

# Optimizing Driver Drowsiness Detection: Evaluating CLAHE and AHE Enhancement Techniques

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## Abstract

Driver drowsiness is a critical factor in road safety, and early detection can be key to preventing accidents. This research focuses on improving the accuracy of drowsiness detection by enhancing the contrast of driver facial images using image processing techniques. Specifically, the study explores the effectiveness of Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) in this context. The research utilizes the Drowsy Driver Detection (DDD) dataset, which includes facial images categorized into Drowsy and Non-Drowsy classes. AHE and CLAHE techniques are applied to preprocess these images, aiming to improve contrast and subsequently enhance drowsiness detection accuracy. Evaluation metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR) are employed to assess the quality of the processed images. The findings indicate that CLAHE performs better than AHE in terms of image enhancement. CLAHE achieves significantly lower MSE (93.90) compared to AHE (103.92), along with higher PSNR (28.41 for CLAHE vs. 27.97 for AHE) and SNR (0.49 for CLAHE vs. 0.04 for AHE) values. These results suggest that CLAHE effectively enhances contrast and improves image clarity. The success of CLAHE as a contrast enhancement technique highlights its potential application in real-time driver monitoring systems. In conclusion, this research underscores the importance of image preprocessing techniques like CLAHE in advancing driver safety technologies, emphasizing their potential to enhance the performance of drowsiness detection systems in practical driving scenarios.

**Keywords:** drowsiness detection, contrast enhancement, histogram equalization

## 1 Introduction

Traffic accidents remain a leading cause of fatalities worldwide [1]. Among the contributing factors to accidents is driver drowsiness, which can significantly impair attention, and reaction time, and increase the likelihood of crashes [2]. Therefore, early detection and prevention of drowsiness are crucial for reducing accident risks and enhancing driving safety [3]. One effective method to detect signs of fatigue is through facial analysis. By examining a driver's face, it's possible to identify cues indicative of drowsiness. However, the quality of face detection can be affected by image contrast [4]. Low-contrast images are common in various driving conditions, which underscores the importance of enhancing image contrast to improve the extraction of facial features and the accuracy of detection [5]. Enhancing image contrast can aid in improving the visibility of facial expressions and subtle cues that indicate fatigue, thereby facilitating more accurate and timely detection of drowsiness. This approach could potentially be integrated into advanced driver assistance systems (ADAS) to enhance real-time monitoring of driver state and mitigate the risk of accidents due to drowsiness-related impairment [4], [6].

Techniques for enhancing image contrast can be categorized into two main types: indirect techniques and direct techniques [7]. Indirect techniques aim to enhance contrast by manipulating the

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image histogram, which represents the distribution of pixel intensities, without directly altering the pixel values themselves. On the other hand, direct techniques directly modify the pixel values to increase contrast more explicitly [8]. One widely used indirect technique is Histogram Equalization (HE), which is among the earliest methods devised for contrast enhancement in digital [9]. HE works by redistributing pixel values across the entire range of intensity levels present in the image. This redistribution is achieved by transforming the image histogram to achieve a more uniform distribution of pixel intensities, thus enhancing image contrast [10]. Furthermore, an advanced version of HE is known as Contrast Limited Adaptive Histogram Equalization (CLAHE) has been developed to overcome some of the limitations of basic HE [11], [12].

CLAHE divides the image into smaller regions or blocks and performs histogram equalization independently on each block. By limiting the contrast enhancement within each block, CLAHE prevents the over-amplification of noise and maintains local contrast, leading to more effective and visually pleasing contrast enhancement across the entire image [13]. In summary, while HE and CLAHE are both indirect methods of contrast enhancement, CLAHE offers improved adaptability and control by operating on local image regions, thereby producing more desirable and natural-looking contrast improvements compared to global histogram equalization techniques. These techniques play a vital role in improving image quality and can be particularly useful in applications such as face detection where enhanced contrast can aid in feature extraction and analysis [4], [5]. By leveraging advanced contrast enhancement techniques like Adaptive Histogram Equalization (AHE) and CLAHE, researchers aim to optimize image contrast levels to facilitate more effective feature extraction and enhance the performance of drowsiness detection systems. The novel element of this study is the focused application of advanced contrast enhancement techniques, particularly CLAHE, to optimize image quality for face-based drowsiness detection. While CLAHE and AHE are adaptable techniques utilized in a variety of image processing applications, their usefulness in face-based drowsiness detection is highlighted by the specific difficulty of identifying small facial cues that indicate drowsiness in driver [14]. The intentional employment of CLAHE and AHE in this area is critical for increasing the visibility and clarity of these subtle cues, thereby boosting the accuracy and reliability of drowsiness detection systems designed for driver safety technology [15]. This study emphasizes the targeted and impactful application of CLAHE and AHE to fulfill the specific requirements of face-based drowsiness detection, contributing to advances in driver safety.

This research focuses on optimizing driver drowsiness detection through contrast enhancement using CLAHE. CLAHE was selected over other techniques due to its ability to enhance local contrast effectively without introducing excessive noise, making it well-suited for face-based drowsiness detection applications. The primary contribution of this research lies in the deliberate choice of CLAHE as a contrast enhancement technique for optimizing driver drowsiness detection. CLAHE offers advantages over other methods by effectively enhancing local contrast while minimizing noise, which is critical for accurately detecting subtle facial cues associated with drowsiness in drivers. This research aims to advance the field of driver safety technology by providing innovative solutions that enhance the accuracy and reliability of drowsiness detection systems.

This research aims to advance the field of driver safety technology by providing innovative solutions that enhance the accuracy and reliability of drowsiness detection systems. In real-world applications, the implementation of AHE and CLAHE for drowsiness detection involves camera-based systems mounted within vehicles typically on the dashboard or rear-view mirror to capture facial images of the driver. These images are then processed using contrast enhancement techniques like AHE and CLAHE to improve the visibility of critical facial features under varying lighting conditions, such as during nighttime or in tunnels. By integrating these preprocessing techniques into real-time monitoring systems, such as Advanced Driver Assistance Systems (ADAS), the system can better detect subtle signs of fatigue, including eye closure, yawning, and head tilts, thereby reducing the risk of drowsiness-related accidents.

Furthermore, this article is structured to provide a comprehensive understanding of the research process and outcomes. In Section 2, we review existing literature and related work in the field of image processing for drowsiness detection, highlighting key studies and methodologies. Section 3 outlines the materials used and the methods employed in this study, including details of contrast enhancement techniques and facial feature extraction algorithms. Moving forward to Section 4, we delve into the experimental results obtained from applying contrast enhancement techniques to

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improve the accuracy of face-based drowsiness detection. This section includes analyses, findings, and discussions based on empirical data gathered during the experiments. Finally, in Section 5, we summarize the key findings, draw conclusions based on the results, and discuss implications for future research directions in the domain of driver safety and image processing.

## 2 Literature Review

Early detection and prevention of driver drowsiness is crucial for reducing accident potential and enhancing driving safety. This review focuses on examining the utilization of AHE and CLAHE techniques to enhance image contrast in facial detection for drowsiness detection applications. The relevance of applying these contrast enhancement techniques specifically to driver facial detection is emphasized to gain insights into their impact on drowsiness detection. Previous studies have explored AHE and CLAHE techniques in various application domains based on image processing.

Kalyani and Chakraborty (2020) conducted research focusing on the application of HE, AHE, and CLAHE to improve contrast in MRI medical images, aiming for clearer and more accessible analysis. The study evaluated these techniques using metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR). The findings revealed that CLAHE demonstrated superior performance compared to HE and AHE in enhancing contrast and improving the quality of MRI medical images. This research highlights the effectiveness of CLAHE specifically in medical imaging contexts, suggesting its potential applicability in other image processing domains, including facial analysis for driver drowsiness detection [16].

Saiwaeo et al. (2022) conducted a comparison of image quality enhancement techniques aimed at improving contrast and detail in facial skin images for subsequent analysis. The researchers explored four different image enhancement techniques: HE, CLAHE, Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE), and Min-Max Contrast Stretching. Through their evaluation, CLAHE emerged as the most effective technique for enhancing image quality, achieving the highest level of clarity, and facilitating enhanced image processing capabilities. This finding underscores the superiority of CLAHE over other methods in the context of facial image enhancement, indicating its potential utility in various applications, including driver drowsiness detection where clear and detailed facial features are essential for accurate analysis and decision-making [17].

Nugroho et al. (2021) conducted a study focusing on the application of CLAHE to preprocess histogram-based features for lymphoma classification using the K-Nearest Neighbors (KNN) Algorithm. In this research, CLAHE was employed in the preprocessing stage to enhance image contrast, thereby improving the quality and discriminative power of image features used for classification. The study demonstrated significant performance improvements after applying CLAHE, with the classification model achieving an average accuracy of 85.5% and lymphoma specificity of 90.3%. These results highlight the effectiveness of CLAHE in enhancing image contrast and consequently improving the accuracy of classification tasks in medical image analysis. The findings suggest that CLAHE could similarly benefit other image processing applications, including facial analysis for driver drowsiness detection, by enhancing feature extraction and improving detection accuracy based on image characteristics [15].

Ngo et al. (2020) conducted research aimed at mitigating weather effects on visual image quality and enabling advanced processing capabilities. The study utilized a method combining fog removal based on dark channels prior with the Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique. By applying CLAHE to enhance contrast, the results obtained from fog removal were further improved, leading to clearer and more specific images despite adverse weather conditions. Experimental results from this study demonstrated the effectiveness of the proposed method, achieving a Mean Squared Error (MSE) of 0.256, which corresponds to a Peak Signal-to-Noise Ratio (PSNR) of 54.043. These metrics indicate a significant improvement in image quality and clarity, highlighting the potential of CLAHE in conjunction with other image processing techniques to enhance visibility and facilitate accurate analysis under challenging environmental conditions. This approach underscores the versatility and effectiveness of CLAHE in various image enhancement applications, including those relevant to driver safety and facial analysis for drowsiness detection [18].

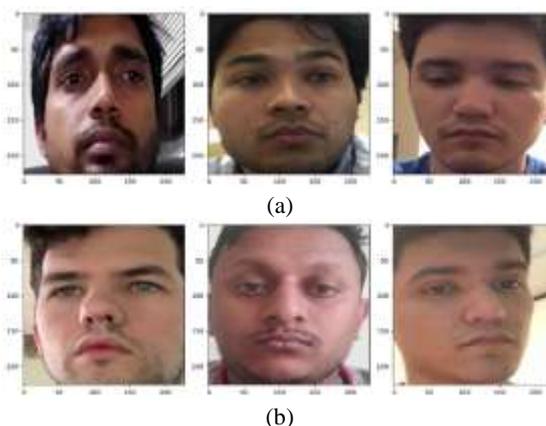
Studies by Saiwaeo et al. (2022) and Ngo et al. (2020) underscore the effectiveness of CLAHE in improving image quality and clarity, particularly in facial image enhancement applications. CLAHE enhances the visibility of subtle facial cues associated with drowsiness, crucial for accurate detection and recognition of drowsiness-related features in drivers. Nugroho et al. (2021) illustrate how CLAHE significantly improves the accuracy of classification tasks by enhancing image contrast. This improvement directly impacts the detection and recognition stages of image analysis, leading to more reliable and robust outcomes in medical image classification tasks. The research on CLAHE and AHE for driver drowsiness detection represents a critical advancement in optimizing image quality to enhance detection and recognition stages in driver safety technologies. This broader perspective reinforces the significance of leveraging advanced image enhancement techniques, like CLAHE, to improve the accuracy and reliability of facial analysis for drowsiness detection, paving the way for more effective and robust drowsiness detection systems.

### 3 Research Method

The research workflow for image contrast enhancement using Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) techniques involved a systematic series of steps, conducted on a DGX A100 computer using the Python programming language. Figure 2 illustrates the key stages of this workflow.

#### A. Data Sources

The study utilized the DDD (Driver Drowsiness Dataset) available on Kaggle, comprising facial images of drivers extracted and cropped from the "Real-life drowsiness" video dataset. The extraction process involved using VLC software to extract video frames as images, followed by processing with the Viola-Jones algorithm to isolate facial regions of interest. The DDD dataset includes 41,793 facial images categorized into two classes: "Drowsy" (22,348 images showing signs of drowsiness while driving) and "Non-Drowsy" (19,445 images depicting drivers in a normal driving state), as shown in Figure 1.



**Figure 1. Samples from the DDD (driver drowsiness dataset) depicting (a) drowsy condition and (b) non-drowsy condition.**

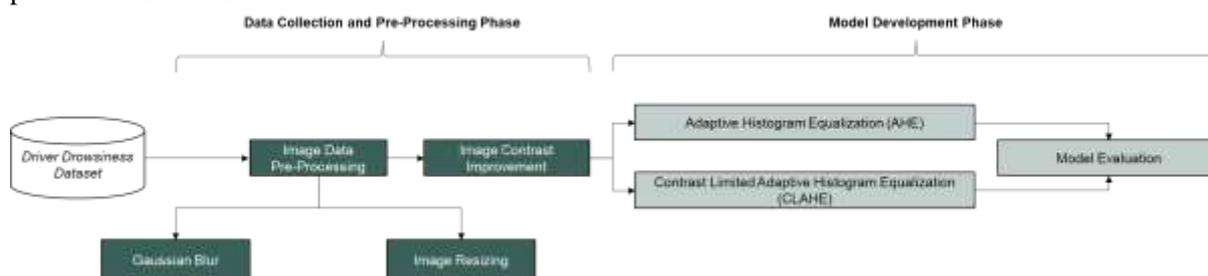
This dataset is crucial for face-based drowsiness detection research as it provides relevant conditions for drowsiness analysis. Researchers can use this dataset to train and test drowsiness detection models with various image processing techniques, including contrast enhancement methods like AHE (Adaptive Histogram Equalization) and CLAHE (Contrast Limited Adaptive Histogram Equalization). The study aims to enhance the accuracy of face-based drowsiness detection using this representative dataset and effective image processing techniques.

#### B. Research Workflow

The research workflow, as illustrated in Figure 2, outlines the systematic process undertaken to enhance image contrast using Adaptive Histogram Equalization (AHE) and Contrast Limited

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Adaptive Histogram Equalization (CLAHE). Figure 2 visualizes this workflow from data preparation to evaluation, highlighting the integration of image preprocessing, enhancement, and assessment phases within a unified framework.



**Figure 2. Research workflow for image contrast enhancement using AHE and CLAHE techniques**

Initially, the facial image dataset was categorized into two schemes: a full dataset comprising all available images and segmented datasets classified based on specific image characteristics. This categorization enabled more focused analysis and comparative evaluation within particular image groups. All images were resized before applying contrast enhancement algorithms to ensure uniform dimensions, which is essential for maintaining consistency throughout the processing pipeline. A Gaussian Blur filter was used during preprocessing to improve image quality and reduce noise. This step plays a vital role in smoothing the image and minimizing the impact of unwanted artifacts that may interfere with contrast enhancement.

The core processing phase involved implementing both AHE and CLAHE techniques. AHE enhances contrast by redistributing pixel intensities across the entire image, while CLAHE operates on localized image blocks and limits contrast amplification to prevent noise exaggeration. These approaches were selected for their effectiveness in improving the visibility of facial features, which is crucial in driver drowsiness detection tasks. Several quantitative metrics were employed to assess the contrast enhancement methods' performance. These include Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR), and algorithm execution time. These metrics provided a comprehensive evaluation of both the visual improvements achieved and the computational efficiency of the techniques.

## 4 Results and Analysis

This section presents a comprehensive evaluation of the research results, examining each stage in detail. The analysis begins by visualizing the impact of image enhancement on the image dataset, showcasing the adjustments in contrast. Finally, the model's performance is evaluated using Performa evaluation for image enhancement MSE, PSNR, SNR and time execution.

### A. Data Preparation

Image resizing is the process of changing the size dimensions of an image while maintaining proportionality. This involves adjusting the number of pixels by adding or removing them to scale the image up or down. Proportion and aspect ratio should be considered to avoid distortion. Common resizing algorithms include Nearest Neighbor, Bilinear Interpolation, and more complex methods like Lanczos or Bicubic Interpolation. Resizing is used for web layout adjustments, print resizing, and adapting images to different screen resolutions. It's essential for optimizing image appearance across various mediums and devices [19]. In this study, images were resized from their original size to dimensions of 224x224 pixels with 3 color channels (224x224x3) to standardize input sizes for subsequent analysis and processing. This resizing to 224x224 ensures compatibility with deep learning frameworks, promotes efficient model training and inference, preserves aspect ratio for accurate analysis, and balances image detail with computational efficiency for tasks like driver drowsiness detection using facial analysis techniques [20]. In this study, a Gaussian Blur technique with a kernel size of 5 was applied to smooth or soften images by blurring small details. Gaussian Blur uses a Gaussian filter, applying weights based on pixel distances to create a natural blurring effect that reduces pixel noise and enhances image uniformity. This technique is commonly used in

image processing for noise reduction and creating desired visual effects in photography or graphic design [21].

#### B. Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) operates similarly to traditional histogram equalization but with a localized approach known as local histogram processing [22]. This technique involves performing histogram equalization separately for each block (or sub-image) of the main image [23]. The size of these blocks can vary based on image characteristics or research requirements, commonly ranging from 2x2, 4x4, 8x8, 16x16 pixels, or other specified sizes. In AHE, the histogram equalization process is independently applied to each block within the image. This localized approach allows for contrast enhancement tailored to specific regions, making it effective for images with varying contrast levels across different areas. By adapting histogram equalization to smaller blocks, AHE enhances contrast locally, improving the visibility of image details and textures [12].

$$H_{(i)} = \sum_{x, y \in \text{tile}} p(i, x, y) \quad (1)$$

equation (1) the histogram  $H_{(i)}$  represents the distribution of pixel intensities for the specified intensity  $i$  within the designated image block or tile. This process forms the foundation of AHE by allowing for adaptive contrast adjustments based on local pixel intensity distributions [24].

#### C. Contrast Limited Adaptive Histogram Equalization

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a technique derived from Adaptive Histogram Equalization (AHE) but with a more generalized approach [14]. Unlike Histogram Equalization (HE), which acts globally on the entire image, CLAHE divides the image into smaller local areas (tiles) and independently applies AHE to each of these areas to enhance adaptive contrast based on local histogram equalization computed from pixel regions [25]. In this study, a clip limit value of 2.0 was used. The CLAHE algorithm proceeds by first partitioning the original image into sub-images or tiles of a specified size  $M \times N$ , representing localized regions within the image. Next, histograms are computed for each sub-image by tallying the occurrences of pixel intensities within the respective tiles [26]. Subsequently, the histograms for each image tile are adjusted or clipped based on a specified clip limit. If the histogram for a tile exceeds this limit, pixel values are scaled down to ensure that no histogram bin surpasses the specified threshold. The average number of pixels at each gray level can be calculated using a specific formula (Equation (2)) [27], providing further insight into the distribution of pixel intensities within the processed image.

$$N_{avg} = \frac{N_{CR-XP} * N_{CR-YP}}{N_{gray}} \quad (2)$$

Equation (2) calculates the average pixel value ( $N_{avg}$ ) within a sub-image based on pixel counts along the X ( $N_{CR-XP}$ ) and Y ( $N_{CR-YP}$ ) dimensions, divided by the total gray levels ( $N_{gray}$ ).

$$\text{Clip Limit (CL)} = N_{clip} \times N_{avg} \quad (3)$$

the equation (3) defines the clip limit (CL) used in contrast enhancement. Here,  $N_{clip}$  controls contrast limitation, ensuring controlled enhancement and a natural appearance [28].

#### D. Performa Evaluation

Contrast enhancement improves image quality by enhancing the contrast compared to unprocessed images, resulting in visually noticeable improvements. However, visual inspection alone lacks comprehensive and specific characterization. To address this, quality parameters such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR) are employed to evaluate contrast enhancement techniques [29]. These metrics offer quantitative measures that assess the effectiveness of contrast enhancement, providing valuable insights into image quality improvements beyond subjective visual assessments. Mean Squared Error (MSE) calculates the average squared difference between corresponding pixel values of two images. A lower MSE

value indicates better image similarity [29]. The error between two images is defined by the formula. Peak Signal-to-Noise Ratio (PSNR) measures image quality based on peak error. A higher PSNR value signifies better image quality [30]. Signal-to-Noise Ratio (SNR) compares signal power to noise power in the image. A higher SNR value indicates better image quality [29].

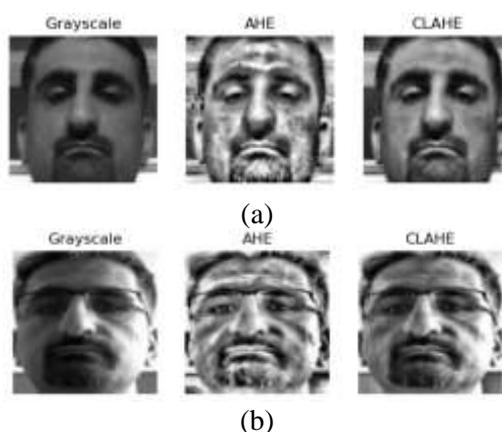
#### E. Modeling Result

The experimental results in Table 1 analyze the performance of image contrast enhancement techniques, namely Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), for driver drowsiness detection using facial images.

**Table 1. Average comparison of contrast enhancement techniques**

Algoritma	MSE	PSNR	SNR	Time
AHE	103.92	27.97	0.04	00:00:32.9
CLAHE	93.90	28.41	0.49	00:00:33.1

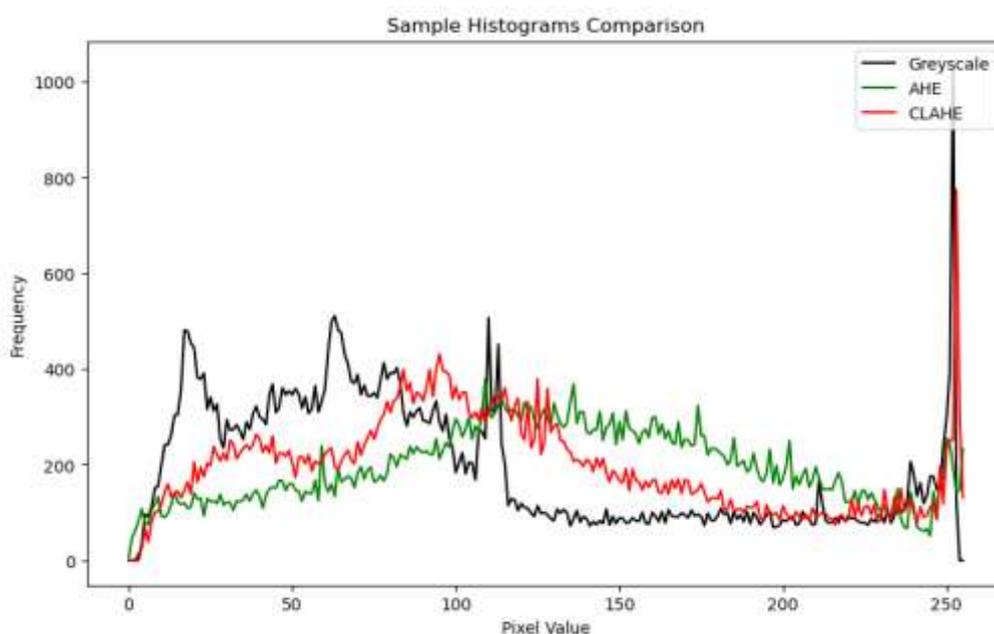
The experimental results presented in Table 1 highlight a performance comparison between two contrast enhancement techniques, Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), within the context of driver drowsiness detection based on facial images. According to the findings, CLAHE achieved a notably lower Mean Squared Error (MSE) of 93.90 compared to AHE's MSE of 103.92, indicating better preservation of image details and reduced distortion. A lower MSE typically indicates better preservation of image details and reduced overall error, suggesting that CLAHE may perform better in terms of retaining critical image features [26]. CLAHE also exhibited a higher Peak Signal-to-Noise Ratio (PSNR) of 28.41, suggesting improved image fidelity and quality compared to AHE's PSNR of 27.97. A higher PSNR signifies better image fidelity and quality in CLAHE-processed images compared to those processed with AHE. This indicates that CLAHE may produce clearer and more visually appealing results [31]. The signal-to-noise ratio (SNR) was substantially better with CLAHE (0.49) compared to AHE (0.04), signifying enhanced image contrast and noise reduction. A higher SNR implies better contrast enhancement and noise reduction in CLAHE-processed images, which is beneficial for improving image clarity and feature visibility [32]. Despite a slightly longer execution time of 33.1 seconds for CLAHE versus 32.9 seconds for AHE, the superior performance of CLAHE in key image quality metrics underscores its effectiveness in enhancing image contrast and maintaining critical image details for driver drowsiness detection systems. This aspect highlights a trade-off between processing speed and image quality enhancement. The slightly longer execution time of CLAHE may be acceptable considering the improvements in image quality achieved. The visual results of implementing both techniques can be observed in Figure 3, providing a visual representation of the contrast enhancement achieved by each algorithm.



**Figure 3. Visual comparison of contrast enhancement techniques for drowsy (a) and non-drowsy (b) conditions.**

Figure 3 presents visual samples illustrating the application of both techniques under Drowsy (a) and Non-Drowsy (b) conditions. The samples reveal that Adaptive Histogram Equalization (AHE) tends to generate images with higher contrast compared to Contrast Limited Adaptive Histogram Equalization (CLAHE). AHE adapts image contrast while preserving local contrast levels; however, it can result in overly high contrast if not properly constrained. In contrast, CLAHE showcases superior performance in detailing both foreground and background elements in the images, yielding more intricate visual representations. By partitioning the image into sub-blocks and applying adaptive histogram equalization to each block, CLAHE effectively maintains local contrast without compromising image details.

These observations highlight that CLAHE achieves a more balanced and controlled contrast enhancement compared to AHE, which may prioritize higher contrast at the risk of losing image detail. This underscores the importance of selecting the appropriate technique based on specific application needs and desired visual outcomes, where CLAHE emerges as a favorable choice for enhancing contrast while preserving image clarity and detail. The results emphasize the significance of considering trade-offs between contrast enhancement and image fidelity when implementing image processing techniques for applications like face-based drowsiness detection.



**Figure 4. Sample histograms comparing histogram equalization (AHE) and clip limit adaptive histogram equalization (CLAHE).**

In the visual histogram comparison, it is evident that the fluctuations observed in CLAHE are closer to those of the greyscale base image compared to AHE. This proximity indicates that CLAHE's contrast enhancement is more aligned with the original image's characteristics, resulting in a more stable and consistent enhancement. Conversely, AHE exhibits higher fluctuations from the base image in its histogram visualization. These pronounced fluctuations suggest that AHE's contrast enhancement is not uniformly applied across the entire image. The regions with higher fluctuations in AHE could potentially lead to over-enhancement, resulting in unnatural or overly contrasted areas within the image.

The contrast-limited approach of CLAHE effectively addresses these issues by adapting the contrast enhancement to suit the local characteristics and limitations of each image area. By constraining the contrast within specified limits (defined by the clip limit parameter), CLAHE achieves a more balanced and tailored enhancement. This adaptive method helps maintain a natural appearance in the enhanced image while avoiding the risk of over-enhancement seen in AHE. Overall, CLAHE provides a more controlled and visually appealing enhancement compared to AHE, as depicted in the histogram visualizations shown in Figure 4.

## 5 Conclusion

Based on the analysis of facial images from the Drowsy Driver Detection (DDD) dataset using Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), CLAHE demonstrates superior performance compared to AHE. The results show that CLAHE achieves lower Mean Squared Error (MSE), higher Peak Signal-to-Noise Ratio (PSNR), and improved Signal-to-Noise Ratio (SNR) scores, indicating better image quality enhancement. This suggests that CLAHE, with its localized contrast limiting approach, effectively enhances facial image quality, which is crucial for accurate face-based drowsiness detection systems. These findings emphasize the importance of choosing CLAHE over AHE for enhancing image contrast while preserving image clarity and quality, contributing significantly to the reliability and accuracy of face-based drowsiness detection systems such as those used in driver safety applications. Future research directions should focus on optimizing CLAHE parameters, integrating with advanced machine learning models, enabling real-time implementation, evaluating on diverse datasets, and incorporating multimodal cues to enhance driver drowsiness detection systems.

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