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Automatic drowsiness detection system to reduce road accident risks

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ABSTRACT

Drowsy driving poses a significant risk to road safety, often equated with impaired driving due to its detrimental effects on cognitive function. This study presents a real-time drowsiness detection system utilizing the YOLOv5 algorithm, enhanced with contrast limited adaptive histogram equalization (CLAHE) technique, to improve detection in low-light conditions. The proposed method analyzes visual cues indicative of drowsiness, such as eye closure and head nodding, leveraging advanced computer vision techniques. A dataset was augmented from 1,056 original images to 2,112 images via CLAHE, resulting in significant improvements in model performance. Experimental results indicate that the model achieves a mean average precision (mAP) of 0.959, with precision and recall values of 0.9529 and 0.9528, respectively, underscoring the effectiveness of CLAHE in enhancing image quality and overall detection performance. The application developed from this model provides timely alerts to drivers, aiming to prevent accidents and promote road safety. This research contributes to the advancement of automated safety systems in vehicles, particularly under challenging lighting conditions.

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1. INTRODUCTION

The detection of drowsiness is a very useful aspect for many people, especially for drivers. This is all the more important given that drivers require an optimal level of awareness and focus when driving a vehicle. Drowsy driving is comparable to driving under the influence of alcohol, as both can significantly impair a driver's cognitive function and performance.

Research by Rahmadiyani and Widyanti [1], it was found that 79% of 217 respondents in Indonesia had driven while drowsy, and 32% of them almost had fatal accidents. These findings emphasise the importance of implementing a drowsiness detection system to prevent accidents caused by inattentive drivers. In this context, drowsiness detection systems can play an important role in preventing unwanted incidents and protecting the safety of drivers and other road users. Data from the Bandung City Police Station also reinforces this, recording 495 traffic accidents, of which 135 were caused by drowsiness, inattention, and fatigue. In addition, between January and September 2018, there were 380 traffic accidents, with 99 cases related to drowsiness, inattention, and fatigue.

A possible solution is to implement a drowsiness detection system using advanced computer vision and machine learning techniques [2]. This system analyzes facial and behavioral cues such as eye closure, head nodding, and changes in facial expressions in real-time to assess driver alertness. It uses object detection to identify key facial areas like the eyes, nose, and mouth, tracking movements that indicate fatigue. When drowsiness is detected, the system can sound an alarm or even initiate an emergency stop. This capability minimizes errors and provides timely alerts, enhancing driver and passenger safety by preventing accidents caused by driver fatigue. With effective detection technology in place, we can warn drivers before drowsiness impairs their concentration, so that preventive measures can be taken quickly and effectively. This not only contributes to individual safety, but also has a positive impact on overall traffic safety.

Park *et al.* [3] developed deep drowsiness detection (DDD) with support vector machine (SVM) networks, achieving 73.06% accuracy in detecting driver drowsiness through RGB videos. Suresh *et al.* [4] developed a drowsiness detection system using convolutional neural network (CNN), achieving 86.05% accuracy on the MRL Eye dataset by classifying eye conditions (open/closed) and issuing alerts when drowsiness is detected. Huu *et al.* [5] Developed a lane and obstacle detection system for self-driving cars using YOLO, achieving 97.91% accuracy for lane detection and 81.90% for obstacle detection. Dima and Ahmed [6] applied YOLOv5 for American Sign Language (ASL) recognition, achieving 95% precision and 98% mAP 0.5. In this study [7], a system utilizing YOLOv5 for face mask detection is proposed, capable of identifying one or more individuals wearing masks in various scenarios. The detection system accurately identifies mask usage in local image elements, video segments, and real-time camera footage. The system achieves a recognition accuracy of 0.945, representing a substantial improvement over other algorithms.

Based on these studies, YOLOv5 was chosen for drowsiness detection in this study due to its proven ability in object recognition. In previous studies, drowsiness detection was achieved with good accuracy. This is due to the use of quality datasets, which consist of images with optimal lighting, high resolution, and good visual clarity. In reality, not all video recordings from car dashboards produce ideal videos. There are some video results that lack lighting, low resolution and even noise and video blur. This can be seen in research [8] with the title "A Survey on Image Data Augmentation for Deep Learning", in the Journal of Big Data highlighting that accuracy can decrease when the quality of the dataset is not optimal, then the study also states that noise, missing data, or unbalanced data sets can cause model performance to be less than optimal and accuracy is reduced. Therefore, this research aims to develop a drowsiness detection system that can monitor the signs of drowsiness in drivers using datasets that are not ideal, such as datasets with minimal or dark lighting. With this, object detection is expected to assist drivers in preventing accidents and facilitate their use in the form of applications that can detect drowsiness in nighttime, dark, or low-light conditions. The hope of this research is that the developed detection system is able to improve road safety by providing early warning to drowsy drivers, especially in low lighting conditions, and can be widely adopted in vehicle-based applications that utilize real-time technology. In addition, it is expected that the contrast limited adaptive histogram equalization (CLAHE) augmentation method can be an effective solution to improve object detection performance in various lighting situations, thus making a significant contribution to the development of a more sophisticated and responsive driving safety system.

2. METHOD

2.1. Contrast limited adaptive histogram equalization

Adaptive histogram equalisation (AHE) is another image preprocessing type that aims to increase the contrast by calculating the histogram for each part of the image separately and redistributing the brightness values. This technique is effective for enhancing local contrast and emphasising edges in different areas of the image [9]. However, AHE has the disadvantage that it tends to magnify noise, especially in relatively homogeneous areas. To overcome this problem, a variant called CLAHE was developed. CLAHE is a variant of AHE that manages excess contrast enhancement by limiting amplification, thus preventing unwanted noise enhancement. CLAHE works on small areas in the image, called tiles, instead of processing the entire image at once [10], [11]. After processing, adjacent tiles are merged using bilinear interpolation to remove the boundaries between areas. This method is very effective in enhancing the contrast of images with uneven lighting or low contrast. In addition, CLAHE can also be applied to colour images to improve the overall contrast [12].

As shown in Figure 1, the CLAHE algorithm can be broadly divided into three main stages: tile division, histogram equalization, and bilinear interpolation, with additional sub-processes such as excess calculation and redistribution to ensure balanced contrast. Firstly, the input image is divided into small parts called tiles. For instance, the input image can be divided into four tiles [13]. On each tile, histogram equalisation is performed using predefined clip boundaries. The histogram equalisation process consists of five main steps: calculating the histogram, determining the excess values, distributing the excess, further redistributing, and applying the scaling and matching using the cumulative distribution function (CDF) [14]. The histogram is generated by dividing the image into multiple bins for each tile, where each bin value that exceeded the clip limit was accumulated and redistributed to the other bins. After that, the CDF is generated based on the histogram. These CDF values are then scaled and mapped according to the pixel values of the input image. Finally, the tiles are reordered using bilinear interpolation, resulting in an image with enhanced contrast.

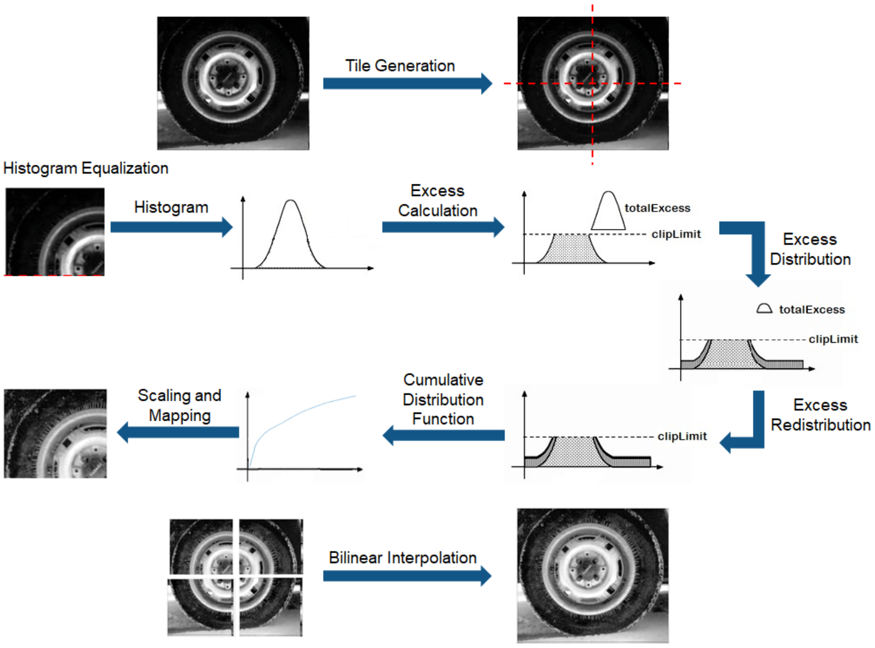


Figure 1. CLAHE algorithm

Based on the comparison between three models to improve datasets with poor or dark lighting, it is found that the CLAHE model from the research of [15] showed good results with a test set MAP of 86.77%, precision of 82%, recall of 87%, F1-score of 84%, and IoU of 63.92%. Research by Yin *et al.* [16] with Light-YOLO was able to achieve mAP of 90.28% at 0.5 IoU, but was still less effective in handling conditions with very minimal lighting. Meanwhile, the research of developed LIDA-YOLO [17] which achieved the highest mAP of 56.65% on the ExDark dataset, but this model has limitations on domain adaptation and mixed lighting. Based on the comparison results, this study decided to use CLAHE to improve the quality of the under-exposed dataset. CLAHE is an image processing technique that adaptively enhances contrast in each part of the image, making it more suitable for clarifying edge definition and avoiding excessive noise enhancement, especially in uniform images. The advantages of this method are very useful in enhancing image contrast in low light conditions. In addition, this research uses YOLO as the basis for object detection in an application designed to provide warning alarms to drowsy drivers, so as to detect signs of drowsiness in real-time even at night or in low-light conditions by utilizing CLAHE to improve the quality of less than ideal datasets.

2.2. Integration of clahe into YOLOv5 model

This research integrates YOLOv5 for real-time object detection, specifically for detecting signs of drowsiness in drivers and CLAHE is applied to improve image quality, especially in low or uneven lighting conditions. The CLAHE technique serves to improve the local contrast in under-exposed images, so that YOLOv5 can better detect objects in difficult lighting conditions, such as at night or in environments with limited light [18]. A representation of how the integration process is clearly shown in Figure 2.

This dataset of 1,056 images from Kaggle identifies sleepiness based on visual cues such as slow eye closure and head tilt. Manual annotation was performed to mark the eyes and head with bounding boxes, categorising them as ‘sleepy’ or ‘awake’, which improved the model's ability to detect sleepiness patterns, even in low-light or unclear conditions. The labelled dataset was divided into 80% for training, 10% for validation, and 10% for testing, ensuring a balanced approach to model training, tuning, and evaluation. After performing data division, the next step is to perform augmentation on the dataset. The dataset used in this research initially consists of a total of 1,056 original data. After the augmentation process using the CLAHE method, the amount of data doubled to 2,112 data. This augmentation not only improves the image quality under poor lighting conditions, but also enriches the variety of data available, thus improving the model's ability to recognise drowsiness patterns.

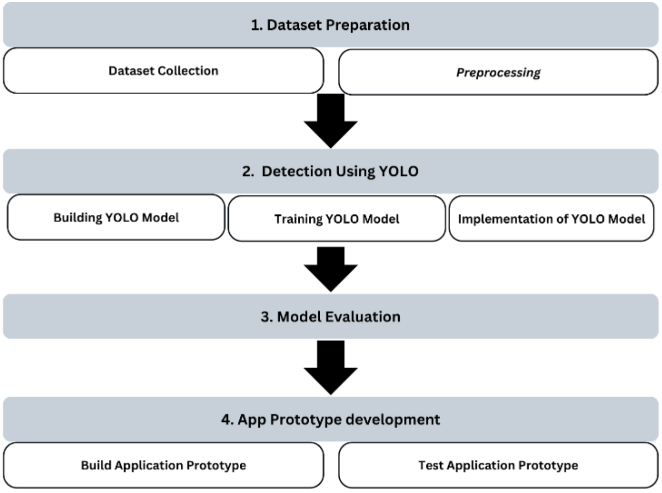


Figure 2. Method

The application of CLAHE to YOLO aims to improve image quality on dark or poorly lit datasets. The process seen in Figure 3 starts by dividing the image into small tiles and calculating a local intensity histogram for each tile. By applying CLAHE, the image's histogram is stretched, enhancing areas that may have limited intensity ranges (as seen in underexposed conditions), resulting in a clearer and more balanced image [19]. Importantly, the technique also prevents over-amplification by setting a clipping limit, which ensures that noise is minimized, and only relevant details are emphasized [20]. The CLAHE configuration involves setting the clip boundary value at 2.0 and dividing the image into 8×8 tiles to calculate the local histogram [21], [22]. By increasing the contrast, the performance of the model in training and testing can be improved, so it is expected that the drowsiness detection model can be more responsive in identifying signs of drowsiness in drivers.

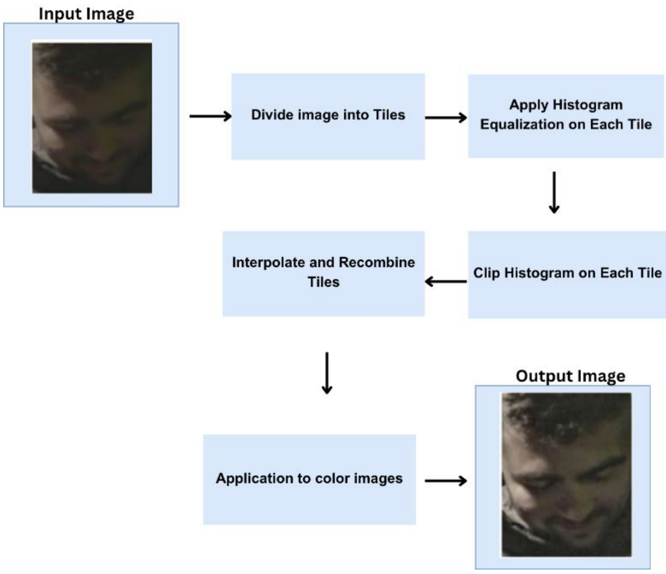


Figure 3. Application of CLAHE

Next, hyperparameter tuning was conducted to optimize the model's performance, these parameter settings are described in detail in Table 1. Parameters such as batch size, epochs, and optimizers were adjusted based on validation results. Both SGD and Adam optimizers were tested along with batch sizes of 32 and 64, to refine the model's performance in detecting drowsiness. This tuning was critical to prevent overfitting or underfitting and ensure accurate and reliable predictions [23], [24].

Table 1. Tuning parameter configuration

No	Parameter	Size
1	Optimizer	SGD, Adam
2	Epoch	50, 100, 200
3	Batch	32, 64

Before conducting the model training process, the model architecture that will be used is required. This research uses the YOLOv5 architecture, which consists of several convolutional layers that progressively detect features related to drowsiness. The architecture was pre-configured, allowing for automatic setup based on the model's specified parameters. Training involved exposing the model to labeled data, teaching it to recognize drowsiness-related behaviors [25]. As a result, the trained model was expected to perform well in detecting drowsiness with high accuracy.

In this research, training a drowsiness detection model involves using YOLOv5 in a machine learning or deep learning algorithm to teach the model to recognise drowsiness patterns from a labelled dataset, as in the image above. The model is trained to identify signs such as sleepy eyes or head movements, with parameters adjusted to achieve high accuracy. After training, the model is evaluated using a separate test dataset to assess its ability to detect signs of sleepiness that have not been seen before. Metrics such as mean average precision (mAP), accuracy, precision, recall, and F1-score were used, along with false positive and false negative error analysis. High mAP and low misclassification indicate the readiness of the model for real-world use, while low mAP indicates the need for further improvement.

After completing the model training, the next step is to start the application development. As shown in Figure 4, the application development process begins with prototyping using Figma. Figma was chosen because of its ability to facilitate collaboration and visual prototyping, so that it can speed up the application design process. After the prototype is complete, the next step is to develop the model, which is converting the model into the TensorFlow Lite (TFLite) format. The TFLite format is used because it is lighter and optimized for mobile devices, making it suitable to be applied to Android applications. Next, the converted model is transferred to Android Studio to start the develop application process, which is the development of the application based on the prototype that has been made. After the application has been developed, the last step is deploy, which is the process of implementing and testing the application on the target device to ensure the application works properly.

Figure 4. Application prototype development

3. RESULTS AND DISCUSSION

3.1. Augmentation result

After labeling the collected dataset, the next step is to augment the dark or low-light images to brighter images using CLAHE. CLAHE successfully enhances the quality of dark images, making them brighter and improving contrast by adjusting the distribution of light intensity pixels. This augmentation enriches the dataset with better variations, improving the model's performance during training and testing.

Figure 5 shows the results of augmenting the dataset using CLAHE, which successfully brightened the images and improved contrast. By adjusting the light intensity pixel distribution, CLAHE enhances the dataset's quality, providing better variations. This improvement enriches the dataset, ultimately enhancing the model's performance during training and testing.

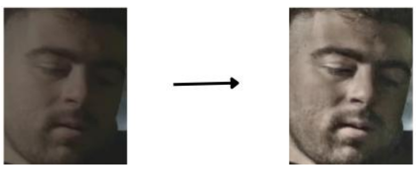


Figure 5. Results of augmentation using CLAHE

3.2. Parameter tuning results

It can be seen in Table 2, that 12 experiments have been conducted with different parameter sizes for each experiment and it can be seen that in experiment 10 with SGD optimiser parameters, epoch size 100, batch size 64, has higher accuracy results with an mAP50 value of 0.959, compared to the other 11 experiments which show mAP50 values varying from 0.60 to 0.94. In general, it can be seen that the combination of SGD optimiser with epoch 100 and batch 64 gives the best performance in terms of detection accuracy on this dataset. From these results, it can be concluded that the optimal combination of parameters to improve model performance on this dataset is at trial 10, with these results this study uses the SGD optimiser with epoch 100 and batch 64 at trial 10.

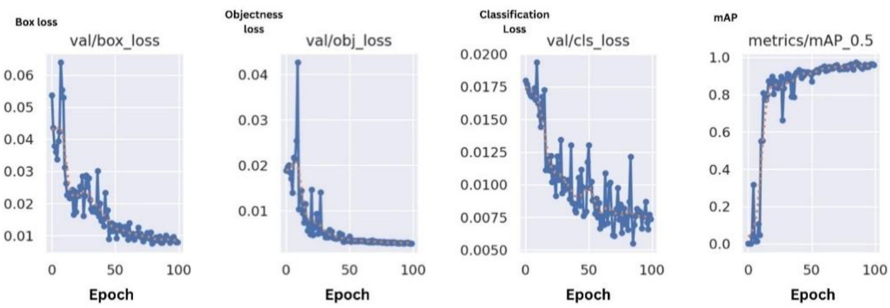
Table 2. Parameter tuning results

Experiment	Optimizer	Epoch	Batch	MaP50
1	Adam	50	32	0.80
2	Adam	50	64	0.77
3	Adam	100	32	0.84
4	Adam	100	64	0.67
5	Adam	200	32	0.90
6	Adam	200	64	0.87
7	SGD	50	32	0.70
8	SGD	50	64	0.60
9	SGD	100	32	0.87
10	SGD	100	64	0.959
11	SGD	200	32	0.94
12	SGD	200	64	0.90

3.3. Training and accuracy results

After undergoing the stages of dataset collection, labeling, data augmentation, and parameter tuning, the next step is to proceed with model training. At this stage, the drowsiness detection model is trained using the prepared dataset. The purpose of training the model is to enable it to understand and recognize patterns within the dataset, thus providing accurate predictions when presented with new data.

Based on the training results shown in Figures 6(a) to (d) (the x-axis represents the number of epochs, and the y-axis represents the loss or mAP value), the model shows stable and consistent performance over 100 epochs. The graph shows a significant decrease in the val/box_loss, val/obj_loss, and val/cls_loss values as the number of epochs increases. This decrease indicates that the model is gradually able to learn important features from the training data, thereby reducing the errors in predicting the bounding box, object, and classification.



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

Figure 6. Training results for 100 epochs: (a) box loss, (b) objectness loss, (c) classification loss, and (d) mean average precision (mAP@0.5)

The training process was completed after 100 epochs with a result of obj_loss 0.00567 and cls_loss 0.008525, demonstrating the model's ability to make accurate bounding box predictions, distinguish objects from the background, and classify objects well. The image size stabilized at 640 pixels during training. The metrics/mAP_0.5 graph shows consistent improvement, with an average mAP_0.5 precision of 0.959, indicating precise and accurate object detection. The model reached optimal performance after 100 epochs.

Table 3 shows that using CLAHE augmentation on the dataset gives better results compared to the original dataset without augmentation in detecting drowsiness. In the original data without augmentation, the model achieved Weighted avg values of 0.908 in precision, 0.9056 in recall, and 0.9056 in F1-score. In contrast, with CLAHE augmentation, the Weighted avg results increased to 0.9529 in precision, 0.9528 in recall, and 0.9528 in F1-score. These results confirm that CLAHE augmentation significantly improves the model performance, especially in terms of precision, recall, and F1-score, by improving the quality of the images so that models can detect drowsiness more precisely.

Table 3. Metrics of the drowsiness detection model

Data	Metric	Precision	Recall	F1-score
Original	Awake	0.9411	0.8727	0.9056
	Drowsy	0.8727	0.9411	0.9056
	Weighted avg	0.9082	0.9056	0.9056
CLAHE	Awake	0.9464	0.9636	0.9549
	Drowsy	0.9600	0.9411	0.9504
	Weighted avg	0.9529	0.9528	0.9528

3.4. Application results

The drowsiness detection application developed in this research uses the YOLOv5 model that has been integrated into the TFLite format to run efficiently on Android devices. The application is designed to access the user's camera directly and process the video in real-time to detect signs of drowsiness in the driver. These detections are displayed as a bounding box surrounding the detected area of the user's face, along with a confidence score indicating the accuracy of the detection. If the app detects signs of drowsiness, such as closed eyes or head tilt, it will automatically issue an alarm sound to wake up the driver.

The app was tested on Android devices with a minimum specification of 2.0 GHz Octa-core processor and 4 GB RAM to ensure optimal performance. The test results were carried out in two different lighting conditions, namely light (daytime) and dark (nighttime). This test aims to evaluate the application's ability to detect drowsiness in real-time and provide important insights for further development.

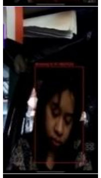
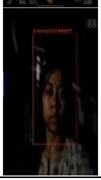
Table 4 presents the results of drowsiness detection in bright and low-light conditions, including the detection success rate and confidence value obtained. When tested in real-time, the developed drowsiness detection application successfully detects the driver's face in dark conditions, as well as being able to detect early signs of drowsiness, such as when the eyes start to half close or almost close. This demonstrates the ability of the application to continue functioning optimally in low-light environments, such as when driving at night. The CLAHE method applied in this study plays an important role in improving image quality by balancing the contrast between light and dark areas, so that details of the driver's face, such as the eyes and mouth, remain clearly visible. Furthermore, the app is able to detect the driver's face well, even in low-light conditions. Although detection is possible in complete darkness, the presence of reflected light from street lighting or other vehicle lights helps to enhance the clarity of facial features. Even though the reflections are fast-moving and dynamic due to the movement of the car, the detection performance remains stable and accurate.

3.5. Discussion

This research aims to improve driver drowsiness detection by applying CLAHE for image quality enhancement in low light conditions and YOLOv5 for object detection. While previous studies have examined fatigue detection using deep learning, they have not specifically addressed challenges in low-light conditions. This research therefore fills the gap by improving the detection accuracy across different lighting conditions, which is a key factor in real-world applications. The results show that the application of CLAHE significantly improves detection accuracy in low-light conditions, with a 7% improvement in mAP and a stable confidence score between 85% to 93%.

Future research needs to expand the dataset and consider additional data such as body posture or physiological signals to improve the robustness of the system. Optimising the processing speed of CLAHE and the inference model can also improve real-world applications. Overall, the integration of CLAHE with YOLOv5 was shown to improve drowsiness detection, especially in low-light conditions, without compromising real-time performance. With further development, the system has strong potential to improve driver safety in a variety of driving conditions.

Table 4. App evaluation results

Conditions	Photo	Description	Confidence score (%)	Inference speed (ms)	Memory usage (MB)	Total latency (ms)
Light		Detected	92	55	135	110
Light		Detected	91	53	134	108
Light		Not detected	49	52	133	100
Dark		Detected	93	46	122	96
Dark		Detected	91	43	115	93
Dark		Not detected	67	46	118	92

4. CONCLUSION

In conclusion, drowsiness detection is essential to ensure road safety, especially for drivers who need to maintain a high level of awareness. To address this issue, a drowsiness detection system using advanced techniques such as YOLOv5 and CLAHE is implemented. The proposed system enhances drowsiness detection in low light conditions by using CLAHE to improve image quality. The experimental results show that integrating CLAHE with YOLOv5 significantly improves the detection accuracy, achieving an mAP of 0.959. This approach not only supports effective drowsiness detection, but also emphasises the potential for wide applicability in vehicle-based safety systems, ultimately contributing to the reduction of road drowsiness-related accidents.

For future developments, it is recommended to design the application for compatibility with additional platforms such as iOS for Apple devices and Windows Phone to expand the user base. Moreover, creating a drowsiness detection model for integration with dashcam-connected cameras in vehicles could facilitate real-time monitoring and alert drowsy drivers, ultimately helping to prevent road accident.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

The authors used publicly available data from an open-source dataset (Kaggle) that contains facial images of drowsy individuals. The dataset was published with informed consent obtained by the original authors. No new human data were collected in this study.

ETHICAL APPROVAL

This study used publicly available facial image data from an open-source dataset. No new data were collected from human participants by the authors, and no personal identifiable information was involved. Therefore, ethical approval was not required for this research.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the 'Frame Level Driver Drowsiness Detection (FL3D)' dataset at Kaggle: https://www.kaggle.com/datasets/matjazmuc/frame-level-driver-drowsiness-detection-fl3d. The dataset is publicly accessible and was used in accordance with its open data license.

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