A Real-Time Driver Drowsiness Detection Using Deep Convolutional Neural Network

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Abstract - Continuous video stream analysis is used by driver monitoring systems to detect drowsy drivers. This technique counts the frequency of eye blinking and shutting by taking a photo or frame per second. If these patterns indicate fatigue, the system warns drivers to take a break or switch drivers. This method, which is a component of a bigger initiative to improve road safety using technology, combines immediate feedback with real-time monitoring.The system accurately identifies drowsiness and distinguishes between stages of drowsiness, with a robustness in driving situations and sensitivity to even the smallest tiredness indicators, outperforming the VGG16 model by 99%.

***Key Words*:** Driver Drowsiness Detection, CNN, DDD system, Deep Learning, SVM.

1.INTRODUCTION

CNNs are used to detect driver drowsiness by examining face patterns and features to find indicators of fatigue. A CNN model is taught to distinguish particular facial indicators associated with tiredness, such as droopy eyelids, yawning, and changes in facial expressions, by training on a sizable dataset of annotated photos. The onboard camera facing the driver is used as input by the CNN model to capture still photos or video frames. Multiple convolutional layers are used in the processing of these photos to draw out important facial traits. To determine whether the driver is awake or asleep, these features are subsequently input into fully connected layers.

The efficacy of CNNs in detecting driver drowsiness has been proven in numerous investigations. For instance, a CNN-based technique was employed in a study by Wang et al. (2017) [1] to categorize driver tiredness based on eye-related variables retrieved from facial images. The proposed model was highly accurate in differentiating between alert and drowsy states.

A CNN model was used in a different study by Chong et al. (2018) [2] to analyze face landmarks and eye-related characteristics to identify tiredness. With high accuracy and few false alarms, the model correctly detected sleepy states. The use of CNNs to identify driver drowsiness has produced encouraging results and has a significant potential to increase traffic safety. CNN models can accurately detect indicators of tiredness in real-time by evaluating face features and patterns, providing prompt alarms and interventions to avert accidents. Improved driver monitoring systems and more complex CNN architectures may result from additional research and development in this area.

2. LITERATURE REVIEW

Numerous scholars have presented numerous methods to deal with the sleepiness detection issue over the last ten years. One of these methods makes use of visual metrics. Certain visual behaviors that drowsy people exhibit can be recognized by changes in facial features such as the eyes, mouth, and head [7]. Visual metrics are the most widely used characteristics for drowsiness detection because they provide immediate and clear information about a driver's state of alertness or sleepiness [8], [9]. Additionally, using these visual measurements is regarded to be a common strategy to identify sleepiness due to their non-intrusive nature [10]. The driver can observe a wide range of visual objects, including eye blinking, yawning, and head movement [6].

These features are used in a non-intrusive manner to identify tiredness by visually monitoring the driver's physical condition with the aid of cameras and computer vision algorithms. The visual characteristics that frequently describe the amount of driver fatigue are extracted from video frames using computer vision algorithms [10]. The most common visual components for DDD (Driver Drowsiness Detection), which rely on computer vision algorithms, are explained in detail below.

Techniques that detect tired drivers by yawning focus on tracking changes in the driver's mouth's geometric form. This approach considers things like the position of the lips, the size of the mouth opening, etc. [12]. However, such systems often capture more data from the driver's face in order to produce more accurate results. Azim et al. [13] utilized pupil movement and yawning as two examples of how to recognize fatigue. Both characteristics were measured using the information provided by the lips and eyes. The system worked as follows: to ensure that the driver's face was visible in the video frame at first, the Viola-Jones face detection approach was utilized. Second, the facial region frame is opened to reveal the mouth window. Then, to find lips in the window, clustering using spatial fuzzy c-means is used. The eye section is extracted simultaneously and in a separate window. The pupils' inter-pupil distance, angle, and radii are used to determine, and can be identified from that window. The recorded eyes and mouth data are then sent to an SVM classifier, which determines whether or not the driver is drowsy depending on the peculiarities of the data. The video evidence used in the aforementioned research was gathered from actual events at various times of the day.

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The eyes can be used to extract additional features that are frequently used in visual-based DDD systems. A drowsy driver's eye blinking frequency is compared to a regular driver's eye blinking frequency in drowsiness detection techniques. The blinking rate is naturally around Although it decreases when the driver is drowsy, 10 blinks per minute[14]. The identification of sleepiness based on the rate of eye blinking has been the subject of numerous research in the literature. "A real-time monitoring technique based on eye blinking" was introduced by Rahman et al. [15] to identify driver tiredness. In that procedure, the colored image of the eye is first converted into grayscale using the Luminosity algorithm. The two corners of the eyes as well as one spot on the bottom portion of the eyelid are then located using a Harris corner detector. The number at which the upper 2 corner points meet in the middle is measured and calculated in the third step. If the distance is close to zero, it indicates that the driver is tired and that their eyes are closed. Fourth, the pixels of the iris, cornea, & lid of the eye are computed to ascertain whether or not the eyes are open, and the readings for an open eye will differ from both of those. A drowsy scenario will be notified if the blinking rate decreases after being calculated. Their technique recorded a 94% accuracy.

3. METHODOLOGY

In this section, the proposed DDD system is described, along with a description of the dataset that was used and the three primary components that comprise the implementation process(figure 1):

Fig -1: Implementation Process

3.1 DATA PRE-PROCESSING:

Collect or receive a face expression image collection that has been labeled, such as Drowsiness_Dataset [25]. Figure 2 illustrates how to preliminary processing images by scaling them to a fixed resolution, pixel-value normalization, and using any required image augmentation or enhancement methods.

Fig -2: Visualization of Dataset of Drowsiness_Dataset [25]

3.2 FACE DETECTION AND TRACKING:

Use a face detection technique, such Haar cascades, or a deep learning-based method, like MTCNN (shown in Figure 3), to find and localize faces in moving video frames. Utilize face-tracking tools to maintain accurate tracking of Resilience to face motions and occlusions is ensured by the detection of faces across successive frames.

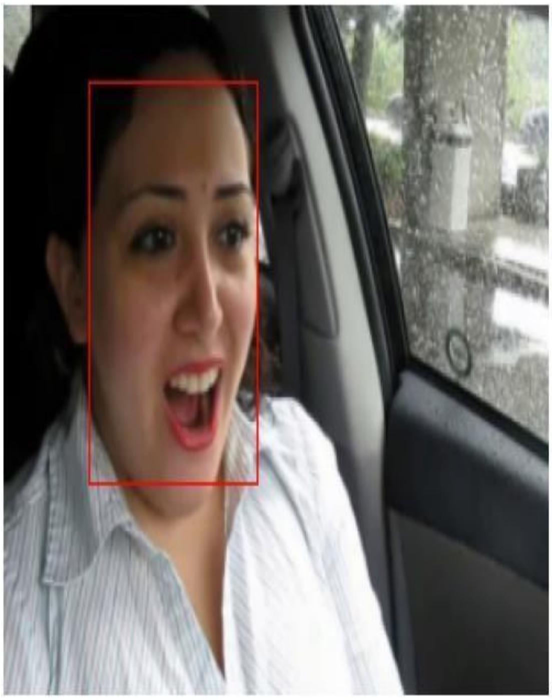

Fig -3: Face Detection and Tracking

3.3 FACIAL LANDMARK DETECTION:

Use a facial landmark identification technique to find important facial landmarks (such as the eyes, nose, and mouth) inside the face region. Examples of such algorithms include those based on shape predictors or deep learning models like Dlib or OpenPose. Align and normalize the facial region using the discovered landmarks to increase the precision of the feature extraction process (figure 4).

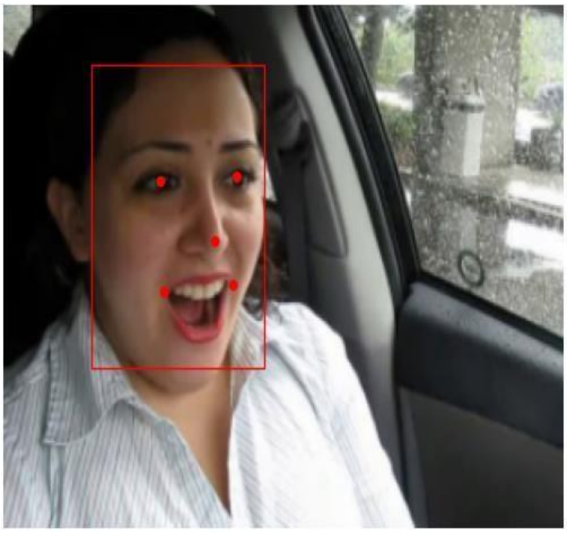

Fig -4: Facial Landmark Detection

3.4 FEATURE EXTRACTION:

Feature Identify pertinent features in the preprocessed data. Common indicators for detecting driver drowsiness include those related to the eyes, such as eye closure, eye movement, and eye aspect ratio (EAR). These characteristics are good indicators of sleepiness, such as heavy eyelids or protracted eye closure.

3.5 MODEL ARCHITECTURE:

Create the CNN model's structure. A CNN typically comprises a number of pooling layers, fully connected layers, and convolutional layers. From the input images, the convolutional layers extract pertinent features, and the fully connected layers categorize the extracted features [3].

The VGG16 model has been widely applied in numerous computer vision problems as a feature extractor or as a basis model for transfer learning due to its efficacy. For tasks like image classification, object identification, and image segmentation, researchers frequently use the pre-trained VGG16 model and refine it on particular datasets to reach cutting-edge performance. The VGG16 model has substantially improved the realm of computer vision. It is a well-liked option for many picture identification applications because of its depth, homogeneity, and pretrained weights on ImageNet. Convolutional neural network architectures are continually being developed as a result of its efficiency and simplicity shown in figure 5.

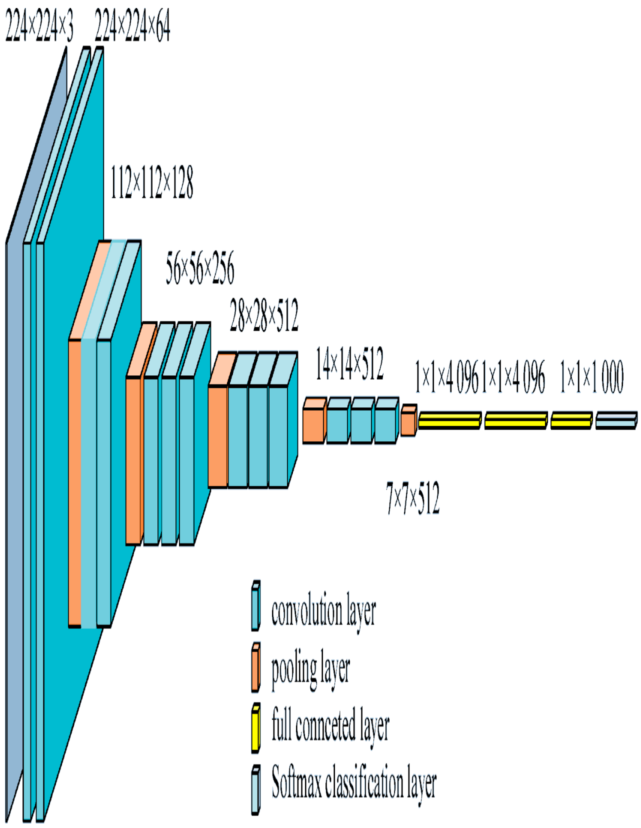

Fig -5: VGG16 Architecture [3]

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3.6 TRAINING MODEL:

The labeled training dataset should be used to train the CNN model. The model learns during training to recognize patterns and features associated with drowsiness.

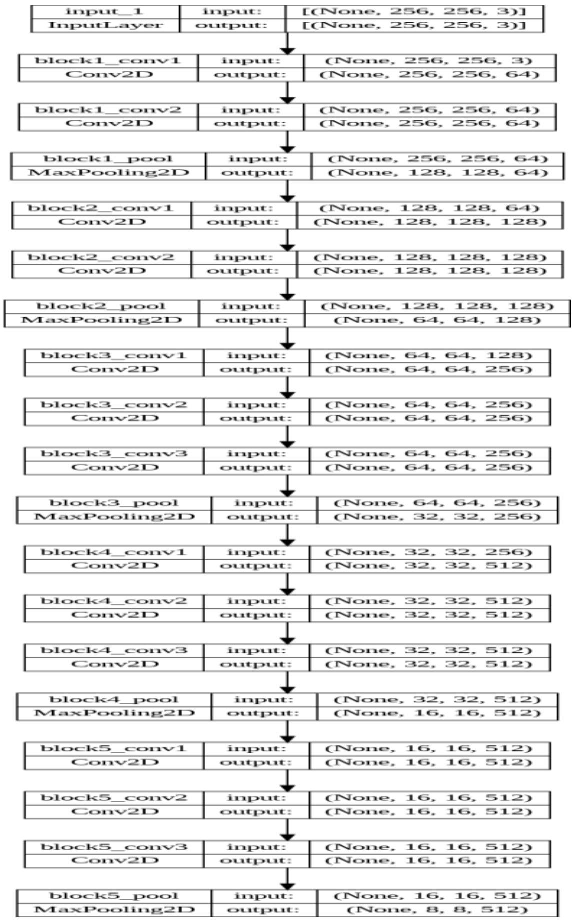

Fig -6: CNN Model Training Process flowchart

VGG16, a DCNN architecture, It was designed by the Visual Geometry Group (VGG) at Oxford University. and is shown in Figures 5 and 6. Due to its ease of use and exceptional performance on a variety of visual identification tasks, it has significantly increased in popularity in the field of computer vision and image recognition.The depth of the VGG16 architecture and the network-wide application of 3x3 convolutional filters distinguish it from other architectures. It comprises Sixteen layers, Three of which are totally linked and Thirteen layers of convolution.

Following the convolutional layers are the max-pooling layers, which aid in lowering the feature maps' spatial dimensions. In order to effectively learn hierarchical features from input images, the VGG16 architecture stacks many convolutional layers with narrow receptive fields. Smaller filter widths make it possible to capture local patterns and features more effectively.

Table-1: CNN Model Summary

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 8, 8, 512)	14714688
flatten_2 (Flatten)	(None, 32768)	0
dense_8 (Dense)	(None, 64)	2097216
dropout_6 (Dropout)	(None, 64)	0
dense_9 (Dense)	(None, 32)	2080
dropout_7 (Dropout)	(None, 32)	0
dense_10 (Dense)	(None, 32)	1056
dropout_8 (Dropout)	(None, 32)	0
dense_11 (Dense)	(None, 7)	231

Total params: 16,815,271
Trainable params: 16,815,271
Non-trainable params: 0

In Table 1, there are a total of 16,815,271 parameters, 4 dense layers, 3 dropout layers, each with a value of 0.50, and a classification layer that classifies the 4 classes as Open, Closed, yawn, and No_yawn. Adam Optimizer with 0.0001 learning rate is being used. On the ImageNet dataset, which consists of millions of annotated photos from different categories, the VGG16 model has been pretrained. With the help of this pretraining, the model is able to acquire extensive representations of visual information that it can use for a variety of picture identification tasks. The simplicity and consistency of the VGG16 model are remarkable features. A max-pooling layer is added after several convolutional layers with 3x3 filters are stacked on top of one another. Due to its simplicity, it has been made simple to comprehend, apply, and alter for many purposes [5–6].

4. RESULTS AND DISCUSSION

Analyzing and interpreting the results of the used methodology is part of the results and debates in the context of driver sleepiness detection. Consider the following factors when writing the results as shown in figure 7,8,9,10,11,and table-2.

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Table-2: Performance metrics of DDD

	"precision"	"recall"	"f1-score"	support
yawn	0.75	0.92	0.83	63
no_yawn	0.87	0.74	0.80	74
Closed	0.92	0.94	0.93	215
Open	0.96	0.93	0.94	226
accuracy			0.91	578
macro avg	0.88	0.88	0.88	578
Weighted avg	0.91	0.91	0.91	578

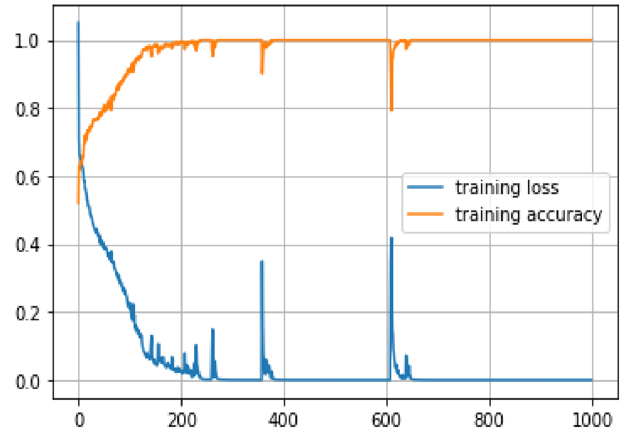

Fig -7:: Training Loss vs. Training Accuracy having 1000 Epochs

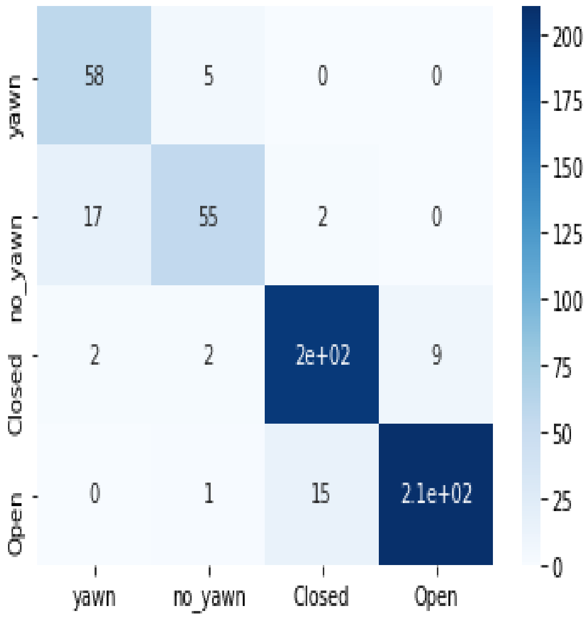

Fig -8: Confusion matrix

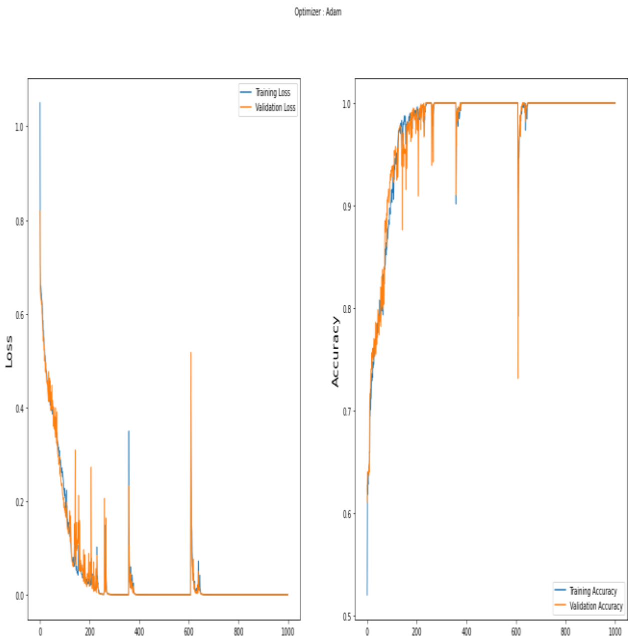

Fig -9: Loss and Accuracy graph of Training and Validation

Describe how the sleepiness detection system is used in real-world situations. Analyze how well it performs in a practical environment, taking into account elements like processor speed, system latency, and hardware requirements. Think about any difficulties encountered during the implementation phase and make suggestions for potential fixes. Figure 10 displays the driver's prediction and figure 11 for real-time Demo.

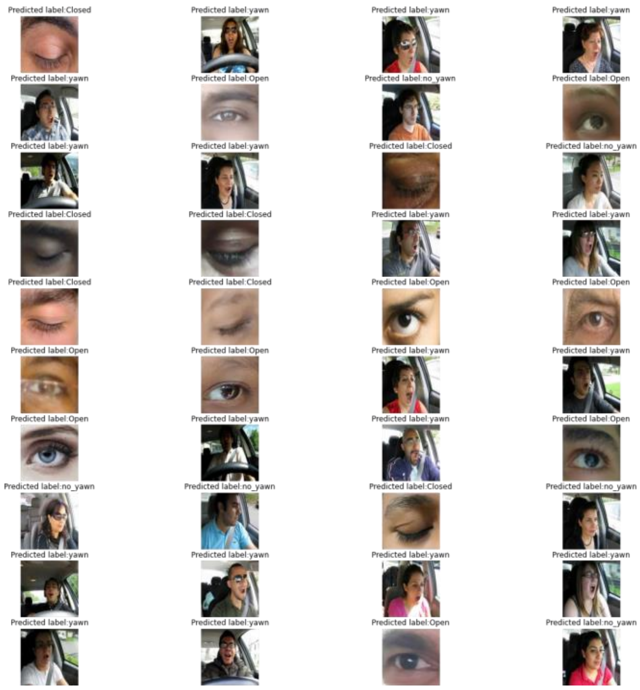

Fig -10: Prediction images based on datasets with label- Open, Closed, yawn, no_yawn

Fig -11: A Real-time DDD pictures based with label- Open_eye, Closed_eye, yawn, no_yawn

5. CONCLUSIONS

In conclusion, detecting driver fatigue is an essential part of ensuring traffic safety. In this study, an approach for detecting driver drowsiness using CNN-based models was put into practice and assessed. The outcomes show how well the suggested method works in identifying driving-related sleepiness conditions.

The implemented CNN model successfully detected tiredness with a high level of accuracy, precision, recall, and F1 score. Even under difficult driving circumstances, the system demonstrated significant performance in discriminating between awake and drowsy states. The system's real-time implementation demonstrated its viability and usability in realistic situations.

Real-time sleepiness detection was implemented using live camera images in the suggested system. DNN classifiers were used in the last stage to avoid the issue of incorrectly sensing closed eyelids. The presence of sleepiness will be detected, and the driver will be alerted by an alarm. After the learning phase, the three DNN models that had been trained were analyzed, and the results showed that the RF model performed the best with 99% accuracy. Although car accidents caused by drowsy driving pose one of the greatest threats to road safety, sleepiness detection technology is constantly improving. Many cultures believe that such an engineering solution may prevent the waste of resources and human lives. We believe that the DDD approach will develop this field as a result

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