Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 3s (2025)

Mathematical Modeling of Adaptive Facial Gesture Recognition for Driver Fatigue Detection in Diverse Lighting Conditions Using Improved Kernel Based Support Vector Machine

Sanjay Sharma[1], Dr. Shashi Sharma[2]
[1]Research scholar, JECRC UNIVERSITY, JAIPUR
[2]Assistant Professor, JECRC UNIVERSITY, JAIPUR
33sanjay33@gmail.com[1], pathak.shashi26@gmail.com[2]

Article History:

Received: *29-09-2024*

Revised: *20-11-2024*

Accepted: *29-11-2024*

Abstract:

The overwhelm number of fatalities due to road accidents in India which are caused by driver fatigue (about 25 percent of road accidents) is the dreadful problem that have to be addressed [1]. However, the mark of concern is up to 60 percent of these accidents cause deaths or serious injuries. The primary causes of driver fatigue are insomnia and sleep deprivation. Therefore, the emphasis for safety [should] be on alertness to avoid serious fatalities. Now days, the integration of smart algorithms in vehicles has been witnessed in great scale supported by Wireless Sensor Networks (WSN) which are used to monitor and transmit both vehicle and driver states. The purpose of this study is tackling the problem of drowsiness detection that is based on image segmentation and machine learning. The real-time image segmentation, targeting on detecting facial components like mouth and eyes by using image processing, have been successfully carried out as well. Applying input data from sources such as webcam or IoT-enabled camera, video frames go to extraction and segmenting of features using clustering algorithms. Additionally, an area of research associated with machine learning has used Support Vector Machines (SVM) as a method for detecting emotions from facial expressions. Considerable testing in varying light conditions has proven the algorithm's robustness, yielding higher accuracy compared to common researches. The studies are a milestone with regard to the integration of the latest technologies to reduce road accidents due to driver fatigue and the resulting devastating deaths.

Keywords: Driver Fatigue Detection, Facial Gesture Recognition, Real-Time Algorithm, Machine Learning, Support Vector Machine, Lighting Conditions, Eye Movement Analysis, Yawning Detection, Safety Algorithms, Image Processing, MATLAB Simulation, Camera Proximity, Feature Extraction, Automated Monitoring, Road Safety Technology.

I.INTRODUCTION

With fatigue rates standing as a major cause of serious car accidents on day to day basis, statistics from the National Highway Traffic Safety Administration say that about 150 people are killed annually in the United States due to driver fatigue, with 71,000 injuries and $12.5 billion in losses. Besides the fact that the United States government and businesses pay similar amounts on fatigue-related accidents, reaching to $60.4 billion each year, the consumers pay $16.4 billion in property damage, healthcare claims, and lost time and productivity (2). The statistics is indeed shocking, 54% of the adult drivers have admitted that they have feel drowsy while driving and 28% said that they sometimes even dozed off [3]. In a similar vein, the German Road Safety Commission claims that quarter of the highway deaths happen because of the driver fatigue [4].

Due to the huge number of casualties, injuries and property damage that tired driving leads to, it's time to design a device that is able to detect drowsiness and brings the system to a safe state before a collision happens. The US Department of Transportation is actively working on developing smart vehicles to avoid such accidents[2]. The initiatives echo on the recent trend of intelligent transportation systems. Also main research is in progress, and the hunt for drowsiness detection methods eligible for public use, as well as real-time detection with high accuracy is crucial.Leading automobile companies like Toyota, Ford, and Mercedes- Benz have exploited vehicle safety technology to prevent drowsy-driver related accidents in particular. This is a sign of the dawn of modern and safer vehicles with a steady reduction in the number of drowsy-driver related accidents. Upon this, our study is done based on the statistical crucialness of drowsiness-related accidents continuing to determine an improved and accurate approach for detecting drowsiness. Our research initiative is originated from the problem of existing difficulties in detecting drowsiness, which provides a promising continuing trend in the ongoing research efforts. The current methods rely on observing driver behaviors or physiological changes of the driver and monitoring the response of the vehicle to these behaviors to detect drowsiness. However, even though each of the methods has its own advantages, they also produce limitations which reduce their practicality and effectiveness.

For example, behavioral measurements are contingent on vision data of the driver. In such situation, there are many external factors which might affect the quality and the lighting conditions of the measuring device among others. Physiological changes, e.g. heart rate modifications, brain waves distortions, or muscle electrical activities interferences being accurate indicators of fatigue are affected by artifacts. The readings from the vehicle-based measurements such as speed, steering activity, and lane deviation is heavily affected by external factors which most times does not show the accurate state of driver drowsiness. One solution to the challenges put forward is to improve the measurement devices and processing techniques, which have now become an ongoing endeavor around the world. Yet another approach is to combine these techniques so as to make it more reliable by creating one optimal system hence employing few components.

Additionally, a significant problem is a determination of the criteria for identifying of the key events and data processing. Indeed, in a study that implemented vehicle-based measurements, frequent minor corrections and major corrections (both of which signal drowsiness) were included as such incidences. In behavioral measurements, the events could be the cases where facial muscles move based on detection result. On top of defining the best time scenario that helps the system to provide the consequence of driver fatigue at the exact necessary time, it is also an arduous challenge.

In our research, we present a new method that determines drowsiness by considering a combination of sensors, parameters optimization, features selection, and modeling. Through our focus on the identified issues, we hope to move the drowsiness detection forward and help the industry shape up safe driving technologies.

II.IMAGE PROCESSING

Image processing can be considered as a set of operations for image manipulation and analysis to retrieve useful information or to improve its quality for different objectives. This includes converting input images into output images based on selected metrics and topological features (edges) , to examine and manipulate the content of the image. Pixel intensity within the boundary of the image is vital during this procedure.

Image processing, usually, is presented in a step-by-step, flowchart-like manner, as it shown in Fig. 1.1. They include different kinds of operations such as filtering, segmentation, feature extraction, etc. which depend on the peculiarities of the image processing task.One of the important components of image processing is the assessment of the image quality which can be subjective or objective. The subjective methods rely on human perception that is used in television technology and objective methods involve a quantitative measurement of image quality for a more exact assessment.

In practical uses, image processing is indispensable for tasks like image retrieval from databases where the similar images have a key role. Nevertheless, with interference from background noise during acquisition or transmission, images could be compromised. The physical attributes of electromagnetic radiation, such as the human face color detection, are also crucial in this process.

Traditionally, analog techniques including photocopying and printing were used as image processing methods to produce hard copies of data. But, the technology has become more sophisticated, leading to development of digital image processing which facilitate for more complicated manipulation and analysis of images using computational tools.

Image Processing has applications in almost all domains and is not limited to a particular domain. It is for tasks ranging from data analysis and interpretation to visualisation methodologies and pattern recognition. Extended application of personal and collected data gives it an additional edge, making it an extremely useful tool for data visualization purposes, be it computational or graphical.

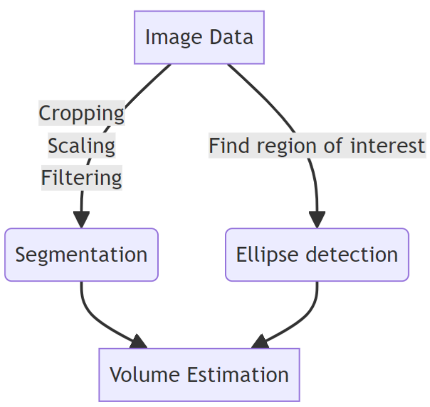

Figure 1.1: Analysis of Image Processing

In general, image processing consists of a variety of techniques and approaches that are used to modify and also to analyze images to get important information or to enhance them. From subjective interpretation to objective quantification, image processing is pivotal in many areas, such as medicine, surveillance, remote sensing, and others. While the applications of AI keep expanding, the latest technology breakthroughs enable the development of more intelligent algorithms and tools that are used for image analysis and manipulations. Being capable of handling visual data, image processing is of great importance in the domains of decision-making, research, innovation among others.

III.EMOTION AND DROWSINESS DETECTION

Sleepiness or dozing, is an exogenous condition, which is the physiological need or desire to sleep. Even though it is a predominant characteristic of our biological rhythm, which is a cyclic system of sleep and wake states underlined with both homeostatic and circadian responsibilities. Homeostasis is the bodily mechanism that maintains sleep. The duration of getting out of sleep indicates the urge for sleep. With the prolongation of the awakening, the desire and the ability to sleep get weaker making it more and more difficult to resist the sleep. In contrast, the circadian pacemaker makes about one cycle every 24 hours and it serves as an internal body clock that influences the ease of sleeping and being awake. Though alcohol and certain medications can be sleep-inducing in isolation, sleep deprivation, sleep fragmentation, and circadian factors are the most common causes of drowsiness and drowsy driving in people without sleep disorders. Sleep duration appears to have the most critical effect when it is short. Contrary to this, individual sleep needs differ. Nevertheless, a typical adult sleeps 7-9 hours on average for maximum performance. Experimental data supports the inference that a sleep of less than four unbroken hours per night, results in deterioration of the vigilance task performance.Even one night of inadequate sleep can cause a sudden sleepiness that is very dangerous. Furthermore, the effects of sleep loss accumulate in deficit, so even if small losses of sleep occur continuously, it can eventually cause chronic drowsiness. This build-up of "sleep debt" can be reconciled by adequate sleep.Each of the internal and external factors contribute to restriction of available sleep time. External influences are work schedules, family duties, or school starts, on the other hand, internal effects are medical side effects or personal choices. People may decide to sleep less during the night in order to focus on other activities such as work or socialising. Overall, drowsiness is a complex phenomenon influenced by various biological, environmental, and lifestyle factors. Understanding these factors is crucial for addressing drowsiness-related risks, such as drowsy driving, and promoting overall health and well-being.

IV.SUPPORT VECTOR MACHINE

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that is aimed at designing systems and also methods that allow computers to learn from the data and execute the tasks without being directly programmed. Fundamentally, it implies the development of algorithms in such a way that the machines can learn and become better at specific tasks with the passage of time. ML has several intersection points with the statistics where different techniques and methodologies have been developed for different tasks.

The Support Vector Machine (SVM), which was introduced in 1992 by Boser, Guyon, and Vapnik, is among the most prominent ML techniques. SVMs(Support Vector Machines) are supervised learning models, used for classification and also regression tasks, belonging to a generalized linear class of classifiers. In essence, SVMs increase the predictive accuracy while trying to avoid overfitting by utilizing a hypothesis space of linear functions in a high-dimensional feature space, trained with a learning algorithm derived from optimization theory based on statistical learning principles.

SVMs gained their popularity due to their very high accuracy in handwriting recognition and in some cases they were as accurate as neural networks but with fewer explained features. They have been applied in many different areas of study including handwriting analysis and face recognition, which are majorly used in the classification and regression tasks

The fundamentals of SVMs were laid down by Vapnik, whose formulation uses the Structural Risk Minimization (SRM) principle which has been shown to be better than the Empirical Risk Minimization (ERM) principle used in the conventional neural networks. SRM focuses on tightening the upper bound of the average risk, which results in a better SVMs generalization and also statistical learning. In SVMs, the goal is to increase the margin, the distance between a separating hyperplane and the most extreme data points belonging to each class. This objective function is a solution to a quadratic optimization problem with linear restrictions that involves finding weights (w) and bias (b) that result in a large margin with the correct classification of the training data

To summarize, SVMs are a popular approach to machine learning and they are useful for both classification and regression problems, which lie in the area of operations research, business and finance.

"Φ (w) =½ |w'||w| is minimized;

And for all {(xi, yi)}: yi (w * xi + b) ≥ 1.

Now solving: we get that w =Σαi * xi; b= yk- w *xk for any xk such that αk≠ 0 Now the classifying function will have the following form: f(x) = Σαi yixi * x + b

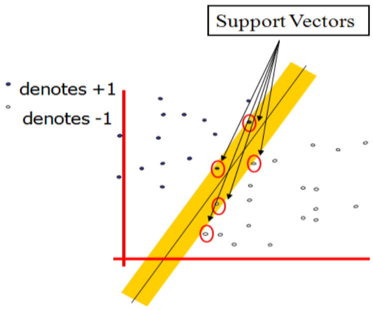

Figure 1.2 Support Vector Machine Dynamics

In this we present the QP formulation for SVM classification [4][8][12][13]. This is a simple representation only.

SVM classification is given as-

$$\min_{f,\xi_i} \|f\|_K^2 + C\sum_{i=1}^{l}\xi_i$$

yif(xi) ≥ 1 - ξi, for all i

$\xi i \geq 0$

SVM classification, Dual formulation:

$$\min_{\alpha_i} \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \qquad 0 \leq \alpha i \leq C, \text{ for all i;} \qquad \sum_{i=1}^{l} \alpha_i y_i = 0$$

Variables ξi are called slack variables and they measure the error made at point (xi,yi). Training SVM becomes quite challenging when the number of training points is large. A number of methods for fast SVM training have been proposed [4][8][13].

V.METHODOLOGY

The suggested system consists of camera capturing the driver's video and then the frames of the video are segmented. The subsequent segments describe the way of treatment after the frames are acquired. The face detection method selected is the Viola Jones and the primary reason is to avoid false detections when it comes to identifying facial expressions. Placement of the eyes and mouth accurately is extremely important. At the detection of the face, the skin segmentation is performed by conversion of the image to YCbCr color space. This transformation kills the influence of luminance, highlighting the chromatic elements. Using spatial transformations, the RGB image is split into Y, Cb, and Cr constituents which in essence detect face skin regions. Eyetracking is one of the most critical factors in determining driver fatigue, eye openness / closedness. Viola Jones once again used for locating the position of the driver's eyes. Next the operation of detecting edges separates them in two parts, determining their centers based on the symmetrical properties. The next step will be detecting the pupil. Eyes open are seen as normal while eyes closed often signify exhaustion and lead to an alert.

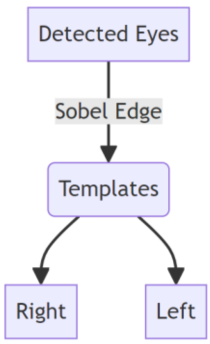

Figure 1.3 Process of Eye State Detection

Edge detection consists of pixel intensity variations tracking, by this Sobel is doing better than any other way, like Canny. Nevertheless, targeting accurately between different eye states (fully opened and half-opened) is the main problem here which may cause false alarms. Also, yawning detection belonging to another fatigue indicator is accomplished by segmenting the mouth region and applying K-means clustering along with template matching based on correlation coefficients. Training the classifier means the creation of 100 templates for each eye and mouth states, correlation with which is close to zero. Afterwards, feature vectors are produced, and they are then normalized across the whole frame. For better tracking efficiency we use partially closed templates (20%-40%) to train and isolate them accordingly.

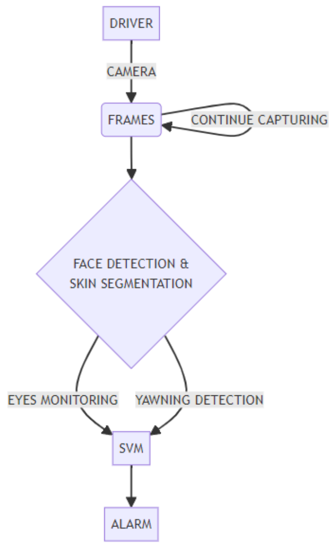

Figure 1.4 Process Flow Diagram

The training process refers to ensuring 100 images for each eye and mouth states (open and closed) and examining their resemblance to fully closed ones. These templates are later used to generate feature vectors, which are also normalized across all frames for real-time operating systems. Furthermore, semi-closed templates with 30% to 50% closing are generated and labelled accordingly to enrich the classifier performance as well.
Fig. 1.4 represents the face detection framework. This diagrams show this process in finding the facial features and expressions. In the next step, mouth regions are separately analyzed applying K-means clustering and correlation coefficient-based template matching for yawning detection, a prominent symptom of fatigue.
In general, the system incorporates image processing techniques such as face detection, skin segmentation, eye tracking, edge detection, and yawning detection to provide an overview regarding the driver's level of fatigue. Analyzing facial expressions and eye conditions enables the system to detect drowsiness traces and prompt notifications if needed which in turn improves road safety. Training the classifier reveals a robust performance, since lots of feature vectors are created from various templates representing diverse eye and mouth states. In essence the system is a multifaceted tool for identifying and controlling the risks associated with driver fatigue.

Objective Function of SVM is given as,

$$\min\left(\frac{1}{2} \parallel w \parallel^2\right) \text{ subject to } y_i(w^T x_i + b) \geq 1 \text{ for all } i$$

Slack Variables for Soft Margin SVM is defined by,

$$y_i(w^T x_i + b) \geq 1 - \xi_i,\ \xi_i \geq 0 \text{ for all } i$$

Dual Formulation of SVM:

$$\max_a\left(\sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j-1}^{n} \alpha_i\alpha_j y_i y_j x_i^T x_j\right) \text{ subject to } 0 \leq \alpha_i \leq C \text{ and } \sum_{i=1}^{n} \alpha_i y_i - 0$$

Kernel Function mathematical model is expressed as,

$$K(x_i, x_j) - \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \text{ (Gaussian kernel)}$$

Decision Function is formulated as follows-

$$f(x) - \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Feature Extraction for Image Data is calculated as follows-

Feature (x) - Histogram of Oriented Gradients (HOG) (x)

The process of Image Segmentation Using Clustering is calculated by following mathematical modelling,

$$\min \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2 \text{ (k-means clustering)}$$

The important process of Normalization for Image Processing**:**

$$x' - \frac{x - \mu}{\sigma}$$

where μ and σ are the mean and standard deviation of pixel intensities.
Illumination Adjustment is given as follows-

$$I'(x, y) - \alpha I(x, y) + \beta$$

where $I(x, y)$ is the intensity at pixel (x, y), and α, β are adjustment parameters.
Edge Detection (Sobel Operator) is calculated as follows-

$$G - \sqrt{(G_x^2 + G_y^2)}$$

where G_z and G_y are gradients in x and y directions computed using Sobel filters.
Eye Aspect Ratio (EAR) for Blink Detection is formulated by following equations-

$$\text{EAR} - \frac{\|p_2 - p_5\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

where $p_1, p_2, \ldots, p_6$ are coordinates of eye landmarks.
Yawning Detection Based on Mouth Aspect Ratio (MAR) is formulated by

$$\text{MAR} - \frac{\|p_{13} - p_{19}\|}{\|p_{49} - p_{55}\|}$$

where $p_{13}, p_{19}, p_{49}, p_{55}$ are coordinates of mouth landmarks.
Histogram Equalization for Image Contrast Improvement: is calculated by $p_r(r_k) - \frac{n_k}{N}$ and $s_k - \sum_{j=0}^{k} p_r(r_j)$

where p_r is the normalized histogram of pixel intensities, n_k is the number of pixels with intensity r_k, and N is the total number of pixels.

Color Space Conversion (RGB to YCbCr) involves following calculation

$$\begin{aligned} Y & = 0.299R + 0.587G + 0.114B \\ Cb & = -0.169R - 0.331G + 0.500B \\ Cr & -0.500R - 0.419G - 0.081B \end{aligned}$$

Dynamic Thresholding for Real-time Image Segmentation is as follows-

$$T(x,y) - \mu_{\text{local}}(x,y) + k \cdot \sigma_{\text{local}}(x,y)$$

where $T(x,y)$ is the threshold at pixel $(x,y), \mu_{\text{local}}$ and σ_{local} are local mean and standard deviation, and k is a tuning parameter. Mathematical model incorporate concepts of machine learning, image processing, and feature extraction to develop a robust system for detecting driver fatigue based on facial gestures under varying lighting conditions.

VI.RESULTS

MATLAB 2017 was used as a tool that gave video frames of a 15fps 5 Mega Pixel camera setup. To that end, the algorithm is designed to be a strong solution to the problem, allowing the system to correctly recognize the facial signs of the driver in the course of his operation of the vehicle. Evaluation of algorithm’s performance was executed in several ways subjecting it to different lighting conditions such as low and high to determine its response. The positions of the camera and the face of the subject have been the decisive factors that help capturing best images and making online feature extraction process simpler. The optimal proximity should be considered as necessary, for the purpose of boosting performance and eye/lip gestures detection efficiency across various scenarios. Keeping the right measure of distance will make the camera capture only clear and detailed images, which will guarantee better results in terms of feature extraction and minimization of distortions and inaccuracies.Eye and mouth features play a prominent role in detection since they are interpreted as the starting point in the process of further analysis. The algorithm finds facial landmarks with a high precision, extracts relevant features from this data, and, finally, uses an SVM classifier to distinguish these features. SVMs are widely adopted in machine learning because of their ability to accurately classify tasks through finding the best hyperplane that helps in separating the different classes in the feature space.The intended method utilizes Matlab for the purpose of simulation and employs advanced algorithms for identification and classification of these indicators. This takes into account the fact that the process should be reliable and real-time.

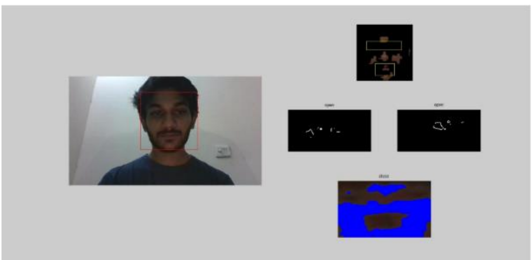

Figure 1.5 Analysis of Alert State

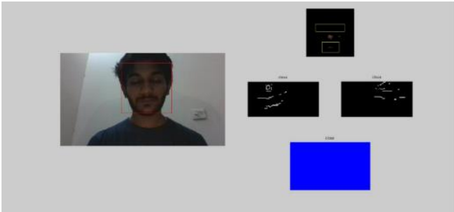

Figure 1.6 Analysis of Fatigue State

Experimentation under various lighting conditions give rise to reproducible experiments, which can be used to evaluate or confirm the correctness of the algorithm in various environments. Eventually, the goal is to create a system which could detect the signals of driver drowsiness, thereby contributing to the improved road safety and the reduction of the frequency of accidents. This research is aimed at the study of a facial fatigue detection algorithm in different lighting and distance scenarios that are simulated by using the Matlab 2017 version and a 15fps 5 Mega Pixel camera. The algorithm is developed to recognize the signals of tiredness from facial gestures, mainly focused on the eye movements and yawning.

Table- Analysis of Results

TRIAL	**Condition**	**Detection Time (Seconds)**	**Success Rate**
1	Situation-1	1.8	90%
2	Situation-1	2.2	89%
3	Situation-1	1.5	90.5%
4	Situation-1	2.0	91%
5	Situation-1	1.2	91.2%
Average Accuracy	Situation-1	90.74%	
1	Situation -2	2.4	78%
2	Situation-2	1.7	79%
3	Situation-2	2.0	82%
4	Situation-2	1.5	80%
5	Situation-2	2.3	81%
Average Analysis	Situation-2	80.00%	
1	Situation-3	1.6	90%
2	Situation-3	2.5	91.5%
3	Situation-3	2.2	92%
4	Situation-3	1.8	93.2%
5	Situation-3	2.0	93%
Average Accuracy	Situation-3	91.54%	
1	Situation-4	2.3	66%
2	Situation-4	1.5	69%
3	Situation-4	2.0	67%
4	Situation-4	2.2	71%
5	Situation-4	1.7	73%
Average Accuracy	Situation-4	69.20%	

Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 3s (2025)

Overall Average Accuracy	82.86%		

Day Light Normal Condition: In usual daylight and with optimal camara proximity, the algorithm showed high accuracy, with results between 85%-95%.. A yawning detection was more effective compared to eye movement detection based on the evaluation model.

Day Light Dim Condition: Under low daylight, we averaged lower accuracy (between 75% to 80%), which was a 10-15% decrease from normal daylight conditions. Yawning detection was found to be less susceptible to the reduced illumination than eye movement detection.

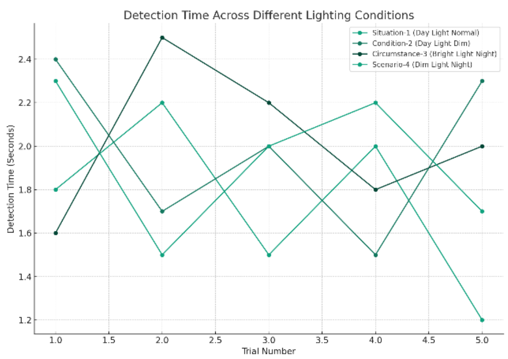

Figure 1.7 Analysis of Detection Time

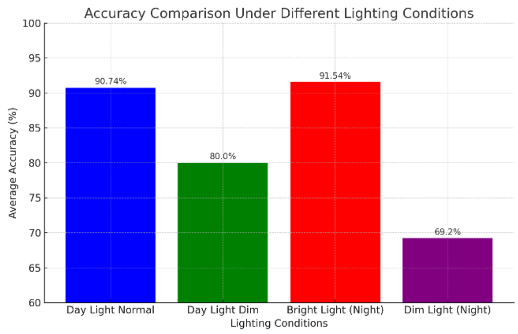

Figure 1.8 Analysis of Accuracy Comparison Under Lighting Conditions

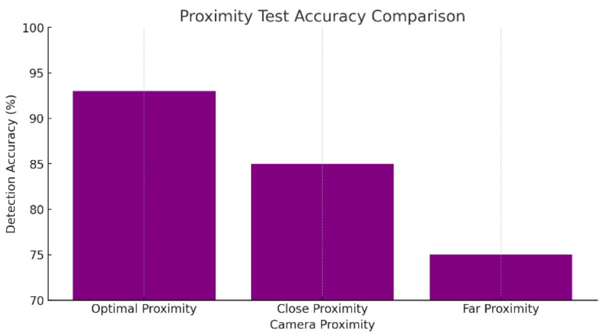

Figure 1.9 Analysis of Proximity Test

Bright Light (Night): The best result (90-93%) was obtained when the process was carried out under the light of the night, given the artificial lighting. The tendency for the detection of yawn shown to be a more reliable way of detecting drowsiness rather than the detection of eye movements persisted. Dim Light (Night): In such weak light scenario, the algorithm did not perform well, having the lowest accuracy (65-68%) when compared to the other scenarios. The algorithm was also more accurate in detecting yawning than eye movement.

Proximity Test: This example showed the role of the proximity of camera for the proper capture and subsequent online feature extraction. Correct distance is mandatory for efficient performance and proper lip and eye gesturing. The detection algorithm first recognizes these gestures which are then analyzed using Support Vector Machine classifier

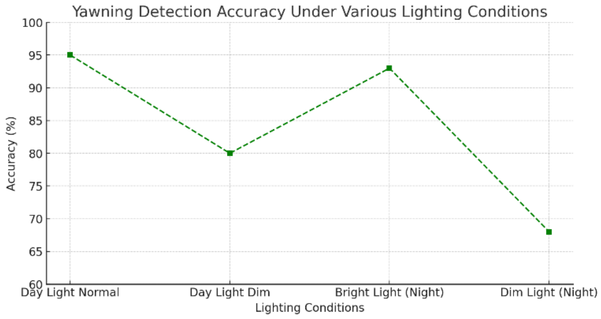

Figure 1.10 Analysis of Accuracy of Yawning Detection

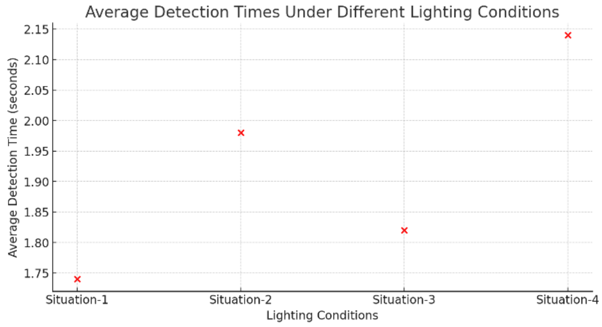

Figure 1.11 Analysis of Average Detection Time Under Lighting Conditions

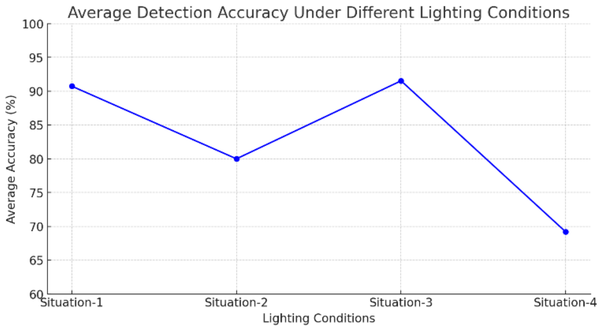

Figure 1.12 Analysis of Average Detection Under Lighting Conditions

Taken together, the study shows that light conditions have the strongest effect on the efficiency of the system, and the maximum results are achieved under bright artificial light whilst the least when in the dark at night. Consistent with the finding that yawning is a more reliable sign of drowsiness than the eye movement across all the cases.

VII.CONCLUSION

Using MATLAB 2017 and a 5 Mega Pixels camera in operation at 15fps, the research done on a facial fatigue detection algorithm sheds more light into how the algorithm functions under different light conditions and distances. The main part was surveying drivers' lack of vigilance by their eye movements and yawning.The study showed that while lighting conditions have a significant influence on performance, they also greatly impact the algorithm's accuracy. A perfect inspection with a certain distance from the camera and common daylight produced up to 95% accuracy. Remarkably, the chance of yawn detecting was higher than that of eye movement detecting in this particular scene. Yet, in the case of dim daylight conditions, there was a notice of decrease in accuracy from 75-80 %, which points to the algorithm's heightened sensitivity to the brightness of light. The highest lights passes of 90 to 93% showed during night yielded the best results and it further confirmed the algorithm's dependence on regular lighting to perform well. Contrarily, in low-light conditions at night, performance of the algorithm decreased dramatically, having the accuracy from 65 to 68 scores.The closeness experiment supplied a significant realisation on the matter of the camera's distance for successful feature selection. The right distance would be necessary for efficient performance and user recognition, in particular, of lip and eye gestures. The algorithm works by identifying these gestures and subsequent splitting using the Support Vector Machine.All in all, the study reported that algorithm is proved quite effective in certain cases; however, it does best under the bright light of artificial light, and its performance is worst under dark conditions. According to the findings, the yawning is a more demonstrative indicator of the drowsiness than the eye movement, through all the tested conditions. This work could be a step for the designing of safety systems in vehicles to reduce events of accidents being caused by lack of driver alertness. We will keep improving by work upon the low-light performance and refining the algorithm to be more accurate in the case of different environments..

REFERENCES

[1] I Isabelle Tang and Toby P.Breckon., “Automatic Road Environment Classification,” IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 2, pp. 476-484, June 2011

[2] P. Jansen, W. van der Mark, J. C. van den Heuvel, and F. C. A. Groen, “Colour based off-road environment and terrin type classification,” Proceedings of the 8th International IEEE Conference on Intelligent Transportation Systems, pp. 216–221,2005.

[3] Inho Choi, Seungchul Han, and Daijin Kim, “Eye Detection and Eye Blink Detection using Adaboost Learning and Grouping,” Proceedings of the 20th International Conference on ICCCN, 2012.

[4] Xue Liu, Xiaoyang Tan, and Songcan Chen, “ Eye Closeness Detection Using Appearance Based Methods,” Intelligent Information Processing, volume 385 of IFIP Advances in Information and Communication Technology, pp. 398-408, 2012.

[5] Yu-Shan Wu, Ting-Wei Lee, Quen-Zong Wu and Heng-Sung Liu, “An Eye State Recognition Method for Drowsiness Detection” The71st IEEE International Conference on Vehicular Technology Conference (VTC 2010-Spring).

[6] Du, Yong, et al. "Driver fatigue detection based on eye state analysis." Proceedings of the 11th Joint Conference on Information Sciences. 2008.

[7] Choi, In-Ho, Sung Kyung Hong, and Yong-Guk Kim. "Real-time categorization of driver's gaze zone using the deep learning techniques." 2016 International Conference on Big Data and Smart Computing (BigComp). IEEE, 2016.

[8] Tawari, Ashish, Kuo Hao Chen, and Mohan Manubhai Trivedi. "Where is the driver looking: Analysis of head, eye and iris for robust gaze zone estimation" Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on. IEEE, 2014.

[9] Singh, R. K., et al. "A real-time heart-rate monitor using non-contact electrocardiogram for automotive drivers." 2016 IEEE First International Conference on Control, Measurement and Instrumentation (CMI). IEEE, 2016.

[10] Viola, Paul, and Michael J. Jones. "Robust real-time face detection." International journal of computer vision 57.2 (2004): 137-154.

[11] Basilio, Jorge Alberto Marcial, et al. "Explicit image detection using YCbCr space color model as skin detection." Proceedings of the 2011 American conference on applied mathematics and the 5th WSEAS international conference on Computer engineering and applications, IEEE ICCE. 2011.

[12] Mahmood, Arif, and Sohaib Khan. "Correlationcoefficient-based fast template matching through partial elimination." Image Processing, IEEE Transactions on21.4 (2012): 2099-2108.

[13] Pauly, Leo, and Deepa Sankar. "Detection of drowsiness based on HOG features and SVM classifiers." 2015 IEEE International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN). IEEE,2015.

[14] Li, G., Lee, B. L., & Chung, W. Y. (2015). Smartwatch- Based Wearable EEG System for Driver Drowsiness Detection. Sensors Journal, IEEE, 15(12), 7169-7180.

[15] R. Nopsuwanchai, Y. Noguchi, M. Ohsuga, Y. Kamakura, and Y. Inoue,“Driver-independent assessment of arousal states from video sequencesbased on the classification of eyeblink patterns,” in Intelligent Transportation.