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Vital Sign Monitoring System and Analysis with CNN

Ganesh T. M.*
*M. Tech,
Department of Electronics & Communication Engineering,
Vidya Academy of Science & Technology,
Kerala, India

Vandana M**
**Asst. Professor,
Deptartment of Electronics & Communication Engineering,
Vidya Academy of Science &Technology,
Kerala, India

***Abstract*—Vital monitoring systems are becoming more popular in the monitoring of health and physiological data. This study describes a vital sign monitoring system that continuously monitors and collects vital data, which is then shown on a mobile device. It can assess muscle activity, heart rate, and sleep apnea.The abnormal variations in vital data can predict the risk of heart failure, and it also includes an alert system that can notify the relevant medical officials if necessary. The suggested system consists of a microprocessor, an ECG sensor for heart rate monitoring, and an EMG sensor for muscular activity monitoring. A CNN model that classifies heatbeat data into anomalies is also proposed, as well as a CNN-based sleep apena prediction model. The CNN model examines the heart arrhythmia conditions, and using this model, heart beats are classified into five categories and taken the loss and accuracy. To predict sleep apnea, the random forest method is utilised to classify ECG signals.**

***Index Terms*—Vital signs detecting device; Electrocardiography; electromyography; sleep apnea.**

I. Introduction

It proposes a wearable device or system for monitoring heart rate variability, stress, muscle activity, and sleep apnea. It aids in the collection of numerous vital signs indicating a person's health and their transmission to the cloud for post-processing via wired or wireless communication. Wearable devices with IoMT have opened up new possibilities in fields including smart healthcare, fitness, and yoga. Over half a billion individuals use wrist-worn fitness trackers alone throughout the world. Long-term biosignals can be tracked and biometric data can be wirelessly transmitted to the cloud via wearable Internet-of-Things devices. They can employ high-speed Bluetooth to acquire sensor data from wireless body sensors or the patient's smartphone to monitor basic vital indicators.

Nowadays, research on wearables that measure vital signs is progressing at a rapid pace. As a result, the garments may be beneficial to older people because it is not always possible to continuously monitor vital data. Many fitness and medical devices are available today that monitor and provide data on vital and medical parameters such as calories burned, efforts made, oxygen saturation level, hypertension, heart rate variability, and breathing rates.. To connect to other devices, such as a cell phone, these gadgets employ Bluetooth Low Energy (BLE) technology. Although some firms, such as Fitbit and Garmin, have the functionality of building their phone applications (apps) to receive data with restricted features, this is the biggest disadvantage of these devices. A system that can analyse acquired data for accuracy, consistency, and viability is required. The information gathered is useful for medical considerations. By setting a threshold value, an automatic message will be sent to medical practitioners if the parameter reaches that value. As a result, medical professionals can keep an eye on the data and administer medications to the patient on time.

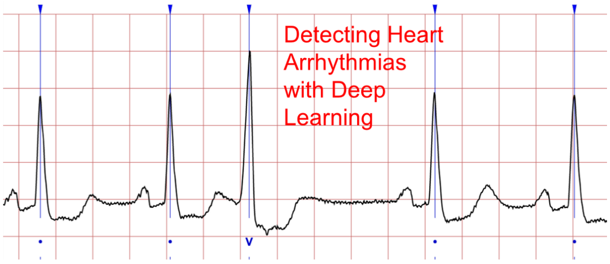

Fig. 1. ECG Waveform

[1]

This study presents a garment-like wearable device that continuously measures vital signals and delivers the data to the cloud, where it is processed and made available via mobile. And, using CNN, distinct types of heartbeats are analysed, and the results are presented accordingly. The model loss and accuracy are derived from this, and the condition of sleep apnea is also predicted using CNN and classified using a random forest algorithm. The remaining portions of this work are made as follows. The related works are addressed in Section 2. Section 3 provides a description of the wearable systems research as well as the scope of the study. The idea and approach of the research schemes are covered in Section 4. Section 5 reports the outcomes and an analysis of the proposed system. Section 6 marks the conclusion of the essay.

II. Related works

Because of the growing popularity of wearable systems, extensive research and development of wearable devices that measure vital signs is helping to maintain good health. These systems are especially beneficial for the elderly, babies, and those with cardiac conditions, as they continuously monitor for anomalies and inform medical personnel if necessary.

An integrative literature analysis was done to evaluate the factors that influence ward nurses' vital sign monitoring practise in detecting and reporting worsening. There were twenty papers in total. The review was synthesised using a structural component of a Nursing Role Effectiveness Model framework, which covers patient, nurse, and organisational variables. Patient variables include physical signals and aberrant vital signs, as well as indications of worsening reported by patients. Nursing variables include clinical knowledge, roles and responsibilities, and reporting of dropping vital signs. Organizational variables include workload, technology, and the design of observation charts.

Author [2] proposed a system in which psychological stress influences a person's physiological parameters. Long-term stress can have negative consequences that may necessitate costly therapies. In persons with a history of borderline personality disorder or schizophrenia, acute stress can be fatal. This study proposes a deep learning-based innovative approach (Stress-Lysis) to self-manage this major health concern in the context of smart healthcare. During physical exercise, the learning system is programmed to monitor a person's stress levels by measuring their body temperature, rate of motion, and sweat.

Author [3] proposed a system in which the proposed convolution neural network can automatically classify ECG signals without the need for manual feature extraction. Doctors frequently advise patients with suspected arrhythmias to wear a Holter to constantly record ECG data for 24 hours or longer. Because the amount of ECG data acquired by the Holter is so huge, it's necessary to employ a computer to analyse the recordings and automatically categorise the types of heartbeats.

Author [4] proposed a system that aids in real-time monitoring of a person's stress level, thereby reducing health risks. Psychological stress is a pressure sensation that causes physiological changes in a person. This study offers iStress, a novel stress detection system that identifies stress levels during physical activity by measuring body temperature, rate of motion, and sweat. The iStress system's model is a neural network technique with a Mamdani-type fuzzy logic controller and over 150 instances.

Author [5] proposed an unique technique for detecting and localising myocardial infarction (MI) using multilead electrocardiograms(ECG) using a multiscale energy and eigenspace (MEES) approach. In this study, the eigenvalues of multiscale covariance matrices and multiscale wavelet energies are used as diagnostic criteria. Support vector machines (SVMs) with both linear and radial basis function (RBF) kernels, as well as Knearest neighbour, are employed as classifiers. The PTB diagnostic ECG database is used to assess datasets containing healthy controls as well as various types of MI, such as anterior, anteriolateral, anterioseptal, inferior, inferiolateral, and inferioposterio-lateral MI. According to the data, the proposed technique can detect MI problems.

III. Research and Advancement on this paper

Clinical examination of a patient's most basic vital signs is the easiest and most successful technique to discover and monitor health concerns in the medical setting. Many disorders can be diagnosed and treated by keeping track of these medical data on a regular basis. The goal of this research is to create a system for monitoring and tracking a patient's numerous vital indicators. The use of a symbolization approach specifically intended for ECG is described, which can represent both the morphology and rhythm of the heartbeat while also reducing the impact of inter-patient variance through baseline correction. A multi-perspective convolutional neural network (MPCNN) uses the symbolic representation of the heartbeat to learn features and classify the heartbeat automatically Author[15]. Monitoring vital indicators such as respiratory rate, blood pressure, and temperature of patients is crucial. Changes in vitals are detected before they worsen, and appropriate intervention and prevention are implemented. Despite their importance in clinical practise, it is still unknown how to adequately monitor and evaluate them.

Wearable technologies for continuous monitoring and analysis of long-term biological data such as electrocardiography (ECG) have seen accelerated expansion as personalised healthcare technology advances. However, existing ECG monitoring systems have limitations, such as the capacity to merely record ECG data, have low accuracy, and perform event-by-event diagnosis at the point of data acquisition Author[12].

- A smart wearable garment analyses the level of muscle activation in athletes using surface electromyography (sEMG).
- There is no HRV analysis to assess a user's stress level.
- There is a lack of understanding and awareness of vital sign variations and their consequences for patient care among nurses and doctors..
- Intermittently observed vital sign trends in critically unwell adult patients on hospital wards and in emergency departments have been the subject of research.

These wearables save data on the cloud and provide users with access to it. Electromyography (EMG) is used in the garment to monitor muscle activity and aid the user in physical treatment. While a few proposed solutions use accelerometer data to assess exercises, indicating individual muscle activity is not enough. A built-in warning system to alert paramedics and users' contacts in the event of an emergency is also missing from the aforementioned solution, along with an accurate assessment of body posture.

A. *Research scope in Vital Sign Monitoring*

For the early detection of patient clinical deterioration in hospital settings, consistent vital sign monitoring is necessary. To assess a patient's condition, nurses frequently measure and record their primary vital signs 23 times every day. The "VitalSCOPE" smart vital sign monitor was created to reduce the labour of nurses and consequently raise the calibre of patient care. The Vital-SCOPE measures body temperature, breathing rate, and pulse rate in real time within 10 seconds

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using a variety of sensors, including a reflecting light sensor, thermopile, and medical radar.

IoT devices are crucial for tracking patients physiological conditions. Some sensors, connected to the body which gathers and evaluate data before sending it to processing centres where appropriate judgments are made. Remote monitoring is a method for providing medical services that makes use of the Internet of Things. By providing medical treatments remotely and avoiding needless hospital visits, remote monitoring is crucial in an emergency. The delivery of medical services to the elderly will be accomplished by a networked e-health system. This system's sensors send signals to the doctors, who can then track the patient's data in real time while also giving emergency healthcare services the most recent information and data insights.

Context awareness refers to a way of determining a patient's state in which the patient's surroundings are taken into account. In the event of a change in the patient's environment, healthcare professionals can now actively monitor alterations in the patient's environment in relation to the patient's physical condition. Studies have demonstrated that changes in a patient's physical well-being caused by environmental changes can affect his or her ability to withstand the negative effects of various diseases to which he or she may have been exposed unknowingly in the past.

When comparing traditional vital sign measurements to automated assessments, a study included in the original systematic review indicated that the latter saved 20 seconds per individual, which the researchers felt was a considerable saving when evaluated in terms of all hospital patients over a year. However, the study did not provide precise data on the accuracy of vital signs taken with machines and monitors. Furthermore, current automated blood pressure monitoring systems appear to be less trustworthy when blood pressure rises. To update this study, data sources will be systematically searched on innovative techniques and vital sign measurement.

IV. Design & Methodology

This section describes the proposed system's design and methodology.

The suggested system is a wearable garment that detects vital signals such as heart rate, muscular activity, and sleep apnea.CNN also examines the analytics to determine whether they are normal or abnormal. A sleep apnea condition test is also performed to determine whether or not a person has sleep apnea. An ECG sensor is used, with electrodes attached to the body and the heart pulse constantly monitored. If the threshold is exceeded, a message is sent to medical personnel. Any change in sensor readings, according to EMG, indicates a notice will be sent to the appropriate medical personnel.

A. Mathematical approach

1) Method to calculate heart rate from ECG: The vitals of the human body are an important issue to consider. The suggested system is depicted in this diagram, which shows how it is delivered through smartphone. In this case, the smartphone serves as an interface for visualising data after

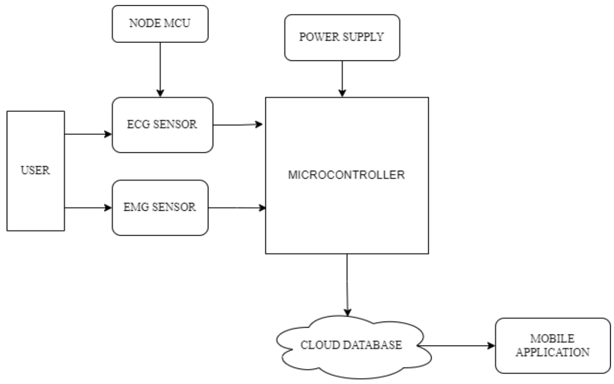

Fig. 2. Block diagram
[2]

it has been analysed for the benefit of the user. The design expects to receive the ECG data in order to detect any abnormalities. The suggested deep learning model detects any anomalies if any exist. A medical official and the user's mobile app receive alerts when anomalies are found. Abnormalities at regular intervals are commonly believed to be a sign of impending heart failure, and a notification is delivered to the user's smartphone application. EMG aids in determining muscle activity and intensity in a specific muscle location. The change in electric potential created at neuromuscular connections as electric signals or action potential pass through is measured using EMG. Voltage is a measurement of the amount of force being applied by the muscle in real time and is used to monitor muscle activity.

Each heartbeat is represented by a P-QRS-T waveform in the graph and collection of different waveforms. The depolarization of the atria, which causes a brief isoelectric phase or condition of near zero voltage and lasts for less than 0.10 seconds, is symbolised by the ”P” wave.

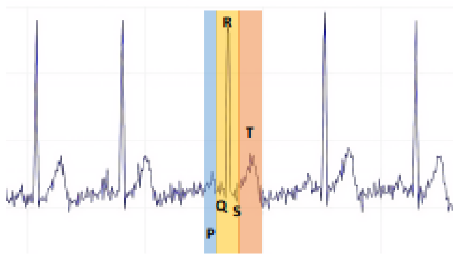

Fig. 3. P,QRS and T segments of ECG
[3]

Before the QRS complex, which is composed of the contraction of the ventricular muscles and lasts for less than 100 milliseconds, there is a brief series of Q, R, and S waves. The T wave, which represents ventricular repolarization and cardiac relaxation, comes after the QRS complex. This is brought on by every single heartbeat. Using the following formula, the heart rate is expressed in beats per minute:

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$$Heartrate(bpm) = \frac{60}{Tr} \tag{1}$$

where Tr denotes the time interval between two consecutive R peaks [1]

B. Heart Arrythmia Detection Using a Convolutional Neural Network

1) Dataset preparation: A dataset with categorization of heartbeats into normal beats, Ventricular and Supraventricular beats, Fusion beats, and Unknown beats is deemed in order to discover problems in ECG. The 48 half-hour ECG excerpts from the MIT-BIH Arrhythmia Dataset, which contains more than 150,000 samples, are used. A total of 100,000 samples were used to train the conceptual model, which was then tested on a total of 22,000 samples.

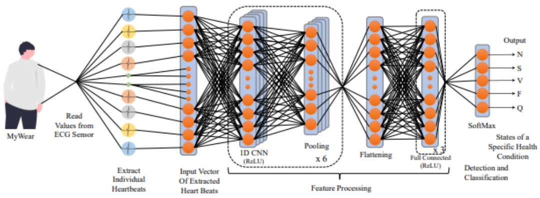

Fig. 4. Convolution Neural Network (CNN) Model explored [5]

The neural network based model's architecture is shown in Figure. It has a 2-stride input stride length and 6 one-dimensional convolutional layers with 64 filters each. The Maxpool layer, which has a pool size of 2 and a stride size of 2, is placed after each convolutional layer. Three Fully Connected Layers are joined to these. Individual class probabilities. The model is used to divide the dataset into four groups based on heart beat rhythm and to predict whether the input heart beat is normal or pathological.

2) Metrics to evaluate the CNN Model:

- Precision:The model's capacity to discern potential heartbeats from the input: [3]

$$P = \frac{TP}{TP + FP} * 100 \tag{2}$$

Recall: The ability of the model to identify all the relevant heartbeats from the predicted possible heartbeats: [4]

$$P = \frac{TP}{TP + FN} * 100 \tag{3}$$

Accuracy:The proportion of the model's accurate predictions to all of its other predictions is as follows: [7]

$$P = \frac{TP + TN}{TP + TN + FP + FN} * 100 \tag{4}$$

C. Methodology

The vital signals of a living organism are an objective measurement of its vital physiological activity.The word "vital" refers to the first and most important step in any clinical evaluation—their measurement and assessment. As part of the initial clinical examinations, the patient's vital signs are evaluated. Patients are triaged at an urgent/prompt care centre or an emergency department based on their vital signs, which indicate the degree of deviation from the baseline to the clinician. The various physiological and pathologic processes that affect these measurements must be understood by healthcare professionals in order to correctly interpret them.

The hardware element begins with a microprocessor, ECG Sensor for measuring heart rate, and EMG Sensor for detecting muscular activity. When it is linked to the body, it continuously monitors the vital data and notifies the appropriate medical professionals if any abnormal changes occur. Along with that, CNN is used to detect heart arrhythmia, and epochs are calculated and training and validation graphs are presented. It establishes whether or not someone has a heart arrhythmia. Additionally, a CNN that is based on sleep apnea is run to determine if a person has the condition. An objective measurement of a living thing's vital physiological activity is provided by its vital signals. The word "vital" refers to the first and most important step in any clinical evaluation—their measurement and assessment. As part of the initial clinical examinations, the patient's vital signs are evaluated. Vital signs, which show the clinician how far the patient has deviated from the baseline, are used to prioritise patients at urgent care facilities or emergency rooms. Healthcare professionals need to be knowledgeable about the various physiologic and pathologic processes that affect these measurements and how to properly interpret them.

V. Result and Analysis

This section discussed the output and various analyses done for the suggested system.

A. Variation of voltage and current generated by a piezo under different surfaces

- ECG lead placement is shown in figure 5.
- RA(Right Arm): The red electrode was inserted into the rib cage's structure near the shoulder, just under the collarbone.
- LA(Left Arm): Under the left collarbone, the yellow electrode is positioned at the same depth as the red electrode.
- LL(Left Leg): The green electrode is located at the bottom of the left rib cage, beneath the pectoral muscles.

When properly interpreted, an ECG can identify and keep track of a number of cardiac conditions, including arrhythmias, coronary heart disease, and electrolyte imbalance. Any physician, including your general practitioner, who suspects you have a cardiac condition may request an ECG, including a cardiologist. This was the test's result, which we will now examine.

In terms of hardware, a Raspberry Pi Pico serves as the controller, and figure 6 illustrates how a node mcu with a wifi

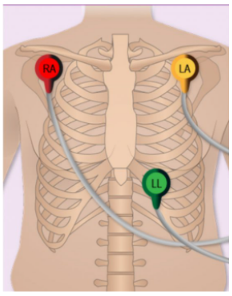

Fig. 5. lead placement(ECG)

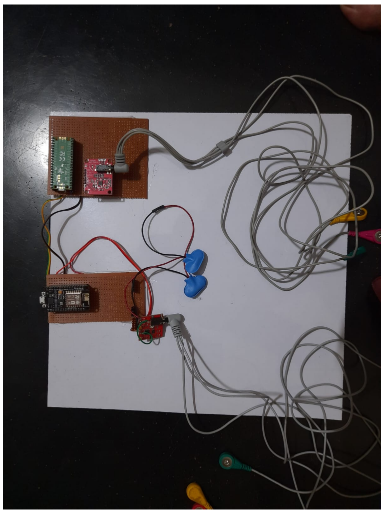

Fig. 6. Hardware prototype

module is used to facilitate connection to a mobile device. Additionally, an ECG sensor and an EMG sensor, both of which measure voltage, are present. An ADC value is created from the voltage and sent to the phone.

The heartbeat is recorded by connecting the electrodes, and the corresponding waveform is obtained, from which the heartbeat is calculated which is depicted in figure 6.

B. *Analysis*

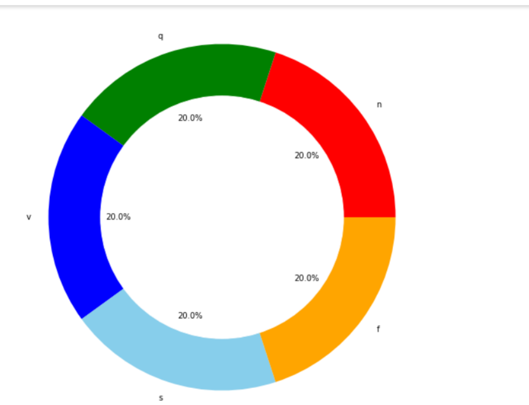

Fig. 7. equlibrium

Figure 7 analyses the heart rhythm here. To start, the data is divided into five groups. Additionally, it makes a big difference when data is divided up into different groups. As a result, all categories are balanced when using the resample technique. Normal beat, supraventricular beat, ventricular beat, fusion beat, and unknown beat are the five categories.

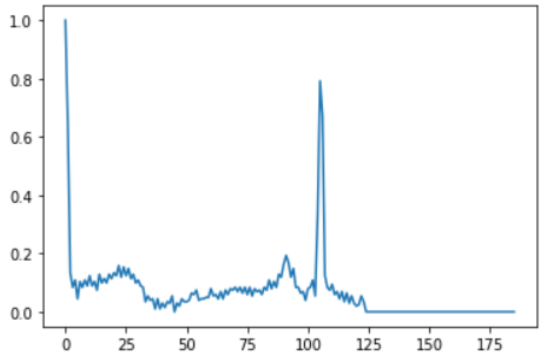

Fig. 8. Normal beat

A typical heartbeat is depicted in Figure 8. When the heart rate is between 60 and 100 beats per minute, it is considered normal.

Tachycardia is defined as a heart rate of more than 100 beats per minute, whereas bradycardia is defined as a heart rate of less than 60 beats per minute. It will be required for you to lie down while taking the ecg. Before putting electrodes, which are small patches, the health care provider will clean various spots on your arms, legs, and chest. In order for the patches to adhere to the skin, some hair may need to be shaved or cut. It's likely that the total number of patches used varies.

The patches are attached to a machine that converts electrical signals from the heart into wavy lines that may be printed on paper. The results of the tests are discussed with you by the doctor.

You must remain motionless throughout the entire procedure. The tester might ask you to hold your breath for a brief period of time during the test. You should be warm and cosy while having your ECG recorded because any movement, especially shivering, can skew the results. This test is occasionally used to search for changes in your heart while you are exercising or under light stress. A stress test is the name for this sort of ECG.

The figure 9 depicts an abnormal heartbeat. It is considered abnormal when the heart rate is less than 60 beats per minute and more than 100 beats per minute.

Histograms are a sort of quantitative data bar plot that divides the data into bins. After you've created a Histogram object, you can change the property values to change the histogram's appearance. This is a representation of the complete class in visual form. The signals have all been plotted out. As a result, we have a basic understanding of the signal's appearance. Each bar in a histogram divides numbers into ranges. More data falls within the range as the bars get taller.

The form and dispersion of continuous sample data are represented by a histogram. Matplotlib is used to plot the

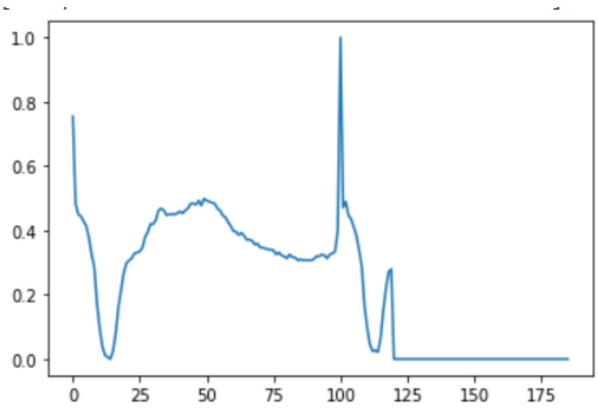

Fig. 9. Abnormal beat

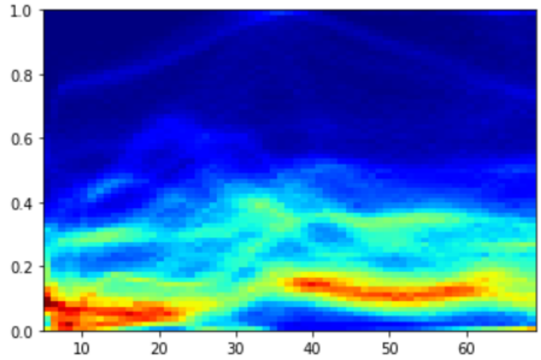

Fig. 10. Histogram plot of normal beat

histogram. Histogram plots are a useful tool for visualising data distributions. Each bar in a histogram groups numbers into ranges. More data falls within the range as the bars get taller.

A normal beat can be changed with Guassian noise. An ECG signal is created, and then sounds are added.The Filter Design and Analysis Tool allows you to create and test filters (FDATool). The 49 possible 'Band stop filter-High Pass filter' combinations made using seven different FIR windows include Bartlett, Chebyshev, Hamming, Hann, Kaiser, Rectangular, and Triangular. In terms of signal intensity, peak-to-peak value, Signal to Noise Ratio (SNR), and Mean Square Error (MSE) of the filtered output, the performance of various window combinations is compared and assessed for filter orders of 350 and 450.

A loss function is used to improve a machine learning technique. The model's performance in these two sets is used to calculate the loss and determine the significance of the loss. It represents the total number of errors made for each example in each training set or validation set. A model's performance after each optimization cycle is indicated by its loss value.

The performance of the algorithm is interpretedly measured by an accuracy metric. After the model parameters have been established, the accuracy of the model is typically calculated as a percentage. It's a metric that assesses how closely your model's predictions match the raw data.

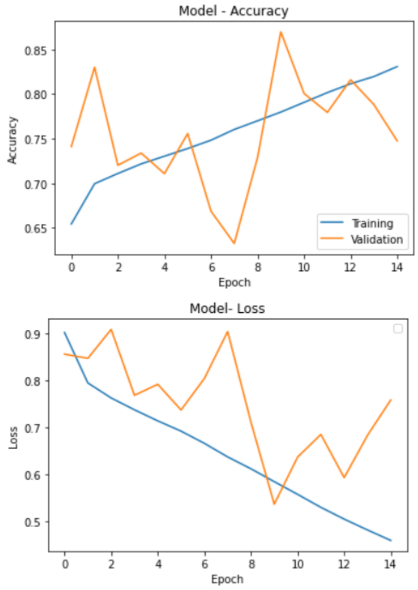

Fig. 11. Accuracy and loss graphs from 15 epochs

C. *Sleep Apnea prediction*

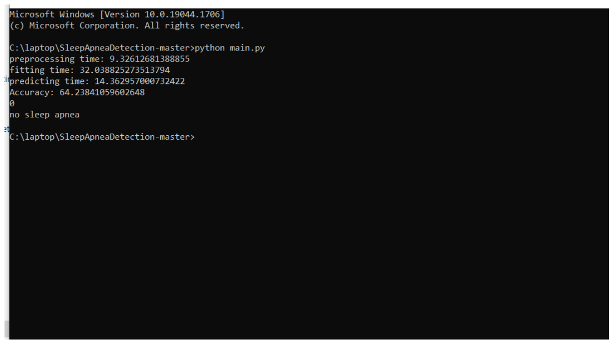

Fig. 12. sleep apnea prediction

sleep apnea (SA) is a sleep-related breathing disorder in which airflow is diminished or totally interrupted despite a continuous effort to breathe. During sleep, the muscles in the back of the throat relax, causing soft tissue to collapse and obstruct the upper airway. This results in partial pauses (hypopneas) and entire stops (apneas) in breathing that last at least 10 seconds when sleeping. The majority of pauses are between 10 and 30 seconds, although they can last up to a minute in some cases. Significant decreases in blood oxygen saturation can occur, with oxygen levels plummeting by up to 40 percentage or more in extreme situations.

From the data, it was predicted if a person has sleep apnea or not; a value of 0 indicates that the person does not have sleep apnea (figure 12). 1 indicates person have sleep apnea (figure13). Training includes preprocessing and fitting, after which it is predicted from test data.

A breathing disorder associated with sleep called sleep apnea occurs when airflow is reduced or completely interrupted despite a persistent effort to breathe. The upper airway becomes blocked when the muscles in the back of the throat

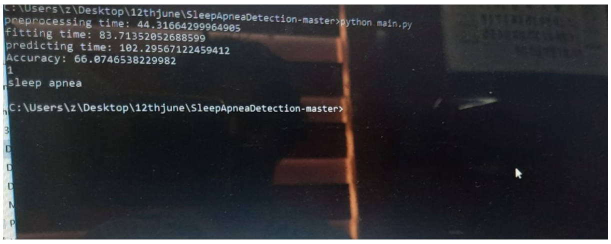

Fig. 13. sleep apnea prediction

relax, causing soft tissue to collapse. This causes breathing to stop completely (apneas) or totally and utterly pause for at least 10 seconds while you are sleeping (hypopneas). The majority of pauses are between 10 and 30 seconds, although they can last up to a minute in some cases. Significant decreases in blood oxygen saturation can occur, with oxygen levels plummeting by up to 40 percentage or more in extreme situations.

VI. Conclusion

Body vitals provide details about the user's lifestyle and habits. By analysing them, the user can obtain knowledge that will enable daily health improvement. The method suggested in this study helps to improve the user's mental and physical state and is based on the analysis of ECG and EMG data. The suggested garment is outfitted with a deep learning model that runs on a cloud server and assists in the detection of any irregularities in the heartbeat and categorises them based on the type of anomaly discovered. With the use of inbuilt sensors that monitor muscle activity and body movement, this garment can aid in the rehabilitation of athletes and sportsmen, resulting in assistance for general body growth. Furthermore, implementing the deep learning model on edge platforms would reduce computing time and resources, resulting in speedier results. This could be a continuation of the proposed garment, as well as a possible future improvement.

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