

RESEARCH ARTICLE

LoLTV: A Low Light Two-Wheeler Violation Dataset With Anomaly Detection Technique

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ABSTRACT Detecting traffic violations is essential for improving road safety, ensuring rule compliance, and maintaining smooth traffic flow. It also aids in holding violators accountable and supports data-driven decision-making for infrastructure enhancements. To address these challenges, the integration of AI-based methods for automated violation detection is increasingly vital, reducing the need for manual oversight. Low-light conditions pose additional difficulties, as violations become harder to detect. In this study, we created a novel dataset containing 1032 images with 1475 two-wheeler violations under low-light conditions. We propose a real-time deep learning system using YOLO-v8 for two-wheeler violation detection. Our system addresses the challenge of low-light conditions by incorporating a real-time low-light video enhancement module. Through comprehensive evaluations, our system has achieved an average precision of 98.2%, recall of 97.5%, and an accuracy of 97.05% when tested on our custom dataset. Notably, it successfully detected 172 out of 188 violations in the test dataset and exhibited 60% faster processing compared to other state-of-the-art methods. This suggests that our system not only outperforms existing methods on public datasets but also excels in terms of performance and accuracy when applied to the specifically constructed low-light traffic dataset. Furthermore, our system's practical scalability is evident through its integration with multiple devices and CCTV systems.

INDEX TERMS Deep learning, low light enhancement, road safety, two wheeler violation detection.

I. INTRODUCTION

A. MOTIVATION

Traffic rule implementation and detection of violations are necessary steps for reducing accidents and injuries, maintaining orderly traffic flow, discouraging reckless driving, and safeguarding the travellers [1]. According to the Ministry of Road Transport and Highways (MoRTH) data, an average of 1,130 accidents resulting in 422 deaths are reported daily, indicating a significant impact on road safety [2]. In 2020, two-wheelers were the most common type of vehicle involved in road accidents, accounting for 36.7% of all accidents. About 40% of these accidents involve riders

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not wearing helmets [3]. Additionally, violations like triple riding, wheelies, and stoppies increase the vulnerability of riders on the roads [4] by disrupting the balance and stability of the vehicle, increasing the risk of accidents [5]. Efficiently and accurately detecting these violations allows authorities to enforce penalties for such violations much more rigorously, thereby reducing the detrimental effect of Indian road culture [6]. It creates an unsafe environment, encourages others to break the rules, shows a lack of respect for the law, increases tensions, and deteriorates road discipline.

Intelligent Transportation Systems (ITS) play a crucial role in detecting, classifying, and addressing traffic violations effectively [7], [8]. ITS enables accurate and real-time monitoring of traffic conditions, ensuring prompt identification and response to violations and anomaly

detection [9]. It leverages surveillance cameras and data analytics to boost anomaly detection accuracy and lower false alarms. Automated enforcement and resource allocation enhance violation detection and deter potential violators. ITS also generates valuable data for insights into prevalent violations and informs evidence-based decision-making for road safety improvements [10]. Ultimately, ITS promotes compliance with traffic rules, creating a safer and more efficient transportation system [11], [12]. Moreover, low lighting conditions can affect the violation detection process as violators cannot be detected due to low light. Hence, enhancement of low light is an important preprocessing step [13]. This has motivated us to develop a two-wheeler traffic rule violation detection system adept at detecting violations by enhancing low-light, thereby helping the concerned authorities monitor and take necessary actions against the violators.

In this paper, our primary contributions include the development of a novel real-time traffic rule violation detection pipeline for low-light conditions. To the best of our knowledge, we are the first to apply the most accurate and recent version of YOLO (You Look Only Once) for two-wheeler traffic rule violation detection. Additionally, we have constructed a low-light two-wheeler traffic anomaly dataset. Furthermore, we propose a unique system that enhances the practical applicability of our solution by seamlessly integrating it with a network of multiple devices and CCTVs. Lastly, we have implemented an automated anomaly storage and alerting system through mail. All of these contributions are discussed in detail later on in the contribution section.

B. RELATED WORKS

Prior studies, such as Doungmala and Klubsuwan [14] in 2016, proposed a helmet detection technique combining two methods to improve detection rates. First, they employed a Haar-like feature-based face detection approach to distinguish individuals wearing full helmets from those without helmets. Secondly, they used the circle Hough transform to differentiate individuals without helmets from those wearing half helmets. In the same year, a technique was introduced by Chiverton [15], leveraging the geometric shape of helmets and variations in lighting across different parts of the helmet. This method used a circular arc detection approach based on the Hough transform, achieving high accuracy in helmet detection. However, despite showing promise, both approaches require further validation due to the limited number of test images used for evaluation, making them less reliable for application in real-world scenarios.

Later approaches, like Vishnu et al. [16] in 2017, employed adaptive background subtraction on video frames to identify moving objects, mainly motorcyclists. Then, they identified individuals who were not wearing helmets by using Convolutional Neural Networks (CNNs) to separate motorcyclists from the detected moving objects. In 2018, Raj et al. [17]

developed a system employing image processing techniques and CNNs to identify helmet violations. The system consisted of three main components: motorcycle detection, helmet vs. no-helmet classification, and motorcycle license plate recognition. While these approaches effectively detected helmet violations, they came with computational complexity and restricted themselves solely to helmet detection, making them unsuitable for real-time applications.

In 2020, Soni and Singh [18] introduced a computer vision system based on Tensorflow and Keras to detect whether a biker was wearing a helmet in real-time. The system vigilantly monitored scenes and identified helmet violations; however, it operated exclusively on images and addressed only one type of violation. To satisfy real-time requirements, recent approaches have become considerably faster, resulting from the advancements in the YOLO algorithm. In 2021, Mallela et al. [19] developed a deep learning framework based on a CNN and YOLO algorithm for detecting triple riding and speed violations on two-wheelers. While the framework leveraged CNNs to quickly identify these violations, it focused only on a single type of violation, and its accuracy was notably low.

Most recent approaches excel in real-time detection as well as accuracy. Charran and Dubey [20] in 2022 proposed an automated system to detect and address various two-wheeler violations, including not wearing a helmet, using a phone while riding, triple riding, wheeling, and illegal parking. They suggested a custom-trained YOLO-v4 + DeepSORT algorithm for violation detection and tracking, along with Tesseract for number plate detection and extraction. Similarly, in the same year, Lavingia et al. [21] designed an automated system for monitoring the violation of traffic rules regarding the number of people sitting on a two-wheeler. The system utilized the YOLO-v3 model for object recognition and a depth estimation algorithm to determine if the distance between individuals on the two-wheeler exceeded a minimum threshold. However, both of the methods accuracy drops significantly under low-light conditions.

Motivated by these drawbacks, we have proposed an architecture that would detect four different types of two-wheeler violations with great accuracy, simultaneously being able to do so in real-time as well as in low-light conditions, making it fit for real-world scenarios.

C. CONTRIBUTION AND ORGANIZATION OF PAPER

Two-wheeler violation detection is crucial for road safety, accident prevention, rule adherence, traffic flow, and legal accountability. Hence, we have developed a real-time two-wheeler violation detection system that would also ensure road safety and allow proper action to be taken against the violators. The following summarizes this work's key contributions.

- 1) We have built a comprehensive dataset of two-wheeler rule violations, comprising over 1000 images and 1400 violations along with their corresponding labels. The dataset consists of four violation classes: not

wearing a helmet, triple riding, wheeling, and stoppie. Each image in the dataset is labelled to indicate the specific type of violation present. The dataset is specifically tailored for enhancing the system's performance in low-light conditions. Thus, most of the captured images are either taken at night or darkened before training the model. The dataset is much more complex and tests the capabilities of the system to a full extent, hence proving to be a valuable resource for training and testing.

- 2) In addition to the dataset, we have developed a real-time system for detecting four types of two-wheeler traffic rule violations. One of the key contributions of the paper is demonstrating the use of the most accurate version of YOLO, YOLO-v8 extra large, unprecedented for traffic anomaly detection in broad daylight.
- 3) Our system includes a low-light enhancement feature, which serves as a preprocessing step to improve video quality in challenging lighting conditions. This enhancement enables accurate detection, particularly in low-light environments where violations might be difficult to spot.
- 4) We have proposed an efficient system for our anomaly detection pipeline, achieved by seamlessly integrating it with a range of interconnected devices. These devices work in coordination, actively participating in the anomaly detection process. Our system is designed for accessibility through diverse devices, enabling users to remotely monitor and receive alerts regarding violations. This collaborative network of devices ensures the seamless interlinking of all components involved in the anomaly detection process.
- 5) We've expanded the advantages of automated anomaly detection to enhance the efficiency of CCTV storage devices. This is achieved through automated recording, specifically during anomaly periods. Furthermore, our system features an automated mechanism for promptly alerting the relevant authorities whenever a violation is detected by capturing images of those violators. These images are then sent via email to the concerning authorities responsible for enforcing traffic regulations. This feature ensures prompt notification and enables authorities to take appropriate action against violators.

The proposed approach's methodology is described in Section II, which includes a preprocessing step for low-light enhancement and YOLO-v8 architecture, where we have trained on our proposed dataset for two-wheeler rule violations. Section III displays the results and analyses drawn from the implemented system. Finally, Section IV concludes the research and outlines potential future work.

II. METHODOLOGY

A. OVERVIEW

YOLO is a leading object detection algorithm in computer vision [22]. It revolutionized real-time object detection by

dividing an image into a grid and directly predicting bounding boxes and class probabilities for objects within each grid cell. With its efficient single-pass architecture, YOLO achieves high detection speeds, making it suitable for applications like autonomous driving and surveillance [23], [24]. Its success lies in its simplicity, accuracy, and ability to handle complex scenes with multiple objects. In this paper, we have used the YOLO-v8 architecture for the detection of two-wheeler traffic rule violations. The most recent state-of-the-art YOLO model, known as YOLO-v8, may be utilised for tasks including object identification, image categorization, and instance segmentation. This version of YOLO outperforms all other preexisting versions in terms of accuracy.

B. NETWORK ARCHITECTURE

In this section, we'll outline our automated traffic violation detection system, consisting of four key components: the development of a custom low-light dataset, enhancing low-light videos, detecting anomalies within the improved footage, and promptly notifying relevant authorities about any identified anomalies.

- 1) Gather low-light footage in real time from sources like CCTVs, mobile cameras, dashcams, or any device with a camera, extract the frames, and process them one by one.
- 2) Real-time low-light video enhancement is implemented to improve the visibility and quality of low-light and night footage, enabling more effective anomaly detection. By enhancing the images in real-time, the system enhances details and reduces noise, enabling better detection and identification of anomalies or irregularities in challenging lighting conditions.
- 3) Automated detection of video frames in real-time for instances of individuals not wearing helmets, more than 2 riders, or dangerous maneuvers like wheelies and stoppies, thereby enabling timely intervention and enforcement actions to promote road safety and adherence to traffic regulations.
- 4) Upon anomaly detection, the system stores the anomaly frame and 'n' seconds of subsequent frames in a database. It then automatically generates an email containing the screenshot, timestamp, and relevant details, forwarding it to the appropriate authority. This ensures secure evidence storage and prompt notification for action.

The system for two-wheeler traffic violation detection in low lighting conditions and automatic mail generation is summarized in Fig. 1. A further explanation of the system is provided below.

1) PRE-PROCESSING

Low-light enhancement is an important pre-processing step for detecting two-wheeler rule violations because many traffic violations occur in low-light conditions, such as during the night or in poorly lit areas [25]. Low-light enhancement enhances footage clarity, improving rule violation analysis,

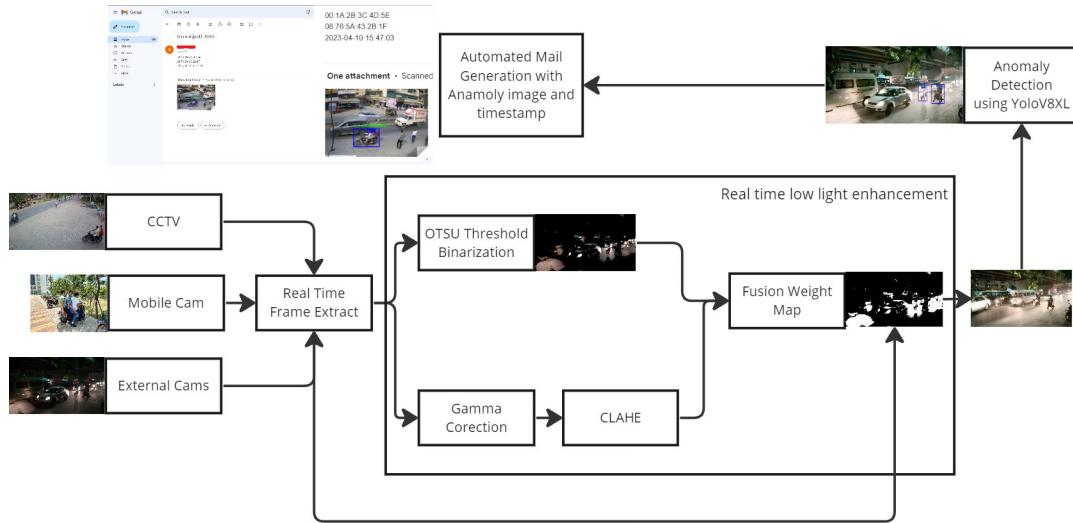


FIGURE 1. Block diagram of two-wheeler violation detection at low lighting conditions with automated mail generation.

reducing false counts, and ensuring precise enforcement of two-wheeler traffic regulations. In this paper, we have used OTSU’s thresholding [26], a popular method for determining the optimal threshold for isolating low-light areas within each frame of video. This allows the system to put more focus on the enhancement of low-light regions, improving their visibility and overall image quality. Let I_{xy}^{RGB} be the value of a pixel in a 24-bit RGB colour low-light image as input. First, the values of the pixel of the lightness image I_{xy} of an input image I^{RGB} are determined as follows:

$$I_{xy} = \frac{I_{xy}^R + I_{xy}^G + I_{xy}^B}{3} \quad (1)$$

This equation represents the calculation of the lightness value I_{xy} at each pixel location (x, y) by taking the average of the corresponding red, green, and blue component values I_{xy}^R , I_{xy}^G , and I_{xy}^B . Thresholding enables the method to be applied to backlit images and videos as well, along with low-light enhancement. The initial step of the process involves generating a threshold from the input image in the first branch. This threshold determines the boundary between the foreground and background regions. By applying this threshold, a binary mask is created, which effectively highlights the areas of interest in the input image.

$$I'_{xy} = \begin{cases} 1, & \text{if } I_{xy} > \phi \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

I'_{xy} represents the intensity of the pixel at position (x, y) in the mask image. ϕ represents the threshold value. The input image is parallelly enhanced in the second branch using gamma correction followed by CLAHE (Contrast Limited Adaptive Histogram Equalization). The CLAHE algorithm consists of three steps: tile generation, histogram equalization, and bilinear interpolation. The input image is broken down into tiles, and histogram equalization is

applied to each tile using a clip limit. Excess pixels are redistributed, and a cumulative distribution function (CDF) is calculated. The CDF values are then scaled and mapped to the input image pixels. Finally, the tiles are stitched together using bilinear interpolation to produce an output image with improved contrast. To enhance the image’s visibility, the gamma conversion is applied to the original image, resulting in the light intensity conversion image, denoted as I_{xy}^γ . The equation is given by:

$$I_{xy}^\gamma = 255 \cdot \left(\frac{I_{xy}}{255} \right)^\gamma \quad (3)$$

For the purpose of calculating the output light-enhanced image’s (O) pixel values, the α -blending of the two lightness conversion images I_{xy}^γ and I_{xy}^{HE} can be expressed as follows:

$$O_{xy} = (1 - \alpha) \cdot I_{ij}^\gamma + \alpha \cdot I_{xy}^{HE} \quad (4)$$

The values of $\alpha \in [0, 1]$. To prevent degradation of the image quality, the input image and the improved image are combined using a weight map. This fusion process yields the final output image, which maintains the image quality while incorporating enhancements. The weighted sum of the pixel value at (x, y) of the input image I and of the low-light improved image O as the pixel value of the resultant improved image \tilde{O} as follows:

$$\tilde{O}_{xy} = \tilde{W}_{xy} \cdot O_{xy} + (1 - \tilde{W}_{xy}) \cdot I_{xy} \quad (5)$$

where \tilde{W}_{xy} represents the pixel value of the smoothed weight map. After determining the ultimate result, the light-enhanced image \tilde{O} , the pixel value at position (i, j) of the output color image \tilde{O}_{xy}^{RGB} is calculated using the subsequent equation:

$$\tilde{O}_{xy}^{RGB} = I_{xy}^{RGB} \cdot \frac{\tilde{O}_{xy}}{I_{xy}} \quad (6)$$

Using this technique, we could enhance the low-light and backlight-affected videos and avoid the problem of false counting while detecting two-wheeler rule violations.

2) VIOLATION DETECTION MODULE

In this paper, two-wheeler rule violations were detected using YOLO-v8. The key principle of YOLO-v8 is that it performs object detection in a single pass of the neural network, making it highly efficient for real-time applications [27]. It generates bounding boxes and class probabilities for items inside each grid cell after dividing the input image into a grid. This approach allows for simultaneous detection of multiple objects in the image. YOLO-v8 incorporates a deep neural network architecture, typically based on the DarkNet framework. It utilizes convolutional layers, downsampling, and upsampling operations to extract and process features at different scales, enabling it to capture both small and large objects effectively. The YOLO-v8 architecture consists of three main components: the backbone, neck, and head [28]. The backbone extracts high-level features from the input image, enabling the model to understand the content and context. It typically comprises a deep convolutional neural network (CNN), such as DarkNet-53 or DarkNet-19. The backbone network consists of multiple stacked convolutional layers, pooling layers, and non-linear activation functions [29]. The YOLO-v8 model serves the purpose of capturing spatial information at various scales and abstraction levels, enhancing object detection. It fuses features from different scales, typically using techniques like feature concatenation or pyramid construction. The head generates object predictions by transforming these features into bounding box coordinates, class probabilities, and relevant attributes. It includes convolutional and detection-specific layers for spatial transformation and dimensionality reduction. The output comprises bounding box predictions, class labels, and confidence scores. This multi-stage architecture enables efficient real-time object detection. We trained YOLO-v8 with our dataset, successfully detecting violations like no helmet, triple riding, wheelies, and stoppies in video footage.

3) AUTOMATIC ANOMALY STORAGE AND MAIL ALERT

We have integrated an automated email alert module into our system. When an anomaly is detected, the system stores the frame along with all the frames for the next 'n' seconds, capturing the anomaly, where n is determined through experimentation. Also, the timestamp for each frame is recorded. This approach has several benefits. It eliminates the need for continuous recording, saving memory consumed by purposeless footage. The CCTV cameras in the network are interconnected via a Digital Video Recorder (DVR) system. The system maintains a table for each CCTV camera, containing the MAC address of each of the neighbouring cameras to this camera. When an anomaly is detected, the central server retrieves the Media Access Control (MAC) address of K-neighbouring cameras from the table, K again

being determined by experimentation. The MAC addresses are used to record footage from the primary as well as neighbouring CCTV cameras, which helps in tracking of violator. The recorded footage is sent to the concerned authorities along with the timestamp of the anomaly and the MAC address of all the CCTV cameras involved via the mail alert system, which runs on a Simple Mail Transfer Protocol (SMTP) server. This comprehensive approach ensures that the necessary footage is captured selectively, saving storage space and facilitating efficient tracking and reporting of anomalies.

III. EXPERIMENT

A. DATASET

In this paper, we have proposed our own two-wheeler traffic rule violation dataset. To the best of our knowledge, it is the first two-wheeler violation dataset on low-light. The dataset consists of a total of 1032 low-light images of two-wheeler traffic rule violations, which include no helmet, triple riding, wheeling, and stoppie. The low-light rule violation dataset was prepared from live CCTV footage and manually captured images and videos from numerous cameras and CCTVs in low-light conditions at IIT Patna, as well as from online sources. A major contribution of this paper that enhances the dataset's effectiveness is the collection of images for the dataset with specialized consent from the Mumbai Police, granting access to confidential CCTV footage with a high frequency of traffic rule violations. This access allowed the model to be trained and tested on the most relevant data, increasing its compatibility with real-life scenarios. The distribution of the aforementioned two-wheeler rule violation dataset is shown in Table 1.

TABLE 1. Two wheeler violation distribution.

Classes	No. of images exhibiting violations	No of annotations of violation across all images
No Helmet	805	1320
Triple Riding	220	220
Wheeling	235	237
Stoppie	215	218

From the table we can observe that there are 4 classes of rule violation. Each class has a certain number of images and their respective annotations. From Fig. 2, it can be observed that there are multiple two-wheeler violation annotations in a single image. For example, in Fig. 'a', it can be observed that there is a single violation made by a single violator. Similarly, in Fig. 'c', we can see that in a single image there are cases of both triple riding and no helmet, and in Fig. 'd' we can see the cases of wheelie and no helmet in a single picture, which falls under the category of multiple violations and multiple violators. Also, there are cases of single violations and multiple violations as shown in the images 'b', 'e', and 'f'.



FIGURE 2. Sample annotation from low light two wheeler violation dataset.

B. EVALUATION TASKS

We evaluate the system across the following tasks:

- 1) Evaluate our pipeline on real-world low-light videos initially to ensure proper low-light enhancement is taking place. This is an important preprocessing step since the present models fail to detect violations in low-lighting conditions.
- 2) To demonstrate real-time detection of two-wheeler traffic rule violations on live footage captured on CCTV, mobile cameras, or any other streaming devices with the highest accuracy.
- 3) Compare our pipeline with other YOLO architectures on our proposed dataset in terms of true positive, false positive, and precision.
- 4) Compare our pipeline with other benchmark datasets on two-wheeler rule violations in terms of precision, recall, and time per detection.
- 5) To evaluate its capability and robustness, the entire pipeline is tested on 10 video feeds. These feeds encompass various scenarios, including both light and dense traffic conditions in low-lighting environments. By subjecting the system to these diverse testing scenarios, its performance can be thoroughly assessed.

C. IMPLEMENTATION DETAILS

The experimental results were obtained using a laptop equipped with 16GB of RAM and a Ryzen 5 4600H processor running at 3.2GHz. The laptop also had an NVIDIA GeForce GTX 1650 graphics card with 4GB of dedicated memory. The operating system was 64-bit Windows 10, and the storage consisted of a 512GB SSD. The experimental implementation utilized Python 3.10 as the programming language, incorporating various libraries such as Ultralytics, OpenCV, PyTorch, NumPy, and Pillow. The YOLO model used for the experiments was the extra-large version, comprising approximately 68 million trainable parameters. For the YOLO-V8x model, the default settings were utilized except for a batch size of 5. The confidence threshold for object prediction was set to 0.5. Real-time detection was achieved at an average rate of 20 frames per second (fps).

To optimize performance, every alternate frame was considered for detection, resulting in a net fps of approximately 40. The dataset used for training and testing the model was collected from various sources. It included footage from CP-PLUS CP/IP CCTV cameras placed at different heights in different parts of the city. Additionally, footage from mobile cameras such as the S21 FE and iPhone 14, as well as a 720p laptop webcam, was included in the dataset. This diverse collection of sources provided a comprehensive dataset for evaluating the model's performance.

IV. RESULTS AND DISCUSSION

The results section is divided into five parts:

- 1) **Section A** examines the effect of low-light enhancement on traffic videos, serving as a crucial preprocessing step.
- 2) **Section B** demonstrates the effectiveness of our methods in detecting two-wheeler violations even under challenging low-light conditions, surpassing the capabilities of other existing methods. Additionally, our approach successfully identifies violations that were previously undetectable.
- 3) In **Section C**, we evaluate our model using precision, recall, true positive, and false positive metrics, providing graphical representations of its performance and comparing it to state-of-the-art methods.
- 4) **Section D** showcases the accuracy of our model through testing on 10 live video footages, reaffirming its robustness and reliability. Lastly,
- 5) **Section E** outlines the implementation of an automated mailing system that promptly sends detailed reports, including timestamps, camera MAC addresses, and anomaly screenshots, to the appropriate authorities, thereby enhancing real-time response and reporting capabilities.

A. LOW LIGHT VIDEO ENHANCEMENT

The following subsection outlines the necessity of a low-light video enhancement preprocessing step for increasing the accuracy of anomaly detection. The visual results of the input low-light frames and their corresponding enhanced frames are depicted Fig. 3. Figs. 3(a) and 3(d) show a low-light image and its enhanced output, respectively, in less traffic conditions; Figs. 3(b) and 3(e) show a low-light image and its enhanced output, respectively in moderate traffic conditions; and Figs. 3(c) and 3(f) show a low-light image and its enhanced output, respectively, in heavy traffic conditions. The yellow boxes in 3(a), 3(b), and 3(c) depicts low-light areas, and the yellow boxes in 3(d), 3(e), and 3(f) depicts parts of enhanced portions.

B. TWO WHEELER RULE VIOLATION DETECTION

In this subsection, we have demonstrated remarkable effectiveness in detecting two-wheeler violations, even in challenging low-light conditions, outperforming existing methods. These conditions typically pose significant



FIGURE 3. Low light images and their enhancements at different traffic conditions.

obstacles to accurate detection due to reduced visibility and the potential loss of crucial details. However, our approach has successfully overcome these challenges and proven its ability to identify violations that were previously undetectable.

Fig. 4 shows two-wheeler rule violation detection under a normal daylight scenario. The initial step involves isolating the two-wheelers and their riders, depicted by blue bounding boxes. The four classes of anomalies are bounded by boxes of different colors. Particularly, no helmet riding and triple riding/overloading are depicted by green and red bounding boxes, respectively, while violations like wheelies and stoppies are marked by black bounding boxes. Multiple detected violations are evident in Figs. 4(a) to Fig. 4(f).

In Fig. 5, we have highlighted the benefit of low-light enhancement in detecting two-wheeler rule violations. Low accuracy while detecting no helmet violation in low-light conditions is evident in Figs. 5(a), 5(b), and 5(c). The violations detected in Figs. 5(d), 5(e), and 5(f) after low light enhancement exemplify the effectiveness of this crucial preprocessing step, which is glaringly obvious in Fig. 5, both visually and quantitatively. It indicates that our methods have surpassed the limitations of existing approaches and are capable of unveiling violations that would have otherwise gone unnoticed. This has substantial implications for improving the overall safety and security of traffic monitoring and enforcement scenarios.

C. QUANTITATIVE AND COMPARATIVE ANALYSIS

Two-wheeler violation detection was performed using YOLO-v8 on our proposed dataset in low lighting conditions. The model was tested on a total of 874 violation annotations, which include instances of no helmet, triple riding, wheelies, and stoppies. Table 2 shows the result of violation detection on our low-light test dataset. During the evaluation of our model on the test dataset, we employed various metrics, including precision, recall, and accuracy. Precision measures the ratio of correctly predicted positive pixels to all predicted positives, while recall measures the ratio of correctly predicted positive pixels to all actual positives. We also obtained accuracy by summing the number of true positives and true negatives and dividing it by the total

TABLE 2. Violation detection on low light test dataset.

Violation	No. of Actual violation	Precision	Recall	Accuracy (%)
No Helmet	482	0.959	0.951	94.80
Triple Riding	155	0.981	0.972	96.42
Wheelie	121	0.995	0.989	98.57
Stoppie	116	0.995	0.989	98.44
Average		0.982	0.975	97.05

number of instances. These evaluation metrics allow us to comprehensively analyze and validate the effectiveness of our model. The evaluation matrices can be formulated as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

where TP represents the number of correctly identified positive instances (violations in this context), TN represents the number of correctly identified negative instances (non-violations), FP represents the number of false positive instances (incorrectly identified as violations), and FN represents the number of false negative instances (violations missed or not detected). From table 2, we can observe that our test data has obtained an average precision of 98.2%, an average recall of 97.54%, and an average accuracy of 97.05% in low lighting conditions.

We have also plotted precision-confidence, recall-confidence, precision-recall, and the F1 curve to analyze the performance of our model in low light as shown in Fig. 6. The precision-confidence curve shows the trade-off between precision and confidence thresholds. Higher confidence leads to higher precision, while lower confidence results in lower precision. The recall-confidence curve depicts the trade-off between recall and confidence thresholds. Higher confidence leads to lower recall, while lower confidence increases recall. The precision-recall curve illustrates the relationship between precision and recall for different confidence thresholds, helping to determine the optimal threshold for a desired balance. The F1 score combines precision and recall into a single metric, providing an overall assessment of the model's performance. A higher F1 score indicates a better balance between precision and recall.

We have also compared our low-light violation detection dataset with other existing YOLO models in terms of precision, recall, and F1 score, as shown in table 3 below. From Table 3, it is evident that the version of YOLO we have used in this paper (YOLO-v8) outperforms all other existing versions in terms of precision, recall, and F1 score when tested on our low-light rule violation dataset.

To evaluate the performance of our system, we conducted comprehensive tests comparing it to state-of-the-art models using similar deep learning frameworks. The dataset used in



FIGURE 4. Two Wheeler violation detection at normal daylight.

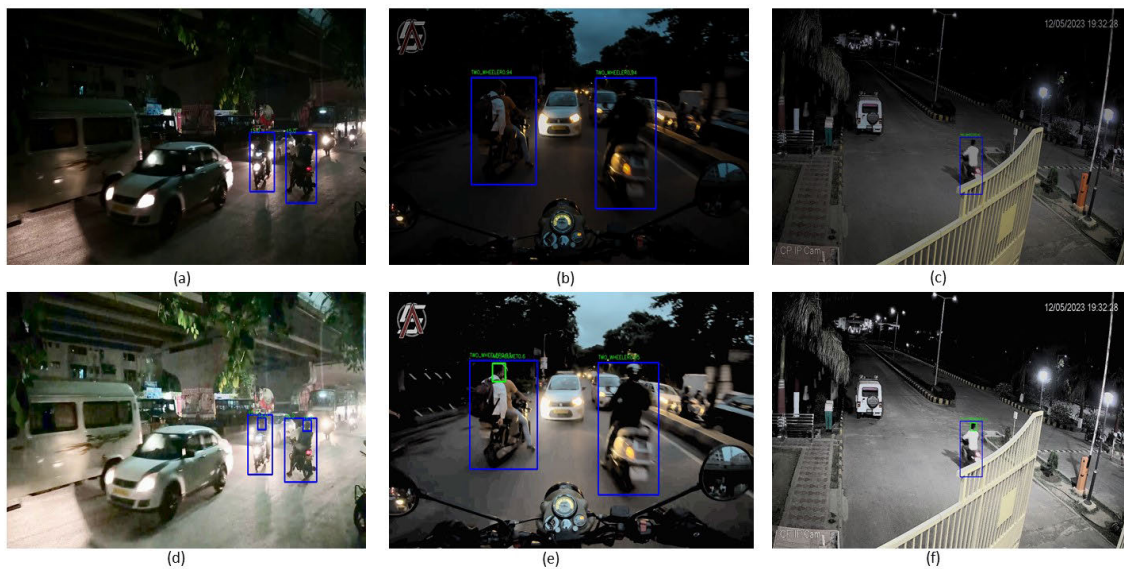


FIGURE 5. Two Wheeler violation detection at night.

our evaluation focuses on two common types of violations: no helmet and triple riding. This dataset consists of 910 video clips captured at 12 observation sites in Myanmar during 2016. Each videoclip has a duration of 10 seconds and is recorded at a framerate of 10 fps with a resolution of 1920×1080 . Notably, this dataset surpasses existing ones in terms of the number of individual motorcycles, totaling 10,006 instances. Each motorcycle in the dataset’s 91,000 annotated frames is meticulously labelled with a bounding box, along with rider numbers per motorcycle and specific helmet usage data. Through these rigorous evaluations, we aimed to assess the efficacy and superiority of our system compared to established models, as shown in Table 4.

From the table, we can observe that our method has achieved a precision of 0.971, a recall of 0.965, and an accuracy of 96.9% on the benchmark dataset discussed above, which is the highest as compared to other methods in the comparison table. Time per detection is obtained to be 0.1 seconds in our case.

D. LIVE VIDEO

The evaluation of our methods also involved testing them on ten high-resolution low-light videos, each approximately one minute long and captured at different frames-per-second rates. These videos represented a range of traffic conditions, providing a diverse and realistic dataset for assessing the

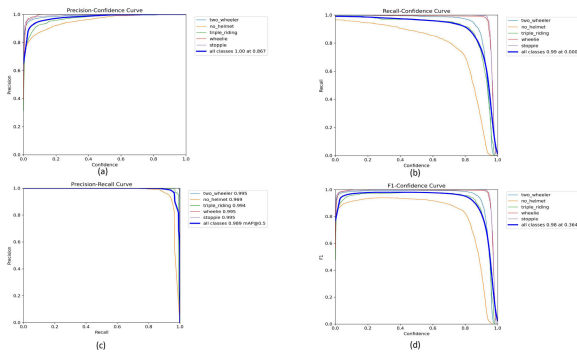


FIGURE 6. Graphical representation of (a) Precision-Confidence curve (b) Recall-Confidence curve (c) Precision-Recall curve (d) F1 curve.

TABLE 3. Comparison with other YOLO models.

Sl no.	Violations	YOLO versions	Precision	Recall	F1 score
1.	No Helmet	YOLO-v3	0.803	0.809	0.805
		YOLO-v4	0.846	0.854	0.849
		YOLO-v5	0.902	0.897	0.899
		YOLO-v7	0.941	0.933	0.936
		YOLO-v8 (ours)	0.959	0.951	0.954
2.	Triple Riding	YOLO-v3	0.811	0.817	0.813
		YOLO-v4	0.854	0.861	0.857
		YOLO-v5	0.923	0.914	0.918
		YOLO-v7	0.962	0.954	0.957
		YOLO-v8 (ours)	0.981	0.972	0.976
3.	Wheelie	YOLO-v3	0.856	0.831	0.843
		YOLO-v4	0.889	0.874	0.881
		YOLO-v5	0.936	0.929	0.932
		YOLO-v7	0.974	0.970	0.971
		YOLO-v8 (ours)	0.995	0.989	0.991
4.	Stoppie	YOLO-v3	0.856	0.831	0.843
		YOLO-v4	0.889	0.874	0.881
		YOLO-v5	0.936	0.929	0.932
		YOLO-v7	0.972	0.968	0.974
		YOLO-v8 (ours)	0.993	0.987	0.995

TABLE 4. Quantitative analysis on benchmark dataset. the best performance is highlighted in bold.

Approach	Precision	Recall	Accuracy (%)	Time per detection
Mallela et al. (2021) [19]	0.914	0.921	91.7	0.24 sec
Arshad and Kumar (2022) [30]	0.921	0.918	92.6	0.15 sec
Charran and Dubey (2022) [20]	0.963	0.940	95.2	0.09 sec
Proposed Approach	0.971	0.965	96.9	0.10 sec

performance of our approach. The results obtained from the video feed are presented in Table 5. Out of a total of 188 violations present in the videos, our methods accurately captured 172 violations. This translates to an accuracy rate of 91.48%, indicating the effectiveness and reliability of our approach in detecting and capturing two-wheeler violations in low-light scenarios. The high accuracy achieved demonstrates the robustness and efficiency of our methods in identifying violations, even in challenging low-light conditions. This indicates

TABLE 5. Two wheeler violation distribution.

Video	Frames per second	Actual Violations	Detected Violations	Error in Violation Detection (%)
Video 1	33	7	7	0.00
Video 2	24	14	13	7.14
Video 3	31	4	4	0.00
Video 4	25	27	25	8.00
Video 5	27	19	18	5.26
Video 6	31	9	9	0.00
Video 7	32	11	11	0.00
Video 8	22	37	33	10.81
Video 9	60	16	15	6.25
Video 10	21	44	37	15.9
Total		188	172	

that our approach is capable of accurately recognizing and flagging instances of non-compliance, contributing to improved traffic monitoring and enforcement. Furthermore, an important aspect of the proposed system is that it achieved a zero false positive rate, meaning that no incorrect violations were mistakenly identified. This highlights the precision and accuracy of our approach to distinguishing genuine violations from other objects or movements, even in low light. Upon analyzing the instances where violations were not detected (false negatives), it was observed that a significant portion of these cases involved individuals wearing caps or unconventional headgear. The model tended to classify such headgear as helmets, resulting in the violations not being captured.

E. AUTOMATED MAIL GENERATION

Automated mail generation plays a pivotal role in efficiently notifying relevant authorities or stakeholders when violations or anomalies are detected. This process involves the automated creation and sending of emails without the need for manual intervention. When a violation or anomaly is identified, the system triggers an automated procedure to generate an email containing pertinent information such as the event’s timestamp, the nature of the violation, and supporting data or images. The email is sent through a mail server or SMTP service, either to pre-configured recipients or dynamically determined based on predefined rules, as shown in Fig. 7. By automating the mail generation, the system ensures real-time notification and response, eliminating the need for manual effort and providing a documented record of events. This streamlines the monitoring process, enhances efficiency, and facilitates further analysis, tracking, and reporting.

Hence, based on the comprehensive qualitative and quantitative analysis presented in the results section, it becomes evident that our method excels not only in optimal daylight conditions but also demonstrates remarkable performance in low-light scenarios. It can effectively detect those violations with high precision that could not be detected under low lighting conditions.

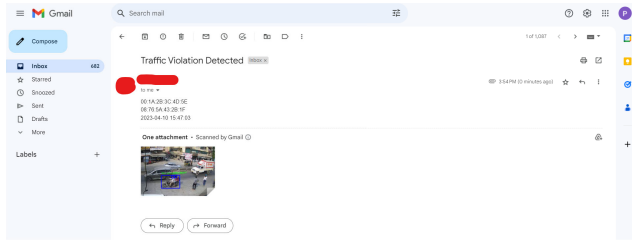


FIGURE 7. Automated mail generated output.

V. CONCLUSION AND FUTURE SCOPE

In this paper, we introduce an innovative low-light traffic rule violation detection system featuring a network of interconnected devices and an automated anomaly storage and notification system for swift alerts to authorities. Additionally, to the best of our knowledge, we have also constructed the first low-light traffic rule violation dataset collected from multitudinous sources. Our system's efficacy is showcased across normal and low-light conditions through diverse metrics. Our system surpasses the most accurate state-of-the-art method by about 1.7% in overall accuracy. By virtue of our dataset encompassing more complex violations compared to others, the fact that our system achieves an impressive accuracy of 97.05% along with a rapid detection speed of 0.1 seconds per detection showcases its practical real-time applicability. Furthermore, the Yolo-v8x model used surpasses existing models in all three parameters, namely, precision, recall, and F1-Score, by 2%, 1.8%, and 1.9% on average, respectively, for all four classes of violations. Overall, our system showcases the potential of deep learning-based approaches for real-time violation detection and contributes to enhancing road safety.

Our future work includes extending the classes of violations detected, incorporating multi-object tracking for better analysis, tracking of violators across multiple frames and devices, and utilizing additional indicators like traffic flow patterns, weather conditions, and road infrastructure to further enhance the accuracy and contextual understanding of violations.

AUTHOR CONTRIBUTIONS

All authors contributed equally to the manuscript.

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