A LIME-Enhanced SVM Framework for Driver Drowsiness Detection in Nighttime Driving Scenarios

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Abstract-Nighttime traffic accidents caused by driver fatigue remain a critical issue, as most visual-based detection systems find it challenging to interpret facial cues under poor lighting conditions. Key obstacles include decreased accuracy in dark settings, difficulties in detecting eye and mouth features, and the impractical nature of real-time approaches that rely on physiological sensors. This study introduces a vision-based drowsiness detection framework that integrates the Adaptive Low-light Image Enhancement (LIME) method with a Support Vector Machine (SVM) classifier employing an RBF kernel. The dataset comprises 11.566 images of eyes and mouths, which are analyzed to extract features like Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and blink frequency. Evaluation results show that the SVM model with the RBF kernel attained 90.94% accuracy, 91.22% precision, and 91.82% recall. This system is effective in detecting drowsiness under low-light conditions and has the potential to be implemented as an early warning feature in vehicles.

Keywords: Drowsiness Detection, SVM, EAR, MAR, Adaptive LIME

1. INTRODUCTION

Driver drowsiness is recognized as one of the main contributors to fatal traffic accidents worldwide. According to the World Health Organization (WHO), driver fatigue plays a significant role in causing traffic accidents, resulting in 1.35 million annual fatalities caused by road accidents worldwide [1]. The risk of accidents increases at night, as drivers tend to experience reduced concentration, and poor lighting conditions further exacerbate the situation [2]. Visual drowsiness detection systems frequently suffer from reduced accuracy under dim lighting, challenges in precisely identifying eye and mouth features, and the impracticality of applying physiological methods like EEG or EOG in real-time vehicle environments [3][4]. Therefore, a more effective and flexible approach is needed, one that can operate reliably even under low-light conditions [5].

Earlier methods utilized infrared eye tracking, pupil recognition, and visual indicators like blinking rates and the Eye Aspect Ratio (EAR). However, these approaches often experience severe performance drops when operating under difficult lighting conditions [5]. One emerging approach involves utilizing facial landmarks to calculate aspect ratios such as the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Research by Djamila et al. (2021) demonstrated that combining EAR and MAR can improve drowsiness detection accuracy up to 92%, particularly in low-light environments [6]. Real-time eye blink detection based on facial landmarks and the formulation of the Eye Aspect Ratio (EAR) has been widely adopted due to its computational efficiency and effectiveness in monitoring eyelid dynamics in video streams[7]. Although relatively robust to minor head movements, this method remains sensitive to occlusion and lighting variations, which reduces its accuracy under nighttime conditions. To address these challenges, several studies have explored image enhancement techniques and the use of more adaptive visual features. Low-light image enhancement methods based on illumination map estimation (LIME) have proven effective in improving visibility and local contrast in images captured under poor lighting conditions[8].

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In addition, data augmentation techniques have been shown to improve the generalization of image detection models, enabling the system to become more adaptive to diverse real-world conditions[9]. Decomposition and enhancement methods have also been developed to restore image details under low-light conditions, providing more stable results[10]. Previous studies further investigated the use of visual behavioral features as indicators of driver drowsiness, where yawning analysis and eye closure were found to provide complementary information that enhances detection accuracy[11]. Moreover, face alignment methods using the Active Shape Model (ASM), when combined with Support Vector Machine (SVM), have been shown to improve the precision of facial feature detection[12].

To address these challenges, this study proposes a face image-based method that integrates image enhancement using Adaptive Low-light Image Enhancement (LIME) and classification with a Support Vector Machine (SVM) employing a Radial Basis Function (RBF) kernel [13][14]. The Adaptive LIME technique enhances clarity in key facial regions, such as the eyes and mouth, in dark images, thereby enabling more precise extraction of EAR and MAR features. Subsequently, the extracted features are used by the SVM model to classify the driver's condition as either "drowsy" or "alert" [15]. This study not only focuses on improving the performance of the drowsiness detection system but also compares the effectiveness of the SVM method with and without the use of Adaptive LIME. Furthermore, its performance is evaluated against other approaches, such as CNN, KNN, Random Forest, and Naïve Bayes. Therefore, this research aims to contribute to the development of a reliable drowsiness detection system for real-world vehicle implementation, particularly under nighttime driving conditions.

2. RESEARCH METHOD

This research aims to design a facial image-based driver drowsiness detection system for nighttime scenarios by employing Adaptive LIME (Low-light Image Enhancement) and an SVM classifier. The methodology involves several stages: data collection, image preprocessing, feature extraction, model training, performance evaluation, and visualization of results. The overall research workflow is systematically structured, as illustrated in Figure 1, which outlines the main stages of this study.

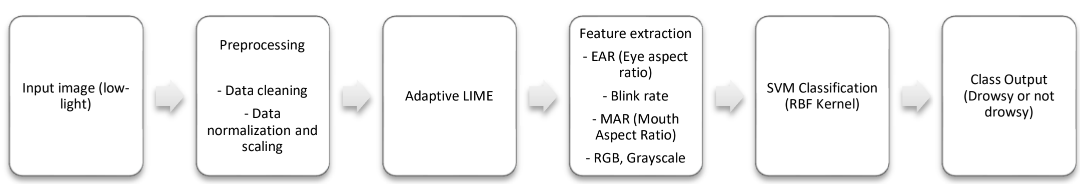

Figure 1. Research Workflow for Drowsiness Detection

2.1 Dataset

A publicly available dataset from Kaggle (hoangtung719), consisting of 11.566 labeled images divided into drowsy and alert categories with a resolution of 64×64 pixels, was utilized. An 80:20 split was applied to the dataset, allocating 9.252 images for training purposes and 2.314 for testing. To identify yawning, which is a key symptom of fatigue, another dataset focusing on the mouth region was incorporated into the system. The labels yawn and no_yawn were used as supporting classes, processed alongside the eye data. To mitigate the issue of imbalanced classes, the dataset was expanded using augmentation techniques like flipping, rotating, and adjusting contrast. This strategy aims to enhance data diversity, enabling the model to achieve better generalization across all classes. Data augmentation is known to improve the generalization capability of machine learning models, particularly when dealing with small or imbalanced datasets [9].

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2.2 Preprocessing Data

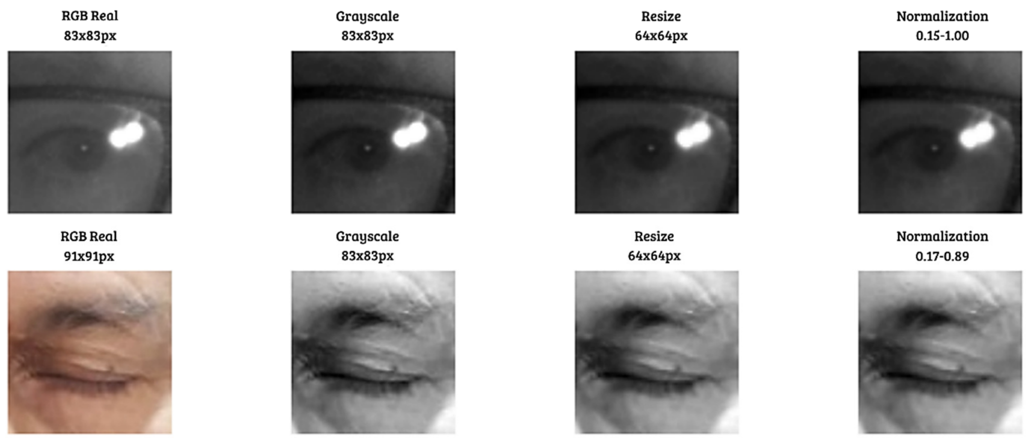

Figure 2. Pre-Preprocessing Stage (Grayscale, Resize, Normalization)

To prepare for model training, several preprocessing operations are applied to the eye images, improving quality and emphasizing critical traits. The first step is resizing the images to a resolution of 64×64 pixels and converting them to grayscale. Pixel values are then normalized to a [0,1] range. Next, filtering is applied to reduce noise, followed by standard histogram equalization to balance initial lighting conditions. These preprocessing procedures are intended to standardize image quality before the enhancement using Adaptive LIME is applied. To ensure consistency across feature scales, Min-Max Scaling is applied to normalize values within the range [0,1]. The normalization formula is defined as follows (1).

$$\boldsymbol{x'} = \frac{(\boldsymbol{x} - \boldsymbol{xmin})}{(\boldsymbol{xmax} - \boldsymbol{xmin})} \tag{1}$$

This process is essential to maintain the stability and performance of the SVM model during training.

2.3 Adaptive LIME

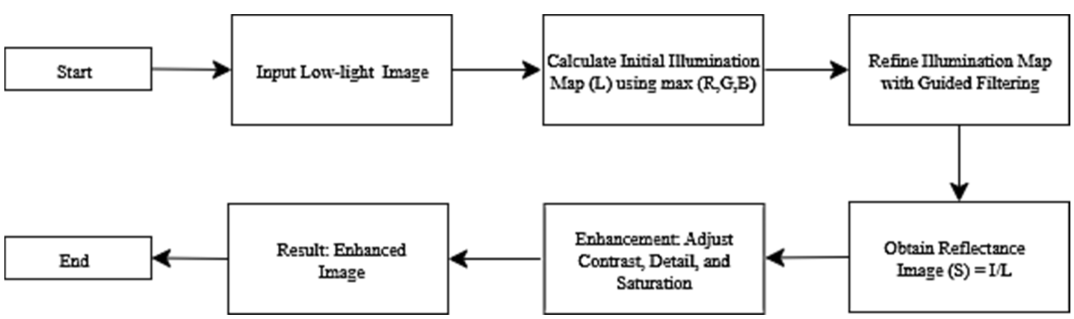

Figure 3. Adaptive LIME

Adaptive LIME (Low-light Image Enhancement) is applied to improve the visual quality of facial images in low-light environments. This approach aims to improve the visibility of key features such as the eyes and mouth, which often appear unclear in dark images. This image enhancement method operates in three main phases. First, the illumination map is estimated by calculating the maximum value of each pixel across the RGB channels using the following formula (2)

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$$L(x) = max(R(x), G(x), B(x)) \tag{2}$$

Second, the estimated illumination map is refined using a guided filtering process designed to reduce noise while preserving object contours. Finally, the image reflectance is restored using the following formula(3)

$$S(x) = \frac{I(x)}{L(x)} \tag{3}$$

Overall, this method enhances visual details in the eye region, thereby supporting more accurate extraction of the Eye Aspect Ratio (EAR) feature. While it improves accuracy, the process also increases the processing time per image, making optimization strategies necessary to maintain efficiency for real-time [8]. An example of the enhanced image results is shown in Figure 4.

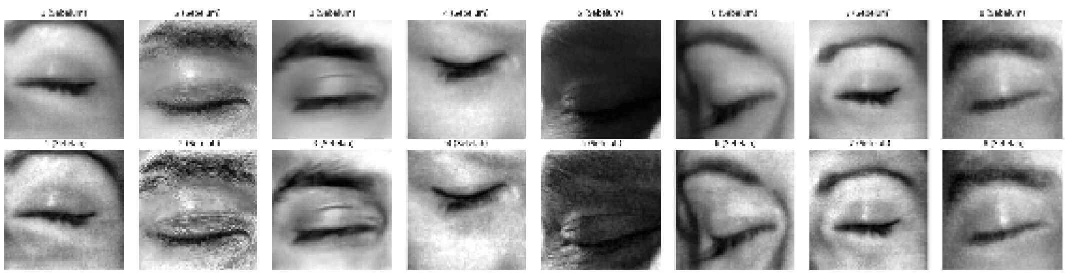

Figure 4. Stages of Eye Image Preprocessing and Enhancement Using Adaptive LIME

As shown in Figure 4, the illustration presents several examples of eye images before and after enhancement. The upper row shows the original low-light eye images, while the lower row depicts the improved results using Adaptive LIME. The enhancement process improves visibility and local contrast, making the eye region more suitable for feature extraction. In addition, Adaptive LIME is lightweight in computation and ideal for real-time applications, making it effective for drowsiness detection systems.

2.4 Feature Extraction

With more explicit input images, the extraction of geometric features becomes more reliable. These features are essential for identifying eye closure and mouth movements, which serve as indicators of drowsiness. This study extracts Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) as the primary features. The Eye Aspect Ratio (EAR) determines the eye's open or closed state based on the proportion between vertical and horizontal distances from six reference points (p1–p6), [7]. The EAR value tends to be high when the eyes are open and decreases significantly when they are closed. EAR is calculated using the following formula (4).

$$EAR = \frac{\|p^2 - p^6\| + \|p^3 - p^5\|}{2 \times \|p^1 - p^4\|} \tag{4}$$

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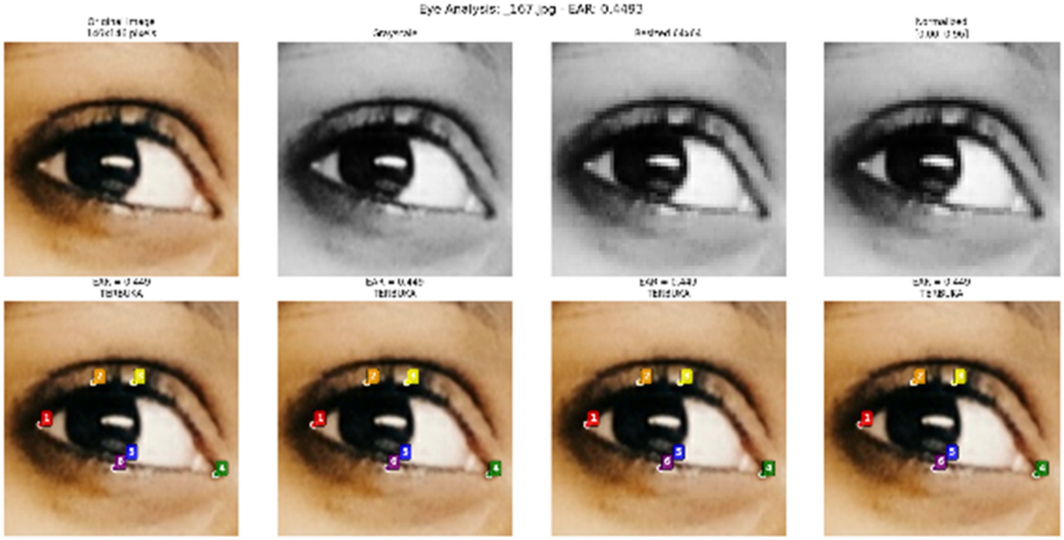

Figure 5. Sample of Eye Landmark Detection and EAR Calculation

If the EAR value falls below the threshold of 0.20, it is considered an indication of closed eyes, which serves as one of the key indicators of drowsiness. In addition, the Mouth Aspect Ratio (MAR) is used to detect yawning activity by analyzing eight inner mouth landmark points (p61–p68) [11].

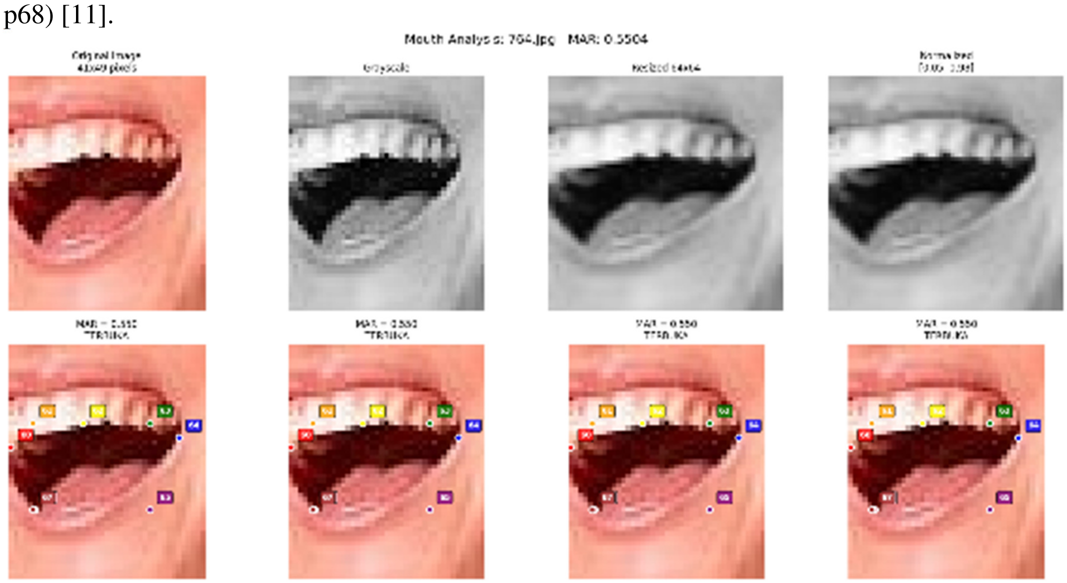

Figure 6. Sample of Mouth Landmark Detection and MAR Calculation

The MAR value increases significantly when the mouth is widely open. The MAR formula is as follows (5).

$$\boldsymbol{threeMAR} = \frac{\|p^{63} - p^{67}\| + \|p^{64} - p^{66}\|}{2 \times \|p_{61} - p_{65}\|} \tag{5}$$

A MAR threshold exceeding 0.60 is used to detect yawning behavior. By combining both features, the system can more accurately recognize signs of drowsiness, both from eye and mouth movements, even under low-light conditions. Although EAR and MAR can be used to detect the condition of the eyes and mouth, their accuracy may decrease when the face is rotated or partially

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occluded. To improve the reliability of feature extraction, Support Vector Machine (SVM)-based methods are often employed to classify feature patterns from various viewpoints [12].

2.5 Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm is an effective classification approach for separating both linear and non-linear data. In this study, SVM is employed to classify driver drowsiness conditions based on visual features such as the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) [7].

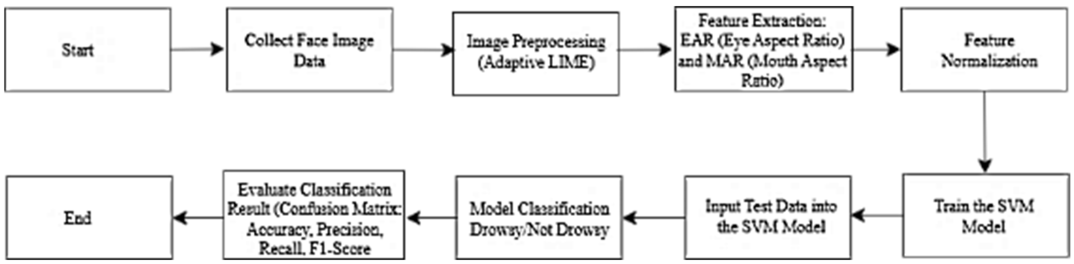

Figure 7. Flowchart SVM

The SVM algorithm identifies the most effective decision boundary to distinguish between drowsy and alert states. To handle non-linear data, the Radial Basis Function (RBF) kernel is employed, which is formulated as follows (6).

$$K(x_i, x_j) = \exp(-\gamma | x_i - x_j|^2) \quad (6)$$

Where γ is a parameter that controls the influence of each data point on the decision boundary. Parameter optimization is performed using GridSearchCV and 5-fold cross-validation to determine the best combination of parameters C and γ [16]. In addition to using EAR, incorporating MAR and yawn frequency features enhances the overall data representation, particularly in low-light scenarios [17]. The application of the SVM method in this system is considered effective, especially when combined with Adaptive LIME image enhancement techniques, which improve feature quality prior to classification [8].

2.6 Model Evaluation

The performance of the model was assessed using five main metrics: accuracy, precision, recall, F1-score, and the Area Under the Curve (AUC). The evaluation criteria are intended to measure how well the model distinguishes between drowsy and alert states using extracted image characteristics. In addition to numerical metrics, a confusion matrix was used to analyze the correct and incorrect classification patterns for each class, while the ROC Curve visualization was employed to evaluate the model's performance across varying decision thresholds. A 5-fold cross-validation scheme was also applied during the tuning process to ensure the model's generalization to unseen data [18].

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3. RESULTS AND DISCUSSION

3.1 Adaptive LIME Dataset and Impact

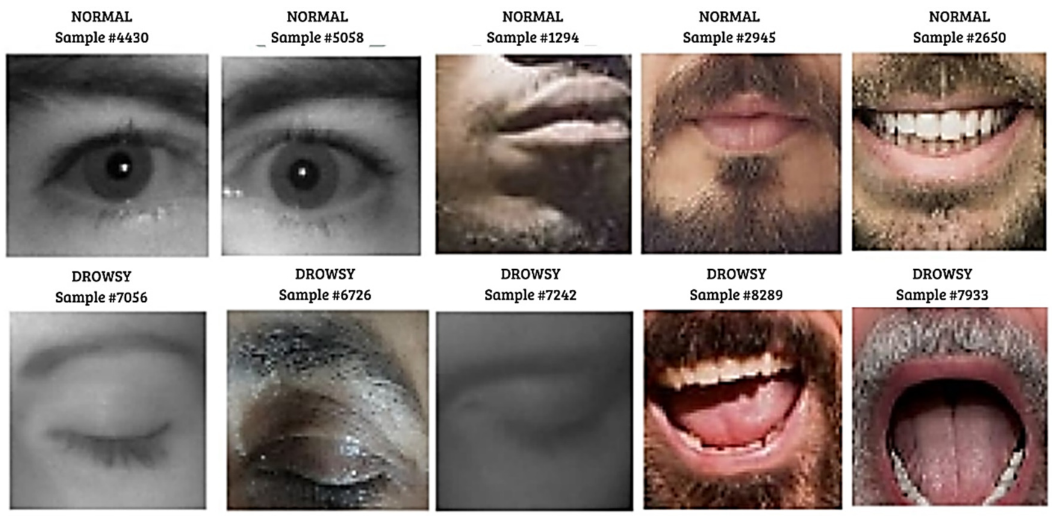

Figure 8. Sample Dataset Images from Drowsiness Detection

The experiment was conducted using 11.566 facial images representing various conditions, including open eyes, closed eyes, yawning, and non-yawning. The dataset was divided into 77.6% for training, 12.3% for validation, and 10% for testing, with a standardized resolution of 64×64 pixels. Applying Adaptive LIME considerably enhanced the visual quality of the eye and mouth regions. This enhancement positively impacted the feature extraction process, particularly for Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). The results demonstrated a notable improvement in system performance following the use of Adaptive LIME:

Table 1. Impact of Adaptive LIME

Metric	**Before LIME**	**After LIME**
Accuracy	85.9%	90.9%
Precision	86.2%	91.2%
Recall	87.1%	91.8%

An accuracy improvement of 5% demonstrates the effectiveness of Adaptive LIME in handling low-light conditions. However, this process adds an average processing time of approximately 0.4 seconds per image, which requires further consideration for real-time system implementation.

3.2 Evaluation of SVM Models

This study applies a Support Vector Machine (SVM) model utilizing three different kernel functions: linear, polynomial, and Radial Basis Function (RBF). Evaluation based on accuracy, precision, recall, F1-score, and AUC reveals that the RBF kernel provides the most optimal performance among the SVM variants.

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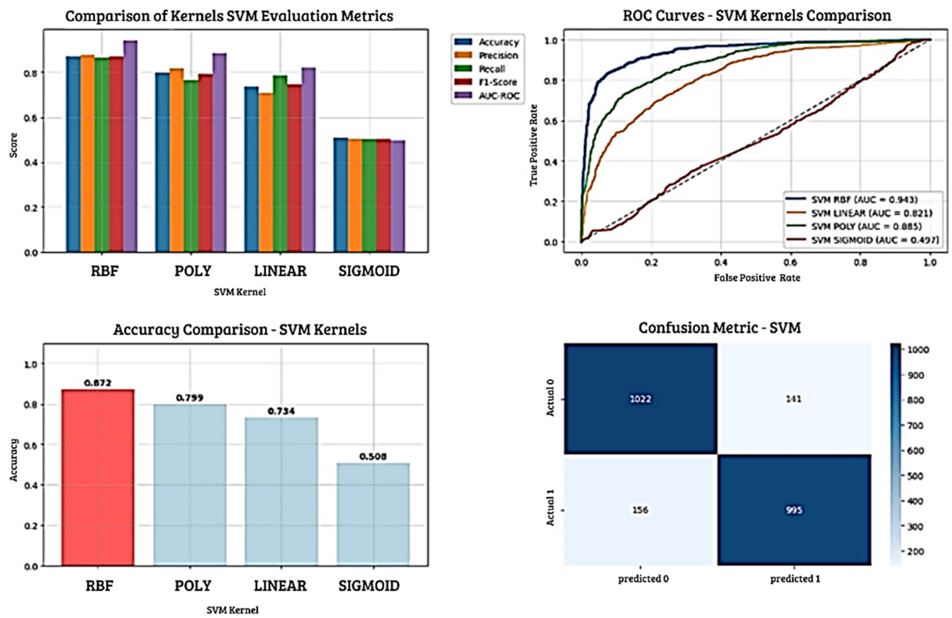

Figure 9. Accuracy Comparison of Each SVM Kernel

Table 2. SVM Peformance with Different Kernels

Kernel	Accuracy	Precision	Recalll	F1-Score	AUC-ROC
RBF	**0.8717**	**0.8759**	**0.8645**	**0.8701**	**0.9428**
Polynomial	0.7986	0.8174	0.7663	0.7910	0.8858
Linear	0.7338	0.7989	0.7461	0.7714	0.8210
Sigmoid	0.5078	0.5053	0.5013	0.5033	0.4972

In Table 2, the Radial Basis Function (RBF) kernel demonstrates the highest performance compared to the other kernels, achieving an accuracy of 87.17%, an F1-score of 87.01%, and an AUC of 94.28%. These results indicate that the RBF kernel is well-suited for image data with non-linear patterns, such as face-based drowsiness detection. The Polynomial kernel ranks second with an accuracy of 79.86%. Although it can handle non-linear patterns, its performance is lower than RBF and it tends to be more sensitive to parameter selection. The Linear kernel provides moderate results, with an accuracy of 73.38%, as it is only optimal for linearly separable data, while visual data such as facial images are generally non-linear. Meanwhile, the Sigmoid kernel shows the lowest performance with an accuracy of only 50.78%, which is close to random predictions, due to its inability to effectively separate classes.

3.3 Comparison with Order Methods

To evaluate the superiority of this approach, the SVM with Radial Basis Function (SVM-RBF) was compared with several other algorithms, including CNN, Random Forest, Naive Bayes, KNN, and others. The evaluation results are presented in Figure 6 and Table 3.

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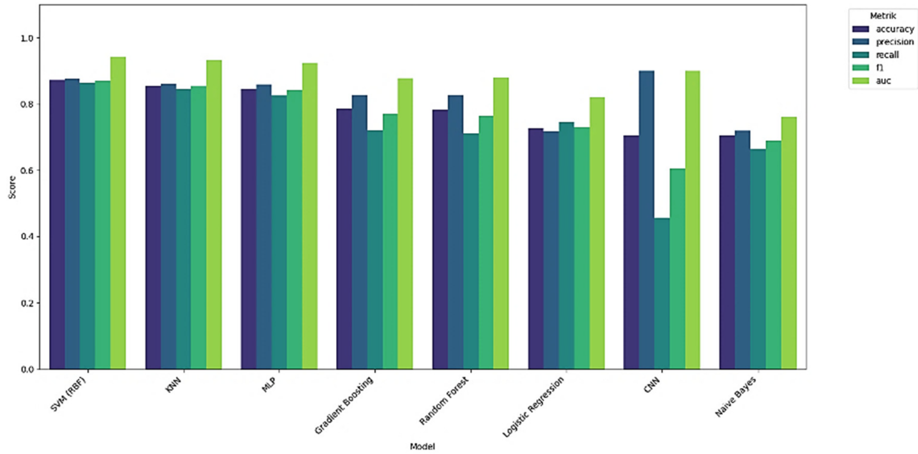

Figure 10. Comparative Analysis of Models

Table 3. Performance Comparison

Model	Accuracy	Precision	Recalll	F1-Score	AUC
SVM	**0.9094**	**0.9122**	**0.9182**	**0.9152**	**0.9656**
CNN	0.8654	0.8855	0.8589	0.8720	0.9362
Random Forest	0.8474	0.8326	0.895	0.8605	0.9232
Gradient Boosting	0.8411	0.8453	0.8616	0.8534	0.9201
MLP	0.8225	0.8174	0.8504	0.8335	0.9073
Logistic Regression	0.8084	0.7951	0.8651	0.8287	0.8989
KNN	0.7768	0.7732	0.8000	0.7864	0.8844
Naive Bayes	0.7409	0.7073	0.8166	0.7570	0.8610

As seen in Table 3, the SVM model using the RBF kernel outperformed other classifiers, including CNN, Random Forest, and KNN. It attained 90.94% in accuracy, an F1-score of 91.52%, and an AUC score of 96.56%, the SVM-RBF model proves its effectiveness in detecting driver drowsiness versus alertness. SVM-RBF outperforms others largely because it handles essential features like EAR and MAR efficiently, avoiding the complexity of deep learning models.

While CNN obtained a fairly high accuracy rate of 86.54%, it demands extensive training data and substantial computational resources. Random Forest and Gradient Boosting also demonstrated good results but tend to be less consistent when dealing with visual data containing noise or low-light conditions. Models such as Naive Bayes and KNN showed the lowest performance, with accuracies of only 74.09% and 77.68%, respectively, due to their simplicity in handling the complex distribution of visual data. Based on these results, it can be concluded that SVM-RBF not only excels in accuracy but is also more efficient and stable when applied to limited datasets with domain-specific features such as eye and mouth ratios.

3.4 Real Data Prediction

The system testing was conducted using real image data captured directly through a webcam. The primary objective of this testing was to evaluate the system's ability to accurately and consistently detect facial landmarks, particularly in the eye and mouth regions of the driver [11]. The information extracted from these landmarks serves as the basis for calculating the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), two key indicators representing drowsiness conditions, such as closed eyes or yawning activity. The system used the dlib library, applying its

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68-point facial landmark model to identify facial structures. The system processes images in real-time from the webcam.

Facial landmarks are automatically extracted by the system to obtain the necessary facial feature points, including the right eye (points 36–41), the left eye (points 42–47), and the inner mouth region (points 61–68) [19]. These points are utilized to calculate two primary features, the Eye Aspect Ratio (EAR) and the Mouth Aspect Ratio (MAR). EAR is used to measure the level of eye openness, which significantly decreases when the eyes are closed, while MAR measures the degree of mouth opening. If the MAR value exceeds a certain threshold consecutively over several frames, it is classified as a yawning activity, which is also a common indicator of drowsiness [20].

Figure 11. Data Prediction

Figure 8 illustrates the visualization results of the drowsiness detection system based on 68 facial landmarks. The calculation of the Eye Aspect Ratio (EAR) uses six specific points around the eyes (points 36–47), where a value below 0.20 for 3 consecutive seconds indicates drowsiness. The Mouth Aspect Ratio (MAR) is computed from eight points inside the mouth (points 61–68), and consistently high MAR values are interpreted as yawning activity. The system records the frequency of eye closure and yawning, displaying the driver's status in real-time. When both indicators exceed their respective thresholds, the system triggers a visual warning and an audible alarm. This method has proven effective even under low-light conditions.

4. CONCLUSION

This research is designed to resolve the issues previously discussed in the introduction section, particularly the challenge of detecting driver drowsiness at night under low-light conditions. Based on the results and discussion, it can be concluded that the application of the

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Adaptive LIME technique has notably improved the visibility and clarity of facial image data, especially in the eye and mouth regions, thereby enhancing the accuracy of the EAR and MAR feature extraction process. Utilizing Support Vector Machine (SVM) with an RBF kernel demonstrated the most effective performance model for classifying drowsy and non-drowsy conditions, achieving an accuracy of 87.17% and an AUC value of 0.9428. The results suggest that combining image enhancement with feature-driven classification greatly enhances the effectiveness of the system. With these results, all research objectives stated in the introduction have been achieved. Moving forward, this system shows promising potential for further development toward real-time implementation by incorporating processing time optimization and direct integration with in-vehicle cameras. In addition, future research can expand the scope of features (such as yawning detection and head movement) and evaluate the system using real-world driving data in dynamic environments.

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