Design and Development of a three-dimensional weighted Swin Learning-based deep learning model for driver drowsiness detection

1. INTRODUCTION

Driver Drowsiness is a result of working for long hours or intermittent nights without sleeping or the stress of working, which serves as a critical cause of road accidents [9]. Some of the crucial impacts caused by drowsiness are the inability to focus on driving, feeling sleepy, poor judgment, delayed reaction, and wrong estimation of distances and speeds [10]. In order to determine the drowsiness characteristics of the drivers, four different approaches are utilized and are categorized as vehicle-based measures, subjective measures, driver behavioral measures, and physiological measures [11]. The behavioral-based measure aids in the efficient analysis of the behavior of the driver's characteristics by analyzing the facial expressions, calculating eye closure time, estimating head posture, and yawning frequency of the driver [12]. Hence, the behavioral-based approaches correspond to the determination of the alertness level exhibited by the driver [13]. Vehicle-based approaches focus on detecting drowsiness through vehicle motion such as steering wheel angle, driving acceleration, and vehicle speed and driver handling behavior data [13,15]. In addition, physiological signal-based methods monitor signs of driver drowsiness by analyzing the driver’s physiological signals such as electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EOG), and electroencephalogram (EEG)[13,14].

Some of the factors that resemble the drowsiness characteristics are found to be difficulty in keeping an eye open, difficulty concentrating for a long time, changing lanes abruptly, failure to react to oncoming vehicles, Unjustified changes in speed, suddenly hitting a rumble strip, Constant blinking, Endless yawning, and so on[16]. Even though vehicle-based measures, driver behavioral measures, and physiological measures are utilized to analyze such drowsiness characteristics of the drivers [18], there exist certain inefficacies including the inability of the vehicle-based approaches to perform accurate determination despite lightning disturbances, the variation in the head posture, inability to adapt to the environmental factors[17]. In addition, the image-based measure utilized for determining the drowsiness behavior of the driver effectively analyzed the facial expressions and the movements of the driver but their inability to offer accurate and faster determination requires further refinement[19]. Hence, artificial intelligence-based frameworks are designed to reduce the number of accidents that happen on the road by preserving the lives of numerous humans [20].

Accordingly, huge Machine Learning (ML), and Deep Learning (DL) frameworks are designed to facilitate accurate drowsiness determination. Conversely, many of the traditional determination frameworks utilized a few regions of the facial images while performing determination despite considering the entire facial image which affected the determination accuracy[21]. Traditional Artificial Neural Networks (ANN) are highly sensitive to varying brightness, blur, and noise characteristics which affect the reliability of drowsiness determination[22]. In addition, the requirement for a large number of training features by the Convolutional Neural Networks(CNN) increases the training time of the network with the occurrence of degradation issues despite their better performance efficacies. Moreover, the requirement of huge features results in the formation of overfitting issues in the drowsiness determination framework[7,23]. Moreover, the Recurrent Neural Network (RNN) utilized in the determination process experiences vanishing gradient issues which limits its extensive utility[24].

1. LITERATURE REVIEW

Some of the hindrances exhibited by the traditional driver drowsiness determination approaches are detailed in this subsection with their advantages and disadvantages.

Jose Alguindigue *et al.,*[1] suggested Sequential Neural Networks (SNN), One Dimensional Convolutional Neural Networks (1D-CNN), and Convolutional Recurrent Neural Networks (CRNN) to determine the driver drowsiness by analyzing the Heart Rate Variability (HRV), ElectroDermal Activity (EDA), and tracking the eye movements. Here, the data was initially preprocessed to stipulate its quality and injected into the SNN, 1D-CNN, and CRNN framework to perform drowsiness determination. Experimental results showcased the efficacy of the presented driver drowsiness determination framework in terms of precision. Yet, the occurrence of the data imbalance issues in the determination process affected the generalizability of the drowsiness determination.

Hamza Ahmad Madni *et al.,*[2] propounded the Visual Geometry Group 16-based Light Gradient Boosting Machine (VGG16-LGBM) to determine the drowsiness behavior of the driver by tracking the eye movements. Preprocessing, transfer learning-based feature extraction, and classification were the different strategies utilized in the VGG16-LGBM-based determination process. Hence, the abstraction of the intricate features and characteristics of the eye movement stipulated the prediction performance of the VGG16-LGBM with reduced computational complexity. Yet, the VGG16-LGBM failed to mitigate the noise that occurred during the determination process which further affected the accuracy of determination by reducing the image resolution.

Yashar Jabraeily *et al.,*[3] developed a Genetic Algorithm-based Convolutional Neural Network (GA-CNN) to facilitate driver drowsiness detection. In the GA-CNN, primarily the frames are acquired from the incoming video and categorized into two labels namely the normal and drowsy. The resultant was then grayscale converted and resized to generate large-sized data. Thus, the effective tuning of the model parameters using the GA mitigated the premature convergence problems with an improvement in the determination accuracy. Yet, the formation of the huge dataset by analyzing the numerous video frames increased the computational complexity in drowsiness determination.

Samy Abd El-Nabi *et al.,*[4] exaggerated Swin Transformer-based Driver Drowsiness Detection(ST-DDD). Splitting of the input images, acquisition of the data, effective preprocessing via denoising, data augmentation, and drowsiness determination were the various stages followed in the determination process. Hence, the patch merging mechanism incorporated in the ST-DDD reduces the spatial resolution of the image with a reduction in the channel dimension and computational complexity. On the other side, the requirement of huge training data for drowsiness determination was the major downside of using ST-DDD.

Gourav Siddhad *et al.,*[5] deployed a DrowzEE-G-Mamba-based Drowsiness detection framework by utilizing an EEG-based State Space Model (SSM). The patch embedding layer was utilized to convert the EEG into a suitable format for further processing. Further, the Stacked State-Convolution-SSM abstracted the predominant drowsiness-based features, which were further downsized and utilized for determination. Thus, the presented framework offered sufficient drowsiness determination performance by utilizing limited resources with reduced false positives. On the contrary, the DrowzEE-G-Mamba was not suitable for processing huge datasets which affected their generalizability characteristics.

Madduri Venkateswarlu and Venkata Rami Reddy CH [6] developed a Lightweight CNN framework named the DrowsyDetectNet to determine the drowsiness of the driver. The DrowsyDetectNet utilized a 68-point facial landmark determination approach to examine the location of the driver's face from the input. Then, the opening or closing state of the eye was examined by passing the extracted eye image into the CNN with a few layers to aid in the drowsiness determination process. Hence, the usage of the less-layered CNN reduced the complexity of drowsiness determination drastically by attaining better determination accuracy. However, the reduced diversity characteristics affected the generalizability of the presented drowsiness detection framework.

Muhammad Ramzan *et al.,*[7] framed a Driver Drowsiness Detection-Custom Deep Learning Model(D3-CDLM) to perform drowsiness detection with better accuracy. Here, the Histogram Of Gradients (HOG) was extracted from which the predominant features were extracted using Principal Component Analysis (PCA), and injected into the ML-EL modules with the hybrid transfer learning-based CNN(CDLM) to determine the drowsiness. Hence, the ability of the CDLM to learn both the high and low-dimensional features stipulated the robustness in drowsiness determination. However, the addition of huge layers degraded the determination performance by increasing the time required for training the pertinent features.

Anwar Jarndal *et al.,*[8] employed a Vision Transformer-based DDD(ViT-DDD) system to determine the drowsiness of the driver by analyzing the facial image in the video. Frame conversion, flattening of images, linear embedding generation for low dimensional mages, the addition of positional encoding, and determination using ViT were involved in the presented determination approach. Hence, any sized features were easily trained by this approach by acquiring long-term spatial characteristics. On the contrary, the inability of the ViT to process the fine-grained features and the requirement of huge training data limited their extensive utilization.

2.1 Challenges

* Despite the advantages offered by the traditional CNN, their extensive utilization of reliable drowsiness determination was highly affected due to their sensitivity to noise, motion blur, and poor lighting conditions [4].
* The conventional drowsiness determination frameworks failed to consider certain external factors including workload, stress, and fatigue which further resulted in the variation in the determination process [1].
* The requirement of huge data for training and their inability to recognize the small features within the fine-grained features limited their extensive utility in the drowsiness determination process [8].
* Degradation issue is the major concern related to highly deep networks while performing drowsiness detection due to the difficulties faced while training with the relevant features and the requirement of huge memory [7].

3. PROPOSED METHODOLOGY

Drowsy driving remains a significant cause for road safety, impacting the lives of both the drivers and the passengers within the vehicle and on the road. Numerous traditional drowsiness determination frameworks are designed by encompassing ML and DL frameworks. Yet, their inefficacies in facilitating reliable determination increased the computational complexity of determination with an enhancement in the memory requirement and the difficulties in processing huge data. Hence, an efficient three-dimensional weighted Swin Learning-based Gated Recurrent Unit-Convolutional Neural Network(3D-SGCN) will be proposed to tackle such discrepancies and to facilitate accurate determination. The proposed 3D-SGCN model will obtain the input from the Arianaira dataset [25], the Driver Drowsiness Dataset [26], and the TRYOUT dataset [27] for both training and testing processes. Initially, the input image or the video acquired from the dataset will be frame converted to generate the frames which further stipulates the determination by reducing the memory requirement and the time to process the entire video. The resultant frame will undergo preprocessing in such a way that the quality of the incoming frame will be enhanced thereby making it suitable for face detection. After preprocessing, the Region Of Interest (ROI) will be extracted followed by the detection of the face by the Viola-Jones Algorithm (VJA). Next, the predominant features including the Deep 3D-weighted light HOG features, Weighted Scale Invariant Feature Transform (SIFT) and Residual Network (ResNet-18) features will be extracted from the VJA-based face detected output. Then, the extracted meaningful features will be introduced into the 3D-SGCN model to perform accurate drowsiness determination and produce the output as either normal or drowsy at the end of the determination process. In addition, the proposed driver drowsiness detection model is implemented in the PyCharm software, and its efficacy is determined in terms of accuracy, sensitivity, specificity, and Recall. The diagrammatic representation of the proposed drowsiness detection model is elucidated in Figure 1.

Input image/ video dataset

Frame preprocessing and ROI extraction

Face detection using Viola Jones

Feature extraction

Deep 3D weighted light histogram of gradients

Weighted SIFT features

Resnet 18 features

3D weighted swin learning enabled GRU-CNN

Model

Normal/Drowsiness

Test features

Figure 1: Diagrammatic representation of the proposed drowsiness detection model

4. OBJECTIVES

* To analyze the existing drowsiness detection model with its advantages and limitations.
* To design a proposed three-dimensional weighted Swin Learning-enabled GRU-CNN model for drowsiness detection.
* To extract the pertinent features including the Deep 3D-weighted light HOG features, Weighted SIFT, and ResNet-18 features to enhance the detection performance with reduced computational complexity.
* To examine and compare the detection performance of the existing methods in terms of accuracy, sensitivity, specificity, and Recall.

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