Driver Drowsiness Detection Using Hybrid Model CNN and LSTM

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Abstract - Driving fatigue is one of the listed causes of road accidents, statistics reveal that driving drowsiness accounts for 25% to 50% of all road traffic crashes. Detection of driver fatigue on time is one key area to increase the safety in road. Various modalities have been studied for drowsiness detection, including EEG, vehicle driving dynamics and eye movements. EEG is incredibly precise but an impractical real world application as it is invasive. Hard to Get but Not AccurateTo track driving behavior, the detection of eyeball movement is used, which is a good balance between speed and effectiveness, but the current system utilizes a high-speed camera and a complex algorithm, making it difficult to implement on embedded platforms. To make progress on these issues, recent work has proposed the use of deep learning solutions trained using extensive datasets with a standard video camera in order to deliver more reasonable substitutes to costly eye-tracking systems.
These recurrent neural networks (RNN), in particular the Long Short-Term Memory (LSTM) networks, are especially suited for this purpose. With one approach, the authors examined 48 × 48 eye patch images obtained from a simulated driving study and obtained 82% accuracy with LSTM and up to an 97% C-LSTM model, respectively. In contrast, other models use CNNs on top of LSTM or BiLSTM network to take advantage of spatial and temporal characteristics of eye movements and facial expressions. These hybrid models can classify eye blinks, closure duration and landmarks of the eyes and register drowsiness, and some of them have been able to achieve 99% accuracy. Contrarily, state-of-the-art techniques from paper [14] apply FaceMesh for facial landmarks localization and yawning detection as IOU and finally, the head pose estimation techniques are implemented for classifying driver attention. The highest reported accuracy of up to 99.71% achieved using ResNet50V2 as a base neural network architecture and trained using NITYMED and NTHU datasets.
Face check using OpenCV, alarm system, and graphical signals

.INTRODUCTION

Drivers falling asleep behind the wheel are a major cause of road accidents worldwide, being responsible for a significant percentage of fatalities and injuries each year. Various studies conducted around the world, such as the ones in the U.S., Germany, Australia, and Thailand, focused on the problem of drowsy
driving and found physiological, behavioral, and vehicle-based cues indicating the presence of the risk. According to some of them, up to 35% of highway deaths happen due to drowsiness. In response, various detection systems have been developed. The most accurate and reliable, but also the most invasive among them, were based on physiological measures such as EEG, ECG, and EOG. Vehicle-based or driving system-based measures were developed using steering and speed, but they were affected by the nature of the route. As a result, the most widespread and non-invasive measures, commonly used in human and in-built vehicle tracking systems, were based on the analysis of facial behavior and included such indicators as eye state, yawning, and head movements. Despite their prevalence, systems like PERCLOS could still be affected by lighting conditions or some types of obstruction, such as glasses, making deep learning increasingly popular among scientists, as it provided reliable information concerning both spatial and temporal features to be used in real-time. CNN was used to extract spatial patterns present in images of drivers' faces. LSTM, given its nature, was able to process sequence patterns in the temporal dimension and identify, e.g., the change in the driver's EAR, MAR, or some other parameter over time, while their combined use increased the system's reliability.

The models created in this way, such as CNN-BiLSTM models, had been showed by recent studies to outperform not only the traditional models but even some other independent deep learning models, especially in such datasets as NTHU-DDD and NITYMED, as they were able to perform well under realistic driving conditions. Such systems could be incorporated into advanced driver assistance systems or similar solutions. However, there were still issues concerning drivers, lighting, and occlusion that needed further work in order to make the created models error-proof and, therefore, efficient in real-world settings.

With the growing number of traffic accidents caused by driver fatigue, there have been many prominent researchers that have created intelligent approaches that monitor the behavior of driver [4][5]. Drowsiness Detection In recent time, deep learning based methods focusing on powerful Convolutional Neural Networks(CNNs) for space feature extraction coupled with Long Short-Term Memory (LSTM) for temporal modeling of eye behavior has been shown promise for drowsiness detection. The goal of this system is to create a real-time, inexpensive, non-invasive driver drowsiness detection system which will monitor the state of eye directly using a web cam which will alert in timely manner in case of fatigue and microsleep. It is based on the idea that driver drowsiness is reflected in both temporal and spatial patterns in eye behavior, such as eyelid closures that frequently or last for a long time.

The project is structured into a series of steps: data collection and preprocessing, CNN-based Eye State Classification, LSTM-based temporal sequence modeling, real-time detection pipeline integration, and model evaluation and deployment. In this post, we will explore the key elements that make up this approach, why we needed to take this approach, along with some of the challenges we had to overcome and the solutions that we implemented over the course of the project.

I.LITREATURE REVIEW

Driver drowsiness detection has emerged over the last decades as a major field of research for road accident prevention, which ultimately can lead to a safer traffic environment. The rapid development of artificial intelligence (AI) and deep learning has given rise to many new systems to solve the problem of real-time driver fatigue detection. These systems try to address issues such as improving detection accuracy, reducing false alarms, better integration with modern vehicular systems, and achieving non-intrusiveness. Researchers have investigated various techniques: basic machine learning techniques, such as Support Vector Machines (SVM) and Random Forests, to more advanced architectures, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and ensembles that combine facial, behavioral, and physiological features. Though promising accuracy is obtained with many methods, challenges remain including problems of illumination, head pose, occlusions, complexity requirements and the necessity of larger and more diverse datasets. Below, we highlight several noteworthy recent contributions in this space.

Earlier detection systems for drowsy drivers strong interest on account of their significant roles in enhancing road safety. Many creative responses to the real operator fatigue detection based on time drivers were studied under the rapid advancement of artificial intelligence and deep learning algorithms. The models were proposed based on a detailed concentration on about better accuracy, less spam alerts.

A site allows developers to follow the process of visualisation or the facial expressions recognition in real-time and integrate with modern car systems.

Das et al. [5] provides a state of the art approach that, by CNN-LSTM and U-Net architectures for real-time driver fatigue detection by analyzing facial movements. The proposed model obtained an accuracy of 98.8 %, which outperformed eg other network VGG-16, GoogLeNet,. AlexNet, and ResNet50. The main advantage of this approach is that it can achieve high accuracy while being nonatomic intrusive. But the environmental lighting conditions and its high computational costs enable the system is sensitive and suffers from the detection problems.

Li et al. (2023) [6] have reviewed the Method of Support Vector (SVM) for drowsiness recognition, and achieve accuracy of 91.92%. The combination of SVMs with other driver assistance systems is a highly feasible solution but falls at issues including the high level of learning to be invested and the possibility external effects stress and fatigue The citation was added to the rest of the sentence to avoid leaving it as a hanging modifier.So instead the correct Computationaly intensive nature causes the system to be sensitive and experienced in solving detection

Ref.	Methodology	Accuracy	Advantages	Limitations/ challenges
[5]	CNN-LSTM	98.8%	High accuracy, real-time detection, non-intrusive, integrates with ADAS systems	Limited exploration of different CNN architectures and temporal dynamics integration
[6]	SVM	91.92%	Can integrate with other driver assistance systems	Need for improved generalization in real-world driving scenarios
[7]	Histogram of Oriented Gradient, SVM	91.6%	Detects drowsiness in real-time	Difficulty in detecting under different head poses and lighting conditions
[8]	Viola–Jones, AdaBoost, Haar Classifier	94%	Real-time detection through eye-blink monitoring	More sophisticated monitoring needed for different driver behaviours
[9]	Artificial Neural Networks, SVM, AdaBoost	98.1%	Challenging environmental conditions like poor lighting can be handled	Lack of robustness in real-world driving situations
[10]	Multimodal Emotion Recognition	RR - 93%	Improved accuracy through fusion of multiple modalities n	Improper use of deep learning architectures and lack of focus on drowsiness detection through temporal analysis
[11]	Viola–Jones, Haar Cascaded Classifier	-	Can minimize accidents caused by drowsiness	Needs improvement in robustness for general use in real-time systems
[12]	CNN-based Emotion Recognition	78.52	High accuracy in detecting emotional states	Investigation needed on the impact of different CNN architectures
[13]	CNN	93.0%	Non-intrusive detection using cameras	Limited exploration of alternative feature extraction techniques
[14]	Viola–Jones, Haar Cascade Classifiers, SVM	93.5%	Effective analysis on the status of eyes	Integration with other data sources for more accurate detection

Table no. 1 Comparative Analysis of Prior Work

II.METHODOLOGY

1. Gathering and Preprocessing Data

(a) Dataset Collection

We used facial images from a dataset to train the model, which is the UTARLDD (Universiti Tunku Abdul Rahman Driver Drowsiness Detection) dataset that consists of labeled drowsy and non-drowsy facial images. Finally, this dataset is a comprehensive collection of images with real-world driving situations ensuring other datasets contain an array of unique conditions such as different lighting, facial expressions, and head poses for the model to learn from.

Inorder for the model to work in the real world, the images should include it captures through different angles,and also in different lighting conditions. The UTARLDD dataset consisted of two classes, which are separated into drowsy and non-drowsy classes, while preprocessing was performed in both classes files to perform similar feature extraction on both classes.

(b) Videos ar landmarked using MediaPipe

The MediaPipe FaceMesh was used for detecting facial landmarks. It detects 468 landmarks of face features in detail, from each image. It consists of landmarks from eye, mouth, and must have a nose coordinates that are important for drowsiness detection.

Based on these landmarks, we computed the following features:

Eye Aspect Ratio (EAR): This feature indicates whether the eyes are open or closed (blinks). EAR is determined by employing the eye landmarks and indicates minor alterations in eye openings (blinking) which may help us indicate short term alerts to drowsiness.

$$\text{"EAR} = \frac{\lVert p_2 - p_6 \rVert + \lVert p_3 - p_5 \rVert}{2 \times \lVert p_1 - p_4 \rVert} \quad \ldots\ldots\ldots\text{(i)}$$

- $p_1..p_2........p_6$ are coordinates of six key eye landmarks.
- Numerator. Sum of the verticals distance
- Denominators horizontal distance

Mouth Aspect Ratio (MAR): This parameter is based on yawning and mouth movements, which are signs that appear when the person is drowsy. MAR is computed based on detected landmarks around the mouth region, that is it detects if the mouth opens significantly as in yawning.

$$\text{MAR} = \frac{\lVert p_{63} - p_{67} \rVert + \lVert p_{64} - p_{66} \rVert + \lVert p_{62} - p_{68} \rVert}{3 \times \lVert p_{61} - p_{65} \rVert} \quad \ldots\ldots\ldots\ldots\text{(ii)}$$

- Top three vertical distance across the mouth are averaged and divided by the horizontal width.
- A significant increase in MAR over time signals yawning behaviour.

Head Pose Ratio : This feature is used to detect the tilt of head which is an indication of and chin to determine movements associated with fatigue (such as nodding off).

$$\text{Head Tilt Angle} = \arctan \frac{(y_{chin} - y_{nose})}{(x_{chin} - x_{nose})} \quad \ldots\text{(iii)}$$

- This track head nodding or tilting that correlates with drowsiness.

(c) Feature Engineering and Scaling

Once we extract the key facial points from each image, we concatenate to form the feature vectors by extracting EAR, MAR and Head pose data along with the facial landmarks vectors. This vector is the input for the model. Features were subsequently scaled using a StandardScaler, which scales the data so that they have a mean of 0 and a standard deviation of 1. Feature Scaling: Due to different scale of features like head pose values and EAR; one feature may get a higher weight when calculating the error; To avoid this need to scale feature to normal range;

2. Architecture of the Model: CNN-LSTM hybrid

At the heart of the proposed method is a CNN-LSTM hybrid architecture to model both spatial and temporal information. The CNN part extracts spatial features of facial landmarks, and the LSTM part models temporal relations between consecutive frames to recognize sustained drowsiness activities over a period of time.

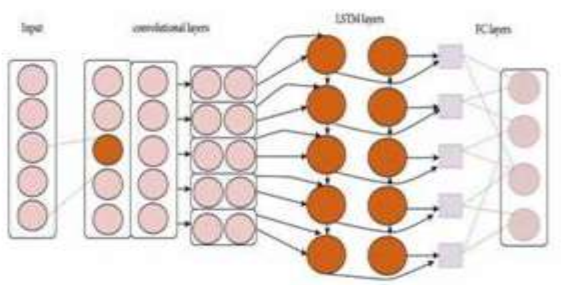

Fig. 1 Architecture of CNN -LSTM

CNN for Extracting Spatial Features

The CNN layers are used to learn spatial features from the facial landmarks. It starts with the 1D Convolutional layers, which are able to learn from the temporal series of facial landmarks. Such convolutions will listen to the spatial patterns of facial expressions of eye closure and head tilt, both of which are tangible (and therefore measurable) features of drowsiness. What happens afterward the convolutional layers is a max-pooling to reduce the data dimensionality while keeping the more relevant characteristics.

The output of the CNN is then flatten and the resulting vector is passed to fully connected dense layers that continue to combine the features into an even more compact representation.

(a) Temporal Dependencies: LSTM

We then reshape the output of the CNN and feed it into a bi-directional LSTM. The LSTM layers learn events spaced apart in time The fact that the LSTM can track a sequence of facial landmarks over time is important, because prolonged states of eye closure or yawning are an indication of driver drowsiness. This captures patterns like prolonged eyelid closure or repeated yawns, indicators of sleepiness that in isolation a CNN might not detect.

LSTM networks are ideal for sequence data as they retain information about previous time steps in a sequence, allowing them to capture long-term dependencies present in the data, and they are appropriate for modeling temporal patterns of drowsiness.

(b) Output Layer

The final output layer is a fully connected dense layer with a sigmoid activation function, returning the binary classification drowsy or non-drowsy. One can set a sigmoid activation function to be within a value between 0 and 1 that reflects whether the driver is drowsy or not. If its value is greater than a threshold (normally 0.5), it classifies the driver as drowsy.

III.Model Training and Evaluation

(a) Training Strategy

Adam optimizer and binary cross-entropy as the loss function was used to train the model. Since it is an adaptive optimizer, that means it automatically adjust the learning rate, with Adam, the training is efficient and stable. We used an early stopping technique which monitors validation loss during training, in order to avoid over fitting and achieve good generalization. When our validation loss does not improve for some number of epochs (let's say 15 epochs), we stop the training and restore the best Weights. Furthermore, we decrease the learning rate by 0.2 every 5 epochs if there is no improvement, in order to stabilize the training process.

(b) Evaluation Metrics

Below is a series of metrics used to evaluate the performance of the model:

Accuracy: The number of correctly classified instances (drowsy or non-drowsy) among all the test data.

Confusion Matrix -The confusion matrix is used to determine how well the model did in terms of classifying either state (drowsy or non-drowsy) accurately in that it displays how many instances of either class were classified correctly or incorrectly.

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Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) were plotted to assess theclassification capability of the model, based upon the true positive{true negative; attempts were made to separate drowsy and non-drowsy states. AUC gives one number about how good the model is in separating the two classes.
These metrics were used to evaluate the model performance on whether driver is drowsy or non drowsy, it is better than accuracy.

4. Real-Time Detection Pipeline
The pipeline for real-time detection combines the CNN-LSTM model and OpenCV for the video frame capturing. The system works as follows:

- Video Capture at 5-10 FPS: A webcam captures frames for video. For every frame, the facial landmarks are detected, for example, by Haar Cascade or Dlib, to obtain eyes and mouth as some examples of a common scenario.
- Landmark Extraction on Faces: These landmarks extracted on every frame using MediaPipe's FaceMesh module. For each of these frames, we will be calculating the Ear (Eye Aspect Ratio), the Mar (Mouth Aspect Ratio) and the Rotation in the head pose ratio.
- Classification: These features are passed through the CNN to predict the open/closed status of the eyes. The sequence of predictions over time is passed to the LSTM, which learns temporal long-term statistics of eye behavior.
- Drowsiness Alert: When the LSTM observes a consistent trend that indicates drowsiness (such as a closed eye or head tilting) It can be a sound or visual trigger to tell the driver that it is time to stop.

IV.RESULT AND DISCUSSION

In this paper, we proposed a hybrid CNN-LSTM architecture based real-time driver drowsiness detection system that extracts both spatial and temporal features of drowsiness from the single input image frame. The system detects important signs of drowsiness based on facial landmark detection, including eye closure, yawning, and head tilt.
This system is non-invasive, using just a camera feed, and the driver state is monitored in real-time. However, it works well in laboratory settings but still requires a lot of optimizations for some scenarios, like different lighting, occlusions, and generalization to other drivers. This real-time driver drowsiness detection system is a noteworthy contribution towards improving road safety, and provides a comprehensive framework for future developments and applications in the automotive setting.

Ref.	Methodology	Accuracy
[5]	CNN-LSTM	98.80%
[13]	CNN	93.0%
[18]	CNN	96.32%
This study	CNN-LSTM-Mediapipe-EAR-MAR-Head pose	98.89%

Table 2. Models Accuracy

This section presents the results when employing a Deep Learning Method (CNN-LSTM) to predict driver Drowsiness based on the Dataset that was divided in a training-test split set.

A. Confusion Matrix
A confusion matrix was created to visualize how the predictions were done by the model. It reflects the count of the correct and incorrect predicted values by the model. A heatmap (Fig.2 To make it easier to understand and relate to how well the model is performing, this matrix was represented under in Fig.

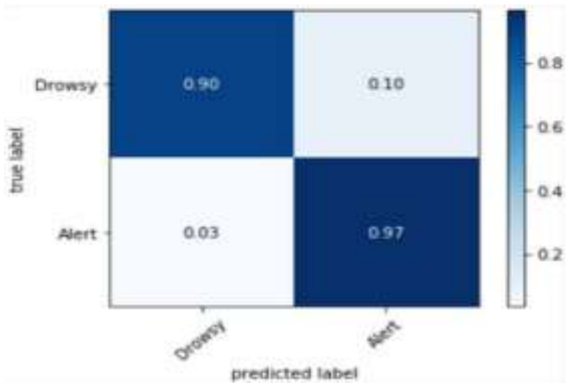

Fig. 2 Confusion Matrix

B. Graphs for Training and Validation
Training and validation curves were plotted to monitor the progress of model learning. Here are the plots of the accuracy and loss throughout the training time for both training and validation sets (Fig. 3). It allows you to know whether or not your model is learning or overfitting.

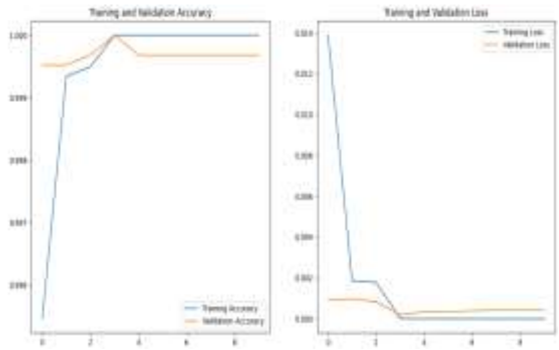

Fig.3 Training and Validation curves

C. ROC Curve

A ROC curve (Receiver Operating Characteristic curve) is plotted (Fig. 4) to show how the model performs at various thresholds. Overall performance of the model is evaluated using AUC (Area Under the Curve) score. First, it is helpful to visualize the trade-off between true positives and false positives with respect to labeling someone as drowsy when they are not.

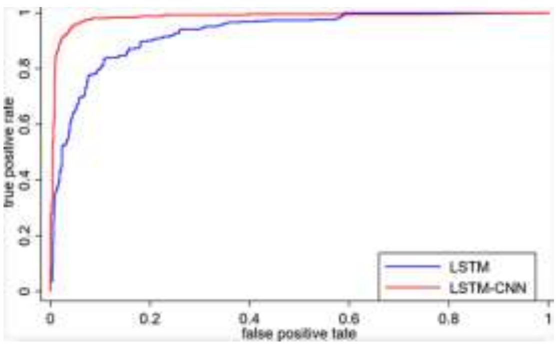

Fig.4 ROC Curves

Basic CNN: The basic CNN model was ineffective with lower accuracy. This is due to the fact that CNN, when it was just being used to extract features from images, used the full image as a feature set which was not very effective.

Combined Model (CNN+LSTM): by incorporating the LSTM (time sequences processing model) with the CNN model, the accuracy raises, yet it is not ideal.

Media Pipe Feature: The most significant performance boost happened when MediaPipe (method that extracts facial landmarks.) was integrated with the hybrid model. The model took this information into account by honing in on the more prominent facial landmarks (i.e, positions of the eyes and mouth), which resulted in a much more accurate prediction.

Best Performing Model: The best performing model that managed to achieve a real-time speed included MediaPipe to extract the landmarks, EAR (Eye Aspect Ratio), MAR (Mouth Aspect Ratio), and head position.

With this complete model, we achieved an accuracy of 98.89% and an F1-score of 98.00%. Combining feature extraction techniques achieved a significant increase in the ability of model to well detect drowsiness.

V.CONCLUSION AND FUTURE SCOPE

In conclusion, we demonstrated the opportunity of using hybrid CNN-LSTM The hybrid CNN-LSTM model was able to detect driver drowsiness in real-time with accuracy. However, the system is functioning well but to make it work for a large scale, there is a large scope of improvement in terms of employing advanced deep learnings, multi-modal data and personalized features. Future work includes mounting it to the embedded platform and an optimization for embedded applications, enhancement of model accuracy, and avoidance of ethical and legal issues. In addition, they effectively capture spatial and temporal features and present a proposed approach for facial landmark extraction using MediaPipe and deep learning to detect drowsiness. Additional facial features, multimodal sensors and environmental scenarios could further validate the model.

Fig.5 – Drowsy States

Fig.6- Non Drowsy State

In conclusion Overall, existing approaches for driver drowsiness detection hold potential; however, they require more refinement. Future Potential Directions:

3D-CNNs, transformers, and attention mechanisms to learn from data that are particularly useful to understand dynamic facial expressions at multiple temporal resolutions and create a robust system that gains strength by its exposure to extreme variances of data.

Ensemble Learning: Utilizing CNN-LSTM with 3D-CNNs and transformers to minimize false positives and improve accuracy.

Integration with ADAS: Integrating drowsiness detection with vehicle safety features such as automatic braking, lane-keeping assist, etc.

Combining multimodal data: Improving the detection of the affection by integrating yawn detection, posture monitoring, speech analysis and physiological data (i.e. heart rate).

Deploying Models on Mobile and Embedded Platform: Preparing the models for edge devices using methods like model compression and deploying using the platforms such as TensorFlow Lite.

Customized detection — relating to each driver by transfer learning, and monitoring targeted indices of fatigue

Cloud-based Analytics: Using cloud storage and IoT data to forecast and longitudinally monitor fatigue in an enterprise-wide manner.

Cross-domain Applications: Adaptations of drowsiness detection to use cases in aviation, heavy equipment, and healthcare.

Privacy and ethical issues, such as user consent, data control, & fairness among other demographics, must also be taken into account, and due legal care must be observed (i.e., ensuring GDPR compliance).

Transparency: Creating Explainable AI (XAI) to enhance trust and comprehensibility of detection decisions.

These guidance demonstrate the scope of future developments in fatigue detection which will lead up not only to safer driving practices but also to extended domains of application in high tariff areas.

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