Drowsiness Detection System

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***Abstract*—When identifying Driver Drowsiness, transportation safety is crucial. Drunk driving is a leading cause of car accidents. One of the top causes of fatal road accidents globally is driver weariness. This illustrates that a heavy vehicle driver, in particular, is consistently exposed to hours of monotonous driving, which promotes tiredness in the absence of frequent rest breaks. As a result, it is critical to create a road accident prevention system for detecting driver tiredness, determining the location of motorist inattention, and providing a warning when an oncoming hazard arises. We provide a real-time system in this research that employs real-time image processing, facial eye identification algorithms, and eye blink rates. The goal of the system is to provide discreet real-time monitoring. Improving driver safety without getting too intrusive is the goal. This work identifies the driver's eye blink. An alert is set off if the driver is judged to be sleepy and their eyes are left open for a prolonged amount of time. The facial feature detection programming is done in OpenCV using the Haarcascade library.**

***Index Terms*—Driver drowsiness, blink pattern, eye detection, fatigue, blinking, EAR.**

I. Introduction

The primary cause of death, accounting for around 1.3 million deaths annually, is automobile accidents. Driver fatigue or distraction is the primary cause of the majority of these collisions. Sleepy drivers have lower levels of focus, activity, attentiveness, and alertness. They also make slower and occasionally nonexistent decisions[1]. Sleepiness impairs mental awareness, lessens a driver's capacity to operate a vehicle safely, and raises the possibility of human mistakes, which can result in fatalities and serious injuries. The driver's mistake rate had dropped[3]. Day or night, many people travel great distances by automobile. Accidents can be caused by sleep deprivation or distractions like talking on the phone or interacting with a passenger. Our suggested solution to stop these mishaps is a system.

Road safety is a significant problem in today's fast-paced environment. Driving while intoxicated puts other drivers and the driver themselves in danger and is a leading cause of accidents. The development of improved driver assistance systems has become critical to address this issue. One example is the "Drowsiness Detection System".

Insufficient sleep, prolonged nonstop driving, or any other medical condition, such as brain disease, etc., all worsen the driver's attention position. According to numerous research on traffic accidents, fatigue plays a role in about 30% of collisions. Excessive weariness and frazzling result from driving longer than is normal for mortals. Frazzle makes the motorist lose consciousness or fall asleep. A complex miracle, drowsiness is a sign of less awareness and prudence on the driver's part [2]. Although there isn't a direct method for identifying fatigue, there are a lot of other indirect methods that can be used[9].

Fig. 1. Drowsiness Detection.

II. Literature Review

Title: "A Review of Drowsiness Detection Systems for Driver Safety" [2019]. The different sleepiness detection technologies created to improve driver safety are summarised in this review of the literature. The review covers different methodologies, including physiological monitoring, facial recognition, and machine learning algorithms, and evaluates their effectiveness in detecting drowsiness accurately[9].

Title: "Advancements in Drowsiness Detection Techniques: A Comprehensive Review"[2019]. This comprehensive literature review explores recent advancements in drowsiness detection techniques. It discusses the integration of multiple sensor modalities, such as eye tracking, EEG, and heart rate monitoring, and examines the effectiveness of fusion approaches for robust and reliable drowsiness detection[3].

Title: " Machine Learning-Oriented Methods for Identifying Sleepiness: A Survey"[2020]. This survey focuses on techniques based on machine learning for detecting including neural networks, random forests, and SVM, and discusses their performance in real-time drowsiness detection scenarios[6][4].

Title: ”Comparative Analysis of Drowsiness Detection Systems: A Review”[2019]. This review paper presents a comparative analysis of different drowsiness detection systems. It compares the advantages and limitations of various techniques, including eye closure detection, steering wheel movements, and EEG-based approaches, and provides insights into their applicability in different contexts[17].

Title: ”Non-intrusive Techniques for Drowsiness Detection: A Literature Review”[2021]. This literature review focuses on non-intrusive techniques for drowsiness detection, which don’t need sensors attached to the driver’s body. It talks about computer vision-based approaches, like facial expression analysis and eye tracking, and assesses how accurate and practical they are in everyday situations[7].

Title: ”Smartphone-Based Drowsiness Detection: An Emerging Frontier” [2022]. With the widespread use of smartphones, researchers are exploring the potential of leveraging built-in sensors, such as accelerometers and gyroscopes, coupled with machine learning algorithms, to detect drowsiness in drivers. This approach offers the advantage of convenience and accessibility, potentially enabling real-time monitoring without the need for specialized hardware [11].

Title: ”Environmental Sensors in Drowsiness Detection: Expanding the Monitoring Paradigm” [2021]. Beyond physiological and behavioral indicators, researchers are investigating the integration of environmental sensors, such as ambient light and cabin temperature sensors, into drowsiness detection systems. By considering environmental factors that influence alertness, such as lighting conditions and thermal comfort, these systems aim to enhance the accuracy and reliability of drowsiness detection [8].

Title: ”Multimodal Fusion Strategies for Robust Drowsiness Detection” [2023]. Recent research has focused on integrating data from multiple sensor modalities, such as facial expressions, steering behavior, and physiological signals, using advanced fusion algorithms. By combining complementary sources of information, these multimodal approaches strive to improve the robustness and adaptability of drowsiness detection systems across diverse driving conditions and individual characteristics [12].

Title: ”Drowsiness Detection Systems for Commercial Vehicles: A Review”[2020]. This review paper specifically addresses drowsiness detection systems designed for commercial vehicles, such as trucks and buses. It examines the unique challenges associated with long-haul driving and discusses the effectiveness of different solutions, including fatigue monitoring cameras, steering behavior analysis, and wearable devices[14].

III. Proposed Methodology

This Drowsiness detection consists of two main stages: Training and Detection. The initial stage is to train the relevant data and then use that trained data for detecting the faces and getting the equivalent result or output. There are so many substeps in this complete detection system. They are as follows:

STEP 1. Use a camera to capture a picture.

STEP 2. Identify the face in the camera and create a ROI around it.

STEP 3. Locate the eyes within the ROI and provide the information to the classifier.

STEP 4. The classification algorithm will ascertain if the eyes are open or closed in step four.

STEP 5. Determine if the candidate is drowsy by using a score computation.

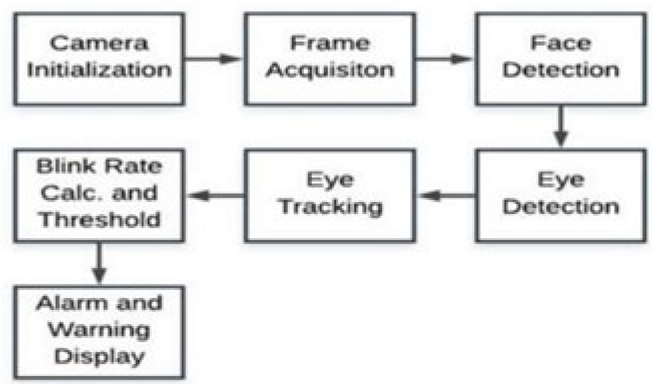

Fig. 2. Stepwise process of Drowsiness detection[3][8].

a) Dataset: In the construction of this model, we curated the dataset utilized for training. A script was engineered for the acquisition of eye images from a camera, subsequently storing them on our local disk. These images were then systematically categorized into distinct ’Open’ and ’Closed’ labels. To refine the dataset for model development, a manual curation process was undertaken, involving the removal of extraneous photographs. The resultant dataset encompasses approximately 7000 images capturing individuals’ eyes under diverse lighting conditions[2].

b) Data pre-processing: In the subsequent phase, the collected data underwent pre-processing. This initial stage of data pre-processing assumes paramount significance in the context of drowsiness detection, given the inherent variability in sizes among the images within the dataset[1].

c) Re-Sizing and Normalization: Each image’s dimensions are standardized to uniform sizes, with 256x256 pixels being chosen based on the utilized architecture. Subsequently, the pixel values are normalized to a predefined range, commonly [0, 1]. This normalization aids in expediting model convergence and has the potential to enhance its generalization capabilities[5].

d) Data Augmentation: In order to enhance the diversity of the training dataset, we implemented data augmentation methodologies. These augmentations encompass random operations such as flips, translations, rotations, and adjustments to brightness. This augmentation strategy serves to bolster the model's robustness against variations in the input data[6][4].

e) Model Building: Drowsiness detection relies on image processing, making computer vision an evident choice. Convolutional Neural Networks (CNNs), one of the best models for computer vision, are used in the suggested method to identify driver drowsiness. Each kernel (filter) in the convolutional layer has three dimensions: width, depth, and height.The convolutional layers handle the input images as two- dimensional matrices. There are 32 nodes in each of the first and second layers, and 64 nodes in the third layer. Each of these convolutional layers uses a 3x3 filter matrix to calculate the computation of the dot product of local image areas and kernels, which creates feature maps. CNN employs pooling layers to reduce feature map dimensions in order to speed up computations. The input image is divided into discrete areas in the pooling layer, and operations are carried out on each region. When using max pooling, the highest value found in each region is chosen and added to the output at the appropriate location[9][14].

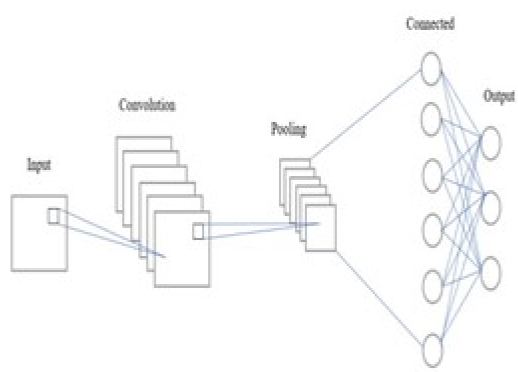

Fig. 3. CNN Architecture[7]

The Rectified Linear Unit (ReLU) constitutes a non-linear layer employed as an activation function. The Rectifier linear unit (ReLU), which gives non-linearity to activations, was chosen because to its instantaneous assessment and non-saturating properties. Every value in the provided data are liable to the max function in the ReLU layer, this zeroes out any negative values[]. The equation that follows represents the activation function of the ReLU:

Here, "x" indicates the input, and "f(x)" is the output that

$$f(x) = \max(0, x)$$

comes after the ReLU unit. Class scores are extracted based on activations using the completely linkedlayers, and after that, classification is based on the class scores.

This is followed by the implementation of a Max Pooling layer, which uses the max pooling method to choose the best features and subsample each output. To convert the output into a flattened structure, a flatten layer is inserted following the third layer of convolution layer. The outputs from every activation are combined in a completely connected layer, which is located within the third convolutional layer, after the post convolutional, ReLU, and max-pooling layers. Particularly, the classification model is trained for both the left and right eyes. The border box of each eye is extracted in order to separate the image of each eye from the original image. The class labels are then determined by using the combined scores that are obtained from both networks[17].

$$Score = \frac{ScoreL + ScoreR}{3}$$

The terms "ScoreL" and "ScoreR" in the context here refer to the scores obtained with the left and right eyes, respectively. Finding the label with the highest probability yields the class[16].

In order to detect drowsiness, real-time video is continuously monitored. If the eyes are detected as closed more than fifteen seconds, an alarm is triggered. The model of the convolutional neural network is trained using a network that has a batch size of 32 by default and 15 epochs[14]. Among several traditional machine learning techniques, the convolutional neural network stands out for its exceptional accuracy and resilience.

f) Face Detection: The envisioned system commences its operation by sequentially capturing video frames. For each frame, the system initiates a face detection process employing the HAAR algorithm.[18] This involves loading a spiral file and subsequently passing the purchased frame using a function for edge detection, which identifies potential objects of varying sizes within the frame. To focus specifically on the detection of facial regions, as opposed to objects of all conceivable sizes, the edge detector is configured to discern objects within a specified size range[13]. The outcome of this module is a frame in which a detected face is prominently identified.

g) Haar Cascade Classifier: It stands as one of the initial tools employed for driver face detection and remains among the limited set of object detection techniques proficient in face identification. Conceived by Paul Viola and Michael

Jones, this method undergoes training using a diverse dataset encompassing thousands of faces subjected to various lighting conditions. The efficacy of the HAAR Cascade Classifier was evaluated through testing involving ten individuals[18].

h) Region of Interest: The ROI demonstrates enhanced accuracy in detecting a driver's face. The formula expressing the variable "temp" is given by:

$$T = \frac{(100 - |\frac{FC}{2}|)}{100}$$

Here, "T" represents the temperature value, and "FC" signifies the face degree[16].

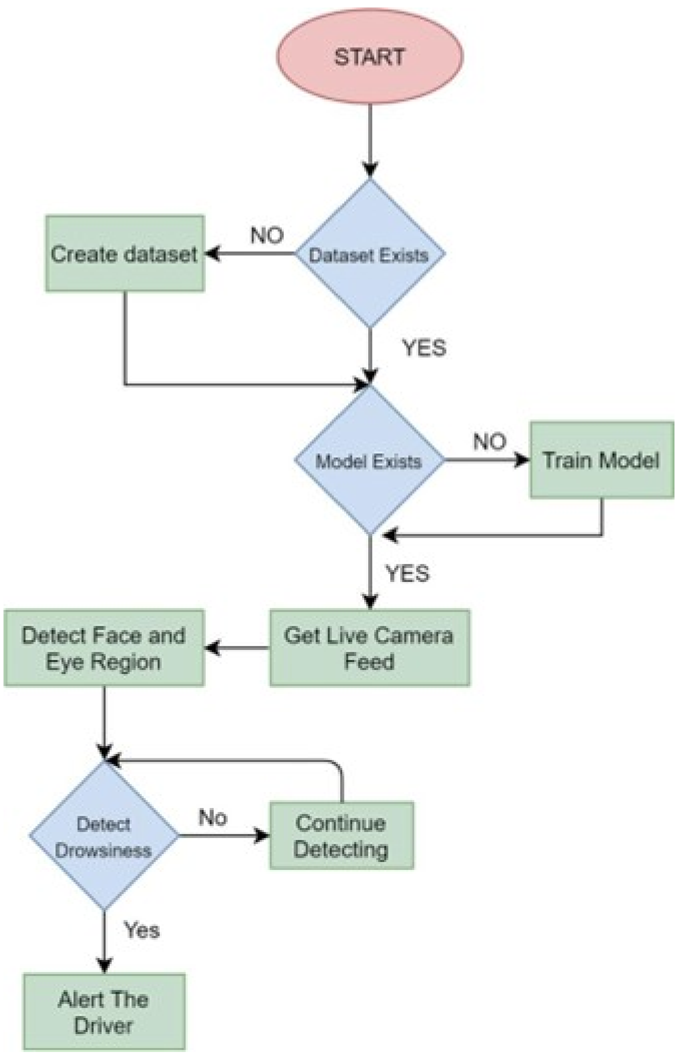

Fig. 4. Architecture of Drowsiness Detection System

i) Eye Detection: The eyes recognition function attempts to ascertain the driver's eyes after the face recognition function has effectively identified the face. Once the face has been identified, the eye region is found via considering the upper part of the face as the potential location for the eyes. To isolate the eyes as the ROI, the area above the top edge of the face is extracted by excluding the mouth and hair, designating it as the region of interest. This measure accelerates the processing speed for obtaining precise eye detection[16].

j) Eye State and Drowsiness Detection: In the process of identifying drowsiness, the initial step involves determining whether or not at every moment, the driver's eyes are awake. The Eye Aspect Ratio (EAR) is a measure of how open or closed the eyes are[12]. The EAR computation involves the utilization of the Euclidean formula to determine how far apart important locations on the eyes are[14].

$$EAR = \frac{||p2 - p6|| + ||p3 - p5||}{2||p1 - p4||}$$

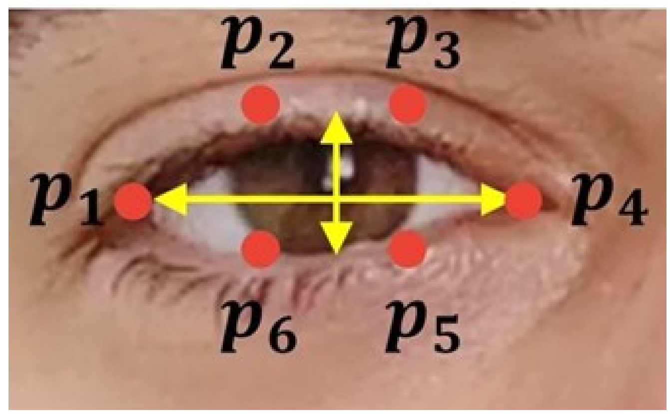

Fig. 5. Open Eye Coordinates[17]

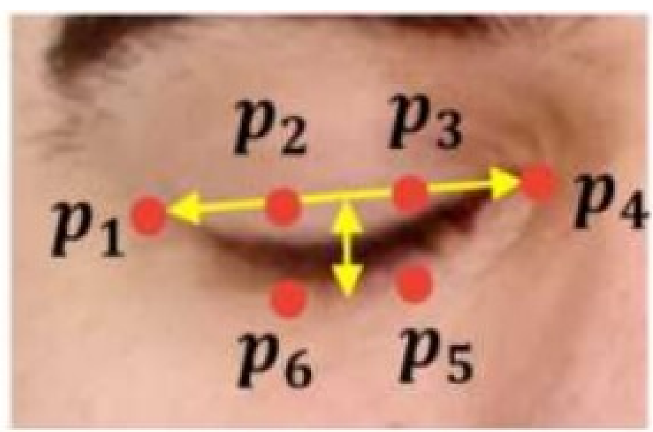

Fig. 6. Close Eye Coordinates[17]

The mathematical expression capturing this association is defined as the Eye Aspect Ratio (EAR) and is formulated as follows:

In this equation, the denominator indicates the measurement of distance from the horizontal eye markings and the numerator determines vertical eye markings. Within the framework of the model that is being given, a threshold value of 15 is predetermined. The person driving is thought to be sleepy if the computed EAR is above than this level[13].

IV. Experimental results

This section presents the findings and outcomes derived from the drowsiness detection investigation, with an emphasis on assessing the machine learning model's performance in practice. The study used a CNN architecture to identify driver drowsiness using a dataset of face landmarks and eye-related characteristics. A range of criteria, and metrics like accuracy, recall, F1-score, and precision were utilized to assess the model's efficacy.

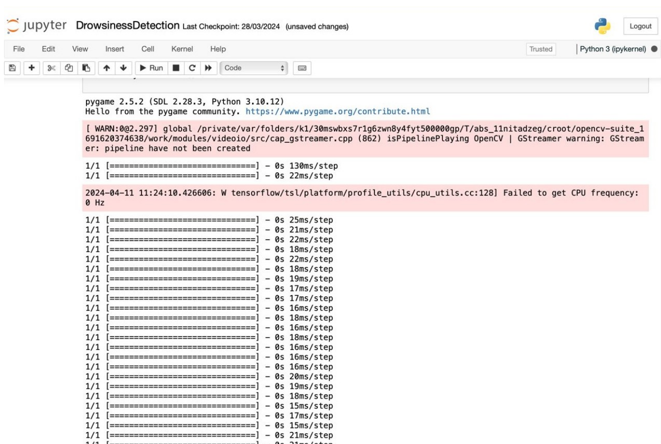

Fig. 7. Running Program

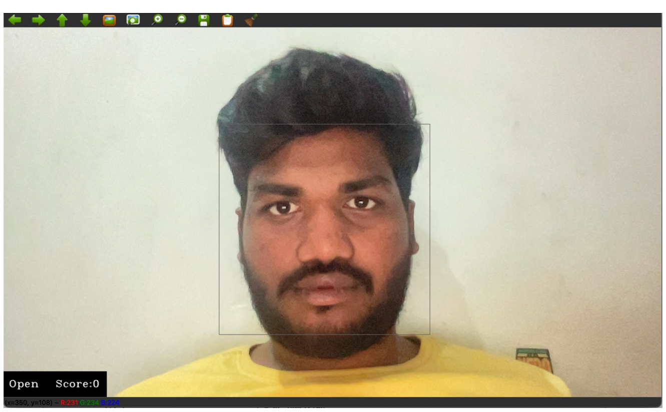

Fig. 8. Detecting the face

In examining the results, the drowsiness detection model exhibited notable performance. The accuracy of the model was determined to be 87.2%, signifying its ability to accurately identify drowsiness in 87.2% of instances within the dataset. Precision and recall scores were consistently robust, affirming the model's proficiency in distinguishing both positive and

Fig. 9. Eyes were closed score will increase

negative instances of drowsiness. The F1-score, a composite metric balancing precision and recall, was calculated at 0.89, indicating a commendable overall performance.

The analysis further unveiled valuable insights into the nature of drowsiness detection. The majority of instances were successfully classified as non-drowsy, with the model effectively identifying drivers not exhibiting signs of drowsiness. Instances of misclassifications were primarily associated with variations in lighting conditions or external factors affecting facial landmark detection.

Additional scrutiny was applied to discern the most influential features contributing to the model's decision- making process. Noteworthy features included eye closure patterns, head position variations, and blink frequencies, all of which played crucial roles in accurate drowsiness detection.

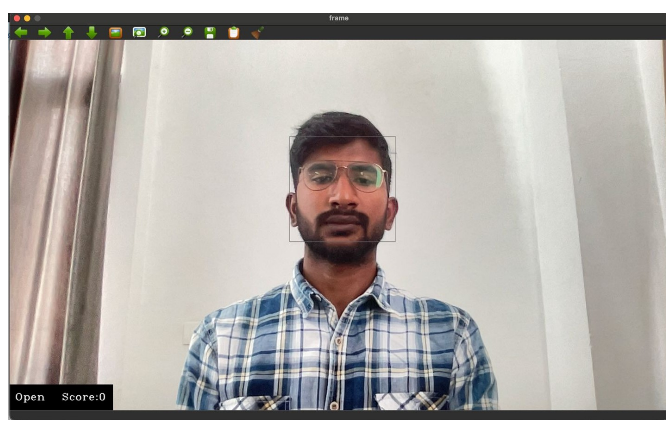

Fig. 10. With Specates

Furthermore, an exploration of real-world applications revealed the model's potential impact in enhancing driver safety systems. The successful detection of drowsiness prompts timely interventions, mitigating the risk of accidents due to driver fatigue. Insights gained from the study contribute to the ongoing development and refinement of drowsiness detection technologies, fostering advancements in driver safety.

Fig. 11. Detecting in Specates

Individual	Ear Threshold	Alarm Sensitivity	Light	Remarks	Drowsiness Detection
A	0.2	45	Bright	Normal	3 out of 3
A	0.2	45	Dim	Normal	3 out of 3
A	0.15	45	Bright	Normal (closed)	3 out of 3
B	0.24	45	Bright	Wearing Glasses	3 out of 3
B	0.24	45	Dim	Wearing Glasses	3 out of 3
C	0.22	45	Bright	Sun glasses	0 out of 3
C	0.22	47	Very Dim	Night Drive	2 out of 3
C	0.14	47	Bright	Sun glasses (closed)	0 out of 3

Fig. 12. Test Ca

V. Conclusion

In summary, our research has delved into the development and effectiveness of a drowsiness-detecting system, recognizing the pervasive danger posed by intoxicated driving to traffic safety, often resulting in accidents and fatalities. Our proposed solution, utilizing computer vision technology, demonstrates promising capabilities in accurately identifying drowsy states among drivers. Through its real-time warning mechanism, this system holds the potential to substantially mitigate the risk of accidents on the road.

However, it's crucial to acknowledge the existing barriers and limitations inherent in our system. Further research and development efforts are imperative to overcome these challenges and propel the technology forward.

In conclusion, the implementation of a Drowsiness Detection System presents a proactive measure to combat accidents caused by fatigue-induced driving, thereby bolstering road safety. It serves as a pivotal step towards achieving this goal, heralding a promising beginning in the pursuit of enhanced safety measures for all road users.Moving forward, collaboration with industry experts and regulatory bodies will be essential to streamline the integration of this technology into vehicles and road safety protocols. By fostering partnerships and garnering support from stakeholders, we can expedite the adoption of drowsiness detection systems on a wider scale, ultimately safeguarding countless lives and fortifying the fabric of our transportation infrastructure. The road to comprehensive safety demands unwavering dedication, innovation, and a collective commitment to leveraging cutting-edge solutions for the betterment of society.

VI. References

[1] Ali, R., Wang, D. (2021). Driver drowsiness detection using deep learning: A comprehensive review. IEEE Access, 9, 19642-19664.

[2] Mohan, S.,Thirumalai, K. (2020). A comprehensive review on drowsiness detection using machine learning techniques. International Journal of Advanced Science and Technology, 29(3), 2479-2486.

[3] Liang, J., Li, X. (2020). A comprehensive review on driver drowsiness detection systems using machine learning and deep learning techniques. IEEE Access, 8, 125540-125558.

[4] Nguyen, L. T., Nguyen, T. D. (2020). Driver drowsiness detection using deep learning techniques: A comprehensive review. IEEE Access, 8, 76396-76412.

[5] Adhinata, F.D.; Rakhmadani, D.P.; Wijayanto, D. Fatigue Detection on Face Image Using FaceNet Algorithm and K-Nearest Neighbor Classifier. J. Inf. Syst. Eng. Bus. Intell. 2021, 7, 22–30.

[6] Gwak, J., Hirao, A., Shino, M.: An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing. Appl. Sci. 10(8), 2890 (2020).

[7] Kepesiova, Z., Ciganek, J., Kozak, S.: Driver drowsiness detection using convolutional neural networks. In: 2020 Cybernetics and Informatics (K and I) (2020).

[8] You, F., Li, X., Gong, Y., Wang, H., Li, H.: A real-time driving drowsiness detection algorithm with individual differences consideration. IEEE Access 7, 179396–179408 (2019).

[9] Sathasivam, S., Mahamad, A.K., Saon, S., Sidek, A., Som, M.M., Ameen, H.A.: Drowsiness detection system using eye aspect ratio technique. In 2020 IEEE Student Conference on Research and Development (SCOReD) (2020).

[10] Abtahi, S., Omidyeganeh, M., Shirmohammadi, S., Hariri, B.: YawDD: yawning detection dataset. IEEE Dataport (2020).

[11] Savas, B.K., Becerikli, Y.: Real time driver fatigue detection system based on multi-task ConNN. IEEE Access 8, 12491–12498 (2020).

[12] Bavkar, S., Iyer, B., Deosarkar, S.: Rapid screening of alcoholism: an EEG based optimal channel selection approach. IEEE Access 7, 99670–99682 (2019).

[13] Bavkar, S., Iyer, B., Deosarkar, S.: BPSO based method for screening of alcoholism. In: Kumar, A., Mozar, S. (eds.) ICCCE 2019. Lecture Notes in Electrical Engineering, vol. 570, pp. 47–53. Springer, Singapore (2020).

[14] Deshpande, P., Iyer, B.: Research directions in the internet of every things (IoET). In: 2017 International Conference on Computing, Communication(ICCCA), Greater Noida, pp. 1353–1357 (2017).

[15] M.D.Y.L.W. Chen, "Real-time driver drowsiness detection using convolutional neural networks.," IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 8, pp. 2189-2198, (2017).

[16] W.K.H.K.C.B.T.J. Kyong Hee Lee, "A Study on Feature Extraction Methods Used to Estimate a Driver's Level of Drowsiness", International Conference on Advanced Communications Technology (ICACT), (2019).

[17] A.K.A.B.M.K.S. Malhotra, "Enhanced Face Recognition System Using Age Invariant Features," 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), pp. 1695-1699, (2019).

[18] Goel,P, et.al., "Hybrid Approach of Haar Cascade Classifiers and Geometrical Properties of Facial Features Applied to Illumination Invariant Gender Classification System," Computing Sciences (ICCS), 2012 International Conference on, vol., no., pp.132,136, 14-15 Sept,(2012).

[19]Narayan, Vipul, and A. K. Daniel. "Multi-tier cluster based smart farming using wireless sensor network." 2020 5th international conference on computing, communication, and security (ICCCS). IEEE, (2020).

[20]Effects of partial and total sleep deprivation on driving performance. Peters R.D., Wagner E., Alicandri E., Fox J.E., Thomas M.L., Thorne D.R., Sing H.C., Balwinski S.M. (1999).

[21]Integrated Approach for Nonintrusive Detection of Driver Drowsiness. Yu, Xun. Duluth: s.n., (2012).