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E3Graphy: A Novel Integrated Model for Bio-signals Acquisition & Disease Detection

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Abstract

Recent technological advancements and the escalating number of Internet of Things-enabled systems have improved health monitoring to a significant level. The human body emits various bio-signals that include Electrocardiograph (ECG), Electromyography (EMG), and Electroencephalogram (EEG). These bio-signals are observed to monitor health status and disease diagnosis. However, noise and power line interference adversely affect the accuracy. To that end, this paper proposes a novel portable health monitoring model, namely, E3Graphy that aims to bridge the communication gap between doctors and patients, thereby, enhancing diagnostics. E3Grpahy integrates the features of ECG, EMG, and EEG in a less power-consuming smaller-sized monitoring model, which comprises sensors, a microcontroller, a Bluetooth module, and a mobile application. Moreover, E3Graphy employs machine learning techniques, such as Support Vector Machine, Naïve Bayes, Neural Network, and Extreme Gradient Boosting to enable early disease detection. Results demonstrate that E3Graphy achieves an accuracy of 90.58% in ECG and 98.28% in EEG, and classifies diseases for ECG with a confidence score of 70.47%.

Discipline: Computer Science and Information Technology

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1 Introduction

Several research studies have revealed that different body movements and activities generate various electrical signals due to the presence of chemical ions, which are termed bio-signals. Among these signals Electrocardiograph (ECG), Electromyography (EMG), and Electroencephalogram (EEG) monitor health status through non-invasive skin-surface transducers (Kaniusas et al., 2012). ECG records the electrical activities of a heart (Islam et al., 2012) and diagnoses heart diseases, such as arrhythmia and heart failure. It employs skin-top sensors to observe electrical signals produced by a heart each time it beats (Smolka et al., 2017). An ECG is required when patients experience chest pain, shortness of breath, dizziness, heart palpitations, rapid pulse, weakness, fatigue, or a decline in their ability to exercise. Similarly, EEG is used to observe brain complications through wave patterns by placing disposable electrodes with thin wires on the scalp. This helps to diagnose a brain tumor, brain damage in case of head injury, brain dysfunction (encephalopathy), brain inflammation (encephalitis), sleep disorders, or strokes (Nyni et al., 2017). Moreover, EMG assesses muscle health and nerve cells that control motor neurons (Alforidi et al., 2018). It is required in cases of tingling, numbness, muscular pain, weakness, cramping, or certain types of limb pain. The aforementioned bio-signals possess different traits and ranges, in terms of frequency and amplitude (Al-Busaidi et al., 2013) (Parameshwari et al., 2013) (Dong-Mei et al., 2009). The frequency ranges for ECG, EEG, and EMG are 0.05-100 Hz, 0-30 Hz, and 0-500 Hz, respectively. Whereas their respective amplitudes ranges are 10μV-5mV, 10μV-5mV, and 0-10 mV. These bio-signals are analyzed manually using separate dedicated devices, which is a time-consuming and expensive activity. Furthermore, these facilities remain unavailable in rural areas of many countries around the globe, especially in developing countries, that deprives people of critical health facilities. This opens new avenues that require the immediate attention of the research community.

1.1 Novelty and Contributions

The individual significance of ECG, EMG, and EEG in diagnostics cannot be denied, however, their integration can further enhance disease identification, which is found lacking in the existing literature. To achieve this aim, we propose a novel integrated model, namely, E3Graphy, that makes the following contributions. E3Graphy:

- integrates the functionalities of ECG, EMG, and EEG.
- enables portability and remains capable of communication through Bluetooth.
- reduces manufacturing costs.
- minimizes the power consumption
- achieves an accuracy of 90.58% in ECG, and 98.28% in EEG, and classifies diseases for ECG with a confidence score of 70.47%.

1.2 Paper Organization

The rest of the paper is organized as follows. Section 2 critically reviews the literature. Section 3 presents the proposed E3Graphy model. Section 4 details the experimental evaluation, and Section 5 concludes the paper with future research directions.

2 Literature Review

ECG, EEG, and EMG are important for the early detection of critical heart, muscle, and brain diseases that are observed using skin-top transducers. The existing literature includes several techniques in this regard, and some of the eminent techniques are discussed below.

A study in Germany reveals that cardiac arrests do not come suddenly and their symptoms appear approximately two hours earlier. The authors (Leijdekkers et al., 2008) propose the use of a mobile application with wearable sensors, which assesses the condition and alerts the ambulance services of the patient's location. This application aims to minimize the delay in calling for emergency services (Leijdekkers et al., 2008). It is observed that technological advancements have improved health monitoring and continuous measurement and monitoring of bio-signals provide vital information regarding the health conditions of a person. A low-cost bio-signal acquisition model is proposed by (Ahamed et al., 2015) to monitor ECG, EMG, and EOG (electrooculogram). Furthermore, a mobile application visualizes the captured signals and processes them. Basic signals along with their corresponding frequencies are obtained, however, noise and power line interference adversely impact the accuracy. In the process of EMG signal acquisition, all other bio-signals are treated as noise, however, ECG signals are important and are helpful in correspondence with EMG signals for better disease detection and carrying out tests, such as athlete stress analysis with heart rate. The authors (Smolka et al., 2017) propose another method for the estimation of heart rate using EMG signals. Several trials are carried out for verification of the model. Among 16 trials, 8 trials achieve 94% accuracy, 2 trials have 90% accuracy, whereas, the remaining 6 results are found incorrect.

The evolution of the Internet of Things-enabled (IoT) health monitoring model has enhanced bio-signals sensors. The work of (Jani et al., 2017) proposes a new ECG and EMG sensor with low cost and less power consumption, i.e., 3.3 volts that is capable of enhanced small muscular movement capturing. Furthermore, Small fabricated Surface Mount Devices (SMD) components reduce the printed circuit boards, hence, increasing the demand for wearable medical applications (Jani et al., 2017). The authors (Nyni et al., 2017) propose a Wireless bio-signal model that extracts and monitors ECG, EMG, and EEG signals to keep a check on health status. This model provides an efficient way to bridge the gap between doctors and patients by providing visual readings to physicians irrespective of their location and helps to overcome the restriction of wired health monitoring models. Modern technology has enabled mankind to develop efficient health monitoring models, where heart rate is considered a vital parameter regarding activities of the cardiovascular model that can be observed through ECG or pulse sensing. A pulse can be observed where the artery is close to the skin. The authors (Arulananth et al., 2017) propose a model that observes heart rate through fingertips, based on the principle of Photo PlethysmoGraphy (PPG). Variations in blood volume are detected with an optical sensing appliance placed around the fingertip. This solution stands helpful for healthcare authorities to deal with an increasing number of patients by providing better diagnosing and treatment services economically (Arulananth et al., 2017). ECG provides an efficient way to diagnose patients with cardiac diseases through non-invasive methods. Atrial fibrillation (AF) is common among cardiac patients with 2% of the general population. Due to variability in ECG, automated diagnosis becomes a challenging task. The work (Xiong1, et al., 2018) proposes RhythmNet, where the convolutional recurrent neural network is trained to extract features from raw ECG arrhythmia detection and classifies them with an accuracy of 82%. The work of (Pyakillya et al., 2017) employs deep learning architecture, where the first layer performs feature extraction, whereas the rest of the layers are responsible for decisions. The proposed solution achieves 86% accuracy.

From the literature study, it is found that individual models for ECG, EEG, and EMG have been proposed, however, the existing literature lacks an integrated model based on ECG, EEG, and EMG. Moreover, portability and power consumption remain critical features that require further enhancement. To overcome the aforementioned gaps, this paper proposes a novel integrated model, namely, E3Graphy, that is detailed in the following section.

3 The Proposed E3Graphy Model

This section presents the proposed E3Graphy model that aims to enhance the diagnosis process, as depicted in Figure 1. E3Graphy uses an AD 8232 sensor module, with disposable electrodes (Bio Protech ECG Electrode specification) to gather information, where signals are acquired using Arduino Mega. Certain threshold frequencies distinguish among bio-signals and microcontroller features. This process stands as a basic level filtration that removes the noise (F. Barrett et al., 2013). Arduino converts analog signals to digital, whereas the HC-05 Bluetooth module connects it to the mobile application (Prasad et al., 2019). A dedicated server is maintained to analyze data received from the mobile application using already trained models. Signal filtration methods and machine learning algorithms are applied for disease detection. Descriptive results are then displayed through mobile applications (Young et al., 2007).

All the aforementioned components are linked to a mobile application through the Internet.

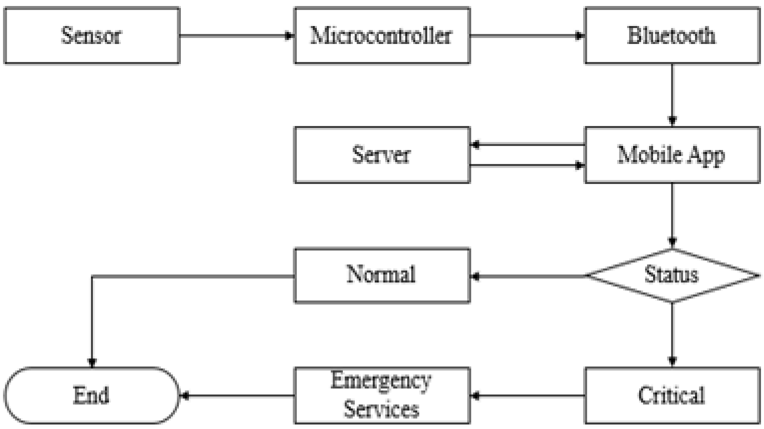

Figure 1 Architectural View of the Proposed E3Graphy Model

Furthermore, if a critical situation is found, the nearest emergency service centers are called for first aid treatment. As one of the basic aims of this model, is to make the model portable and have less power consumption, a 9-volt battery is used to supply power to sustain a microcontroller (Winkler et al., 2007). Figure 2 depicts the flowchart of E3Graphy, where instructions passed by the mobile application are forwarded to the sensor and the obtained signals are transmitted back to the mobile application. The mobile application then forwards the received data to the web server for further analysis. Generated results are displayed on the mobile application and emergency services are called if the situation is critical.

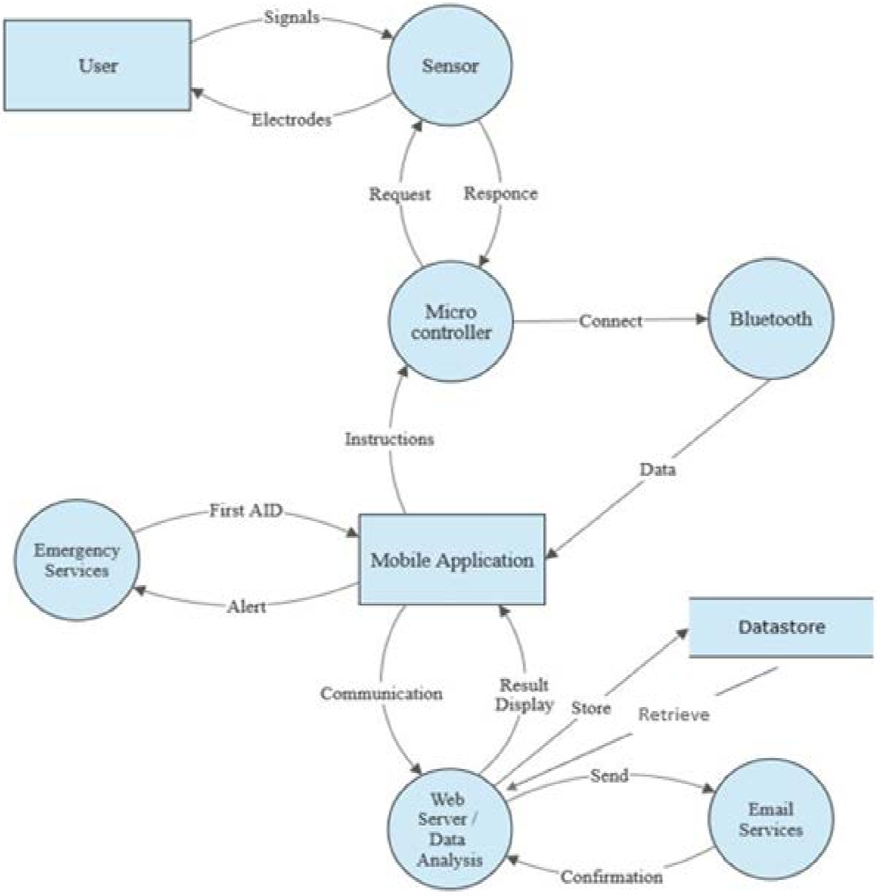

Figure 2 Data Flow Diagram of the Proposed E3Graphy Model

3.1 Data Description

For ECG model training, we use the PhysioNet dataset that includes data from healthy and unhealthy patients having various heart-related diseases obtained (Goldberger, et al., 2000). This dataset contains all the necessary features required for ECG classification, as shown in Table 1. Moreover, an EEG dataset is acquired from (Machine Learning Algorithms for Epileptic Seizures, 2018) that possesses EEG recordings of 23.5 seconds. Each unit of EEG signal, at a one-second interval, is stored in a separate column, i.e., Xi, where Xi is X1, X2, X3,..., Xn, etc. There is a column indicating the health status that shows the mental health of a person having an Epileptic Seizure or not. For EMG, the model is trained to perform basic-level filtration. All the acquired signals are recorded at an interval of 10 seconds.

Table 1 ECG Key Attributes and their Description

S. No	Attribute	Description
1	P	An initial tiny upward movement in ECG observation
2	PR	Computed from the start of the P wave up to the start of the QRS complex
3	QRS	Starts with deflection of Q downwards, high deflection of R upwards, and finishes with S wave downward
4	QT	Calculated from the start of QRS complex up to the end of T wave
5	T	An upward waveform after completion of QRS complex

3.2 Evaluation Measures

The evaluation criteria of models are an important part of the research study. This study includes precision (Menzies et al., 2007; Khan et al., 2016), recall (Jin et al., 2014; Omran et al., 2015), F-measure (Iqbal et al., 2019; Tong et al., 2018), and accuracy (Nahar et al., 2018; Saritas et al., 2019; Wu et al., 2018) as evaluation measures. Table 2 lists the aforementioned metrics alongside their corresponding equations, where TP refers to the true-positive, TN is the true-negative, FP relates to the false-positive, and FN remains the rate of false-negative classifications.

Table 2 Evaluation Measures

	Measure	Equation
1	Precision	$\text{Precision} = \frac{TP}{TP + FP}$
2	Recall	$\text{Recall} = \frac{TP}{TP + FN}$
3	F-measure	$FM = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$
4	Accuracy	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$

3.3 Technique Employed

Data mining analyzes data to obtain new information and patterns. This process helps to improve the quality of clinical decisions, thereby, playing a vital role in the intelligent and modern medical model. Data mining makes use of various ML that enhances the analysis, such as classification, clustering, outlier detection, and regression (Jothi et al., 2015). The classification machine learning algorithms utilized in this work for disease detection include Support Vector Machine (SVM) (Buitinck et al., 2013; Han et al., 2011; Rashid et al., 2020; Bilal et al., 2019; Bilal et al., 2020), Naïve Bayes (Subasi et al., 2019; Rashid et al., 2020), Neural network (Buitinck et al., 2013), and eXtreme Gradient Boosting (XGBoost) (Chen et al., 2020).

3.4 Software Tools

To control and perform various activities through a microcontroller, an integrated development environment provided by Arduino is utilized (Reas et al., 2007). All the basic functions (sensor's signal acquiring through data sending to the mobile application) are programmed in C language. Java is used for the development of mobile applications, whereas server-side communication is handled through Hypertext Preprocessor (PHP) (Gope et al., 2017). Moreover, Python is used for signal filtration and disease detection through machine learning.

4 Performance Evaluation

This section evaluates the performance of the proposed E3Graphy model. To this end, all the components are integrated along with the connectivity of the mobile application through a Bluetooth module, as shown in Figure 3. After acquiring signals, these signals are transferred to the server, where a trained model is placed to analyze and classify the received data.

(a) (b)

Figure 3 (a) Integrated Components (b) Mobile Application

4.1 Evaluation for ECG

ECG signals are obtained by placing electrodes on defined points upon the body. The model acquires readings and transmits them to the server for further analysis and classification. On the server, a trained model with different classifiers is used. Among these classifiers, Neural Network has shown efficient results with the highest accuracy of 90.58%, followed by XGBoost at 79.19%, Naïve Bayes at 70.93%, and SVM at 48.26% accuracy. Additionally, after the classification of signals between normal and abnormal, the XGBoost classifier specifies the expected disease with a confidence score of 70.47% respectively.

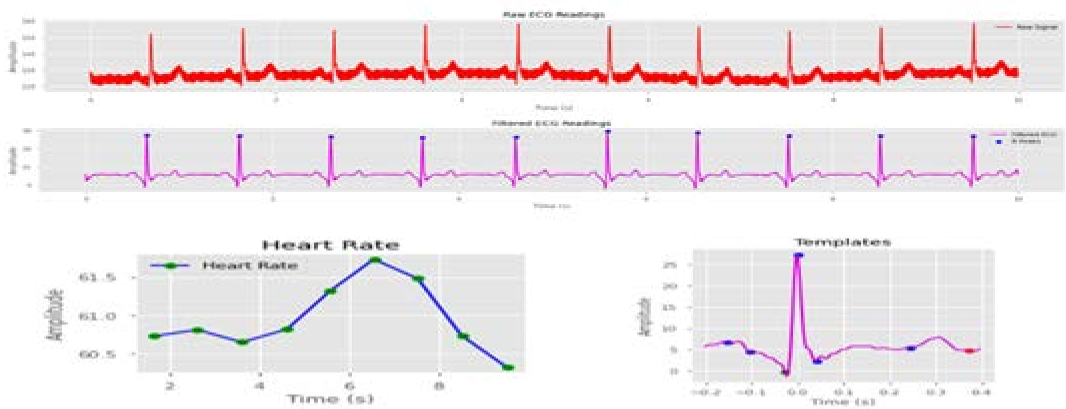

Figure 4 Healthy Subject

The collected samples of a healthy subject with raw ECG containing ambiguous and filtered ECG readings are shown in Figure 4. Similarly, the collected samples of a healthy subject with raw EEG containing ambiguous and filtered EEG readings are shown in Figure 5. The obtained graphs show the difference between a healthy person and a deceased person. During the experimental evaluation, a total of 40 subjects are tested. A brief description of the experimental subjects is shown in Table 3 including age, gender, intervals, heart rate, and result status along with actual status. Here, zero (0) refers to a male subject, whereas one (1) represents a female subject. Similarly, zero (0) means healthy and one (1) stands for a diseased subject.

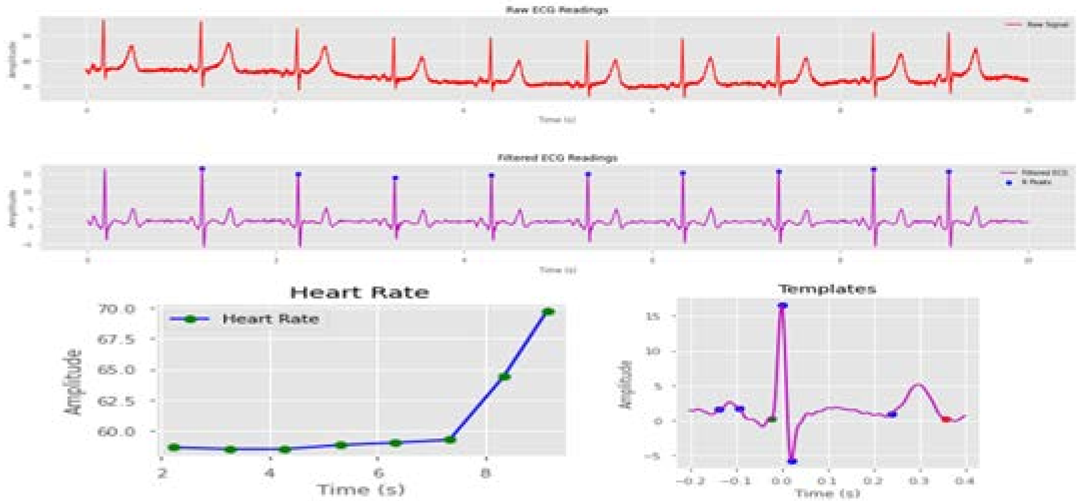

Figure 5 Diseased Subject

Table 3 Test Subjects

S.No	Age	Gender	QRS Interval	P-R Interval	Q-T Interval	T Interval	P Interval	Heart Rate	Status	Actual
1	62	0	588.182	-226.5	462.323	-54.386	57.697	87.764	0	0
2	70	1	460.919	-247.037	336.936	-25.363	34.751	73.435	0	0
3	60	1	238.196	90.632	723.977	321.856	86.080	60.865	0	0
4	77	0	163.007	142.041	622.665	207.197	80.920	60.956	1	1
5	73	0	149.188	176.651	586.412	204.851	111.160	62.368	1	1
6	73	1	154.694	131.527	549.175	176.821	66.618	69.906	1	1
7	81	1	191.712	164.739	675.973	207.300	100.449	47.738	1	1
8	76	1	167.443	203.946	586.842	191.477	103.107	59.182	1	1
9	67	1	887.213	95.262	1660.005	589.622	226.152	53.179	0	0
10	71	0	433.362	-153.043	347.153	-23.413	29.279	85.314	0	0
11	75	1	720.514	-225.978	396.486	-15.340	102.186	84.084	0	0
12	74	0	185.558	143.868	684.000	240.990	98.268	48.389	0	1
13	68	1	209.964	111.691	631.724	210.862	90.338	60.094	1	1
14	73	0	103.144	183.291	476.674	172.581	89.902	78.196	1	1
15	71	1	190.407	118.473	683.380	214.939	96.127	40.856	0	1
16	68	0	389.089	-276.892	360.860	-40.410	182.256	114.504	0	0
17	63	1	509.860	-244.338	397.855	-47.604	55.807	61.728	0	0
18	52	1	536.277	-374.608	293.544	-60.972	93.972	89.676	0	0
19	57	1	500.424	-226.305	331.725	-31.423	61.999	89.911	0	0
20	67	1	-201.117	-1421.174	2054.668	506.398	393.992	74.449	0	0
21	69	1	476.480	-191.046	266.447	-36.283	5.733	71.361	0	0
22	52	1	190.989	35.710	374.668	156.755	57.854	63.870	0	0
23	71	0	140.635	97.968	583.353	203.870	59.435	67.525	1	1
24	23	0	207.012	104.925	551.374	214.384	75.873	80.450	1	1
25	28	0	166.516	133.059	579.387	174.444	82.274	63.231	1	1
26	34	1	197.741	181.291	577.533	219.828	100.305	67.955	1	1
27	31	1	197.741	181.291	577.533	219.828	100.305	67.955	1	1
28	23	1	211.837	108.485	572.249	211.581	79.638	62.419	1	1
29	30	1	134.608	178.343	535.805	189.889	98.523	67.064	1	1
30	21	1	311.255	110.821	673.746	239.206	80.378	59.402	1	1
31	30	0	201.173	146.348	634.881	230.753	108.860	66.401	1	1
32	76	1	352.629	-91.915	215.139	-36.066	22.153	78.133	0	0

S.No	Age	Gender	QRS Interval	P-R Interval	Q-T Interval	T Interval	P Interval	Heart Rate	Status	Actual
33	49	1	365.167	-304.506	-328.339	- 198.843	11.264	51.878	0	0
34	49	1	614.151	55.443	772.939	254.760	204.262	98.716	0	0
35	32	0	210.335	157.777	580.808	191.024	110.183	66.855	1	1
36	21	0	240.216	110.789	580.175	192.875	89.096	78.044	1	1
37	63	1	214.386	-478.476	-580.902	- 294.971	62.925	83.876	0	0
38	60	1	261.627	-266.963	-161.349	- 203.788	11.145	78.200	0	0
39	74	1	-104.918	-272.718	-854.700	- 312.266	60.802	93.954	1	0
40	66	1	54.348	-46.722	58.526	109.907	19.301	86.077	1	0

Results obtained from 40 subjects indicate that our model detected 36 accurate results, whereas 4 subjects fall under the wrong detection. Therefore, we can conclude that our model results with an accuracy of 90%. In the development of our model, we have used 7 classifiers to train our model for disease detection. Among these classifiers, Deep Neural Network achieves the best results with an accuracy of 90.58%, followed by Gradient Boosting at 79.07% and Ada Boost at 76.74%. A graph depicting classifiers' performance in terms of ECG readings is shown in Figure 6.

4.2 Evaluation for EEG

After data pre-processing, a portion of the dataset is executed under the trained model. Figure 7 depicts that SVM has performed better with the highest accuracy of 98.28%, followed by XGBoost at 97.13%, Neural Network & Naïve Bayes at 95.73%.

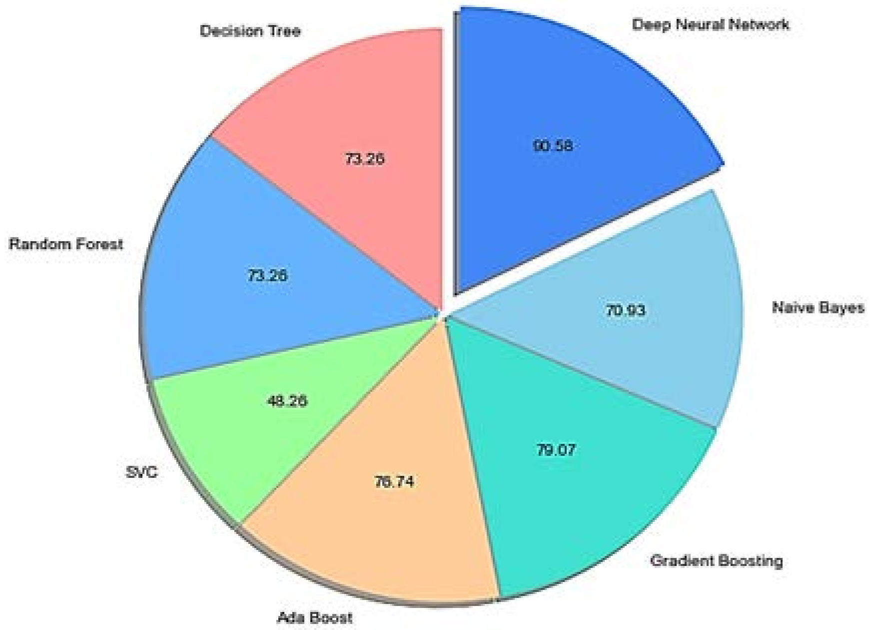

Figure 6 ECG Classifiers Accuracy

4.3 Evaluation for EEG

During the experimental procedure, raw EMG signals are acquired through a non-invasive method by placing electrodes at defined points. These signals were communicated to the server for further analysis. Obtained raw readings of EMG from a subject are shown in Figure 8, which are not readable due to the presence of noise and other factors. After receiving signals at the server, these signals are filtered using BioSPPy. BioSPPy is a toolbox for bio-signal processing, containing multiple pattern recognition and signal processing techniques used for analysis.

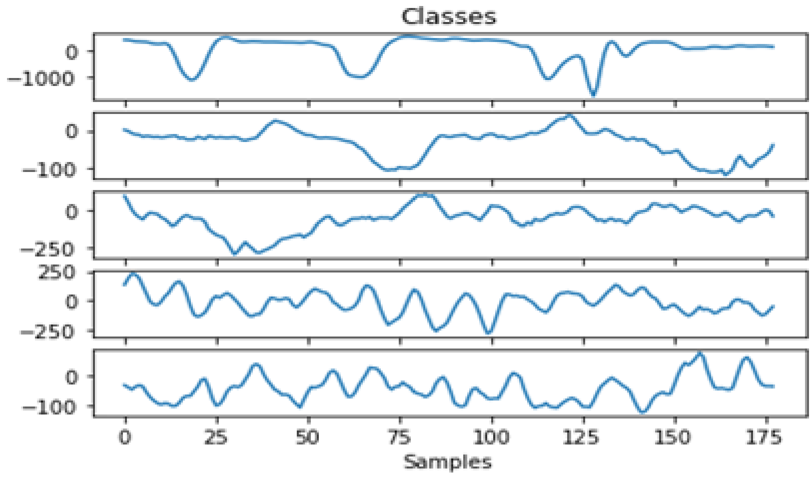

Figure 7 ECG Graphical Readings

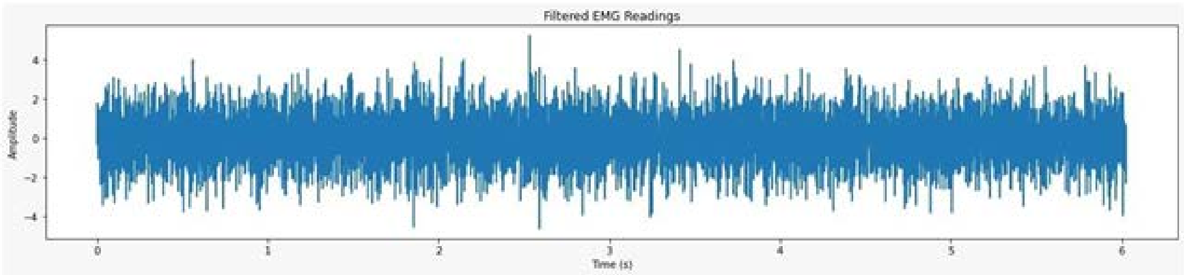

Figure 8 RAW EMG Reading

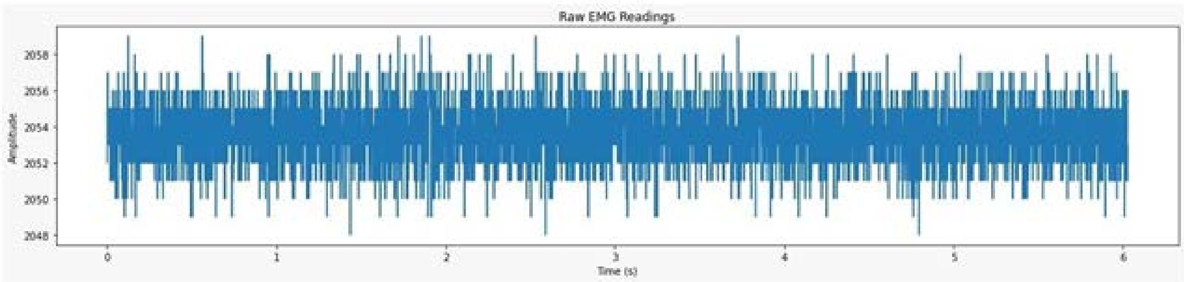

Figure 9 Filtered EMG Reading

During the filtration process, noises and inconsistencies are removed to provide a filtered version of signals for better observation. The improved readings for data extraction are shown in Figure 9, which are ready to use for further description and analysis. These extracted readings will be communicated back to the mobile device for display purposes and are shown in the form of a graph for better observation. Table 4 depicts the various classifier utilized during machine learning for model training and compares their accuracy for ECG and EEG after testing and evaluation.

Table 4 Classifier's Accuracy

S. No	MODEL	ECG	ECG (Disease Specification)	EEG
1	Neural Network	90.58%	61.90%	95.73%
2	Support Vector Machine	48.26%	61.90%	98.28%
3	Naïve Bayes	70.93%	53.33%	95.73%
4	XG Boost	79.19%	70.47%	97.13%

5 Conclusion

In this technological era, health monitoring systems are playing a pivotal role in serving humanity across the globe. These systems exploit various bio-signals, such as ECG, EMG, and EEG for disease diagnostics. However, their accuracy experiences adverse effects due to noise and power line interference. To overcome these issues, we propose a novel portable health monitoring model, namely, E3Graphy, that aims to bridge the communication gap between doctors and their patients, thereby, enhancing diagnostics. E3Grpahy combines the features of ECG, EMG, and EEG to constitute a less power-consuming smaller-sized monitoring model. The proposed model consists of sensors, a microcontroller, a Bluetooth module, and a mobile application. Moreover, E3Graphy employs machine learning techniques, such as Support Vector Machine, Naïve Bayes, Neural Network, and Extreme Gradient Boosting that enable early disease detection that leads to a better cure. Results show that E3Graphy attains an accuracy of 90.58% in ECG and 98.28% in EEG, and classifies diseases for ECG with a confidence score of 70.47%. Future extensions of this work may include the detection of muscular diseases with enhanced accuracy using EMG.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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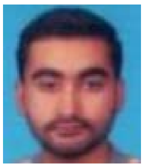

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