SIMULATION BASED ANALYSIS OF DRIVER'S STRESS LEVEL USING PHYSIOLOGICAL SIGNALS

(FİZYOLOJİK SİNYALLER KULLANARAK SÜRÜCÜNÜN STRES SEVİYESİNİN SİMÜLASYON TABANLI ANALİZİ)

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Özge Günaydın

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LIST OF SYMBOLS

ADAS	: Advanced driver-assistance systems
AHA	: American Heart Association
ANS	: Autonomic Nervous System
APA	: American Psychological Association
API	: Application Programming Interface
BPM	: Beat per Minute
CART	: Classification and Regression Trees
CNN	: Convolutional Neural Network
CSV	: Comma Seperated Values
ECG	: Electrocardiogram
EMG	: Electromyogram
GSR	: Galvanic Skin Response
HR	: Heart Rate
HRV	: Heart Rate Variability
IBI	: Inter-beat Interval
KNN	: K nearest neighbor
LDA	: Linear Discriminant Analysis
LR	: Logistic Regression
MLP	: Multilayer Perceptron
NB	: Naive Bayes
NPC	: Non-person Controller
PCA	: Principal Component Analysis
PPG	: Photoplethysmography
RBF	: Radial basis function
RDF	: Random Decision Forest
RESP	: Respiration
SC	: Skin Conductance
SCL	: Skin Conductance Level
SCR	: Skin Conductance Response
SDG	: Sustainable Development Goal
SVM	: Support Vector Machine
TUİK	: Turkey Statistical Institute
UN	: United Nations
VR	: Virtual Reality
WHO	: World Health Organization

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ABSTRACT

The aim of this thesis study is to detect driver's stress with the help of physiological signals. A racing game experiment is designed to understand stressors on the road. One subject played five different levels of a racing game while wearing ECG and EDA sensors. By using the knowledge gained from the racing game experiment about road stressors, a driving simulation was implemented. Four subjects tried to follow a specific route in the simulation with the ECG and EDA sensors attached. The same four subjects also played a simulation game called City Car Driving wearing always the physiological sensors. Using the physiological signals and machine learning algorithms, stress detection was made for all three simulation experiences: The Racing Game Experiment, Simulation Experiment, and City Car Driving Experiment. Also, a publicly available drivers' physiological signals dataset called DriveDB was used for stress detection. The following accuracy rates of stress detection were obtained: 70.77% for the Racing Game Experiment, 86% for the Simulation Experiment, 85% for the City Car Driving Experiment. The analysis of DriveDB dataset yield an accuracy of 69% for detecting low, medium and high stress levels (3 level estimation) vs 91% for the binary stress level detection (stressed vs non stressed).

Keywords: stress detection, ECG, EDA, simulation

RÉSUMÉ

Le but de cette étude de thèse est de détecter le stress du conducteur avec des signaux physiologiques. Une expérience de jeu de course conçue pour comprendre les facteurs de stress sur la route. Un sujet a joué à cinq niveaux différents d'un jeu de course tout en portant des capteurs ECG et EDA. En utilisant les connaissances sur les facteurs de stress de la route tirées de l'expérience du jeu de course, une simulation de conduite a été réalisée. Quatre sujets ont essayé de suivre un itinéraire spécifique dans notre simulation tout en portant un capteur ECG et EDA. Les quatre mêmes sujets ont également joué à un jeu de simulation appelé City Car Driving en portant des capteurs. À l'aide des signaux physiologiques et des algorithmes d'apprentissage automatique, la détection du stress a été réalisée pour l'expérience de jeu de course, l'expérience de simulation et l'expérience de conduite de voiture de ville. En outre, un ensemble de données sur les signaux physiologiques des conducteurs, accessible au public, appelé DriveDB, a été utilisé pour la détection du stress. La plus haute précision de détection de stress 70,77% pour l'expérience de jeu de course, 86% pour l'expérience de simulation, 85% pour l'expérience de conduite de voiture de ville et 69% pour le DriveDB détectant les niveaux de stress faibles, moyens et élevés, 91% pour le binaire détection du niveau de stress.

Mots clés : détection de stress, ECG, EDA, simulation

ÖZET

Bu tez çalışmasının amacı, sürücünün stresini fizyolojik sinyaller yardımıyla tespit etmektir. İlk olarak, yoldaki strese neden olan etmenleri daha iyi kavramak için bir yarış oyunu deneyi oluşturuldu. Bu deney esnasında, bir denek, EKG ve EDA sensörleri takarken yarış oyununun beş farklı seviyesini oynadı. Yarış oyunu deneyinden elde edilen yoldaki stres faktörleri hakkındaki bilgiler kullanılarak bir sürüş simülasyonu hazırlandı. Dört denek, EKG ve EDA sensörü takarken sürüş simülasyonunda belirli bir rotayı izlemeye çalıştı. Aynı dört denek sensörler takılıyken City Car Driving adlı bir simülasyon oyunu da oynadı. Fizyolojik sinyaller ve makine öğrenme algoritmaları kullanılarak Yarış Oyunu Deneyi, Simülasyon Deneyi ve City Car Driving deneyi için stres tespiti yapıldı. Ayrıca, stres tespiti için sürücülerin araştırmacıların kullanımına açık bir fizyolojik sinyal veriseti olan DriveDB veriseti de kullanıldı. Yarış Oyunu Deneyi için % 70.77, Simülasyon Deneyi için % 86, City Car Driving Deneyi için% 85 ve DriveDB için % 69 (düşük, orta ve yüksek stres seviyesi tespiti), %91(stresli ve stressiz sürücü tespiti) en yüksek stres tespiti doğruluğu olarak bulunmuştur.

Anahtar Kelimeler : stres tespiti, EKG, EDA, simülasyon

1. INTRODUCTION

On driver's seat, road rage and stress only lead to bad decisions and can cause deathly mistakes. According to World Health Organization (WHO), approximately 1.35 million people die each year as a result of road traffic crashes. Road traffic injuries are leading cause of death for children and young adults ages 5 – 29 years and number 8th leading cause of death for all ages.[1]

Table 1: Leading causes of death, all ages, 2016

Rank	Cause	% of total deaths
	All Causes	
1	Ischaemic heart disease	16.6
2	Stroke	10.2
3	Chronic obstructive pulmonary disease	5.4
4	Lower respiratory infections	5.2
5	Alzheimer's disease and other dementias	3.5
6	Trachea, bronchus, lung cancers	3.0
7	Diabetes mellitus	2.8
8	Road traffic injuries	2.5
9	Diarrhoeal diseases	2.4
10	Tuberculosis	2.3

2016 WHO Global Health Estimates

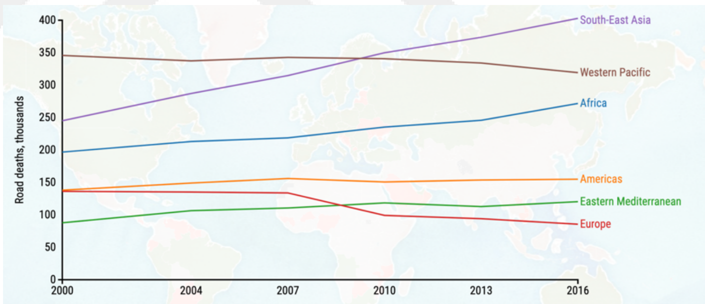

Figure 1.1 Leading causes of death, all ages, 2016

Figure 1.2 Road Deaths between 2000 – 2016

The 2030 Agenda for Sustainable Development, a United Nations (UN) organization, enshrines 17 Sustainable Development Goals (SDGs) and 169 targets to be achieved over the next 15 years. One of their goals is halving the global number of deaths and injuries from road traffic crashes by 2020.[2]

[1] https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries
[2] https://sdgs.un.org/2030agenda

In Turkey, Turkey Statistical Institute (TUİK) published a transportation report in 2018. According to that report, 1 million 229 thousand 364 traffic accident happened in Turkey and 186 thousand 532 of them caused death.[3] The report also listed the causes of traffic accidents, the leading cause being the driver with %89.46. The causes of traffic accidents with injuries between 2002 – 2018 in Turkey are shown in Figure 1.3 below:

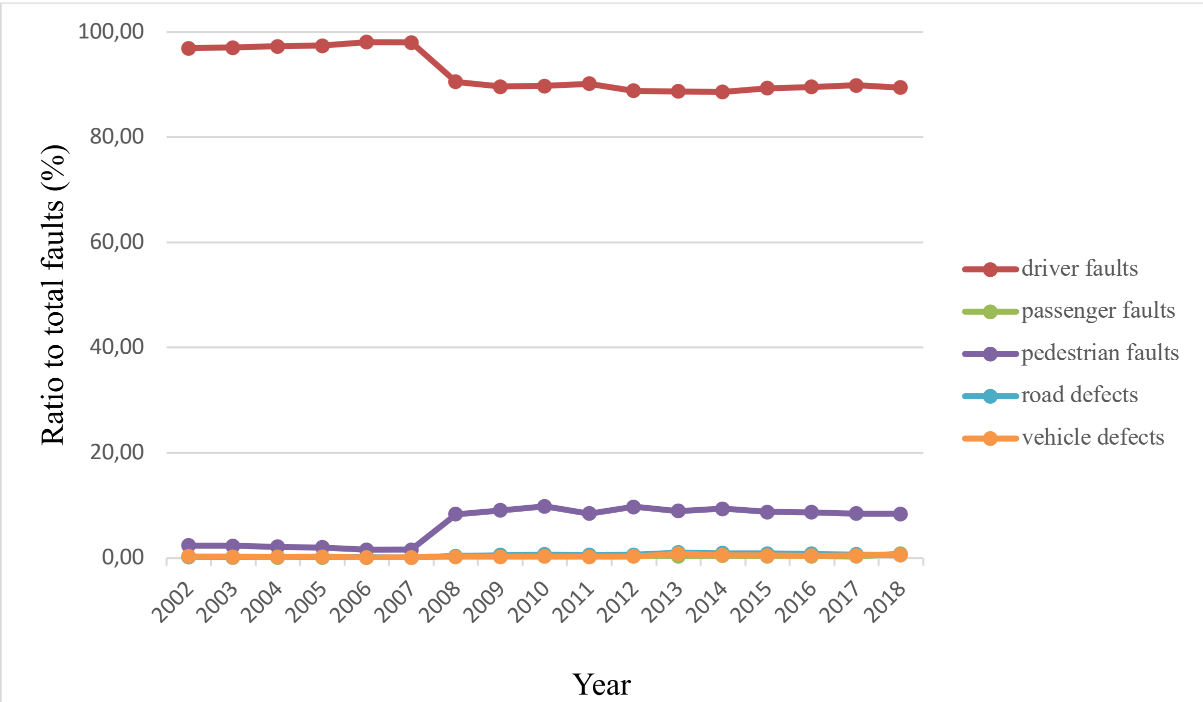

Figure 1.3 The causes of traffic accidents with injuries between 2002-2018, Turkey

As shown in graph, driver faults are the leading cause of traffic accidents with injuries by %89.45 in Turkey. To reduce road traffic crashes, we have to examine the reasons and eliminate them one by one. We can group driver faults as: distracted driving, drunk driving, breaking the speed limits, reckless driving, driving in bad weather conditions, not stopping while the red light is running, driving during nighttime, road rage, drowsy driving, etc. The reason behind most of the driver faults is drivers' mental workload and

[3] https://data.tuik.gov.tr/

stress. High stress state deteriorates decision-making capabilities and situational awareness, leading to poor driving performance (Healey & Picard, 2005).

1.1. Stress

Hans Selye made the first and universal definition of stress as a nonspecific response of the body to any demand. This definition includes every living being from bacteria to humans (Fink, 2016). Stress can also be defined as the reaction of the subject to changes in its internal and/or external environment for homeostasis, the integrity of the subject. Those changes that cause stress in the subject are named as stressors.

Stress is categorized into two different types: eustress and distress according to the subject's response to the stressor being either positive or negative. Eustress is a positive cognitive response to a stressor, associated with positive feelings and a healthy physical state (Lazarus, 1993). Eustress motivates the subject, makes him feel excited, improves performance. It is perceived by the subject as a challenge that can be overcome. Distress is what we usually call as stress, stress with a negative bias (Healey & Picard, 2005). Distress is the type of stress that harms categorization, goal generation, evaluation and decision-making, focus and attention, motivation and performance, intention, communication, and learning which are highly related to driving. In this thesis, distress that decreases driver performance is analyzed. Stress word is used for distress in this report.

Based on the time of exposure to the stressors, stress is divided into three categories: acute stress, episodic stress, and chronic stress (Alberdi et al., 2016). Episodic stress is caused by a frequent periodic stress trigger, and chronic stress by a long-term harmful stress trigger. Acute stress is associated with a short-term stress trigger and leads to a fast and short response. Drivers are usually exposed to acute stress due to sudden changes in their environment, which affect their decision-making ability. Acute stress leads to impaired driving performance that causes more than 80% of car accidents with fatalities and injuries (Stanton & Salmon, 2009, p. 231). For a safe driving experience, the driver needs to focus on road events and signs with all of his attention. He should make fast and appropriate decisions. But stress causes mental workload on drivers, which makes it harder to concentrate on driving action and reduce their situational awareness (Healey & Picard, 2005; Reiner et. al, 2009; Vidulich et. al, 1994).

According to APA (American Psychological Association), acute stress causes an increase in heart rate and stronger heart muscle contractions, with the stress hormones — adrenaline, noradrenaline, and cortisol — acting as messengers for these effects. Repeated acute stress may also contribute to inflammation in the circulatory system, particularly in the coronary arteries, and this is one pathway that is thought to tie stress to heart attack.[4] Every day, drivers are exposed to this type of stress in traffic and react to it with a response that can be measured by subjects' heartbeat, jaw clench, contraction of the arm muscles holding the steering wheel, facial expression, vocal tone, etc... The measure of the response is correlated with stress levels.

[4] https://www.apa.org/helpcenter/stress/effects-cardiovascular

2. LITERATURE REVIEW

2.1. Stress Factors

Various research has been made in the literature to detect different stress types (chronic, episodic, acute). In this thesis, we are particularly interested in chronic stress, which can cause bad driving experiences and lead to traffic accidents.

According to Ghandour et al. (2020), stress factors could be divided into four main categories: driver physical and mental condition, road and traffic conditions, vehicle condition, external disturbance. Internal stress factors include lack of sleep, tiredness, anger, impatience, and driving phobia examined in the driver's physical and mental condition. Passengers in vehicles, mobile phones, in-car application dysfunction, and rough weather conditions can be an example of external disturbance.

For eliminating these stressors, car companies are developing advanced driver-assistance systems (ADAS) like driver stress and drowsiness detection and driver monitoring systems. These systems help the driver to have a better and more comfortable driving experience. However, to establish such systems, the drivers' stress condition must first be detected.

2.2. Detecting Stress

Stress causes changes on human’s physiology: heart rate increases, skin temperature rises, sweating ratio increases. It also causes observable changes on facial expressions (Raichur et al., 2017; Patil et al., 2020; Chiwande et al., 2020) and vocal tone (Harnsberger et al., 2009; Loizou and Christodoulides, 2020). With measuring and identifying these changes stress level can be assessed.

Eye blinks, more specifically eye blink duration, also can give information about the driver's workload. Benedetto et al. (2011) gave different tasks during a driving simulation and measured eye blink rate, and eye blink duration. These experiments were made with 15 subjects.

There are also hybrid approaches that use more than one methodology to detect stress; for example, Haak et al. (2009) use eye blinks, and brain activity gathered from EEG signals.

From the beginning of early studies, physiological signals such as ECG (Electrocardiogram), EMG (Electromyogram), GSR (Galvanic Skin Response), PPG (photoplethysmography) are commonly used for measuring stress. In this thesis, using physiological signals for stress detection was preferred instead of methods that the person can control, such as facial expression or vocal tone.

2.2.1. Detecting Stress Using Physiological Signals

In the literature different tasks were used as stressor and stress detection models built using physiological signals' features as input.

Sandulescu et al. (2015) created an experimental setup consisting of neutral tasks followed by a public speaking task and a cognitive task that could trigger stress in subjects. During these experiments from 5 subjects, BVP, HRV, and EDA signals were gathered. With an SVM classifier, they could detect stress with 80% accuracy.

R. Castaldo et al. (2016) collected ECG signals from 42 students during a verbal examination and in a resting condition after the examination day. From ECG signals, HRV features are extracted. KNN classification algorithm is used and stress is detected with 94.58% accuracy.

Some researchers did experiments with longer durations than 5-30 min. Gjoreski et al. (2016) gathered real-life data from 5 subjects during 55 days with a wristband that can measure BVP, skin temperature (SK), EDA, HR. Smartphones of the subjects used for tagging activities and stressful events. Random Forest (RF) classifier reached 76% accuracy in their dataset.

Mazos et al. (2017) designed an experiment to detect stress, including these tasks: answering neutral questions, preparing a mock job interview, making a presentation for the job interview, completing a cognitive task (counting backward). 18 subjects wore two sensors during the experiments, and EDA, BVP, Speech, Activity signals were gathered. They detected stress 94% accuracy with the AdaBoost classifier.

Some researchers used the driving task as the stress stimulus. In (Healey & Picard, 2005), ECG, EMG, EDA (Electrodermal Activity), and RESP (Respiration) sensors are used, the linear discriminant analysis (LDA) feature extraction method is applied to statistical features. From the analysis of data collected in a real driving experiment from 17 subjects, the accuracy rate for stress detection is obtained as 97.4%. This dataset is publicly available to researchers.

Using the same dataset's ECG data, statistical and non-linear heart rate variability (HRV) features were extracted, the LDA and the principal component analysis (PCA) feature extraction methods are applied, a model is constructed with k nearest neighbor (KNN) classification algorithm. The model's accuracy rate was 81.06% (Wang et al., 2013). In Keshan et al. (2015) statistical HRV features extracted from ECG signal, Decision Tree (J48) detected low, medium, and high stress with 68.66% accuracy. The same model detected stressed and not stressed samples with 97.92% accuracy.

Further information about the dataset which is also used in this thesis, is given in the Chapter 3.4 The DriveDB dataset. ECG, EMG, EDA and RESP signals statistical features were extracted, and Sequential Forward Selection (SFS) algorithm is used for feature selection. SVM reached the highest accuracy as 69% for detecting low, medium, and high stress.

In some experiments, instead of doing a real-life driving experiment, self-made stressor-oriented simulations were used. Karrer et al. (2017) built a realistic driving simulation environment with a mounted setup consisting of two big screens and a steering wheel. They also placed a capacitive hand detection sensor (CHDS) that makes both position and touch detection simultaneously to the steering wheel. 22 subjects participated in the experiments while wearing sensors that gather EDA, ECG, EEG signals. Convolutional Neural Network (CNN) models trained for stress detection. The model that uses only body placed sensors data, reached 82% accuracy, while the model that combined CHDS and body placed sensors data, reached 92% accuracy.

In (Wang et al., 2013), a simulation used with an assembly created using a real car, ECG signals, vehicle data (e.g., steering wheel, brake pedal), and contextual data (e.g., weather conditions and other ambient factors) are collected, convolutional neural network (CNN) is used as the classification method. In some cases, racing games are also used for stress stimuli (Haak et al., 2009)

3. MATERIALS

3.1. The Drivedb Dataset

This dataset was created by J. Healey et al. during her thesis studies and was made publicly available on the PhysioNet website since 2005[5]. Drivedb contains a collection of multiparameter recordings from healthy volunteers, taken while driving on a prescribed route, including city streets and highways in and around Boston, Massachusetts. Seventeen subjects drove the same automobile on the same route while they were wearing sensor kits. ECG, EMG, GSR from hand and foot, HR, and RESP signals were acquired from subjects during the experiment. However, in the publicly available dataset, only ten drives out of seventeen have a complete signal set and marker that indicates low, medium, and high-stress levels. Using the marker information and informative paper about this dataset, driving intervals shown in Table 3.9 were identified. Initial rest and final rest labeled as low-stress level, driving in the highway labeled as medium stress level, driving in the city labeled as high-stress level.

Table 3.1 Duration of DriveDB recordings

Drive	Rest1	City1	Hw1	City2	Hwy2	City3	Rest	Total
Drive05	0	15.13	31.13	38.87	44.93	52.49	67.45	83.23
Drive06	0	15.05	29.54	36.86	43.39	51.03	63.32	78.38
Drive07	0	15.04	31.27	42.23	52.06	59.70	69.85	84.87
Drive08	0	15.00	27.31	34.54	44.05	51.69	65.12	80.19
Drive09	0	15.66	34.87	43.34	48.54	55.60	68.81	68.82
Drive10	0	15.04	30.34	39.00	44.27	51.31	63.37	78.15
Drive11	0	15.02	30.83	38.26	45.41	52.37	64.09	79.08

[5] http://physionet.org/physiobank/database/drivedb/

Drive12	0	15.01	28.42	35.98	42.48	50.54	62.22	77.23
Drive15	0	15.00	27.54	34.78	40.77	47.59	59.71	74.70
Drive16	0	15.01	31.13	38.27	43.39	50.20	64.11	64.10

37 features that are shown in table below are extracted from DriveDB dataset for using with classification models to detect stress.

Table 3.2 DriveDB Features Table

Index	Feature Name	Signal
1,2,3,5,6	Mean of raw signal	Hand GSR, Foot GSR, EMG, RR, HR
4	Root mean square	EMG
7,8,9,10,11	Median of raw signal	Hand GSR, Foot GSR, EMG, HR, RR
12,13,14,15,16	Standard deviation of raw signal	Hand GSR, Foot GSR, EMG, HR, RR
17,18,19,20,21	Variance of raw signal	Hand GSR, Foot GSR, EMG, HR, RR
22,23,24,25,26	First Forward Difference	Hand GSR, Foot GSR, EMG, HR, RR
27,28,29,30,31	Second Forward Difference	Hand GSR, Foot GSR, EMG, HR, RR
32	Label	0: low stressed, 3: medium stressed, 5: high stressed

3.2.The Racing Game Experiment Design & Data Collection

Before creating a driving simulation as the stimulus, a racing game experiment was done with one subject and five different racing game levels. The goal was identifying and understanding the stressors and reproduce some of them in the driving simulation. An experimental setup has been built to detect stress while playing the racing game—a MacBook Pro's webcam used to capture the subject's facial expressions. The subject played five different racing game levels called "GRID Autosport" while he was wearing physiological sensors[6]. BiTalino ® Revolution Plugged Kit's ECG[7] (with three electrodes on hand) and EDA (with two electrodes on hand) sensors were used in these experiments. Figure 3.1, shows the device and sensors that are used to collect data.

Figure 3.1 BiTalino (R)evolution Plugged Kit

Before the experiments started, the EDA sensor electrodes were placed on the palm and two fingertips. EDA sensor placed on palm gave a more noisy, corrupted signal.

Therefore, two electrodes of the EDA sensor were placed to fingertips at the experiments. Unity 3D framework is used for gathering, saving, and analyzing ECG and EDA signals. The sample rate for these signals was chosen 100Hz. For labeling stressors, screen records taken during the experiments were used. Subject watched five records and identified stressors; these stressors were used for labeling. If the subject identified that moment as stressful, it is labeled as stressed; otherwise, it is labeled as unstressed. If there is a stressful moment, the subject also explained the reason.

[6] https://www.codemasters.com/game/grid-autosport/

[7] https://bitalino.com/

Figure 3.2 Screenshot of the Racing Game Scene

After each level subject watched the screen recording of that level and labeled every time second as stressed or not stressed. If this second is labeled as stressed, the subject also explained why. Using these explanations, the main stressors on the road are identified.

Table 3.3 Stressor Table

Index	Stressors
0	Not Stressed
1	Start, Pause, Finish
2	Crash
3	Stop the car
4	Hairpin corner
5	Off-road
6	Crashing barriers

These stressors are used for creating a driving simulation, which will be used in actual experiments to detect drivers' stress levels.

Table 3.4 Duration of Stressing Game Records

Experiment Name	Duration
Record1	644.07 sec
Record2	513.60 sec

Record3	868.12 sec
Record4	439.34 sec
Record5	500.38 sec

43 features were extracted from each of these records, using statistical equations that will be explained in the following section.

Table 3.5 The Racing Game Features

Index	Feature Name	Signals
1, 11, 21, 31	Mean of raw signal	ECG, EDA, phasic EDA, tonic EDA
2, 12, 22, 32	Mean of normalized signal	ECG, EDA, phasic EDA, tonic EDA
3, 13, 23, 33	standard deviation of raw signal	ECG, EDA, phasic EDA, tonic EDA
4, 14, 24, 34	standard deviation of normalized signal	ECG, EDA, phasic EDA, tonic EDA
5, 15, 25, 35	median of raw signal	ECG, EDA, phasic EDA, tonic EDA
6, 16, 26, 36	median of normalized signal	ECG, EDA, phasic EDA, tonic EDA
7, 17, 27, 37	first forward difference mean of raw signal	ECG, EDA, phasic EDA, tonic EDA
8, 18, 28, 38	first forward difference mean of normalized signal	ECG, EDA, phasic EDA, tonic EDA
9, 19, 29, 39	second forward difference mean of raw signal	ECG, EDA, phasic EDA, tonic EDA
10, 20, 30, 40	second forward difference mean of normalized signal	ECG, EDA, phasic EDA, tonic EDA
41	first difference	HR
42	second difference	HR
43	stress label	unstressed: 0, stressed: 1

3.3. The Simulation Experiment Design & Data Collection

The racing game experiment provided insight into stressors on the road. According to our racing game experiment, hairpin corners, barriers, curvy roads, alleyways can increase drivers' stress level.

Different simulations for different platforms (Android, Desktop) have been built as stimuli for detecting stress with Unity3D.

3.3.1. Desktop Version with MapBox

The first approach was creating a simulation with a real-world map. The idea behind this approach was to create a driving environment that drivers are familiar. Driving on the roads that they usually drive in their daily life would provide a more realistic experience to the subjects. For this purpose, two different real-world map providers are used. First, we used MapBox open-source platform, which has a Unity plugin package to get real-world coordinates[8]. Car from Unity Standard Assets package is used as the vehicle[9]. MapBox provides every coordinate on earth as rendered and ready to use. The rendering process must be completed before the simulation starts. MapBox renders a part of the world map according to the coordinates entered before the simulation is started, and it does not render the map again. If the subject drives the car to the edge of the map, it falls off. Therefore, another world map provider is also used within the scope of this thesis.

Using an embedded system that starts the driving experiment and physiological data gathering at the same time, enables an accurate signal interpretation. Therefore, this was one of the main goals of our simulation system. The system should be able to gather

[8] https://www.mapbox.com/
[9] https://assetstore.unity.com/packages/essentials/asset-packs/standard-assets-for-unity-2018-4-32351

data and be a stress stimulus. BiTalino Unity3D package was added to the simulation project to gather EDA and ECG signals and write them to a CSV file.

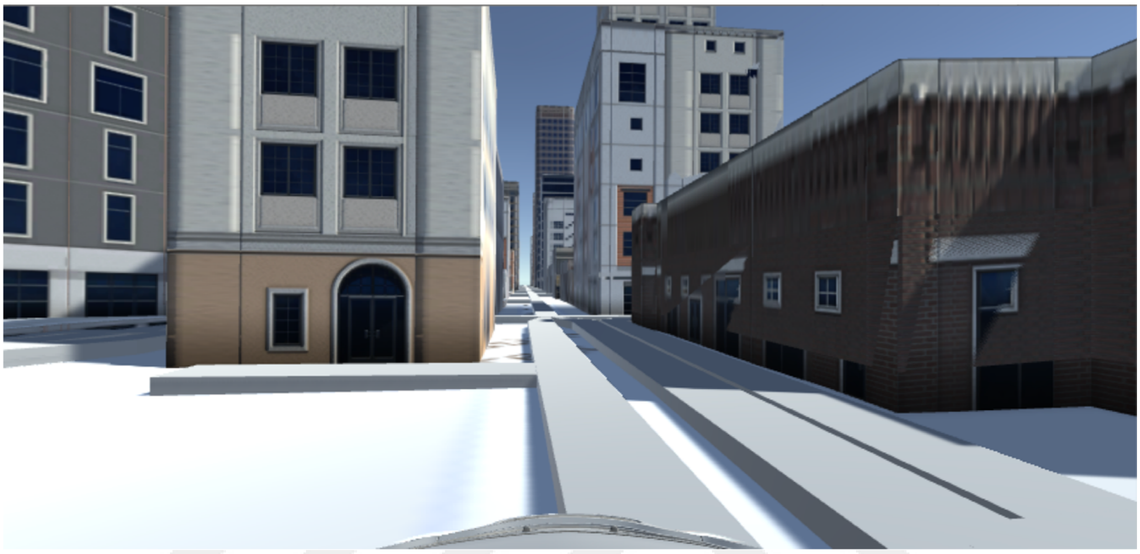

Figure 3.3 Screenshot of MapBox simulation scene

3.3.2. Android Version with MapBox

Using a smartphone for the experiments would provide more mobility and allow us to do experiments in any physical environment. Therefore, an Android version of the same simulation was also created.

In this version, the tilt movements of smartphones are used for vehicle control. After building this version, the virtual reality option was added to the simulation system. A VR helmet was used, but when the subject turns his head to looking around, smartphones understand it as a turning command and turn the vehicle. Therefore, in the VR option, the Myo armband is used for controlling the vehicle[10]. Myo armband has 8 EMG sensor inside, and it can detect movements of the subject's arm. Subjects can wear

[10] https://developerblog.myo.com/author/thalmic-labs/

Myo and turn their hand to the left for turning the vehicle left, right for turning the vehicle right.

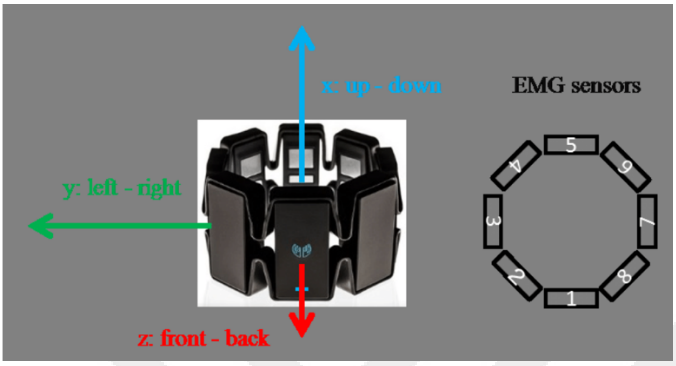

Figure 3.4 The MYO armband

For the integrated system, BiTalino should start data gathering when the subject clicks the android application of our simulation. In the desktop version, BiTalino makes the connection through the serial port. In the android version, it should use the android operation system Bluetooth policy. For making a Bluetooth connection between Bitalino and an android device, a Bluetooth plugin API was needed. We searched for an open-source Bluetooth plugin API for Android in Unity Assets, but there were only commercial packages. The only solution was opening Bitalino from another smartphone in sync, which is against our embedded simulation system goal.

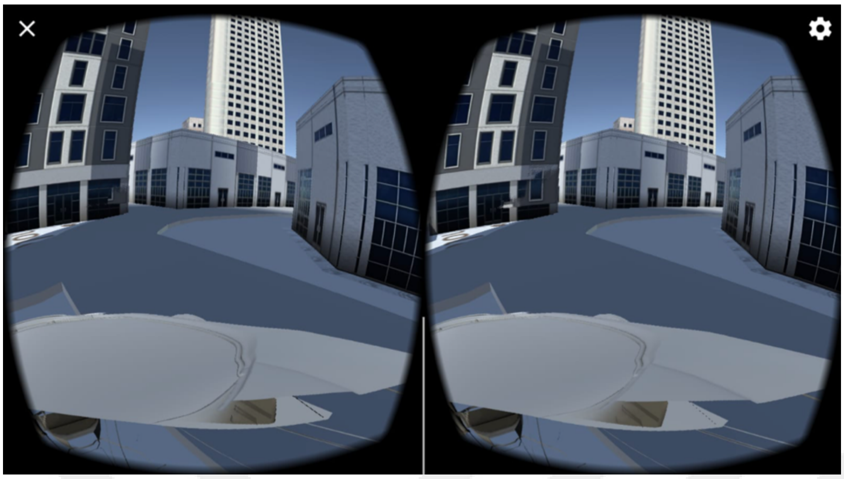

Figure 3.5 Screenshot of Simulation Android Version with VR

3.3.3. Desktop version with Wrld3D

As we mentioned before, roads in the simulation with MapBox have an end. If the subject drives enough in the simulation, he could reach the edge of the road and fall. Another map provider Wrld3D is used to solve this problem, which also has a Unity package[11].

Wrld3D allows specifying the coordinates that will be rendered, but it does not have the whole world covered yet. According to the subjects driving, we used an additional camera attached to the map and moves a little away from the subject to render the map dynamically before the subjects reach the simulation's end.

[11] https://wrld3d.com/

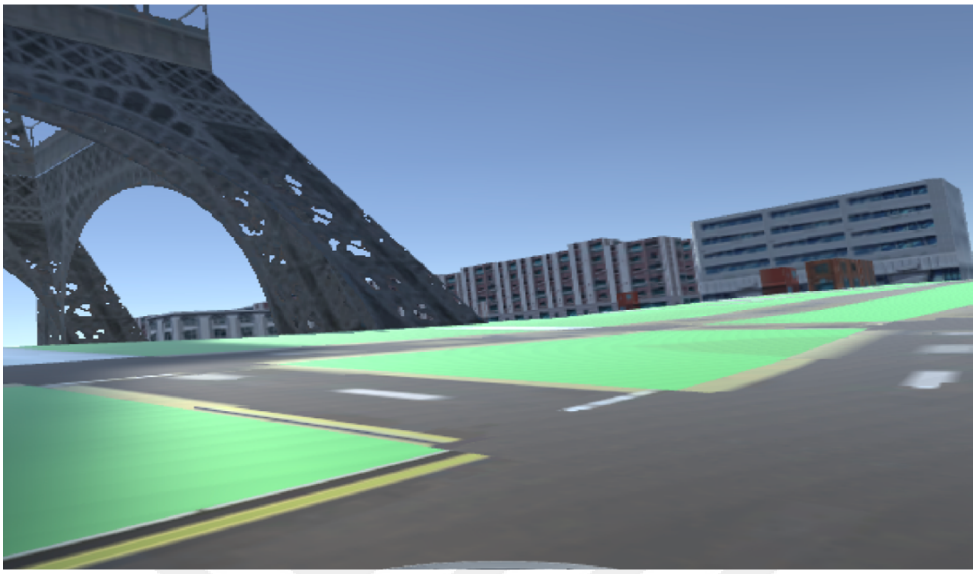

Figure 3.6 Screenshot of Simulation with Wrld3D

In this simulation, we also add a canvas that shows the ECG and EDA graph collected from BiTalino. Instead of using arrows for vehicle control, we decided to use a Logitech G920 steering wheelset that includes the steering wheel, shifts, gas, brake, and clutch to have more realistic driving experience.

Figure 3.7 Steering Wheel Setup

3.3.4. Desktop version with Winridge City

Since both MapBox and Wrl3D map roads are narrow, with buildings that are unrealistic; another simulation was built with Unity3D Windridge City asset. Windridge City has a city template with buildings, trees, tunnels, crosswalk lines[12]. A speedometer that will show the subject's speed was added to the simulation. A minimap that will show where the subject is inside the simulation is also integrated.

[12] https://assetstore.unity.com/packages/3d/environments/roadways/windridge-city-132222

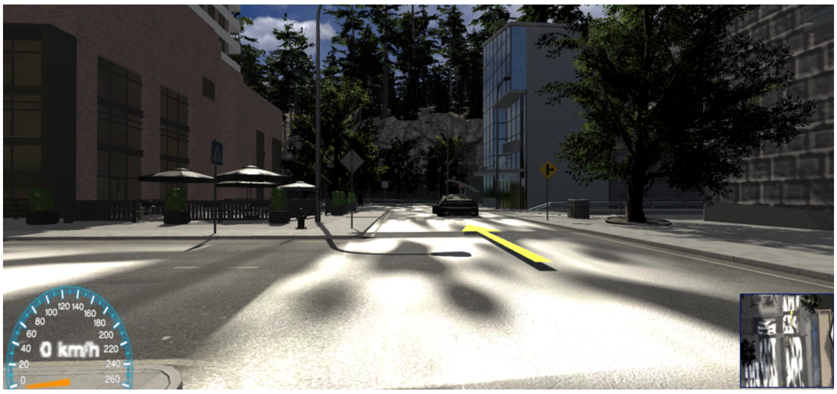

Figure 3.8 Screenshot of Simulation Experiment Design with speedometer, mini-map and guidelines

Pedestrians with sudden moves are a kind of road stressors; therefore, five different pedestrian routes were added to the simulation. Mixamo characters are used as pedestrian models.[13]

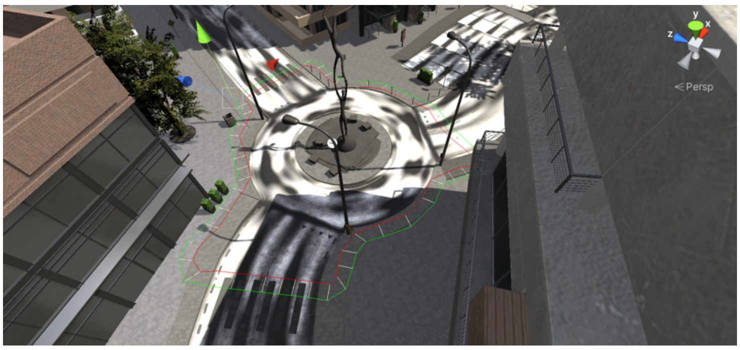

Figure 3.9 One of the pedestrian routes (shown in green and red lines)

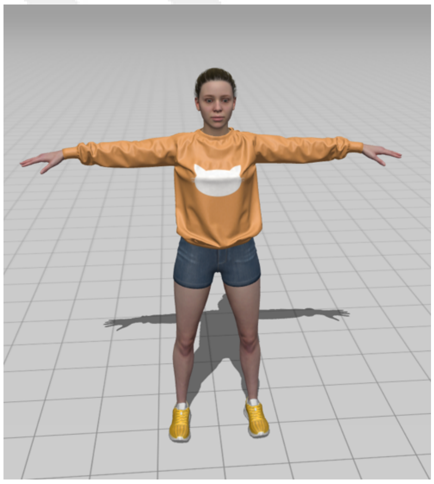

Figure 3.10 An NPC pedestrian

An NPC (non-person controller) car was added to the simulation that will follow a specific predefined route during the experiment. Unity3D's Standard Assets AI-car vehicle was used as an NPC car.

[13] https://www.mixamo.com/#/

Guidelines were added to the scene to create a route for subjects. Hence, every subject would follow the same route and face similar stressors nearly in the same seconds of the experiment. The subject can track the signs from the mini-map screen.

The BiTalino package was also added to have an embedded system, and data acquisition was triggered through the simulation. This simulation version is used for the experiments.

In the experiments, four subject tried to drive along the guidelines and interact with pedestrians and the other car. Just before the experiment, OBS recording software started to capture the screen, and when Unity3D simulation started, BiTalino also started to gather ECG and EDA data with a 1000Hz sample rate simultaneously. All of the subjects have a driving license but only subject three is driving on a daily-basis. The male - female ratio is 1:3, and the mean of ages is 44. Detailed information about subjects is given in Table 3.4.

Table 3.6 The Subject Information Table

Subject No	Gender	Age	Driving Freq
Subject 01	Female	25	Not once in a year
Subject 02	Female	24	Once a month
Subject 03	Male	63	Two times a day
Subject 04	Female	64	Once a week

Before starting the experiments, subjects were informed about the experiment process and how they can keep track of guidelines. Subjects 3 and 4 did not play a video game in their entire life and were not familiar with the controller concept. Therefore, they had a hard time tracking the guidelines and got off the route most of the time. Instantly telling them to turn right or left could be an external stress trigger, so no verbal directives are given. When driving epoch was finished, each subject told to be calm down and rest for three minutes. Subject 4 mistakenly closed the experiment after the driving epoch, another session started for three minutes resting for her. After the experiments finished, video captures were examined, and stress trigger events were noted down like the Racing Game Experiment. Every second with a stressful event is labeled stressed and other seconds were labeled as not stressed.

Table 3.7 Duration of the Simulation Experiment

Subject No	Duration of the experiment (in min)
Subject 1	14.97
Subject 2	7.83
Subject 3	13.36
Subject 4 – driving session	5.72
Subject 4 – resting session	3.11

3.4. City Car Driving Simulation Game Experiment

City Car Driving is a driving simulation game that has some specific tasks, predefined routes, different weather, and traffic conditions[14]. After completing the first experiments with our simulation, subjects also played this simulation game with the same experimental setup. The intuition of this idea is comparing the accuracy of the same classification algorithms using the same features. Detecting stress accuracy rates may depend on the subject's mood, time, and other environmental conditions, but we tried our best to minimize these effects. Subjects made first and second experiments in the same room with the same experimental setup and one after another. The settings of City Car Driving play are shown below (Cardone et al., 2020):

[14] https://store.steampowered.com/app/493490/City_Car_Driving/

Table 3.8 City Car Driving Settings

City Car Driving Settings	Conditions
Weather	• Season: Autumn • Weather condition: Foggy • Time of the day: Daytime
Traffic	• Traffic density: 50% • Traffic behavior: Intense Traffic • Fullness of traffic: 60%
Territory	• Area: New City • Location: Modern district
Emergency Situations	• Dangerous change of status: Often • Emergency braking of the car ahead: Often • Pedestrian crossing the road in a wrong place: Often • Accident on the road: Often • Dangerous entrance of the vehicle into oncoming lane: Rarely

In the City Car Driving simulation game experiments, main task was driving to a gas station. Subject 1 and Subject 2 finished this task successfully, but Subject 3 and Subject 4 couldn't reach final destination point. Duration of City Car Driving simulation game experiment for all subjects is given below:

Table 3.9 Duration of City Car Driving Simulation Game Experiment

Subject No	Duration (in min)
Subject 1	11.73
Subject 2	14.39
Subject 3	12.51
Subject 4	20.55

Same features are extracted from every record of the Simulation Experiment & City Car Driving Simulation Game Experiment that shown below:

Table 3.10 Feature table of experiments

Index	Feature Name	Signal
1, 7, 13, 19	Mean of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
2, 8, 14, 20	Median of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
3, 9, 15, 21	Standard deviation of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
4, 10, 16, 22	Variance of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
5, 11, 17, 23	First forward difference of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
6, 12, 18, 24	Second forward difference of raw signal	ECG, EDA, EDA Phasic, EDA Tonic
25, 31, 37, 43	Mean of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic
26, 32, 38, 44	Median of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic
27, 33, 39, 45	Standard deviation of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic
28, 34, 40, 46	Variance of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic
29, 35, 41, 47	First forward difference of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic
30, 36, 42, 48	Second forward difference of normalized signal	ECG, EDA, EDA Phasic, EDA Tonic

4. METHODOLOGY

4.1.ECG

The electrocardiogram (ECG) signal reflects the variation of the cardiac electrical potential over time. ECG signals contain information about the subject's heartbeat. With this information, the subject's affective state can be estimated.

ECG is a periodic signal (shown in Figure 4.1). The period between two heartbeats is called the inter-beat interval (IBI). The IBI can be calculated by detecting the time interval between two R peaks in the ECG signal's QRS complex. Using IBI, heart rate (HR) and heart rate variability can be measured (Riener et al., 2011)

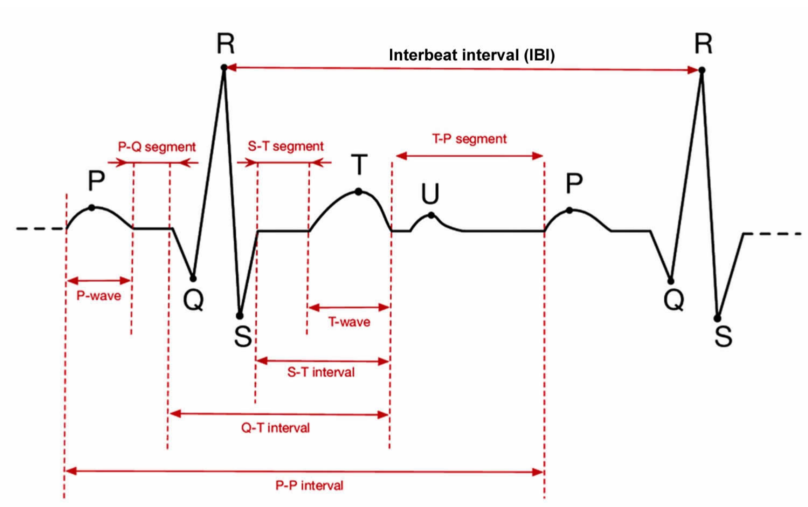

Figure 4.1 Structure of an ECG signal (Riener et al., 2011)

Heart rate is the heartbeat speed measured by the number of contractions (beats) of the heart per minute (bpm). According to the American Heart Association (AHA), activities that can provoke change in heart rate include physical exercise, sleep, anxiety, stress, illness, and drug ingestion. The changes are shown as irregularities between each heartbeat. Therefore, heart rate variability is an essential tool for detecting stress.

4.2.EDA

Electrodermal activity (EDA) is also known as galvanic skin response (GSR) and skin conductance (SC). EDA measures changes in the skin surface's electrical conductivity, which is an Autonomic Nervous System (ANS) activity (Wang et al., 2013). Changes in the electrical conductivity related to sweating ratio. If the sweating ratio increases, electrical conductivity will decrease. Sudden changes in affective states such as panic, stress, excitement, anger cause changes in EDA.

EDA is a sensitive and reliable indicator of stress, according to the previous works in literature. When a person is stressed, he will start to produce ionic sweat, which increases his skin conductance gradually (Zhang, 2017). EDA sensors placed on the palm of the hands, fingertips, and the feet' soles can detect skin conductance changes (Stemmler et al., 2001, p. 282).

The EDA signal can be divided into two components. Skin conductance level (SCL) - tonic component- represents the electrical conductivity at a given point in time. It is an indicator of the general activation of the organism. Skin conductance response (SCR) - phasic component- represents the amount of EDA change in response to a given stimulus (Sioni & Chittaro, 2015). SCR represents the response to short term changes, mostly occurs one-three seconds after an identified cause. The amplitude of the SCR signal proportionate to the importance of the identified cause (Zhang, 2017).

4.3. Feature Extraction

4.3.1. Time-Domain Features of ECG & EDA

From both ECG and EDA signals statistical features shown below extracted (Healey & Picard, 2005; Marcano-Cedeño et al., 2011):

- Mean:

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n$$

- Standard deviation:

$$\sigma_x = \left(\frac{1}{N-1}\sum_{n=1}^{N}(X_n - \mu_x)^2\right)^{1/2}$$

- First Forward Difference Mean for raw signals:

$$\delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1}|X_{n+1} - X_n|$$

- Second Forward Difference Mean for raw signals:

$$\gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2}|X_{n+2} - X_n|$$

- Normalization:

$$\hat{y} = \frac{y - \min(y)}{\max(y) - \min(y)}$$

- First difference:

$$X_{diff1} = \sum_{n=1}^{N-1} |X_{n+1} - X_n|$$

- Second difference:

$$X_{diff2} = \sum_{n=1}^{N-2} |X_{n+2} - X_n|$$

- Median:

After sorted every sample between 1-N.

$$\tilde{x} = X_{\frac{N+1}{2}}$$

- Variance:

$$\sigma_x{}^2 = \frac{1}{N-1} \sum_{n=1}^{N} (X_n - \mu_x)^2$$

Heart Rate Variability (HRV) consists of changes in the time intervals between consecutive heartbeats called inter-beat intervals (IBIs) [1]. Variations in heartbeat between sequential seconds give information about changes in humans' affective states. Therefore, three different types of features were extracted from HRV. For feature extraction, signals were windowed in 30-second frames. Labeled according to the majority of labels in that 30 seconds as stressed or not stressed.

4.3.2. Time-Domain Statistical Features of HRV

In the time-domain analysis, the intervals between consecutive R waves are measured over a duration. The visual result is a tachogram, which plots the heart rate frequency over time [2]. Statistical features listed below can be extracted from time-domain analysis.

- Max RR: maximum value of RR peak
- Min RR: minimum value of RR peak
- Avg RR: average value of RR peak
- Max BPM: maximum value of HR
- Min BPM: minimum value of HR
- SDNN: After ectopic beats (a cardiac cycle that differs in at least 20 % of the duration of the previous one, abnormal beats) removed, the standard deviation of IBI of sinus beats

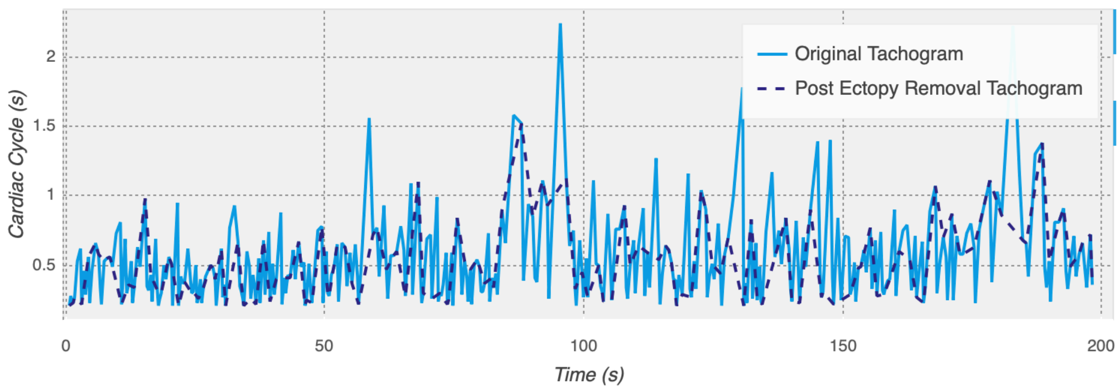

Figure 4.2 Tachograph - subject 1 experiment 1 first 200 seconds

4.3.3. Non-Linear (Geometrical) Features of HRV

Geometrical features can be extracted from the Poincaré plot. The Poincaré plot is a scattergram that has each RR interval plotted against the previous one. The Poincaré plot may be analyzed quantitatively by fitting an ellipse to the plotted shape. The center of the ellipse is determined by the average RR interval [2].

- SD1: standard deviation of Poincaré plot perpendicular to the line-of-identity
- SD2: the standard deviation of the Poincaré plot along the line-of-identity
- SD1 / SD2: the ratio of SD1 and SD2
- NN20: The number of NN intervals differing by >20 ms from the prior interval
- pNN20: The percentage of intervals >20 ms different from the prior interval
- NN50: The number of NN intervals differing by >50 ms from the prior interval
- pNN50: The percentage of intervals >50 ms different from the prior interval

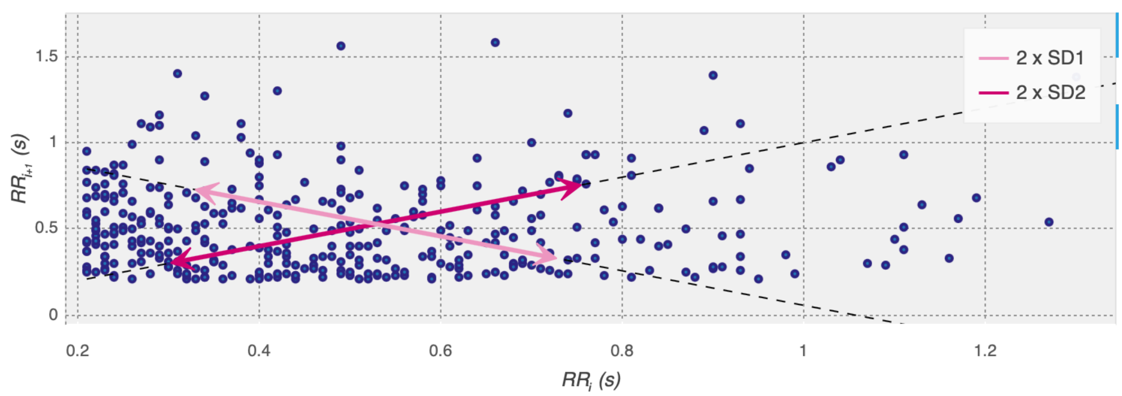

Figure 4.3 Poincare plot - subject 1 experiment 1 first 200 seconds

4.3.4. Frequency-Domain Features of HRV

Frequency-domain measurements estimate the distribution of absolute or relative power into four frequency bands: Ultra Low Frequency (ULF), Very Low Frequency (VLF), Low Frequency (LF), High Frequency (HF).[1]

- ULF power: Absolute power of the ultra-low-frequency band (≤0.003 Hz)
- VLF power: Absolute power of the very-low-frequency band (0.0033–0.04 Hz)
- LF power: Absolute power of the low-frequency band (0.04–0.15 Hz)
- HF power: Absolute power of the high-frequency band (0.15–0.4 Hz)
- LF - HF ratio: Ratio of LF-to-HF power
- Total power: Total power of all frequency bands

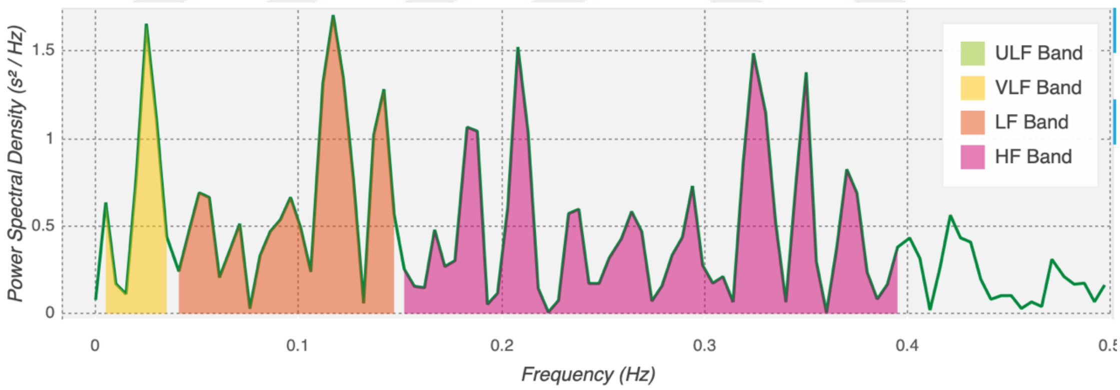

Figure 4.4 Frequency Bands - subject 1 experiment 1 first 200 seconds

4.4.Feature Selection

After the feature extraction step, 68 features were created to use with classification algorithms. To reduce the dimensional space and understand which features are more effective in stress detection, Sequential Forward Selection (SFS) algorithm was used.

The sequential forward selection (SFS) algorithm is a bottom-up search method that starts from an empty feature set and adds features selected by some evaluation function. At each epoch, the feature to be included in the feature set is one of the remaining features at the initial feature set. So, the new feature set should produce a higher accuracy compared with the initial feature set. SFS is used for its simplicity and speed. [3] KNN (K Nearest Neighbor) was chosen as an evaluation function with different k values ($k = 3, 5, 7, 9, ..., 65$).

4.5.Classification Algorithms

In this thesis's scope, datasets generated or downloaded consist of pre-labeled samples as stressed or not stressed. Therefore, for the classification problem, supervised machine learning algorithms were used. In the following sections, used classification algorithms are briefly explained.

4.5.1. Random Decision Forest (RDF)

Random Decision Forest consists of Classification and Regression Trees (CARTs). In a random decision forest tree, each CART tree is generated from a random sample of the training data [28]. Random Decision Forest is an updated version of Random Decision Trees, without overfitting on training data. Our training sets mainly consist of non-stressed samples; therefore, overfitting is a significant threat to our models.

4.5.2. AdaBoost

AdaBoost or Adaptive Boosting Algorithm creates highly accurate prediction rules by combining weak and inaccurate learners. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive because subsequent weak learners are arranged in favor of those instances misclassified by previous classifiers. AdaBoost is sensitive to noisy data and outliers. In some problems, it can be less susceptible to the overfitting problem than other learning algorithms. The individual learners can be weak, but as long as each one's performance is slightly better than random guessing, the final model can be proven to converge to a strong learner. The AdaBoost training process selects only those features known to improve the model's predictive power, reducing dimensionality and potentially improving execution time as irrelevant features do not need to be computed (Schapire, 2013, p. 46). We used the Decision Tree algorithm with AdaBoost as the weak learner.

4.5.3. Naïve Bayes and Bayesian Network

Naïve Bayes algorithm is a simple probabilistic approach that uses Bayes' theorem with strong (naïve) independence assumptions between the features. Naive Bayes is a conditional probabilistic model that can be represented with formulas given below (Sammut & Webb, 2010):

Naïve Bayes uses Bayes probability (formula number) for classifying a new unclassified instanced x with n features given below:

$$x = (x_1, x_2, x_3, \dots x_n)$$

For classifying x into one of k classes Naïve Bayes uses Bayes' theorem given below:

$$p(C_k \mid x) = \frac{p(C_k)\, p(x \mid C_k)}{p(x)}$$

While Naive Bayes assumes conditional independence for each attribute, Bayesian Network specifies which attributes are conditionally independent.

4.5.4. Logistic Regression

Logistic Regression is a statistical algorithm used to predict a binary class such as dead/alive, win/lose, pass/fail, or like in our case, stressed/not stressed. The logistic regression model uses the labeled samples as tuning parameters of a logistic function. A binary logistic regression model is used to detect stress with a dependent variable with two categories (stressed, not stressed.)

4.5.5. Multilayer Perceptron

A multilayer perceptron is shown in Figure 4.6, consist of nodes that are connected in a network. Each node performs a simple function, as shown in Figure 4.5, and passes the result to the network's next node. Input is the not classified sample's features, and output nodes are classes. Weights (denoted as w in the figures) helps to adjust the importance of nodes. The output node with the highest value is the sample's predicted class by the multilayer perceptron model.

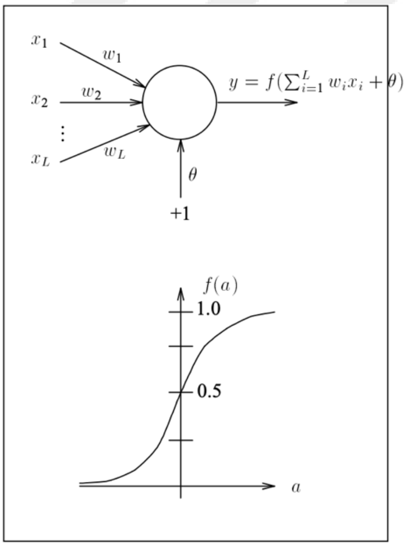

Figure 4.6 Structure of a node

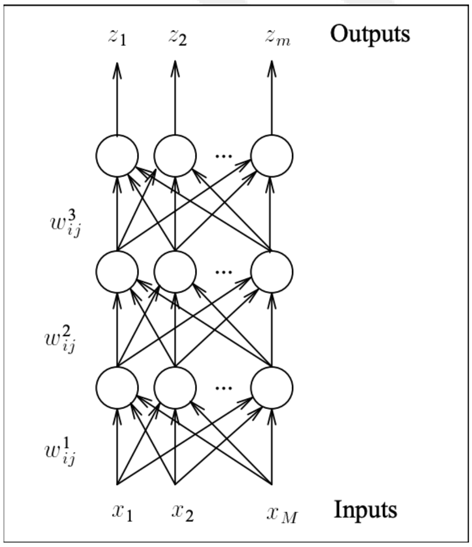

Figure 4.5 Structure of an MLP

4.5.6. K Nearest Neighbor

K Nearest Neighbor is a non-parametric supervised classification algorithm. k is a user-defined constant, and an unclassified sample is classified by assigning the most frequent label among the k training samples nearest to that unclassified sample. Distance between the unclassified sample and k training samples is calculated using a distance metric. Euclidian distance is chosen as the distance metric. Distance between two samples named as p and q that has n features can be calculated using following Euclidian Distance formula:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$$

4.5.7. Support Vector Machine

Support Vector Machine algorithm creates hyperplanes to separate different classes. When a new sample is given as input to an SVM classifier, it will check the sample's position in hyperplane space and return its class as output. Radial basis function kernel is one of the most popular used with SVM classifiers (Chang et al., 2010). The RBF kernel on two samples x and x', represented as feature vectors in some input space, is defined as:

$$\boldsymbol{K}(\boldsymbol{x},\boldsymbol{x}') = \boldsymbol{exp}\,(-\frac{\parallel \boldsymbol{x}-\boldsymbol{x}' \parallel^2}{2\boldsymbol{\sigma}^2})$$

$\parallel \boldsymbol{x}-\boldsymbol{x}' \parallel^2$ is squared Euclidean Distance between two samples and $\boldsymbol{\sigma}$ is a free parameter (Vert et. al, 2004)

5. RESULTS AND DISCUSSION

5.1.DriveDB

From the Drivedb dataset, ten drives (5, 6, 7, 8, 9, 10, 11, 12, 15, and 16) have every signal (ECG, EMG, foot GSR, hand GSR, HR, and RESP) and maker used to detect stress. Statistical features explained in Chapter 3 extracted and used with different classification algorithms to detect stress. At first dataset labelled as low, medium and high stress. K Nearest Neighbor (KNN) (with k=1,3,5), linear Support Vector Machines (SVM-linear), Support Vector Machines with radial basis function (SVM-RBF) supervised classification algorithms are used for creating different models to detect low, medium and high stress. In Table 5.5, detailed information about used features and accuracies of these models are given.

Table 5.1 Accuracy Rate of Classifiers with different feature sets – three stress level

Feature Index	KNN	SVM-linear	SVM-RBF	LR
1,2,3,4,5,6	**0.65 (k=3)**	0.61	0.56	0.48
1,2,3,4,5,6,7,8,9,10,11,12,13	0.52 (k=5)	**0.69**	0.65	0.61
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	0.48 (k=3)	**0.61**	0.56	0.56
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25	0.43 (k=3)	0.56	**0.60**	0.48
All 37 features	0.43 (k=3)	**0.61**	0.56	0.35

As shown in Table 5.5, the SVM-linear classifier gives the highest accuracy as 0.69 probability detects stress correctly. With a smaller feature space, KNN with k=3 also gives relatively accurate classification results. Considering time and space complexity, using KNN for this dataset gives accurate results for detecting stress with 0.65 probability. In every feature set, LR gives the worst accuracy results. These outcomes are used for choosing supervised classification algorithms for detecting stress in Simulation and City Drive experiments.

Table 5.2 Accuracy Rate of Classifiers with different feature sets – two stress level

Feature Index	KNN	SVM-linear	SVM-RBF	LR
1,2,3,4,5,6	0.83 (k=3)	**0.91**	0.78	0.61
1,2,3,4,5,6,7,8,9,10,11,12,13	**0.74 (k=3)**	**0.74**	**0.74**	0.48
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	0.78 (k=3)	0.78	**0.83**	0.39
1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25	0.79 (k=2)	**0.83**	0.79	0.43
All 37 features	0.57 (k=3)	0.73	**0.86**	0.43

Then with driveDB dataset binary classification has been made. Medium and high stress levels are considered as stressed and low stress level considered as not stressed. As shown in the Table 5.6, our classification accuracy increased for every classification algorithm. Our models can make more accurate predictions when it comes to binary stress classification. Also, in binary stress level detection, Logistic Regression gives the worst accuracy rates in every feature set. SVM with a linear kernel reached the highest accuracy rate as 91%. These outcomes are used for choosing supervised classification algorithms for detecting stress in Simulation and City Drive experiments.

5.2.The Racing Game Experiment

The dataset gathered from the racing game experiments has 3525 samples labeled as not stressed and 183 samples as stressed, which is 5% of the samples. AdaBoost, Bayesian Network, Logistic Regression (LR), Multilayer Perceptron (MLP), Naive Bayes, and Random Decision Forest (RDF) algorithms were used for classification. These classification algorithms get nearly the same accuracies for conditions specified in Table 5.1 and Table 5.2. However, for the balanced dataset mentioned in the following paragraphs, RDF gave the best accuracy. Therefore, RDF is chosen as the classification algorithm.

All classification algorithms give a 95% accuracy rate for 3525 samples and 42 features. Even though 95% is a relatively good score, examining the confusion matrix can give a better perspective.

Table 5.3 Confusion Matrix – All Records & All Features

Confusion Matrix	Not Stressed	Stressed
Not Stressed	3406	0
Stressed	174	0

As shown in the confusion matrix, the models predict every sample as unstressed. As a solution, synthetic stressed data was generated with WEKA's SMOTE function. After training with RDF, a model that can detect stressed data was created. Nevertheless, it is open to discussion, how accurately this model can integrate to real-world data.

Table 5.4 Confusion Matrix – All Records with Generated Stress Data & All Features

Confusion Matrix	Not Stressed	Stressed
Not Stressed	3161	245
Stressed	153	2979

In this dataset, every second were labeled separately. If the subject indicated a stressor, we labeled only that second as stressed. Nonetheless, in reality, get stressed has a longer duration than one second. Labels were updated using the following procedure: two seconds before a stressed sample and two seconds after a stressed sample, also labeled as stressed. With this modification, the stressed sample amount increased. A new balanced dataset was created with randomly chosen the same amount of stressed and not stressed samples. With the new balanced dataset and all features, RDF gets 65.3% as an accuracy rate. Also, the confusion matrix of this classification is shown below:

Table 5.5 Confusion Matrix – All Records with Balanced Data & All Features

Confusion Matrix	Not Stressed	Stressed
Not Stressed	418	294

Stressed	199	513

The SFS algorithm described in Feature Extraction was used to reduce dimensionality and increase accuracy. Also, SFS gives an insight into which features make more contributions to stress detection. KNN was used as an evaluation method with k = 3,5,7,9,20. In Table 5.4, the best features for each record and RDF accuracy rates are given. In Fig. 5.3, accuracy rates for various classifiers that used the balanced dataset with all records are given.

As shown in Table 5.6, record 1 has a better classification performance before feature selection. Sometimes, feature selection can cause lost features that lead to better classification results. However, in all other records, the model performance increases significantly.

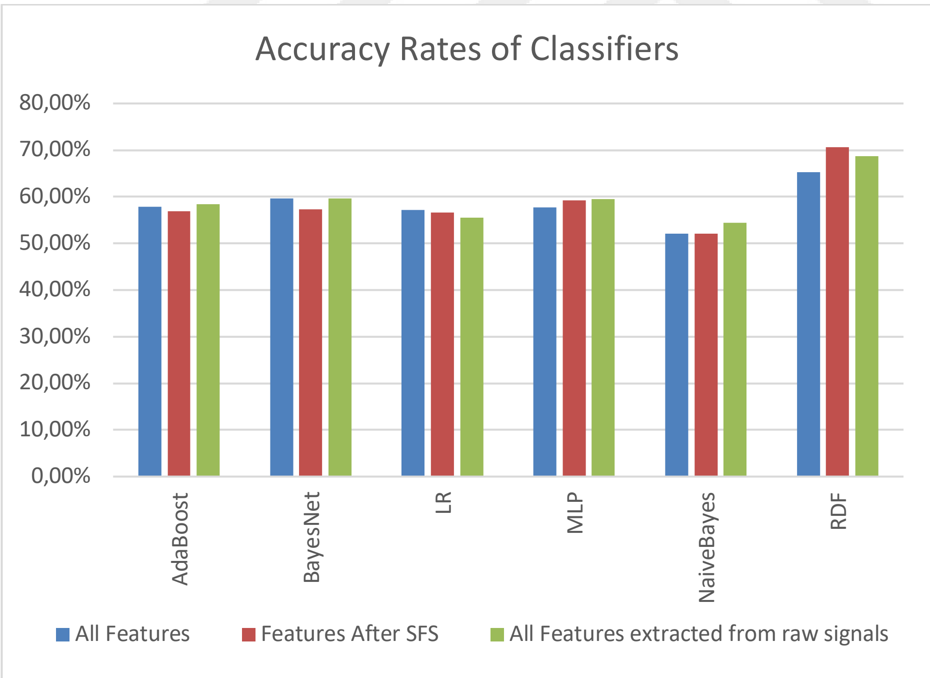

Figure 5.1 Accuracy Rate for Classifiers

Table 5.6 Classification Results - RDF

Record Number	Accuracy Before SFS	Best Features	Accuracy Rate
Record 1	**72.22%**	1,2,3,4,5,10,11,12,21	70.77%
Record 2	67.70%	1,21,41	**72.22%**
Record 3	75.94%	1,11,22	**79.78%**
Record 4	70.94%	1,2,25	**80.31%**
Record 5	70.61%	5,18,21,25,31,35,36	**77.86%**
All Records	65.3%	1,2,3,12,14,20,21,22,23,24,25,26,27,28,29,31,32,33,35	**70.64%**

5.3. Simulation & City Car Driving

In both Simulation and City Car Driving datasets are unbalanced. Not stressed samples are way more than stressed samples. To overcome this problem, we use our experience gained from the Racing Game Experiment. We reduced our dataset sample size by randomly choosing the same amount of unstressed and stressed samples to have a more balanced dataset. Then for each subject separately and for all subjects a KNN model with k=3 used for classification with different feature sets.

Four different feature set were created:

- Feature Set I (12 features): 6 statistical features extracted from raw ECG and EDA,
- Feature Set II (24 features): 6 statistical features extracted from raw and normalized ECG and EDA,
- Feature Set III (24 features with EDA components): 6 statistical features extracted from raw ECG, EDA, and EDA Phasic and EDA Tonic components
- Feature Set IV (48 features): 6 statistical features extracted from raw and normalized ECG, EDA, and EDA Phasic and EDA Tonic components.

Accuracy results for KNN (k=3) using feature sets explained above are given in Table 5.7.

Table 5.7 Accuracy Rate for KNN with k=3, different feature sets

	Simulation Experiments				City Car Driving Experiments			
Subject No	FS – I	FS – II	FS – III	FS – IV	FS – I	FS – II	FS – III	FS – IV
Subject 1	0.52	**0.56**	**0.56**	0.40	**0.57**	0.38	0.52	0.52
Subject 2	0.47	0.47	0.61	**0.63**	0.54	0.46	0.50	**0.64**
Subject 3	0.45	**0.60**	0.56	0.40	0.30	0.43	**0.52**	**0.52**
Subject 4	0.65	0.61	0.64	**0.72**	0.43	**0.48**	0.39	0.43
All Subjects	**0.61**	0.59	0.59	0.59	0.59	0.51	**0.63**	0.62

In Simulation Experiments, accuracies change between 72%-56%, our classifier reaches the highest accuracy for detecting stress with Subject 4 samples using 48 features. Using phasic and tonic components of EDA increased our model's accuracy by 8%. However, according to our results, having phasic and tonic EDA components does not always contribute to stress detection. Using the balanced dataset consists of every subject's driving simulation experiments or Subject 3's balanced dataset samples with phasic and tonic EDA components decreasing accuracy.

In City Car Driving Experiments, accuracies change between 64%-48%, our classifier reaches the highest accuracy for detecting stress with Subject 2 samples using 48 features. Three out of five balanced datasets have better accuracy with phasic and tonic components of the EDA signal.

In both experiment balanced datasets, classifier using normalized and raw signal features together, five out of ten cases outperformed the classifier using the raw signal features only. Our classifier reached similar accuracies and performed slightly better stress detection on the Simulation Experiments balanced dataset.

Features Sets were used with KNN classifiers shown in Table 5.6 consist of only time-domain features of ECG and EDA signals with its phasic and tonic components. From the Simulation Experiment dataset and City Car Driving Experiments, ECG signal HRV were extracted. From HRV, time-domain features, non-linear (geometrical) features, frequency-domain features were extracted. To extract these features, signals windowed in 30 seconds. A vector space with 67 features was created. Therefore, sample size was decreased, individual record base stress detection was not possible. All subjects' records samples were used to create a balanced dataset for Simulation and City Car Driving Experiments. SFS feature selection method was used for reducing feature vector space. The best 65, 63, 61, ..., 3 features are selected, and KNN, SVM, Logistic Regression (LR), Naive Bayes, AdaBoost, Multi-layer Perceptron (MLP), Random Decision Forest (RDF) classifiers trained. In Table 5.8, accuracy rates of these classifiers with all features and best feature sets are given

Table 5.8 Accuracy Rates of Classification Algorithms - Simulation & City Car Driving Experiments

	Simulation Experiments		City Car Driving Experiments	
Classification Algorithm	Feature Set (FS)	Accuracy	Feature Set	Accuracy
KNN (k=3)	All 67 FS, 7 FS, 5 FS, 3 FS	0.71	All 67 FS	0.54
KNN (k=7)	37 FS, 35 FS, 33 FS, 31 FS, 29 FS	0.71	37 FS, 35 FS, 33 FS, 31 FS, 29 FS	0.77
SVM (linear)	All 67 FS	0.64	All 67 FS	0.62
SVM (linear)	53 FS	0.71	59 FS, 57 FS, 53 FS, 51 FS	0.77
LR	All 67 FS	0.64	All 67 FS	0.69
LR	65 FS, 55 FS	0.71	53 FS, 55 FS	**0.85**
Naive Bayes	All 67 FS	0.57	All 68 FS	0.62
Naive Bayes	65 FS, 63 FS, 51 FS, 9 FS, 7 FS	0.57	53 FS	0.69
AdaBoost	All 67 FS	0.64	All 67 FS	0.62
AdaBoost	35 FS, 31 FS, 29 FS, 27 FS	0.79	63 FS, 59 FS, 57 FS, 55 FS	0.69
MLP	All 67 FS	0.71	All 67 FS	0.77
MLP	65 FS	0.71	65 FS, 61 FS	0.77
RDF	All 67 FS	0.71	All 67 FS	0.77
RDF	65 FS, 43 FS	**0.86**	35 FS	**0.85**

The Random Decision Forest classifier gave the highest accuracy with the best 65 features and 43 features as 86% for the all-subject balanced dataset of Simulation Experiments. Using HRV features and a feature selection to find the best features increased our stress detection accuracy from 61% to 86%. Using the SFS feature selection algorithm and eliminating features increased the SVM with linear kernel, Logistic Regression, AdaBoost, Random Decision Forest classifiers accuracy and did not change the KNN, Naive Bayes, and Multi-Layer Perceptron classifiers accuracy. Considering the fact that decreasing the feature vector space also decreases the execution time; instead of using all 68 features, using a feature selection algorithm and finding the best features that represent our dataset better is a more beneficial strategy.

In City Driving Car Experiments, the Random Decision Forest classifier with the best 35 features has the highest accuracy score as 85%. Also, Logistic Regression with the best 55 features and best 53 features yield an accuracy rate of 85%. Only the Multi-layer Perceptron classifier's accuracy didn't change with SFS selected features.

After analyzing the feature sets that make classifiers reach the highest accuracy rates in Simulation Experiments and City Car Driving Experiments, 32 common features are detected. The distribution of features according to their signal and the initial number of features belong to that signal has given below:

- HRV - 9 features / 19 features
- EDA phasic - 7 features / 12 features
- EDA tonic - 7 features / 12 features
- ECG - 6 features / 12 features
- EDA - 3 features / 12 features

From these common features, we can conclude that using HRV related features has improved our stress detection rate. EDA signal's tonic and phasic components have more influence than the EDA signal itself for detecting stress. More information about the feature sets is provided in Appendix - A Feature Sets and Appendix - B Name of the Features.

6. CONCLUSION

Detecting the driver's stress level and adjusting the driving environment can help eliminate one of the traffic accidents reasons. In this thesis, three different driving experimental setups were designed, and physiological signals gathered during every experiment.

In the Racing Game experiment, one subject played five different racing game levels while wearing EDA and ECG sensors. Plays were captured with a screen recorder. Using these recordings, stressed and not stressed labels are created for each second. Statistical features are extracted, and supervised classification algorithms are used for detecting stress. Models trained and tested using every sample of the dataset get a 95% accuracy rate but could not predict even one stressed sample correctly. The same amount of stressed and not stressed samples were randomly picked to make a balanced dataset. Using all records, RDF reached the highest accuracy of 70.64%.

In the Simulation Experiment, the simulation that has been built for this thesis is used. EDA and ECG signals are gathered with a 1000Hz sample rate. Four subjects tried to follow a specific route along in the simulation where they came across pedestrians and different stress triggers. Statistical features extracted from ECG, EDA, phasic and tonic components of EDA. KNN (with k = 3) classifier is used for detecting stress. Classifier got accuracies between 56% - 72%. From ECG signal time-domain (statistical), non-linear (geometrical), frequency-domain HRV features are extracted. The feature vector space increased up to 67 features. Using SFS, best features were identified. KNN, SVM, Logistic Regression, Naïve Bayes, AdaBoost, RDF, Multi-Layer Perceptron machine learning algorithms used for stress detection and results are compared. Using all subjects' records classifiers accuracies varied between 57% - 86%. RDF reached the highest accuracy rate.

In the City Driving Simulation Experiment, a simulation game is used as the driving stress stimulus. The game includes weather and traffic environmental settings that allow modifying the conditions for a more stressful environment. The same four subjects played the game while wearing EDA and ECG sensors, sample rate defined as 100 Hz. Subjects played this game just after the simulation experiment, on the same day, same room with the same setup. Our aim was to minimize the effects of simulation unrelated stressors. Same statistical features were extracted, and the same classifier (KNN) with the Simulation Experiment is used. Accuracies of classifier were obtained between 48% - 64%. Extracting HRV features and using SFS algorithm to reduce feature vector space increased our accuracy rates in Simulation Experiments. Therefore, same approach also applied in here. With HRV features accuracy rates of classifiers varied between 54% - 85%. RDF and Logistic Regression classifiers reached the highest accuracy.

In Simulation and City Car Driving Experiments, majority of the common features that leads to higher accuracy results are HRV features followed by EDA's phasic and tonic components. Instead of using only ECG and EDA signals, extracting new signals features (EDA phasic, EDA tonic, HRV), increased stress detection rate by 14% in Simulation Experiments, and by 21% in City Car Driving Experiments. Only 4 subjects participated in these experiments. Therefore, a relatively small dataset is constructed. To have more generalized results, experiments should be repeated with a larger subject group.

In some simulation versions, to creating roads and driving routes, real-life maps from 3rd party Unity map providers integrated into the simulation. Our intuition was making the driving experience as realistic as possible. We didn't use these versions in our experiments because some of the roads and buildings were missing for Turkey's cities. Also, rendering the map takes time and delays the start of the simulation. There are pedestrian routes and a car controlled by ai in our simulation, but there isn't a traffic light system. A real-life map that includes the subject's daily driving routes and needs less rendering time can be used in further studies. Traffic lights and other traffic dynamics such as policeman, etc. can be added to the simulation.

The Racing Game Experiment was made with one subject; the Simulation & City Car Driving Experiments were made with four subjects. Therefore, our datasets are relatively smaller than publicly available datasets. In future studies, these experiments can be repeated with more subjects to generalize the results. We also worked with a publicly available dataset, the DriveDB, in the scope of this thesis. SVM classification method reached 91% accuracy with only statistical features extracted from Hand GSR, Foot GSR, EMG, RR, and HR. From ECG and GSR signals gathered during the Simulation & City Car Experiments same features were extracted. Our classification models yield accuracies between 30% - 72%. The HRV signal was extracted from ECG, and signal-specific features were used with statistical features to overcome this problem. Our stress detection rates increased significantly.

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APPENDICES

Appendix A. Feature Names

Index	Feature Name
0	Max RR
1	Min RR
2	Avg RR
3	Max BPM
4	Min BPM
5	Avg BPM
6	SDNN
7	SD1
8	SD2
9	SD1/SD2
10	NN20
11	pNN20
12	NN50
13	pNN50
14	ULF power
15	VLF power
16	LF power
17	HF power
18	LF-HF ratio
19	Total power
20	Mean ECG
21	Mean normalized ECG
22	Variance ECG
23	Variance normalized ECG
24	Std ECG
25	Std normalized ECG
26	Median ECG
27	Median normalized ECG
28	ECG mean of first difference
29	ECG normalized mean of first difference
30	ECG mean of second difference
31	ECG normalized mean of second difference

32	Mean EDA
33	Mean normalized EDA
34	Variance EDA
35	Variance normalized EDA
36	Std EDA
37	Std normalized EDA
38	Median EDA
39	Median normalized EDA
40	EDA mean of first difference
41	EDA normalized mean of first difference
42	EDA mean of second difference
43	EDA normalized mean of second difference
44	Mean EDA phasic
45	Mean normalized EDA phasic
46	Variance EDA phasic
47	Variance normalized EDA phasic
48	Std EDA phasic
49	Std normalized EDA phasic
50	Median EDA phasic
51	Median normalized EDA phasic
52	EDA phasic mean of first difference
53	EDA phasic normalized mean of first difference
54	EDA phasic mean of second difference
55	EDA phasic normalized mean of second difference
56	Mean EDA tonic
57	Mean normalized EDA tonic
58	Variance EDA tonic
59	Variance normalized EDA tonic
60	Std EDA tonic
61	Std normalized EDA tonic
62	Median EDA tonic
63	Median normalized EDA tonic
64	EDA tonic mean of first difference
65	EDA tonic normalized mean of first difference
66	EDA tonic mean of second difference
67	EDA tonic normalized mean of second difference
68	Stress Label

Appendix **B.** Feature Sets – Simulation Experiment

FS	Simulation Experiment
65 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67
63 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67
61 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
59 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 30, 31, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
57 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 30, 31, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
55 FS	0, 1, 2, 3, 4, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 30, 31, 33, 34, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
53 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 30, 31, 33, 34, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
51 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 30, 31, 33, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67

49 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 45, 46, 47, 48, 49, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
47 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 45, 46, 47, 48, 49, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66, 67
45 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 45, 47, 49, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66, 67
43 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66
41 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64
39 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53, 54, 55, 57, 58, 59, 60
37 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53, 54, 55, 57, 58
35 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53, 54, 55
33 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49, 52, 53
31 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 49
29 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45
27 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41
25 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 18, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40
23 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39

21 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35
19 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31
17 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27
15 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 26
13 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 26
11 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 26
9 FS	0, 1, 2, 6, 7, 8, 9, 14, 26
7 FS	0, 1, 2, 6, 7, 8, 26
5 FS	0, 1, 2, 6, 26
3 FS	0, 1, 26

Appendix C. Feature Sets – City Car Driving Experiment

	Experiment 2
65 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 29, 30, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67
63 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 29, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
61 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
59 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
57 FS	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
55 FS	0, 1, 2, 3, 4, 6, 7, 8, 9, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 32, 33, 34, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
53 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 32, 33, 34, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
51 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67

49 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 20, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
47 FS	0, 1, 2, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
45 FS	1, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 42, 43, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 63, 64, 65, 66, 67
43 FS	1, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 39, 40, 41, 43, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66, 67
41 FS	1, 6, 7, 8, 9, 14, 15, 16, 17, 19, 21, 23, 25, 26, 27, 29, 31, 33, 35, 37, 40, 41, 43, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66, 67
39 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37, 40, 41, 43, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59, 60, 61, 64, 65, 66, 67
37 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 43, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59, 61, 64, 65, 66, 67
35 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59, 61, 64, 65, 66
33 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59, 61, 64
31 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57, 58, 59
29 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52, 53, 54, 55, 57
27 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52, 53, 54
25 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 49, 50, 52
23 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 45, 47, 48, 50

21 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 37, 40, 41, 48, 50
19 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 33, 35, 40, 48, 50
17 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 25, 27, 29, 40, 48, 50
15 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 21, 23, 29, 40, 48, 50
13 FS	1, 6, 7, 8, 14, 15, 16, 17, 19, 29, 40, 48, 50
11 FS	1, 6, 7, 8, 14, 15, 16, 29, 40, 48, 50
9 FS	1, 6, 7, 8, 14, 29, 40, 48, 50
7 FS	1, 6, 7, 29, 40, 48, 50
5 FS	1, 6, 7, 48, 50
3 FS	1, 7, 48

BIOGRAPHICAL SKETCH

Özge has studied Computer Engineering in Ankara University between 2013 – 2017. In 2017, she enrolled Galatasaray UniversityComputer Engineering Department for master study and started to work as research assistant at Istanbul Kültür University.

PUBLICATIONS

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