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Detection of Driver Drowsiness using Hybrid Learning Model

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Abstract: In this work, two approaches were explored for detecting driver drowsiness: one utilizing a pre-trained model based on Eye Aspect Ratio combined with the RESNET50 architecture, and the other employing a Hybrid Learning Model integrating Haar Cascade Algorithm with Siamese Networks. First, we implement a traditional approach using a pre-trained RESNET50 model combined with EAR to analyze facial features, mainly focusing on the eye region. This method provides a baseline for comparison with the proposed hybrid model. Next, we proposed a novel technique that combines the robustness of the Haar Cascade (HC) Algorithm for facial feature extraction approach with the effectiveness of Siamese Networks for drowsiness classification. Experimental evaluations are conducted using real-world datasets to compare the performance of both methods in different standard matrices. The results indicate the efficiency of the hybrid model, which outperforms the EAR-based RESNET model in accurately detecting driver drowsiness under various conditions and lighting conditions. Overall, this work contributes to the advancement of driver drowsiness detection systems and develops a novel hybrid model that combines the strengths of traditional computer vision techniques with state-of-the-art methods.

Keywords: *Eye Aspect Ratio, VGG19, Haar Cascade Algorithm, Siamese Network.*

1. Introduction

Driver drowsiness detection system is a critical aspect of modern vehicle safety systems to reduce accidents caused by driver fatigue and inattention. Fatigue-related accidents pose a significant risk on roads worldwide, leading to injuries, fatalities, and economic losses. The National Highway and Traffic Safety Administration system estimates that intoxicated driving causes thousands of collisions each year in the US alone. To address this issue, researchers and engineers have developed advanced driver assistance systems (ADAS) capable of detecting the different signs of driver drowsiness and alerting the driver to take corrective action. These systems typically utilize sensors and machine-learning models to analyze real-time driver behavior and physiological signals. It is a critical safety feature in modern vehicles designed to alert drivers when they are becoming tired, helping to prevent accidents caused by driver inattention or sleepiness [1]. The recent literature on relevant efforts in this topic in this report. The techniques applied in each measurement strategy. Lastly, a thorough debate based on the effectiveness of the procedures and the results attained [2]. The system typically monitors various driver-related parameters and vehicle dynamics to assess the driver's state and issue warnings when signs of drowsiness are detected. Seven transfer learning-based deep learning models are developed and evaluated for the driver sleepiness problem at work [3]. Some authors [4] examined the measurements the researchers had taken, which were divided into four categories: behavioral, subjective, physiological, and vehicle-based approaches. This [5] research investigates and assesses several approaches to sleepiness detection. Recently, technology known as driver drowsiness detection systems has monitored drivers' behavior and identified indications of tiredness using a variety of sensors, algorithms, and artificial intelligence [6]. While there are workable algorithms for utilizing EEG to identify driver tiredness, they are inefficient. A fuzzy-based algorithm was used to identify the applied accurate detection method [7]. They [8, 9] proposed a model for integrating the electronica-based vehicle tracking system to identify driver drowsiness and accurate results.

The system uses sensors, cameras, and other monitoring devices to track drivers' behavior. This can include tracking eye movements, head position, facial expressions, steering patterns, and even biometric signals like heart rate and skin conductance. The data collected from the monitoring devices analyzes the different patterns and changes in the driver's behavior to detect signs of drowsiness or fatigue. These signs may include frequent blinking, prolonged eye closure, erratic steering, drifting out of lane, or sudden changes in driving behavior. Once signs of drowsiness are detected, the system evaluates the severity of the situation and determines the appropriate response. It may involve warning the driver, such as an audible alert, visual warning on the dashboard, or even haptic feedback through the steering wheel or seat vibrations. If the system determines that the driver is becoming dangerously tired, it will activate the warning mechanism to alert the driver to the potential danger. The alert is designed to capture the driver's attention and prompt them to take corrective action, such as pulling over to rest or changing their driving behavior. Some advanced systems incorporate machine learning (ML) algorithms to adapt to individual driver behavior over time. By learning from past interactions and responses, the system can improve its accuracy in detecting drowsiness and tailor alerts to each driver's specific needs and habits. Driver

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drowsiness detection systems enhance road safety by helping drivers stay alert and focused during long journeys or monotonous driving conditions. These systems are becoming increasingly common in modern vehicles, with many manufacturers incorporating them as standard safety features. Drowsy driving significantly threatens road safety, contributing to many accidents worldwide. Traditional methods of detecting driver fatigue often rely on rudimentary indicators, such as steering wheel movements or eye blink patterns, which must be revised in accuracy and robustness. In recent years, the emergence of deep learning has offered promising avenues for addressing this challenge. This paper presented a comprehensive study on driver drowsiness detection using a Hybrid Learning Model (HLM) integrating the Haar Cascade Algorithm with Siamese Networks. By levsseraging the capabilities of RESNET50 as a pre-trained model and HML, it aimed to develop a real-time application system to accurately identify signs of driver fatigue based on driver eye movements.

Contribution of the study.

• The primary issue is the drowsy driver's lack of focus, which causes them to react badly to everything on the road. The system used feature selection techniques to improve classification accuracy.

• Adaptive neuro-fuzzy inference systems (ANFIS), a blend of filters and wrapper feature selection methods, were employed in the suggested selection process. The study involved a dataset of 39 car drivers in a simulated driving environment.

• The results indicate the efficiency of the hybrid model, which outperforms the EAR-based RESNET model in accurately detecting.

The rest of the paper is organized as follows: An overview of relevant research on driver sleepiness detection is given in Section 2. The approach used in our work, including dataset collection, preprocessing methods, and model design, is covered in Section 3. The experimental data and measures for performance evaluation are presented in Section 4. Section 5 concludes with recommendations and future research directions.

2. Literature Review

Park et al., [10] research shows an architecture known as deep learning-based drowsiness detection (DDD) [10], which analyzes RGB movies that center on the driver's complete face. The DDD architecture uses three different architectures: VGG-FaceNet, AlexNet, and Flow ImageNet. The output of these network models is merged to classify the level of drowsiness in each frame of the input movies. The authors test their proposed model using the NTHU drowsy driver detection database, and the results indicate an average accuracy of 73.06%. Park et al.'s research [10] examines red, green, and blue movies focusing on the driver's complete face, referred to as the DDD architecture. The pre-trained models use the DDD architecture applied to DDD data for training. The output of these network data is combined to classify the drowsiness in different input video frames. The authors use the NTHU-DDD database to test their proposed model, and their testing findings show an average accuracy of 73.06%. Phan et al. [11] designed the DDD model that detects only the eye region. In this method, the precise eye region is extracted using feature extraction utilizing the Haar Cascade technique, which was first presented by Viola-Jones. The CNN method was used to detect the faces and eyes that collected the data from the database, train their network, and achieve an accuracy of 0.98% for the training and 0.97% for the testing. Phan et al. [13] developed two different approaches for drowsiness detection; the first approach finds the factors that focus on the eyes and mouth utilized by the Dlib functions that help specify the driver's yawning. The second one uses the two pre-trained models, MobileNet-V2 and ResNet-50V2, with transfer learning. The data for training models was collected from various online sources, and an accuracy of 0.97% was obtained. Rajkar et al. [14] presented a new model that extracts the features from the eyes using the Haar Cascade approach. The extraction of ROI mainly focused on the eye and face separately and applied to two databases for training YawDDD and Closed Eyes. The overall accuracy of the proposed approach is 96.56%. Hashemi et al. [15] introduced the model for DDD with the help of pre-trained CNN models like VGG16 and VGG19 combined with transfer learning. The Haar Cascade implemented the feature extension, which extracts the features from the face and finds exciting patterns from the given eyeblink database. The final results were obtained with an accuracy of 98.15% for the proposed approach. Alameen et al. [16] introduced a new model that extracts the spatiotemporal features learned from the inputs of LSTM. The experiments were conducted using two databases, 3MDAD and YawDAD, with a good accuracy of 0.96%.

Gomaa et al. [17] provided several designs that merged LSTM and CNN; the CNNs were pre-trained models already in the public domain. Additionally, the authors suggest their architecture, known as "CNN-LSTM," and use the "NTHU" dataset for testing and training. They outperformed the other four networks with their "CNN-LSTM" network, achieving an accuracy of 98.3% and training cases of 97.31% in the testing phase. A method for detecting drowsiness based on EAR in conjunction with PERCLOS—which determines the percentage of eye closure over a specific duration—was presented by Singh et al. [18]. They extracted eye points using Dlib, which is required for the EAR model. The system's accuracy for the developed method they represented was 80%. Tibrewal et al. [19] proposed a CNN-based model for the drowsiness detection approach. A single eye's worth of photos from the MRL eye database was utilized for testing and learning. The Dlib library was used to extract the ROI for the eyes. Through attention to the eye condition, the authors detected drowsiness with an average accuracy of 94%. When creating systems to assist in driver protection, fuzzy logic [20] proves to be a valuable tool because, on the one hand, it is simple and intuitive to create accurate rules with easily understandable results. On the other hand, these systems have fast computing speeds that enable real-time application. These systems can be used for purposes other than just detecting weariness. For instance, in [21], a fuzzy-based alarm system is suggested to warn drivers of potentially hazardous conditions. A system that measures the driver's mouth and eye-opening to determine whether or not they are fatigued is one of the works that combines fuzzy logic and fatigue detection. It is suggested in [22] that an alarm will sound if the system can detect drowsiness across different situations. Many aspects of their novel approach to simulating driver tiredness were derived from PLSR-based eyelid movement. They employed partial least squares (PLSR) to predict tiredness and solve the strong linear correlations between eye blinking. The primary concept involves positioning two cameras at disparate angles. The two overlapping rings that make up the camera's center are home to many evenly spaced LEDs and their surrounds. While one camera tracks the head with a large field of vision, the other focuses on eye identification with a restricted field of vision. The small-square integration model was presented in [12] to forecast the sleepiness trend. The created sample's accuracy and predictive power are confirmed, suggesting that it offers a novel method of combining various variables to improve the capacity to identify and forecast tiredness. On the other hand, in [23], the authors illustrate the driver's activities during a given period, including the average PERCLOS, the driver's blinking rate, and the head position, all captured in the preceding 60 seconds. The driver's level of fatigue is then ascertained by feeding these factors into a fuzzy inference system (FIS) made up of thirty-two different rules. Recently [24, 25], researchers have conducted a Detection of Driver Drowsiness technology using a machine learning approach to identify the Driver Drowsiness. The suggested [26] hybrid system detects drivers' tiredness using the Convolutional Neural Network algorithm and the Haar cascade classifier. The Raspberry Pi module will track the driver's eyes and sound an alert when necessary. However, the face must move in real-time and have an aspect ratio between 16:9 and 1.85:1. Real-time enhanced deep-learning-based architectures have retrieved and classed those hybrid features as driver weariness [27]. Using a convolutional neural network and deep belief network, a multi-layer-based transfer learning technique was employed to identify driver weariness from hybrid features. The analysis indicates that the hybrid model performs better than other machine learning models.

2.1. Eye Aspect Ratio (EAR)

An essential parameter in drowsiness detection systems is the Eye Aspect Ratio (EAR), especially regarding safety-critical applications like driver fatigue monitoring. The eye's geometry, especially the locations of essential face landmarks found in pictures or video frames, is the source of the EAR measurement. The placements of the eyes and significant facial identifications, such as the corners and midpoints of the eyes and different, are used to determine the EAR. Changes in the EAR over time can reveal differences in eye closure or openness, which suggest weariness or drowsiness. Computer vision techniques usually monitor the EAR in real-time application systems in sleepiness detection systems. The system can sound alarms or initiate preventive measures, like vibrating the steering wheel, sending reminders to the driver, or sounding alarms when the EAR falls below a predetermined threshold or shows patterns linked to drowsiness. The efficacy of the EAR algorithm is attributed to its capacity to precisely identify minute alterations in ocular behavior that preceded periods of tiredness or exhaustion. By detecting fatigue in drivers early on, the risks can be reduced, improving overall road safety. Lastly, the EAR is essential to sleepiness detection systems because it offers a quantitative assessment of eye behavior, which helps spot drowsiness indicators and warns people to respond appropriately. The EAR is a tool used to assess how open someone's eyes are, which is essential for identifying sleepiness symptoms. Finding the lengths between particular facial landmarks identification systems—usually found around the eyes—and calculating the ratio of these distances are the two steps in calculating EAR. Finally, EAR computation can be added to the RESNET50 model architecture to track eye movements in real time while inference is made.

$$\mathrm{EAR} = \frac{||\mathrm{L}_2 - \mathrm{L}_6|| + ||\mathrm{L}_3 - \mathrm{L}_5||}{2 \cdot ||\mathrm{L}_1 - \mathrm{L}_4||}$$

$\mathrm{L}_1 - \mathrm{L}_4$ −outer corner of the left and right eyes (usually the outer canthus).

$\mathrm{L}_2 - \mathrm{L}_6$ −Top of the eye (usually the top eyelid).

$\mathrm{L}_3 - \mathrm{L}_5$ −bottom of the eye (usually the bottom eyelid).

3. Resnet50:

A pre-trained ResNet50 model architecture specifically designed for detecting driver drowsiness. ResNet50, short for Residual Network with 50 layers, is a widely-used neural network architecture known for its depth and effectiveness in image-based classification analysis. The ResNet50 architecture comprises convolutional layers and shortcut connections, enabling efficient training and testing of deep neural networks. Convolutional Layer: Applies a series of learnable filters on the input image to produce feature maps. Max Pooling Layer: Reduces the features and mapping spatial dimensions of each feature, helping extract the most relevant information while reducing computational complexity. Residual Blocks: These blocks introduce skip connections (or shortcut connections) to jump over some layers, which helps combat the vanishing gradient problem during training. The exact equations within a residual block involve convolutions, batch normalization, and activation functions like ReLU. Global Average Pooling: Determines the constant length of each vector irrespective of the input size by calculating the average of each mapped feature. Fully Connected Layer: This layer links each neuron in the layer above to each neuron below. Output Layer: Using the softmax network layer for the classification approach and fine-laying the output probabilities for each class. Figure 1 indicates the Architecture Diagram for the RESNET50 system of different layers and each layer explanation given below.

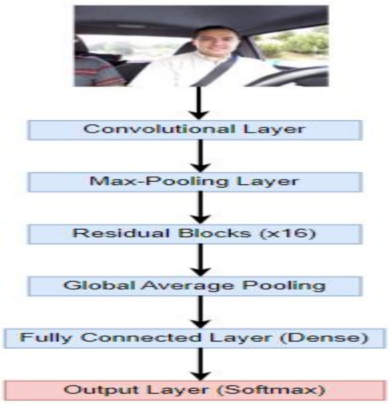

Fig 1: Architecture Diagram for RESNET50

3.1 Dataset Description

The dataset containing 1000 training and 500 testing images was gathered from the Kaggle dataset. All these images were taken from various persons using a DLSR camera. In testing data, 300 images belong to Females and 200 to males. Figure 2 represents the sample images of the driving system and how the male and female persons used DLSR camera images.

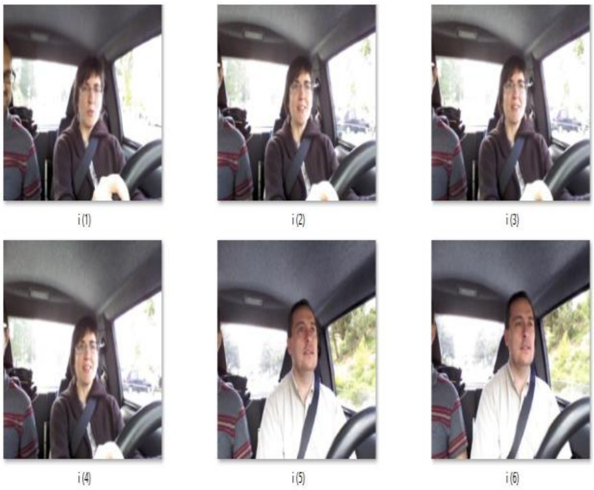

Fig 2: The Sample Image Dataset

4. Hybrid Learning Model (HLM)

One major factor that contributes to traffic accidents globally is driver drowsiness. The ability to detect and mitigate drowsiness in real time has become a paramount concern for ensuring road safety. Traditional approaches to drowsiness detection often rely on single-modal data sources or simplistic algorithms, which may need more robustness and accuracy in real-world scenarios. To resolve these issues and address these limitations, we have proposed a novel Hybrid Learning Model (HLM) that integrates the Haar Cascade Algorithm (HCA) with Siamese Networks (SN) for driver drowsiness detection. This hybrid approach leverages the strengths of both computer vision and deep learning techniques to achieve enhanced performance and reliability.

4.1 Haar Cascade Algorithm (HCA)

The Haar Cascade Algorithm is a popular computer vision technique for object detection. It operates by analyzing patterns of contrast in images, making it well-suited for detecting different facial features like eyes, mouth, nose etc. In the context of drowsiness detection, the HCA can efficiently identify key facemask landmarks indicative of drowsiness, such as closed eyes or drooping eyelids. Images, both positive and negative, are used to teach the HCA. Negative photos lack the target object, whereas positive images show instances of the object, such as eyes. By taking features from the images, the algorithm gains the ability to discriminate between positive examples and those that are negative throughout training. It uses Haar-like features, which characterize the contrast between neighboring rectangular areas in an image. Throughout the image, these attributes are computed at various scales and places. The integral images were used to calculate Haar's different features. Regardless of the region's size, the integral picture enables the calculation of the sum of the pixel values within any rectangular part of the image in a consistent amount of time. The system uses the AdaBoost learning algorithm to choose a limited number of crucial features from the broader collection of Haar-like features. AdaBoost uses the training and testing of the data to train weak classifiers iteratively, assigning larger weights to incorrectly classified examples in different iterations. These weak classifiers are combined into a final robust classifier based on weights. A cascade of classifiers is created from the trained AdaBoost classifier. An input image is only sentto the following stage of the cascade if it completes the preceding stage, which comprises several weak classifiers. It makes it possible to reject non-object portions in the image efficiently. To ascertain whether the target object is present in every area of the input image, the HCC applies the cascade of classifiers while swiping over it at various scales and locations during the detection phase.

Generally, you would train the classifier on positive instances of alert driver faces and bad examples of drowsy or distracted driver faces to modify the HCA for DDD. The training involves feeding the HCA many positive and negative instances, allowing it to learn the distinguishing features of alert and drowsy/distracted driver faces. The trained classifier may then identify the presence of alert or sleepy faces in real-time video streams from a driver monitoring system. To increase tiredness detection accuracy, you should include additional attributes or methods like head posture estimate or eye closure detection.

4.2. Siamese Networks (SN)

SN is a class of DNN designed to learn the similarity between pairs of inputs. SN can be trained to discern subtle differences between alert and drowsy facial expressions in drowsiness detection. By learning a representation of facial features that captures the nuances of drowsiness, SN enables more accurate and robust detection compared to traditional methods. It comprises two identical sub-networks (hence the name "Siamese") that share the same parameters and architecture. These sub-networks process different input samples, and their outputs are compared to measure similarity. For driver drowsiness detection, Siamese Networks would typically feed pairs of inputs into the network, one representing an alert driver and the other representing a potentially drowsy driver. The network then learns to compare these inputs and determine whether they are similar or dissimilar, indicating the level of driver drowsiness.

The following steps help to detect driver drowsiness detection:

Input: LetI_1 and I_2 represent two input samples (e.g., images of a driver's face).

Sub-networks: Each input data I_i is processed by a shared network system to obtain the corresponding feature extraction.

$\mathrm{X}_1 = \mathrm{Subnetwork}(\mathrm{I}_1)$

$\mathrm{X}_2 = \mathrm{Subnetwork}(\mathrm{I}_2)$

Distance Metric: A distance metric is applied to the output representations to measure their similarity. A common choice is a Euclidean distance:

$$\mathrm{D}(\mathrm{I}_1, \mathrm{I}_2) = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{k}} (\mathrm{I}_{1\mathrm{i}} - \mathrm{I}_{2\mathrm{i}})^2}$$

Decision Threshold: Based on the distance/similarity measure, a decision threshold is applied to determine whether the inputs are similar or dissimilar:

$\mathrm{D}(\mathrm{I}_1, \mathrm{I}_2) \leq \mathrm{Threshold}$,then inputs are similar (alert)

$\mathrm{D}(\mathrm{I}_1, \mathrm{I}_2) > Threshold$,then inputs are dissimilar (potentially drowsy)

Training Objective: The network is trained to minimize a loss function that penalizes incorrect similarity judgments. Common choices include contrastive loss or triplet loss.

Optimization: We used multiple parameters of the Siamese Network, which are optimized based on techniques like gradient descent to minimize the chosen loss function.

The proposed HLM combines the strengths of the HCA and SN to create a synergistic approach to drowsiness detection. The HCA is utilized for efficient facial feature extraction, providing the SN with informative input representations. The SN, in turn, leverages DL capabilities to analyze these representations and infer the drowsiness state of the driver with high precision.

4.3 Performance Metrics

Several metrics can be considered to assess various systems' performance and effectiveness. The confusion matrix mainly focused on count values based on the obtained results.

True Positive(TP)	False Positive(FP)
False Negative(FN)	True Negative(TN)

Fig 3: Confusion Matrix

$$\textbf{Precision} = \frac{TP}{TP + FP}$$

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\textbf{Recall} = \frac{TP}{TP + FN}$$

$$\textbf{Specificity} = \frac{TN}{TN + FP}$$

$$\textbf{F1} - \textbf{Score} = 2 * \frac{(P * R)}{(P + R)}$$

5. Experimental Results

The experimental research was conducted using several algorithmsthat showed the performance of the given parameters.

Table 1: The overall performances of Existing and Proposed Algorithms

Algorithms	Acc	Pre	Sn	Sp	F1-Score
CNN	87.34	86.98	83.98	84.34	83.45
ANN	91.45	92.23	93.67	90.12	91.87
HLM	98.56	97.23	97.42	98.87	97.56

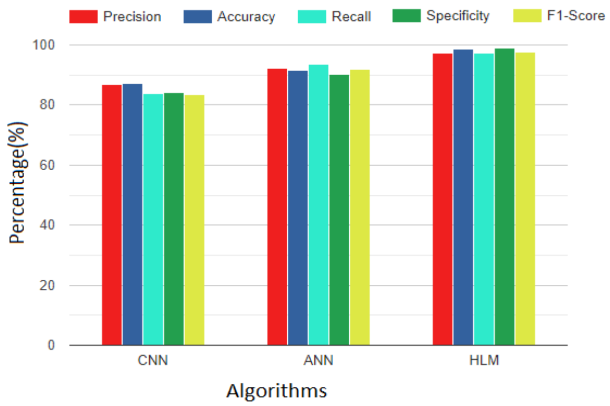

Fig 4: Performance of Algorithms

5. CONCLUSION

This paper proposes a hybrid-based learning approach (HLM) for driver drowsiness detection systems by integrating the Haar Cascade Algorithm with Siamese Networks. Through extensive experimentation and evaluation of real-world data, we have demonstrated the effectiveness of our approach in accurately identifying drowsiness patterns in drivers. Our results indicate that combining the Haar Cascade Algorithm for facial feature extraction and Siamese Networks for drowsiness classification yields superior performance compared to individual methods. The HLM achieves high accuracy, sensitivity, and specificity in detecting drowsiness cues, thus enhancing the safety of drivers and passengers on the road. Furthermore, the computational efficacy of the proposed method makes it suitable for real-time application of vehicle deployment, providing timely alerts to drivers and potentially preventing accidents caused by a drowsy driving technology process. Nevertheless, there are more opportunities for improvement and further research directions and approaches. Fine-tuning the parameters of the HLM and exploring alternative architectures for Siamese Networks could further enhance its performance. Additionally, investigating the robustness of the model under various environmental conditions and driver demographics would contribute to its applicability in diverse scenarios.

Conflicts Of Interest

Authors must identify and declare any personal circumstances or interests perceived as inappropriately influencing the representation or interpretation of reported research results. If there is no conflict of interest, please state, "The authors declare no conflict of interest."

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