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ECG Emotion Detection (EED)

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Abstract

Stress and fear are two important emotions which can help in the interpretation of mental situations during a certain task. Stress is mainly defined as a state of mental or emotional strain or tension resulting from adverse or demanding circumstances. Under stress, the quality of the output may deviate from the expected results out of that task, such as gaming. Thus, stress must be identified, and that task must be halted to ensure quality of work and mental wellbeing of the do-er. Similarly, situations, such as cheating during an examination, come along with fear. Such unforeseen situations can be avoided if we detect fear in real time. In this project, we are aimed to automate stress and fear detection using electrocardiogram (ECG) signals, of the heart, as an application of Artificial Intelligence.

Executive Summary:

Emotions play an important role in a person's daily life and can influence their decisions in their day-to-day lives. However, it is not always possible to decipher what a person is feeling. Technology has evolved to such an extent where a person's current psychological state can be detected using advanced and enhanced Artificially Intelligent algorithms. AI can be used to develop a system which extracts such information from a person's electrocardiogram (ECG). Since stress and fear are linked to ECG as heart rates and rhythms alter when these emotional switches occur, they can be monitored and detected automatically using Artificial Intelligence.

The purpose of this document is to analyze different deep learning and machine learning models for feature extraction and classification of ECG so that we can develop a model of our own for fear and stress detection from an ECG signal. The intended audience for this document are the researchers that are exploring AI models for emotion detection specifically, fear and stress.

This document also elaborates the project vision we have for our project, "ECG Emotion Detection (EED)" system. The need to develop such a system is dire so that the efficacy of a certain task can be improved. As humans, our emotional imbalances affect the efficiency of any task that we may be performing. There are two emotions that have a major effect on any ongoing task, fear and stress. Thus, we plan on developing a system to detect fear and stress which can then help us perform tasks more efficiently.

Our project's objectives include, classifying emotions of stress and fear using ECG signals, improving accuracy and preciseness of already built models, real time categorization of emotional imbalances, designing 3 lead ECG scanner device using ECG sensor kit and storing the timestamps during which emotional imbalances were identified under the observation period.

The document then goes on to elaborates the detailed literature review of previous researches done in accordance with the chosen topic and gives the detailed knowledge of each technique. Since our topic focuses on ECG classification thus, we have done vast research in this area. ECG classification has three major parts that are signal preprocessing, feature extraction and classification. Thus, we have gathered a vast amount of literature review regarding these topics. The research work has provided us insights such as, most of the models have been developed using deep learning techniques rather than machine learning.

Table of Contents

Table of Contents i
List of Tables iv
List of Figures v
Chapter 1: Introduction 1
1.1 Purpose of this Document 1
1.2 Intended Audience 1
1.3 Definitions, Acronyms, and Abbreviations 1
1.3.1 Definitions 1
1.3.2 Acronyms and Abbreviations 1
Chapter 2: Project Vision 3
2.1 Problem Domain Overview 3
2.2 Problem Statement 3
2.3 Problem Elaboration 3
2.4 Goals and Objectives 3
2.5 Project Scope 4
2.6 Sustainable Development Goal (SDG) 4
2.7 Conclusion 4
Chapter 3: Literature Review / Related Work 5
3.1 Definitions, Acronyms, and Abbreviations 5
3.1.1 Definitions 5
3.1.2 Acronyms and Abbreviations 5
3.2 Detailed Literature Review 6
3.2.1 Feature Extraction from ECG Signal 6
3.2.2 Classification of ECG 10
3.3 Literature Review Summary Table 16
3.4 Conclusion 18
Chapter 4: System Requirement Specification 20
4.1 List of Features 20
4.2 Functional Requirements 20
4.2.1 Reading Live ECG from the Subject 20
4.2.2 Converting Signals into an Image 20
4.2.3 Extracting Important Features of the Signal 20
4.2.4 Classifying the Signal 20
4.3 Quality Attributes 20
4.4 Non-Functional Requirements 20
4.4.1 Reliability 20
4.4.2 Performance 21
4.4.3 Availability 21
4.4.4 Reusability 21
4.5 Assumptions 21
4.6 Hardware and Software Requirements 21
4.6.1 Hardware Requirements 22
4.6.2 Software Requirements 22
4.7 Use Cases 22
4.7.1 Connecting Electrodes 23
4.7.2 User Getting Response 23
4.7.3 Examination Officer Assistance 24
4.8 Graphical User Interface 24
4.9 Database Design 24

4.9.1 ER Diagram 24
4.9.2 Data Dictionary 24
4.10 Risk Analysis 25
4.10.1 Chip failure 25
4.10.2 Internet Failure 25
4.10.3 Electrode not placed correctly 25
4.11 Conclusion 25
Chapter 5: Proposed Approach and Methodology 26
5.1 Data Reading 26
5.2 Data Pre-processing 26
5.3 Classification 26
5.3.1 Long Short Term Memory (LSTM) 27
5.3.2 VGG – 19 27
5.4 Conclusion 28
Chapter 6: High-Level and Low-Level Design 29
6.1 System Overview 29
6.1.1 System Design 29
6.1.2 Data Collection 29
6.1.3 Model Training 30
6.2 Design Considerations 30
6.2.1 Assumptions and Dependencies 30
6.2.2 General Constraints 30
6.2.3 Goals and Guidelines 31
6.2.4 Development Methods 31
6.3 System Architecture 32
6.3.1 ECG Scanner 33
6.3.2 Pre-processing 33
6.3.3 Classifier 34
6.4 Architectural Strategies 34
6.4.1 Tools and Software 34
6.4.2 Hardware 34
6.4.3 Database 34
6.4.4 Raw Data 35
6.4.5 Using Existing Technologies 35
6.4.6 Future 35
6.5 Domain Model/Class Diagram 35
6.6 Sequence Diagrams 36
6.7 Policies and Tactics 37
6.7.1 Tools 38
6.7.2 Coding Guidelines 38
6.7.3 Testing the Software 38
6.7.4 Maintenance of Software 38
6.8 Conclusion 38
Chapter 7: Implementation and Test Cases 39
7.1 Implementation 39
7.1.1 Implementation of Input 39
7.1.2 Implementation of Model Training 39
7.1.3 Implementation of Classifier 40
7.2 Test Case Design and Description 40
7.2.1 Test Case for Subject Not Connected (1) 40

7.2.2 Test Case for Subject Not Connected (2) 40
7.2.3 Test Case for Invalid Reading (1) 41
7.2.4 Test Case for Invalid Reading (2) 41
7.2.5 Normal Emotion Test Case (1) 42
7.2.6 Normal Emotion Test Case (2) 43
7.2.7 Fear Emotion Detection Test Case (1) 43
7.2.8 Fear Emotion Test Case (2) 44
7.2.9 Stress Emotion Detection Test Case (1) 44
7.2.10 Stress Emotion Detection Test Case (2) 45
7.3 Test Metrics 45
Chapter 8: User Manual 46
8.1 Connections 46
8.2 Application 47
Chapter 9: Experimental Results and Discussion 48
Chapter 10: Conclusion and Future Work 49
References 50

List of Tables

Table 1: Summary of Models for Feature Extraction and Classification of ECG Signal........16
Table 2: User Table..24
Table 3: EmotionTimeStamp Table...25

List of Figures

Figure 1: Entity Relationship Diagram 24
Figure 2: High-level Architecture Diagram 32
Figure 3: Low-level Architecture Diagram for ECG Scanner Component 33
Figure 4: Low-level Architecture Diagram for Pre-processing Component 33
Figure 5: Low-level Architecture Diagram for Classifier Component 34
Figure 6: Model Diagram 35
Figure 7: Classification of ECG using CNN 36
Figure 8: Classification of ECG using LSTM 37
Figure 9: Stress Classification 37
Figure 10: Connecting ECG Electrodes on theSubject 46
Figure 11: Start Button 47
Figure 12: Sample Classification Visualization 47
Figure 13: Plotted AD8232 Data 48
Figure 14: Demonstrations of Sample Model 48

Chapter 1: Introduction

Emotions play an important role in a person's daily life. They effect a human being's thoughts and behavior and can influence their decisions in their day-to-day lives. However, it is not always possible to decipher what a person is feeling. Sometimes even the person experiencing the emotions is unable to categorize them. However, with the evolution of technology Artificially Intelligent models have emerged that can predict the existing emotional state of a person.

Technology has evolved to such an extent where a person's current psychological state can be detected using advanced and enhanced Artificially Intelligent algorithms. Such an application has been in great demand where emotions are being used to extract the current situation of a subject in a particular event.

AI can be used to develop a system which extracts such information from a person's electrocardiogram (ECG). Since stress and fear are linked to ECG as heart rates and rhythms alter when these emotional switches occur, they can be monitored and detected automatically using Artificial Intelligence. ECG signals, taken from a person during the execution of a task, are fed to the model in real time. The model then classifies the ECG signal to detect the current emotional situation and notifies accordingly

1.1 Purpose of this Document

The purpose of this document is to analyze different deep learning and machine learning models for feature extraction and classification of ECG so that we can develop a model of our own for fear and stress detection from an ECG signal. The document discusses different types of models for ECG classification and how studies done on them can provide insights in our task. This document aims to study different ECG classification models so that we can develop our own with a high accuracy.

1.2 Intended Audience

The intended audience for this document is the researchers that are exploring AI models for emotion detection specifically, fear and stress.

1.3 Definitions, Acronyms, and Abbreviations

1.3.1 Definitions

Electrocardiogram: A tool used to measure the electrical activity of the heart.
Convolutional Neural Network: A type of neural network that focuses on image processing.
Feature Extraction: The process of transforming raw data into numerical features that can be processed while preserving the information in the original data set.
Classification: An ordered set of related categories used to group data according to its similarities.
Arduino: An open-source electronics platform based on easy-to-use hardware and software. Arduino boards are able to read inputs.

1.3.2 Acronyms and Abbreviations

ECG: Electrocardiogram

EED: Electrocardiogram Emotion Detection

AI: Artificial Intelligence

DL: Deep Learning

ML: Machine Learning

CNN: Convolutional Neural Networks

Chapter 2: Project Vision

This section elaborates the project vision we have for our project, “ECG Emotion Detection (EED)” system. It focuses on the problem at hand and what our goals and scope for the project.

2.1 Problem Domain Overview

ECG electrodes will be attached to the body of a volunteer for data collection. The data will be read by ECG Arduino sensor AD8232. The sensor will be connected to the computer through the Arduino module. As the data is read, the signal will be processed, noise will be removed, and the preprocessed data will be fed to a real time model to predict the nature of emotions in the subject. The emotions of the subject will be altered using different surrounding distractions such as sudden buzzer sounds, Video clips, light changes, phone rings etc., so that the model’s working capability can be measured.

2.2 Problem Statement

The need to develop such a system is dire so that the efficacy of a certain task can be improved. As humans, we always tend to support a variety of emotional imbalances which may affect the ongoing task.

2.3 Problem Elaboration

As humans, our emotional imbalances affect the efficiency of any task that we may be performing. There are two emotions that have a major effect on any ongoing task, fear, and stress. Thus, we plan on developing a system to detect fear and stress which can then help us perform tasks more efficiently.

We should judge if the assigned candidate is in suitable emotional conditions to carry on with a task. An example of that is driving a car. There is a high probability of having an accident if someone under stress is asked to drive a car. Commonly, it is difficult to analyze the stress from that person’s facial expression, but heart rhythm fairly tells us if that person is suitable for driving the car as it is an involuntary change.

Moreover, the element of cheating, say in an exam, is always a question to the honesty of the candidate. When a person tends to cheat, heart rhythm suddenly changes because of the emotion of fear that develops in him. This rhythm can tell us more about the candidate’s performance in any examination with a defined integrity.

2.4 Goals and Objectives

Our project’s objectives include:

- Classifying emotions of stress and fear using ECG signals,
- Improving accuracy and preciseness of already built models integrated to perform such classification,
- Real time categorization of emotional imbalances under a specific condition,
- Designing 3 lead ECG scanner device using ECG sensor kit,
- Storing the timestamps during which emotional imbalances were identified under the observation period.

2.5 Project Scope

Our project mainly uses artificial intelligence to classify ECG signals in the categories of stress and fear. Since real time data must be collected and fed to the model, ECG sensor kit is to be used which will detect and convert electrical signals from the heart into a continuous rhythm. Using the concepts of Internet of Things, a 3-lead ECG device may be built using Arduino to sync the ECG device and the web application. A web application may be built to provide a better user experience and block chain technology may be used to store timestamps of altering emotion identification and subject's details.

2.6 Sustainable Development Goal (SDG)

As we are working on performance-based analysis of a subject, it clearly covers the SDG of good health and wellbeing. Stress may adversely affect the physical and mental health of a person. During such medical conditions, a burden of tasks may prove to be fatal or at least a complete mental breakdown, such as over burden of tasks in case of a student. Similarly, the SDG of peace, justice and strong institutions is also being covered in this project. Many companies and institutions conduct various tests before making people their part. Equal opportunity of showing the capability is available to every candidate applying but this can become biased due to the element of cheating. Thus, justice may prevail as cheating can be avoided by deploying this project.

2.7 Conclusion

In a nutshell, we discussed why our project is relevant to production in this chapter. We focused over domain Overview, Elaborations, Goals, Objectives, and Scope. We also figured some important development goals which will contribute to the society in some way or the other.

Chapter 3: Literature Review / Related Work

The following section elaborates the detailed literature review of previous research done in accordance with the chosen topic and gives the detailed knowledge of each technique.

3.1 Definitions, Acronyms, and Abbreviations

3.1.1 Definitions

Electrocardiogram: A tool used to measure the electrical activity of the heart.

Arrhythmia: An irregular heartbeat which in some cases can lead to cardiovascular diseases.

Convolutional Neural Network: A type of neural network that focuses on image processing.

Cardiovascular Diseases: Diseases related to the heart muscle.

Recurrent Neural Network: A type of neural network where connection between nodes can create a cycle.

Generative Adversarial Networks: Machine learning frameworks that create new data instances that reassembles training data.

Random Forest: Machine learning method that operates by constructing a multitude of decision trees at training time.

3.1.2 Acronyms and Abbreviations

ECG: Electrocardiogram

AI: Artificial Intelligence

ML: Machine Learning

CWT: Continuous Wavelet Transform

CNN: Convolutional Neural Network

MLP: Multi-Layer Perceptron

RNN: Recurrent Neural Network

CVD: Cardiovascular Diseases

CCA: Canonical Correlation Analysis

VA: Ventricular Arrhythmia

VT: Ventricular Tachycardia

VTA: Ventricular Tachycardia Arrhythmia

RF: Random Forest

GAN: Generative Adversarial Networks

LSTM: Long Short-Term Memory

HOS: Higher-Order Statistics

ReLU: Rectified Linear Unit

TTS: Takotsubo Syndrome

AMI: Anterior Myocardial Infarction

3.2 Detailed Literature Review

Our topic focuses on ECG classification thus we have done vast research in this area. ECG classification has three major parts that are signal preprocessing, feature extraction and classification. Thus, we have gathered a vast amount of literature review regarding these topics.

3.2.1 Feature Extraction from ECG Signal

For ECG classification there are three important steps: signal pre-processing, feature extraction and classification of the ECG signal. An ECG signal or record cannot be properly classified without feature extraction first. Thus, this section gives detailed literature review about research work done regarding feature extraction. Extensive work has been done to extract features from raw ECG samples before classifying them.

According to [1], it is mentioned that early detection and identification of cardiovascular diseases (CVDs) can save important human lives. CVDs can be identified using ECG analysis. Several methods have been used to automate the classification of CVDs, but accuracy benchmarks are not clinically useful until now. Furthermore, salient ECG features vary over population and even may vary in the same person at a different time. Such challenges have led them to produce a solution which generalizes the classification of ECG, achieving maximum possible accuracy.

The data set used to train and test this model is from MIT-BIH containing 4000 recordings from 47 patients. Each signal is generated from a 2-lead ECG machine with a 360 Hz sampling frequency. ECG signals were recorded with an 11-bit resolution over the 10-mV range. The grouping of arrhythmias is reduced to 5 general classes namely Normal (N), Supraventricular Ectopic Beat (SVEB), Ventricular Ectopic Beat (VEB), Fusion Beat (F), and Unknown Beat (Q).

Before classification, data preprocessing is done to mainly remove the noise in the ECG signal. For this purpose, two median filters are used to produce baseline wanderings. These wanderings were then superimposed on the ECG signal to remove the noise and new baseline-corrected ECG signals were obtained.

Segmentation of the sequences is done to obtain a beat sample. For this purpose, 90 samples before and 110 samples after the R-peak were taken.

After preprocessing, Continuous Wavelet Transform (CWT) is used to obtain frequency components of the time-based signal. Figure below shows a pictorial representation of frequency and amplitude graphs. Scalograms produced are of 100 x 200 in size each.

The CNN model used a backpropagation algorithm to train the weights across the layers. ReLu, Batch Normalization and pooling layers are also used. After the last operation, a 64-dimensional feature is obtained. Noting that the size of the original scalogram is 100 × 200, we resampled it to 100 × 100 to reduce the computational cost. Another input of RR intervals is made available to the model. Combined features are then fed to a fully connected neural network for classifying the arrhythmia type. While training the model, 0.001 learning rate is used which is reduced by 0.1 times after every 5 epochs. 1024 batch size is used for 30 times. i.e., 30 epochs.

Several other models were tested for the same data type and results described to be more accurate for this model on an average scale with an average accuracy of 98.74%.

Their proposed model has proved to be accurate and precise. The generalization can be potential for leading this model into deployment. Furthermore, due to the poor availability of data in class F, it showed a significantly low performance in terms of accuracy. Moreover, labeling of ECG data is costly and tedious, thus an unsupervised learning model would be cost effective.

Meanwhile, the authors of [2] suggest that the neural network used to diagnose diseases from an ECG can also be used for sex and age classification which can be done by training the model using ground truth labels that specify the important features the network has to learn instead of using the human-selected features.

The purpose of the research article is to understand the characteristics that are chosen by the neural network for ECG analysis. The article puts forward two hypotheses. First, convolutional neural networks select linearly correlated signal features that are comparable to the ones determined by humans. Second, human-recognizable features to a degree, can explain the output of the model and best explain when the human-recognizable features are used non-linearly. To test these hypotheses, a model was made which extracted neural network features and determined its correlation to the human-recognizable features.

A 12-lead ECG signal is divided into 5 waves: P for atrial depolarization, Q, R and S for ventricular depolarization, and T for ventricular repolarization. The process for human extracted features is non-linear and includes selecting specific components of the signal that will be useful. For this research article, the MUSE system was used to extract the human-recognizable features.

The deep convolutional network used was one that was trained for age and sex classification. The dataset used consisted of 100,000 ECGs and was collected from Mayo Clinic records from January 1994 and February 2017. Half the samples were used to train the model and the other half to test the model.

Canonical correlation analysis (CCA) was used to determine the correlation between neural networks and human-selected features. Also, a simple linear model was used to reconstruct human-recognized ECG features from neural network features. In this research article the outcome of two neural networks was predicted using human characteristics through linear and non-linear models. The R^2 value was used to explain the variance of the models meaning if the value of R^2 is 1, then 100% of the human features can be explained by the output of the neural networks.

According to the results, for age prediction the values of R^2 achieved were 0.571 and 0.702 for linear and non-linear models respectively. For sex prediction the values of R^2 achieved were 0.494 and 0.685 for linear and non-linear models respectively. The results concluded that the correlation of human extracted features was above 85% with 13 of the strongest age AI features and 15 of the strongest sex AI features. To sum it up, neural networks extract features from ECG signals in a way similar to human specialists and they also provide further details that help in better performance.

Another article, [3] proposed feature extraction by converting ECG signals to images. Ventricular arrhythmia (VA) is irregular rhythm of the heart ventricular which if not treated causes damage to the heart muscle and can result in death. An electrocardiogram (ECG) is a non-invasive diagnostic tool that interprets and records ECG signals that can be used to diagnose different types of arrhythmias. However, ECG signals are non-linear which makes it difficult to analyze them. Thus, manually assessing the ECG signal is tedious and time-consuming.

There are many different types of arrhythmias and one such type is polymorphic ventricular tachycardia (VT) called Vfib which is the most dangerous of its kind. There are different techniques for identifying VT which includes modified Karhunen–Loeve transform, which is through pattern recognition. Using pattern recognition methods on ECG data to detect arrhythmias is becoming increasingly popular.

This study proposes a new deep learning model for VTA classification and classification of other types of arrhythmias. The article proposes converting normalized ECG data to 32x32 binary images which has never been done before. The study uses deep convolutional neural networks (CNN) for VTA detection and entropy-based feature selection to select the finest features which are then trained. The deep CNN used for feature extraction are VGG19, AlexNet and Inception-v3. The model is trained and the deep features are extracted from different output layers using transfer learning. For final feature classification, supervised learning classifiers are used.

The dataset used was MIT-BIH. The data is split in equal halves for training and testing sets. Five different experiments were conducted to evaluate the results. First, the AlexNet model was used for feature extraction by performing activations on the Fully Connected layer FC7. An accuracy of 91.2%, FNR of 8.0%, sensitivity of 91.9%, and specificity of 90.5% were achieved while using Cubic SVM as final stage classifier. Second, the VGG19 model was used for feature extraction by performing activations on the Fully Connected layer FC7. An accuracy of 92.1%, FNR of 7%, sensitivity of 93.0% and specificity of 92.0% was achieved using quadratic SVM as a classifier. Third, the InceptionV3 model was used by performing activations on the Avg-Pool layer. An accuracy of 91.5%, FNR of 7.7%, sensitivity of 92.2% and specificity of 90.9% was achieved with Quadratic SVM. Fourth, combining the features extracted from the above three models an accuracy of 96.6%, FNR of 3.0%, sensitivity of 97.12% and specificity of 95.99% was recorded on Cubic SVM. Fifth, the entropy-based feature selection was performed. An overall accuracy of 97.6% was achieved.

Likewise, researchers in article [4] state that, according to the World Health Organization, around 30% of all deaths that occur in a year are caused by Cardiovascular diseases (CVDs). All CVDs show their impact on the beating process of the heart and these diseases can be detected from ECG of the heart. Scientists can diagnose these diseases by detecting any abnormalities in the ECGs. A lot of work has already been done to identify the normal and abnormal states of the heartbeat. This research describes how a machine learning method can be used to analyze ECG datasets for the diagnosis of heart diseases. Using this method, the model will be trained to make accurate predictions of the disease. To use such an algorithm, we first need to deal with the abnormalities in the dataset. The ECG signal contains artifacts and noise in it. There are many filter techniques that are carried out to denoise ECG signals. The wavelet transform method is a good technique to detect P, QRS, and T peaks in the signal, with a 99% detection rate. Kalman filtering is an advanced method for detection of features in ECG, reaching good accuracy results in ECG signal processing. For classification of ECG, many training and testing algorithms are present which work well in pattern recognition. Many researchers deal with ECG complex classification problems by using hybrid computational algorithms with neural network solutions, as these types of solutions show strong robustness and highly accurate prediction.

The methodology used in this research includes a filtration approach for the ECG signals. To eliminate the noise from the signal, construction of the bandpass filtering approach is performed here. A time domain coefficient has been used to achieve better accuracy levels of the dataset in order to denoise the data. Noisy datasets are analyzed by using feature coefficients for many decomposition iterations of bandpass filtering. It has a variable filter decomposition level which is based on the variation in input ECG signal. For better visibility, an adaptive function approach transformation used after denoising the signal and the interval is computed using time-domain and frequency domain components. To find features like P and R peaks in the ECG signal, the proposed algorithm shows a higher accuracy and detection rate. Normally the algorithm used to detect QRS complexes is Pan-Tompkins algorithm. The proposed algorithm should be near to the ideal perfection in heartbeat detection.

Random forest algorithm is used in the proposed structure which is based on multiple decision trees. This model will train the data very fast consisting of more than 60 decision trees. Following is a diagram of the proposed structure of the decision tree.

The proposed model is compared with 350 samples for training and testing. Our proposed research work is splitting the data into train and test for minimizing the overlap problem in classes. This segmentation approach is highly interpretable and classes are balanced with high accuracy. Using 5 lead probe sensor output as source of raw data the procedure is an independent data classification. This structure performs on two decision trees with the help of the Random Forest method to fuse the final classification decision. We achieved higher accuracy, sensitivity, and minimum execution time of our algorithm. Except for computation time, other metric parameters are a bit lower than the hybrid version of the learning algorithm. But the application of the proposed method is directly the medical field diagnosis sector. Therefore, this sector should be provided the result with time constraints. The overall performance of the model is improved and compared to the existing method for optimization purposes. These measuring metrics are performed to find the effectiveness of class with the help of labels.

To conclude, to classify class-appropriate balancing segments, the random forest proves to be a better method. This research shows the ECG signal analysis with an RF machine learning algorithm. This approach has solved imbalanced classes and overfitting problems with a suitable decision tree approach. This research article detects QRS complexes from ECG signals and verifies the specified features for classification. This algorithm clearly demonstrates that algorithms other than machine learning are possible and effective to extract and classify ECG signals for diagnosis and other medical purposes.

3.2.1.1 Summary

Much work has been done on feature extraction from ECG sample as it is an important step towards the classification of the ECG. In article [1] feature extraction is done using Continuous

Wavelet Transform (CWT) to obtain frequency components of the time-based signal. After which classification is done using a backpropagation-based CNN and an accuracy of 98.74% was achieved. Article [2] focuses on feature extraction and age and sex classification. For this MUSE system was used to extract the human-recognizable features and then a deep CNN was used for age and sex classification. This article proved that neural networks extract features from ECG signals in a way similar to human experts. According to [3], feature extraction can also be done by converting the ECG records into images. Here a few different models were used for feature extraction. With the AlexNet model an accuracy of 91.2% was achieved, with VGG19 model accuracy of 92.1% was achieved, with InceptionV3 model an accuracy of 91.5% and combining the feature extraction of all three models an accuracy of 96.6% was achieved. [4] uses fusion-based method for detection of features in ECG after which Random Forest was used for classification which obtained an accuracy of 96.5%.

3.2.1.2 Critical analysis

In article [1] several other models were compared to the proposed model and it preformed the best giving an accuracy of 98.74%. However, the results could have been improved if there was more availability of data in class Fusion Beat (F). Moreover, labeling of ECG data is costly and tedious, thus an unsupervised learning model would be cost effective. The model proposed in [2] also performed very well and proved that neural networks extract features from ECG signals in a way similar to human specialists and they also provide further details that help in better performance. However, the correlation of human extracted features was only above 85% with 13 of the strongest age AI features and 15 of the strongest sex AI features which can be further improved. [3] uses several different models for feature extraction. Individual models gave an accuracy of around 91%-92% however, a combined model using the feature extraction properties of all three models gave an accuracy of 96.6%. Thus, it can be seen that a combined model worked better than individual models. In [4], the model in comparison to other models preformed best with an accuracy of 96.5% and proved that machine learning methods can also work well for classifying an ECG signal.

3.2.1.3 Relationship to the proposed research work

Our project requires us to classify an ECG signal to detect fear and stress. In order to do that we must first extract specific features from an ECG signal to reach our goal. Thus, we need to develop a model for feature extraction before classification. For this reason, this research on feature extraction from ECG signal can prove to be quite resourceful.

3.2.2 Classification of ECG

The third and most important step in classification of an ECG signal is the classification of the signal. This is the part where a model, can be deep learning or machine learning, is developed to classify the ECG signal. Thus, this section gives detailed literature review about research work done regarding classification of an ECG signal. There are many recent studies on ECG classification through deep and machine learning models in an urge to improve accuracy, sensitivity and preciseness.

Several steps have been taken to automate ECG classification such as in [5]. From several machine learning algorithms to different deep learning classifiers such as RNN and CNN, accuracy is always tried to be enhanced. One major aspect that these works limit is the understanding of local and global precise segments and thus lose important information underlying an ECG wave. The purpose of this research is to retain such important information by proposing a novel convolutional neural network with non-local convolutional block attention module (NCBAM).

The working of the model consists of 3 stages. First, the preprocessed signal is supplied to a 33-layer residual network to extract the spatial features. The extracted spatial features are further forwarded into NCBAM to combine spatial and temporal features. The fusion is then pushed into a 1D convolutional layer which processes the class of the input signal.

2 datasets are used in this research. One dataset is from MIT-BIH arrhythmia database and the other is PTB-XL ECG database. In the MIT-BIH dataset, each signal is generated from a 2-lead ECG machine with a 360 Hz sampling frequency. ECG signals were recorded with an 11-bit resolution over the 10-mV range. The grouping of arrhythmias is reduced to 5 general classes namely Normal (N), Supraventricular Ectopic Beat (SVEB), Ventricular Ectopic Beat (VEB), Fusion Beat (F), and Unknown Beat (Q). 21,837 ECG records are available in the PTB-XL dataset from 18,885 different patients. A 12-lead ECG recorder recorded these samples at a 100 Hz sampling frequency for 10 seconds each (NORM: normal ECG, CD: conduction disturbance, MI: myocardial infarction, HYP: hypertrophy and STTC: ST/T changes).

For the MIT-BIH dataset, data is divided into 80 to 20 ratio with 80% being the train data. Unbalanced data was catered through data augmentation. For PTB-XL dataset, stratified random sampling is used to produce 10 segments per ECG sample.

After training, the test set is used to verify the accuracy of the proposed model. 98.64% accuracy has been achieved by training the model using the MIT-BIH dataset. Similarly, the same model when trained by PTB-XL dataset, 93.14% accuracy has been achieved. Reduced accuracy is mainly due to noise.

Thus spatial, channel and temporal information of an ECG signal are combined using a matrix. This immensely increased the interpretation of the ECG signal. Some limitations to this research include no availability of demographic data, and no indulgence of other biomedical signals for classification purposes.

Research article [6] highlights how the deep learning model has been used for ECG classification.

Up till now, the progress in ECG analysis has been hindered by the lack of datasets available. The issues faced are that the available datasets are too small and mostly contain only single lead recordings. Also, the data exists in raw form with no evidently defined tasks with consistent evaluation procedures which limits the comparison of different algorithms. However, these issues have been resolved by the recent availability of 12-lead ECG PTB-XL dataset.

A deep-learning-based time series classification algorithm was used. The ICBEB2018 dataset was also used to show the prospect of transfer learning from PTB-XL to other ECG classification datasets.

The PTB-XL dataset consists of ten seconds long 21837 records, 52% of which are male. According to the SCP-ECG standard the ECG statements used for annotation were divided into three categories, a total of 71 statements were used which were divided into 44 diagnostic, 12 rhythm and 19 form statements. ICBEB2018 dataset used for transfer learning comprises 6877 of 6 to 60 seconds 12-lead ECGs.

This research article focuses on inferring diagnostic, rhythm and form ECG statements using multilabel classification.

The resnet- and inception-based convolutional neural networks were the best results. Moreover, the results of transfer learning proved to be especially effective on small datasets and presented promising prospects. For gender prediction an accuracy of 84.9% was achieved.

To sum it up, the lack of appropriate datasets available has hindered the progress in the field of ECG analysis. This research article presents the first results based on the PTB-XL dataset for deep-learning-based classification algorithms which opens up a number of possibilities for future researchers.

According to [7], an ECG plays a very important role in diagnosing cardiac diseases. One such cardiac disease is cardiac arrhythmia which is detected by the ECG by recording the heart signal. Arrhythmias can be classified as life-threatening and non-life threatening. This research article focuses on the non-life-threatening arrhythmias that can cause deterioration of the heart muscle if left untreated.

This research article uses the MIT-BIH arrhythmia dataset. However, this dataset is imbalanced which can make the training of the model very challenging and affect the accuracy of the deep learning model. The MIT-BIH dataset contains 30-minute-long 48 records of people of different genders and ages.

This study proposes using generative adversarial networks (GAN) to generate synthetic heartbeats and thereby restore the balance of the dataset. GAN consists of two neural networks, a generator to produce data samples similar to the original and a discriminator to discriminate the samples as either real or fake.

The dataset is classified as in categories and 15 classes with each class belonging to a category. The categories are N, S, V, F and Q. the classes belonging to category N are NOR, LBBB, RBBB, AE and NE, to category S are APC, AP, BAP and NP, to category V are PVC, VE and VF, to category F is VFN and to category Q are FPN and UN.

The deep learning model is based on deep convolutional neural networks following two deep learning approaches. The first approach classifies the heartbeat into one of the 15 classes known as an end-to-end approach. The second approach first classifies the heartbeat under five main categories and then classifies it into one of the classes in that category known as two-stage hierarchical approach. A single learning method is used to disregard hand-engineering features by combining feature extraction, feature reduction, and classification altogether.

After the dataset has been balanced using generative adversarial networks, an overall accuracy of 98.30% and precision of 90.0% were achieved by the first approach and an overall accuracy of 98.00% and precision of 93.95% were achieved by the second approach. To put it altogether, an accuracy above 98.0%, precision above 90.0%, specificity above 97.4%, and sensitivity above 97.7% has been achieved using only the data of lead 1.

Article [8], proposes a deep learning model for arrhythmia classification. Arrhythmia is an irregular heartbeat which in some cases can lead to cardiovascular diseases. An automated system for arrhythmia detection can be very useful in handling and treating heart problems. An ECG is a machine that records the heart's electrical activity and is used to diagnose heart diseases such as arrhythmia.

This research article proposes using multi-model deep learning algorithms to detect arrhythmias from the ECG records. Here two deep learning models are used. Firstly, a model (CNN-LSTM) that is a combination of convolutional neural network (CNN) and long short-term memory (LSTM) network is used to extract classical features and learn the temporal representation of the ECG data. Secondly, a model (RRHOS-LSTM) that is a combination of RR intervals, higher-order statistics (HOS) and (LSTM) network is used to identify abnormality heartbeat classes. The above two models are combined using a meta-classifier to formulate them into a final result. This result is then verified by another model to reduce false positives.

The dataset used was MIT-BIH arrhythmia dataset which is highly imbalanced and thus made the classification of arrhythmia very challenging. This issue was resolved by training the models on sub-sample datasets of the training data. A weight loss function was also used to solve this problem. The dataset consists of 30 minutes long 48 records. The dataset divided the data into sixteen different types which were categorized in 5 categories according to AAMI recommends: Normal (N), Ventricular ectopic beat (VEB), Supraventricular ectopic beat (SVEB), Fusion (F), and Unknown beat (Q).

Previously, machine learning algorithms have been introduced to detect features extracted from the ECG however, there are quite a few limitations on the work done. One limitation is that the existing models are not scalable. Another is that the accuracy is not high and the false positive rate is high.

The two evaluation methods of arrhythmia classification are: class-oriented and subject-oriented. In class-oriented all the records are first combined and then split into train and test sets. In subject-oriented a patient's record could either be in the test or train set but not in both. This research article uses a subject-oriented patient-independent evaluation method.

The training set was split into 90%-10% for bagging models and verification model combined (90%) and meta-classifier (10%) respectively. For training bagging models Adam optimizer was used with a batch size of 256 and for training verification and meta-classifier models RMSProp optimizer was used with a batch size of 128. The learning rate used was 0.001. The evaluation was done based on six metrics: accuracy (Acc %), F1 score (F1 %), specificity (Sp %), sensitivity (Se %), positive predictive value (PPv %), and Cohen's Kappa (k).

The results showed an overall accuracy of 95.81% which is more than 1% from the nearest state-of-the-art method. According to the results, values of 97.48% for N, 66.19% for SVEB, 94.55% for VEB and 41.67% for F were achieved. The sensitivity of 98.03%,65.51%, 93.91%, and 19.33% respectively were achieved for the four classes. The averages of F1 score are greater than 3% and the averages of positive predictive value are greater 8% compared to all other methods. The results proved that the proposed method is superior to all previous methods for ECG classification.

In article [9] the author explains that, cardiovascular diseases (CVDs) are causing the huge numbers of fatalities in recent times. These diseases can be diagnosed by analyzing electrocardiograms produced by ECG machines. ECG machines detect the electrical signal produced in the body during a heartbeat and represent it in a waveform. These waveform signals are used to extract features from them, like P wave QRS complex, and RR interval etc. This research uses the MIT-BIH and PTB Diagnostic ECG database. This study proposes a technique to train a modified deep learning method while ensuring its stability. The techniques used in these two datasets are the CNN model, CNN + LSTM, and CNN + LSTM + Attention Model.

For classification of ECG, attention method will be employed to “clarify” key characteristics such as recurrent or convolutional layers. In this research two functions were used, ReLU (Rectified linear unit) and Swish. ReLU is a transfer or activation function. It helps the neural network decide whether or not to output yes or no by mapping output to values depending on the model function. ReLU is outperformed by Swish on deep networks in many domains’ areas, like image classification and machine translation. According to the results, an average accuracy of 99.12% is achieved (with precision, recall, and F1-score value are equal) by using CNN classification model, CNN + LSTM model classification achieved 99.3% average accuracy. CNN + LSTM + Attention Model classification reached 99.29% average accuracy.

In this article, different deep learning techniques, used to classify a heartbeat are applied and are analyzed thoroughly. In this research, accuracy of the model was improved by scrutinizing the datasets. As the proposed model includes ten residual blocks, there is a possibility of overfitting the data. Naturally, the enlarged dataset makes it harder to classify data during the testing phase because of the human factor. After all these difficulties, the proposed model still managed to achieve high levels of accuracy as shown by the results. This demonstrates its ability to produce very accurate predictions with a 99.12 percent accuracy rate for the CNN model, 99.3 percent accuracy for the CNN + LSTM model, and 99.29 percent accuracy for CNN + LSTM + Attention Model.

[10] states successful implementations have already been made in the classification of ECG wave rhythms for identifying cardiovascular diseases like cardiac arrhythmias. While other heart related problems like Takotsubo Syndrome (TTS) and acute anterior myocardial infarction (Ant-AMI) show quite similar rhythms on ECG and thus are difficult to classify and identify. Thus, this research has been conducted to use Machine Learning (ML) to classify, and mainly distinguish between, these two wave rhythms.

Data set in this research was produced in Yokohama Minami Kyosai Hospital where 56 patients with TTS and 112 patients with AMI were enrolled in the dataset after 1-to-1 random matching was performed among the two rhythms. 12 lead ECG device was used for data collection. 80% of data was used to train and the remaining 20% was used as test data.

The model is composed of univariate logistic regression and is trained on the prediction data. 11 models were tried on the data and after analysis, tree classifier model (model_ET) and light gradient boosting machine (model_LGBM) were adopted.

With these results, it can be concluded that despite having significantly low accuracy rates, both Model_ET and Model_LGBM algorithms produced classical prediction ML models. Although successfully producing results, the limitations involved due to a limited data set such as no external validation (using separate external test data), no ECG variations, and no validation in other similar clinical populations. As well as the ECG system they used is not used usually worldwide.

In article [11], it is explained that, an electrocardiogram (ECG) is a simple, quick, safe, and painless way of recording the electrical activity generated and conducted in the heart. It is an effective non-invasive tool for various biomedical applications such as measuring the heart rate, examining the rhythm of heartbeats, diagnosing heart abnormalities, emotion, and physical recognition, and biometric identification.

There are three types of features analyzed in this research, firstly the morphological features. These features can be done by calculation of entropies like P, T, QRS complex. Next are the temporal features. These features can be extracted by measuring the distance among different samples. Measurement of such distances help in evaluating variability in heart rate and disturbance in signal periodicity. Temporal features are the most relevant as they observe time behavior and are commonly used in AF detection systems. Thirdly, the statistical features, such as energy, mean, standard deviation, max-min kurtosis and skewness are used to analyze the data of a population or disease.

For learning of our model various machine learning models can be used such as Support Vector Machine (SVM), Long Short-Term Memory (LTSM) and Convolutional Neural Network. These models are highly accurate but extremely time consuming and need large computational resources. Here a traditional Neural Network is used to analyze behavior of ECG in prediction, detection and prediction. an accuracy of 91% was achieved on AF detection using this model. Using deep learning models has solved many difficulties of normal neural networks. Models can automatically learn features from raw data without any features engineering needed. Accuracy levels of up to 98,0 and 99,9%, indicating that these models are clearly superior to those traditional ones, but with a need of huge amounts of train data and the process is extremely time consuming. Another popular way to analyze ECG is using a Convolutional Neural Network. In this process the input data is first transformed to a higher dimension abstraction by applying it on a convolutional layer. Then in the pooling layer the data is shaped into a 1D representation. And the last layer is used to estimate the outputs as it consists of a perceptron.

This research proposes a comparison of development and performance between Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models using the signals of the MIT-BIH database, based on the use of several sets of morphological, temporal, statistical and time frequency features. For innovation, the periodic signals Jitter and Shimmer were analyzed and used to make the feature set, as well as feature maps resulting from the Scattering transform, which is not tested on ECG up till now. Resultantly, a maximum accuracy of 91.96% and 98.17% are achieved for MLP and LSTM respectively. Moreover, using the Hilbert transform, a new method for detecting the R peaks in ECG signals, has also developed.

3.2.2.1 Summary

Article [5], proposes a novel convolutional neural network with non-local convolutional block attention module for classification of ECG signal. The model consisted of 33-layer residual network to extract the spatial features, NCBAM to combine spatial and temporal features and a 1D convolutional layer for classification. Two datasets were used and an accuracy of 98.64% was obtained with MIT-BIH dataset and accuracy of 93.14% was obtained with PTB-XL dataset. In [6], a deep-learning-based time series classification algorithm was used on the PTB-XL dataset for classification of age and sex. The ICBEB2018 dataset was also used to show the prospect of transfer learning from PTB-XL to other ECG classification datasets. For gender prediction an accuracy of 84.9% was achieved. [7] proposes using generative adversarial networks (GAN) to generate synthetic heartbeats and thereby restore the balance of the dataset. The deep learning model used is based on deep convolutional neural networks following two deep learning approaches: end-to-end approach and two-stage hierarchical approach. An accuracy above 98.0% was achieved. Article [8] proposes multi-model deep learning algorithms to detect arrhythmias from the ECG records consisting of CNN-LSTM and RRHOS-LSTM models. An accuracy of 95.81% was achieved. Study in [9] proposes a technique to train a modified deep learning method while ensuring its stability. The techniques used in these two datasets are the CNN model, CNN + LSTM, and CNN + LSTM + Attention Model. An average accuracy of 99.12% is achieved using CNN classification model, CNN + LSTM model classification achieved 99.3% average accuracy and CNN + LSTM + Attention

Model classification reached 99.29% average accuracy. In [10] a model composed of univariate logistic regression was proposed and trained on the prediction data. 11 models were tried on the data and after analysis, tree classifier model (model_ET) and light gradient boosting machine (model_LGBM) were adopted. Research paper [11] proposes a comparison of development and performance between Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models using the signals of the MIT-BIH database, based on the use of several sets of morphological, temporal, statistical and time frequency features. An accuracy of 91.96% and 98.17% are achieved for MLP and LSTM respectively.

3.2.2.2 Critical analysis

In article [5] the proposed model preforms well on dataset MIT-BIH, whereas with dataset PTB-XL an accuracy of only 93.14% is achieved due to the presence of noise in the ECG samples. In order to achieve better performance, noise should be removed from the samples. Other limitations to this research include no availability of demographic data, and no indulgence of other biomedical signals for classification purposes. [6] states a low accuracy of 84.9% was achieved due to the lack of appropriate dataset availability. In [7] only 1-lead ECG has been used to perform the experiment. Using a 12-lead ECG the accuracy can be improved. Article [8] proposes using a multi-model deep learning algorithms however, one limitation that is faced is that the existing models are not scalable. Another is that the accuracy is not high and the false positive rate is high. [9] proposes a technique to train a modified deep learning method while ensuring its stability and thus high accuracies of above 99% have been achieved. The model in [10] produced low accuracy rates because of the limitations involved due to a limited data set such as no external validation, no ECG variations, and no validation in other similar clinical populations. As well as the ECG system they used is not used usually worldwide.

3.2.2.3 Relationship to the proposed research work

We are working on classifying an ECG signal to detect fear and stress. In order to do that we first need to have an understanding of the models used to classify an ECG sample. So that we can develop a model of our own to classify fear and stress from an ECG record. For this reason, this research on classification of ECG signal can prove to be quite resourceful.

3.3 Literature Review Summary Table

Table 1: Summary of Models for Feature Extraction and Classification of ECG Signal

The summary of various models for feature extraction and classification of ECG signal in the past from 2020-2022 is presented here.

No.	Name, reference	Author(s)	Year	Dataset	Accuracy	Description
1.	Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network, [1]	Tao Wang, Changhua Lu, Yining Sun, Mei Yang, Chun Liu and Chunsheng Ou	2021	MIT-BIH	98.74%	Two median filters were used to remove noise, Continuous Wavelet Transform (CWT) was used for feature extraction and a backpropagation-based CNN was used for

						classification of CVD
2.	Deep neural networks learn by using human-selected electrocardiogram features and novel features, [2]	Zachi I. Attia, Gilad Lerman and Paul A. Friedman	2021	Collected from Mayo Clinic records from January 1994 and February 2017	85%	MUSE system was used to extract the human-recognizable features and then a deep CNN was used for age and sex classification
3.	Fusion based feature extraction analysis of ECG signal interpretation–a systematic approach, [3]	Mahwish Naz, Jamal Hussain Shah, Muhammad Attique Khan, Muhammad Sharif, Mudassar Raza and Robertas Damaševičius	2021	MIT-BIH	97.6%	Converted ECG signals to images for feature extraction and used a deep CNN to classify VT
4.	Fusion based Feature Extraction Analysis of ECG Signal Interpretation – A Systematic Approach, [4]	T. Vijayakumar, R. Vinothkanna and M. Duraipandian	2021	Collected	96.5%	Bandpass filtering approach was used for removing noise, fusion based feature extraction was used and then Random Forest method was used for classification of CVD
5.	Automated ECG classification using a non-local convolutional block attention module, [5]	Jikuo Wang, Xu Qiao, Changchun Liu, Xinpei Wang, YuanYuan Liu, Lianke Yao and Huan Zhang	2021	MIT-BIH and PTB-XL	MIT-BIH: 98.64% PTB-XL: 93.14%	Uses a novel convolutional neural network with non-local convolutional block attention module for classification of ECG signal
6.	Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL, [6]	Nils Strodthoff, Patrick Wagner, Tobias Schaeffter and Wojciech Samek	2021	PTB-XL and ICBEB2018	84.9%	A deep-learning-based time series classification algorithm was used for classification of age and sex
7.	Generalization of Convolutional Neural Networks	Abdelrahman M. Shaker, Manal Tantawi, Howida A.	2020	MIT-BIH	98.0%	Uses GAN to generate synthetic heartbeats and

	for ECG Classification Using Generative Adversarial Networks, [7]	Shedeed and Mohamed F. Tolba				thereby restore the balance of the dataset and a deep CNN to classify ECG
8.	An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification, [8]	Ehab Essa and Xianghua Xie	2021	MIT-BIH	95.81%	Proposes multi-model deep learning algorithms to detect arrhythmias from the ECG records
9.	Classification of Arrhythmia in Heartbeat Detection Using Deep Learning, [9]	Wusat Ullah, Imran Siddique, Rana Muhammad Zulqarnain, Mohammad Mahtab Alam, Irfan Ahmad and Usman Ahmad Raza	2021	MIT-BIH and PTB Diagnostic ECG	CNN: 99.12%, CNN + LSTM: 99.3% and CNN + LSTM + Attention Model: 99.29%	Proposes a technique to train a modified deep learning method while ensuring its stability
10.	Machine learning of microvolt-level 12-lead electrocardiogram can help distinguish takotsubo syndrome and acute anterior myocardial infarction, [10]	Masato Shimizu, Makoto Suzuki, Hiroyuki Fujii, Shigeki Kimura, Mitsuhiro Nishizaki and Tetsuo Sasano	2022	Collected from Yokohama Minami Kyosai Hospital	98.74%	A model composed of univariate logistic regression was proposed
11.	A Brief Review on Electrocardiogram Analysis and Classification Techniques with Machine Learning Approaches, [11]	Pedro Henrique Borghi	2021	MIT-BIH	MLP: 91.96% and LSTM: 98.17%	Proposes a comparison of development and performance between MLP and LSTM models

3.4 Conclusion

Upon exploring various models, work has been done on feature extraction and classification of an ECG signal. Many models have been developed, within which some achieved higher accuracy than others. One point to note is that most of the models have been developed using deep learning techniques rather than machine learning, thus when developing a model of our own, we plan to use deep learning model. Another important aspect is the dataset, which is vital to train and test a model. MIT-BIH proves to be a popular publicly available dataset however, it might not be suitable for our project thus we may use another dataset more suitable to our needs or may develop our own repository to train the model we are going to work. This research will prove to be quite helpful in developing a model of our own for classification of ECG signal into stress and fear.

Chapter 4: System Requirement Specification

In this chapter we will discuss what the EED system will do and how it will be expected to perform. We will also discuss the requirements, functionality, and some use cases of EED system.

4.1 List of Features

- Data Collection
- Realtime recording of ECG signal
- Reproducing image from the signals
- Feature extraction
- Classification of Signal in Stress and Fear

4.2 Functional Requirements

4.2.1 Reading Live ECG from the Subject

System should be able to read and feed continuous ECG readings/waveforms to the model as real time classification of the signals is to be implemented.

4.2.2 Converting Signals into an Image

As classification would be done using deep neural network i.e., CNN, the fed signal is to be converted into intervals of images which will be further processed and classified.

4.2.3 Extracting Important Features of the Signal

System will extract features from the fed image of the signal using a pre-trained CNN. Such features shall be helpful in predicting the classification of the waveform for the recorded ECG in real time. The features, after extraction, will be passed to a fully connected layer which will classify the signal

4.2.4 Classifying the Signal

After preprocessing and feature extraction of the signal through CNN, the fully connected layer from its previously learned capabilities should be able to classify the signal probabilities aiming normal, stress and fear.

4.3 Quality Attributes

Following are some quality attributes of EED system

- Reliability
- Efficiency in terms of performance
- Availability
- Reusability

4.4 Non-Functional Requirements

4.4.1 Reliability

The system should be reliable and perform all functionalities as promised. In case of a failure it should be able to recover instantaneously from the start and start reading and classifying immediately.

4.4.2 Performance

- The system shall be able to give response to the user's request in real time.
- The system shall allow user to access the system within 10 seconds.
- The system should be able to accommodate real time classification of the rhythm to detect change in rhythm features immediately.

4.4.3 Availability

- The system shall be readily available to give response to the user's requests.
- The system should be available to always detect ECG signals when needed.

4.4.4 Reusability

4.4.4.1 Code Reusability

The code should be divided into modules based on the functionality so that it favors code reusability.

4.4.4.2 System Reusability

The system should be able to detect and classify ECG signals on a consistent basis and should not fail after a specific period of working capability.

4.5 Assumptions

Following are some assumptions made for the system.

- Most important part of the system is the data that is to be fed to the system for classification. In this case, it is kept in mind that data provided through reading is always reliable and error free.
- The data collection is done using the ECG Arduino scanner AD8232. It is assumed that this scanner will work ideally for each signal
- Our project is also dependent on emotion reliability as it is always assumed that the subject would depict real emotions every time when they are being subjected to data collection.
- Concerning the device placement, subject's posture, and movement, it can be possible that background noise interrupts the reading values. Therefore, it is assumed that the user will sit ideally in the situation of being under observation.
- The data collected from the sensor will be converted into an image for better classification probability. In this case, it is assumed that the image, produced every time, will always adhere to the maximum resolution requirement for optimum classification.

4.6 Hardware and Software Requirements

Following are the hardware and software requirements that will be required to develop and deploy the project.

4.6.1 Hardware Requirements

Following is the list and respective uses of hardware required in the development of our system.

4.6.1.1 ECG Sensor Kit (AD8232)

It is the most important component of the system as it will read continuous raw ECG waveforms and supply it to the system for further processing.

4.6.1.2 Disposable ECG Electrodes

The electrodes will attach to the subject's body for physically reading the rhythm and send an electronic impulse to the Arduino sensor.

4.6.1.3 ECG Cables

A set of 3 cables will be required to connect electrodes with the reading sensor for sensing heart rhythm.

4.6.1.4 Arduino Module

This module, acting as a controller and a connection between the computer and the sensor, will connect the whole system together.

4.6.1.5 Breadboard

It will act as the power supply to the Arduino module as the module will be placed on the board. ECG sensor kit will also be placed over the same board

4.6.1.6 Jumper Wires

These are needed to connect the Arduino and the sensor kit with each other for connectivity and data exchange.

4.6.1.7 USB - AB Cable

This cable will connect the Arduino module with the computer to supply the raw data.

4.6.2 Software Requirements

- Google Colaboratory
- Arduino IDE
- T3 processing IDE
- MATLAB
- Excel
- VS-Code
- Database

4.7 Use Cases

Following are the main use cases of the system.

4.7.1 Connecting Electrodes

<table>
<tr><td>Name</td><td colspan="3">Connecting electrodes use case</td></tr>
<tr><td>Actors</td><td colspan="3">System operator</td></tr>
<tr><td>Summary</td><td colspan="3">The system operator will attach the electrodes at the correct body parts of the subject to read the heart rhythm of the subject</td></tr>
<tr><td>Pre-Conditions</td><td colspan="3">The operator must have previous knowledge of exactly where the electrodes are to be placed and should have practiced it before professionally deploying himself into this task</td></tr>
<tr><td>Post-Conditions</td><td colspan="3">None</td></tr>
<tr><td>Special Requirements</td><td colspan="3">Any unnecessary hair must be removed from the subject’s body part as it would become painful to remove electrode after the process is completed</td></tr>
<tr><td colspan="4" align="center">Basic Flow</td></tr>
<tr><td colspan="2" align="center">Actor Action</td><td colspan="2" align="center">System Response</td></tr>
<tr><td>1</td><td>Operator places electrodes at the right places</td><td>2</td><td>Starts to classify the signal received</td></tr>
<tr><td colspan="4" align="center">Alternative Flow</td></tr>
<tr><td>3</td><td>Operator places electrodes at wrong places</td><td>4</td><td>System responds inappropriately without any classification</td></tr>
</table>

4.7.2 User Getting Response

<table>
<tr><td>Name</td><td colspan="3">User getting response use case</td></tr>
<tr><td>Actors</td><td colspan="3">User</td></tr>
<tr><td>Summary</td><td colspan="3">The user using the system will get live feedback of stress related emotions from the system</td></tr>
<tr><td>Pre-Conditions</td><td colspan="3">Electrodes should be attached to the user and the system is started for data feeding and classifying the signals</td></tr>
<tr><td>Post-Conditions</td><td colspan="3">User, based on system’s response, decides whether they should pursue to the task they are obliged to</td></tr>
<tr><td>Special Requirements</td><td colspan="3">None</td></tr>
<tr><td colspan="4" align="center">Basic Flow</td></tr>
<tr><td colspan="2" align="center">Actor Action</td><td colspan="2" align="center">System Response</td></tr>
<tr><td>1</td><td>User provides their ECG to the system</td><td>2</td><td>System classifies the ECG</td></tr>
<tr><td>3</td><td>User does certain task</td><td>4</td><td>System responds with respective classification</td></tr>
</table>

4.7.3 Examination Officer Assistance

Name	Examination officer assistance use case		
Actors	Examination officer		
Summary	The examination officer will be able to examine real time users' response about their honesty in doing a certain task		
Pre-Conditions	Electrodes should be attached to the user and the system is started for data feeding and classifying the signals		
Post-Conditions	None		
Special Requirements	None		
Basic Flow			
Actor Action		**System Response**	
1	User provides their ECG to the system	2	System classifies the ECG
3	User does certain task	4	System responds with respective classification

4.8 Graphical User Interface

No GUI will be implemented as output and system interactions can easily be controlled using system's console.

4.9 Database Design

This section reflects the database design of the proposed system.

4.9.1 ER Diagram

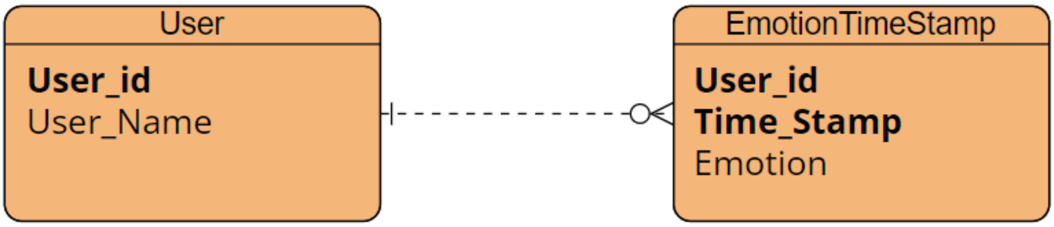


Figure 1: Entity Relationship Diagram
This is an entity relationship diagram for database of EED.

4.9.2 Data Dictionary

Table 2: User Table
This is data dictionary of User Table.

Field Name	Data Type	Length	Constraint	Description
User_id	int	10	PK	User ID, Auto Generated
User_Name	Varchar	30	Not Null	Name of the user

Table 3: EmotionTimeStamp Table

This is data dictionary of EmotionTimeStamp Table.

Field Name	Data Type	Length	Constraint	Description
User_id	int	10	Composite Keys	User ID, from user table
Time_Stamp	date&time	-		Date and time of emotion
Emotion	varchar	20	Not Null	Emotion of the user detected

4.10 Risk Analysis

Some of the risks analyzed for the app are as listed below.

4.10.1 Chip failure

The chip is sensitive to voltage and electrical fluctuations. A slight spike might damage the ECG sensor kit which in turn fails to produce expected signals of ECG

4.10.2 Internet Failure

The trained model will be backed up over a server such as google. This model could only be accessed remotely using internet. Failure of internet will result in loss of data prediction of the system.

4.10.3 Electrode not placed correctly

In case of displacement of electrodes or mounting wrong wire combination over electrodes the reading becomes invalid.

4.11 Conclusion

In this chapter, we discussed about complete system requirements of EED system. We comprehensively defined database used for EED, ran down system requirements including both hardware and software, demonstrated functional and non-functional working requirements, and made logical use cases for a smooth working model.

Chapter 5: Proposed Approach and Methodology

The EED project is composed of 3 separate modules: Data reading, data pre-processing and data classification. This chapter describes in detail how EED system performs each of its modular functions. This chapter covers the details of how the module is defined, its importance in the system, its working inside the system, any algorithms used to run the module etc.

5.1 Data Reading

This section defines how our system will effectively reads continuous ECG of a subject under observation and feeds it into the system.

The approach that we are planning to use includes assembling an ECG device using a 3-lead ECG-sensor kit controlled by an Arduino controller. The device will be connected to the computer using a USB cable and we will use software such as Arduino IDE and T3 Processing IDE to process and plot the raw data on the system. The signal generated will be a 360 Hz analog signal. The data will be collected from various volunteers. As we are only focusing on two of the emotions, stress, and fear, we will create environments to evoke these emotions. For stress data collection we are planning on conducting interviews whereas for evoking fear we plan to instantaneously disrupt the person, for example by using a buzzer that makes a loud noise. The signal will then be stored in our database as both images and raw data as we plan on classification based on both types of data. This signal will then be used as input to the classifiers to train and test the models.

After training the module, Same setup will be used to predict emotions of a subject in real time. A window size will be specified and signals from the window will be passed to the model for prediction.

This is one of the cheapest and efficient ways of collecting ECG and using it for helpful purpose as is being used in the EED.

5.2 Data Pre-processing

The raw ECG collected using the sensor will contain some noise. Noise adds a bad attribute to feature extraction and must be dealt with before using data for classification.

Before classification the signal will be pre-processed to remove any noise and hence achieve better accuracy. For noise removal, algorithms such as the Butterworth bandwidth filter will be used. The next step is to extract the necessary features such as R-R interval, QRS complex, BPM etcetera for classification of stress and fear. For this purpose, we plan on using the Continuous Wavelength Transform (CWT) algorithm.

These pre-processing techniques improve the quality of data collected in the study and in turn increases the accuracy of the system

5.3 Classification

In initial stages, we will classify the data both sequentially as well as imagery: CNN for classification of stress and fear from images and LSTM for classification of the emotions from sequential data.

5.3.1 Long Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) model is an algorithm that tries to imitate the human mind the way it works to uncover the underlying relationships in the given sequential data. It is a deep learning model that is capable of learning long term dependencies. It is dependent on three things: current long-term memory of the network (cell state), output at the previous point in time (previous hidden state) and the input data at current time step. It consists of three gates: forget, input and output gate. The forget gate is used to filter out which parts of long-term memory should be forgotten. The input gate is used to determine what information is worth retaining and the output gate ensures that only the necessary information is output.

5.3.2 VGG – 19

A fixed size of (224 * 224) RGB image is given as input to this network which means that the matrix is of shape (224,224,3). The only preprocessing that is done is that they subtracted the mean RGB value from each pixel, computed over the whole training set. It uses kernels of (3 * 3) size with a stride size of 1 pixel, this enables them to cover the whole notion of the image. Spatial padding is used to preserve the spatial resolution of the image. Max pooling is performed over a 2 * 2 pixel windows with stride 2. This is followed by a Rectified linear unit (ReLu) to introduce non-linearity to make the model classify better and to improve computational time as the previous models used tanh or sigmoid functions this proved much better than those. Implements three fully connected layers from which first two are of size 4096 and after that a layer with 1000 channels for 1000-way (ImageNet Large-Scale Visual Recognition Challenge) ILSVRC classification and the final layer is a SoftMax function.

So, in simple terms VGG is a deep CNN used to classify images. The layers in VGG19 model are as follows:

- Conv3x3 (64)
- Conv3x3 (64)
- MaxPool
- Conv3x3 (128)
- Conv3x3 (128)
- MaxPool
- Conv3x3 (256)
- Conv3x3 (256)
- Conv3x3 (256)
- Conv3x3 (256)
- MaxPool
- Conv3x3 (512)
- Conv3x3 (512)
- Conv3x3 (512)
- Conv3x3 (512)
- MaxPool
- Conv3x3 (512)
- Conv3x3 (512)
- Conv3x3 (512)
- Conv3x3 (512)
- MaxPool
- Fully Connected (4096)

- Fully Connected (4096)
- Fully Connected (1000)
- SoftMax

5.4 Conclusion

Once the system classifies the ECG signal, the output will be displayed on the console and the timestamp of when the emotion was observed will be recorded in our database. This defines how the EED system will work and how modules will proactively interact to achieve a smooth workflow.

Chapter 6: High-Level and Low-Level Design

In this section, we will discuss high-level and low-level designs of the EED system.

6.1 System Overview

In this section, we will discuss the overall overview of the EED system. This will include all steps starting from designing the system architecture, collecting dataset, training the model, feeding the data to the system and the output presented to the user in response.

6.1.1 System Design

Following describes the compositional structure of the system.

6.1.1.1 Data Reading

The system should first read the data from the user. This data will be raw ECG values. The values will be collected from the ECG Sensor kit AD8232 and controlled using Arduino Module. The Arduino module will act as a bridge between the model (computer), Sensor and the user using it. The ECG electrodes pass the electronic signals collected from the subject's body to the sensor which is available for sensing the intensity of the signals. These signals are passed to the computer by the Arduino controller module using USB-AB cable. The data will be data points and respective time intervals at which these points are picked up by the sensor.

6.1.1.2 Raw Data Conversion to Images

The data supplied to the system using the sensor will then be used to produce images. Image resolution is a key aspect in this regard. A higher resolution would mean more learned features and hence better classification. Thus, a higher frequency-data is necessary to produce the desired images.

6.1.1.3 Data Preprocessing

The images produced will then be preprocessed to remove any noise from them. Noise reduction is an important mechanism as this will filter out any extraneous noise and actual reading of the signal will be obtained. Classification accuracy drastically improves as background noise is removed. Noise can occur due to many factors: movement of body parts, refraction in electrodes, loose electrical components, sensor's uncertainty, etc.

6.1.1.4 Classification

The classification will be done on the final preprocessed image. Images of fixed time intervals, containing a heartbeat, will be input to the system continuously until the user is detached from the system. System will classify those images in real time between normal, stress or fear.

6.1.1.5 Classification Storage

Time stamps with the emotion will also be stored in a database which can later be examined to identify the subject's emotional condition as required.

6.1.2 Data Collection

The dataset will be collected within the premises of the university. This dataset will be used to train and test the model's performance. The need to collect the dataset is necessary as this will be an optimal example of how a user would behave from the same cultural background in the confined boundaries of this project.

6.1.3 Model Training

The CNN model used in the system will be trained and tested using the dataset collected. The model will then be used to classify the subject's emotion in real time as continuous ECG signals are fed to the system.

6.2 Design Considerations

This section describes many of the issues which need to be addressed or resolved before attempting to devise a complete design solution.

6.2.1 Assumptions and Dependencies

6.2.1.1 Assumptions

- Most important part of the system is the data that is to be fed to the system for classification. In this case, it is kept in mind that data provided through reading is always reliable and error free.
- The data collection is done using the ECG Arduino scanner AD8232. It is assumed that this scanner will work ideally for each signal
- Our project is also dependent on emotion reliability as it is always assumed that the subject would depict real emotions every time when they are being subjected to data collection.
- Concerning the device placement, subject's posture, and movement, it can be possible that background noise interrupts the reading values. Therefore, it is assumed that the user will sit ideally in the situation of being under observation.
- The data collected from the sensor will be converted into an image for better classification probability. In this case, it is assumed that the image, produced every time, will always adhere to the maximum resolution requirement for optimum classification.

6.2.1.2 Dependencies

As the system is all about subject emotions, the system is highly dependent on the user's availability to work. In case no one relates to the system, the system will not be able to perform its function at all.

6.2.2 General Constraints

Some constraints and limitations that have a significant impact on the design of the system's software are stated below.

6.2.2.1 Age

Age is a factor that is important in classification. Different age groups have different responses to external factors.

6.2.2.2 Sex

Males and females depict separate intensities of rhythm changes when subject to an instantaneous change.

6.2.2.3 Ethnicity

Different groups of people pose different changes in rhythm in an emotional hit. Thus, training the model greatly relies over the group of people the model will be used at.

6.2.2.4 Heart Disease

Heart rhythm may alter in case the subject is already experiencing any arrhythmia. Thus, this should also be considered imperative when classifying the signal.

6.2.3 Goals and Guidelines

6.2.3.1 Improved Accuracy

Accuracy is an important part of this system, as higher accuracy of the system leads to better identification of instantaneous emotional change in the person.

6.2.3.2 Robust Classification

System should be able to differentiate between the classification of stress and fear from normal ECG rhythms robustly to depict higher preciseness.

6.2.3.3 Data Repository

Data collected and labelled should be generic in terms of possible fear rhythms detected within the interval of the beat.

6.2.4 Development Methods

We will be using Scrum development methodology for our project development. Scrum is an agile development methodology used in the improvement of Software dependent on iterative and steady cycles. We will divide our work and create different sprints which will take a certain timeline to complete. This timeline will be no longer than one week. After each sprint completion we will hold a 10–15-minute meeting to keep track of our progress and re-plan the whole progress accordingly. Scrum is flexible which makes it easier to make changes or to add new functionalities in a project, so it is reasonable to use this development method. Since our project is complex in nature which requires both development and some research, scrum is a best suited methodology for it.

6.3 System Architecture

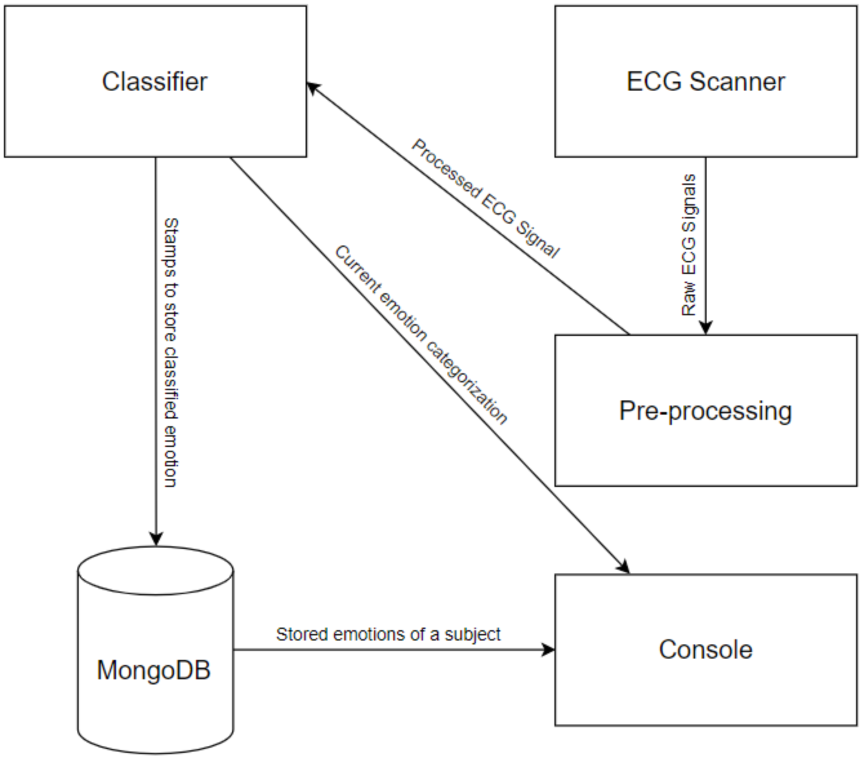


Figure 2: High-level Architecture Diagram
This is a high-level architecture diagram of EED.

The diagram above breaks down our system into three main components: ECG scanner, pre-processor, and classifier. We also have a database to store our results. The ECG scanner will be used to collect raw ECG signals from people using electrodes connected to an ECG device. The ECG scanner produces raw ECG data which is then pre-processed. The processed data is then passed to the classifier which classifies the ECG signal as fear or stress. Then the timestamps when the emotion is classified will be stored in a database. The emotion will then be displayed on the console

6.3.1 ECG Scanner

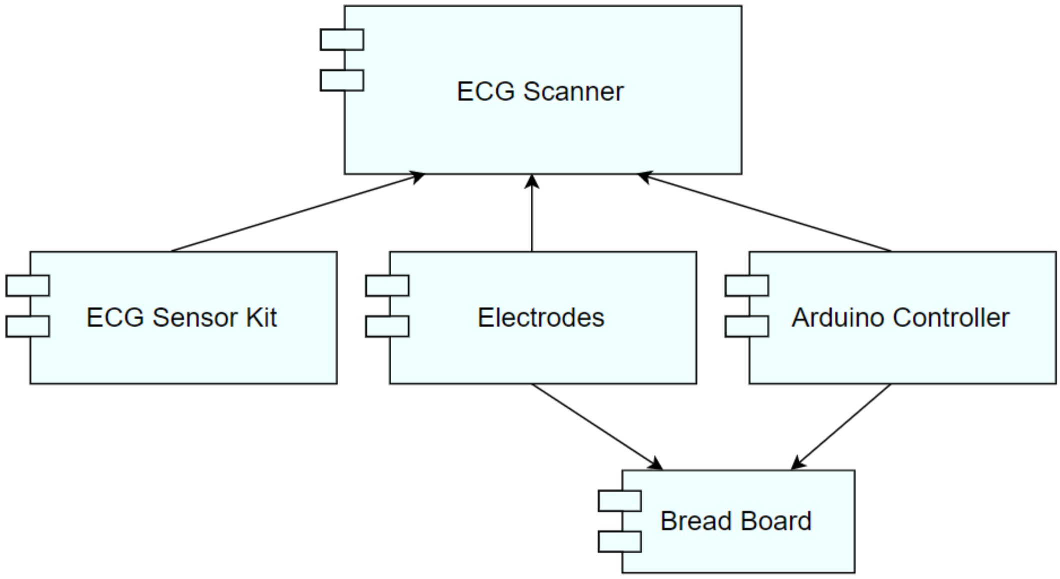


Figure 3: Low-level Architecture Diagram for ECG Scanner Component
This is a Low-level Architecture Diagram for ECG Scanner Component of EED.

ECG scanner is composed of Sensor kit, electrodes, and Arduino controller. The combination of IoT devices makes up the signal recorder component. This component captures raw ECG signals from the subject and supplies it to the system connected using USB-AB Cable.

6.3.2 Pre-processing

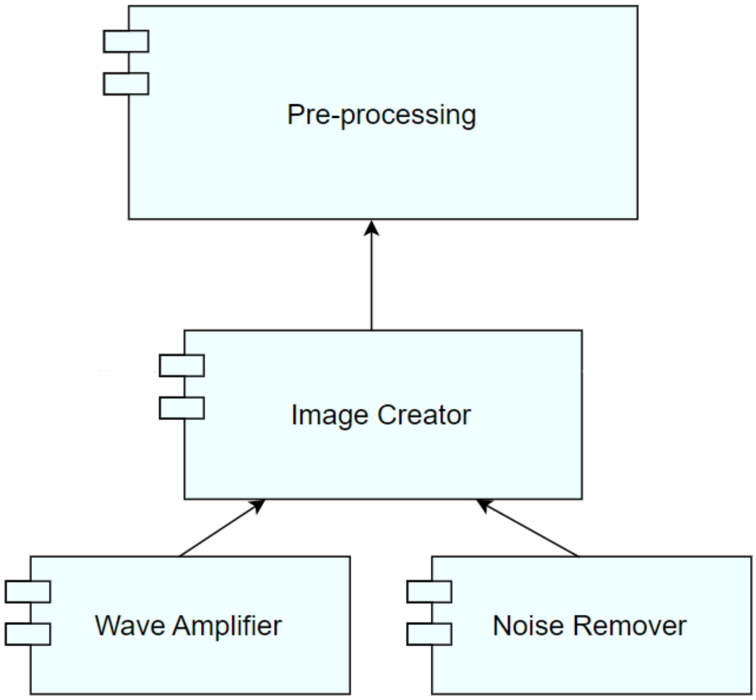


Figure 4: Low-level Architecture Diagram for Pre-processing Component
This is a Low-level Architecture Diagram for Pre-processing Component of EED.

ECG waveform image is created by reducing noise and amplification of dead waves. This pre-processed image is formed by this pre-processing component which supplies the image to the classifier for emotion recognition.

6.3.3 Classifier

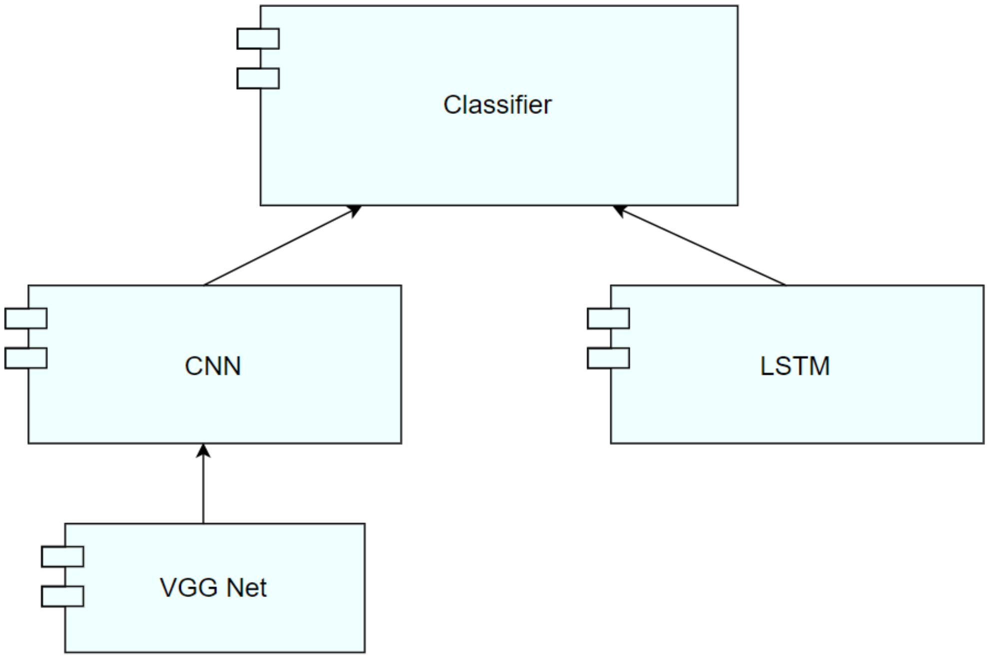


Figure 5: Low-level Architecture Diagram for Classifier Component
This is a Low-level Architecture Diagram for Classifier Component of EED.

The classifier, consisting of CNN and LSTM modules, will classify the emotions in the received data into their respective categories. The classifiers are pretrained and tested before deploying in the project.

6.4 Architectural Strategies

6.4.1 Tools and Software

As mentioned in the hardware requirements, we are using Arduino in the ECG device, this leads us to the use of Arduino IDE to build and compile the codes for Arduino. Likewise, another software, P3 processing IDE to extract signal values from the device. In addition, we plan to use Google Colaboratory to build and train ML models.

6.4.2 Hardware

The hardware used in this model is a custom-built ECG device. The usage of our own built devices will provide us with better signal acquisition and flexibility in using it. This will greatly help us in collection of our own dataset for training and testing of the model.

6.4.3 Database

Since we plan to collect samples of ECG signals from multiple people to create our own dataset. We would require a database system to store those signals. MongoDB will be used to store

ECG signals of each person along with their respective emotions. MongoDB is easy to use and fast, yet extremely flexible to integrate with different systems.

6.4.4 Raw Data

The classification of ECG signals with high accuracy is only possible with efficient training of the model. For this purpose, we require quality raw data, which will be used in both training and testing of the model. To acquire this all-important raw data, we plan to use an openly available ECG databases i.e. WESAD, SWELL, YAAD. Along with these databases we will use signals collected by our own device. The device will also be used to get real time ECG signals from the body.

6.4.5 Using Existing Technologies

All the components of this model are open source even the hardware used to build the ECG device is easily available. Every module used in the proposed methodology is well known and openly available on the internet. There is no new technology introduced in this system, it demonstrates a better use of existing technologies to perform efficient classification of emotions.

6.4.6 Future

The proposed model is a novel approach to detect stress and fear in ECG signals. It can be integrated with specialized hardware for use in real time scenarios. In future, the model can be used with wearable ECG devices, which will make it practical to use in various applications. Like, this model along with wearable ECG can be used to detect fear in individuals during an examination, thus making the examination cheat proof. A combination of wearable ECG and stress detection can be used during high stress tasks like Gaming, to make the person avoid extra stress which is harmful for health.

6.5 Domain Model/Class Diagram

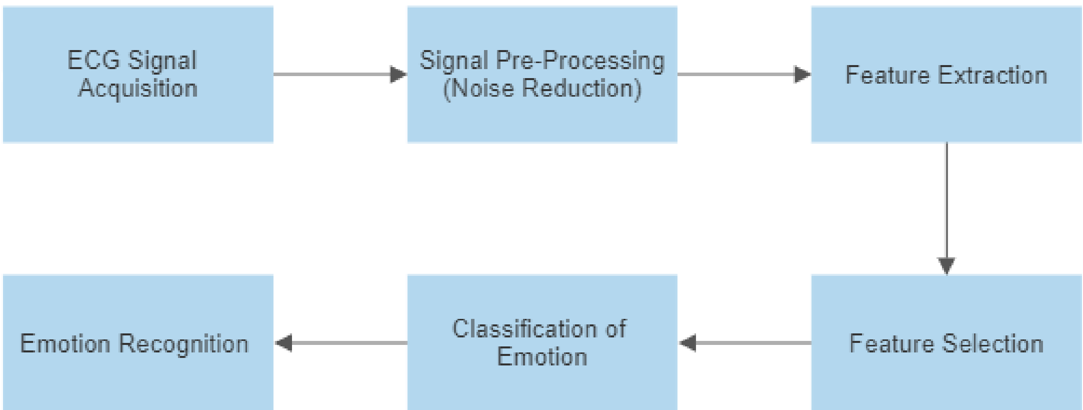


Figure 6: Model Diagram
This is the model diagram of EED.

The above figure explains the proposed model. The system starts with and ECG device which is designed and assembled by the team. This device consists of a 3-lead ECG-sensor, which is controlled by an Arduino. The Arduino will be connected to the computer using a USB cable. The device will provide us with a 360 Hz analog signal. These signals will be used as input to the system. These signals will also be converted into images which would serve as input for convolutional neural networks. The next step is to pre-process the signal. The signal obtained by the sensor is full of noise. This noise must be eliminated for accurate emotion detection. So, now a noise detection algorithm i.e. Butterworth bandwidth filter, will be used, which completes pre-processing of the signal. The next step is to extract different features like R-R interval, QRS complex, BPM, etc. For this purpose, we will use the Continuous Wavelength Transform (CWT) algorithm to extract features from raw signals. ECG signals have hundreds of different features which provide us a lot of information about the person. As mentioned earlier, we are interested only in stress and fear emotions, we do not require all those features. We will select some specific features of interest and move on to the all-important classification steps. In this step, we will feed the extracted features to the system which will use them to detect and classify the emotion i.e. fear, stress, normal. Simultaneously, we will also perform classification of these emotions using VGG NET which is a convolutional neural network. The images of preprocessed ECG signals will be used by the CNN to classify them into different emotions.

6.6 Sequence Diagrams

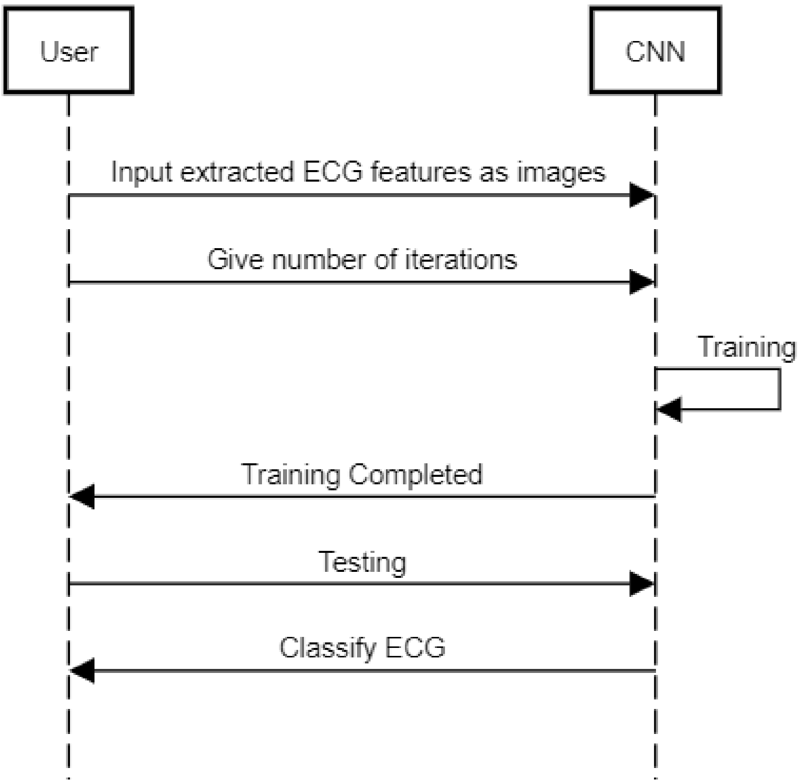


Figure 7: Classification of ECG using CNN
Figure shows how we are going to use CNN to classify ECG

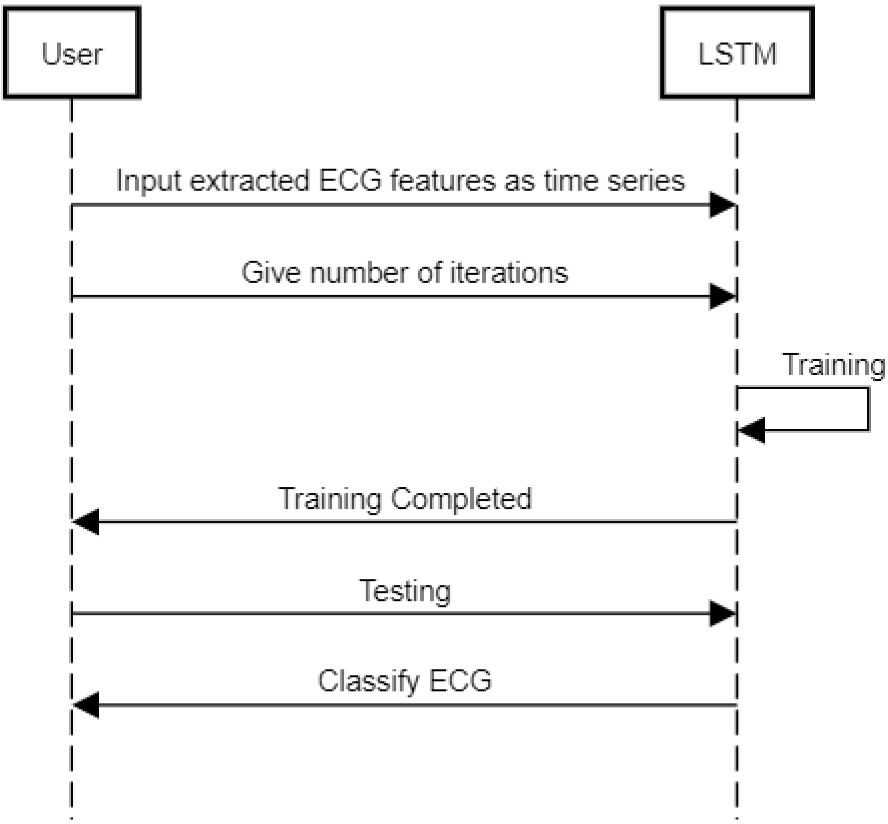


Figure 8: Classification of ECG using LSTM
Figure shows how we are going to use LSTM to classify ECG

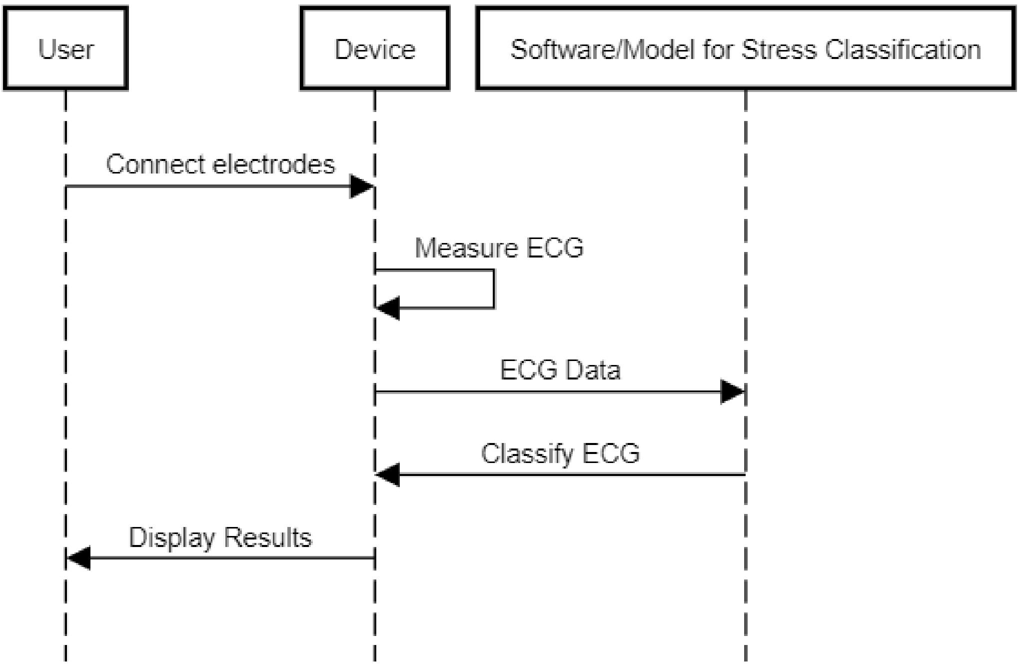


Figure 9: Stress Classification
Figure shows how we are going to use the device for stress classification from ECG

6.7 Policies and Tactics

The following are the considerations for the policies that would be followed in the project.

6.7.1 Tools

For training and testing our classification models we will use Google Colaboratory and Visual Studio Code. We will also use google drive to maintain the databases that we will use to train our models. We will also use MATLAB for the purpose of processing the data as most of the databases available to us are in .mat format which we will convert into images and time series. To store the data, we will use Excel. As we are making a hardware device for the collection of ECG data, we will also use software such as Arduino IDE and T3 processing IDE for this purpose.

6.7.2 Coding Guidelines

During the programming phase of the project, rules and standards set in python would be followed. Also, we will focus on styling guidelines for our code to keep our code understandable.

6.7.3 Testing the Software

The accuracy of the different models would be tested with testing data after training the model on the training data that we are going to use from pre-existing datasets publicly available to us. We will also use data that we are going to collect using our device for testing the models.

6.7.4 Maintenance of Software

The software will be kept updated and further functionalities can be added such as enhancing the dataset. We will ensure that everything is kept up to date including the models and the datasets with appropriate labels so that it is efficient to use with the models.

6.8 Conclusion

This chapter proves to be an important part of the document as it is composed of design speculations of the system. We highlighted important aspects of design in detail and ran through the methodologies used to develop an efficient, industry targeted project. We also demonstrated component interactions through component and architecture analysis in the subsections.

Chapter 7: Implementation and Test Cases

In this chapter, we will identify how we implemented our proposed idea. We will also discuss demonstrations with visuals to make sure that the reader of this document becomes aware of how this project can be used in working. We will also talk over test cases which can help you with understanding of inputs, processing, and outputs of the project.

7.1 Implementation

This subsection talks about concrete implementation of the proposed idea. We will discuss how we used a dataset from WESAD to convert raw data into meaningful ECG imaging. After that, we will see how these images were augmented and used to train the deep neural networks. The imaging was produced using sequential raw values of ECG data; thus LSTM was also used to classify those signals. Later, we test accuracies of both types of models and concluded our future goals.

7.1.1 Implementation of Input

WESAD dataset consists of stress data of 15 individuals observed for a certain amount of time with different environmental conditions. The raw data of these ECG signals are available in this dataset. These raw values are used as input to the model. The raw values are also mapped onto images by plotting them linearly using matplotlib library of python. These two types of data were used to train different models of the project for prototyping.

7.1.2 Implementation of Model Training

Implementation was done in two parts.

7.1.2.1 Deep Convolutional Networks

First part was training the models over image data using deep convolutional layers of VGG 16 and publicly available trained models over the ECG signal for disease detection. Transfer learning methodology was used to train these models. Transfer learning is an efficient technique to extract important features of a small dataset relating to the features of the data the model is being trained over previously. In this way, the pretrained model learns faster and accurately the classes among the supplied data. VGG 16 in this case was used as a control model as it is being trained over 14 million images categorizing over 23,000 categories of things like houses, cars, dogs, etc. This helped in training the model as it was pre-trained to learn about different features of shapes. The fully connected layer was removed in this purpose.

The main experiment was with the pretrained disease detection CNN models. They are related to our work as they were already trained on vast datasets of ECG imaging which means they already have extracted ECG waveform features. Transfer learning in such related environment proved more accurate in terms of ECG emotion detection as pretrained models can learn precise features of ECG waveforms in retraining for our problem.

7.1.2.2 Long Short-Term Memory

Another possible way of doing this is by providing the sequential data of ECG waveforms (amplitude values) to LSTM which is the most model in existence for classifying sequential continuous data.

7.1.3 Implementation of Classifier

After training the models, classification was done. Many classifiers such as sigmoid are available to classify the data into normal and stress emotions. These classifiers were introduced in a fully connected layer attached to the retrained models produced by transfer learning.

7.2 Test Case Design and Description

This subsection will demonstrate the possible inputs and their outcomes from the EED system.

7.2.1 Test Case for Subject Not Connected (1)

Subject Not Connected			
Test Case ID:	*1*	**QA Test Engineer:**	*Syeda Khadeejah Rizvi*
Test case Version:	*1*	**Reviewed By:**	*Omama Kashan*
Test Date:	*04-27-2023*	**Use Case Reference(s):**	*Connecting Electrodes*
Revision History:	*None*		
Objective	*The user should connect all the electrodes*		
Product/Ver/Module:	*Classify emotions through ECG*		
Environment:	*Hardware: ECG device connected to the laptop using USB cable* *Software: Any software that can plot the ECG*		
Assumptions:	1. *Device is connected to the laptop and working correctly.* 2. *The laptop has the software installed needed to plot ECG*		
Pre-Requisite:			

Step No.	**Execution description**	**Procedure result**
1	*The electrodes are not connected to the user*	
2	*The user clicks the plot button*	*A flatline is displayed*
Comments: The test case is passed. Our system is working properly.		
☒*Passed* ☐*Failed* ☐*Not Executed*		

7.2.2 Test Case for Subject Not Connected (2)

Subject Not Connected			
Test Case ID:	*2*	**QA Test Engineer:**	*Syeda Khadeejah Rizvi*
Test case Version:	*2*	**Reviewed By:**	*Omama Kashan*
Test Date:	*04-27-2023*	**Use Case Reference(s):**	*Connecting Electrodes*
Revision History:	*None*		
Objective	*The user should connect all the electrodes*		
Product/Ver/Module:	*Classify emotions through ECG*		
Environment:	*Hardware: ECG device connected to the laptop using USB cable* *Software: Any software that can plot the ECG*		

Assumptions:	*1. Device is connected to the laptop and working correctly* *2. The laptop has the software installed needed to plot ECG*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*Only two of the electrodes are connected to the user*		
2	*The user clicks the plot button*	*A flatline is displayed*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.3 Test Case for Invalid Reading (1)

Invalid Reading			
Test Case ID:	*3*	**QA Test Engineer:**	*Syeda Khadeejah Rizvi*
Test case Version:	*3*	**Reviewed By:**	*Omama Kashan*
Test Date:	*04-27-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*The user should get a accurate/ correct ECG result*		
Product/Ver/Module:	*Classify emotions through ECG*		
Environment:	*Hardware: ECG device connected to the laptop using USB cable* *Software: Any software that can plot the ECG*		
Assumptions:	*1. Device is connected to the laptop and working correctly* *2. The laptop has the software installed needed to plot ECG* *3. The electrodes are connected correctly*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The electrodes are not connected to the user*		
2	*The user clicks the plot button*	*The ECG is displayed*	
3	*The user moves a lot*	*The ECG reading is distorted with a lot of noise*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.4 Test Case for Invalid Reading (2)

Invalid Reading			
Test Case ID:	*4*	**QA Test Engineer:**	*Syeda Khadeejah Rizvi*
Test case Version:	*4*	**Reviewed By:**	*Omama Kashan*
Test Date:	*04-27-2023*	**Use Case Reference(s):**	*User Getting Response*

Revision History:	*None*		
Objective	*The user should get a accurate/ correct ECG result*		
Product/Ver/Module:	*Classify emotions through ECG*		
Environment:	*Hardware: ECG device connected to the laptop using USB cable* *Software: Any software that can plot the ECG*		
Assumptions:	4. *Device is connected to the laptop and working correctly* 5. *The laptop has the software installed needed to plot ECG* 6. *The electrodes are connected correctly*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The electrodes are not connected to the user*		
2	*The user clicks the plot button*	*The ECG is displayed*	
3	*The laptop is connected to the charger*	*The ECG reading is distorted with a lot of noise*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.5 Normal Emotion Test Case (1)

Normal ECG			
Test Case ID:	*5*	**QA Test Engineer:**	*Muhammad Umer*
Test case Version:	*1*	**Reviewed By:**	*Khadeejah Rizvi*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED should be able to successfully identify normal ECG*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The subject is in normal condition*	*EED outputs a constant normal recognized emotion*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.6 Normal Emotion Test Case (2)

Normal ECG			
Test Case ID:	*6*	**QA Test Engineer:**	*Muhammad Umer*
Test case Version:	*1*	**Reviewed By:**	*Khadeejah Rizvi*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED misclassifies the normal ECG*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The subject is in normal condition*	*EED does not outputs a constant normal recognized emotion*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.7 Fear Emotion Detection Test Case (1)

Fear Emotion Detection			
Test Case ID:	*7*	**QA Test Engineer:**	*Muhammad Umer*
Test case Version:	*1*	**Reviewed By:**	*Khadeejah Rizvi*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED should be able to successfully identify the fear emotion*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The subject is in normal condition*	*EED outputs a constant normal recognized emotion*	
2	*A fear emotion is introduced in the subject*	*The model accurately classifies the newly introduced fear emotion*	
Comments: The test case is passed. Our system is working properly.			

☒*Passed* ☐*Failed* ☐*Not Executed*

7.2.8 Fear Emotion Test Case (2)

Fear Emotion Detection			
Test Case ID:	*8*	**QA Test Engineer:**	*Muhammad Umer*
Test case Version:	*1*	**Reviewed By:**	*Khadeejah Rizvi*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED misclassifies the fear emotion*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	
1	*The subject is in normal condition*	*EED outputs a constant normal recognized emotion*	
2	*A fear emotion is introduced in the subject*	*The model misclassifies the newly introduced fear emotion as some other emotion*	
Comments: The test case is passed. Our system is working properly.			
☒*Passed* ☐*Failed* ☐*Not Executed*			

7.2.9 Stress Emotion Detection Test Case (1)

Stress Emotion Detection			
Test Case ID:	*9*	**QA Test Engineer:**	*Omama Kashan*
Test case Version:	*1*	**Reviewed By:**	*Muhammad Umer*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED should be able to successfully identify the stress emotion*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			
Step No.	**Execution description**	**Procedure result**	

1	*The subject is in normal condition*	*EED outputs a constant normal recognized emotion*
2	*A stress emotion is introduced in the subject*	*The model accurately classifies the newly introduced stress emotion*
Comments: The test case is passed. Our system is working properly.		
☒*Passed* ☐*Failed* ☐*Not Executed*		

7.2.10 Stress Emotion Detection Test Case (2)

Stress Emotion Detection			
Test Case ID:	*10*	**QA Test Engineer:**	*Omama Kashan*
Test case Version:	*1*	**Reviewed By:**	*Muhammad Umer*
Test Date:	*27-04-2023*	**Use Case Reference(s):**	*User Getting Response*
Revision History:	*None*		
Objective	*EED misclassifies the stress emotion*		
Product/Ver/Module:	*Emotion Recognition Module*		
Environment:	*Software: the model is loaded on the server for classification* *Hardware: the device is connected to the system*		
Assumptions:	*All electrodes are placed correctly over the subject and there is no electrical interference involved*		
Pre-Requisite:			

Step No.	**Execution description**	**Procedure result**
1	*The subject is in normal condition*	*EED outputs a constant normal recognized emotion*
2	*A stress emotion is introduced in the subject*	*The model misclassifies the newly introduced stress emotion as some other emotion*
Comments: The test case is passed. Our system is working properly.		
☒*Passed* ☐*Failed* ☐*Not Executed*		

7.3 Test Metrics

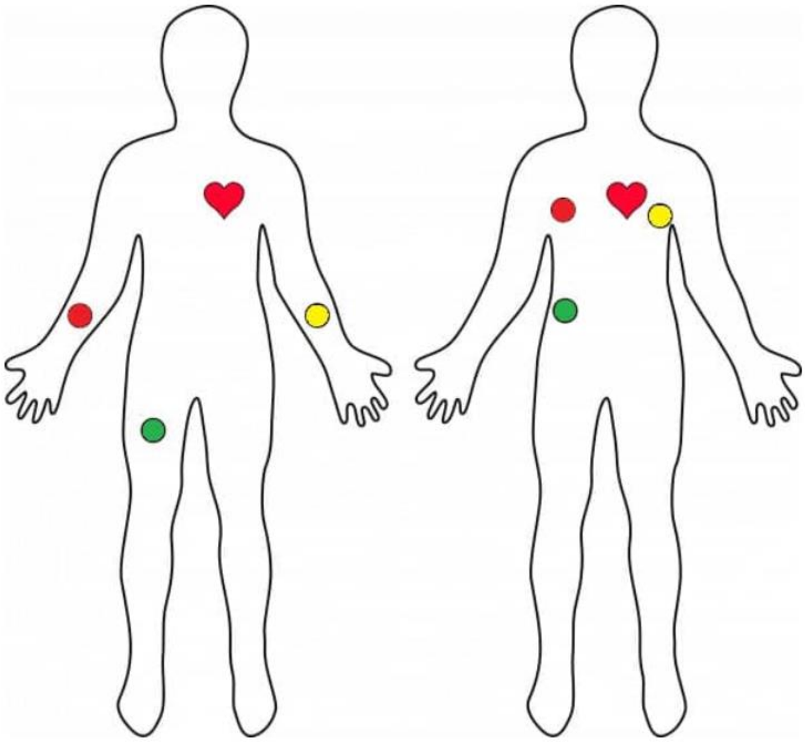
Metric	**Value**
Number of Test Cases	10
Number of Test Cases Passed	10
Number of Test Cases Failed	0
Test Case Defect Density	0%
Test Case Effectiveness	100%
Traceability Matrix	Traceability matrix is provided separately as excel file.

Chapter 8: User Manual

This section will help the subject, using the EED system, to start easily and professionally classifying their current emotions.

8.1 Connections

In the very first step, electrodes will be connected to the body. The three electrodes which are green, red, and yellow in color will be connected as shown in figure to the body.



Red: RA (Right Arm)

Yellow: LA (Left Arm)

Green: RL (Right Leg)

Figure 10: Connecting ECG Electrodes on the Subject
This is an observation of Connecting ECG Electrodes on the Subject

Now connect the ECG device with the computer using USB cable.

Before starting the application, make sure that the following conditions are fulfilled.

- The person should be relaxed, should not be moving.
- No noise should be present during the procedure.
- No metallic object should be present near ECG device.
- No electrical devices or wires passing near ECG device.
- Make sure the computer/ system is properly earthed.
- It is recommended that system should be running on battery instead of direct AC.

8.2 Application

Once the user is connected to the electrodes correctly and there is no interference, the user will open the application. Upon opening the application, the user will see a start button.

Figure 11: Start Button
This is an observation of System's Start Button

The user will then click the start button above and the real time emotions of the user will be displayed on the screen. One of following are three boxes which will be shown on the screen.

Figure 12: Sample Classification Visualization
This is an observation classification visualization of the system

Chapter 9: Experimental Results and Discussion

Firstly, we assembled and connected the components of the ECG device and tried to plot the raw signals acquired from the AD8232 sensor. The signal had a lot of noise in it due to the sounds and movements in the body. Following is an image of the plotted signal which will be preprocessed in future.

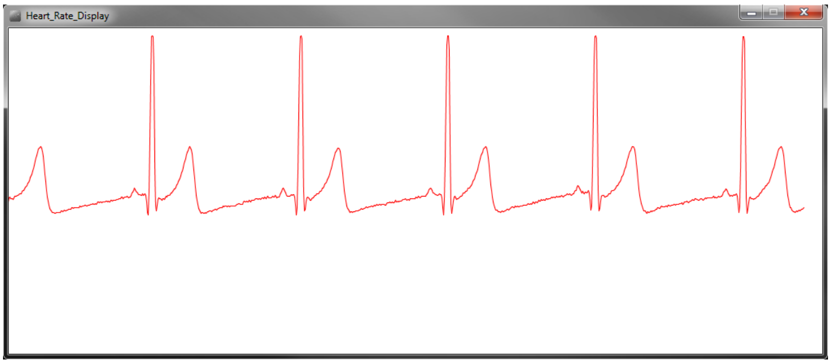


Figure 13: Plotted AD8232 Data
This is an observation of plotted AD8232 image data using raw values from sensor.

Secondly, we tried to classify ECG signals for stress detection using images and Convolutional Neural Network. We used the WESAD database to gain images for feeding to the VGG image classifier for training purposes. A prototype image classification of stress in ECG using VGG-Net gave us an accuracy of 75-80 percent.

Lastly, we trained and tested an ECG classification model which uses raw ECG signals to classify between normal and abnormal signals. Following is a sample demonstration of this model

Figure 14: Demonstrations of Sample Model
This is an observation of demonstrations of sample model run in prototype.

This model showed us an approximate accuracy of 85 percent on classifying normal and abnormal ECG signals.

Chapter 10: Conclusion and Future Work

Our emotions influence any task that we may be performing in our daily lives. Two negative emotions i.e., stress and fear have a significant effect. Thus, our goal is to classify these emotions using ECG.

Hitherto we have done immense research work on models used for classification of ECG. Our research enabled us to choose the best suited models for classification of stress and fear through ECG signals. For classification of stress and fear through ECG images, our research showed that CNN provided the best results whereas, for classification through sequential data LSTM seemed to perform well. We also explored various datasets containing ECG signals with the labels that we required. During our research we came across AMIGOS, WESAD, Dreamer and SWELL which we deemed useful for training and testing our models.

Thus far we have done image mapping from the WESAD dataset as we did not have any dataset available that consisted of ECG image data. We have also done preprocessing for the classification models and developed models for stress classification through images using CNN and through sequential data using LSTM yet.

Moreover, we constructed the 3 lead ECG scanner device using the ECG sensor kit which we will use to collect our own dataset. One problem that we have been facing has been noise in the ECG samples. Thus, we will need to take measures to remove as much noise as possible before feeding our data samples to the classifiers.

We plan on building, training, and testing models for fear classification through ECG images and sequential data as well. Further plans include collecting our own dataset using the device that we have built, real time categorization of emotional imbalances under a specific condition and storing the timestamps during which emotional imbalances were identified under the observation period.

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