

MENTAL AND PHYSICAL HEALTH MANAGEMENT SYSTEM USING MACHINE LEARNING, COMPUTER VISION AND IOT SENSORS

submitted in partial fulfilment of the requirements for the award of
Bachelor of Technology Degree

in

Information Technology

by

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DEPARTMENT OF INFORMATION TECHNOLOGY

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **AHILA R R (38120007)** and **POOJA BALAKRISHNAN (38120058)** who carried out the project entitled “**MENTAL AND PHYSICAL HEALTH MANAGEMENT SYSTEM USING MACHINE LEARNING, COMPUTER VISION AND IOT SENSOR**” under my supervision from **JANUARY 2022** to **MAY 2022**.

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ABSTRACT

Stress is a major concern in daily life, as it imposes significant and growing health and economic costs on society every year. Stress and driving are a dangerous combination and can lead to life-threatening situations, evidenced by the large number of road traffic crashes that occur every year due to driver stress. In addition, the rate of general health issues caused by work-related chronic stress in drivers who work in public and private transport is greater than in many other occupational groups. An in-vehicle warning system for driver stress levels is needed to continuously predict dangerous driving situations and proactively alert drivers to ensure safe and comfortable driving. As a result of the recent developments in ambient intelligence, such as sensing technologies, pervasive devices, context recognition, and communications, driver stress can be automatically detected using multimodal measurements. This critical review investigates the state of the art of techniques and achievements for automatic driver stress level detection based on multimodal sensors and data. In this work, the most widely used data followed by frequent and highly performed selected features to detect driver stress levels are analyzed and presented. This review also discusses key methodological issues and gaps that hinder the implementation of driver stress detection systems and offers insights into future research directions.

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LIST OF ABBREVIATIONS

S.No	ABBREVIATIONS	EXPANSION
1.	ANN	ARTIFICIAL NEURAL NETWORK
2.	LRNN	LAYER RECURRENT NEURAL NETWORK
3.	SVM	SUPPORT VECTOR MACHINES
4.	BN	BAYESIAN NETWORKS
5.	DBN	DYNAMIC BAYESIAN NETWORK
6.	DT	DECISION TREE
7.	ANFIS	ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM
8.	HMM	HIDDEN MARKOV MODEL
9.	KNN	K-NEAREST NEIGHBOURS
10.	NMC	NEAREST MEAN CLASSIFIER
11.	LDA	LINEAR DISCREMENT ANALYSIS
12.	GSR	GALVANIC SKIN RESPONSE

CHAPTER 1

INTRODUCTION

Driving is a perceptual motor skill that entails multiple situations and consequently results in varying levels of stress. Stress is an important factor in driving because it can increase the risk of getting into a vehicle crash by affecting driver performance. The world death records issued by the World Health Organization (WHO) show that road traffic crashes cause over 1.2 million deaths annually (Sauer Zapf, 2012). This issue creates a significant cost in terms of loss of life and productivity for governments and societies. Stress has been identified as one of the most significant reasons for vehicle crashes.

1.1. STRESS AND CONSEQUENCES FOR DRIVING

Stress can be defined as a non-specific bodily response to a combination of external demands and internal concerns. Stress can be distinguished in the concept of eustress (positive stress) and distress (negative stress) (Selye, 1956). Eustress occurs when an individual's perceived ability to cope outweighs their perceived external demands. It can help an individual to increase their creativity and productivity and motivate them to perform a specific task. However, distress occurs when there is an imbalance between an individual's ability to cope and their perceived external demands. This sort of stress is dangerous and can cause negative consequences. In daily life, we often use the term "stress" to describe negative stress rather than positive stress. In this review, the term "stress" also refers only to negative stress. Stress is generally caused by an unpleasant intervener in the form of real events, called a stressor, and is affected by the subject's individual and ambient parameters, which are called the subject's context. Therefore, the external demands, known as a stressful situation, refer to the stressor and ambient parameters, while the internal concerns refer to the subject's individual parameters. There are three classes of stress: acute, episodic, and chronic. Acute stress is caused by a short-term stressor, and cortisol is secreted at high levels during the initial phase of stress to prepare the body for a fast and appropriate reaction (Selye, 1956). Professional drivers are prone to prolonged or continuous stressors, which can lead to chronic stress.

1.2. STRESS AND VEHICLE CRASH

Successful driver performance is a fundamental issue for preventing vehicle crashes, and a driver's success is often determined by adapting their behavior with respect to changes in environment and complexity of context while driving (Schmidt & Lee, 2005). Unsuccessful driver performance causes over 80% of vehicle crashes that result in fatalities and injuries. Driver performance can be negatively affected by stress, which then can cause traffic violations and crashes. This is because stress causes both high mental workload and negative moods in drivers (Fresson, 2008). High mental workload may result in inadequate information processing and imperfect perception. It can also cause cognitive distraction, which is one of the most common reasons for drivers' distraction. A driver's cognitive distraction may lead to impaired decision-making capabilities. As a result, high mental workload due to stress lead to deterioration of driver performance. Negative moods, such as anger and aggressiveness, can be induced in stressful driving situations.

1.3. CHRONIC STRESS CONSEQUENCES FOR PROFESSIONAL DRIVERS

Chronic stress is a serious issue for professional drivers, as it adversely impacts on their general physical and mental health. Bus drivers' exposure to chronic occupational stress can increase their chance of developing cardiovascular problems. Gastrointestinal and musculoskeletal disorders are also considered a consequence of chronic stress for professional drivers. Post-traumatic stress disorder is also reported as a common chronic mental health issue in ambulance and bus drivers.

1.4. CURRENT METHODS TO MEASURE STRESS MODALITIES

The human body generally employs the fight-or-flight response to instantaneously make decisions during a stressful situation, including how to avoid its negative outcomes. For example, avoiding accidents during dangerous driving conditions. The nervous system is responsible for executing this strategy in three consecutive steps: sensing, perceiving, and responding to stress. Central and peripheral nervous systems are the two key components that control different organs of the body and work together to regulate the fight-or-flight response. In this regard, the sensory nerves collect information related to a stressful situation and send them to the brain

as the main core of the central nervous system. The brain processes the received information and individual parameters to perceive the stress level (perceiving), and finally sends proper responses through somatic and autonomic motor nerves to different parts of the body for voluntary and involuntary reactions (responding). The fight-or-flight response can be monitored through different modalities to measure driver stress.

1.5. PSYCHOLOGICAL EVALUATION

Psychological evaluation is mostly used as a stress marker or ground truth in stress recognition domains. There are various questionnaires, known as clinical stress questionnaires, which are employed for this evaluation, such as the Stress Self Rating Scale. A weakness of this approach is that drivers may find it difficult to recall acute stressful events, as the questionnaires are usually conducted at the end of experiments. There are also some self-reporting methods that can provide flexible ways to measure driver stress, either during driving (Rodrigues, 2015) or after driving. A common method is the N-point Likert scale: drivers score their stress level using a predefined range of scores, such as 1 (non-stress) to 6 (high stress). Another method is categorization: drivers select a category of stress from a predefined stress category group, such as low, medium, and high stress. However, it should be noted that filling out questionnaires or self-reporting during driving is not practical for safety reasons. Annotation is a common technique that helps drivers to answer abstract self-reporting methods. However, this study noted that increasing the frequency of annotation will increase the driver's mental workload. Using a combined method to incorporate both online and offline annotation, a study by asked bus drivers to wear smart clothes, called a vital jacket, and to tag stressful situations by pressing an embedded button on the jacket while driving. They also added a stress thermometer system to confirm the driver's stress level while driving, on a scale of not-at-all stressful to extremely stressful. The driving paths were recorded using GPS during the experiment and then visualized using Google Earth. The bus drivers, by reviewing the recorded paths, provided a brief explanation for the stressful events followed by their stress intensity evaluation.

1.6. MEASURING DRIVERS' INTERNAL PHYSIOLOGICAL RESPONSES

The autonomic nervous system regulates physiological stress responses through the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). When the human body needs to react quickly to eliminate a stressor, the SNS is activated. The PNS is activated when the body needs to be in a relaxed state. These physiological stress responses can be measured through different bio signals (biochemical or physiological). The level of adrenaline and cortisol in various body fluids such as blood, saliva, or urine can be used as the two main biochemical measurements to detect stress, as stressful situations increase the level of these hormones in the body. Although adrenaline is a well-known biomarker for stress, measuring the level of this hormone to detect driver stress is not recommended because it is measured by invasive methods, such as blood sampling. In contrast, cortisol levels can be determined from saliva, which does not require invasive sampling methods. Other bio signals used to detect driver stress levels are physiological data such as heart rate activity, blood pressure, electrodermal activity, respiration response, muscle activation, skin temperature, and pupillary response.

1.7. CORTISOL LEVEL

The sympathetic nervous activity caused by driver stress can be evaluated using salivary cortisol levels. In a study, salivary amylase activity was employed to assess acute stress effects on vehicle drivers. In this study, 20 young female drivers were recruited, and each driver spent 21 minutes in a driving simulator. During this time the participant's salivary amylase activity was measured every 3 minutes. This study demonstrates two points: first, the feasibility of measuring this biomarker non-invasively during driving tasks, to facilitate monitoring of driver stress levels; second, the use of saliva as a biomarker to obtain an objective ground truth for assessing driver stress, as an alternative to the current subjective ground truth methods.

1.8. HEART ACTIVITY

Driving in stressful situations activates the sympathetic part of the ANS, which results in a sudden increase of heart activity and puts the driver's body in the-fight-or-flight response mode against the stressor. This means that the heart pumps blood through the body faster and so oxygen is delivered faster to the body's organs to

prepare the driver to react. Among different indicators of heart rate activity, heart rate and heart rate variability have been widely used in detection of driver stress levels. Generally, these two parameters can show the fluctuation of the ANS which directly affects heart activity, allowing the physiological body response toward a stressful situation to be observed.

1.9. ELECTRODERMAL ACTIVITY.

Another reliable physiological signal to detect driver stress is electrodermal activity (EDA), also called skin conductance response (SCR) or galvanic skin response (GSR). A body's physiological response to a stressful situation results in continuous variations in the electrical activity of skin, which can be measured on the hand (palm area, first and middle fingers) or on the foot (soles) by using EDA sensors. The correlation between EDA signal and drivers' stress levels have been investigated by several studies. There are different statistical EDA features that have been commonly used to analyze driver stress, such as mean, standard deviation, mean amplitude, peak rise time, peak amplitude, first absolute difference, and mean of the first difference. EDA response is characterized by a tonic component and short-term phasic responses (Braithwaite, Watson, Jones, & Rowe, 2013). Tonic component or skin conductance level (SCL) can reflect psycho-physical activation, and varies between individuals (Kappeler-Setz, Gravenhorst, Schumm, Arnrich, & Tröster, 2013). The frequency range of this component is between 0 and 0.05 Hz. The average and variance level of the tonic component are two commonly used features in detecting driver stress level. Summary of the startle magnitudes, duration, and the area of SCR orienting responses, sum of durations, sum of magnitudes, sum of estimated areas, and frequency of occurrence are extracted from EDA features and used to discriminate the drivers' stress levels as well (Healey & Picard, 2000). There are several studies which have used EDA signals with other modalities to enhance performance of driver stress classification. In one of these studies, 12 features were extracted from the physiological signals of 10 drivers, which include EDA, ECG, and respiration (Healey & Picard, 2000).

1.10. RESPIRATION ACTIVITY

Change in respiration activity is a physiological response to stress and emotional state. The respiration system serves as a metabolic and homeostatic regulator of depth and speed of breathing. Stressors can increase respiration activity. The respiration responses of drivers can be collected in different ways, including wearing belt sensors, placing a thermistor into the nose and mouth, and using a flow meter. A group of statistical features – such as mean, standard variation, skewness, and kurtosis – is extracted from respiratory signals to detect drivers' stress levels. The result shows that there is a significant correlation between these features and stress levels. Another common feature in this domain is respiration rate (RSPR). This feature is the number of detected peaks in the respiratory signal per minute where each of the peaks is related to a chest expansion (Soman, 2013). A high correlation between this feature and drivers' stress levels are reported by. In another study, RSPR was also extracted from 10 drivers' respiratory signals and then divided into high and low breathing rates.

1.11. MUSCLE ACTIVATION ELECTROMYOGRAPHY (EMG)

Muscular reactions caused by stressful driving situations can occur unconsciously even when no physical activity is required (Healey, Seger, & Picard, 1999). Stressful situations can affect this reaction by increasing muscle activity (Lundberg, 1994) which can be measured using electromyography (EMG) signals. These signals are recorded from the drivers' shoulders (e.g., the trapezius muscle) or facial muscles (e.g., the masseter muscle) to analyze their stress levels. Statistical features such as mean, root-mean square (RMS), zero crossing rate (ZCR) and root-mean quad (RMQ) are extracted from the EMG signals to detect drivers' stress levels. Among these features, ZCR has been found to be more correlated to drivers' stress levels than other features, since high levels of driver stress can increase muscle constriction resulting in a high ZCR value (Soman, 2014). There are several studies that focused on the fusion of EMG with other physiological signals to improve the system of detecting drivers' stress levels. It has been shown that fusion of ECG with EMG signals to detect two levels of drivers' stress (low and high) is promising (Soman, 2014).

1.12. SKIN TEMPERATURE (ST)

Another physiological signal used to detect driver stress is skin temperature. In stressful driving situations, SNS activity causes peripheral vasoconstriction in the body, thereby decreasing the driver's skin temperature. Current methods can provide a contactless and passive solution for monitoring driver skin temperature continuously by using thermography sensors in the vehicle. Nose, cheek, forehead, and jaw regions on the face, which contain abundant arterioles and arteriovenous anastomoses, are used as skin temperature features to monitor drivers' stress and mental workload. It measured drivers' skin temperature, cardiovascular response, and contextual parameters to stressful driving situations. Temperature data through the finger (Tsf), nose (Tsn), cheek (Tsch), jaw (Tsj) and forehead regions (Ts fh) are collected. Two cardiovascular parameters, normalized pulse volume (NPV) and total peripheral resistance (TPR), were also used to detect peripheral vasoconstriction. The result shows that a gradual increase in a driver's stress level can cause peripheral vasoconstriction and decrease the thermal signature of drivers' faces in the supraorbital region, which is immediately above the eye socket, was measured to detect the mental workload of drivers.

1.13. PUPILLARY DILATION

It has been shown that pupillary response is another promising physiological signal for detecting driver stress (Pedrotti, 2014). The ANS continuously regulates tuning of pupil size, which is known as pupillary dilation. The pupil is dilated – i.e., its diameter increases – by SNS activity when the body is under stress. To this end, pupil diameter (PD) can be a good indicator of drivers' stress levels. Pedrotti, (2014) employed a classifier based on the neural network and wavelet transform to detect the stress levels of drivers using PD, EDA, and a self-assessment questionnaire. They reduced the sample rate of PD signals from 50Hz to 1.5625Hz, and then applied a Haar wavelet with 5 decomposition levels to the PD signals to extract meaningful information from low- frequency bands. The result of the study showed that PD could classify drivers' stress levels significantly (79% accuracy) while the performance of EDA was poor.

CHAPTER 2

LITERATURE SURVEY

2.1. Facial Expression Method

Some studies have focused on analyzing stress levels of drivers using facial expression response (FER). Negative emotions such as anger and disgust which are caused by driver stress were recognized by FER (Gao, Yuce, & Thiran, 2014). They used a near-infrared camera to monitor drivers' faces and extracted 49 facial landmarks from each frame of the video using a face tracker. Then, holistic, and local texture features from each frame were extracted to recognize drivers' anger and disgust.[1] They achieved 85% accuracy among 49 subjects using an SVM classifier in a one-vs-all manner.

2.2. Vocalization Technique

Drivers' stress (Bořil et al., 2012), behavior (Angkititrakul, Petracca, Sathyanarayana, & Hansen, 2007), distraction (Boril, Omid Sadjadi, Kleinschmidt, & Hansen, 2010) and mental workload (F. Chen et al., 2012) may change human vocal production. Stress levels of drivers were detected by using their voice waveforms (Fernandez & Picard, 2003). Vocalizations of drivers were recorded while they were engaging in several mental tasks such as adding up two numbers.[2] The Teager energy operator and multi-resolution analysis via wavelet transforms techniques were used to extract sub-band energy from each voice waveform frame. Then, cepstral coefficients using the sub-band energy were calculated for each frame. The classification step, in this study, involved two approaches. In the first approach, the features within vocalizations were used to classify four drivers' stress levels using 5 different hidden Markov models classifiers. In the second approach, the features across vocalizations were used to classify four drivers' stress levels using SVM and artificial neural network (ANN) classifiers. The highest accuracy obtained among the 7 classifiers was 51.22%. Some studies have investigated stress levels of a group of drivers through voice analysis while they were engaging in secondary activities such as doing mental tasks, operating the radio, and talking on a cell phone (Bořil et al., 2012; Li, Jain, & Busso, 2013)

2.3 Vehicle Dynamic Data

The effects of stress on a driver can be measured indirectly through dynamic data

obtained from the vehicle. This data can be collected through different systems such as CAN-Bus (Bořil et al., 2012; Rigas et al., 2012; Rodrigues et al. 2015), GPS tracking (Rigas et al., 2012), driving simulators, mobile phones and orientation sensor (Lee et al., 2017). One study used PPG signals and steering-wheel motion data – captured using a 9 degree-of- freedom orientation sensor to detect drivers' stress (Lee et al., 2017). In the study, 3 stress detection models were built using SVM classifiers with different kernel functions. The proposed model using SVM-RBF kernel function was found to be the optimal, with an accuracy of 95.38%. Lanata et al. (2015) proposed a model based on the fusion of vehicle dynamic data (steering wheel, car velocity and driver response time) with physiological responses (EDA, HRV and respiration) to detect three stress levels of drivers.[2] This study was conducted in a driving simulator and contained 3 driving sessions simulating different conditions, namely, relaxed, stress level 1 and stress level 2. Statistically significant differences in both physiological responses and vehicle dynamic data across the experiments were observed in the study. Previous findings in the literature (Rigas et al. 2012) also confirm that vehicle dynamic data can complement data from drivers' physiological responses in building a more accurate stress model. Vehicle dynamic data (steering wheel and speed) were used to detect the stressed or neutral state of drivers while talking on a cell phone (Bořil et al., 2012). Standard deviation and energies of high frequency components of wavelet decomposition from the steering wheel and speed data were extracted in the study. The proposed model shows that the fusion of steering wheel and speed data with vocalization data in detecting stress level of drivers is promising (achieved 88.2% accuracy).

2.4 Contextual Data Analysis

Any stressful driving situation contains contextual parameters and stressors that induce a certain level of stress in the driver. Contextual parameters that can affect drivers' stress and performance are known as vehicle crash factors (Hennessy, Wiesenthal, & Kohn, 2000; Hill & Boyle, 2007, Tchankue et al., 2013).[3] Measuring contextual parameters along with the other stress responses can be beneficial for building a more accurate driver stress level detection system. Generally, contextual parameters can be divided into two categories: internal and external.

2.5 Internal Parameters

A driver's internal or individual parameters that can easily affect stress levels are important contextual data. A driver's mood can influence their brain's analysis of driving stressors, so stress is affected by whether that mood is positive or negative. Some studies demonstrated that negative moods, like aggression or frustration, can increase the risk of vehicle crash (Hemenway & Solnick, 1993; Underwood, Chapman, Wright, & Crundall, 1999; Deffenbacher et al., 2003).[4] Other studies showed that driver mood can be affected by different factors, such as driving at a certain time of a day, drinking coffee before driving (R. R. Singh et al., 2013), having a stressful day at the office (Matthews et al., 1998; Hennessy et al., 2000) and continually experiencing stressful events while driving (Hennessy et al., 2000). Another individual parameter, which has a high impact on perceived level of stress, is driver personality. Eysenck's personality questionnaire (EPQ) defines neuroticism/stability, psychoticism/sociability, and extraversion/ introversion as three major personality dimensions (Eysenck & Eysenck, 1975). Neuroticism can increase driver stress level directly (Matthews, Dorn, & Glendon, 1991) in that the perceived stress level by drivers who score high on neuroticism, in any stressful driving situation, may be higher than average. Psychoticism is closely linked to lacking in empathy (Eysenck & Eysenck, 1975), so drivers who score high on psychoticism have a low susceptibility to stress (Matthews et al., 1991; Furnham & Saip, 1993).[5] The level of perceived stress by this group of drivers, in any driving stressful situation, may be lower than average, which may explain their apparent tendency to exhibit risky driving behaviors (Sümer, 2003).

2.6 Environmental Parameters

Driver stress is also affected by environmental parameters such as driving in heavy traffic, heavy rain, icy roads, night-time driving, and being trapped behind a slow-moving vehicle (Rigas et al., 2011), as well as family and work-related issues (Gulian, Matthews, Glendon, Davies, & Debney, 1989; Novaco et al., 1990).[6] These environmental parameters can be divided into 4 groups of data:

- 1) weather-related conditions,
- 2) visibility-related conditions,
- 3) driver–environment interactions (Hill & Boyle, 2007) and
- 4) driving routes (Hennessy et al., 2000). (See Table 3.3) Hill & Boyle (2007),

used environmental parameters related to visibility-related conditions, weather-related conditions, and driver–environment interaction, along with internal parameters, to evaluate drivers' stress.[7] The results show that the extracted parameters from the weather-related conditions and driver–environment interaction groups are more correlated to high levels of drivers' stress compared to the visibility-related conditions.

CHAPTER 3

METHODOLOGY

SYSTEM ARCHITECTURE

Initially we send an electric signal called a GSR sensor (galvanic skin response) with a +5V DC current to check stress levels and depression, and then a 3.3V to check any other physical changes or disturbances like perspiration, pressure, or cardiac functions. We transform the machine's sensor to a sensor module using Low Pass Filter and High Pass Filter, which allows us to transfer the signals. After delivering the sensor, the blood pressure is pulled down and then raised to display changes as the voltage is reduced to 0.5 and 0.2. Because it's impossible to precisely identify changes due to variances, we add a low pass filter and a high pass filter with a 10K-Ohm resistance, and then convert the raw signal to an analogue signal. Our 0.2,0.3 volts will be boosted to 0.8 or 0.9 volts by the operational amplifier before reaching the ADC. The signal is processed and examined in the Microcontroller to see if it is leveled/conditional or unconditional, and the data is transferred via IOT, which can be seen in the device. To connect with Wi-Fi, use the TX module (transmitter module). When a Visual Display is the app that we installed to view our cellular device. Data Storage is the database that we generated in the WIFI cloud that we can refer to and access the data in the future. Following the prediction of an issue in our physical and mental state, the data received will be prompted in our device prior to our safety, which falls under the computer vision technology where hardware and IOT are interfaced with each other.

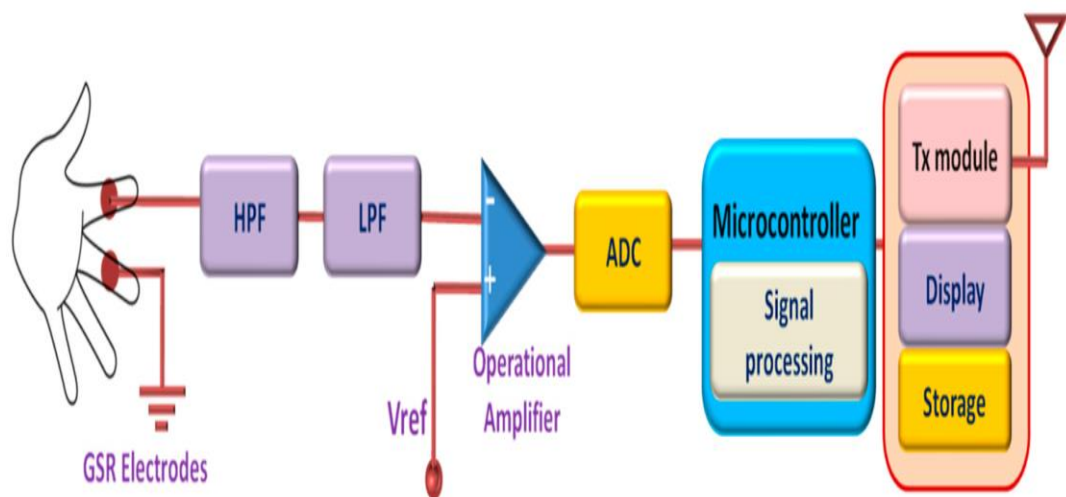


FIG. 3.1. SYSTEM ARCHITECTURE

The focus of this paper is to review state-of-the-art techniques and systems to detect driver stress levels. To structure this review, a general framework for an automatic and continuous driver stress- level detection model is presented in Figure 3.1. The best modalities for data collection (signal acquisition) are reviewed in section 3.5. Data analysis is a key approach for evaluating stress after collecting data from different modalities. Data analysis contains pre-processing, feature generation, feature selection, feature reduction and machine-learning steps. This process helps to identify the relationship between stress and data modalities. Stress evaluation needs to take advantage of each of these steps to make the stress recognition process partially or fully automated, and to explore the hidden related patterns within a large amount of data and implicit correlations. It is therefore of great interest to use different methods and investigate their roles in this domain to get a desirable outcome. The reviewed studies in this section are reported in more detail in Table 3.1.

Table 3.1. Physiological signals and related features used to analyze driver stress.

SIGNAL	REFERENCE	FEATURE
ECG	Healey & Picard, 2000; Healey & Picard, 2005; Yamakoshi 2007; Katsis, 2008; Rigas, 2008; Yamakoshi 2008; Akbas, 2011; Rigas, 2011; Deng, 2013; Wang, 2013; Singh, 2013; Munla, 2015; Rodrigues, 2015; Lanatà, 2015; Heikoop, 2017.	Heart rate (HR): mean, standard deviation (SD). PPG: mean, variance, SD, signal energy, time duration, bandwidth, time–bandwidth product dimensionality, cardiac output, PPG instantaneous, pulse height, PPG rise, PPG fall, PPG cardiac, NPV. Heart rate variability (HRV) (time domain): mean of the first difference (MFD), mean of R-to-R intervals (MRR), SDRR, MNN, SDNN, RMSSD, pNN20, pNN50, NN50, triangular interpolation of the NN

		interval histogram (TINN), heart rate variation from baseline. HRV (frequency domain): LF/HF ratio, HF, LF, very low frequency (VLF), total power (TP). HRV (nonlinear analysis): sample entropy, detrended fluctuation analysis (DFA), DFA-$\alpha 1$ and DFA-$\alpha 2$, SD1, SD2. HRV (time-frequency domain analysis): VLF, LF and HF by using wavelet and short time Fourier transform (STFT) analysis.
EDA	Avcı, Akbaş, & Yüksel, n.d.; Healey & Picard, 2000; Healey & Picard, 2005; Rigas, 2008; Katsis, 2008; Akbas, 2011; Rigas, 2011, 2012; Deng, 2013; Singh & Queyam, 2013b; Singh, 2013; Lanatà, 2015; Ollander, Godin, Charbonnier, & Campagne, 2017	Mean, variance, SD, mean amplitude, peak rise time, peak amplitude, half-recovery, peak energy, rise rate average, decay rate average, percentage decay, number of peaks, rate of SCR, first absolute difference (FAD), MFD, mean rise duration, number of SCR, latitude, the amplitude sum of SCRs (AmpSum), the phasic area under curve, the max phasic amplitude, mean of SCR, variance of SCR, mean of SCL, variance of SCL, number of the nonspecific response, frequency, magnitude, duration, area of orienting responses, sum of frequency of occurrence (SF), sum of durations, sum of magnitudes (SM), sum of the estimated areas (SA), mean of positive derivative,

		mean of absolute derivative, proportion of positive samples in derivative , number of local maxima.
EMG	Katsis, 2008; Soman, 2014; Zheng, 2015	Mean, RMS, ZCR, RMQ.
ST	Yamakoshi, 2007; Shastri, 2008; Yamakoshi, 2008	Finger temperature (Tsf), nose temperature (Tsn), cheek temperature (Tsch), jaw temperature (Tsj), forehead temperature (Tsfh).
Blood Pressure	Yamakoshi, 2008	Systolic blood pressure, mean blood pressure, diastolic blood pressure.
Pupil Dilation	Pedrotti, 2014	First different pupil diameter, wavelet decomposition detail for pupil diameter.

Table 3.2. Physical signals and related features used to analyze driver stress

Signal	Reference	Feature
Face	Gao, 2014	Facial Expression (FER): local DCT feature, local descriptors.
Vehicle Dynamic Data	Bořil, 2012; Rigas, 2012; Lanata, 2015; Lee, 2017	Steering wheel angle (SWA): wavelet decomposition energy for SWA; standard deviation of SWA (SDSWA), SDSWA rate, sample entropy; area under the SWA curve; number of sign changes of SW; Mean and SD of SWA differences between two consecutive skids; reaction time; SWA first peak; SWA second peak; first response time of SWA, first ability time of SWA. Steering wheel motion (SWM) captured by

		orientation sensor (Y-axis): mean, SD, variance, average squared power, median, root mean square, range difference max and mean, sum power spectrum energy (0-8 Hz), mean power frequency (0-8 Hz), Shannon entropy energy (0-8 Hz), peak power frequency (0-8 Hz), median power frequency (0-8 Hz), percentage of point outside the control eclipse, weighting function outside the control eclipse. Speed: Wavelet decomposition energy, sample entropy, SD, average. Deceleration: Average. Heading Change: Average magnitude in heading changes. Throttle: Average. Engine performance: Engine's rounds per minute (RPM). Throttle: average. Engine performance: Engine's rounds per minute (RPM).
vocalization	Fernandez & Picard, 2003; Boril, 2010; Bořil, 2012	Mel frequency cepstral coefficients (MFCC), Perceptual linear prediction cepstral coefficients (PLPCC), mean and SD center bandwidths and frequencies of the first four formants (F1, F2, F3, F4) extracted from voiced speech segments.

Table 3.3. Contextual data and related features used to analyze driver stress.

Context Type	Reference	Context Name	Data Collection Method
Internal /Individual	Matthews, 1991; Hennessy, 2000; Hill & Boyle, 2007; Cantin, 2009;	Personality traits, mood, gender, age, gender, number of crashes, commuting, alcohol consumption per week, driving behavior history, years driving experience.	Questionnaire
External / environmental	Novaco, 1990; Hill & Boyle, 2007; Rigas, 2011; Miller & Boyle, 2013	Route data: direction of travel, driving on mountain roads. Weather-related conditions: heavy rain, no rain, rain, snow, cold weather, icy and slippery roads. Visibility-related conditions: night-time driving, road visibility, driving behind large trucks. Driver–environment interactions: braking due to slower drivers, drivers’ work-related problems, driver’s family disturbances, and traffic density.	Questionnaire, mobile GPS, vehicle GPS, forward-looking camera, CAN-bus system

3.1. PRE-PROCESSING

The first critical step in modelling driver stress levels is pre-processing and noise reduction of input data. Data can easily become corrupted by instrumentation and magnetic noise, body movement, and poor electrode skin contact. Pre-processing techniques remove all unwanted artefacts and provide purer data for the feature extraction step. This issue has been addressed by several studies in the domain of driver stress-level detection. Baseline wander, muscle noise, and electrode misplacement are the most frequent sources of noise in ECG data, leading to detection of false-positive stressful events. A low-pass Butterworth filter can be used to remove baseline wander and muscle noise in drivers' ECG signals (Rigas, 2011). Extremely noisy blocks of bus drivers' ECG signals were detected and removed using a standard deviation filter method (Rodrigues, 2015). For HRV signals, R peak detection algorithms may make mistakes in calculating inter-beat (RR) intervals from ECG signals. Lanate, (2015) applied an adopted piecewise cubic spline interpolation method to correct these technical artefacts in RR intervals and then manually checked and removed physiological artefacts, which include ectopic beats and arrhythmic events, in RR intervals. To compensate for any artefacts in drivers' EDA signals generated by baseline wander, sensor and body movement, different filter methods have been used in the literature. A smoothing filter (moving average) was used to find high frequency noises in drivers' EDA.

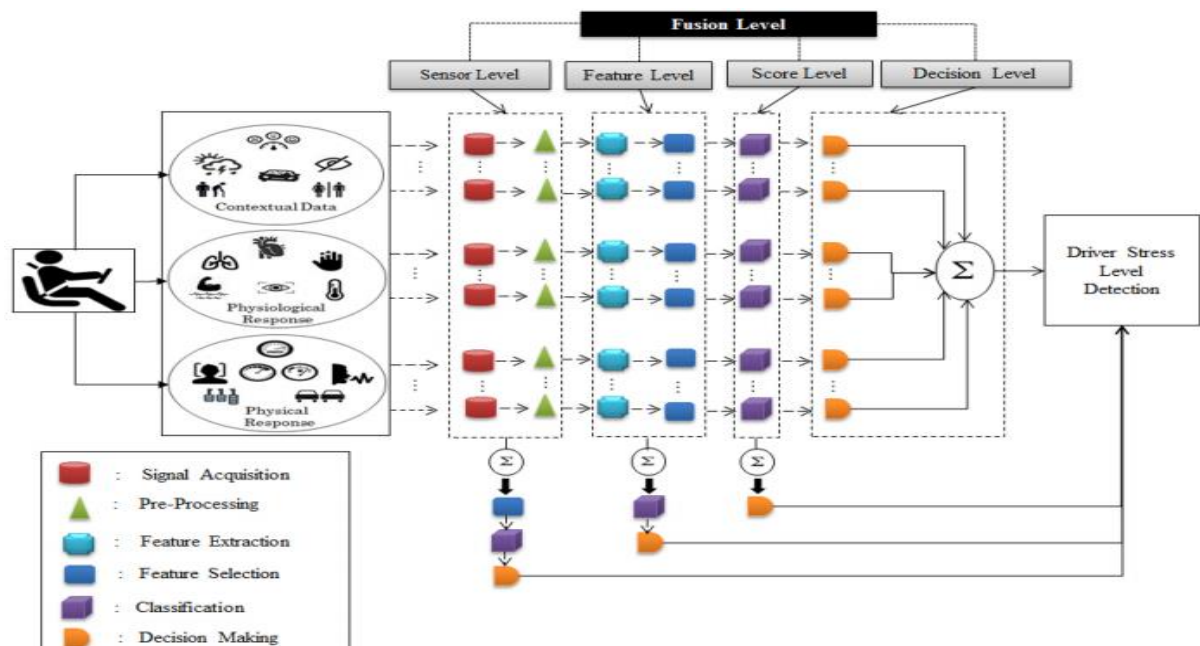


FIG. 3.2. DRIVER STRESS-LEVEL DETECTION FRAMEWORK.

In another study, body movement noises in drivers' facial EMG signals were removed by using a Butterworth low pass filter (500 Hz) (Christos D. Katsis, 2008). Pose variation as a source of noise in drivers' facial expression data was removed using an adapted least square method (Gao, 2014). A fast Fourier transformation technique, adapted to a based noise cleaning approach, was used to remove substantial noise in the supraorbital region from drivers' temperature signals (Shastri, 2008). Bořil, (2012) used a full wave spectral subtraction method to reduce noise in drivers' vocalization signals. In addition, other studies used KNN algorithms to correct missing data (Rigas, 2011) and normalization techniques to remove the role of inter-subject variability (R. R. Singh, 2013; Rodrigues, 2015; Lanatà, 2015). Table 3.2 sets out the features extracted from the physical signals reviewed. In this table, most of the vocalization features were extracted from time-frequency and frequency domains, while the extracted features from vehicle dynamic data are from time, non- linear, and time-frequency analyses. The features extracted from contextual data (both individual and environmental conditions) are presented in Table 3.3. To investigate the general quality features for driver stress recognition based on real- time and simulated driving scenarios, which features are repeated more frequently or performed more successfully in driver stress classification, we summarized the most widely used data and their commonly extracted features in this domain. (See Table 3.4) Based on the literature, among the physiological signals, ECG, EDA, respiration, and EMG signals show the most remarkable data, and their correlated features are presented in the table.

Table 3.4. The most widely used data and their commonly extracted features to build driver stress recognition model

Data	Experimental setting	Features
ECG	Simulator	Mean, SD, SDNN, RMSSD, pNN50, TINN, MRR, SD of RR, LF/HF ratio, LF, VLF.
	Real-Time	Mean, SD, MNN, SDNN, RMSSD, pNN20, pNN50, NN50, MFD, MRR, LF/HF ratio, LF, VLF, HF, TP.
	Simulator	Mean, FAD, mean of SCR, variance of SCR, Amp Sum.

EDA	Real-Time	Mean, mean amplitude, peak rise time, peak amplitude, half- recovery, peak energy, rise rate average, decay rate average, percentage decay, number of peaks, rate of SCR, FAD, MFD, frequency, magnitude, duration, area of orienting responses, SF, sum of duration, SM, mean of positive derivative, mean of absolute derivative, proportion of positive samples in derivative , number of local maxima.
Respiration	Simulator	Mean of RESP, SEM, MFD, MSD, SDFD, and SDBA, difference between max and min value of breathing amplitude, kurtosis, RESP frequency (0-0.1), RESP frequency (0.2-0.3), and RESP frequency (0.3-0.4).
	Real-Time	Mean of RESP, SD of RESP, RSPR, HR / RESP ratio, PPGRSP; max, min, and mean breathing amplitude, MFD, maximal respiration – mean of respiration (range), RESP frequency (0-0.1), RESP frequency (0.1-0.2).
Vehicle Dynamic Data	Simulator	Steering wheel angle (SWA): area under the SWA curve; number of sign changes of SW; Mean and SD of SWA differences between two consecutive skids; reaction time; SWA first peak; SWA second peak; first response time of SWA, first ability time of SWA.
	Real-Time	Average of vehicle speed, average of vehicle deceleration, average magnitude in vehicle heading changes, average of Throttle, RPM.
Contextual data	Simulator	Age, years driving experience, commuting, alcohol consumption per week.
	Real-Time	Age, gender, number of crashes, Weather condition (no rain, rain, heavy rain), snow, cold weather, icy and slippery roads, braking due to slower drivers, traffic density.

3.2. FEATURE SELECTION

Increasing the number of extracted features causes high computational costs and

introduces unnecessary noise, which reduces the accuracy of classification algorithms (Kira & Rendell, 1992). A feature space with high dimensions impedes target classification learning. Feature-selection methods help to reduce redundant features and negative effects of high-dimensionality. Different feature-selection techniques search for the best subset of features based on evaluation functions to enhance overall classifier performance. Generally, these methods are divided into 4 groups, namely, filter, wrapper, embedded (Kudo & Sklansky, 2000; Alba, García-Nieto, Jourdan, & Talbi, 2007; Nakisa, 2017) and hybrid methods (Min & Fangfang, 2010; Wang & Liu, 2016). In the domain of driver stress detection, these methods are employed in some studies to improve performance.

3.3. FILTER METHODS

Filter methods use ranking techniques – which are used for their simplicity and good success in different applications – to order the features. Ranking techniques score each feature based on its relevance to an outcome variable and use a threshold to remove the features below the threshold. Several studies have applied filtering methods to explore the features most relevant to different levels of drivers' stress. Deng, (2013) extracted 22 features from drivers' EDA, EMG, respiration, and HR signals, and then used a filtering method, which first measured the efficiency of the features separately and then calculated diversity among the features. The feature sets selected by this method were then combined using a combinatorial fusion method to detect 3 stress levels of drivers.

3.4. WRAPPER METHODS

Wrapper methods find heuristically suboptimal feature subsets by applying search algorithms. Sequential forward floating selection (SFFS) is a wrapper method used in the literature which iteratively finds the near optimal subset of the features. This method first starts with a null subset and, based on defined criteria, evaluates the features, and then adds the features which satisfy the criteria to the subset. The algorithm is designed to modify the criteria if some features are excluded. In this case, based on the criteria, the features in the subset will be ordered and the worst feature is removed from the subset. By using this dynamic process, increasing, and decreasing the features in the subset, the SFFS method gradually reaches the near-optimal feature set. Healey and Picard (2000) applied SFFS on 11 features which

were extracted from drivers' ECG, EDA, and respiration signals. Seven features were selected by SFFS and then fed to a KNN classifier. The recognition rate of the proposed model was reported as 88.6%. Olander, (2017) used an exhaustive feature-selection method to find the best subset of features from each set of ECG, EDA, respiration, and EMG signals. Next, to find the optimal signal combination, an exhaustive search method was applied on the selected features from the signals. The result indicated that the combination of ECG, EDA, and respiration signals to distinguish drivers' rest from stress has the optimal performance (accuracy: 87.3% $\pm$ 2.8) among different signal combinations. In another study, SFFS was applied on 20 features extracted from drivers' PPG signals and steering-wheel motion data (Lee, 2017).

3.5. EMBEDDED METHODS

Embedded methods seek to decrease the computation time for training different subsets computed in the wrapper methods (Chandrashekar & Shahin, 2014). Wang. (2013) applied a "feature-based transformation recognition" technique, which consists of feature extraction, selection, and reduction steps. They applied kernel-based class separability (KBCS) as a feature selection method, and PCA and LDA as feature reduction methods, to select the most relevant and important drivers' ECG features, and then a KNN classifier was used to build a stress model. The proposed model shows an acceptable performance compared to the same studies which used multiple signals and features.

3.6. HYBRID METHODS

Hybrid methods try to combine filter and wrapper methods to increase the efficiency and accuracy of feature selection. The hybrid method is used in a driver stress level detection model to enhance the performance of the model (R. R. Singh, 2013). The filter method was a combination of entropy and variance techniques whereas the wrapper method was an integration of two sequential feature selection techniques, namely, sequential backward selection (SBS) and sequential forward selection (SFS). First, the filter selection techniques were applied separately to find a relevant subset of the features. Next, the results were subjected to bitwise conjunction ("ANDed") to provide a new subset of the features. In the next phase, applying the wrapper method, the SBS and SFS techniques selected several features together.

Finally, the results from both techniques were compared and 27 features were selected. In addition to this result, they applied an ad-hoc feature mask to ensure that no significant clinical features were lost, and the results subjected to bitwise disjunction (“Oared”), providing 30 features.

3.7. MACHINE LEARNING APPROACHES

Machine learning approaches are employed to build a model which can detect or predict the stress levels of drivers (supervised learning) or cluster them (unsupervised learning). These methods try to explore the patterns most related to drivers’ stress levels. The classifiers used in this domain range from linear classifiers, such as linear mixed model, and linear SVM; non- linear classifiers, such as ANN, and SVM with polynomial and Gaussian kernels; and probabilistic classifiers, such as naïve Bayes classifier (NBC).

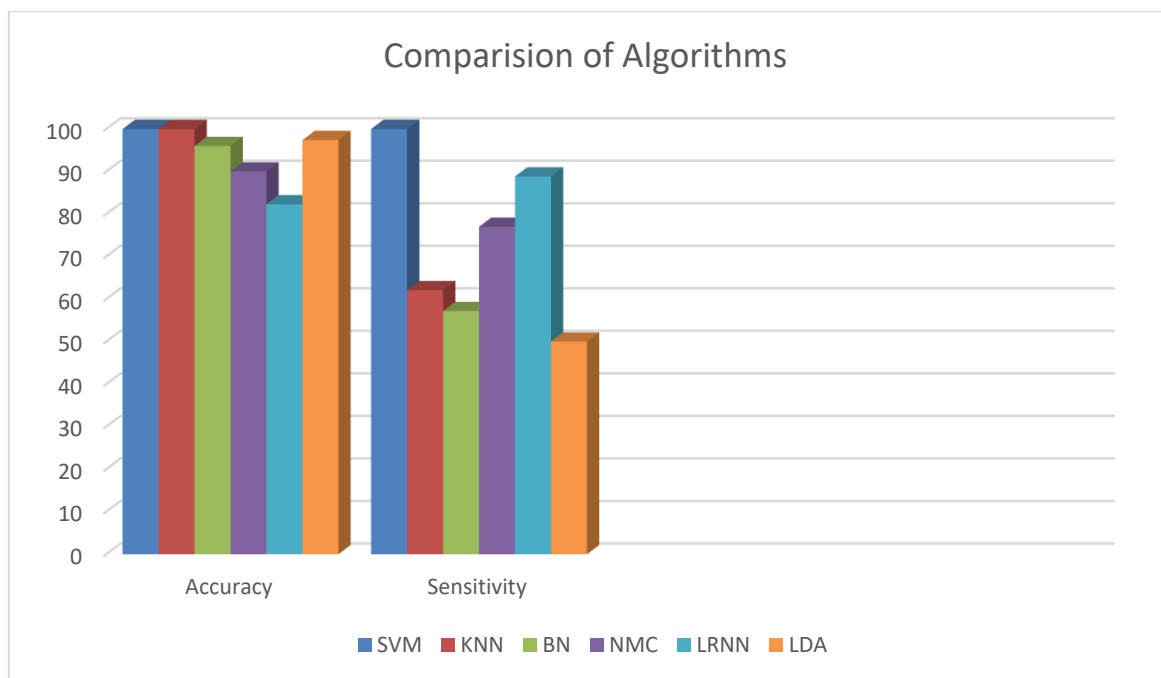


FIG 3.3. Algorithm Comparison

3.8. ARTIFICIAL NEURAL NETWORK (ANN)

An ANN simulates brain function through mathematical functions (Fyfe, 2005), and aims to solve machine learning problems by combining a large amount of processing elements (neurons) which are highly interconnected and work together (W. C. Huang, 2006). Generally, an ANN consists of three types of artificial neurons

– input, hidden, and output neurons – which are organized in layers. Each neuron is connected to all the neurons in its layer and a value (weight) is assigned to the connection between them. The neurons also send an activation value to each of the neurons in the next layer. This value is measured based on their output value and the weight between them and their connected neuron in the next layer. Therefore, the connection between the neurons in an ANN can be explained as follows: step (1) input values are assigned to the input neurons; step (2) in the hidden layers, each neuron sums the received activation values from its connected neurons and then determines its output value by using a transfer function; step (3) a similar process is done in the output layer to generate the output values of the neural network.

3.9. LAYER RECURRENT NEURAL NETWORK (LRNN)

LRNNs have a similar mechanism to feed-forward neural networks but they have feedback connections to capture dynamic temporal patterns (Medsker & Jain, 1999). In recurrent neural networks, inputs are dependent on each other, and each output is the function of its corresponding inputs and previous states (Q. Liu & Wang, 2008). LRNNs have internal feedback loops in each hidden neuron which allows them to store the previous states. In this process, the output of each hidden neuron is stored in a context unit, then fed to the hidden neuron after a predetermined delay. Based on the latency in drivers' responses to stressful driving situations, an LRNN can handle these delays by using its context units. To this end, this dynamic neural network and 6 different static neural networks were used separately to detect 3 stress levels of 19 drivers from their physiological data (Singh, 2013).

3.10. SUPPORT VECTOR MACHINES (SVM)

Another classification method is SVM (Hsu, Chang, Lin 2003), which has been used for high- dimensional problems. This algorithm is a discriminative classifier that iteratively searches to find the optimal hyperplanes to separate training samples accurately. The selection of these hyperplanes is based on two criteria: first, the hyperplanes must separate training samples accurately, and second, there must be a greatest possible distance between support vector points and the hyperplanes. SVM deals with nonlinear problems by using kernel functions which map non-linear separable data into high-dimensional space, then finds the optimal hyperplanes.

SVM classifiers, with 3 different kernel functions – linear, polynomial and Gaussian – were used to detect stress of 28 drivers using their PPG signals and steering-wheel motion data (Lee, 2017). The highest accuracy (95.38%) was obtained using an SVM-Gaussian kernel function classifier.

3.11. BAYESIAN NETWORKS (BN)

A BN is designed as a probabilistic model that allows representation and reasoning with uncertain data (Friedman, Geiger, & Goldsmith, 1997). It is a graphical model which contains nodes and links. Each node represents a feature and has a set of possible values. The link between two nodes represents a direct dependency between their features, which are quantified by conditional probability. A naïve Bayes classifier (NBC) is a special variant of BN in which class nodes have no parent and there is no link between nodes related to features, and the feature nodes just link to the class nodes. An NBC offers a competitive performance against other sophisticated classification methods such as decision trees and ANN (G. H. John & Langley, 1995; Theodoridis & Koutroumbas, 2006). Furthermore, this method can handle high- dimensional data easily, due to its short training time (Hand, Mannila, & Smyth, 2001). Rigas, (2012) collected ECG, EDA, and RSP signals along with some vehicle dynamic data from 13 drivers, and then built two different BN models to detect drivers' stress. The first model (BN1) used the physiological signals to detect drivers' stress and achieved 82% accuracy on the test dataset. The second model (BN2) merged BN1 with two NBCs to make a model which supported mutual relations between stress and event detection. The NBCs were used to detect overtaking and hard braking events by using the vehicle dynamic data. BN2 achieved 96 % accuracy on the test data.

3.12. DYNAMIC BAYESIAN NETWORK (DBN)

A DBN is represented as a probabilistic framework for uncertainty knowledge information (Murphy, 2002). This method is an extended version of BN for dynamic processes. Each node represents a feature value in a specific time and the relationships between nodes are determined based on their occurrence times. Rigas (2008) applied a three-layer DBN model to detect 3 stress levels of a driver: natural, low, and medium-high. This model was built using the driver's ECG and EDA signals and achieved an overall accuracy of 71.2 %. In the study, the DBN architecture

involved layers of risks, diseases, and symptoms, inspired by medical expert systems. Driving events were used in the risk layer, the driver's stress levels were used in the diseases layer and extracted features from the driver's ECG and EDA signals were used in the symptoms layer.

3.13. DECISION TREE (DT)

A DT is a popular classifier which represents decision rules (Safavian & Landgrebe, 1990). Features are represented as nodes and class labels are represented as leaf nodes. The structure of a DT is determined based on dataset homogeneity. This means that features are inserted into the tree nodes based on their ability to split training samples into their actual classes. To this end, the best splitter or feature is selected by using a greedy search algorithm and inserted in the root node. Then the training samples, based on the feature values, are divided into various branches. If all the sub-samples in a branch belong to a specific class label, it leads to a leaf node and the branch is marked to be not extended anymore. Otherwise, DT finds the best splitters or feature for sub-samples in the branch to divide the samples into more branches. This process will be repeated until there is no branch to be extended. In one study, DT, and tree-augmented NBC were hybridized to classify 4 stress levels of drivers (Katsis, 2011). The accuracy of this method was reported as 71.9%, measured using a 10-fold cross-validation technique.

3.14. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

An ANFIS classifier (Jang, 1991) is counted as a powerful discriminator by integrating an ANN (multilayer feedforward network) and fuzzy reasoning. This algorithm combines the advantages of these two methods to solve classification problems (Chang & Chang, 2006). An ANFIS classifier can work with numerical data or experts' knowledge, and extract fuzzy rules from them (Kia, Norouz, Carse, Vinney, & Rabbani, 2006). An ANFIS classifier includes a premise and consequent parameters which together play a significant role in improving classifier performance. Katsis (2008) used an ANFIS classifier to classify 4 emotion classes of drivers using physiological signals and achieved 76.7% accuracy. The classifier was based on the combination of a least squares (forward pass) and gradient descent method (backward pass). This combination was selected due to its high efficiency in tuning the premise and consequent parameters to improve the

performance of the ANFIS classifier. In the forward pass step, the ANFIS consequent parameters were optimized by applying the least squares method, and then in the backward pass step, its premise parameters were adjusted using the gradient descent method based on the fuzzy set.

3.15. HIDDEN MARKOV MODEL (HMM)

The HMM is a classifier which can work with a wide range of time series data. In a simple Markov model, labels are the hidden states and observations linked to the labels are the visible states. This classifier predicts future states based on the following assumptions. The current observation is generated from a hidden state at time t . This hidden state, based on the Markov property, is dependent on the previous hidden state at time $t-1$. Therefore, an HMM classifier finds all possible sequences of labels for a sequence of observations and computes probability distributions over each of the sequences of labels, and then the best label sequence is selected to assign to that sequence of observations. Although HMM classifiers have been employed in different domains, they are well-known in the speech recognition domain (Ghahramani, 2001). Fernandez et.al (2003) used 5 different HMM classifiers to recognize 4 stress levels of drivers using their voice waveforms. The selected classifiers were hidden Markov model (HMM), autoregressive hidden Markov model (ARHMM), factorial hidden Markov model (FHMM), hidden Markov decision tree (HMDT), and a mixture of simple hidden Markov models (M- HMM). The best classification accuracy was obtained using the M-HMM classifier (51.22%).

3.16. K-NEAREST NEIGHBOURS (KNN)

A KNN classifier is a simple and effective algorithm uses a probabilistic approach to classify new samples based on a similarity measure (e.g. distance). In the training step, the algorithm only stores all samples in the training dataset. In the test step, for each test sample, the algorithm finds k most similar training samples (neighbors), and then selects the most frequent class label among them (Altman, 1992). This label is assigned to the test instance as its class label. Although a KNN classifier is conventionally used in biometric and stress management systems, it is more computationally expensive than other classifiers. A KNN classifier was used to distinguish low, medium, high, and very high stress levels of 10 drivers using their ECG, EDA, EMG and RSP signals (Healey & Picard, 2000). The accuracy of this

model was reported as 88.6%. Wang (2013) used a KNN classifier to discriminate two drivers' stress levels using ECG signals and achieved an averaged recognition rate of 97.78% (5 cross fold validation).

3.17. NEAREST MEAN CLASSIFIER (NMC)

An NMC is a simple and linear classification algorithm which is based on a template matching approach. This classifier discriminates new samples based on a similarity measure (e.g. distance). An NMC stores all samples in the training dataset. The mean point of each class label is determined based on the corresponding training samples. Then, NMC assigns each test sample to a class label whose mean is closest to the test sample. Used NMC, KNN, and multilayer perceptron to detect 3 stress levels using physiological and physical data of 14 drivers. These classifiers are representative of template matching, probabilistic, and decision boundary construction approaches respectively. To evaluate the classifiers' performance, a leave-one-subject-out cross-validation technique was employed. It has been shown that the NMC had the best performance, achieving over 90% accuracy.

3.18. LINEAR DISCERNMENT ANALYSIS (LDA)

An LDA is a linear classifier which aims to maximize class separability and reduce computational costs by projecting a d -dimensional sample onto a k -dimensional subspace (where $k < d$). LDA performs this approach in 5 steps: step (1) computes a d -dimensional mean vector for each class label; step (2) computes two $d \times d$ -dimensional scatter matrices called a between-class scatter matrix and a within-class scatter matrix; step (3) computes the d -dimensional eigenvectors and corresponding d -dimensional eigenvalues for the calculated scatter matrices; step (4) drops the $(d-k)$ eigenvectors with lowest eigenvalues to reduce the dimensionality of the sample; step (5) transforms the sample onto the reduced feature space. An LDA classifier was used to build a general/personal driver stress-level detection model through physiological signals, and to classify drivers' stress into three levels (low, medium, and high) using their EDA, ECG, respiration, and EMG signals. The recognition rate of the proposed model was reported as 97.4%. collected ECG and EDA signals of 6 drivers and built 3 personal stress-detection models for each driver using SVM-linear kernel function, SVM-quadratic kernel function and LDA classifiers. The result indicated that the built models using the LDA

classifier were almost better than the other models built by the other classifiers.

3.19. FUSION TECHNIQUES

Detecting driver stress level using different modalities may not attain perfect accuracy due to different issues such as nonideal machine-learning techniques, incomplete training, resulting in false negative and false positive (Blasco, Chen, Tapiador, & Peris-Lopez, 2016). Combining different modalities can help to overcome some of these limitations and build a more accurate and reliable driver stress recognition model. Modality fusion is defined as the integration and combination of different types of data collected from a subject(s) to detect different affects. Modality fusion can be performed at any level of data analysis, such as sensor-level, feature-level, score-level, or decision-level fusion. Most of the reviewed studies used feature-level fusion techniques to build their driver stress-level detection model. In feature-level fusion, all the extracted features from each modality are combined into one vector for use in the next data analysis step. Combining different modalities at feature-level has been demonstrated to be an effective way to build a driver stress-level detection model.

SYSTEM'S ADVANTAGES

- The library provides a framework to use at a level of managing circumstances, including, but not limited to, parallelization of tree improvement employing all your CPU social class during organizing.
- Appropriate Computing is used to orchestrate very large models employing a group of devices.
- Out-of-Core Computing is used for unfathomably large datasets that do not fit into memory.
- Keep improving data plans and estimating how much gear to use.

CHAPTER 4

FRAMEWORK IMPLEMENTATION & EVALUATION

To develop an automated system that proactively detects driver stress levels, data needs to be collected, transferred, pre-processed, reduced, integrated, and used to make the final decision automatically. To increase driving safety, this system needs to present a practical solution that continuously, unobtrusively, and automatically detects driver stress levels at an early stage. Reviewing the literature shows several methodological issues which hinder the implementation of such a system. These issues can be grouped into six major categories: (i) data quality, (ii) data set, (iii) modality fusion, (iv) data analysis, (v) system acceptability, (vi) driving scenario. Sections 4.1 to 4.7 discuss how these categories may be considered open research problems in the domain of driver stress-level detection.

4.1 Data Quality

Collecting high-quality data is essential to the success of any stress detection system. Therefore, data collection should be carried out meticulously to obtain data that is accurate, efficient, secure, relevant, timely and appropriately represented. Generally, the quality of data can be corrupted by different issues such as inadequate sampling rates of recording devices and the presence of noise in the data. Some studies employed recording systems with high sample rates to overcome this issue. However, it should be noted that any real-world driving scenario will potentially cause noise and artefacts in data. Although different filtering methods have been applied to cope with this issue., more accurate and reliable algorithms are still needed to detect and remove different types of noise associated with drivers' data, especially noises caused by body movement. Another challenge in data quality is correct annotation of recorded data. Recorded signals are commonly annotated by using self-reporting methods, which is entirely subjective, and different drivers may have different psychological responses to the same stressful driving situation. Thus, developing an objective metric to measure driver stress levels can help to address this issue.

4.2 Data Set

Using publicly available data sets has several benefits, such as facilitating a fair comparison of all experiments and reducing the workload of researchers. However, the number of available public datasets in this domain is limited due to ethics and

privacy issues. The only public driver physiological data set in this domain was collected by Healey (2000). The database contains a collection of different physiological data (e.g. ECG, EMG, EDA and RSP) from 17 drivers who were driving around one hour or more in Boston city streets and highways. Another data set includes survey data from a study that assessed drivers' perceived stress in different driving situations, such as driving on various roads, in traffic jams, and weather-related scenarios (Hill & Boyle, 2007). The survey collected information related to the users' requirements from an advanced traveler system (Ng, Barfield, & Mannering, 1995). The data was collected through a mail-back survey which was distributed in 1994.

4.3 Modality Fusion

Integrating modalities is an essential approach to obtain a more accurate detection model where unimodal data cannot represent a full understanding of driver stress levels, especially in real-world driving situations. Although modality fusion can help to build a more efficient and accurate model, the main challenge is in integrating the modalities (sensor, feature, score, or decision). Among the different fusion techniques, feature-level fusion has been used in most of the reviewed studies. Although fusion in the feature level has been shown to have an acceptable performance, there are still a range of sub-issues associated with it, such as asynchrony between the modalities, selecting the optimal window size for different modalities and increasing computational cost by increasing number of features. For other fusion techniques, more research is needed to investigate their roles in building a more accurate and reliable driver stress detection system.

4.4 Data analysis

Another challenging issue which affects the performance of a real-time driver stress recognition system is high dimensionality of data. This issue is addressed by using feature-based methods, especially feature selection and reduction. These methods remove the redundant and irrelevant data to improve the performance of the system. Applying and evaluating dimensionality reduction techniques to enhance the automatic detection of driver stress level performance is an open research challenge that needs to be investigated further. Recently, evolutionary computation algorithms, particularly particle swarm optimization and differential evolution, have

been shown to be effective as feature selection methods in affective detection. In addition, the literature suggests it is worth exploring new features and investigating new feature extraction analyses that have greater correlation with driver stress levels. For example, nonlinear analysis of HRV signals (which is in the early stage of use) was shown to have more correlation to stress levels of drivers compared with the frequency domain analysis of HRV signals.

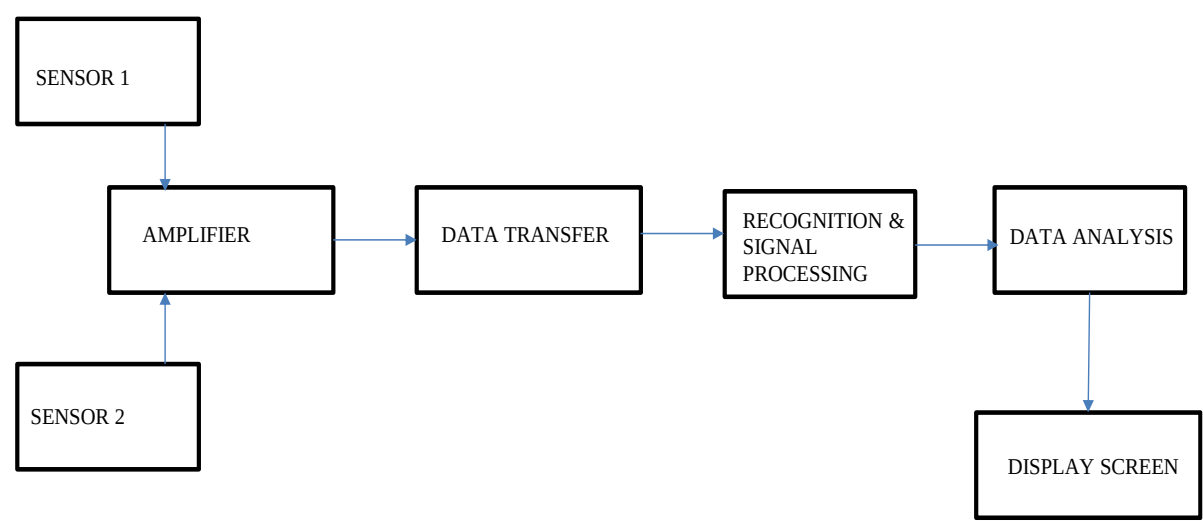
4.5 System Acceptability

Another important issue is the acceptability of such a system by car drivers in terms of the method of collecting the data. A system may be considered acceptable when it can record data in an unobtrusive and non-invasive manner. The data related to driver physical responses and context can be easily tracked and measured in an acceptable way, but the correlation between these types of data and driver stress levels has been investigated much less than physiological signals. Further studies are therefore required to investigate the correlation between these modalities and drivers' stress. Although physiological signal data has been researched more thoroughly, the body contact sensors which record physiological responses may not be practical for continuous stress monitoring of drivers. Using body contact sensors is an obtrusive method that can restrict drivers' movements and increase their awareness of being monitored.

4.6 Driving scenario

It has been proved that drivers' stress responses obtained from simulated and actual driving scenarios are different. Drivers' tension levels in simulated driving scenarios are low compared to their tension levels in real-time scenarios since the risk of crash is zero. Therefore, different driver stress levels can be observed better from real- world driving experiments. However, recording stress levels of drivers in real-time environments using intrusive physiological sensors may affect driving safety and cause vehicle crashes. For safety and ethical reasons, it is therefore very hard to evaluate drivers' stress levels in real-time driving situation. Today's advanced driving simulators have the advantage of well-designed visual, rotation and sound systems that provide a highly realistic sensation which is close to a real driving feeling. These simulators provide an efficient and reliable way to study driver stress responses by using driving scenarios which are repeatable.

Fig 4.1 Framework of the proposed system



CHAPTER 5

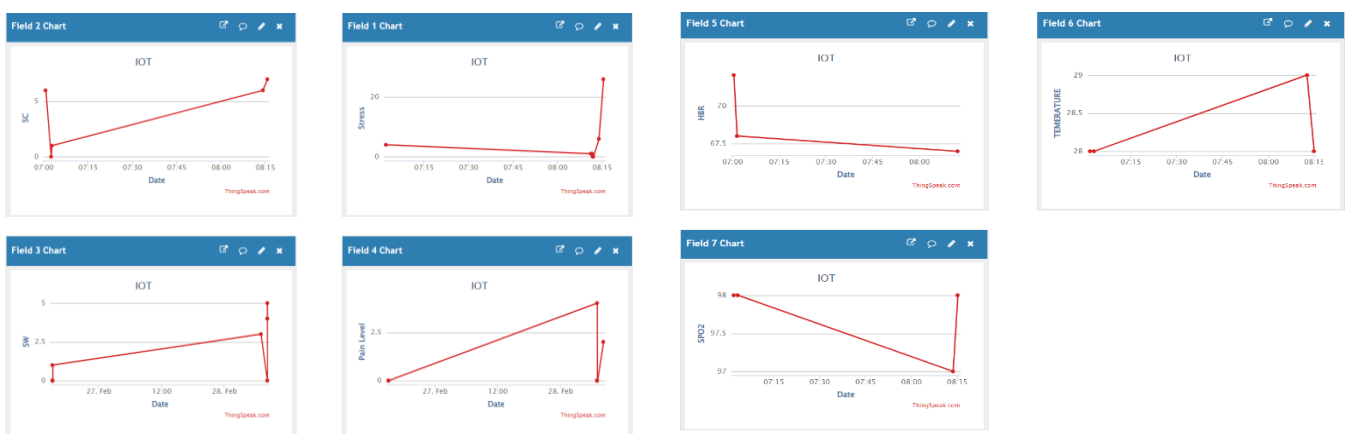
RESULTS AND DISCUSSION

Stress is a main reason for vehicle crashes. Prolonged exposure to different driving stressors may also cause health problems in professional drivers. Due to the ever-increasing fatality rate and economic losses related to driver stress, an in-vehicle system for early detection of driver stress levels is essential to increase drivers' safety. This system should continuously detect driver's stress levels, predict dangerous driving situations and, at an early stage of detecting an increase in stress, alert the driver proactively. The findings from several studies in the domain of smart cars have shown that such a system can not only increase driving safety but can also cause positive impacts on drivers' driving patterns and behaviors. In addition to improved safety, such a system may have an additional benefit of preventing harmful long-term consequences of stress in professional drivers, and could lead to a more efficient economy, environment (optimizing fuel consumption, greenhouse gas emissions and so on) and society (social and psychological response). In this review, a general framework of a multimodal driver stress detection system was presented. This framework involves two main parts: data collection and data analysis. Data collection includes different modalities, such as psychological, physiological, physical, and contextual data, which are used to measure driver stress. We have reviewed the most recent works related to these modalities and discussed their limitations. Data analysis includes computational techniques, such as pre-processing, feature generation, feature selection, feature reduction and machine learning techniques, which were comprehensively discussed.

A summary of the reviewed literature that used different modalities and machine learning methods to build driver stress recognition model can be found in Table 3.6. Among the different modalities, physiological responses have been used widely in the domain of driver stress detection, but there are still some challenges related to this modality that need to be addressed. Generally, physiological changes due to stress are subject-dependent and vary from subject to subject. Therefore, it is difficult to make a general model that suits all drivers, and a system would need to be able to adapt itself to everyone's physiology. Another challenge is that body contact

sensors for physiological monitoring are not practical for a continuous driver stress level detection system since they are too obtrusive for real-world driving situations. Physical and contextual data can be collected using less intrusive and more practical methods suitable for real-life situations. As physical and contextual data are also potentially correlated to stress levels of drivers, future studies should target these data more in building an automatic driver stress-detection system. It has been shown that the different modalities can complement each other to create a more robust driver stress detection model; therefore, considering multimodal approaches to build the optimal system is essential in this domain. One of the major issues is in combining or integrating the modalities in the fusion levels (sensor, feature, score, or decision). Applying effective data collection and analysis methods to address methodological issues to build such a system is also recommended for further research.

Different assessments in the field of clever vehicles have shown that this sort of device might additionally foster security as well as unequivocally influence drivers' driving styles and affinities Adjacent to redesigned security, this sort of device may in like manner enjoy the extra benefit of hindering the long-range effects of tension in drivers, achieving an even more innocuous to the environment economy. A precis of the reviewed literature that used exclusive modalities and device gaining knowledge of techniques to construct driving force strain popularity version may be observed. However, there are nevertheless a few demanding situations associated with the modality that had to be recognized.



CHAPTER 6

CONCLUSION AND FUTURE WORK

It has been demonstrated that exceptional modalities may complement each other to develop a superior motive force pressure detection model; hence, considering multi-dimensional approaches to build the most desirable machine is critical in this arena. Integrating the modalities within the fusion levels is one of the major challenges (sensor, feature, rating, or decision). The ability to explore rating-stage and stage mix in extra assessment and work on the overall execution of the model may be substantial. As a result, creating a universal version that fits all drivers is difficult, and a device that adapts to everyone's physiology is required. Another issue is that frame touch sensors for physiological tracking aren't appropriate for a continuous driving force strain degree detection device since they're too visible in real-world use. Physical along with circumstantial data can be gathered using procedures that are less invasive and more practical in real-world situations. Because body and contextual data are likely to be linked to drivers' stress levels, future study should focus on those variables more when developing an automated driving force strain-detection system.

FUTURE WORK:

- For reasons of register time and memory resources, the execution of the evaluation was common. The goal of the strategy was to go via open resources to establish the model. Among the primary compute execution aspects are:
- Tragic Execution that is aware, with a different approach to missing data values. Continued to design with the objective that you can likewise keep an overall fitted model on new data.

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APPENDICES

A. SOURCE CODE

```
#include <ESP8266WiFi.h>;
#include <WiFiClient.h>;
#include <ThingSpeak.h>;

WiFiClient client;
const char* ssid = "IOT"; //Your Network SSID
const char* password = "123456789" ; //Your Network Password
unsigned long myChannelNumber = 1663294; //Your Channel Number (Without Brackets)
const char * myWriteAPIKey = "M3GSRQDI8QVN1ENR"; //Your Write API Key

void setup()
{
  Serial.begin(9600);
  WiFi.begin(ssid, password);
  ThingSpeak.begin(client);
}

void loop()
{
  clc
  clear all
  close all

  L=5;M=5;N=5;LX=1;LY=1;LZ=1;DX=LX/L;DY=LY/M;DZ=LZ/N;dt=0.001;
  for time=1:10;
    for i=1:L;
      for j=1:M;
        for k=1:N;
          x(i)=i*DX;
          y(j)=j*DY;
          Z(k)=k*DZ;
          u(i,j,k,time)=sin(x(i))*cos(y(i));
          v(i,j,k,time)=sin(x(i))+cos(y(i));
          w(i,j,k,time)=x(i)*exp(-x(i).^2-y(j).^2);
        end
      end
    end
  end

  for i=1:L;
    for j=1:M;
      for k=1:N;
        x(i)=i*DX;
        y(j)=j*DY;
        Z(k)=k*DZ;
```

```

        roh(i,j,k,time)=x(i)*exp(-x(i).^2-y(j).^2);
    end
end
end

for t=1:time;
for i=2:L-1;
    for j=2:M-1;
        for k=2:N-1;
            aa(i,j,k,time+1)=(1/dt+u(i,j,k,time)/DX+v(i,j,k,time)/DY+w(i,j,k,time)/DZ);
            bb(i,j,k,time+1)=(u(i+1,j,k,time)-u(i,j,k,time))/DX+(v(i,j+1,k,time)-
v(i,j,k,time))/DY+(w(i,j,k+1,time)-w(i,j,k,time))/DZ);
            roh(i,j,k,time+1)=(-
roh(i,j,k,time)*bb(i,j,k,time+1))/aa(i,j,k,time+1)+roh(i,j,k,time);
        end
    end
end
end
end

```

```

ThingSpeak.writeField(myChannelNumber, 1,i, myWriteAPIKey);delay(1000);
ThingSpeak.writeField(myChannelNumber, 2,j, myWriteAPIKey);delay(1000);
ThingSpeak.writeField(myChannelNumber, 3,k, myWriteAPIKey);delay(1000);
ThingSpeak.writeField(myChannelNumber, 4,l, myWriteAPIKey);delay(1000);

```

```

ThingSpeak.writeField(myChannelNumber, 5,m, myWriteAPIKey);delay(1000);
ThingSpeak.writeField(myChannelNumber, 6,n, myWriteAPIKey);delay(1000);
ThingSpeak.writeField(myChannelNumber,7,0, myWriteAPIKey);delay(1000);
}

```

B. SCREENSHOTS

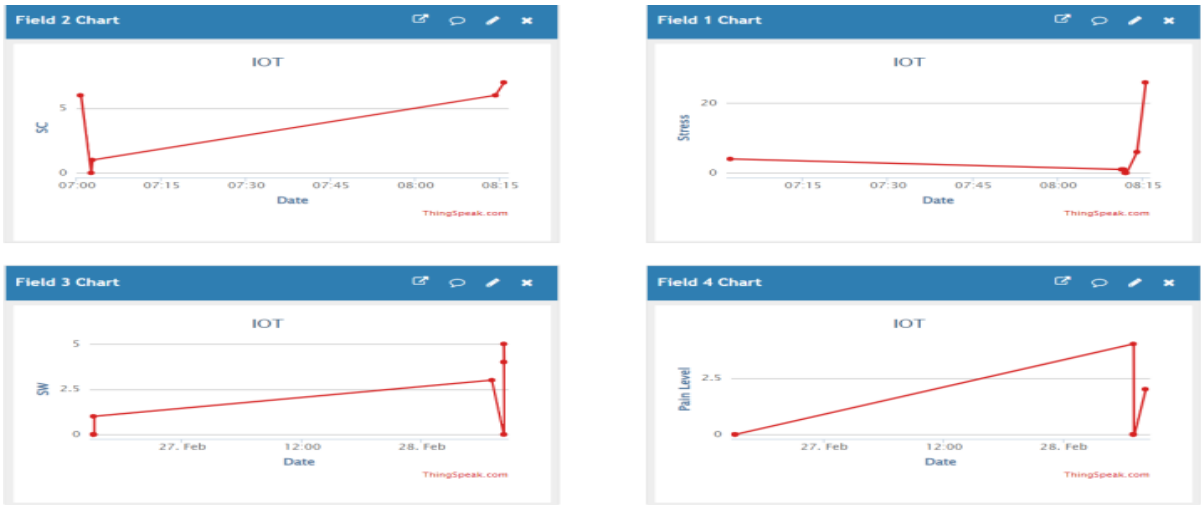
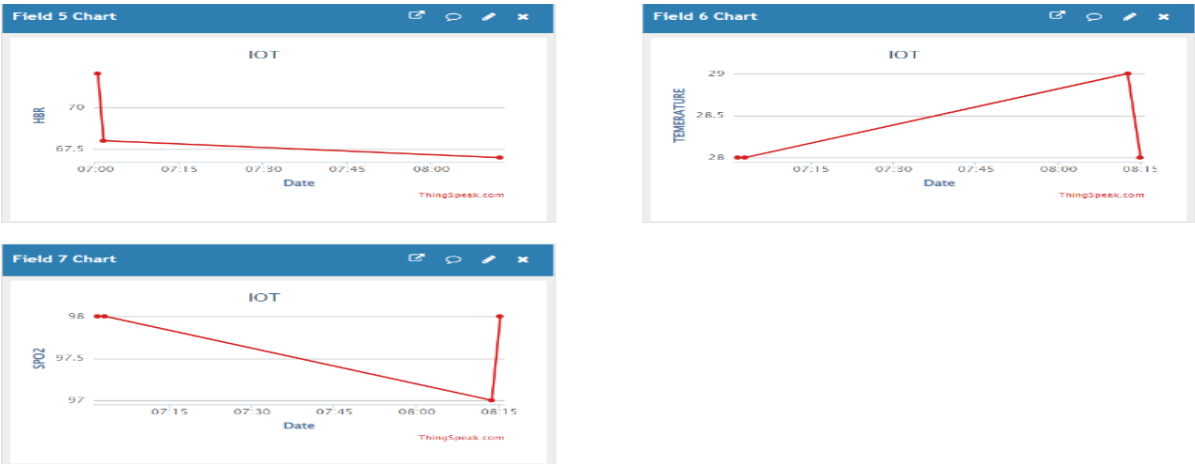


Fig1 & Fig 2: Measures displayed in ThingSpeak



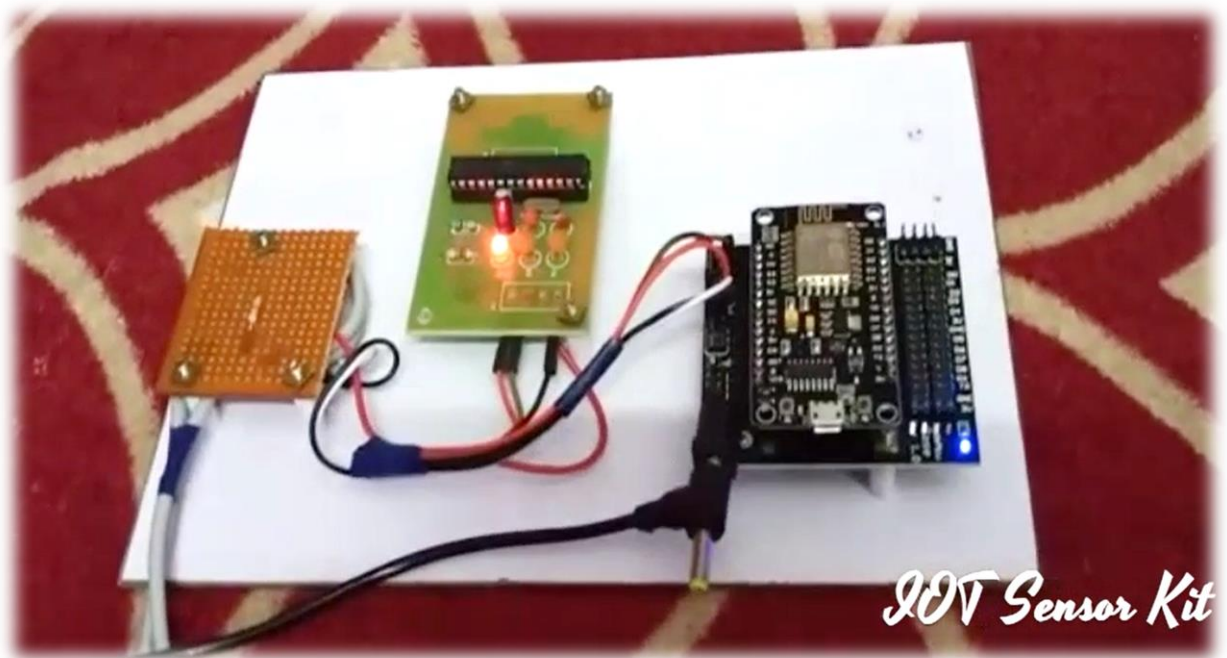


Fig 3 & Fig 4: IOT KIT Display



C. PUBLICATION WITH PLAGIARISM REPORT

MENTAL AND PHYSICAL HEALTH MANAGEMENT SYSTEM USING MACHINE LEARNING, COMPUTER VISION AND IOT SENSORS.

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Abstract: Beforehand, medical care the executive's frameworks were especially centered around actual wellbeing and ignored the emotional wellness. With innovation that incorporate all circles of life, the advantages of innovation in medical services stay unimaginable. An individual's feeling, internal heat level and pulse can give smart data on both psyche and body. This paper exhibits a total medical service the executive's framework that considers both physical just as emotional wellness. IoT sensor organization and nodemcu is utilized to gather an individual's internal heat level and pulse and all the while put away in a data set. The paper additionally incorporates a feeling acknowledgment concept which is constructed utilizing the Mini-Exception emotion detection model and convolutional neural organization engineering to monitor the individual's feeling. A characteristic language handling chatbot has been utilized to empower a virtual specialist for the client and assist the client with giving a fundamental analysis. The information acquired is then put away in Cloud. The result of this execution shows that perhaps the suggested framework can reduce the duty of experts, encourage them to be more aware of their physiological well-being, and, lastly, the recommended strategy will increase the availability of medical services.

Keywords: Galvanic Skin Response Sensor, Nodemcu, Wi-Fi device, IoT sensors, Computer Vision (CV), Display, Convolutional Neural Network (CNN), Physical Health, Mental Health.

1. Introduction

Given our unavoidably unpleasant and chaotic lifestyles, here exists a necessity to develop a framework that can screen an individual's health and psychological well-being for their success. In almost every field, innovation has proven to be beneficial. Previously, innovations were primarily focused on an individual's physical strength, with mental well-being receiving special attention. Why the need to evaluate an individual's mental well-being is due to the frequency of suicides because of sadness has increased. A necessity to incorporate the improvisations in innovation in the development of physical and mental strength of individuals, with a gradual slope in the use of medical care usage items and camera placed in each device. Hence, an individual's life has gotten easier. Therefore, it is now simple for a person to learn about and track their own health. These data will aid professionals in gaining a better understanding of the individual in the future. Likewise, the present continual epidemic has made expert advice extremely difficult to get by, and there is a need for people to make their decisions from afar. In this way, a bot acts as a digital expert and provide them with a basic conclusion. Between 2020 and 2025, the amazing medical services wearable business is expected to grow by 21.4 percent. As a matter of fact, there will be a need for devices that aid us in assessing both physical and psychological well-being.

2. Literature Review

[1] Rajdeep Kumar Nath, Graduate Student Member, IEEE, and Himanshu Thapliyal, Senior Member, IEEE "Brilliant Wristband-Based Stress Detection Framework for Older Adults with Cortisol as Stress Biomarker" distributed in the year 2021.- The objective of this undertaking is to create, plan and test the adequacy of a pressure identification model for more seasoned people using a wrist-worn sensor gadget. [2] Wei Li1 and Yanbu Chai and Fazlullah Khan and Syed Room Ullah Jan and Sahil Verma and Varun G. Menon and Kavita and Xingang Li "A Comprehensive Survey on Machine Learning-Based Big Data Analytics for IoT-Enabled Smart Healthcare System" distributed in the year 2021. - This venture exploration will give medical services experts and government associations understanding into the freshest advancements in AI denied huge information examination for shrewd medical services. [3] Xinglong Wu1, Chao Liu, Lijun Wang, Muhammad

Bilal "Web of things- empowered ongoing wellbeing checking framework utilizing profound learning" distributed in the year 2021. - The method is viewed as a helpful device for diagnosing extreme issues in competitors, like cerebrum growths, heart issues, disease, etc. [4] Muhammad Imran, Umar Zaman, Imran, Junaid Imtiaz, Muhammad Fayaz, and Jiangshan Gwak "Far reaching Survey of IoT, Machine Learning, and Blockchain for Health Care Applications: A Topical Assessment for Pandemic Preparedness, Challenges, and Solutions" in the year 2021. - This exploration gives an exhaustive assessment of creating IoT advancements and blockchain in medical care applications. [5] Yash Jain, Hermit, Atharva Brute, Aditya Vora "Mental and Physical Health Management System Using ML, Computer Vision and IoT Sensor Networks" distributed in the year 2020. - The result of this execution shows that the proposed approach can limit specialists' weight, urge them to be more aware of their wellbeing, and, at last, make medical services more open. [6] Preenoo Valsalva, Tariq Ahmed Barham Boamah, Ali Hussain Omar Baboon "IoT Based Health Monitoring System" distributed in the year 2020. - is introduced, in which approved individuals might get to this information saved money on any IoT stage, and medicines are analyzed by specialists at far in view of the qualities got. [7] Héctor Espinoza, Gerhard Kling, Frank Mc Groat, Mary O'Mahoney, Xenia Zionville "Assessing the effect of the Internet of Things on usefulness in Europe" in the year 2020.- Knowing that IoT is a yet in its beginning phases of improvement, we find a positive impact of the IoT on efficiency, but little. [8] H. Varshney, A. S. Alachlor and M. Sarfraz, "IoT Based eHealth Management System Using Arduino and Google Cloud Fire store", in 2019. - We investigate the execution and plan of an IoT (web of things) checking and estimating framework involving Arduino in this article. This gadget utilizes an Arduino microcontroller and an ESP8266 NodeMCU as a WI-FI module to impart and store ongoing patient wellbeing information to Google Firebase. [9] Moreot, B, Glucksberg B.S, Butte A.J, "A call for profound learning medical services" in the year 2019. - We accept present age has more interest to construct more brilliant medical services frameworks in which the ideal therapy choices are advanced measurably from electronic wellbeing record information utilizing profound learning draws near. [10]

3. Proposed Solution

The recommended solution includes an emotion prediction system, a facts collection system that will employ a range of medical sensors with a chatbot that functions as a virtual doctor. The world passing records gave by the World Health Organization show that streetcar crashes cause over 1.3 million passing reliably. Driving is a perceptual engine capacity that incorporates different circumstances and thusly accomplishes fluctuating degrees of tension. Stress is a colossal part in driving since it can manufacture the bet of getting into a vehicle crash by affecting driver execution. This issue makes a huge expense for the degree that death toll and efficiency for state run associations and social orders. Stress and hypertension is stated as one among the focal purposes behind vehicle damages and crashes. Australian public setback reports besides show that pressure is among the ten driving purposes behind deadly mishaps. Adjoining broadening the bet of crashing, stress can additionally affect the overall amplex of expert drivers.

3.1. Problem Definition

With our extremely hectic and chaotic lives, a system that can monitor a person's overall health for their wellbeing is needed. It's essential in every field that technology has shown to be beneficial. Previously, technologies mostly focused on a person's physical health, but mental health was largely ignored. There was a need to monitor a person's mental health as the frequency of suicides due to depression increased. Considering a proposed structure for a multimodal driver stress check framework, it moreover follows significant level system for changed driver stress certification and investigates their efficiencies. Considering the audits, this paper talks about the stream key difficulties and proposes considerations for future work in building a practical framework that can unmistakably, unassumingly, and appropriately see driver energies of tension. For traces on pressure interest and mentioning, we recommend the per client to Sharma et al. Our work is in like manner not vague from a past report that great lights on affirmation of office business related strain through multimodal information. To the degree that we could know, this is the basic survey that explores the information, methodologies, and issues that should be addressed for executing such an arrangement in vehicles to augment driver security.

4. System Architecture

Initially we send an electric signal called a GSR sensor (galvanic skin response) with a +5V DC current to check stress levels and depression, and then a 3.3V to check any other physical changes or disturbances like perspiration, pressure, or cardiac functions. We transform the machine's sensor to a sensor module using Low Pass Filter and High Pass Filter, which allows us to transfer the signals. After delivering the sensor, the blood pressure is pulled down and then raised to display changes as the voltage is reduced to 0.5 and 0.2. Because it's impossible to precisely identify changes due to variances, we add a low pass filter and a high pass filter with a 10K-Ohm resistance, and then convert the raw signal to an analogue signal. Our 0.2,0.3 volts will be boosted

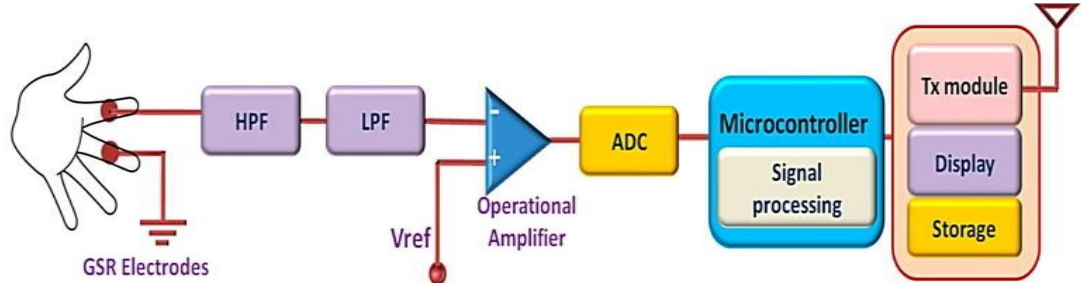


Figure 1: System Architecture

to 0.8 or 0.9 volts by the operational amplifier before reaching the ADC. The signal is processed and examined in the Microcontroller to see if it is leveled/conditional or unconditional, and the data is transferred via IOT, which can be seen in the device. To connect with Wi-Fi, use the TX module (transmitter module). When a Visual Display is the app that we installed to view our cellular device. Data Storage is the database that we generated in the WIFI cloud that we can refer to and access the data in the future. Following the prediction of an issue in our physical and mental state, the data received will be prompted in our device prior to our safety, which falls under the computer vision technology where hardware and IOT are interfaced with each other. The following Figure 1 states the architecture flow of our proposed system.

5. Methods And Frameworks Approached

Aim of this paper is to analyze the most developed methods and ideas of the systems for detecting the emotional stress levels. To shorten the above research, this shows a normal basic blueprint for a model to measure the stress levels automatically and continuously. In Segment 2.5, the optimum data collecting modes (signal capture) are discussed. After collecting data from several modalities, analyzing the data becomes the highlighted idea to evaluate tension. Feature creation, Pre-processing, concept reduction, characteristic selection including machine learning are all phases in data analysis. This procedure aids in the detection of voltage-data modality's relationships.

5.1. Pre-Processing

The preprocessing and denoising of the incoming data are a critical initial step in estimating driver stress levels. Magnetic noise, bodily mobility, instrumentation, and low electrode contact with the skin may quickly distort data. Pre- processing procedures eliminate any undesirable artefacts from the data and prepare it for feature extraction.

5.2. Preference For a Feature

Increasing the number of extracted options leads to higher system costs and generates unavoidable sounds, which affects the correctness of the algorithms used. The mastery of objective types is hampered by a characteristic location with excessive dimensions.

5.3. Filtering Methods

To reserve the capabilities, filter approaches utilize rating systems, which may be used for their simplicity and practicality in a variety of applications. Ranking techniques evaluate each characteristic's connexion to a final outcomes variable and apply a threshold to exclude capabilities that fall below it.

5.4. Wrapper Techniques

Wrapper techniques employ seek formulae to understand heuristically suboptimal characteristic units. ordered ahead floating preference. Sequential Feature Selector (SFFS) is known as a wrapper approach implemented to find the most suitable division of options repeatedly.

5.5. Embedded Techniques

Embedded approaches ask for a reduction in the time it takes to teach totally unique subsets calculated using wrapper techniques developed the "Characteristic-based Completely Transformation Recognition" system

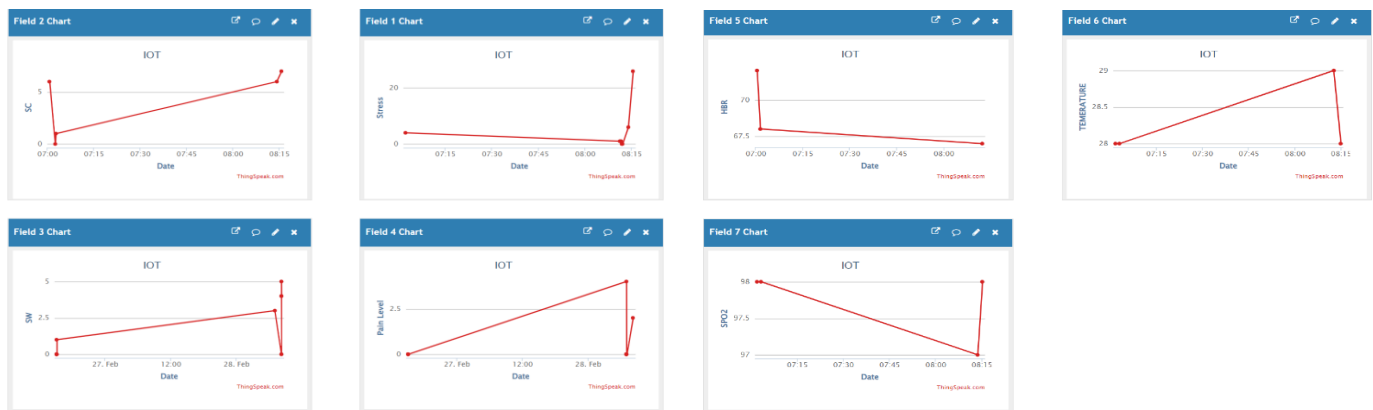


Figure 2: Results Displayed on Thingspeak

Data Gained	Performance Measured	Relating G To
ECG and EMG	100% accurate and folds 10 classification with 100% rate and sensitivity along with specificity	Accuracy holds up to 100% and 10 classification folds with rate: 81.27% and sensitivity in 62.14% and specificity as 88.83%
Electrocardiograph y	Recognition rate of 97.78% and holding 5 Folds	--
ECG, EDA, RSP Vehicle dynamic data	Accuracy: 90%	KNN (No accuracy is reported) multilayer perceptron (no accuracy is reported)
ECG, EMG, EDA, RSP	Accuracy: 97.4%	--
ECG, EDA, RSP, facial EMG	Accuracy is of 71.9%	Tree augmented NBC and KNN
ECG and EMG	Accuracy of 80.3%	ANFIS's (Accuracy: 77.7%)

Table 1:Shows the Significant Categorization Approaches for Various Levels of Operator Stress.

6. Modules Implementation

Statistics must be noted, transmitted, analyzed, deduced, combined, and then utilized to conclude to a decision on a regular basis to grow an autonomous device that proactively predict motive force strain stages. To improve riding safety, this device must give a practical solution that measures motive force strain levels constantly, unobtrusively, and on aregular basis.

- 6.1. **Data Quality:** Collecting notable statistics is critical to the achievement of any strain detection gadget. Therefore, statistics series must be completed meticulously to achieve statistics this is correct, green, secure, relevant, well timed, and correctly represented. In general, the excellent of statistics may be disrupted through specific troubles consisting of insufficient sampling costs of gathering gadgets and the non-absence of noise withinside the statistics.
- 6.2. **Data Set:** Using publicly to be had statistics units has numerous benefits, consisting of facilitating a truthful evaluation of all tests and decreasing the workload of scientists. Therefore, the wide variety of to be had public datasets on this area is confined because of ethics and privateness troubles.
- 6.3. **Modality Fusion:** Combining modalities which is a critical method to achieve an extra correct detection version wherein unimodal statistics cannot constitute a complete expertise of motive force strain degrees, particularly in real- global riding situations.
- 6.4. **Data Analysis:** Few other difficult problems which impacts the overall results of the real-time motive force strain reputation gadget is excessive dimensionality of statistics. This problem is addressed through the usage of characteristic- primarily totally based strategies, particularly characteristic choice, and discount.

7. Results & Discussion

Automobile accidents are frequently caused by stress. Long-term exposure to exclusive driving stresses can

also lead to fitness issues in professional drivers. Because of the rising number of fatalities and financial losses linked to driving force strain, an in-car device for early detection of driving force strain phases is critical for boosting drivers' safety. This device must continually monitor the driving force's strain levels, anticipate dangerous driving circumstances, and, if an increase in strain is detected early enough, inform the motive force proactively. Different assessments in the field of clever vehicles have shown that this sort of device might additionally foster security as well as unequivocally influence drivers' driving styles and affinities. Adjacent to redesigned security, this sort of device may in like manner enjoy the extra benefit of hindering the long-range effects of tension in drivers, achieving an even more innocuous to the environment economy. A precis of the reviewed literature that used exclusive modalities and device gaining knowledge of techniques to construct driving force strain popularity version may be observed in Table 3.6. However, there are nevertheless a few demanding situations associated with the modality that had to be recognized.

8. Conclusion

It has been demonstrated that exceptional modalities may complement each other to develop a superior motive force pressure detection model; hence, considering multi-dimensional approaches to build the most desirable machine is critical in this arena. Integrating the modalities within the fusion levels is one of the major challenges (sensor, feature, rating, or decision). The ability to explore rating-stage and stage mix in extra assessment and work on the overall execution of the model may be substantial. As a result, creating a universal version that fits all drivers is difficult, and a device that adapts to everyone's physiology is required. Another issue is that frame touch sensors for physiological tracking aren't appropriate for a continuous driving force strain degree detection device since they're too visible in real-world use.

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