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RESEARCH ARTICLE

Novel Transfer Learning Approach for Driver Drowsiness Detection Using Eye Movement Behavior

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ABSTRACT Driver drowsiness detection is a critical field of research within automotive safety, aimed at identifying signs of fatigue in drivers to prevent accidents. Drowsiness impairs a driver's reaction time, decision-making ability, and overall alertness, significantly increasing the risk of collisions. Nowadays, the challenge is to detect drowsiness using physiological signals, which often require direct contact with the driver's body. This can be uncomfortable and distracting. This study aimed at detecting driver drowsiness through eye movement behavior imagery of the driver. We utilized a standard image dataset based on the eye movement behavior of drivers to conduct this research experiment. We proposed a novel transfer learning-based features generation which combined the strengths of the Visual Geometry Group (VGG-16) and Light Gradient-Boosting Machine (LGBM) methods. The proposed VGLG (VGG16-LGBM) approach first extracts spatial features from input eye image data and then generates salient transfer features using LGBM. Experimental evaluations reveal that the k-neighbors classifier outperformed the state-of-the-art approach with a high-performance accuracy of 99%. The computational complexity analysis shows that the proposed approach detects driver drowsiness in 0.00829 seconds. We have enhanced the performance through hyperparameter tuning and validations using k-fold validation. This research has the potential to revolutionize driver drowsiness detection, aiming to prevent road accidents and save precious lives.

INDEX TERMS Driver drowsiness, eye images, eye behavior, machine learning, deep learning, transfer leaning.

I. INTRODUCTION

Driver drowsiness refers to a state of fatigue or sleepiness that impairs a driver's ability to operate a vehicle safely [1]. It significantly contributes to road accidents worldwide, as it affects a driver's reaction time, decision-making abilities, and overall alertness. The consequences of driving while drowsy can be as severe as those associated with drunk driving, including a diminished capacity to maintain lane position, judge distances, and process the information from the driving environment effectively [2]. The losses due to driver drowsiness are extensive and multifaceted, impacting individual and public safety. On a personal level, drowsy driving increases the risk of accidents, leading to potential

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injuries or fatalities. From an economic perspective, these accidents can result in substantial financial costs associated with vehicle repairs, medical bills, insurance premiums, and legal fees. On a broader scale, driver drowsiness contributes to traffic congestion due to accidents [3], emergency response, and clean-up efforts, further affecting economic productivity and the efficiency of transportation networks.

The loss due to accidents encompasses a broad range of financial, emotional, and societal impacts. Between 2000 and 2016, there was a notable increase in both the overall case fatality rate and human damage resulting from road accidents in China, with a 19.0% and 63.7% rise respectively [4]. A survey conducted in Ontario, Canada in 2002 found that over 58% of 750 drivers admitted to driving while fatigued or drowsy, and 14.5% reported falling asleep at the wheel within the past year [5]. The United States National Highway Traffic Safety Administration estimated that the economic toll from fatigued or drowsy driving amounted to $12.4 billion annually [6].

This research applied advanced Transfer learning mechanisms [7] for driver drowsiness detection. Transfer learning is a powerful technique in deep learning that involves taking a pre-trained neural network model and fine-tuning it for a different task. This approach has been increasingly applied in various domains, including driver drowsiness detection and leveraging eye movement behavior image data. By utilizing a pre-trained Convolutional Neural Network (CNN) model, such as VGG-16, we can harness the model's already learned hierarchical feature representations and pass them to machine learning models for learning. When applying transfer learning to driver drowsiness detection, the lower layers of the pre-trained network, which capture generic features like edges and textures, are typically kept frozen. In contrast, the upper layers are fine-tuned to adapt to the specific features relevant to drowsiness detection, such as eyelid droopiness, blink rate, and eye closure duration. This fine-tuning process allows the network to learn from the eye movement behavior data and accurately classify the driver's state as alert or drowsy.

The significant research contributions of our study regarding driver drowsiness detection are as follows:

- We proposed a novel transfer learning-based features generation approach VGLG, which combined the strengths of the VGG-16 and LGBM methods. The proposed VGLG approach first extracts spatial features from input eye image data and then generates salient transfer features using LGBM.
- We have built four machine learning and two deep neural network techniques for comparison. Each model's results are validated using k-fold validation and enhanced performance through hyperparameter tuning. In addition, we determined the computational complexity, entropy feature space, and real-time layers feature extractions.

The remaining study is organized as follows: Section II provides a comprehensive review of existing studies, highlighting the advancements in driver drowsiness detection methodologies. Section III outlines the design and implementation details of our novel approach. Section IV presents the findings of our experiments, offering a detailed analysis of the performance of our proposed methodology compared to existing techniques. Finally, Section V summarizes the key contributions of our work, highlighting the significance of our findings in advancing the field of driver drowsiness detection.

II. LITERATURE ANALYSIS

In the literature analysis section dedicated to Driver Drowsiness Detection Using Eye Movement Behavior, a comprehensive review of existing studies reveals a multidisciplinary approach that intertwines cognitive science, computer vision, and automotive engineering. The consensus among researchers underscores the critical role of eye movement metrics–such as blink rate, blink duration, and saccade velocity as reliable indicators of driver fatigue. Technological advancements have facilitated the development of sophisticated eye-tracking systems capable of real-time monitoring, leveraging algorithms and machine learning models to accurately predict drowsiness onset.

The research study [9] aims to detect driver drowsiness through eye detection. In this experiment, the NITYMED dataset is utilized, which contains various levels of drowsiness and videos of drivers. Different deep-learning models are employed in this study. The results demonstrate that using Convolutional Neural Networks (CNN) for drowsiness detection in the eyes yielded the highest accuracy. Specifically, ResNet50V2 achieved the best results, with an accuracy of 98%. However, the study faced challenges due to low dataset samples and the use of classical approaches.

The research study [8] proposed a method for detecting drivers' eye movements using deep learning models to mitigate road accidents. In this experiment, a drowsiness dataset, which is publicly available on Kaggle, was utilized. It comprises 2,900 images categorized into four different states: open, closed, yawning, and no yawning. The study found that the VGG-16 model yielded poor results, whereas the CNN model achieved efficient outcomes with an accuracy of 97%. The evaluation metrics further indicate a precision of 99%, with both recall and F1 scores also at 99%. The study mentioned that classical approaches were used, which were seen as limitations.

The research study [10] introduces driver drowsiness detection through eye movement to enhance road safety by preventing accidents. This proposed study adopts techniques that analyze drivers' behaviors, specifically focusing on visual cues to distinguish between opened and closed eyes. For this experiment, images with a resolution of 450×320 pixels were utilized. The findings demonstrate that the deep learning model, specifically a Neural Network (NN), attained the highest accuracy rate of 98%. However, the study acknowledges limitations associated with the employment of classical neural network approaches.

TABLE 1. The summary of analyzed literature work.

Ref	Year	Dataset Used	Applied Technique	Performance Score
[8]	2023	Drowsiness dataset	CNN	97%
[9]	2023	NITYMED	ResNet50v2	98%
[10]	2023	Image dataset	NN	98%
[11]	2023	driver drowsiness detection dataset	ML	98%
[12]	2023	NTHU-DDD dataset	Hybrid model	91%
[13]	2023	Eye Image dataset	ML	80%
[14]	2023	wrist-worn device used to collect data	ML algorthim bagging and boosting	89.4%
[15]	2023	EEG dataset	ML	85.6%
[16]	2024	video-based driver drowsiness detection (VB-DDD) dataset	common spatial pattern (CSP) algorithm	94%
[17]	2024	Video based dataset	ResNet50 model.	98%

The research study [11] proposes a method for driver drowsiness detection using visual features. This experiment utilizes a driver drowsiness detection dataset collected from National Tsing Hua University. The proposed visual features are extracted from a video obtained from a camera installed on the dashboard. Various machine learning models are employed in this study, achieving the highest accuracy of 98%. However, the study acknowledges limitations, including the use of classical approaches.

The research study [12] proposes a method to detect drowsiness by integrating both non-intrusive and intrusive approaches. The experiments utilize the NTHU-DDD dataset, which includes data from 36 individuals displaying various behaviors indicative of drowsiness, such as yawning, slow blinking, dozing off, and the wearing of glasses or sunglasses under varied lighting conditions both during the day and at night. The dataset categorizes instances into drowsy and non-drowsy states. In this study, a hybrid model combining MTCNN for facial feature recognition and a GSR sensor for physiological signal analysis achieved an accuracy rate of 91%. However, the study reported lower performance scores due to certain limitations.

The research study [13] proposes a method to address the significant issue of drowsiness. In this experiment, an eye image dataset is utilized to detect the driver's eyes within a specific range. The system alerts the driver by triggering an alarm when an increased rate of drowsiness is detected. Various machine learning techniques are employed in this study, yielding efficient results. The machine learning model achieved an accuracy of 80%, which contributes to reducing accidents. However, the study achieved low performance scores due to limitations.

The research study [14] proposes a wearable device designed to detect drowsiness. To ascertain whether the driver is asleep, it utilizes a comfortable wearable device based on signal processing techniques. This study employs various machine learning models, with Random Forest (RF) achieving an accuracy rate of 89.3%. Furthermore, machine learning algorithms that utilize bagging and boosting techniques have achieved the highest accuracy, at 89.4%. However, the study reports lower performance scores, identifying limitations associated with classical methods.

The research study [15] proposes a PBCI (Brain-Computer Interface) scheme using EEG (electroencephalogram) brain signals developed to detect human drowsiness during driving. In this experiment, an EEG dataset from 12 right-handed male subjects was utilized, with EEG signals recorded at a frequency of 125Hz. Among all seven classifiers tested–decision trees (DT), discriminant analysis (DA), logistic regression (LR), naïve Bayes (NB), support vector machines (SVM), k-nearest neighbor (kNN), and ensemble methods–the ensemble approach achieved the most efficient results. The overall accuracy reported was 85.6%. However, the study acknowledges that it achieved lower performance scores, suggesting limitations with classical methods.

The research study [16] focuses on the detection of driver drowsiness by analyzing facial features and landmarks. This experiment utilizes two public datasets, in addition to creating a specific video-based VBDDD (Video-Based Driver Drowsiness Detection) dataset. Two distinct types of features, temporal and spatial, are extracted for analysis. The CSP (Common Spatial Pattern) algorithm is employed to enhance the performance across different classes of samples. The results demonstrate that this method achieved excellent performance.

The research study [17] proposes a real-time drowsiness detection system that utilizes a simple camera to analyze the ratio of eye closure and mouth opening. This system is designed to identify drowsy behavior in drivers and alert them to their condition to prevent accidents. The study is segmented into two parts: offline and online procedures. By employing various deep learning models, the research achieves efficient results. The lowest accuracy observed is with the VGG-16 model at 97%, while the highest accuracy is attained using ResNet50, which achieves 98%. However, classical approaches were noted as limitations.

A. RESEARCH GAP

In our investigation, we identified several research gaps pertaining to driver drowsiness detection.

- Previous research predominantly utilized classical machine learning methods and relied heavily on sensor data, with little to no focus on eye movement analysis specifically.

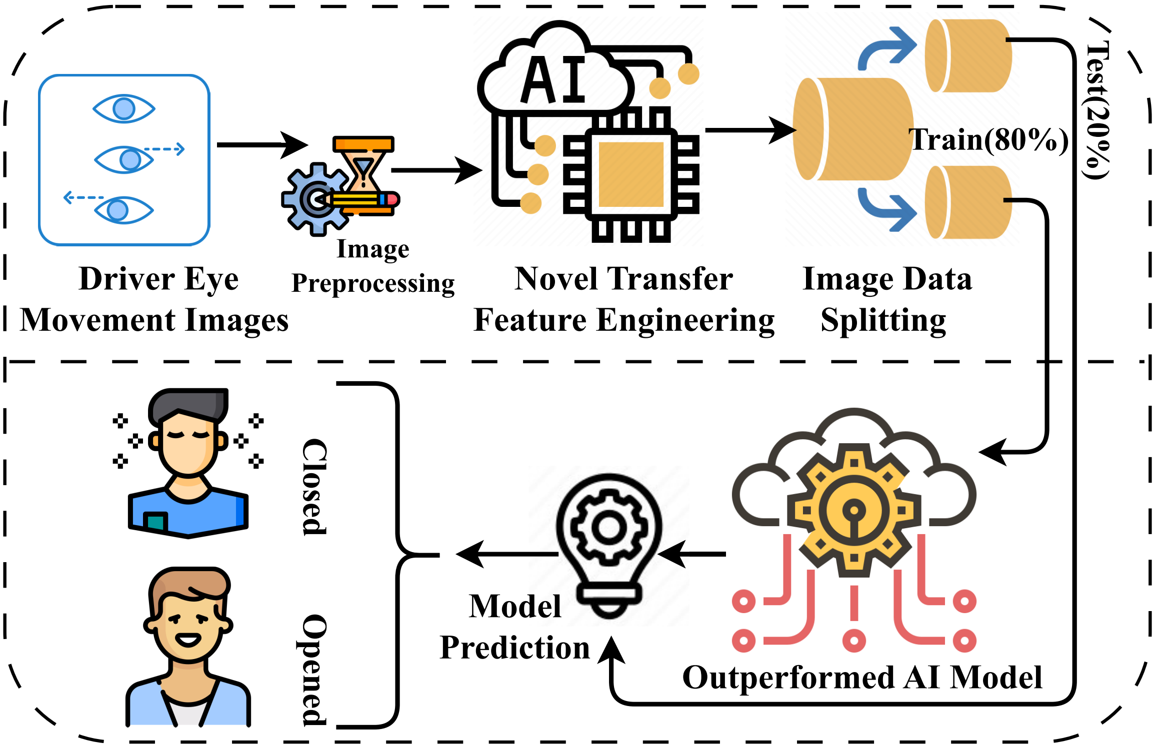


FIGURE 1. The workflow architecture analysis of proposed methodology.

- Moreover, these studies often reported low performance scores. However, our research introduces an innovative approach by applying transfer learning mechanisms, which have significantly enhanced the detection accuracy. This novel methodology not only addresses the limitations of prior studies but also opens new avenues for more effective and reliable drowsiness detection systems.

III. PROPOSED METHODOLOGY

This section delved into the materials and methods employed for detecting driver drowsiness by analyzing the eye movements of drivers. We have clearly outlined the image dataset used to develop the applied neural network approach. The performance scores for each method are revealing and demonstrate their potential for real-time driver drowsiness detection.

Figure 1, illustrates the step-wise working flow of our novel proposed research methodology. In our research methodology, we initially accessed a standard dataset comprising eye movement records of drivers. Following this, we preprocessed the images, ensuring they were properly formatted for further analysis. We then proposed a novel approach based on neural networks that employs transfer learning to extract salient features from the eye movement dataset of drivers. This extracted data was subsequently divided into training and testing sets with an 80:20 split ratio. We trained several advanced machine learning models using the training portion of the data and evaluated their performance on the test set. The models were further refined through hyperparameter tuning to enhance their accuracy and efficiency. The AI model that demonstrated superior performance through this validation process was then employed for the detection of driver drowsiness, utilizing the eye movement data as its primary input. This comprehensive methodology aims to leverage the capabilities of advanced neural networks and transfer learning to improve the accuracy of driver drowsiness detection systems.

A. EYE MOVEMENTS IMAGE DATABASE

This study utilized a standard dataset [18] comprising 4,103 eye images of drivers, meticulously labelled as either open or closed eye movements. This dataset was generated using UnityEyes, a cutting-edge eye-synthetic simulator renowned for its ability to produce high-quality data. UnityEyes facilitated the creation of a diverse and representative collection of eye movement recordings, encompassing subjects from a wide range of demographics acquired under variable lighting conditions. These recordings were captured under controlled driving scenarios, ensuring a realistic and applicable dataset for the study. The sample images from the dataset are visualized in Figure 2.

B. IMAGE PREPROCESSING AND FORMATIONS

In the initial phase of our research, the image dataset is imported and subjected to basic preprocessing to standardize the input data for subsequent analysis. A crucial step in this preprocessing is resizing each image to a uniform

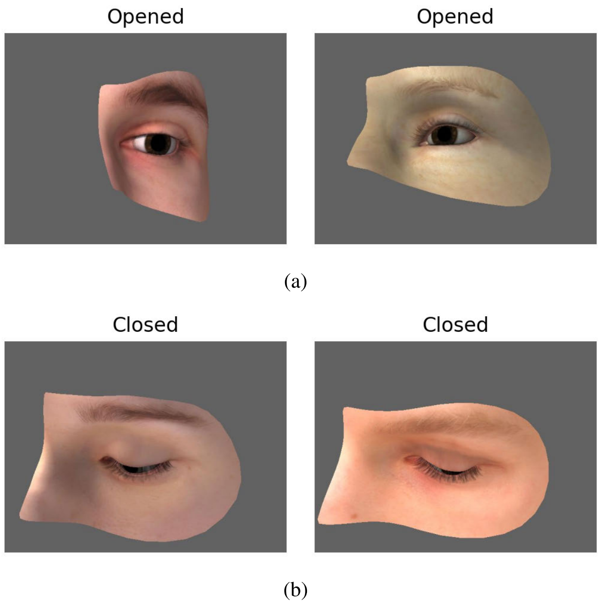


FIGURE 2. The sample closed and open eye movement images.

dimension of 256 × 256 pixels, ensuring that all images are of the same scale and thus compatible with the neural network architecture designed for image classification tasks. Moreover, to facilitate supervised learning, the target classes were encoded as 'Closed': 0 and 'Opened': 1, representing the two categories of interest in our study. A detailed analysis of the dataset's composition is conducted, with findings presented in Figure 4. This chart elucidated the distribution of samples across the two target classes, revealing a nearly balanced dataset. Such balance is crucial as it prevents model bias towards the more prevalent class, thus enhancing the reliability and generalizability of the predictive model developed from this dataset.

C. NOVEL PROPOSED TRANSFER FEATURES GENERATION

In the realm of drowsiness detection through driver eye movement behaviors, our research introduces a novel method named VGLG, combining the strengths of the Visual Geometry Group (VGG-16) and Light Gradient Boosting Machine (LGBM) approaches. The architecture of the proposed approach is illustrated in Figure 10. This novel approach leverages transfer learning for enhanced feature generation, marking a significant advancement over traditional techniques. Initially, the VGLG method processes an image dataset through the VGG-16 architecture training, a deep convolutional network known for its efficacy in extracting spatial features from images. This crucial step enables the isolation of intricate patterns and characteristics within the eye movement data, which are indicative of the driver's alertness levels. Subsequently, these extracted features are fed into the LGBM, a powerful gradient-boosting approach that excels in generating predictive features from data. By harnessing LGBM's capability to refine and enhance these spatial features, VGLG produces highly salient features that are optimally suited for detecting signs of drowsiness with unprecedented accuracy. Our empirical research conclusively demonstrates that the VGLG method substantially outperforms existing state-of-the-art classical methods in the domain of drowsiness detection.

Algorithm 1 contains the unique workflow of our novel proposed transfer learning method.

Algorithm 1 VGLG Algorithm

Input: Eye movement images data.
Output: New Transfer features.
initiate;
1- $S_{vgg16} \longleftarrow VGG16_{prediction}(X)$ // $X \in eye\ movements\ images\ set$, here X is input images data and S_{vgg16} is generated rich level spatial features.
2- $S_{lgbm} \longleftarrow LGBM_{probabilities\ prediction}(S_{vgg16})$ // here S_{lgbm} is the generated novel probabilistic based transfer features.
3- $F_{prob} \longleftarrow S_{lgbm}$ // here F_{prob} is the final transfer learning based probabilistic features set used for driver eye movement detection.
end;

D. EMPLOYED ARTIFICIAL INTELLIGENCE APPROACHES

Driver drowsiness is a critical issue that significantly impacts road safety. Fatigue-related accidents can lead to severe consequences, making it essential to develop effective drowsiness detection systems. In recent years, artificial intelligence (AI) techniques have shown promise in addressing this challenge. One approach involves analyzing eye movement behavior to detect signs of drowsiness.

- **Convolutional neural network (CNN):** CNN Driver drowsiness detection using CNNs focuses on analyzing eye movement behavior to identify signs of drowsiness [19], [20]. The process involves data collection from videos of drivers, feature extraction of eye regions, and utilization of a custom-designed CNN architecture. This architecture includes convolutional layers, batch normalization, dropout layers, and fully connected layers. The trained CNN achieves high accuracy in detecting drowsiness based on eye movement patterns, contributing to safer driving and reduced accidents. The convolution operation in a convolutional layer can be described mathematically as follows:

$$Y_{ij} = (F * X)_{ij} = \sum_m \sum_n F_{mn} \cdot X_{i+m,j+n} \tag{1}$$

  where:
  - X represents the input image matrix.
  - F denotes the filter (or kernel) matrix.
  - Y is the output feature map resulting from the convolution.
  - i, j are the spatial indices for the output feature map.
  - m, n are the indices iterating over the filter dimensions.

  This equation represents the core operation within a convolutional layer, where the filter F is applied

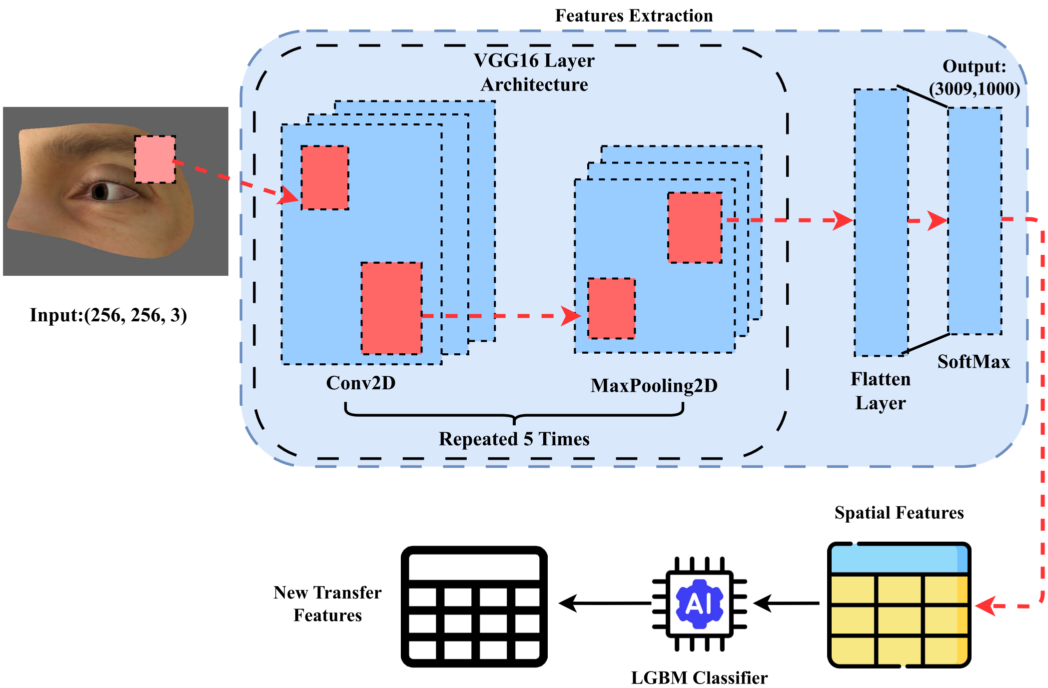


FIGURE 3. The transfer features generations mechanism of novel proposed VGLG approach.

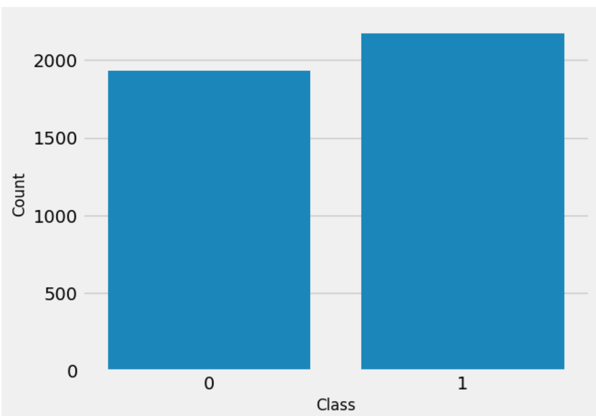


FIGURE 4. The Bar chart-based target label data distributions analysis.

across the input image X to produce a feature map Y, highlighting specific features in the input image.

- **Visual Geometry Group (VGG-16):** VGG-16 model, proposed by Karen Simonyan and Andrew Zisserman, is a deep neural network designed for large-scale image recognition [21], [22]. It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 employs small 3×3 convolutional filters, replacing larger filters used in previous models. These smaller filters enhance non-linearity and allow the network to converge faster. The model achieves remarkable accuracy in image classification tasks, making it a valuable choice for drowsiness detection based on eye movement behavior. The basic mathematical representation of the VGG-16 model applied to this task can be summarized as follows: Given an input image X, the model applies a series of convolutional operations. Each convolutional layer L_i in the VGG-16 architecture transforms the input as follows:

$$L_i(X) = \text{ReLU}\left(W_i * X + b_i\right) \tag{2}$$

where W_i and b_i are the weights and bias of the i-th layer, X is the input to the layer, and $*$ denotes the convolutional operation. ReLU (Rectified Linear Unit) is applied for non-linear activation.
After certain convolutional layers, a max-pooling operation is applied:

$$P_i(X) = \text{MaxPooling}(L_i(X)) \tag{3}$$

- **K-Neighbors-Classifier (KNC):** KNC algorithm analyzes images of a driver's eyes to assess their drowsiness status [23], [24]. Specifically, it measures the Eye Aspect Ratio (EAR), which represents the duration of eye closure (blinking). When the EAR indicates drowsiness, warning alarms are triggered at different levels of drowsiness during driving. The KNC algorithm classifies these levels based on the time eyes remain closed or the blinking rate, enhancing road safety by alerting fatigued drivers. Let $X = \{x_1, x_2, \ldots, x_n\}$ be the feature vector extracted from the image, and let $D = \{(X_1, y_1), (X_2, y_2), \ldots, (X_m, y_m)\}$ be the training dataset where X_i is the feature vector of the ith training example, and y_i is its label (e.g., 0 for alert, 1 for drowsy).

The Euclidean distance between the feature vector X of the new image and a feature vector X_i in the dataset can be calculated as:

$$d(X, X_i) = \sqrt{\sum_{j=1}^{n}(x_j - x_{ij})^2} \quad (4)$$

where x_j is the jth feature of vector X, and x_{ij} is the jth feature of vector X_i.

- **Light Gradient-Boosting Machine (LGBM):** LGBM is a gradient-boosting algorithm that efficiently handles large datasets [25], [26]. In the context of driver drowsiness detection, it leverages features extracted from eye movement behavior images. These features could include eye closure duration, blink rate, and other relevant metrics. The LGBM constructs an ensemble of decision trees, optimizing for accuracy and speed during prediction. Learning from labeled data identifies patterns associated with drowsiness and non-drowsiness, enabling real-time assessment of a driver's alertness level. Its robustness and ability to handle high-dimensional feature spaces make it a valuable tool for enhancing road safety. Let:
  - X be the feature vector extracted from eye movement behavior images.
  - Y be the binary label (1 for drowsiness, 0 for alertness).
  - β_t represent the learned coefficients for each tree.
  - $h_t(X)$ be the prediction of the t-th tree.

  The log-odds of drowsiness are modeled as:

$$\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \sum_{t=1}^{T}\beta_t h_t(X) \quad (5)$$

- **Logistic Regression (LR):** LR is a widely used binary classification algorithm [27], [28]. In the context of drowsiness detection, it analyzes features extracted from eye movement behavior images. These features could include metrics like eye closure duration, blink rate, and other relevant parameters. LR models the probability of a driver being drowsy based on these features. It estimates the log odds of drowsiness and applies a sigmoid function to convert them into probabilities. If the probability exceeds a predefined threshold, the system alerts the driver. LR's simplicity, interpretability, and efficiency make it suitable for real-time applications in road safety. Let:
  - X be the feature vector extracted from eye movement behavior images.
  - Y be the binary label (1 for drowsiness, 0 for alertness).
  - β represent the learned coefficients.

  The logistic function (sigmoid) transforms the linear combination:

$$P(Y=1|X) = \frac{1}{1+e^{-\beta X}} \quad (6)$$

  The log-odds (logit) can be expressed as:

$$\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \beta X \quad (7)$$

- **Random Forest (RF):** RF approach combines multiple decision trees to create an ensemble model [29], [30]. In the context of drowsiness detection, it leverages features extracted from images of the driver's eyes. Initially, a single-shot scale-invariant face detector identifies the face in the image. Subsequently, facial features related to eye fatigue, such as yawns, head posture, and eye closure, are extracted. Finally, the RF technique analyzes these features to assess the driver's drowsiness level. The RF model's robustness and ability to handle complex feature interactions make it effective for real-time monitoring and accident prevention. Let:
  - X be the feature vector extracted from eye movement behavior images.
  - Y be the binary label (1 for drowsiness, 0 for alertness).
  - T be the number of decision trees in the Random Forest.

  The prediction for each tree t is given by:

$$\hat{Y}_t = f_t(X) \quad (8)$$

  The ensemble prediction is obtained by averaging individual tree predictions:

$$\hat{Y}_{\mathrm{RF}} = \frac{1}{T}\sum_{t=1}^{T}\hat{Y}_t \quad (9)$$

E. HYPER-PARAMETERS OPTIMIZATIONS

We conducted hyperparameter optimization for the applied neural network techniques, and the selected parameters are detailed in Table 2. Hyperparameter optimization significantly enhances the performance accuracy and generalization of the applied methods. We identified the optimal hyperparameters through a recursive process of training and testing, utilizing a k-fold cross-validation mechanism. This analytical approach has proven effective in improving the performance scores of driver drowsiness detection.

IV. RESULTS AND DISCUSSIONS

In this section, we focused on driver drowsiness detection, experimental results are derived from the application of various methods analyzing eye movement images. To ensure the reliability and accuracy of the findings, numerous model evaluation parameters are employed. These parameters facilitated a comprehensive assessment of each method's performance, enabling the identification of the most promising approaches in detecting driver drowsiness.

A. EXPERIMENTAL SETUP

The experimental setup for the detection of driver drowsiness through eye movement images is meticulously designed to

TABLE 2. **Hyperparameter optimizations analysis of applied neural network models for image analysis.**

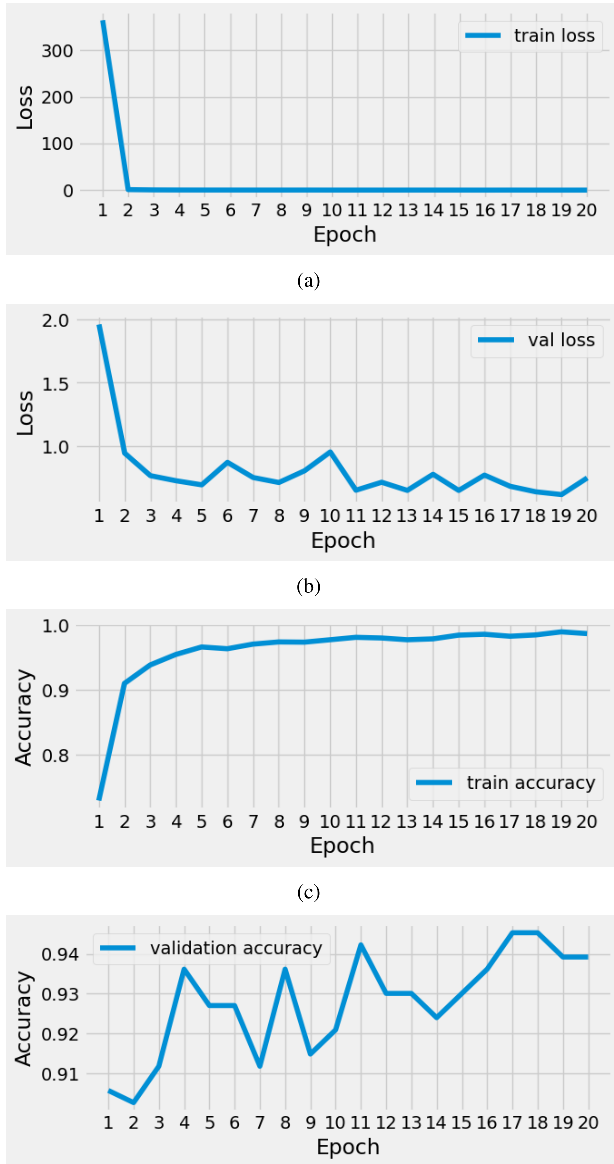
Method	Hyperparameters Tuning
LGBM	n-estimators=300, boosting-type='gbdt', learning-rate=0.1, num-leaves=31
RF	max-depth=300, criterion="gini", splitter="best", n-estimators=300
LR	penalty='l2', max-iter=100, tol=1e-4, solver='lbfgs'
KNC	weights='uniform', n-neighbors=2, metric='minkowski', leaf-size=30
CNN	input_shape = (256, 256,3), activation= 'sigmoid', loss='binary-crossentropy', optimizer='adam', metrics=['accuracy']
VGG16	iinput_shape = (256, 256,3), activation= 'sigmoid', loss='binary-crossentropy', optimizer='adam', metrics=['accuracy']

ensure the reliability and accuracy of the results. Utilizing the Google Colab platform, the study harnessed the power of a GPU-accelerated backend, which is critical for processing the extensive data involved in this research. This setup is equipped with 13 GB of RAM and 90 GB of storage capacity, providing the necessary computational resources to handle the demanding tasks of image analysis and machine learning model training. To rigorously evaluate the performance of the applied machine learning models, a comprehensive suite of metrics is employed. These included accuracy, precision, recall, and F1 scores, which together offered a nuanced view of the models' effectiveness in correctly identifying signs of drowsiness from eye movement images.

B. RESULTS WITH CLASSICAL CNN METHOD

In our study, we initially implemented a classical CNN model to analyze a specific time series dataset. The training process and its impact on model performance are detailed in Figure 5. Initially, the model exhibited high loss scores and low accuracy, attributable to the random weight initializations typical at the start of training. As training progressed, the CNN learned to fine-tune its parameters, leading to a gradual improvement in accuracy and a decrease in loss scores. Despite these improvements, performance metrics remained around 90%, indicating a relatively low-efficiency level. This suggests that while the model learns from the data, there remains a significant need for performance enhancement strategies to further refine and improve its predictive capabilities.

The study on driver drowsiness detection using a CNN model, as detailed in Table 3, demonstrates that the model can identify drowsiness with a 91% accuracy rate for unseen data. However, the performance notably declines for the specific task of recognizing the 'eye closed' class, indicating a critical area for improvement. Despite the high overall accuracy, these results underline the necessity for further enhancements in the model's capability to ensure more reliable detection of driver drowsiness, particularly in critical situations where the driver's eyes are closed. This suggests that while CNN models hold promise for this application, optimization, and refinement are essential for achieving the levels of performance required for real-world deployment.



(a) (b) (c) (d)

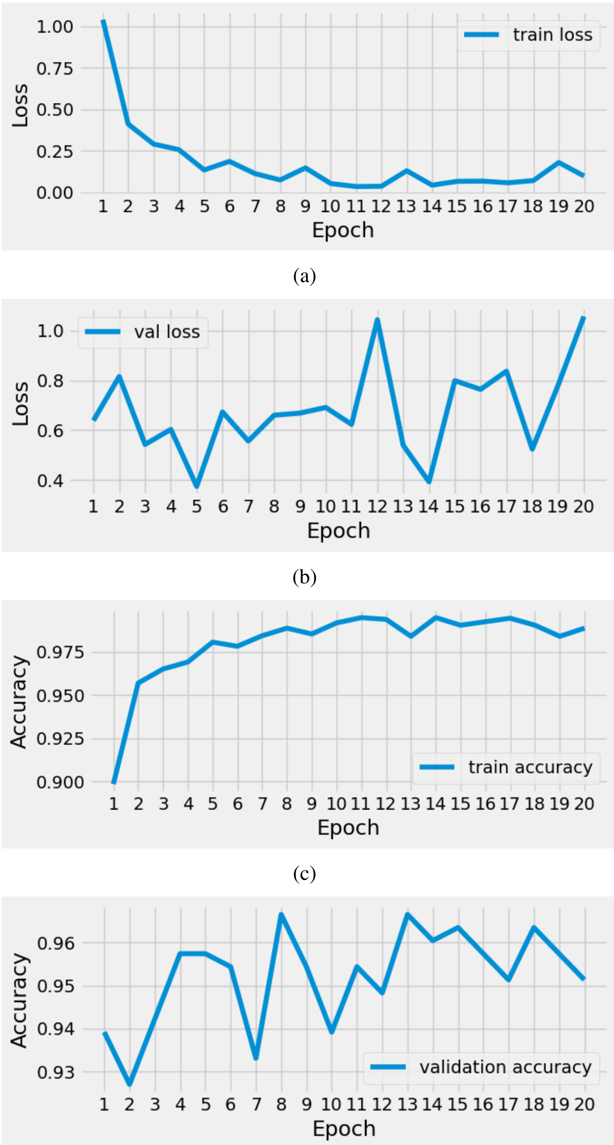
FIGURE 5. **Time series performance of applied classical CNN method during the training.**

TABLE 3. **Classification report results of CNN model for testing data.**

Accuracy	Loss	Target	Precision	Recall	F1
0.91	1.7053	closed	0.89	0.92	0.91
		opened	0.93	0.90	0.91
		Average	0.91	0.91	0.91

C. RESULTS WITH CLASSICAL VGG-16 METHOD

In our study, we initially implemented a classical VGG16 model to analyze a specific time series dataset. The training process and its impact on model performance are detailed in Figure 6. Initially, the model exhibited high loss scores and low accuracy, attributable to the random weight initializations typical at the start of training. As training progressed, the VGG16 learned to fine-tune its parameters, leading to a gradual improvement in accuracy and a decrease in loss



(a) (b) (c) (d)

FIGURE 6. Time series performance of applied classical VGG16 method during the training.

scores. Despite these improvements, performance metrics remained around 92%, indicating a relatively low-efficiency level. This suggests that while the model learns from the data, there remains a significant need for performance enhancement strategies to further refine and improve its predictive capabilities.

The study on driver drowsiness detection using a VGG16 model, as detailed in Table 4, demonstrates that the model can identify drowsiness with a 94% accuracy rate for unseen data. However, the performance is notably moderate for the specific task of recognizing the 'eye closed' class, indicating a critical area for improvement. Despite the high overall accuracy, these results underline the necessity for further enhancements in the model's capability to ensure more reliable detection of driver drowsiness, particularly in critical

TABLE 4. Classification report results of VGG16 model for testing data.

Accuracy	Loss	Target	Precision	Recall	F1
0.94	1.0757	closed	0.97	0.90	0.93
		opened	0.97	0.91	0.94
		Average	0.94	0.94	0.94

TABLE 5. Testing results with spatial features of VGG16.

Method	Accuracy	Target	Precision	Recall	F1
KNC	0.68	closed	0.65	0.68	0.67
		opened	0.70	0.67	0.69
		Average	0.68	0.68	0.68
LGBM	0.91	closed	0.88	0.94	0.91
		opened	0.94	0.89	0.91
		Average	0.91	0.91	0.91
LR	0.70	closed	0.69	0.67	0.68
		opened	0.71	0.73	0.72
		Average	0.70	0.70	0.70
RFC	0.89	closed	0.86	0.91	0.88
		opened	0.91	0.87	0.89
		Average	0.89	0.89	0.89

situations where the driver's eyes are closed. This suggests that while VGG16 models hold promise for this application, optimization, and refinement are essential for achieving the levels of performance required for real-world deployment.

D. RESULTS WITH NOVEL PROPOSED TRANSFER APPROACH

In this section, we examine the performance results of our novel proposed transfer learning approach in detail. Our approach leverages a transfer mechanism specifically designed to extract salient features from driver eye images. By utilizing this method, we created a new feature set that was then comparatively evaluated. The comparative analysis aimed to assess the effectiveness and efficiency of the feature set generated through our transfer learning approach, demonstrating its potential benefits in applications requiring accurate eye movement and attention tracking, such as driver monitoring systems for enhanced road safety.

1) RESULTS WITH SPATIAL FEATURES

In this section, we aimed to evaluate the effectiveness of Spatial Features extracted via the VGG16 model in driver drowsiness detection. We fed these Spatial Features into various machine-learning models and assessed their performance. According to the results presented in Table 5, the Light Gradient Boosting Machine (LGBM) method stood out by achieving satisfactory performance scores, while other machine learning approaches yielded moderate results. This outcome suggests that although Spatial Features extracted from eye images of drivers hold potential, the majority of tested machine-learning models fail to fully leverage these features. Therefore, it is imperative to explore alternative transfer learning mechanisms that could enhance the performance of utilizing prominent Spatial Features for improved driver drowsiness detection.

TABLE 6. Testing results with novel proposed transfer learning features.

Method	Accuracy	Target	Precision	Recall	F1
LGBM	0.98	closed	0.98	0.99	0.98
		Opened	0.99	0.98	0.98
		Average	0.98	0.98	0.98
LR	0.98	closed	0.98	0.98	0.98
		opened	0.99	0.98	0.98
		Average	0.98	0.98	0.98
RFC	0.98	closed	0.98	0.99	0.98
		opened	0.99	0.98	0.98
		Average	0.98	0.98	0.98
KNC	**0.99**	**closed**	**0.98**	**0.99**	**0.98**
		opened	**0.99**	**0.98**	**0.99**
		Average	**0.99**	**0.99**	**0.99**

2) RESULTS WITH NOVEL PROPOSED FEATURES

The evaluation of novel proposed features in applied machine learning methods for driver drowsiness detection demonstrated significant improvements in performance metrics, as detailed in Table 6. The experiments highlighted the effectiveness of the proposed transfer feature engineering technique, with applied machine learning models like LGBM, LR, and RFC achieving performance scores around 98%. Notably, the proposed KNC method outperformed traditional approaches, achieving an exceptional accuracy score of 99%. This analysis underscores the significance and potential of the novel proposed feature engineering approach in enhancing machine learning applications, particularly in the context of driver drowsiness detection, showcasing its superior performance compared to classical methods.

In addition to our comprehensive analysis, we conducted histogram-based comparisons, as illustrated in Figure 7, to further substantiate our findings. The analysis explicitly demonstrated that the utilization of solely spatial features yielded suboptimal results in the context of driver drowsiness detection. However, a significant enhancement in performance was observed when we integrated both spatial features and class probability features, as proposed in our approach. This integration facilitated a more nuanced and accurate detection mechanism, ultimately leading to markedly higher performance scores. Therefore, the data convincingly supports the superiority of our proposed method for detecting driver drowsiness, highlighting the critical role of combining spatial and probabilistic features to achieve optimal detection accuracy.

This analysis focused on driver drowsiness detection, various predictive models are evaluated for their accuracy and reliability. According to Figure 8, which presents the confusion matrix-based prediction error rates for each model, a comprehensive analysis reveals that all models demonstrated a commendable performance with notably high rates of correct predictions and minimal instances of incorrect predictions. Among these, the proposed KNC method emerged as particularly noteworthy, recording only 12 instances of incorrect predictions while correctly identifying the remaining cases. This striking outcome underlines the effectiveness of the KNC approach, validating its superior performance in the context of driver drowsiness detection. The findings suggest that the KNC method is a highly reliable tool for identifying signs of drowsiness among drivers, thereby contributing to enhanced road safety measures.

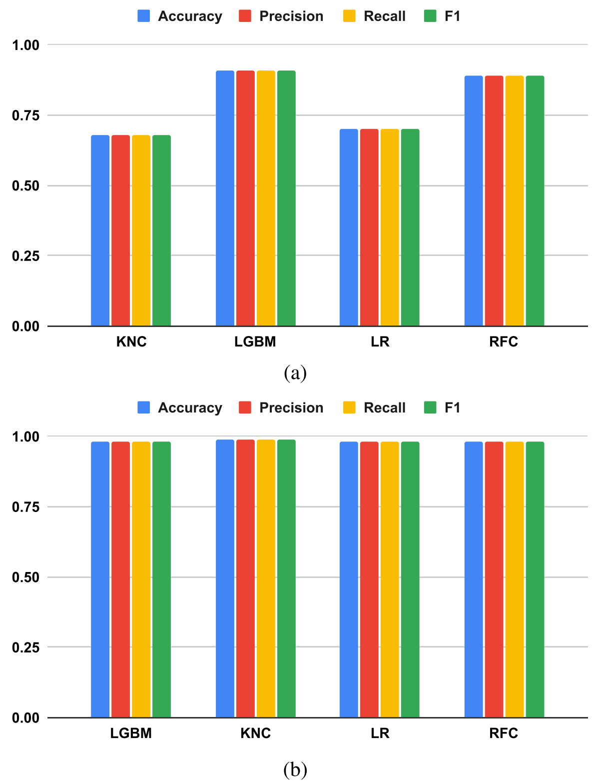


FIGURE 7. Histogram chart-based results comparisons of spatial and novel features.

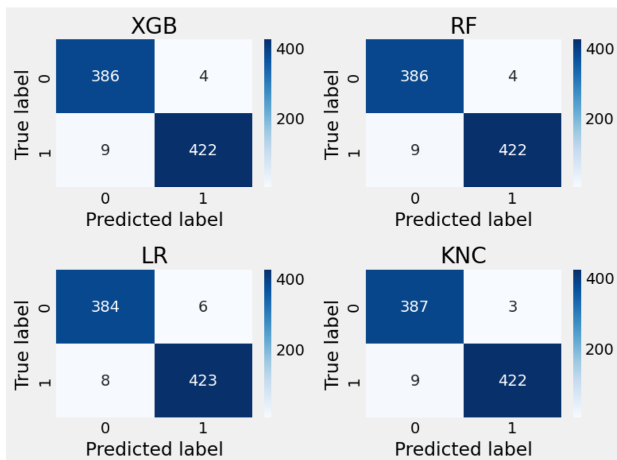


FIGURE 8. Confusion matrix-based performance validation of applied learning techniques.

E. NOVEL TRANSFER NEURAL LAYERS FEATURES EXTRACTION

In this section, we have successfully demonstrated the application of transfer learning and feature extraction using our proposed approach, as illustrated in Figure 9. Our analysis focuses on the extraction of spatial features from

TABLE 7. Results validations of applied machine learning methods.

Method	Kfold	Accuracy	Standard deviations (+/-)
LGBM	10	0.98	0.0031
LR	10	0.98	0.0038
RFC	10	0.98	0.0041
KNC	**10**	**0.98**	**0.0051**

TABLE 8. Runtime computational complexity analysis of applied methods.

Method	Runtime computations (seconds)
LGBM	0.03252
LR	0.00585
RFC	0.05832
KNC	**0.00829**

sample images of drivers' eyes. This process involves identifying and extracting prominent features from each image, which are critical in understanding the visual cues indicative of the driver's state, such as alertness or fatigue. By harnessing these extracted features, we have been able to construct machine-learning models that exhibit high accuracy scores. This achievement underscores the effectiveness of our method in not only accurately capturing essential visual information from the eye images but also in leveraging this information to enhance the predictive capability of the models.

F. K-FOLD CROSS-VALIDATION ANALYSIS

After achieving high-performance scores, we employed k-fold validation mechanisms, specifically dividing the dataset into 10 folds, to validate the efficacy of each applied method for driver drowsiness detection. The results, as detailed in Table 7, underscore the robustness of our methods, with performance scores consistently exceeding 98% and exhibiting minimal standard deviation. This comprehensive analysis not only confirms the high accuracy of our applied methods but also demonstrates their generalizability across different data segments, reinforcing their potential applicability in real-world scenarios for enhancing driver safety.

G. COMPUTATIONAL COMPLEXITY ANALYSIS

The computational complexity analysis for driver drowsiness detection methods, as depicted in Table 8, highlights the efficiency of the proposed KNC detection algorithm. The analysis reveals that the KNC method can identify critical driver drowsiness in just 0.008 seconds, outperforming other tested algorithms in terms of speed. This indicates that the KNC detection algorithm not only achieves rapid detection times but also implies potential for real-time application in driver safety systems, where quick response times are crucial for preventing accidents caused by drowsy driving.

H. ENTROPY FEATURE SPACE ANALYSIS

To investigate the cause of high-performance scores in detecting driver drowsiness, we conducted a feature space analysis on newly created transfer features, as depicted in Figure 10. Our analysis revealed that these novel transfer features are highly linearly separable, indicating that our proposed innovative approach successfully extracts features that significantly contribute to the model's effectiveness. Consequently, this analysis supports the conclusion that the newly developed features play a crucial role in efficiently detecting driver drowsiness, underscoring the value of our proposed method in enhancing performance in this domain.

TABLE 9. State-of-the-art method comparisons with the proposed approach.

Ref	Proposed Technique	Performance Score
[8]	CNN	97%
[12]	Hybrid model	91%
[13]	ML model	80%
[14]	Bagging and boosting	89%
[15]	ML model	85%
[31]	YOLO network	73%
[32]	Yolo V3	98%
[33]	YOLO network	87%
Our	**Novel VGLG**	**99%**

I. STATE OF THE ART STUDIES COMPARISONS

For a fair comparison, we performed the state-of-the-art method comparisons as described in Table 9. Most previous studies utilized classical machine learning and neural network frameworks. We proposed a novel transfer of features. Comparisons reveal that our novel approach outperformed state-of-the-art studies with high-performance scores for driver drowsiness detection.

In addition, we have compared our proposed method with benchmark datasets and recent work such as YOLO models in this analysis. The comparison results also show the superiority of our novel proposed approach or image classification.

J. ABLATION STUDIES

This subsection demonstrates the performance effects of the ablation study conducted to assess the proposed transfer learning-based system by systematically removing specific components. This ablation analysis contributes to evaluating the overall performance results based on the significance of each component.

Primarily, we evaluated the performance impact of our novel proposed VGLG and KNC approach compared to traditional neural network models. The results indicate that upon removal of the proposed VGLG and KNC approach, we observed noteworthy results. However, by employing our invented transfer learning approach, the KNC method outperformed state-of-the-art methods with a high performance accuracy of 99% in detecting driver drowsiness. This analysis underscores the superiority and effectiveness of the proposed approach over classical methods.

The findings from this ablation study analysis highlight the significant importance of our proposed approach in detecting driver drowsiness. Overall, the results of the ablation study reinforce the robustness of our method.

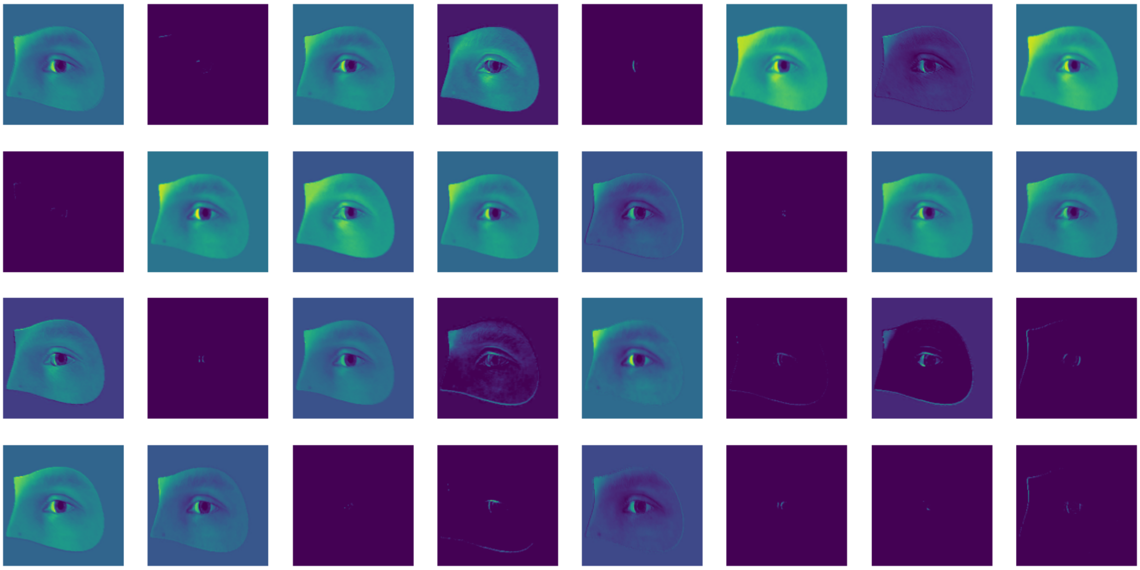


FIGURE 9. The proposed features extraction mechanism analysis from a driver eye image movement.

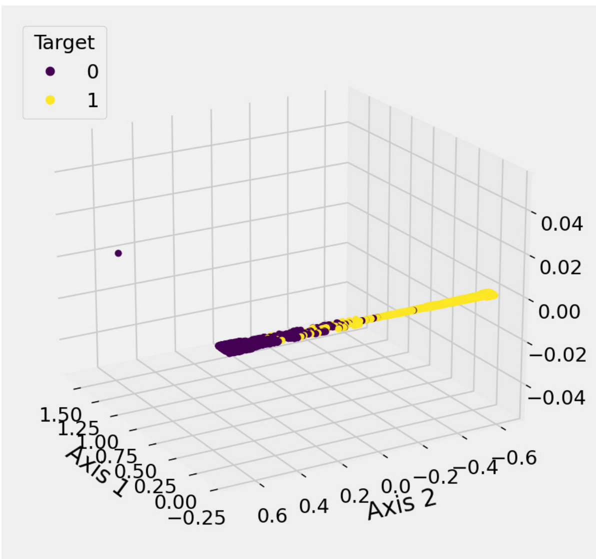


FIGURE 10. The feature space analysis of newly created transfer features.

K. DISCUSSION AND STUDY LIMITATIONS

This research aims to leverage eye movement behavior as a significant indicator of drowsiness, utilizing transfer learning to enhance detection accuracy. However, it's essential to recognize that while our findings are promising, the accuracy of the drowsiness detection system can still be improved. Further exploration into more advanced neural network architectures could potentially yield better performance and more robust detection capabilities.

One of the significant discussions around our approach is the potential for applying more sophisticated neural network models. Current advancements in deep learning and neural networks, such as CNNs and recurrent neural networks (RNNs), offer avenues for exploration. These models could enhance the system's ability to learn complex patterns in eye movement behavior associated with drowsiness, thereby improving detection accuracy.

Moreover, the computational complexity of our proposed method is another area for discussion and improvement. While we aim to develop a system that is both efficient and effective, the balance between computational demands and real-time performance is crucial, especially for in-vehicle systems where processing power and energy consumption are limited. Future research could focus on optimizing the model to reduce computational complexity without compromising detection accuracy. This might involve investigating lighter models or techniques such as model pruning and quantization, which can significantly reduce the computational load.

In our proposed transfer learning-based feature engineering approach from image data, specifically eye scans of a driver during driving, several limitations and challenges emerge as some disadvantages. Firstly, the variability in lighting conditions within the vehicle presents a significant challenge. The effectiveness of feature extraction can be drastically affected by changes in natural light throughout the day or artificial light sources at night, compromising the consistency and reliability of the derived features. Secondly, the quality of the camera capturing the eye scans plays a crucial role in the fidelity of the image data. Lower-quality cameras may introduce noise and reduce the resolution of the images, thereby hampering the transfer learning model's ability to accurately identify and extract relevant features. This issue is exacerbated in dynamic driving environments where vibrations and movements can further degrade image quality.

The scope of our research is primarily focused on eye movement behavior as an indicator of drowsiness, which, while significant, does not account for all possible drowsiness indicators. Other physiological or behavioral signals, such as heart rate variability or yawning, could also be integrated into the detection system to improve its accuracy and robustness.

V. CONCLUSION AND FUTURE DIRECTIONS

This study aimed to detect driver drowsiness through the imagery of eye movement behavior. We utilized a standard image dataset reflecting drivers' eye movement behavior for this research experiment. We proposed a novel transfer learning-based feature generation method that combines the strengths of the VGG-16 and LGBM methods. The proposed VGLG approach first extracts spatial features from input eye image data and then generates salient transfer features using LGBM. Experimental evaluations revealed that the k-neighbors classifier outperformed the state-of-the-art approach with a high-performance accuracy of 99%. The computational complexity analysis shows that our proposed approach detects driver drowsiness in 0.00829 seconds. We enhanced the performance through hyperparameter tuning and validations using k-fold validation.

A. FUTURE WORK

In future research, we aim to further improve performance scores by refining our proposed machine-learning model. A significant focus will be on the design and deployment of our model within a camera-based application specifically tailored for real-time driver drowsiness detection. This advanced application will not only detect signs of driver fatigue more effectively but will also incorporate a timely alert system designed to prevent accidents.

The tests on human subjects will also be performed to validate the proposed method for real-time driver drowsiness detection.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript. Any affiliations, or relationships with organizations or entities that might pose a conflict of interest with the subject matter discussed in this work are hereby disclosed.

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