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DRIVER DROWSINESS WARNING AND DETECTION

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ABSTRACT- All around the world there are many road accidents every hour, some are due to drink and driving, lack of sleep, lack of attention on the wheel and many more reasons, which can be risky for the passenger as well as people on roads. The most common situation is lack of sleep which can make the driver careless while driving, these things cannot be ignored. To avoid such situations driver drowsiness detection system is very efficient to detect drowsiness by calculating and judging the rate of driver's eye blink rate and eyeballs size through camera and the program attached to it. Driver drowsiness detection system is based on CNN-machine learning algorithm which is implemented completely offline and can alert with the help of alarm if the driver is feeling drowsy.

Keywords: Driver drowsiness detection, Convolutional neural network, Real-time monitoring, Machine learning

INTRODUCTION

Driver drowsiness is one of the major factors of crash on roads in all over the world. According to the NHTSA, it is approximately about 100k accidents are caused by driver fatigue in USA each year, resulting in over 1.5k fatalities and 71k injuries (National Highway Traffic Safety Administration, 2021). The issue of drowsy driving is not limited to the US alone; it is a global problem that needs to be addressed [1].

Driver drowsiness detection is a vital topic of study that aims to prevent accidents caused by driver fatigue. Over the years there has been a growing interest in this technology and various techniques have been developed to detect drowsiness in drivers. These techniques include physiological and behavioral-based methods. Physiological- based methods measure the driver's physical responses to fatigue, such as heart rate, blood pressure, and brain activity, while behavioral-based methods detect changes in the driver's behavior, such as steering wheel movements and vehicle speed [2].

ML algorithms have lately been employed in driver sleepiness detection systems. These algorithms are capable of detecting patterns in physiological and behavioral data collected from drivers and can predict their drowsiness levels accurately. The algorithms use different features, such as eye movement, facial expressions, and head movements, to detect drowsiness in drivers [3] [4].

The development of driver drowsiness detection systems is essential in improving road safety and reducing accidents caused by driver fatigue. These systems can alert drivers to take breaks when they become too tired, reducing the risk of accidents. Moreover, they can also provide feedback to fleet managers, who can use the information to develop policies that encourage drivers to take breaks when they become too fatigued [5].

In conclusion, driver drowsiness detection is an important area of research that can significantly improve road safety. The advancement of efficient and dependable detection technologies has the potential to minimize the frequency of accidents caused by driver drowsiness. This technology has the potential to save many lives and should be given more attention by researchers and policymakers.

LITERATURE SURVEY

Computer vision, machine learning, and other technological advancements have played a crucial role in drowsiness detection. One of the primary reasons for auto accidents is driver inattentiveness, which can be caused by various factors, including fatigue-induced drowsiness. Researchers have explored several methods to detect drowsiness, including biological, behavioral, and vehicular methods. Various solutions have been proposed, including those that utilize machine learning algorithms, computer vision, and other technological tools. Additionally, advances in vehicle components and bio-signaling have also contributed to the development of effective drowsiness detection systems.

One method shown that a driver's sleepiness level may be identified by extracting face characteristics. The approaches were tested using NTHU-DDD video dataset. The features analyzed include head position, eye blinks, and mouth state. The driver's head angle contributes in determining head yaw and pitch angle. PERCLOS is used to track eye blinks. The FACS action unit is used to monitor yawning. The face is detected on the display, and the parameters of all other identified features, such as yawns, eye blinking, head movement, and pitch angle, are presented. A threshold is assigned to each attribute. Drowsiness is stated to be identified if the parameter value exceeds the threshold value [6].

An alternative approach that considers facial features such as the nose, lips, and eyes is utilized for detection of drowsiness. To detect the face from 2D pictures derived from video frames, the approach uses a histogram of directed gradients and a linear support vector machine. Once recognized, the algorithm calculates the position of facial landmarks using their respective coordinates. Measurements of the nose length ratio (NLR), eye aspect ratio(EAR), and mouth opening ratio(MOR) are used to extract features for categorization. The driver is classified as being sleepy if these variables go beyond a particular threshold. The system's accuracy is validated through the analysis of its collected data [7].

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Numerous studies have examined visual behaviors combined with machine learning to develop drowsiness detection systems. Other approaches have investigated the use of bio-signal equipment or vehicle components, but without integrating machine learning algorithms. The Support Vector Machine (SVM), Bayesian classifier, Hidden Markov Model (HMM) [8], and CNN are instances of machine learning approaches that have been used. All of these techniques have been shown to be highly accurate for various face features. However, SVM, HMM, and Bayesian classifier techniques are more expensive to train than CNN. As the model size increases, so does the cost and computational requirements [9].

DATASET

The Drowsiness Dataset from the Kaggle platform is used in this study. This dataset contains 2 categories of photos named Test and Train. Two classes from the Dataset will be used in this project.

The data features are: -

1. There are 2900 photos in total across two categories in the collection.

2. There are 433 photos in Test folder and 2467 photos in Train folder.

3. Both Test and train folders consist of

4 folders "Closed", "Open", "No- yawn", "Yawn".

The data divided into a data for train and data for test in 85% - 15% ratio respectively.

Figure 1. Two main categories of Dataset, Test and Train folders

PROPOSED SYSTEM

The objective of the proposed system is to enhance accuracy and reduce the execution time of the fatigue and drowsiness detection system. The system comprises the following components:

3.1. Webcam:

A webcam is utilized to capture an input image.

3.2. Image Resizing:

The input image is resized to a standardized format.

3.3. Haar Classifier:

A Haar classifier is an algorithm that is trained to detect specific objects in an image. The classifier works by overlaying the positive image over a set of negative images. The training process is typically performed on a server and is divided into multiple stages. By utilizing these components, the proposed system can accurately detect fatigue and drowsiness in real-time. The system's improved accuracy and reduced execution time can enhance road safety and prevent accidents caused by drowsy driving.

3.4 Convolutional Neural Network model:

Convolutional Neural Network model is a type of deep learning algorithm that is used in driver drowsiness detection systems. This model is designed to automatically extract relevant features from images and identify patterns that distinguish between a drowsy and an alert driver. In the context of driver drowsiness detection, a Convolutional neural network model is trained on a

dataset of images that depict both drowsy and alert drivers [10]. The model is then used to classify new images and determine whether the driver in the image is drowsy or alert.

The CNN model typically comprises of several layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for feature extraction, while the pooling layers sample down the features to reduce the complexity of the model. The fully connected layers classify the input image based on the extracted features

[11]. CNN models have proven to be highly effective in driver drowsiness detection systems due to their ability to learn complex features from images. These models can detect subtle changes in facial expressions and eye movements that are indicative of drowsiness, allowing them to accurately detect driver fatigue and prevent accidents on the road is trained to detect specific

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objects in an image. The classifier works by overlaying the positive image over a set of negative images. The training process is typically performed on a server and is divided into multiple stages. By utilizing these components, the proposed system can accurately detect fatigue and drowsiness in real-time. The system's improved accuracy and reduced execution time can enhance road safety and prevent accidents caused by drowsy driving.

3.5 Eye Region of Interest

Eye Region of Interest (ROI) extraction involves identifying the exact location of the eyes in an image. To accomplish this, the image is cropped to a region near the eyes using image cropping techniques, since the activity of the eyes is the main focus. This technique helps to reduce the total area of the picture, making it easier to identify the eyes. To extract the ROI, the image is cropped to approximately two- fifths to three-fifths of the total area of the picture in the upper region. This technique enables the separation of the eyes to be performed accurately. Overall, the ROI extraction process plays a crucial role in driver drowsiness detection systems by enabling the identification of subtle changes in the eyes that indicate drowsiness. By extracting the ROI, the system can focus on the critical areas of the image and accurately detect driver fatigue, thereby improving road safety.

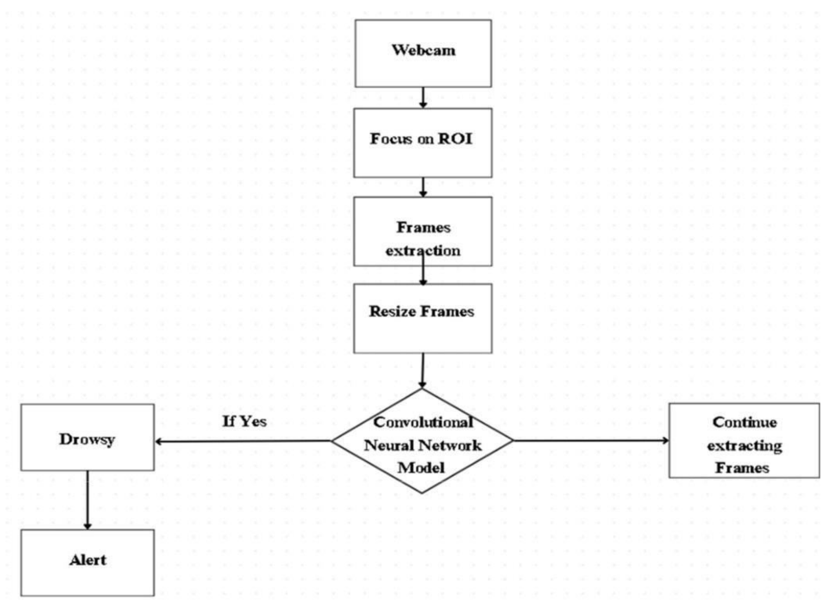

Figure 2. Block diagram of Driver Drowsiness Detection System

IMPLEMENTATION

4.1 Webcam

The webcam is a critical component of driver drowsiness detection systems. OpenCV is a popular library used to perform image processing tasks using programming languages such as Python. This library is utilized in the driver drowsiness detection system to perform real-time face detection using the webcam as the primary camera. OpenCV provides several functions that enable the system to access the webcam and capture frames in real-time. These frames are then processed using advanced computer vision techniques to detect and classify driver fatigue accurately. The webcam's ability to capture high-quality images in real-time is critical to the success of driver drowsiness detection systems. By utilizing OpenCV's image processing capabilities, the system can perform complex computations on the captured frames, enabling accurate detection of drowsiness in drivers.

Requirements: -

1. Python 3.10.4
2. OpenCV
3. NumPy
4. Tensorflow 2.10.1
5. Haar Cascade eye classifier

4. 2 Image resizes.

Image resizes is an essential component of driver drowsiness detection systems. The OpenCV library provides several functions to resize the input image to a standard format. The Haar Cascade classifier supports either a single face detection or multiple faces detection, allowing for cropping or resizing of an image while ensuring the person in the original picture appears in the resized version [12].

4.3 Haar Cascade Classifier:

A Haar cascade classifier is an algorithm for machine learning that detects objects. It works by training on both positive and negative pictures that include the object of interest. After that, the trained classifier can recognize the item in new Frame. The Haar cascade classifier is utilized in driver sleepiness detection systems to recognize the driver's face and eyes.

4.4 Haar Cascade with OpenCV:

OpenCV is an open-source computer vision library that is widely used in driver drowsiness detection systems. OpenCV provides various functionalities to apply the Haar cascade classifier to detect objects in images and videos [13].

4.5 Frame Acquisition

Frame acquisition involves capturing the frames from the video feed in real-time. The frames are then analyzed to identify changes in the driver's face and eyes. By capturing the frames continuously, the system can detect driver drowsiness accurately [14].

4.6 Measuring EAR Implementation

Measuring the Eye Aspect Ratio (EAR) is a common method used to detect drowsiness in driver drowsiness detection systems. EAR involves measuring the ratio of the distance between the eyes to the length of the eye opening. As drowsiness sets in, the eyelids droop, causing a decrease in the EAR value. The system can use this decrease to detect driver fatigue and alert the driver [15].

4.7 Convolutional neural network model

The first line of code imports the necessary modules from the Keras library to construct the model. An instance of the Sequential model is then created to stack layers and build the neural network architecture. To this model, a 2D convolutional layer is added with 32 filters, a 3x3 kernel size, and a rectified linear unit (ReLU) activation function. The input shape of the layer is set to 24x24x1 to accommodate grayscale images. Subsequently, a 2D max pooling layer with a 2x2 pool size is added to down sample the feature maps generated by the previous convolutional layer. The model is then updated with another 2D convolutional layer, this time with 64 filters, a 3x3 kernel size, and a ReLU activation function. Another 2D max pooling layer with a 2x2 pool size is then added. A third 2D convolutional layer is also added with 128 filters, a 3x3 kernel size, and a ReLU activation function, followed by another 2D max pooling layer with a 2x2 pool size. The output of the previous layer is then flattened into a 1D array using the Flatten () function. Next, a dense layer with 64 neurons and a ReLU activation function is added, followed by a dropout layer with a dropout rate of 0.5 to prevent overfitting during training. Finally, a dense layer with a single neuron and a sigmoid activation function is added to the model to produce a probability output for the binary classification task. To train and evaluate the model, it is compiled using the Adam optimizer, binary cross-entropy loss function, and accuracy.

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TESTING

The model is loaded using the "load model" function from Keras. A test image of an eye is loaded and preprocessed by resizing and reshaping to the required input shape of the model. The preprocessed image is then used to make a prediction using the "predict" function on the loaded model. The prediction result is printed to the console indicating whether the eye is open or closed based on the prediction probability. Finally, the test image is displayed using Matplotlib. Testing code uses the OpenCV, NumPy, and Matplotlib libraries to load, preprocess, and display the test image, and to make predictions using the pre-trained CNN model.

Figure 3 depicts the train and test accuracy vs the number of epochs. Figure 4 depicts the train and test loss vs the number of epochs.

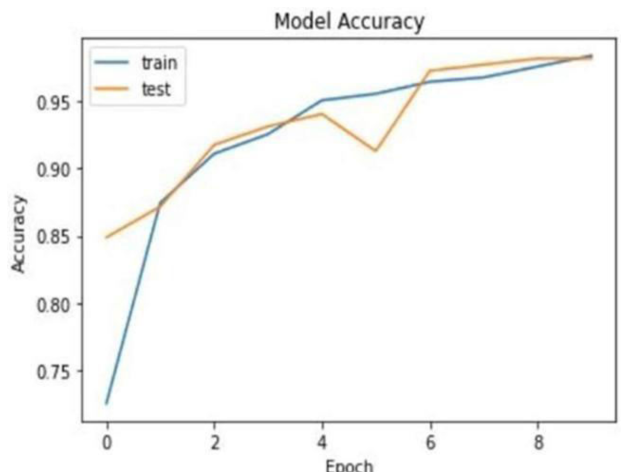

Figure 3. Train & Test accuracy vs. Number of Epochs

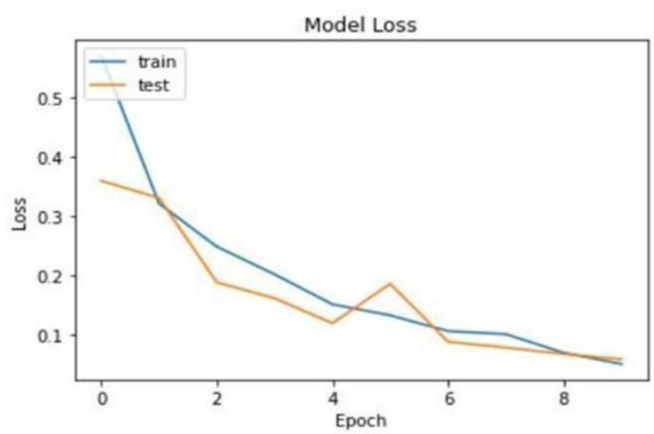

Figure 4. Train & Test loss vs. Number of Epochs

RESULT

We have applied our method to several images of eyes and have obtained results. A positive result means that the algorithm correctly identifies closed eyes as closed and open eyes as open.
To evaluate the performance of our method, we tested it on images of open eye. Figure 5 shows the result that our system produced when applied to an image of an Open eye. As the figure demonstrates, our system correctly identifies the eye as being open.

```
1/1 [==============================] - 0s 164ms/step
The eye is open.
```

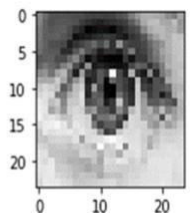

Figure 5. Model Test Result

In certain instances, our method produced results that indicated the eye was open when it was actually closed, and vice versa. The influence of light and its reflection, in our opinion, may have contributed to this disparity. To evaluate the performance of our system, we have included several Figures. Figure 6 lists the system's precision, recall value, and F1-score. Figure 7 includes a confusion matrix.

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	109
1	0.99	0.97	0.98	109
accuracy			0.98	218
macro avg	0.98	0.98	0.98	218
weighted avg	0.98	0.98	0.98	218

Figure 6. Classification report

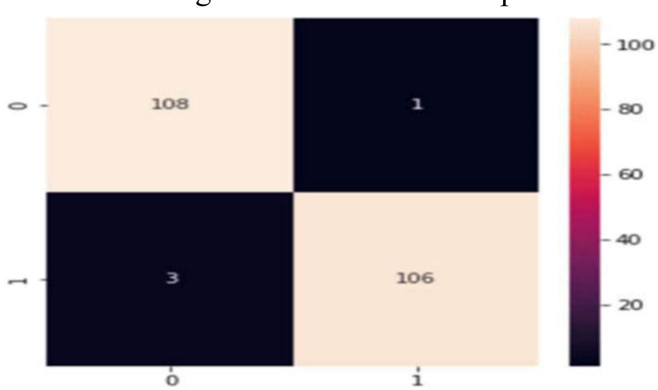

Figure 7. Confusion Matrix

FUTURE SCOPE

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Driver drowsiness detection systems are emerging as a vital technology for enhancing road safety by preventing accidents due to driver fatigue. The future scope of this technology is promising and can be summarized as follows:

The continuous advancements in machine learning and computer vision will result in more precise and dependable drowsiness detection systems.
The integration of drowsiness detection technology with other safety features such as lane departure warning and automatic emergency braking will further enhance the overall safety of vehicles.

The adoption of this technology in commercial vehicles, including trucks and buses, can improve the safety of long-distance transportation.

Drowsiness detection systems can also be combined with wearable devices such as smart watches to provide real-time alerts to drivers. With the increasing popularity of autonomous vehicles, drowsiness detection technology will become a crucial safety feature in self-driving cars.

The use of drowsiness detection systems can significantly reduce the number of accidents caused by driver fatigue, leading to a considerable reduction in fatalities and injuries on the roads.

CONCLUSION

Driver drowsiness detection systems is designed to help drivers stay awake while driving, in order to reduce the risk of accidents caused by drowsiness. In this research paper, experiments were conducted in a well-lit room with consistent lighting conditions. However, it's important to note that there were some limitations in this study. For example, the performance of our system may be affected by varying light conditions and the darkness of a person's skin. Therefore, further testing is needed to evaluate the effectiveness of our system under different lighting conditions and skin tones. Despite these limitations, the study demonstrates the potential of driver drowsiness detection systems in improving road safety. With further research and development, these systems could become an essential tool for preventing accidents caused by driver fatigue. Results demonstrate that this model can accurately detect driver drowsiness with high precision, recall value, and F1-score. CNN model achieved a classification accuracy of over 98% on both the training and test datasets. CNN model also successfully identified the drivers who were drowsy, and alerted them with a visual and auditory warning.

REFERENCES

1. "National Highway Traffic Safety Administration," 2021. [Online]. Available: https://www.nhtsa.gov/risky-driving/drowsy-driving...

2. S. K. Kushwaha, " A review on driver drowsiness detection system. International Journal of Computer Sciences and Engineering," vol. 6, no. 1, pp. 16-21, 2018.

3. X. G. S. H. X. Zhu, "Real-time driver drowsiness detection based on machine learning techniques.," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 4, pp. 1524-1533, 2020.

4. 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.

5. D. R. A. &. R. R. De Silva, " Drowsiness Detection for Driver Safety: A Review," IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR), pp. 258-263, 2020.

6. 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.

7. R. P. Ashish Kumar, "Driver Drowsiness Monitoring System using Visual Behaviour and Machine Learning," IEEE Conference, 2018.

8. S. R. Eddy, "Current Opinion in Structural Biology," ELSEVIER, vol. 6, no. 3, pp. 361-365, 1996.

9. S. G. a. A. K. S. Sinha, "Emerging Data Security Solutions in HADOOP based Systems: Vulnerabilities and Their Countermeasures," 2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2019.

10. B. K. a. J. R. S. Padamata, "A machine learning approach for driver drowsiness detection," International Journal of Engineering Research and Applications, vol. 10, no. 11, pp. 58-65, 2020.

11. Vedant Kaushish, Nitesh Singh, Kunal Maggo, Preeti Nagrath, Rachna Jain, "Driver Drowsiness Detection System with OpenCV and Keras," in Proceedings of the International Conference on Innovative Computing & Communication (ICICC), 2021.

12. 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.

13. G. Bradski, "The OpenCV Library. Dr. Dobb's Journal of Software Tools," 2000.

[Online]. Available: https://www.drdobbs.com/embedded-systems/the-opencv-library/184404319.

14. S. Choudhry, "Driver Drowsiness Detection System: A Review," International Journal of Engineering & Technology, vol. 7, no. 3.23, pp. 128-133, 2018 2018.

15. S. D. S. G. A. J. B. Sukrit Mehta, "Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio," in Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur - India, 2019.