of a high-cost, high-performance camera. This research aims to classify cricket strokes using a wearable device.

3.3 Proposed System for Biometric Monitoring

Wearable devices can measure the sportsperson's physiological parameters, monitoring his pulse rate, temperature, and strain experienced. The most significant advantage is that the values are measured in a non-invasive manner. In addition, the devices are wrist wearable and easy to handle.

The second part of the research focuses on developing a wearable device that measures the strain encountered by a cricket player while playing various strokes during his training session and measuring other basic parameters like heart beat rate and temperature.

The magnitude of vibration on the muscles during various strokes may lead to strain and overload the players. In games such as cricket, the delivery speed of the ball is greater than 150kmph for fast bowling. The batsman has to release a proper shot to encounter the ball with such high velocity. Therefore, there are possibilities for the arm to get strained. Measuring muscle activity at this point gains importance. A system is proposed to measure a cricket player's strain, temperature, and heartbeat rate. From these details, the information about the player's physical state can be derived. The proposed system consists of three modules: 1) Wearable sensor module for recording strain, temperature and heartbeat rate 2) Processor module, and 3) User Interface module to access real-time details. All complex process is performed in the processor itself. Figure 3.7 shows the device's position on the forearm.

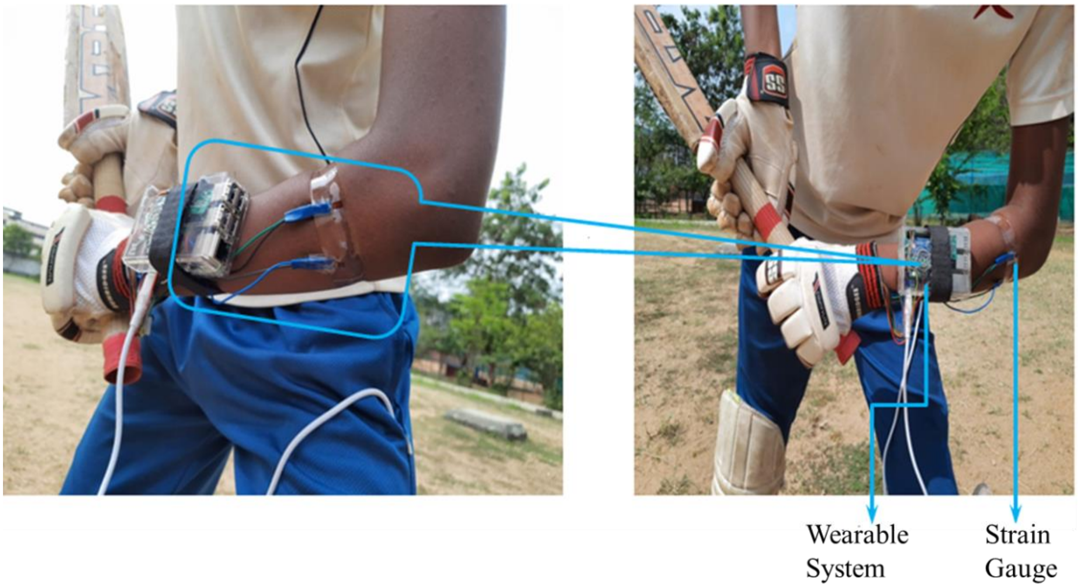


Figure 3.7 Device Position for Biometric data acquisition

3.3.1 System Architecture

The system hardware is designed to measure the player's biometric information. The wearable device is placed on the player's gloves to acquire the data. Strain gauge sensors are placed on either side of the elbow to record muscle contraction while playing various shots. The heartbeat sensor is placed on the fingertip, and the temperature sensor is placed on the wrist of the player. The sensor placement does not disturb the player's performance. This data acquisition module operates solely measuring biometric data of the player in real-time. The strain gauges are well identified as they provide good accuracy, light weight, flexibility with low sampling frequency, and can measure the strain. Chu et al. explained the usage of strain gauges in the respiratory rate measurements and the volumetric change measurements in humans.

Basically, the training lasts for 2 to 4 hours, so the module is powered by Lipo rechargeable battery with a specification of 10000mAh battery that can last for 2 days and is easily rechargeable to be used for a prolonged time. Figure 3.8 depicts the block diagram representation of the proposed wearable device hardware.

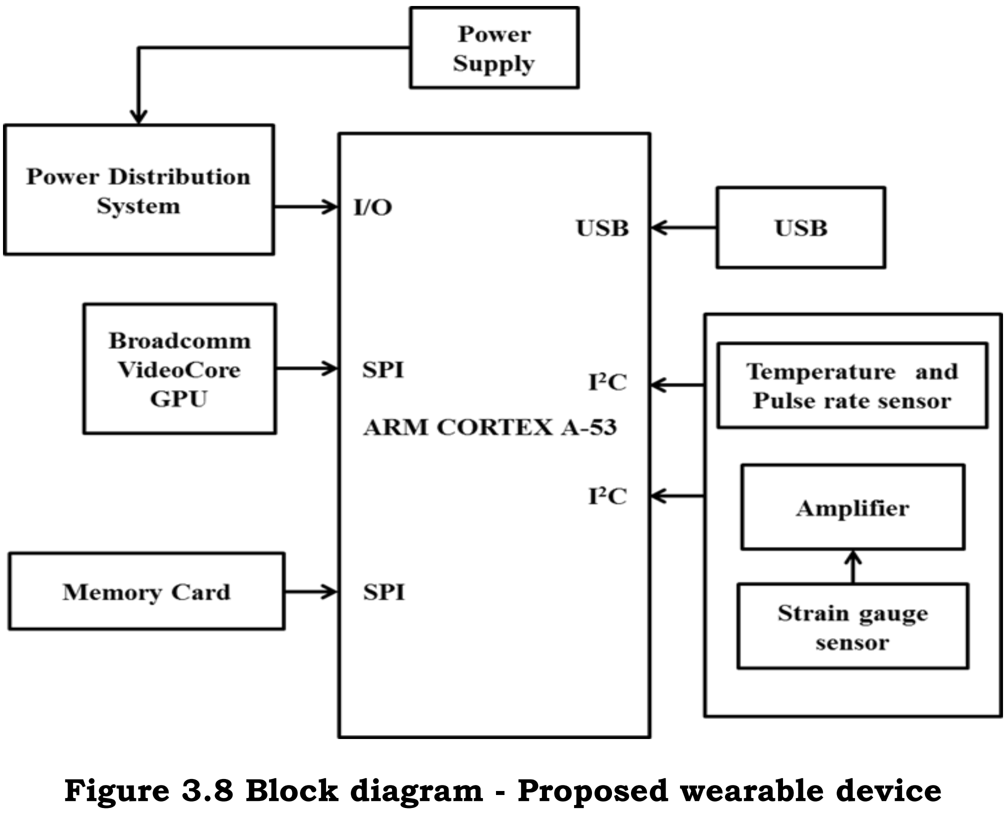


Figure 3.8 Block diagram - Proposed wearable device

The processor employed is a 64 bit RISC ARM Cortex A-53 processor. Since the input from the strain sensor is too low, it is amplified by HX711 amplifier, and it is interfaced with the processor via the I2C bus. Also, temperature and pulse sensor is the other input to the Processor, and they are connected through ADS 1115, an analog to digital converter (ADC). External memory can also be connected to the Processor. With the inbuilt Wi-Fi module, data can be transferred to the user from the processor. The strain gauge sensor and its amplifier, heart rate sensor and temperature sensor are integrated into a separate module to avoid misplacement. They can be easily replaced in case of damage. The module is fabricated separately to hold the sensors. Conductive tracks for ADC, amplifier, resistors and interface with the processor are designed and laid out on the printed circuit board. This board is then interfaced with the processor. So the circuit remains undisturbed, and the sensors can be replaced easily in case of impairment. Figure 3.9 and 3.10 shows the hardware setup and the fabricated printed circuit board.

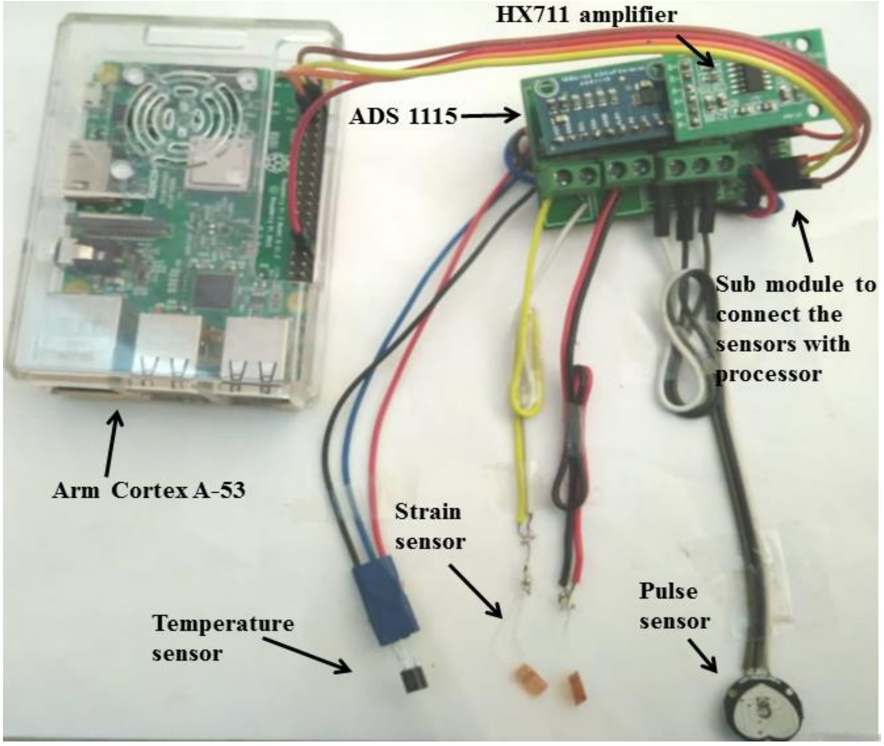


Figure 3.9 Hardware setup of the wearable device

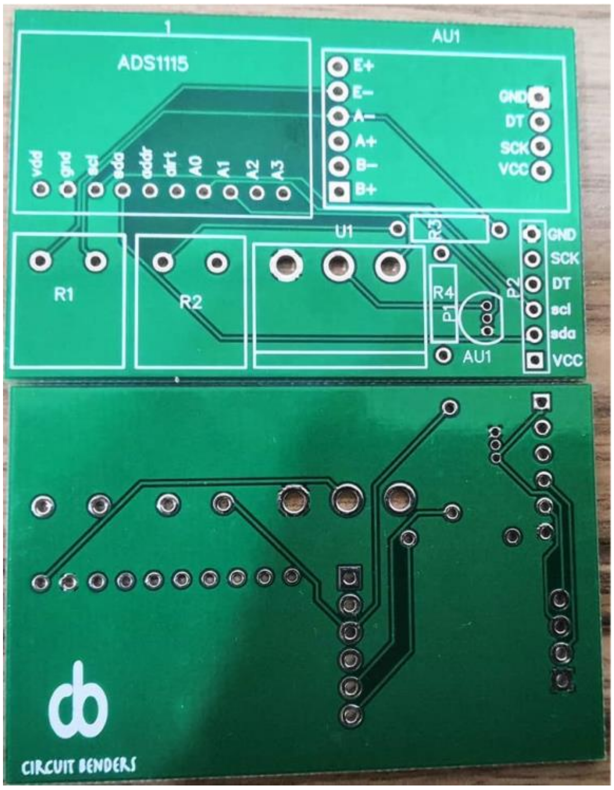


Figure 3.10 Sub module - Fabricated PCB front and back view

3.3.2 Biometric Data Acquisition

This section looks into the details of obtaining biometric data such as strain, temperature and heart rate. Cricket players were used for testing the proposed system performance. Figure 3.11 shows the workflow model.

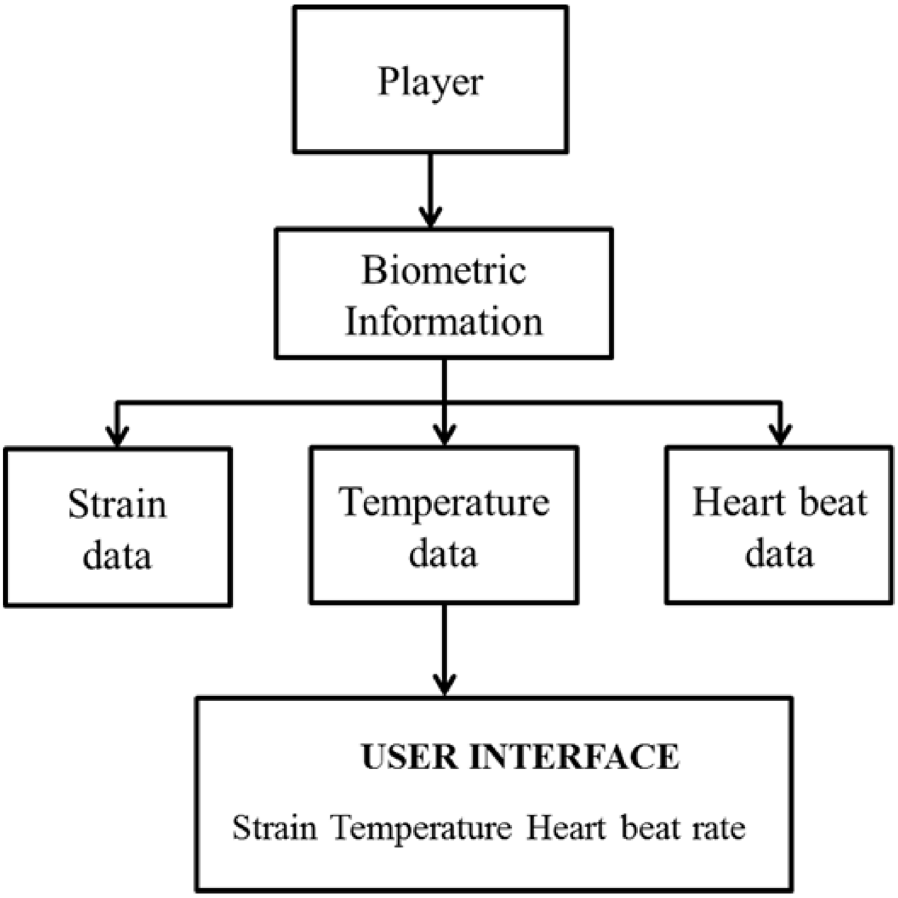


Figure 3.11 Work flow model of Biometric data acquisition

Strain in muscles might happen due to repeated activity in a particular portion of the body. During training sessions due to eagerness and involvement the player might overstrain his muscles without knowing that his body is strained too much. It is now essential to concentrate on the health aspects of the player during their sports activity. So the system aims to measure the temperature and heart rate of the player. Table 1 gives the features of the wearable prototype system.

Table 3.1. Characteristics of Moniotring System

Sensors Used	Strain gauge sensor - 350Ω, Gauge factor – 2 Pulse sensor - +3V/+5V Temperature sensor - −55°C to 150°C
Sensed Parameter	Strain in arm muscles, Heartbeat rate, Body Temperature
Connectivity	Wifi
Dedicated User Application	Yes
Real time Bio-feedback	Yes
Method	Non-invasive
Battery	Lipo rechargeble battery-10000mAh
Wearable	Wrist worn
Easy replacement in case of sensor damage	Yes, separate hardware for the sensor module

3.3.3 Strain Measurement

Strain gauge sensor can measure strain in the human arm. These low-powered piezo-resistive sensors can be integrated with the processor and Wi-Fi units and thereby can be useful in monitoring the strain in sports activity in everyday training sessions. Furthermore, strain measurements can predict the location of injury and the performance of the safety wear being used by the batsman etc. This work demonstrate that it is possible to measure strain in the arm using a wearable strain sensor placed directly on the arm of the player. Strain in the arm is increased when the elbow is moved into greater degrees of rotation and inversion.

This research work presents a method for measuring strain using a strain gauge sensor and data acquisition is performed by the low power processor. Figure 3.12 shows the signal conditioning done by the Wheatstone bridge and discretized by HX711, which is an analog to digital converter (ADC) connected externally to the processor.

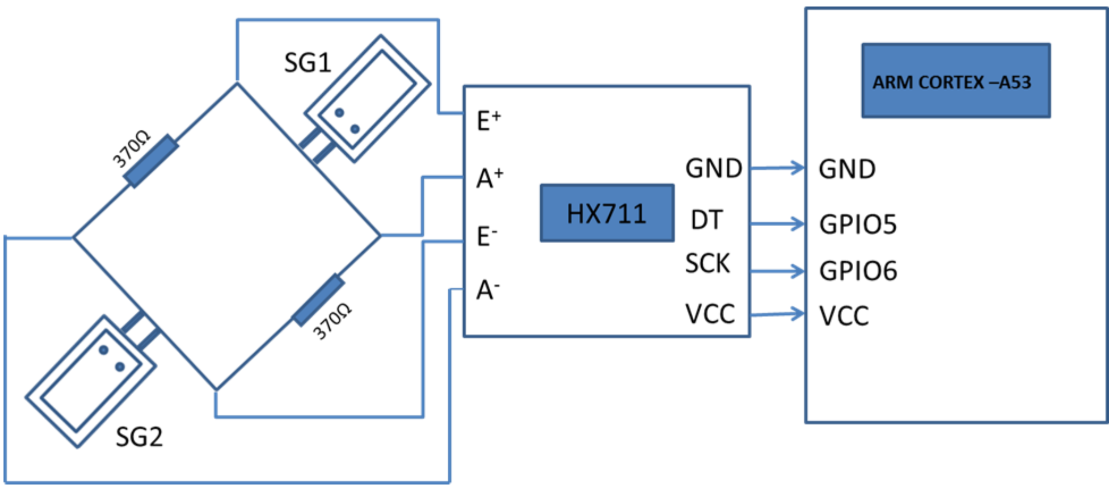


Figure 3.12 Interfacing diagram of strain gauge with the processor

3.3.4 Heart rate Measurement

On-field heart rate and physiological fitness make the player more active if his fitness level is maintained from the beginning until the last ball. This is the current demand in the modern sports field. The player's vital signs such as temperature and heartbeat are captured in real-time to know the fatigue and endurance of the player during his practice sessions. Wireless communication has enabled wearable devices embedded with sensors and wifi to easily communicate physiological information to the user via smartphone or his laptop. For this reason, researchers are developing devices to be incorporated in training sessions to monitor the players health parameters and physical fitness.

The pulse sensor has a detector to detect the volume changes in the blood vessel. This happens due to the pumping action of heart muscles. It works based on the principle of photo electricity. The pulse sensor has a light sensor on one side and an amplifier circuit on the other side. The LED on the front side of the sensor is placed on the wrist of the player. The emitted light will fall on the vein directly, and the rate of blood flow can be monitored from which the heartbeat can be calculated. The analog output from the pulse sensor is interfaced to the processor through ADS1115 ADC module via I2C communication since the processor accepts only digital inputs.

3.3.5 Temperature Measurement

Skin temperature is important in many researches and applied settings. The sensors can be affixed directly to the skin surface.

LM35 is the temperature measuring sensor that gives out an analog signal proportional to the temperature. The sensor does not require any external calibration. It is a precision integrated circuit with an accuracy of ±1/4°C. LM35 temperature sensor supports direct skin contact, continuous temperature measurement and measures the body temperature (in °C). The scale factor is 0.01V/°C. LM35 sensor placed on the wrist is connected to the processor through one of the channels of ADS1115 ADC module, and the output format is adjusted to get a working thermometer in Celsius. Since continuous temperature output is unnecessary, the temperature was recorded every 200 seconds.

3.4 Smart Health Monitoring System for a Sports Person using IoT

Heart diseases are now becoming a big problem in the last few decades. Recently the research has turned its focus towards the real-time monitoring of physiological variables and parameter monitoring. So it is high time the health parameters along with performance metrics of a sportsperson have to be monitored. So technology provides solutions where a person's heart rate and heart rate behavior can be observed in real-time regularly. The first step is to take the ECG signal for any heart-related diseases. The ECG signal is used to determine heart rate and help diagnose any heart attacks and heart failure. By analyzing these signals, heart problems can be alleviated at the initial stage. Literature shows that there are sudden unexpected deaths in sports players. When the player is in critical state of hitting the runs, especially at the nearing end of the over, he becomes emotionally unstable. Such strong emotions like stress, fear and anxiety stimulate the sympathetic nervous system causing more sweat to be secreted. Studies reveal that cardiac problems have a direct impact on stress. GSR sensor is a reliable index for stress. It is based on the conductive principle. GSR sensor can identify those emotions by fixing two electrodes on the fingers of the hand. These are light in weight, non-invasive, and can be easily fixed.

Suppose a person is under stress the skin conductance increases. GSR sensors are used for health monitoring in athletes. Heart rate variability and GSR together act as a biomarker to find the mental status of a sportsperson. This would help the physical trainers to alter the training load accordingly.

3.4.1 Hardware Development

The proposed system consists of hardware and application development. The ECG sensor is used to monitor the heart activity of the sportsperson. These raw data are fed as input to the microcontroller unit (MCU). The MCU used here is ESP 8266, which has an inbuilt wifi module. The sensor data are transmitted to the cloud server via the internet. These are further processed and provide feedback to athletes and trainers through mobile applications.

The standard form of taking an ECG signal is to use a 12 lead placement system. But it is not portable and feasible all the time. This paper utilizes the advantage of using three lead monitoring systems with 3 electrodes which are portable and can be easily handled. Three electrodes are placed on the chest rather than limbs to pick up the electrical signal without artifacts. Initially the work started with measuring the ECG signal of a player using an AD8232 ECG module. This module measures the high noise, low amplitude ECG signal with a very good amplification and helps to obtain a clear ECG signal with distinguished P,Q,R,S and T points. The block diagram, the hardware and the output obtained from MATLAB are shown in Figure 3.13.and 3.14. The AD8232 ECG module with disposable electrodes is placed on the chest to collect the heart's electrical signal. It is interfaced with the ATmega328P Arduino microcontroller.

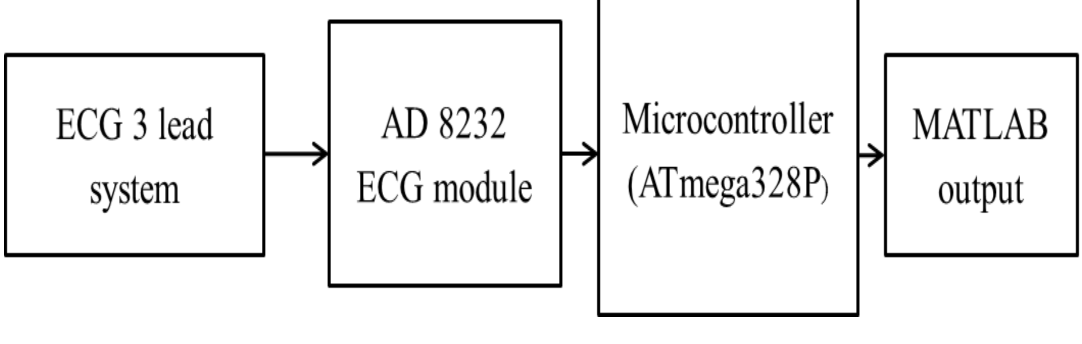
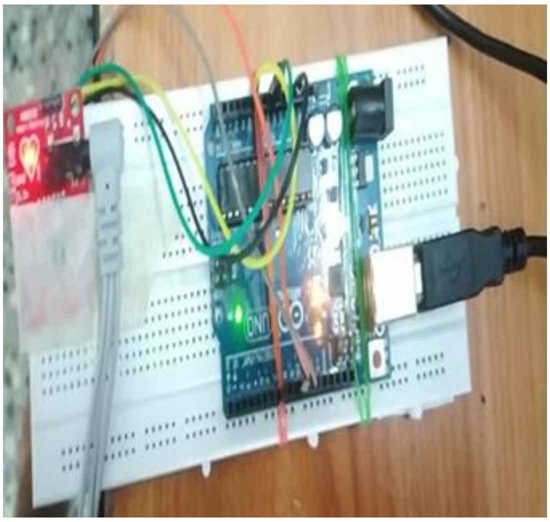


Figure 3.13 Block diagram of the hardware module



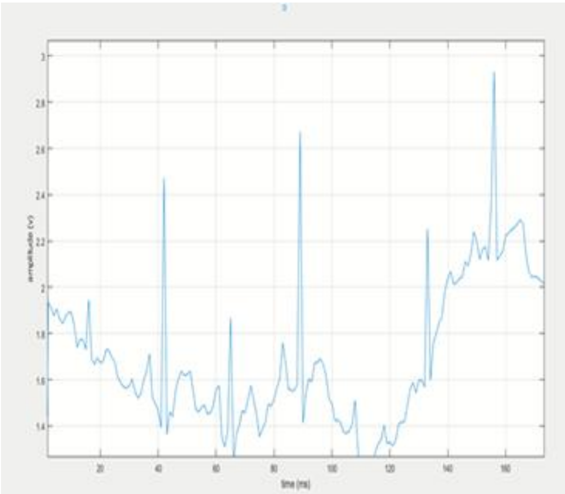


Figure 3.14 Hardware and MATLAB output with ATmega328P

3.4.1.1 Enabling with a phone application (I upgrade)

In the above system the output is seen only in MATLAB. So we went for upgrading the system, in which the player can see the real-time data in his smartphone itself instantly using the application. ESP 32 comes with a low power Bluetooth module and a microcontroller. This reduces the cost of a separate module for interfacing wirelessly as it is integrated with Bluetooth, wi-Fi and the controller. Figure 3.15 and 3.16 shows this setup.

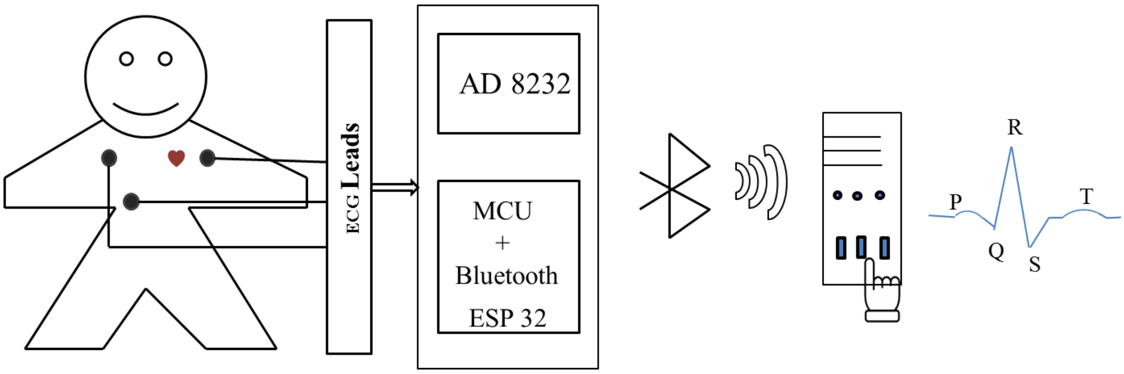


Figure 3.15 Block diagram with phone application

Figure 3.16 Hardware setup with ESP 32

3.4.1.2 Interfacing with the Internet of Things (II upgrade)

The above module uses only Bluetooth, in which the distance is limited only to10m in diameter. It means the player can access the details only if he has his mobile phone within this limit. This drawback is overcome by using the internet of Things (IOT), where the player and the coach can view the health parameters anywhere.

The ECG and GSR sensor is interfaced with ESP 8266. The waveform is sent to the IOT cloud platform to make the signal available online. The physiological details can be seen from anywhere. Figure 3.17, 3.18 and 3.19 explains the block diagram of the interfacing with IoT, physical implementation and the placement of the wearable device on the forearm. The workflow model is shown in Figure 3.20. Table 2 explains the features of the wearable system.

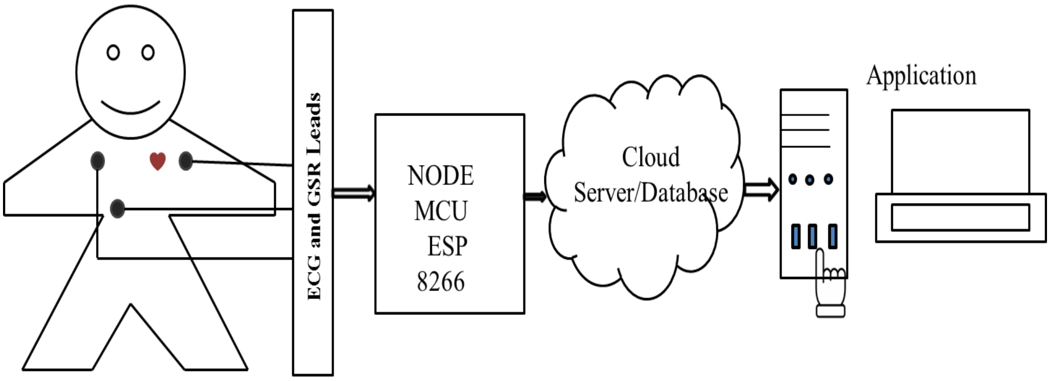


Figure 3.17 Block diagram of the interfacing module with IoT

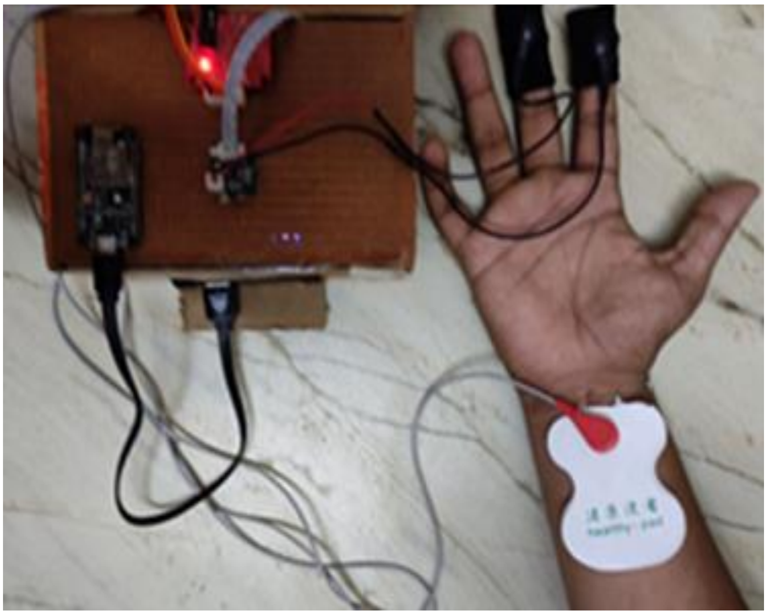


Figure 3.18 Physical implementation for monitoring ECG and stress

Figure 3.19 Interfacing ECG and GSR sensor module with ESP 8266

Table 3.2. Key features of wearable system

Parameters	**Specification**
Sensing Platform a. ECG sensor	AD 9232 Power: 3.6v Output voltage: 0-3.3v
b. GSR sensor	Operating voltage: 3.3/5V Input signal: Resistance Output signal: Voltage
Wi-Fi module	Node MCU Power: 3.3V
Communication Protocol	Wifi IEEE 802.11
Enabling Technology	IoT
Dedicated user Application	Yes
Real time Bio-feedback	Yes
Method	Non-invasive
Wearable	Wrist worn

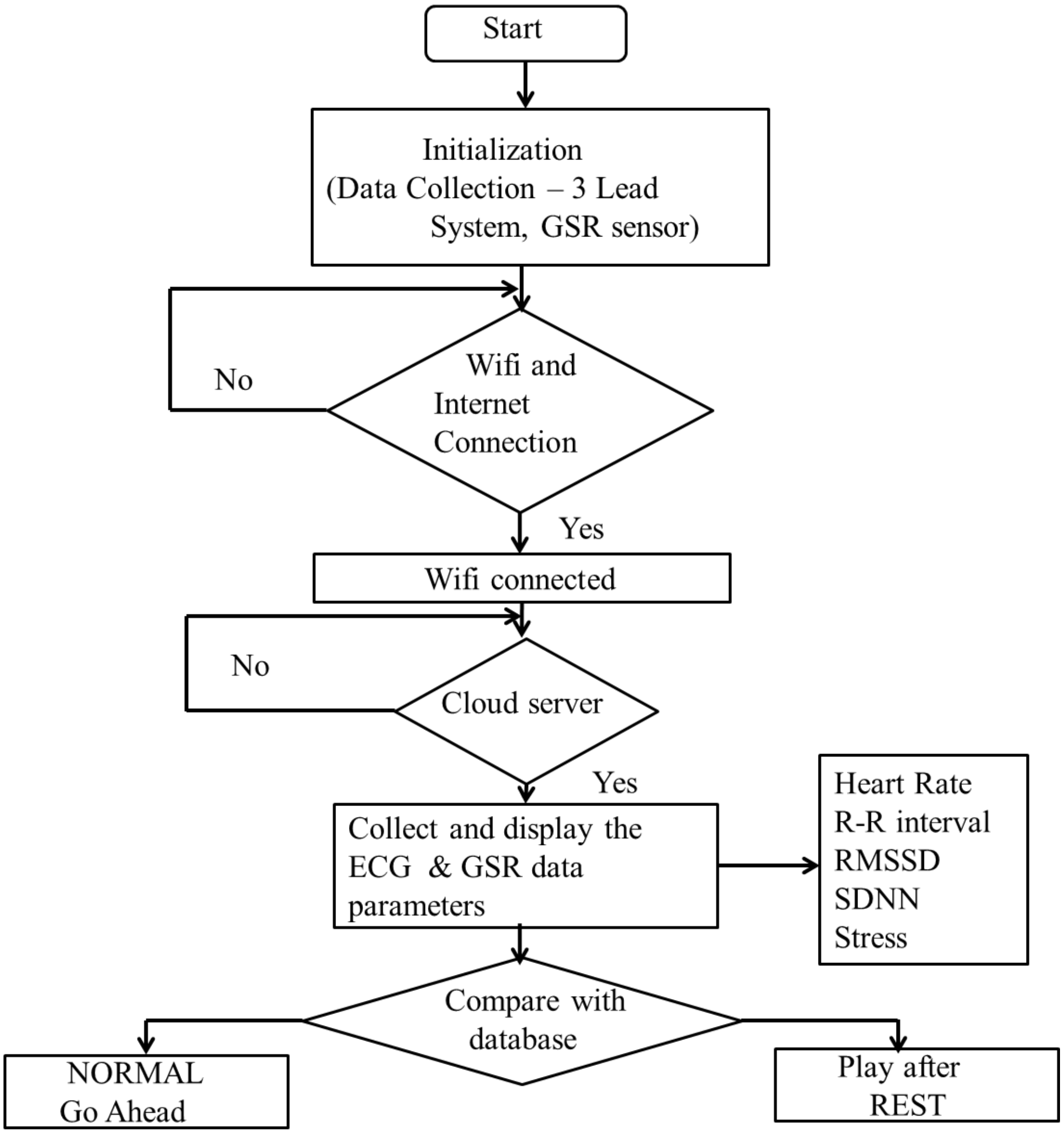


Figure 3.20 Workflow model for monitoring health parameters

3.5 Software Application

A new application named 'FIT ON to play' is developed dedicatedly to monitor and maintain a database of the players parameters. Collecting the data alone will not be useful. These signals can be transmitted in real-time over the internet for further analysis. IoT helps ECG signals to be transmitted through a gateway. Bluetooth, Zigbee, Wi-Fi and LAN are some communication protocols, out of which Wi-Fi is used here. This data can be sent to cloud storage for analyzing and processing. This computer technology helps to view the report on smart devices. The SQL database management system is employed to manage data. The trainer and the player receive the health-related data by simply logging on to the application. Feedback is thus instantly provided to the player as well as his trainer.

The parameters are calculated with equations 3.6, 3.7 and 3.8. And the computed values are given out to the player in real-time.

Heart rate = $\frac{1000}{RR_i} * 60bpm$ ------------(3.6)

mean RMSSD = sqrt$\{mean((RR_{i+1} - RR_i)^2)\}ms$ ------------(3.7)

SDNN = sqrt$\left\{\frac{\sum_{i=1}^{N}(RR_i - mRR)^2}{N-1}\right\}ms$ ------------(3.8)

RMSSD is the root mean square of the successive differences between normal heartbeats. It is calculated as the square root of the mean square difference between the current and previous RR interval. RR is the R to R interval, which is the time period between the two consecutive R and R intervals. SDNN is the standard deviation of NN intervals. NN term is used instead of RR, and they represent the beat to beat interval. SDNN is calculated as the square root of the ratio of the sum of the squares of the difference between the RR interval and the mean RR interval with N-1.

These parameters are used to find the physiological details of the player and give him the instant feedback.