Integrated Physiological Signal-based Biomarkers for Automatic Stress Detection

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A thesis submitted to the Department of Computer Science and Engineering
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B.Sc. in Computer Science

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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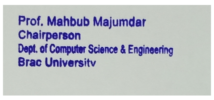

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Abstract

Numerous mental intentions and life rates are responsible for dispensing mental stress. It's an essential purpose behind delivering numerous cardiovascular ailments. Identifying and addressing the effect of stress on the creation of automatic identification of different levels of mental stress thus provides a crucial path for progressive research to tackle stress. This paper presents an investigation on mental stress identification with the guide of preparing the Electrocardiogram (ECG), Galvanic Skin Response (GSR) chronicles utilizing Hjorth Parameters, Autoregressive, Shannon entropy and few other features that were used in finding best features using Wrapper and BorutaShap function. The primary reason for this experiment was to evoke particular affective states in the participants. ECG, GSR recordings of 40 people while watching short videos was used from AMIGOS Dataset. Random Forest Classifier(RF), Logistic Regression(LR) and K-Nearest Neighbor Classifier(KNN) are used to detect stress and have achieved an accuracy of 82.23%, 79.84%, 78.48% respectively. These results can be used to make a device capable of identifying and measuring the stress levels experienced by individuals, so that stress can be better managed as short-term or long-term stress still poses a risk of harm to physiological and mental health.

Keywords: Electrocardiogram (ECG); Galvanic Skin Response (GSR); Stress detection; Wrapper; BorutaShap; Random Forest;

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ECG Electrocardiogram

GSR Galvanic Skin Response

$HANV$ High Arousal Negative Valence

HRV Heart Rate Variability

PPG Photoplethysmogram

RF Random Forest

Chapter 1

Introduction

1.1 Importance of the Research

Stress is a characteristic reaction of the human body to an outer dangerous power. Common physiological reactions remember changes for a pulse, beat, skin temperature, pupil dilation, and electrodermal action (EDA) among others[13][35] [20]. Albeit little degrees of stress can effectively affect the body, stress likewise adversely influences memory, focus, and making decisions[31][25]. Elevated levels of long haul pressure are frequently connected with various negative well-being impacts, including nervousness, despondency, and untimely maturing. Physiological pressure is a typical most recent life illness.It is a developing issue and it has become an unavoidable aspect of our day by day life. Stress is a factor that makes mental trouble, regardless of whether physical, mental, or enthusiastic, and is the body's reaction to a danger or request brought about by outer factors, for example, relational issues, contamination, physical climate, and inner variables that consider the absence of rest, sadness, desires, and an indispensable factor for human wellbeing. It might impact propensities and variables that raise the danger of coronary illness: hypertension and cholesterol levels, smoking, physical inertia, and eruption. These mental pressure types can be recorded as acute and chronic[41]. Acute stress is a brief sort of pressure and not continually going on for quite a while. For our exhibition file, this sort of stress is continually fundamental. While chronic stress can likewise bring about a few consistent changes in our body boundaries, for example, pulse, pulse, internal heat level, and so on[17]. As stress may cause a perpetual sickness, it is fundamental to remember it in the beginning phase, likewise avoiding different issues that may emerge from physiological pressure.

1.2 Existing Approaches

Many studies related to stress recognition were discovered during the literature review. Han,[55] proposed a stress monitoring system that is based on personal physiological signals: ECG, GSR, PPG collected using wearable devices in controlled and everyday settings. They used three classifiers (KNN, SVM, and Naive Bayes) for stress detection. Kalinkov, et al,[49] used SVM for HANV detection on the MAHNOB-HCI database. The database consisted of physiological signals: ECG, GSR, PPG that were used in the detection of HR and HRV. Zhang, et al[47] used their own dataset which consists of RR intervals for ECG signals. They used SVM and 5-fold cross-validation for stress detection. Nath, et al[58] presented validation of a stress model using cortisol as a biomarker for stress. Their dataset consisted of physiological signals PPG and GSR.

1.3 Process Argument

Currently, there are no specific ways to detect or measure stress in real life. Mainly questionnaires are used for this purpose which can be awed due to many memory biases and many other reasons. But by using physiological signals we can solve the problem and to classify these signals and extract features from them, machine learning is the popular way. Recently, machine learning has been used for many kinds of classification or regression problems. According to the writing study for stress detection there, a ton of machine learning procedures was utilized for the identification of stress. This is the explanation machine learning is being utilized in this paper for the detection of stress.

1.4 Working process

After extracting features from ECG and GSR signals, we process our data for training our model. Our dataset was full of features as we merged two physiological signals. By using the wrapper method and BorutaShap algorithm, we decreased the dimension of features. Moreover, the Wrapper method determines the relationship between variables and finds a suitable subset of functions for the desired machine learning algorithm. Furthermore, BorutaShap can give not simply an unrivalled subset of features, it can in like manner give the most careful and consistent overall part rankings that can similarly be used for model enlistment all the while. Therefore, we can train our model with the best subset of features to classify stress detection.

1.5 Conclude

The problem statement is to identify stress from physiological signals ECG, GSR using a strong and better classification model. Here in this paper, RF, LR and KNN were used to detect stress using Hjorth Parameters, Autoregressive, Shannon entropy, and a few other features through choosing the best features subset by Wrapper and BorutaShap function.

Chapter 2

Related Work

Stress is delineated as a physical, psychological, or emotional determinant that fabricates psychological disquietude. It can emerge from some incident or thought that makes you feel annoyed, angry, or anxious. Stress is the body's reaction to a challenge or demand. It may actually be triggered by external causes (e.g. discomfort in the workplace, behavioural issues, pollution, toxin, physical environment, poor work) along with internal reasons (e.g. presence of sickness and injury, lack of sleep, exhaustion, and expectations). However, tension can be helpful in short bursts, for instance, whether it lets you avoid the danger or hit a completion date. Yet chronic stress is detrimental to physical and mental health[4]. Stress may influence habits and causes that raise the risk of heart disease: elevated blood sugar and cholesterol levels, smoking, physical inactivity, and overstatement. A lot of studies have also been undertaken to detect the effect of acute stress on the production of automated recognition of different types of mental stress.
Han,[55] proposed a framework of stress disclosure that provides objective quotidian medical care determined on personal physiological signals like electrocardiogram (ECG), photoplethysmogram (PPG), and galvanic skin response (GSR). To track stress far and wide the wearable applications, Shimmer3 ECG, Shimmer 3 GSR+, and Empatica E4 wristband were utilized. They regulated guided stress test on 17 participants and the device adequately distinguish stress for 10 fold cross affirmation with a 94.55 percent accuracy and 85.71 percent accuracy for cross-validation subject wise. The program measures tension with a precision of 81.82 percent in daily settings. Kalinkov, et al,[56] proposed a new system for the automated disclosure of high rushing negative valence status front end processing of the biological signal. Pre pro signal Cessation of ECG and EDA signals, extraction features, and vector function post-processing are the three components of the front end. Distinct front end contour was appraised for the automated disclosure of high arousal negative valence status. A standard experimental protocol was implemented through the evaluation that uses the MAHNOB-HCI data collection. Markova, et al,[50] present a restricted method of selection of attributes that uses Fisher separation characteristic valuation followed by reduction of post-processing varietal. As contemplated to expedite the subsequent election data modeling and classification aspects, post-processing consolidates the task-specific obstruction into the feature selection process. For acute stress apprehension based on biological signals, the implied method was validated in an experimental setup. Markova, et al,[52] thought about the automated discovery of negative feelings and high arousal negative-valence (HANV) states that

are like intense pressure happening in explicit environmental factors. Their experimental assessment said that the Advantages of Individual Autonomous Labels Demonstrating Sound video stimuli and individual constructed models explicit labels auto-announced. In light of the labels themselves detailed, they report that those are acquired with just a little additional effort generally improved precision of HANV discovery by up to 5Markova, et al,[51]considered the comprehensive method and usage of a wearable device prepared to do consistently observing and recording negative feelings, elevated levels of excitement feeling, and high-excitement negative-valence states from physiological signs like skin conductivity and ECG. The client-server architecture was used to build this system. Shimmer-3GSR+ and Shimmer-3ecg are used to gain biological signals, which were then conveyed to a mobile device utilizing Bluetooth connection. . The phone acted like the UI and portrayed the assortment and transmission of information to the server, which held all assignments identified with signal handling and grouping. The deliberately planned software fused both server-side information handling and recognition function, as well as the UI and the customer side information correspondence. They record test results for various designs of the parallel indicators of negative feelings, a serious extent of passionate expectation, and high-excitement conditions of negative-valence.

A three-step attribute selection process is proposed by Markova, et al,[54] which builds on phases of evaluation of individual and person-specific characteristics. They have received a subset of attributes that are both task-specific and customized to the standard of each user's results. To validate the suggested method on the ASCERTAIN database, suited to high-arousal negative-valence identification, an experimental setup based on physiological signals was held. Two physiological signs, Galvanic Skin Reaction (GSR) and Photo-plethysmograph (PPG), were used by Nath, et al,[58] to validate a stress recognition model using cortisol as a biomarker of stress. GSR and PPG signals from a total of 13 participants along with saliva samples collected at time points were collected during the course of the experiment. With the model obtaining 93 percent, 99 percent, and 96 percent precision , recall, and f1-score respectively in forecasting the occurrence of stressful events, we obtained an overall accuracy of 92 percent. Zhang, et al,[47]] used Electrocardiogram (ECG) signals to analyze the autonomic real-scene stress response. Electrocardiogram (ECG) data were obtained from 16 subjects at the final analysis of the semester and after the winter break. The support vector machine (SVM) and the five-fold cross-validation were used to characterize the dataset. Poor and stressful data sets were categorized using vector support machine (SVM) and obtained 93.75 percent of the precision of 87.5 percent of the binary classification of high stress and low stress accordingly. The average of the RR interval series and the average of the absolute values of the second generalized RR interval series variations is chosen by a 5-fold cross-validation sequential backward selection algorithm. Sirampracas, et al,[45] proposed a stress analysis approach using different physiological cues such as ECGs and GSR. In this study, the stress in the work environment was considered to mimic stress at the workplace and signal data was collected. SVM was then designed and evaluated with either possibly the best-defended features or variations of features. With more than 90% accuracy, the model was able to classify stress, enabling the authors to infer that the features of HR, HRV, and GSR were sufficient to detect stress in time and frequency domains accurately. Betti et al,[43] proposed the use of a portable physiological transmitter for tension management. Maastricht

Acute Stress Tests have been undertaken and numerous physiological signals have been collected, along with ECGs, EDAs, and EEGs. The suggested SVM achieved 86.0 percent accuracy after learning and observed correlations between the handcrafted features and the calculated cortisol level, known as the stress biomarker. The research confirmed the viability of tracking tension with the proposed wearable sensor device by defining these similarities. Although previous studies indicate that acute stress leads to unnecessary motivation and parasympathetic stimulation[40], heart rate rises, and blood sugar decreases; level heterogeneity, the accumulated effect of long-lasting actual non-vocal stress-provoking autonomic system activities has yet to be discovered. Markova, et al[57] introduce the introduction of the CLAS data collection, a multidisciplinary resource that was intentionally built for research assistance and technology development (RTD) activities aimed at automatic identification of a specific state of mind. The dataset featured Coordinated physiological signal recordings such as Plethysmography (PPG), Electrocardiography (ECG), ElectroDermal Activity (EDA), and 62 stable volunteer accelerometer and metadata details described three immersive tasks and two perceptive tasks to be conducted. A collaborative study of the success rate of the immersive activities and information gained via the questionnaire and physiological recordings make it possible to carry out a multifaceted evaluation of individual states of mind. Yoo, et al,[19] propose a neural network-based emotion estimation algorithm that uses heart rate variability (HRV) and galvanic skin response (GSR) to create a human-computer interface that is adaptive to the user's articulated emotions. In this study, while electrocardiogram (ECG) and GSR signals were calculated, a video clip approach was used to generate basic emotions from participants. An emotional effect on the autonomic nervous system (ANS) expresses these signals. In order to classify emotions from new stimulus sets, the derived properties that are emotion-specific characteristics of these signals are applied to the artificial neural network. Udovicic, et al,[46] analyzes only GSR and PPG signals due to its suitability for execution on a basic wearable interface that can capture signals from a person without losing comfort and privacy. Using images from the Geneva adaptive Image Archive (GAPED) archive, a complete database storage program was developed. In the post-processing method, they used normal statistical features and power spectral density (PSD) as features and support vector machine (SVM) and k-nearest neighbours (KNN) as classification tasks. Wen, et al,[38] procured blood oxygen (OXY), galvanic skin reaction (GSR), and heart rate (HR) fingertip saturation, while 101 subjects are individual basis incited for laughter, frustration, grief, and terror in films. In multi-subject GSR, the first derivative of GSR (FD-GSR) and HR, the multi-variant correlation approach describes affective physiological changes. The correlation study reveals that multi-subject HR, GSR, and FD GSR heterogeneity, respectively, have common intra-class effective patterns. An overall correct rating of 74 percent is achieved for the quinary classification of laughter, anger, sorrow, fear, and the baseline condition. A method of physiological angry emotion identification was introduced by Chang, et al,[29]. A particular planned emotion induction experiment is conducted to collect four physiological signals from participants, namely electrocardiogram, galvanic skin responses (GSR), blood volume spike, and spike. For training angry emotion pattern curves, the Support Vector Regression (SVR) has been used. Experimental results suggest that the proposed approach produces high identification rates. Wioleta[36] presented a concern with the use of cues for physiological emotion identification. They identify the types of sensors and physiological reactions. The models of sentiments, the techniques of elicitation of feelings, are discussed. In the literature with the use of physiological cues for emotion detection, there is also a short overview of research advances presented. This gives rise to assumptions about problems and potential future research. A method of emotion detection based on a physiological signal was recorded by Kim, et al[18]. The system was created as a user-independent system to operate on the basis of physiological signal databases derived from various subjects. The input signals, all of which were obtained from the body surface without much pain, were the electrocardiogram, skin temperature variance, and electrodermal movement, and may represent the effect of emotion on the autonomic nervous system. Preprocessing and function extraction techniques were devised in order to derive emotion-specific features from short-segment signals. A help vector machine was introduced as a pattern classifier to overcome this difficulty. The correct-classification ratios for 50 subjects were 78.4% and 61.8% for the identification of three and four groups, respectively.

Bagherzadeh, et al,[48] choose pictorial stimuli from International Affective Picture Systems for emotion elicitation. To acquire enthusiastic reactions, physiological signals, for example, galvanic skin reaction, pulse, breathing rate, and skin temperature were estimated. Four types of passionate incitement named Positive Valence High Arousal, Positive Valence Low Arousal, Negative Valence High Arousal, and Negative Valence Low Arousal were exhibited in a gathering of solid volunteers. Linear and Quadratic Discriminant Analysis and the description of the emotional class are used and compared. If the classification is limited to a particular person's responses, the results of the classification indicate high accuracy. If the problem is generalized to the whole population, however, the accuracy drops considerably. For stress evaluation, a GSR-based pattern recognition system is suggested in[27]. While this work utilizes non-research centre data to discover levels of pressure, it utilizes just a GSR sensor that isn't as touchy contrasted with different systems. Information was gotten from five people for about a month during working hours. The paper closes, nonetheless, that GSR information isn't sufficient for high precision to evaluate feelings of anxiety. It is recommended that the paper ought not to utilize this data to record their sentiments. To help exactness for stress recognition, we utilize a blend of sensors, ECG, GSR, and PPG in our methodology. Likewise, while evaluating strain, we assemble standard setting information from clients and use it.

An activity-aware mental stress identification device that also considers physical activity is proposed in[53]. By means of three exercises: sitting, standing, and strolling, the machine gathers ECG, GSR, and accelerometer information for 30 minutes. Lab-based pressure activities, for example, the Stroop Color and Word Test and mental math additionally comprise his trial method. This examination finds that physical exercises impact mental pressure. Nonetheless, while it offers a connection between stress and physical exercises when evaluating pressure, it doesn't perceive the everyday setting, for example, the gadget isn't conveyed in regular settings.

A robotized stress recognition and help technique dependent on five physiological signs is recommended in[42] : breathing rate, pulse, peripheral capillary, and oxygen saturation. Via a laboratory-based experiment, which takes 94 minutes, knowledge is gathered from 32 participants. Their machine-based learning strategy is taught

and tried in a controlled climate where members are approached to direct some pressure tests. In any case, this technique experiences two downsides regarding its use in ordinary conditions, it isn't practical to convey a portion of the sensors utilized in this examination in persistent checking, and the strategy doesn't consider disturbances and difficulties that happen in the day by day life.
Specialists focus on the ANS that changes physiological exercises to give a continuous pressure appraisal. Two segments of the ANS [1] are the parasympathetic sensory system and the sympathetic sensory system. While resting, the parasympathetic sensory system is liable for moving the body. Then again, to shield the body, the sympathetic sensory system is responsible for "battle or flight" reactions. The sympathetic sensory system drives the body's cycles into movement under pressure[24]. To distinguish individual pressure, a few examinations use pulse, well being propensities, and other basic signals because of the progression of sensor innovation. A difference appears in their own and related works. It sums up the sensors conveyed, the climate of the test, the test time, and the testing exercises. Changes in hormones are utilized to dissect pressure reactions by mental pressure tests to trigger pressure, for example, the Trier Social Stress Test[10]. Salivary cortisol was found to relate with worry in these strategies and has been utilized as a pressure factor in clinical use from that point forward[23]. In addition to salivary cortisol, leukocytes are used for stress evaluation[22]. White blood cells react to stress hormones in the blood. While these techniques can give a legitimate pressure assessment, due to their issues regarding cost, deferral, and the requirement for physical examples, they are not achievable to be utilized progressively ceaseless far off pressure checking in everyday settings. Sun, et al,[30], present a method for detecting activity-aware mental stress, In three assignments, ECG, GSR, and accelerometer information were gathered from 20 members: sitting, standing, and strolling. We acquired standard physiological estimations and estimations for each undertaking when clients were presented to mental stressors. The action information extricated from the accelerometer enpermitted us to accomplish 92.4 percent mental pressure arrangement exactness for 10-overlay cross approval and 80.9 percent precision for characterization between subjects. Inferable from a more extensive comprehension of potential issues brought about by persistent pressure and attributable to ongoing advances in innovations that incorporate non-nosy methods of ceaselessly assembling target measures to follow the degree of worry of people, the issue of pressure the executives have gotten developing consideration in related examination networks[33]. Trial examinations have just demonstrated that the degree of stress can be estimated dependent on GSR investigation and discourse signals. In this paper, they talk about how characterization techniques can be utilized to naturally survey patterns of intense pressure dependent on information found in a person's GSR or potential articulation. A portrayal of plant pressure and an overall idea of stress, including a rundown of expected significant common and anthropogenic pressure factors, are introduced[8]. White light or laser instigated chlorophyll fluorescence of pre-obscured leaves has been demonstrated to be a truly reasonable instrument for early identification of worry in plants just as for recovery examinations. Emotional Computing, one of the wildernesses of exploration on human-PC collaboration, endeavours to give PCs the capacity to react to the full feeling conditions of a purchaser suitably[21]. They propose to separate highlights from the client's physiological signs because of the fundamental online assessment of these full of feeling states, which can be han-

dled by learning design acknowledgement frameworks to recognize emotional states. The physiological signals tracked to derive characteristics used by three learning algorithms were applied to signal processing techniques: NB, SVM, and DT for classifying between relaxation and stressed.

Chapter 3

Background Work

Strain, as well as heart activity, blood pressure, and various stress hormones can be measured by several biological tests. Two biological criteria, ECG and GSR, derive different characteristics from these signals to identify the strain, have used in our work. In this section, the concept of biological characteristics is clarified.

3.1 ECG

Electrocardiography is an electromotive force versus time graph of the electrical operation of the heart by means of electrodes mounted on the skin. These wires sense small electrical variations that are the result of cardiac muscle depolarization and repolarization during each cardiac cycle. Measuring the amount of electrical activity passing through the heart can provide information about the heart's relative size to determine whether it is overworked or distended. In various cardiac irregularities, including cardiac rhythm disruptions, insufficient coronary artery blood ow, and electrolyte disturbances, and other variations occur in the usual ECG pattern. The ECG has three major integrants: the P wave, which depicts atrial depolarization; the QRS complex, which depicts ventricular depolarization; and the T wave, which depicts ventricular repolarisation in Figure 3.1 . In addition, (ECG) is a basic measure that can be used to evaluate the euphony and electrical movements of the heart. The sensing element attached to the skin is used to detect electrical signals produced by the heart every time it beats. Electrocardiographs monitor the heart's cardiac activity and are used to diagnose illness, identify abnormalities, and learn about the overall function of the heart. Contractions in the heart walls that drive electrical currents and generate distinct potentials in the body produce electrical signals. This electrical activity can be measured and registered in an ECG by putting electrodes on the skin. ECGs are non-invasive, making them a useful tool for evaluating the performance of a patient's heart, such as measuring how well blood flows to the organ. During each pulse, a stable heart has an orderly progression of depolarization that begins with pacemaker cells in the sinoatrial node, extends across the atrium, and travels through the atrioventricular node. Node down into the package of His and Purkinje fibers, scattered over the ventriculus and to the left [28]. This ordered process of depolarization results in the distinctive tracing of the ECG. The ECG transmits a significant volume of knowledge to a trained clinician on the anatomy of the heart and the operation of its electrical conduction mechanism [12]. The ECG can also be used, amongst many other things, to calculate the rate and rhythm of heartbeats, the size and position of the chambers of the heart, the frequency of any injury to the muscle cells or the conduction mechanism of the heart, and the effects of heart drugs.

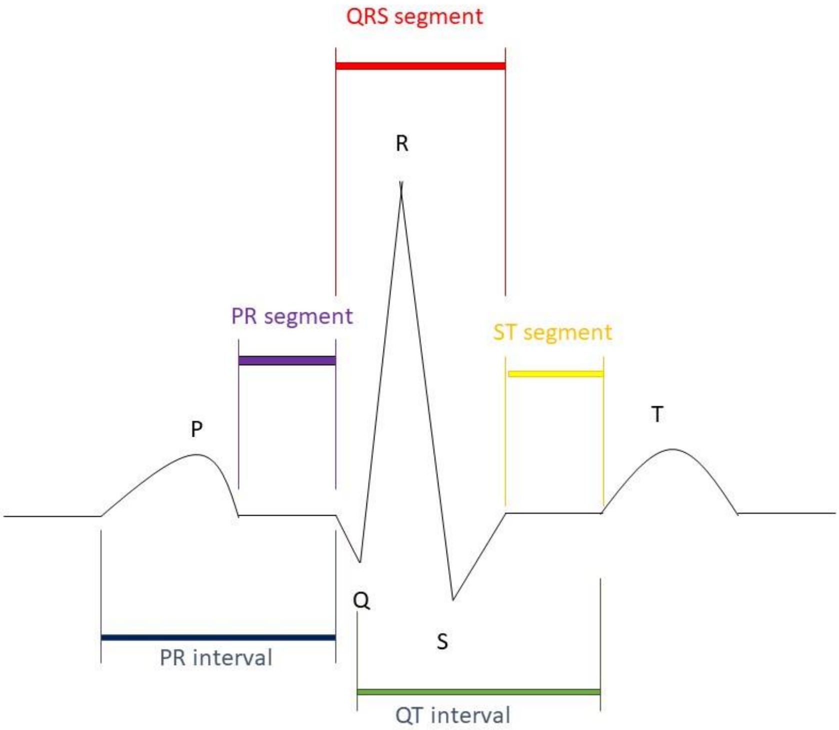

Figure 3.1: Ecg Signal

3.2 GSR

Galvanic skin response leads to variations in the action of the sweat gland, which are the intensity of the emotional reaction of the participants. The time of the signal results from two additive systems, one of which is the tonic base level generator, which tends to vary very slowly, and the other is the faster-variating phasic component. In the continuous data stream, differences in phasic behavior can be observed, while these bursts have a steep inclination to a distinctive high and a steady decline relative to the base level. In response to the stimuli, there are significant changes in the action of the GSR, which is named Event-Related Skin Conductivity Reaction (ER-SCR). Otherwise recognized as GSR peaks, these reactions may provide stimulus with details about emotional excitement in Figure 3.2 . Non-Stimulus-locked Skin Conductivity Responses (NS-SCR) are referred to as other peaks in GSR activity that are not related to stimulus appearance. Quantitative evidence can be applied to emotional excitement experiments using skin conductivity values or the number of GSR peaks. It is easier to find new findings and to draw new discoveries about human behavior with more evidence at hand. Even as the sweat gland reacts to the SNS, a raise in sweating produces an increase in the movement of the skin in a stressful environment. It may also be used as a voltage indicator. We're focused on the GSR parameter, skin conductivity. Galvanic Skin Response arises from the automatic stimulation of sweat skin surface. The sweating of hands and feet is caused by sympathetic activation: if we are emotionally excited, the GSR data reveals distinctive shapes that can be observed from naked eyes, that statistically quantified [32]. The conductivity of the skin is recorded non-invasively using two electrodes placed on the skin with minimal preparation time and cleaning time. Compared with other neuro-methods like the fMRI or EEG, where longer planning and calibration phases are very normal, this enables GSR measurements even more relaxed for respondents [34]. With GSR, actual physical objects, images, pictures, noises, sights, food probes and other sensory sensations, as well as behavioral and mental experiments may be tested for the influence of some emotionally stimulating content, product, or service [11]. Possible implementations, together with the GSR response are very easy to calculate, they cover a fascinating variety of academic areas and market analysis.

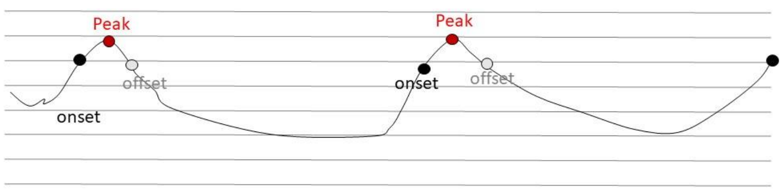

Figure 3.2: GSR signal

Chapter 4

AMIGOS Dataset

We used the AMIGOS data set. But we didn't use all of the info. We've just been using the short video experiment. Neurophysiological signals have been documented in this database using wearable sensors that enable independence because they use wireless technology. However, we have only used the pre-processed ECG and GSR. AMIGOS is a data collection on individuals and groups for effects, personality and mood analysis. The data-set consists of profiles, scores of the participants, external annotations, neuro-physiological recordings and video recording of the participants. There are anonymized participants' data, personality profiles and mood (PANAS) in the profiles, ECG and GSR signals in neuro-physiological recordings and frontal HD, full-body, depth videos of a short experiment in video recording.
The physiological signals have been recorded by using wearable sensors that were wireless. Moreover, these data have been saved in the database.ECG was caught utilizing the all-encompassing Shimmer 2R5 stage with an ECG module board (256 Hz) utilizing three electrodes, two of which are mounted as a source of perspective on the privilege and left arm convicts, and the third on the inward substance of the left lower leg. This set-up empowers exact distinguishing proof of pulses just as the full QRS ECG complex. GSR signal recorded utilizing the Shimmer 2R stage reached out with the GSR module board (128 Hz), with two cathodes set at the center phalanges of the center and pointers of the left hand.
In this short video experiment, 40 volunteers watched in Figure 4.1 and Figure 4.2 a compilation of 16 short effective film extracts in Table 4.1. There were emotional videos chosen to evoke particular affective states in the participants(duration¡250s). Each participant was in individual settings and evaluated each video in valence, excitement, dominance, familiarity, and liking, and selected fundamental emotions such as sadness, surprise, neutral, fear, happiness, anger, and disgust. Recordings of this test were commented on remotely by 3 annotators on the sizes of valence and excitement.
After labeling the data, we have found stress in 153 among 523 persons and the remaining 370 persons are under non-stress in Figure 4.3.

Table 4.1: Information of the 16 short videos

Video	Duration	Film	Clips
10	96	August Rush	6
13	57	Love Actually	4
138	122	The Thin Red Line	7
18	83	House of Flying Dagger's	5
19	126	Exorcist	8
20	65	My girl	5
23	112	My Bodyguard	7
30	76	Silent Hill	5
31	155	Prestige	9
34	66	Pink Flamingos	5
36	68	Black Swan	5
4	91	Airplane	6
5	112	When Harry Met Sally	7
58	64	Mr Beans Holiday	4
80	102	Love Actually	6
9	75	Hot Shots	5

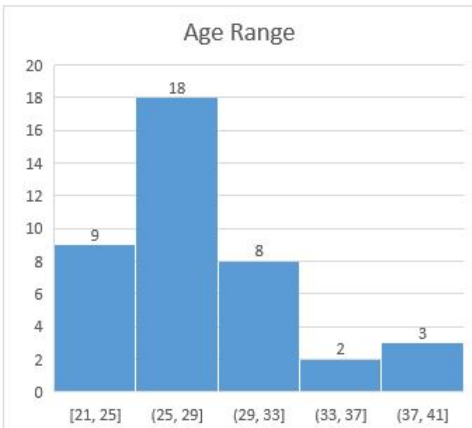

Figure 4.1: Age Range of the Volunteers

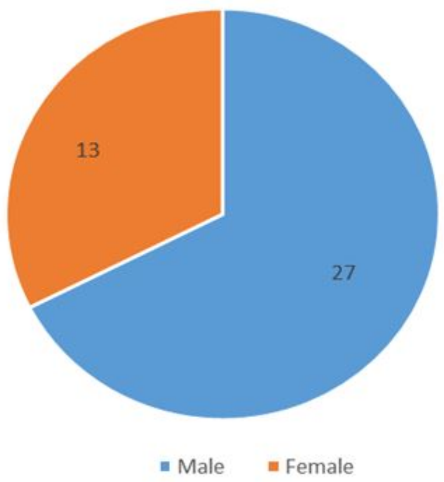

Figure 4.2: Number of male and female volunteer

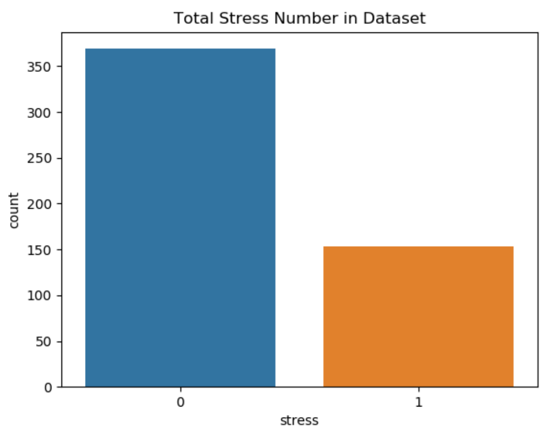

Figure 4.3: Total Stress Number in Dataset

Chapter 5

Proposed Methods

We used the AMIGOS data set. But we didn't use all of the info. We've just been using the short video experiment. Neurophysiological signals have been documented in this database using wearable sensors that enable independence because they use wireless technology. However, we have only used the pre-processed ECG and GSR. Our proposed methods have been showed in the Figure 5.4 . Begin with, we have extracted so many features from the ECG signal like Autoregressive Model, Statistical[57], Frequency Domain[57], Hjorth Parameters, Wavelet, Shannon Entropy and Multifractal Wavelet.

5.1 Classifiers

In order to predict stress, we have used different classifiers in our research. In particular, we have used RF, LR and KNN.

5.1.1 Random Forest

The Decision Tree is an effectively perceived and deciphered calculation and henceforth a solitary tree may not be sufficient for the model to take in the highlights from it. Then again, Random Forest is additionally a "Tree"- based calculation that utilizes the characteristics highlights of different Decision Trees for deciding in Figure 5.1 [44][37][15].

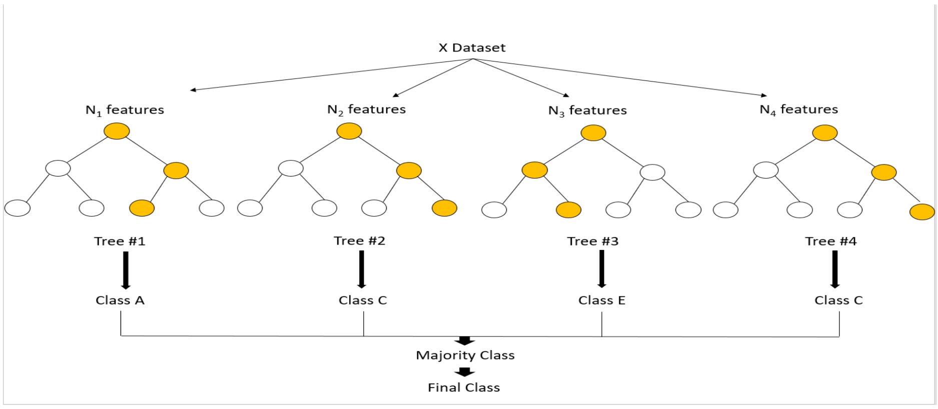

Figure 5.1: Random Forest Classifier.

Subsequently, it very well may be alluded to as a 'Forest' of trees and thus the name "Random Forest". The term 'Random' is because of the way that this calculation is a timberland of 'Randomly created Decision Trees'. Moreover, the expectation from every one of them lastly chooses the best arrangement by methods for casting a vote.

5.1.2 Logistic Regression

Logistic regression is one of the basic and common algorithms used to solve the problem of classification. Moreover, the logistic function, also called a sigmoid function. The sigmoid function is a numerical capacity used to map the anticipated values to probabilities[6][7]. It takes values between 0 and 1 be that as it may, never precisely at those cutoff points .

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{5.1}$$

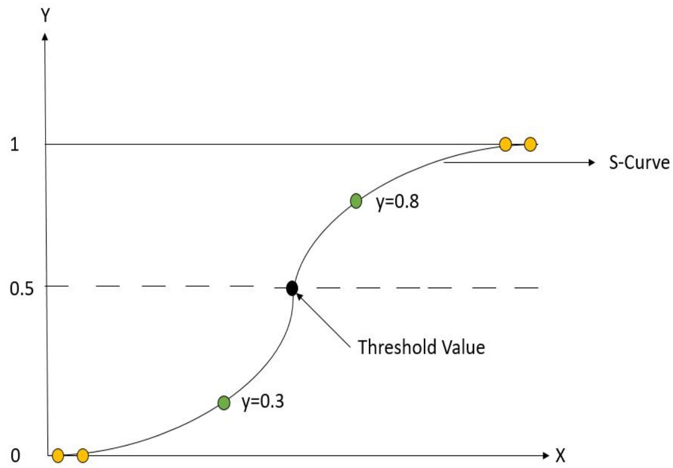

Figure 5.2: Logistic Regression.

In the event that we need to order if an email is a spam or not, on the off chance that we apply a Linear Regression model, we would get just consistent qualities somewhere in the range of 0 and 1, for example, 0.4, 0.7 and so forth. Then again, the Logistic Regression expands this straight relapse model by setting an edge at 0.5, subsequently the information point will be named spam if the yield esteem is more prominent than 0.5 and not spam if the yield esteem is lesser than 0.5 in Figure 5.2. Along these lines, we can utilize Logistic Regression to characterization issues and get precise predictions.

5.1.3 K-Nearest Neighbor

KNN is an example-based classifier utilized in numerous clinical applications.KNN calculation allocates the imprint to the preparation occasions that are nearer to the element space utilizing a larger part vote[39][26][16][9]. KNN gets the chance of likeness with some science we may have learned in our childhood finding out the detachment between centers around a chart. To start with, introduce K to a picked number of neighbours. From that point forward, for each example information, KNN ascertains the separation between the question model and the current model from the information. Along these lines, KNN includes the separation and list of the guide to an arranged assortment. Following, KNN sorts the arranged assortment of separations and records from littlest to biggest by the separations. At last, KNN picks the principal K passages from the arranged assortment just as gets the names of the chose K sections. Be that as it may, for relapse, a characterization it restores the mean of the K names and the mode of the K names individually[14]. Therefore in Figure 5.3, k-th point classification will be class 1.

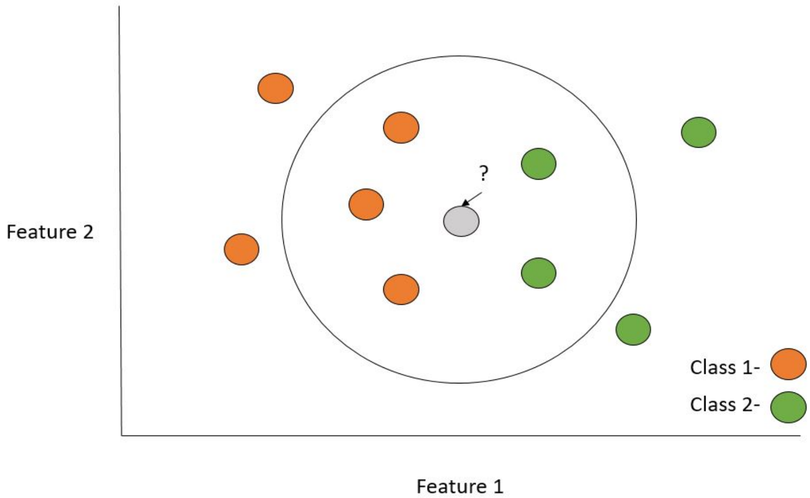

Figure 5.3: K-Nearest Neighbor Classifier.

5.2 Feature Extraction

Highlight extraction is identified with dimensional decrease. During the time spent element extraction, it is required to contain applicable data from the information with the goal that the ideal errand can be performed by utilizing this decreased portrayal rather than the total data. At that point, we utilized underlying strategies for Matlab and different Python libraries to extricate highlights. which are mentioned below: (1) Mean heart rate (Statistical Feature— ECG), (2)Mean RR (Statistical Feature— ECG), (3)Mean (Statistical Feature— ECG), (4) Max NN interval (Statistical Feature— ECG), (5) Min NN interval (Statistical Feature—

ECG), (6) pNN50 (Statistical Feature— ECG), (7)SDNN (Statistical Feature— ECG), (8) RMSSD (Statistical Feature— ECG), (9) SD1(Short term variability) (Statistical Feature— ECG), (10) SD2(Long term variability) (Statistical Feature— ECG), (11) Power in (0-0.04) Hz (Frequency Domain Features— ECG), (12) Power in (0.04- 0.15) Hz (Frequency Domain Features— ECG), (13) Power in(0,15-0.4) Hz bands (Frequency Domain Features— ECG), (14) Normalized powers in VLF band (Frequency Domain Features— ECG), (15) Normalized powers in LF band (Frequency Domain Features— ECG), (16) Normalized powers in HF band (Frequency Domain Features— ECG), (17) The power in VLF band in percent (Frequency Domain Features— ECG), (18) The power in LF band in percent (Frequency Domain Features— ECG), (19) The power in HF band in percent (Frequency Domain Features— ECG), (20) HRV (Frequency Domain Features— ECG), (21) Number of peaks (Peak's Statistical Features— GSR), (22) Max amplitude of the peaks (Peak's Statistical Features— GSR), (23) Min amplitude of the peaks (Peak's Statistical Features— GSR), (24) Mean conductance of the peaks (Peak's Statistical Features— GSR), (25) RMS (Peak's Statistical Features— GSR), (26) Standard deviation of the peaks (Peak's Statistical Features— GSR), (27) Mean absolute value of the peaks (Peak's Statistical Features— GSR), (28) Skewness of the peak's distribution(Peak's Statistical Features— GSR), (29) Kurtosis of the peak's distribution (Peak's Statistical Features— GSR), (30) Mean resistance (Signal's Statistical Features— GSR), (31) First quartile (Signal's Statistical Features— GSR), (32) Second quartile (Signal's Statistical Features— GSR), (33) Third quartile (Signal's Statistical Features— GSR), (34) Interquartile range (Signal's Statistical Features— GSR), (35) Percentile 2.5 (Signal's Statistical Features— GSR), (36) Percentile 10 (Signal's Statistical Features— GSR), (37) Percentile 90 (Signal's Statistical Features— GSR), (38) Percentile 97.5 (Signal's Statistical Features— GSR), (39) Hjorth parameters, (40) Autoregressive model, (41) Shannon entropy, (42) Wavelet

Auto-regressive Model

Based on the former act the autoregressive(AR) model forecasts plausible conducts. It is utilized to forecast if there is a connection amid values in time series and values that forerun and succeed them. Former data is solely utilized to model the actions. The method is de facto a linear regression of the data in the ongoing series contrary to single or more former values in the same series[59]. The model of AR is denoted by the equation:

$$x_t = \alpha + \beta_1 x_{t-1} + \beta_2 x_{t-2} + ... + \beta_m x_{t-1} + B_t \tag{5.2}$$

Where:

- $x_{t-1}, x_{t-2} ... x_{t-m}$ are the past series
- B_t is white noise
- and α is defined by:

$$\alpha = \left(1 - \sum_{i=1}^{m} \beta_i\right)\gamma \tag{5.3}$$

where γ is the process mean, m is the order.

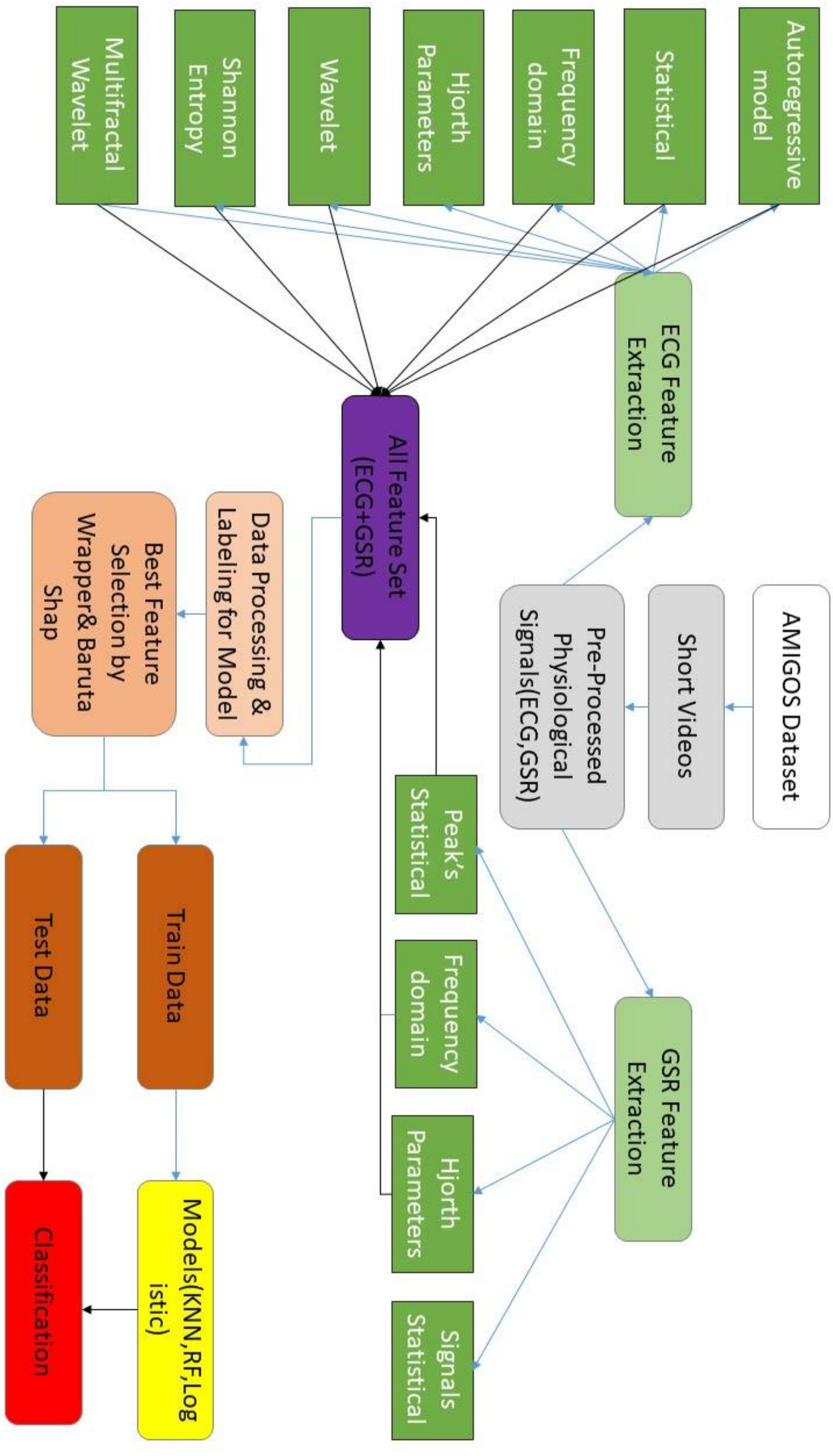

Figure 5.4: proposed methods

Hjorth Paramets

The Hjorth Parameters are statistical property measures used in time domain signal processing. Hjorth has three parameters activity, mobility, and complexity

Hjorth Activity The signal power, the variance of a time function, is expressed by the activity parameter. This may mean the surface area of the frequency-domain power spectrum. This is expressed by the equation below:

$$Activity = var(y(t)) \tag{5.4}$$

Where the signal is represented by y(t).

Hjorth Mobility The mobility parameter reflects the mean frequency or the proportion of the power spectrum's standard deviation. This is defined as the square root of the variance of the first y(t) signal derivative divided by the y(t) signal variance.

$$Mobility = \sqrt{\frac{var(\frac{dy(t)}{dt})}{var(y(t))}} \tag{5.5}$$

Hjorth Complexity The change in frequency is represented by the Complexity parameter. The parameter correlates the resemblance of the signal to an unadulterated sinusoidal wave, where the value coincides with 1 if the signals are more identical.

$$Complexity = \frac{Mobility(\frac{dy(t)}{dt})}{Mobility(y(t))} \tag{5.6}$$

Wavelet

Wave like quivering that commences at zero, surges, and afterwards diminishes to zero with a volume is called Wavelet. It can be envisioned as a brief quivering of the recordings of a seismograph or heart screen. Wavelets are pointedly contracted to have an explicit attribute that makes them convenient for the disposal of signals. Wavelets can be associated with known segments of an impaired signal using convolution in order to elicit data from the obscure portion[3].

Shannon Entropy

Based on the frequency of the symbols, the Shannon entropy equation provides a way to estimate the average minimum number of bits required to encode a string of symbols[2]. Shannon's entropy equation:

$$S(x) = -\sum_{i=0}^{N-1} q_i \log_2 q_i \tag{5.7}$$

Here, q_i is the likelihood of a given symbol in the Shannon entropy equation.

Hence, we have extracted Multifractal wavelet, Peak's Statistical[57], Frequency Domain[57], Hjorth Parameters[5] and Signal's Statistical [57] from GSR signals.

After extracting all the features we merge the features of ECG and GSR. Following, we process the data as there are some missing values or invalid values or outliers. We removed the invalid data for training our model accurately. As we merged two physiological signals our dataset was full of features. We reduced the dimension of features by using wrapper method and BorutaShap algo.

Wrapper Method

Wrapper approaches operate by evaluating a subset of features using a machine learning algorithm that uses a search strategy to look through the space of possible subsets of features, evaluating each subset based on the quality of a given algorithm's output. The Wrapper approach defines the relationship between variables and finds the appropriate subset of functions for the desired algorithm for machine learning. Typically, the wrapper techniques result in higher predictive accuracy than filter techniques.

BorutaShap

BorutaShap is a method of wrapper features collection that incorporates both the Boruta feature excerpt algorithm and the shapely values. The consolidation has exhibited that the initial Permutation Importance approach performs both in terms of speed and consistency of the generated function subset. This function not only offers an enhanced subset of features but also it can postulate the most dependable and coherent global feature ranking that can also be utilized for model obstruction concurrently.

By wrapper method, we get the best feature subset for logistic regression and by BarutaShap we get the best feature subset for random forest classifier as well as for KNN. With the best feature subset, we train our model to classify stress detection. Both of these techniques interact with the classifier.

Chapter 6

Experimental Result and Discussion

Wrapper and Boruta-Shap have been used for dimension reduction from all features set. ‘SE Features (5,12,17,23,47)’, ‘lfnu’, ‘WVAR feature (2,3)’,‘HRfeature1 are the subset of best features that have been achieved through Wrapper shown in Table 6.1 . Shannon Entropy’s features 5th and 12th value of the 1st block, 1st and 7th value of 2nd block, 15th value of the 3rd block, from 11 wavelets of variance 2nd and 3rd coefficient, low-frequency normalization are the elements of the subset of the best features. Additionally, ’SD2’, ’vlf percent’, ’lf percent’, ’WVAR feature [1,9]’,’SDNN’ are the best feature subset accomplished by Boruta-Shap. From Wavelet of variance 1st and 9th value, percentage of very low frequency and low frequency, standard deviation of NN interval have been included in the subset of the best features. Using these features, we have got 82.27% highest accuracy through random forest classifier in Boruta-Shap and 79.84% highest accuracy through Logistic Regression in Wrapper.

The most intuitive measure of success is accuracy and it is just the extent of accurately anticipated perceptions to add up to perceptions. Moreover, The training accuracy is the precision of a model on models it was built on. The test accuracy is the precision of a model on models it has not seen. In the following Table 6.2, we have shown training accuracy and testing accuracy. In Boruta-Shap, the training accuracy of Random Forest is 100% the highest, and also the testing accuracy of Random Forest is 82.27% the highest one. However, in Wrapper, the testing accuracy of Logistic Regression is 79.74% the highest one. On the other hand, KNN has lagged behind in training and testing both of the cases.

Better the viability, better the exhibition, and that is actually what we need. Also, it is the place the ’Confusion Matrix’ comes into the spotlight. Disarray Matrix is an exhibition estimation for AI portrayal. It is a table with 4 novel mixes of envisioned and genuine qualities. It is incredibly helpful for estimating Recall, Precision, Specificity, Accuracy. Initially, True certain methods the classifier anticipated positive and it’s actual. Furthermore, True Negative methods the classifier anticipated negative however it’s actual. Thirdly, False certain methods the classifier anticipated positive yet it’s bogus. Fourthly, False-negative methods the classifier anticipated negative and it’s bogus. By using confusion matrix from Figure 6.1 to Figure 6.6, we calculated the F1 score, recall, and precision in the Table 6.3.

Firstly, precision tells us how many out of all instances that were predicted to be

Table 6.1: Stress detection accuracy by different machine learning classifiers

	Random Forest classifier (Accuracy)	**Logistic Regression (Accuracy)**	**KNN (Accuracy)**
Boruta-Shap (parameters:'SD2','vlf percent','lf percent', 'WVAR-feature[1,9]', 'SDNN')	82.27%	79.84 %	74.68 %
Wrapper (parameters: 'SEFeatures [5,12,17,23,47]' ,'lfnu', 'WVAR-feature [2,3]','HRfeature1)	73.41%	79.74%	78.48 %

Table 6.2: Training vs Testing accuracy of models.

	Random Forest Classifier		Logistic Regression		KNN	
	Train-Accuracy	Test-Accuracy	Train-Accuracy	Test-Accuracy	Train-Accuracy	Test-Accuracy
Boruta Shap	100	82.27	71.33	79.84	79.45	78.48
Wrapper	100	75.94	69.75	79.74	82.61	74.68

Stress, are actually belonging to Stress. It is an important measurement to validate the performance. Precision can be calculated as,
Precision= (Trues positives)/(True positives + False positives)
So by using precision we can say that out of 153 confirmed Stress cases Logistic Regression has got 100 precision and 66.67 precision based on the feature subset of Boruta-Shape and Wrapper which is a good score.
On the other hand, KNN achieved 28.57 precision and 50 precision based on features of Boruta-Shape and Wrapper which is a low and moderate score respectively. Following, Random forest got 60 and 44.44 precision based on features of Boruta-Shap and Wrapper which indicates Boruta-Shap based features worked well on where Random Forest predicted to be Stress, are actually belonging to Stress. Secondly, Recall tells us the ratio of correctly predicted positive Stress from all the actual Stress. Recall can be calculated as,
Recall= (Trues positives) / (True positives + False positives)
We have the best recall score through a random forest of 52.94 based on the feature subset of Boruta-Shap which is a moderate score and a low score of 23.53 based on the feature subset of Wrapper.Then we got a low recall score through Logistic regression of 05.88 based on the feature subset of Boruta-Shap and a low recall

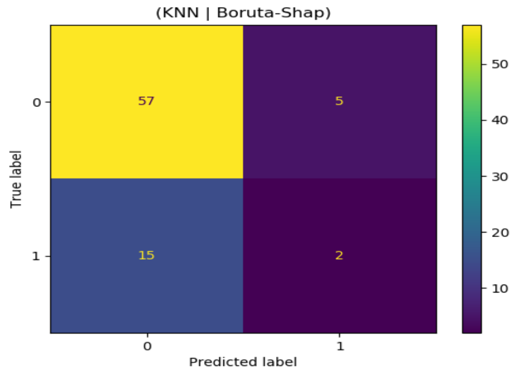

Figure 6.1: Disarray framework of KNN dependent on highlight subset of Boruta-Shap.

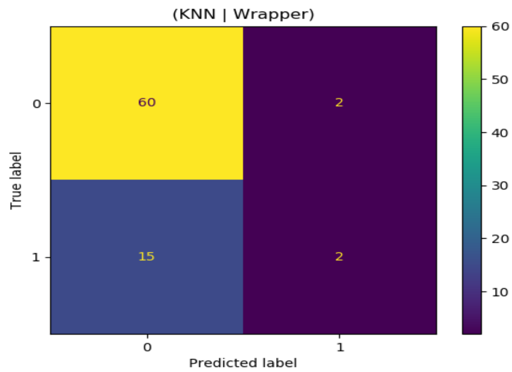

Figure 6.2: Disarray framework of KNN dependent on highlight subset of Wrapper.

score of 11.76 based on the feature subset of Wrapper.Also, we got a low recall score through kNN of 11.76 based on the features subset of Boruta-Shap and low recall score of 11.74 based on features subset of Wrapper.
At long last, the F1 score is the most significant incentive for approving the presentation of the model. it is the weighted normal of Precision and Recall. Along these lines, this score contains both bogus negatives and bogus positives. The F1 score is a perplexing variable so it's not instinctively straightforward as Accuracy. When there is lopsided class dissemination F1 score esteem is a higher priority than the Accuracy esteem. F1 score can be calculated as,
F= 2*(R * P) / (R + P) Where F denotes F1 score, R denotes Recall, P denotes Precision.
In our model, we achieved the best F1 score through Random Forest of 56.27 based on features subset of Boruta-Shap and low F1 score of 30.77 based on feature subset of Wrapper. Then, we again got a low F1 score through Logistic regression of 20.00 based on features subset of Wrapper and a low F1 score of 11.11 based on features subset of Boruta-Shap. Also, we got very low F1 scores of 16.67 and 19.04 through kNN based on Boruta-Shap and Wrapper respectively.
Clearly, we can infer that the Random Forest Classifier is a good model by watching all performance-based scores as well as its accuracy. Our Proposed model best classifier had an accuracy of 82.27% in detecting stress.

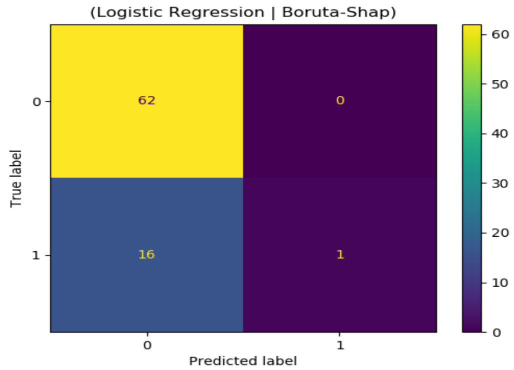

Figure 6.3: Disarray framework of LR dependent on highlight subset of Boruta-Shap.

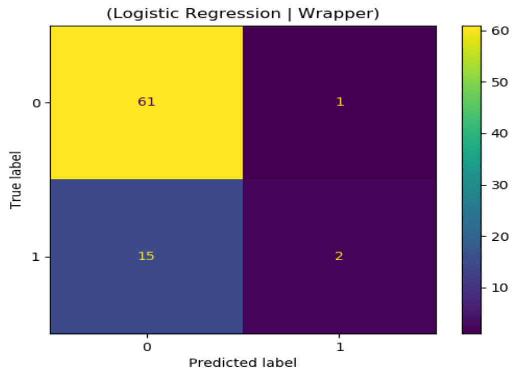

Figure 6.4: Disarray framework of LR dependent on highlight subset of Wrapper.

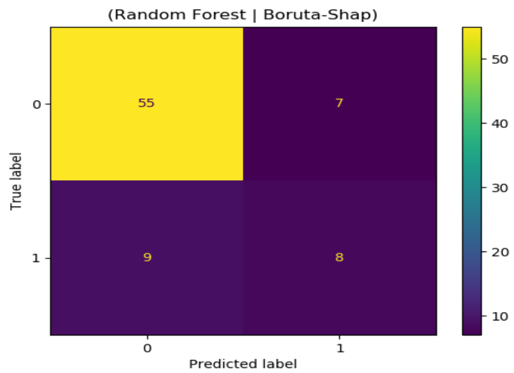

Figure 6.5: Disarray framework of RF dependent on highlight subset of Boruta-Shap.

Table 6.3: F1 score, Recall and Precision of proposed models.

	Random Forest			Logistic Regression			kNN		
	F1	Recall	Prec.	F1	Recall	Prec.	F1	Recall	Prec.
Boruta Shap	56.25	52.94	60.00	11.11	05.88	100	16.67	11.76	28.57
Wrapper	30.77	23.53	44.44	20.00	11.76	66.67	19.04	11.74	50

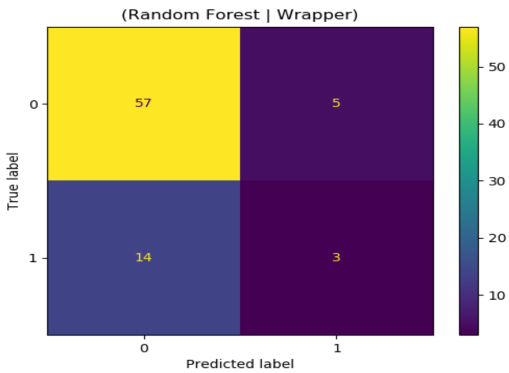

Figure 6.6: Disarray framework of RF dependent on highlight subset of Wrapper.

Chapter 7

Conclusion

In this paper, we investigated mental stress identifiers by utilizing Hjorth Parameters, Autoregressive, Shannon entropy, and other physiological signal based features. ECG and GSR recordings from the AMIGOS dataset was utilized for this paper. By implementing essential models, we were successful to identify stress from the dataset. We only used machine learning for stress detection. The results of our classification indicate that our method and analysis offer a helpful identification of stress. Later on, this may help other researchers to include deep learning methods and eliminate the manual feature extraction complication.

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