Technical Journal, University of Engineering and Technology (UET) Taxila, Pakistan Vol. 29 No. 1-2024
ISSN:1813-1786 (Print) 2313-7770 (Online)

A Mobile-Edge-Based Smart Driver Drowsiness Detection System

M. S. Janjua[1], I. Safdar[2], B. Jamil[3], H. Ijaz[4]

[1,2,3,4]*Department of Computer Science and Information Technology, University of Sargodha, Sargodha, Pakistan*

[3]bushra.jamil@uos.edu.pk

Abstract- Driver drowsiness a major cause of frequently occurring roadside collisions worldwide, can stem from medical problems, non-stop traveling on long trips, and the increased comfort level in modern vehicles. Drowsiness detection systems (DDS) can help avoid such incidents by notifying the drivers in time to stop travel. Therefore, in this study, we have introduced a mobile-edge-based driver drowsiness detection system capable of generating real-time alerts for drowse drivers. By leveraging mobile-edge technology, our system captures the visual behavioral characteristics of driver's facial expressions like eye closure and eye-aspect ratio to detect the drowsiness level in drivers. The proposed algorithm uses Google Vision's technology for processing images to detect faces and calculation of eye aspect ratio to detect driver drowsiness. Our developed system detects the drowsiness of drivers with 97.2% accuracy, 94.4% precision, and 99.8% recall. The developed system is thus faster, scalable, privacy-preserving, less costly, and reliable for real-time applications as the processing is faster using edge computing.

Keywords- Driver Drowsiness, Sleepiness, Transportation Safety, Driver Fatigue Detection, Image Processing

I. INTRODUCTION

Drowsiness or sleepiness is a state of fatigue or a strong desire to fall asleep, which can sometimes cause small intervals of unconsciousness known as microsleeps. It causes reduced responsiveness, wakefulness, decreased cognitive activity, and degrading overall performance [1]. The leading cause behind drowsiness is a lack of quality sleep at night rather than quantity. However, another reason is traveling on distant routes without taking breaks, especially at night. Moreover, sleepy people coming back from work may also be involved. Some medical conditions like diabetes, chronic pain, or metabolism consequences such as hypothyroidism or hyponatremia also stimulate the drowsiness condition. Other medical science rationales are using medications such as antihistamines, tranquilizers, and sleeping caplets. In this current era, the amenity level in vehicles is an arduous indication by drivers, which also tends to provoke drowsiness and increase in drivers' drowsiness. A medley of causes ranging from mental states and lifestyle choices to severe medical conditions spans drowsiness. Drowsiness is detrimental for drivers because a drowsy driver can fall asleep at the wrong times, causing accidents.

A drowsy driver is four times more likely to get into a collision than an active one. As per data provided by the National Highway Traffic Safety Administration (NHTSA), driver drowsiness causes roughly 91,000 car crashes annually. Approximately 1,550 persons die, 71,000 are wounded, and $12.5 billion is lost financially annually as a result of these collisions [2]. A study by the US National Sleep Foundation (NSF) found that around 28 percent of drivers Dozed off while driving and approximately 54 percent of drivers had driven while sleepy [3]. According to NHTSA, most crashes confine a single person in a vehicle, driving at high speed with no proof of operating brakes. These accidents often occur on rustic roads and highways. According to a study by the German Road Safety Council, driver drowsiness contributes to 25% of traffic accidents [4]. According to the data provided by the Pakistan Bureau of Statistics, the total number of accidents recorded in 2020-2021 is 9701, including 5436 person casualties and affecting 12894 automobiles [5]. Public statistics indicate that each year, roughly 1.3 million people expire while driving, and between 20 and 50 million people grieve for non-dead harms sustained as a result of traffic fatalities [6].

Above stated facts reveal that drowsiness plays a significant role in compromising a driver's performance. Therefore, there is a need to take preventive measures such as heightened awareness of well-rested driving, recognizing signs of drowsiness, adequate sleep. To overcome the drowsiness of the individual, visual distractions, stink features, auditory signals, and haptic feedback can be helpful. Existing technologies to detect the driver's drowsiness rationales upon physiological sensors, such as Electroencephalogram (EEG), Electrocardiogram (EOG), and ECG

Electrocardiogram (ECG), outperform. However, they are expensive and complex to install in everyday life as they involve intricated environments that drivers cannot afford while driving. These facts stress the importance of developing a smart driver drowsiness detection system (DDS) that can monitor the activeness of the driver and reduce the risks of accidents in the early stages.

The drowsiness detection systems monitor the symptoms of drowsiness in drivers and send timely alerts to prevent road accidents. These DDS systems integrate with different vehicle sensors to monitor the symptoms of drowsiness in drivers. Initially, these DDS systems were Cloud Internet of Things-based (CIOT) that used centralized cloud servers to process the data of these systems to detect drowsiness [7]. These CIOT-based DDS systems face the issue of latency and privacy issues that cause a delay in sending timely alerts to drivers in real-time systems. Therefore, edge computing technology is a cutting-edge solution to process data locally, perform real-time and instantaneous analysis of critical factors of drowsiness, and send timely alerts in case of real-time driving.

We are going to pursue the idea of an edge computing-based driver drowsiness system that can work smoothly on Android OS. It will let the driver use this feature not in a portable manner, but it will also let them use this system without the need for the internet. The key idea behind this goal was that the internet isn't available everywhere a driver can drive. So, for this point, the existing approaches don't work anymore. Moreover, this system will be based on the Android OS, which is the most common OS all over the world. So, it is easily available for all intended users. This system will also be available to the users for free of cost. In existing systems, there were many user interface and user experience bugs. Those weren't updated with the passage of the modern era, so, we also updated the application system interface to the level where users can easily interact with it with a friendly user interface.

The mobile devices integrated with edge computing are a portable and promising solution to process data locally and send timely alerts by accessing driver states in a real-time environment. Mobile Edge Computing (MEC) refers to a network framework that offers cloud computing services closer to the end user's location. Unlike cloud computing where the data is sent to large datacenters, MEC reduces both latency and bandwidth usage by processing data process data on a wide range of local devices and computers. This results in faster response times for real-time applications and services, like smart homes, augmented reality, and online gaming, etc. Moreover, MEC augments privacy and security by locally processing sensitive data. As MEC minimizes the load on centralized data centers, this results in efficient resource utilization and reduced cost. Mobile-edge-based DDS systems enhance the idea of edge-based DDS systems using sensors embedded in smartphones or mobile devices that generate data to detect drowsiness and process it locally at these devices without using external servers. These mobile-edge-based DDS systems use different computer vision and machine learning algorithms to detect a driver's drowsiness by analyzing the data obtained from sensors embedded in smartphones or mobile like facial expressions, eye movements, etc. These mobile-edge-based DDS systems process all data locally on these devices without using external cloud servers and generate timely alerts.

To combat drowsiness, we propose a hybrid mobile-edge-based DDS system in this paper, which includes visual and audio alerts to notify the driver when drowsiness is detected. We have used smartphones or mobile devices having different sensors, such as the front camera to continuously monitor the driver states and Google's Vision technology for the driver's face and eye detection. We propose an artificial intelligence-based algorithm for drowsiness detection and alert generation. Furthermore, the proposed vision framework in this paper is fully compatible and a native framework embedded in Android, so there will be no compatibility cases or misconfigurations. Deploying it on a mobile device will grow its acceptance rate due to its high availability.

The proposed work makes the following major contributions:

- We present a review of existing driver drowsiness techniques, their advantages and disadvantages.
- We propose a Smart Driver Drowsiness Detection algorithm that analyses the driver's behavior in real-time by providing prompt alerts to drowsy drivers, thus preventing road accidents.
- As the developed system is implemented on the edge, it reduces latency and improves responsiveness by faster data processing at the mobile/edge devices.
- The proposed algorithm is cost-effective, privacy-preserving, and scalable as it can seamlessly integrate into current smart devices with ease. It does not need any additional sensors and thus is more convenient and comfortable.

The organization of this paper is outlined as follows: Section 2 presents related work. Our suggested drowsiness detection algorithm is shown in Section 3. The performance assessment and the results are discussed in Section 4, and Section 5 concludes the paper.

II. Related Work

This section presents some existing methods proposed for driver drowsiness detection. One of the initial methods is based on driving patterns, road conditions as well as condition of vehicles. These methods use lane positions, steering wheel movement, and lateral deviations for drowsiness detection [8].

To identify the driving patterns, Krajewski and fellows [9] analyze and monitor the deviation between the car's position and the designated road lane. They achieved 86% accuracy using micro-adjustment correlations. The proposed drowsiness detection system depends upon the vehicular approach that includes road and vehicle characteristics, and driving skills.

Saradadevi proposes a driver tiredness detection system by analyzing mouth and yawning [10]. The proposed technique initially finds the driver’s mouth from input images and after that, these mouth images are trained using a Support Vector Machine. After that, to detect yawning SVM is used. The authors claim that the proposed algorithm provides much better results when compared with systems that use geometric features.

Another approach in this regard is to use data collected from physiological sensors for example data acquired from Electroencephalogram (EEG). EEG signals can monitor brain activities. The three main signals alpha, delta, and theta can be used to measure driver drowsiness. The alpha signal just slightly rises whereas the delta and theta signals climb sharply in sleepy drivers. Mardi and fellows [11] claim that this is the most accurate technique that provides more than 90% accuracy. But the major problem with this technique is that it needs too many sensors for drowsiness detection which is annoying for drivers.

Leng and fellows [12] present the wearable-type sleepiness detection technique. They use their own designed wristband and skin sensor. The collected data is then sent to the mobile for evaluation. They extracted five features from this data: heart, respiratory, and pulse rate, stress level, as well as adjustment counter. These features are then classified using an SVM classifier to detect drowsiness. The proposed technique achieved about 98.02% accuracy.

Siwar Chaabene and fellows also propose a drowsiness detection system using EEG signals using bio-medical signal processing and deep learning (DL) [13]. The presented method works in two phases: In the first phase of data acquisition, the signals are collected from a wearable headset for recording different EEG channels and their annotations. After signal collection data augmentation is performed to solve the overfitting problem and increase accuracy. In the second step, the model is analyzed using a deep learning framework. The model uses Keras for data classification. The authors claim to achieve 90.42% accuracy for drowsiness detection.

Another behavioral approach for drowsiness detection used by researchers is based on facial features like eye blinking, head tilting, and yawning frequency. Assari and Rahmati use facial expressions to detect driver drowsiness detection [14]. The proposed system initially cuts the background from the input image to detect the face and then, they use horizontal projection and template matching for drawing facial expressions. In a later stage, the drowsiness is detected via changes in facial components. The changes in eyebrow rising, yawning, and eye closure are selected as initial indicators of sleepiness. The obtained results suggest that the proposed technique work generates alerts even in the presence of glasses.

Hariri and fellows use mouth and yawning behaviors for drowsiness detection [15]. They use a modified Viola-Jones [16] object detection algorithm for the movement of the face and mouth. Eye blinks per minute are used for drowsiness detection by Danisman and fellows [17]. They suppose that eye blinking increases with the increased drowsiness.

Convolution Neural Networks (CNN) have successfully been applied in computer vision for example facial recognition, image segmentation and recognition, and object detection. Dwivedi and fellows use light CNN to detect Drowsy drivers and achieve about 78% accuracy [18].

Park and fellows use an architecture composed of three networks for drowsiness detection [19]. To extract the image feature, they use AlexNet [20], as the first network, composed of three FC Layers and five CCNs. VGG-FaceNet [21], as the second network is used for face feature extraction. Flow-ImageNet [22], as the third network, is used for behavioral feature extraction. The authors claim about 73% accuracy in drowsiness detection.

Venkata Rami present a drowsiness detection technique using a CNN [23]. They also used the Viola-Jones object detection algorithm to extract face and, eye regions. They apply a stacked deep CNN in the training phase from dynamically identified keyframes of the camera. The softmax activation function is used for classifying the sleepy or non-sleepy driver. The obtained results reveal that the proposed technique is above 90% accuracy.

Jabbar and fellows use a Multilayer Perceptron Classifier (MLP) for the detection of drowsiness using embedded systems [24]. The developed system detects facial expressions from images. After that, the gathered data is sent to the pre-trained model for drowsiness detection. The main advantage of the proposed method is to decrease the model size. The achieved accuracy of the proposed method is 81%.

Zhong developed a driver drowsiness system using machine learning [25]. They use OpenCV for training the dataset. The main objective of the proposed technique is to detect both extreme and soft signals of drowsiness. Their dataset includes videos of about 30 hours of 22 drivers. The authors use

OpenCV for the extraction of a single frame per second for drowsiness detection. The main drawback of the proposed technique was that it is not suitable for mobile environments.

Rajmohana and fellows [26] present a drowsiness detection system based on Convolution Neural Networks and Bi-directional Long-Term Dependencies. They track the face and eye blinking through a video camera. The system performs detection in four stages: In the first stage face of the driver is extracted. Secondly, the Euclidean algorithm is applied to extract the eye from the image. Thirdly, eye blinking is continuously observed. Lastly, when sleepiness is identified, an alert message is generated accordingly.

Ahmad and fellows present a model to evaluate driver fatigue using CNN and VGG16 models. They achieve 97% and 74% accuracy using CNN and VGG16 respectively [27]. Pham proposes a driver drowsiness detection system using IoT and DNN improved using LSTM, VGG16, and DenseNet [28]. They use facial landmarks for fatigue detection and if the driver is found sleepy a warning is generated using the Jetson Monitoring System.

Table 1, presents the comparison of the proposed techniques in terms of technique used, algorithm applied, and the obtained accuracy.

Table 1. Comparison of Proposed Techniques Used

Techniques Used	**Algorithm**	**Acc.**	**Ref**
Steering behavior	correlations	86%	[9]
Mouth and yawning analysis	SVM	81%	[10]
EEG signals		90%	[11]
Wrist sensors	SVM	98%	[12]
EEG signals	Deep learning	90.4%	[13]
Facial Feature Extraction	Template matching	-	[14]
Mouth and yawning analysis	Viola-Jones	-	[15]
Facial Feature Extraction	Light CNN	78%	[19]
Facial Feature Extraction	Viola-Jones + CNN	90%	[23]
Facial Feature Extraction	MLP	81%	[24]
Facial Feature Extraction	CNN + Bidirectional LSTM	94%	[26]
Facial Features	CNN, VGG16	97% 74%	[27]
Facial Landmarks	LSTM, VGG16, DenseNet	98%	[28]

Existing Driver Drowsiness Detection techniques reliance on sensors that can be uncomfortable for drivers to wear for extended periods. Additionally, some of these techniques may not be able to accurately detect drowsiness in all drivers, as each person's behavior and symptoms of sleepiness can vary. Another limitation is the cost of some of these techniques, which can be prohibitive for some individuals or companies. Finally, some techniques may be prone to false alarms, which can be frustrating for drivers and lead to less confidence in the technology. These drawbacks highlight the need for innovative solutions like Mobile-Edge-Based Smart Driver Drowsiness Detection that can overcome these limitations and provide accurate and reliable detection of drowsiness in drivers.

III. PROPOSED SYSTEM

This Section presents our proposed technique to detect the drowsiness of a driver.

Figure 1 shows the proposed methodology that we have used for a smart driver drowsiness detection system. In the first step, the driver face is captured through the camera. To isolate the face from the camera overlay, we have leveraged the capabilities of Google Vision API. Google Vision API uses different general-purpose tools to identify various features and objects within images, including facial attributes and expressions such as eye closure, yawning, and head positioning for drowsiness detection. We processed our video frames through API to identify potential signs of drowsiness in the facial features. We have tested the performance of our system manually by manually annotating data. To build an overlay for the camera display, we utilize camera overlay capability. For the detection of face position, the getPosition() method of Android is used that is present inside the view class. To track the position of the face this overlay encompasses the canvas method. Then using a draw method the canvas and textual alerts are put on camera to generate the user alarms. To compute the eye-aspect ratio (EAR) an open probability function is applied on frames to detect the driver dowsiness as shown in Figure 2. To compute EAR the distance between the eye's top and bottom end is added and then, it is divided by the eye's horizontal distance as given in equation 1.

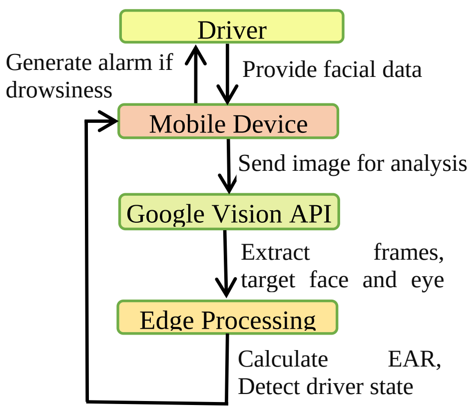

Figure 1: Proposed Methodology

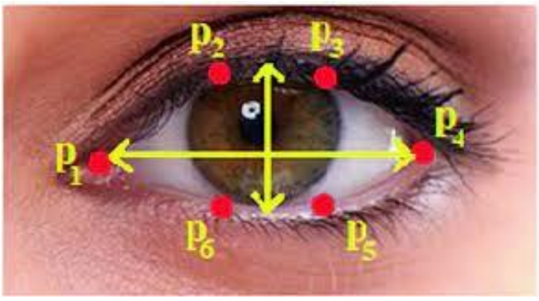

Figure 2: Eye Aspect Ratio

EAR = [d2 − d6] + [d3 − d5]/2[d1 − d4] (1)

The Android cameras use Dlib (68 pts) Facial Landmark Detector and Dlib library for eye detection. All the identified frames are used to calculate the eye's vertical distance (VD). This VD is the width of the image after frame detection through FLD as shown in Figure 3.

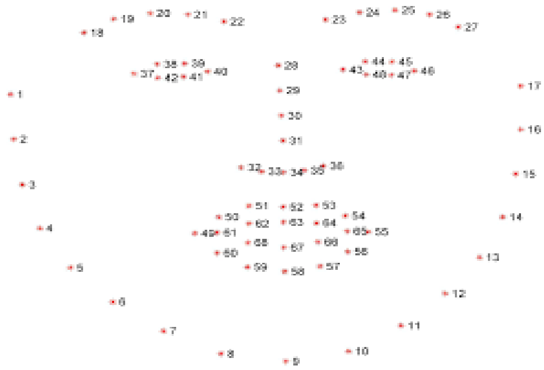
Figure 3: Facial Landmark and Eye Detection

Google Vision API uses the facial landmark figure with numbered points around the eyes, mouth, face and neck to detect drowsiness by examining key physiological markers. These physiological markers include eye aspect ratio (EAR), which is determined by the spatial arrangement of facial landmarks surrounding the eyes; yawning is determined by measuring the separation between landmarks on the upper and lower lips around the mouth; head position is determined by the landmarks surrounding the face and neck to detect tilted and nodding movement to detect sudden or gradual drops in head position indicating drowsiness. Eye Vertical Distance (VD) divided by Total Eye Vertical Ratio (TVR) is used to compute open eye probability as given in Equation 2.

RATIO = VD / TVR (2)

This obtained ratio is the open-eye probability that is used to detect driver drowsiness by comparing it with the standard drowsiness threshold value. As this detection technique is implemented on the edge, therefore, a quick alert can be generated for the drowsy driver. The vision technique uses pre-trained machine learning models which are used through Representational State Transfer (REST) API. By assigning labels to images classification can be done fastly

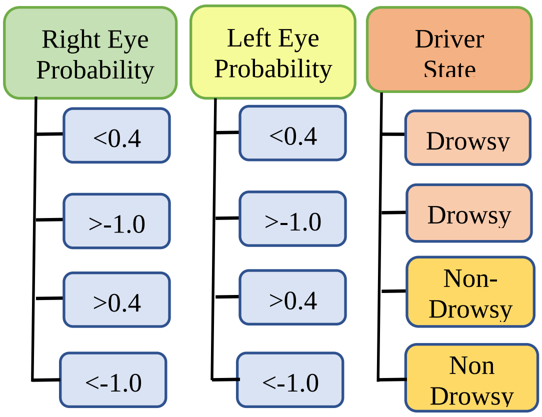

Figure 4: Eye Aspect Ratio Ranges

Figure 4 shows our used label formats. According to the figure if the EAR is less than 0.4 or greater than -1.0 the driver state is classified as drowsy. However, if the EAR is greater than 0.4 and less than -1.0 the driver state is classified as non-drowsy. Our proposed algorithm is given as follows.

Algorithm 1

Input: Image Frame
Output: Driver State
Isolate face from camera overlay
Detect face
Track face position
Detect Eye
Calculate the distance between the eye's top and bottom
Compute the eye-aspect ratio using equation (1)
Calculate open-eye probability using equation (2)
Assign labels for classifying drivers as sleepy or non-sleepy

Equation 3 presents the calculation for time complexity for the driver's drowsiness detection.

T(n, m, f, T) = O(f . T. (n.m + C + A)) (3)

Where nxm is the resolution of each frame, *f* is the frame rate, T is the total processing time, *C* is the complexity of detecting facial features per frame and *A* is the complexity of analyzing these features per frame for drowsiness detection. *f*.T represents the total number of processed frames, and (*n.m* + *C* + *A*) is the combined per-frame complexity of preprocessing, feature detection, and drowsiness analysis of the image.

IV. EXPERIMENTAL RESULTS

In this section, we present the experimental results of our developed system. For this purpose, we have tested our system on several drivers in real-time conditions. Table 2 presents the eye state results.

Table 2. Eye States Matrix for Drivers

Driver #	Frames	FOES	FCES	TOES	TCES
1	480	16	0	279	185
2	410	4	0	71	335
3	290	9	0	167	114
4	375	12	1	214	148
5	390	13	0	247	130

A false open-eye state (FOES) shows that the eyes are open but the captured frame indicates the drowsy state. A false closed-eye state (FCES) means that the eyes are closed but the system chooses this frame as drowsy. A true open eye state (TOES) indicates that the eyes are open and the captured frame shows the active driver state. A true closed-eye state (TCES) means that the eyes are closed and the system correctly classifies this frame as drowsy.

Confusion Matrix
A confusion matrix is a useful matrix to evaluate the effectiveness of a supervised machine learning model. The class labels are presented along the x-axis while the predicted class labels are presented along the y-axis. The diagonal values indicate the correctly classified classes while in-correct predictions of each class are presented in off-diagonal cells. Figure 5 shows the confusion matrix for our drowsiness detection system.

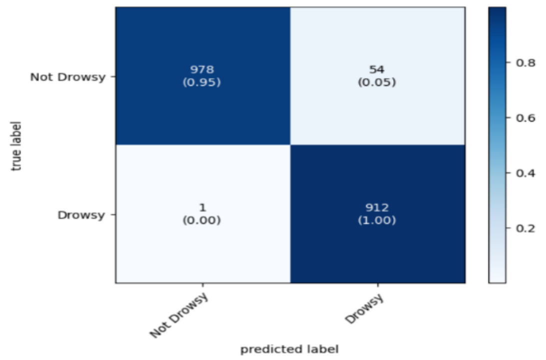

Figure 5: Confusion Matrix

The figure indicates that our proposed system correctly differentiates between an active or drowsy driver most of the time. Using the confusion matrix we have also calculated accuracy, precision, and recall for our proposed system.

Accuracy
Accuracy is the most commonly used metric that indicates the degree to which something is correct or precise. It is a desirable attribute that shows that the results are reliable and trustworthy. The accuracy is calculated using Equation 4.

$$A = \frac{TOES+TCES}{Total\ number\ of TOES+TCES+FOES+FCES} \quad (4)$$

TOES (true positive) represents the count of correctly classified non-drowsy drivers, and TCES (true negative) denotes the number of drowsy drivers accurately classified as drowsy by the system. While, FOES (false positive) is the count of alert drivers falsely identified as drowsy by the system, and FCES (false negative) denotes drowsy drivers wrongly identified by the system as alert drivers. Using our proposed system, we have achieved an accuracy of about 97.2%.

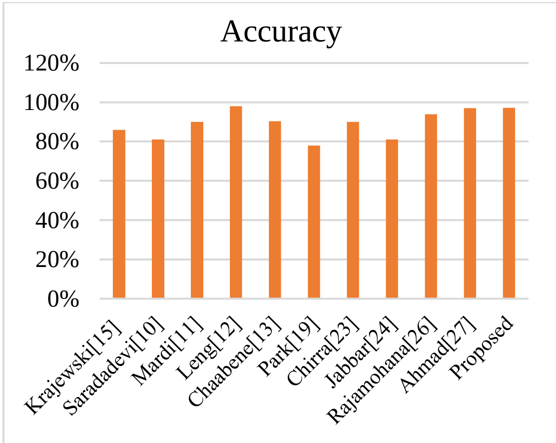

Figure 6: Accuracy comparison with existing techniques

Figure 6 compares the accuracy of our proposed model with existing drowsiness detection systems. The graph shows that the accuracy of most of the existing algorithms is below 90%. However, Mardi and fellows [11] achieve an accuracy of about 96% while the accuracy of our proposed system is 97.2% which is greater than other existing techniques.

Precision
Precision is a metric that helps evaluate the performance of the suggested classification model. It measures the accuracy of positive predictions. Precision is calculated using equation (5).

$$Precision = \frac{Number\ of\ true\ positive}{Total\ number\ positive\ predictions} = \frac{TOES}{TOES+FOES} \quad (5)$$

Where TOES is the total number of accurately classified non-drowsy drivers and FOES denotes the misclassified non-drowsy drivers. We have achieved 94.4% precision using the proposed technique.

Recall
Recall is also an important metric to measure the effectiveness of predictive models. It is used to

measure completeness and helps to determine the ability of the model to identify relevant cases in a particular dataset. Recall can be calculated using equation 6.

$$Precision = \frac{Number\ of\ true\ positive}{Actual\ positives} = \frac{TOES}{TOES+FCES} \qquad (6)$$

Where TOES is the total number of accurately classified non-drowsy drivers and FCES denotes the misclassified active drivers. Our proposed system achieved 99.8% recall.

User Acceptance

User acceptance is the process of verifying that a system meets the requirements of the intended users. It entails testing the system to ensure that it is user-friendly and satisfies their requirements., and is fit for purpose.

As our proposed system is Android-based and drivers do not need any other sensors this results in 68% of user acceptance which is better as compared to techniques proposed in [9, 15, 21, 28].

User Experience

User Experience is related to the overall experience of a user while using a system. It encompasses every facet of the user's interaction, from the user interface and usability to the emotional response that the user has while using the product or service. The ultimate aim of user experience is to increase user satisfaction and Quality of Service.

To enhance the user experience for the drivers we have provided a proper user guide within the application which leads to a User Experience rate of almost 80% that is again much improved than the existing techniques.

V. CONCLUSION

In this paper, we present an edge-based, real-time, smart driver drowsiness detection system that generates quick alerts for a drowsy driver. We have used visual behavioral characteristics like the eye-aspect ratio to identify a drowsy driver. The proposed technique uses Google Vision technology to calculate the driver's Eye Aspect Ratio. The experimental results suggest that we achieved an accuracy, precision, and recall of about 97.2%, 94.1%, and 99.8% respectively. Moreover, our proposed approach does not need connectivity to the internet as the data is processed on the edge device. Due to this our developed system is more responsive, as well as it has features like scoring accuracy, user-friendly, collaborative, and efficient design.

In the future, robust, reliable lightweight AI models should be developed for edge devices to generate more timely alerts for drowsiness detection in different lighting and weather conditions. These models should be made more energy efficient so that they can help with drowsiness detection, especially on long-haul trips where power sources may not be readily available.

REFERENCES

[1] El-Nabi, S. A., El-Shafai, W., El-Rabaie, E. S. M., Ramadan, K. F., Abd El-Samie, F. E., & Mohsen, S. (2024). Machine learning and deep learning techniques for driver fatigue and drowsiness detection: a review. Multimedia Tools and Applications, 83(3), 9441-9477.

[2] Paul Stephen Rau. "Drowsy driver detection and warning system for commercial vehicle drivers: field operational test design, data analyses, and progress". In: 19th International Conference on Enhanced Safety of Vehicles. Citeseer. 2005, pp. 6–9.

[3] Can, D. B. G. E. S. (2010). Save your life this memorial day. National Sleep Foundation (NSF): Arlington, VA, USA.

[4] World Health Organization. (2020). European regional status report on road safety 2019. World Health Organization. Regional Office for Europe.

[5] Pakistan Bureau of Statistics. Pakistan Bureau of Statistics. 2021. URL: https://www.pbs.gov.pk/sites/default/files/tables/social_statistics/tarffic_accidents_annaul__09_02_2021.pdf.

[6] World Health Organization. Global status report on road safety 2015. World Health Organization, 2015.

[7] Sharma, R., Goyal, K. K., & Mahato, S. K. (2023, March). Development of IoT-Based Drowsiness Detection and Smart Alert System for Accident Prevention in Automobiles. In International Conference on Production and Industrial Engineering (pp. 305-313). Singapore: Springer Nature Singapore.

[8] Shaik, M. E. (2023). A systematic review on detection and prediction of driver drowsiness. Transportation research interdisciplinary perspectives, 21, 100864.

[9] Krajewski J et al. "Steering wheel behavior-based estimation of fatigue. The fifth international driving symposium on human factors in driver assessment, training and vehicle design". In: (2009), pp. 118–124.

[10] Mandalapu Saradadevi and Preeti Bajaj."Driver fatigue detection using mouth and yawning analysis". In: International journal of Computer science and network security 8.6 (2008), pp. 183–188.

[11] Mardi Z, Ashtiani SN, and Mikaili M. "EEG-based drowsiness detection for safe driving using chaotic features and statistical tests.

Journal of medical signals and sen- sors”. In: (2011), pp. 130–137.

[12] Leng, L. B., Giin, L. B., & Chung, W. Y. (2015, November). Wearable driver drowsiness detection system based on biomedical and motion sensors. In 2015 IEEE SENSORS (pp. 1-4). IEEE.

[13] Chaabene, S., Bouaziz, B., Boudaya, A., Hökelmann, A., Ammar, A., & Chaari, L. (2021). Convolutional neural network for drowsiness detection using EEG signals. Sensors, 21(5), 1734.

[14] Assari, M. A., & Rahmati, M. (2011, November). Driver drowsiness detection using face expression recognition. In 2011 IEEE international conference on signal and image processing applications (ICSIPA) (pp. 337-341). IEEE.

[15] Hariri, B., Abtahi, S., Shirmohammadi, S., & Martel, L. (2012). A yawning measurement method to detect driver drowsiness. Technical Papers.

[16] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[17] Danisman, T., Bilasco, I. M., Djeraba, C., & Ihaddadene, N. (2010, October). Drowsy driver detection system using eye blink patterns. In 2010 International Conference on Machine and Web Intelligence (pp. 230-233). IEEE.

[18] Dwivedi, K., Biswaranjan, K., & Sethi, A. (2014, February). Drowsy driver detection using representation learning. In 2014 IEEE international advance computing conference (IACC) (pp. 995-999). IEEE.

[19] Park, S., Pan, F., Kang, S., & Yoo, C. D. (2016, November). Driver drowsiness detection system based on feature representation learning using various deep networks. In Asian Conference on Computer Vision (pp. 154-164). Cham: Springer International Publishing.

[20] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25.

[21] Parkhi, O., Vedaldi, A., & Zisserman, A. (2015). Deep face recognition. In BMVC 2015-Proceedings of the British Machine Vision Conference 2015. British Machine Vision Association.

[22] Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2625-2634).

[23] Chirra, V. R. R., Uyyala, S. R., & Kolli, V. K. K. (2019). Deep CNN: A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State. Rev. d'Intelligence Artif., 33(6), 461-466.

[24] Jabbar, R., Al-Khalifa, K., Kharbeche, M., Alhajyaseen, W., Jafari, M., & Jiang, S. (2018). Real-time driver drowsiness detection for android application using deep neural networks techniques. Procedia computer science, 130, 400-407.

[25] Grant Zhong et al. Drowsiness Detection with Machine Learning. 2019. URL:https:// towardsdatascience.com/drowsiness-detection-with-machine-learning-765a16ca208a.

[26] Rajamohana, S. P., Radhika, E. G., Priya, S., & Sangeetha, S. (2021). Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM). Materials Today: Proceedings, 45, 2897-2901.

[27] Ahmed, M. I. B., Alabdulkarem, H., Alomair, F., Aldossary, D., Alahmari, M., Alhumaidan, M., ... & Zaman, G. (2023). A deep-learning approach to driver drowsiness detection. Safety, 9(3), 65.

[28] Phan, A. C., Trieu, T. N., & Phan, T. C. (2023). Driver drowsiness detection and smart alerting using deep learning and IoT. Internet of Things, 22, 10070