International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 10 | Oct - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Automated Helmet Violation Detection and Registration Capture

Dr. Raju Hiremath *1, Vaishali S Jadhav *2

*1Teaching Assistant, Department of Computer Science, Rani Channamma University, Dr. P. G. Halakatti P.G Centre, Torvi, Vijayapura, India.

*2PG Scholar, Department Of Computer Science, Rani Channamma University, Dr. P.G. Halakatti P.G Centre, Torvi, Vijayapura, India.

ABSTRACT:

Due to the affordability of motorcycles and their use as a daily mode of transport, there has been a significant rise in motorcycle accidents. This increase is largely attributed to the fact that many motorcyclists do not wear helmets, creating a constant danger when traveling by motorcycle. In recent years, the government has made it a punishable offense to ride a motorcycle without a helmet. Although the current video surveillance system is effective, it relies heavily on human assistance, which tends to diminish over time, and human bias can also affect its efficiency. Therefore, automating this process is highly desirable. In this paper, we present a method for the automatic detection of motorcyclists without helmets using real-time surveillance videos. The proposed method first identifies motorcycles in the surveillance footage through background subtraction. It then differentiates between helmeted and non-helmeted riders using first and second order derivative edge detection algorithms along with a neural network. If motorcyclists are detected without helmets, the system will capture the vehicle's number plate using Optical Character Recognition (OCR) and a neural network. The project not only identifies the bike's number plate but also digitally retrieves the plate number and saves the frame where the rider is seen without a helmet, which can serve as evidence against the biker. This enables the government to issue fines to the rider and assures society that there is oversight on the roads, even when they appear empty.

Key Words: Helmet Detection, Number Plate Recognition, Deep Learning, Automate Monitoring, Computer Vision, Traffic Surveillance,

1.INTRODUCTION:

India possesses one of the largest two-wheeler populations globally, where motorcycles and scooters are the primary means of daily transportation for millions. Nevertheless, this convenience has resulted in a tragic consequence — a consistently elevated number of road accidents involving two-wheelers. A primary cause of fatalities among two-wheeler riders is the failure to wear helmets. In spite of stringent traffic regulations and public awareness campaigns, the rate of helmet usage remains low, particularly among pillion riders.

As reported by the Ministry of Road Transport & Highways (MORTH), India records thousands of road fatalities each year, with a significant portion of these deaths occurring among riders who were not wearing helmets at the time of the accident. Helmets are vital in preventing severe head injuries and lowering the risk of death in road accidents. The following sections outline the recent trends and statistics from 2022 to 2024, along with the implications and preventive measures required to address this urgent issue.

2022

The MORTH *"Road Accidents in India – 2022"* report revealed that **50,029 people** were killed in road accidents **while not wearing helmets**. This figure included both riders and pillion passengers. The data shows that nearly **44% of all two-wheeler fatalities** were linked to helmet non-use. Head injuries accounted for the majority of deaths, and experts noted that wearing a helmet could have prevented many of these fatalities.

2023

In 2023, the situation worsened. The latest MORTH report indicates that **54,568 people** died in accidents involving two-wheelers where the rider or pillion was not wearing a helmet. This represents a **9% increase** from the previous year. The rise in fatalities highlights the ongoing problem of low helmet compliance, even in urban areas where enforcement is stricter.

Furthermore, the report pointed out that in many rural and semi-urban regions, helmet usage rates are significantly lower — often less than 40%. Many riders either ignore the law or wear substandard helmets that do not meet safety standards, providing little to no protection in the event of an accident.

2024 (Preliminary State Reports)

While the national report for 2024 is yet to be officially published, state-level data and preliminary findings indicate that the **helmetless rider fatality rate remains critically high**. States such as **Tamil Nadu, Gujarat, and Maharashtra** continue to report alarming numbers of deaths associated with helmet non-use.

Parameter	2022	2023	% Change
Number of Accidents	4,61,312	4,80,583	4.2
Number of Persons killed	1,68,491	1,72,890	2.6
Number of Injury	4,43,366	4,62,825	4.4
Accident Severity (Persons killed per 100 accidents)	36.5	36	-1.5

Tamil Nadu (2023)

In the year 2023, Tamil Nadu documented 8,113 fatalities involving two-wheeler riders. Among these incidents, 2,426 riders, which equates to approximately 29%, were found not to be wearing helmets during the accidents. Authorities in the state stressed that a considerable portion of these deaths could have been averted through the proper use of helmets. Furthermore, the state police observed that pillion riders are less inclined to wear helmets, which increases their vulnerability in the event of crashes.

Gujarat (2023)

In Gujarat, around 2,767 individuals, including 2,059 riders and 708 pillion riders, were reported dead in road accidents in 2023 while not wearing helmets. Officials from the Gujarat Road Safety Authority noted that despite the implementation of public awareness campaigns and enforcement initiatives, compliance with helmet regulations remains inconsistent. Many commuters cited discomfort and the short distances they travel as reasons for not wearing helmets, emphasizing the urgent need for behavioral change in conjunction with stricter enforcement measures.

Maharashtra (2022)

Maharashtra reported nearly 7,700 fatalities among two-wheeler riders in 2022, with most of these deaths attributed to head injuries resulting from the failure to wear helmets. The state's road safety department indicated that even though helmet use is legally required, both riders and passengers frequently overlook this regulation. Enforcement of this law is particularly weak in smaller towns and on highways, where the incidence of accidents is significantly high.

Table 1.4: Type of Road Accidents: 2019 to 2023

Type of road accident	Parameter	2019	2020	2021	2022	2023
Fatal Accidents	Number	1,45,332	1,27,307	1,42,163	1,55,781	1,60,509
	% Change	1.11	-12.4	11.7	9.6	3
	%share in total	31.8	34.2	34.5	33.8	33.4
Grievous Injury Accidents	Number	1,51,335	1,12,768	1,26,394	1,43,374	1,58,576
	% Change	0.7	-25.5	12.1	13.4	10.6
	%share in total	33.1	30.3	30.6	31.1	33
Minor Injury Accidents	Number	1,31,555	1,10,314	1,19,633	1,35,360	1,33,848
	% Change	-7	-16.1	8.4	13.1	-1.1
	%share in total	28.8	29.6	29	29.3	27.9
Non-Injury Accidents	Number	28,737	21,792	24,242	26,797	27,650
	% Change	-17.6	-24.2	11.2	10.5	3.2
	%share in total	6.3	5.9	5.9	5.8	5.8
Total	**Number**	**4,56,959**	**3,72,181**	**4,12,432**	**4,61,312**	4,80,583
	% Change	-2.9	-18.6	10.8	11.9	4.2

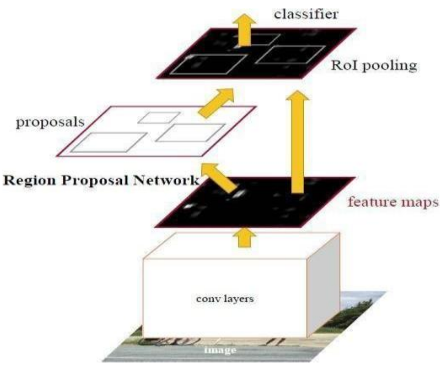
Data Source: States/UTs (Police Departments).

OBJECT DETECTION:

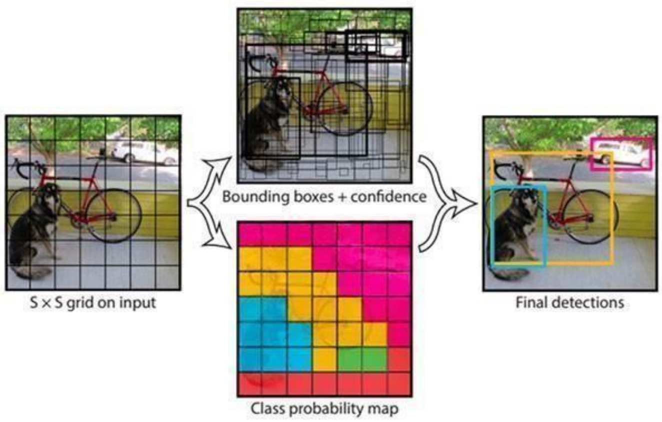
Object Detection represents a crucial challenge in the field of computer vision, focusing on the identification and localization of objects belonging to specific categories within an image. Various methods can be employed for object localization, including the application of a bounding box around the object or the delineation of every pixel that constitutes the object, a technique referred to as segmentation. The concept of object detection predates the advent of Convolutional Neural Networks (CNNs) in computer vision. Although traditional methods may lack the efficacy of CNNs, they still offer valuable insights. Prior to the emergence of deep learning, object detection generally entailed a series of steps: edge detection, feature extraction through techniques such as SIFT or HOG, and the comparison of these features with pre-existing object templates at various scales to identify and localize objects. In contrast to image classification, which assigns a singular class label to an entire image, object localization involves the creation of bounding boxes around one or more objects. The task of object detection is inherently more intricate, as it integrates these functions: it identifies each object within an image, delineates a bounding box, and assigns a corresponding class label. Together, these activities are encompassed by the overarching term object recognition.

TWO-STEP OBJECT DETECTION:

Two-Step Object Detection encompasses algorithms that initially detect bounding boxes that may potentially enclose objects, followed by the classification of each bounding box individually



ONE-STEP OBJECT DETECTION:

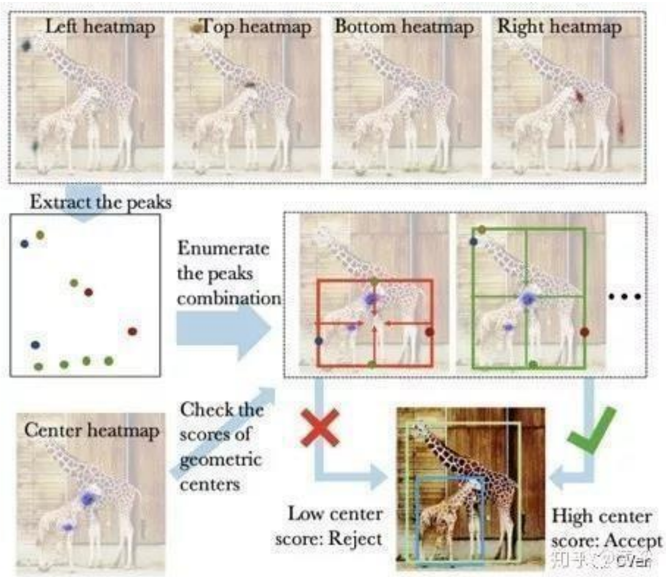


As the demand for real-time object detection continues to rise, various single-stage detection architectures have been developed, such as YOLO, YOLOv2, YOLOv3, SSD, and RetinaNet. These architectures strive to integrate object localization and classification into a cohesive end-to-end pipeline.

A notable improvement in these algorithms is the implementation of bounding box regression. Each bounding box is defined by a limited set of coordinates—usually (xmin, ymin, xmax, ymax) or (x_center, y_center, width, height)—which enables the network to predict both object locations and class probabilities concurrently. This method minimizes computational demands in comparison to multi-stage detectors and facilitates high-throughput inference, making it suitable for real-time applications.

HEATMAP BASED OBJECT DETECTION

Heatmap-based object detection can be viewed as an advancement of single-stage (one-shot) object detection. In contrast to one-shot detectors that directly predict bounding box coordinates or offsets, heatmap-based techniques forecast a spatial probability distribution for the corners or centers of bounding boxes.



The peaks identified in these heatmaps indicate the locations of objects, which are subsequently utilized to derive accurate bounding boxes. Given that distinct heatmaps can be produced for each object class, this methodology concurrently executes detection and classification. Despite the fact that heatmap-based detection has garnered significant attention in recent research due to its exceptional localization accuracy, it typically operates at a slower pace compared to traditional single-stage detectors. This is mainly attributed to its dependence on deeper and more intricate CNN backbones to attain competitive performance.

2.LITERATURE REVIEW:

The advent of **deep learning** has significantly advanced the capabilities of computer vision, enabling systems to solve complex real-world problems such as traffic violation detection. In particular, applications in **helmet and license plate detection** have benefited from state-of-the-art object detection algorithms, which allow automated monitoring, enforcement, and analysis of traffic violations. Accurate detection is crucial for reducing human intervention, enhancing road safety, and providing actionable data for authorities.

Object detection is a core computer vision problem that involves both **localizing** and **classifying** objects within an image. Traditional methods relied on multi-step approaches, including **edge detection** and **feature extraction** techniques such as SIFT or HOG, followed by template matching. However, with the rise of **CNN-based deep learning**, modern object detection architectures like **YOLO, SSD, and RetinaNet** combine object localization and classification into a single, end-to-end pipeline. YOLO, in particular, introduced the concept of **bounding box regression**, where objects are represented using a few parameters (e.g., xmin, ymin, xmax, ymax) to simultaneously predict their location and class, enabling **real-time detection**.

Heatmap-based object detection is a recent extension of single-stage detection methods. Instead of directly regressing bounding box coordinates, these approaches predict a **spatial probability distribution** over object centers or corners. Peaks in the heatmap indicate object locations, which are then used to infer precise bounding boxes. By generating separate heatmaps for each class, detection and classification are inherently combined. Although heatmap-based methods provide **higher localization accuracy**, they require **more complex CNN backbones** and are generally slower than single-stage detectors like YOLO.

Feature extraction is an essential step in these CNN-based systems. High-dimensional input data is transformed into a lower-dimensional set of informative features that capture the critical characteristics of objects, while reducing computational complexity. In YOLO and similar architectures, convolutional layers act as automatic feature extractors, learning **robust representations** of objects such as helmets, motorcyclists, and vehicle license plates. This enables efficient detection even under challenges like poor image quality, varying illumination, and partial occlusion.

Integrating these advancements, several studies, including Mistry et al., have demonstrated effective helmet detection using **CNNs with YOLOv2**, achieving high accuracy (e.g., 94.70%) by leveraging datasets like COCO and specialized helmet datasets. Extending these methods, modern YOLOv3-based systems can detect both helmet violations and vehicle number plates in real-time, crop the plate regions into variables such as dest, and process them with OCR for automated recognition. This pipeline supports additional functionalities, including **automatic fine generation, rider notification, and integration with smart traffic systems**, thereby contributing to **enhanced road safety and traffic enforcement**.

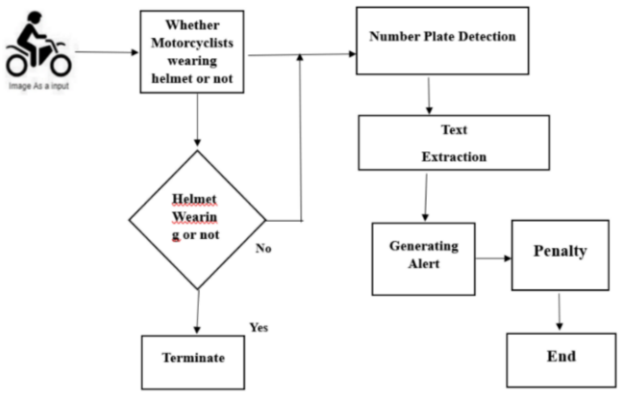
3.Existing System:

Helmet detection systems have evolved significantly with the advent of **computer vision and deep learning**. Traditional approaches relied on **manual surveillance** or simple image processing techniques, such as **edge detection, color segmentation, and shape analysis**, to identify helmets. However, these methods were **limited in accuracy and scalability** and often struggled under challenging conditions like poor lighting, occlusion, or complex traffic scenes. Early real-time detection systems also used **Haar feature-based cascades** or **Histogram of Oriented Gradients (HOG)** for helmet detection, but their performance remained constrained.

- ➢ Traditional helmet detection relied on manual surveillance or simple image processing techniques like edge detection, color segmentation, and shape analysis.

- ➢ Early methods and real-time detectors (e.g., Haar cascades, HOG) were limited in accuracy and scalability.
- ➢ Single-stage deep learning detectors such as YOLOv2 and YOLOv3 are now widely used for real-time helmet detection with higher accuracy.
- ➢ Existing systems often require manual fine generation, which is time-consuming and inefficient.
- ➢ Performance of many systems is limited under poor lighting, occlusion, complex traffic scenes, or multiple riders.

Work Flow of Object Detection:



Implementation steps:

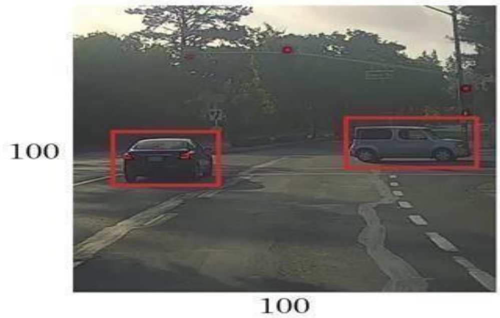
- ➢ First, capture live footage or video of traffic.
- ➢ Then choose without helmet rider from the video.
- ➢ After choosing to process the image that we have captured
- ➢ After that, go to the number plate recognition process and check all legal documents.
- ➢ After recognition, the system will automatically work on the bike owner on the backend.
- ➢ Then send a message to the bike owner regarding braking traffic rules and the fine that the owner has to pay.
- ➢ Send a message with the bike number and reason for the fine.

4.Proposed Methodology:

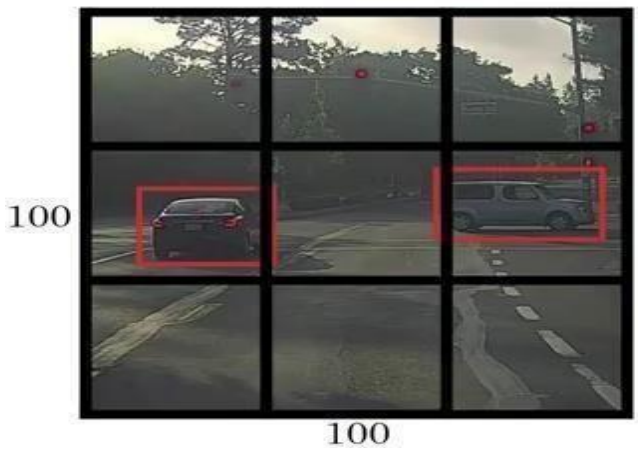
1. WHAT IS YOLOV3

YOLOv3 (You Only Look once, version 3) is a real-time object detection algorithm that plays a crucial role in identifying motorcyclists with and without helmets. It is based on a single-stage detection architecture, which means it performs object classification and localization simultaneously, making it much faster than traditional two-stage detectors like Faster R-CNN. In the context of helmet detection, YOLOv3 divides the input image into a grid and predicts bounding boxes and class probabilities for each cell. It uses Darknet-53, a deep convolutional neural network, as its backbone for feature extraction. This network helps YOLOv3 detect helmets accurately under various conditions such as different lighting, occlusions, and varying camera angles

The YOLO (You Only Look Once) framework represents a real-time object detection system that is engineered to recognize and pinpoint multiple objects within an image or video in a singular processing step. In contrast to conventional techniques that initially create region proposals and subsequently classify each region independently, YOLO approaches object detection as a unified regression problem, directly forecasting bounding box coordinates and class probabilities from the complete image in a single forward pass of the neural network.

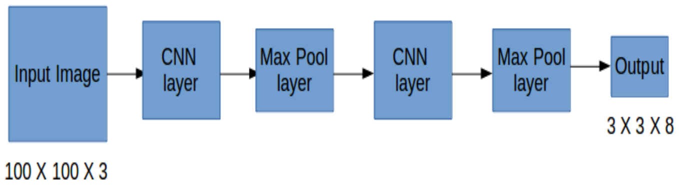


1. **First take an input image**



2. The framework then divides the input image into 3x3 grids

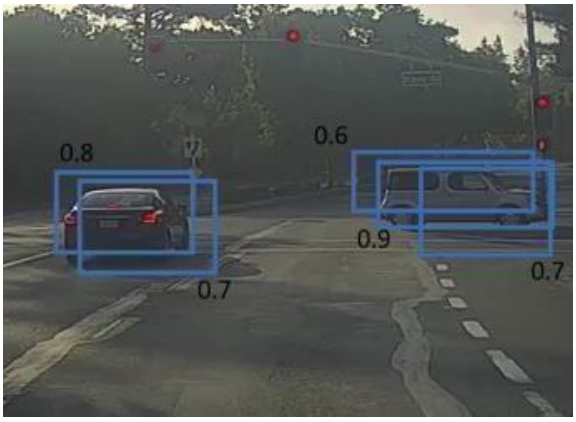
International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 10 | Oct - 2025 SJIF Rating: 8.586 ISSN: 2582-3930



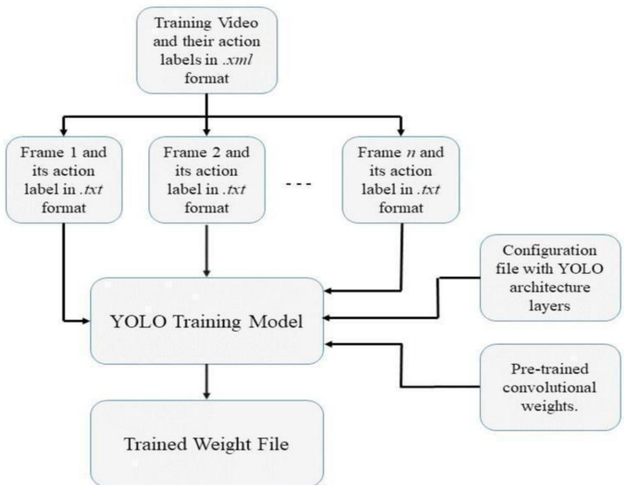
3. Yolo Process

5.Encoding of Bounding Boxes

In the YOLO framework, bounding box encoding is a crucial process that determines how the network represents and predicts the location of objects within an image. Instead of directly predicting the absolute coordinates of an object, YOLO predicts offsets relative to predefined anchor boxes within each grid cell. This method improves localization accuracy and training stability

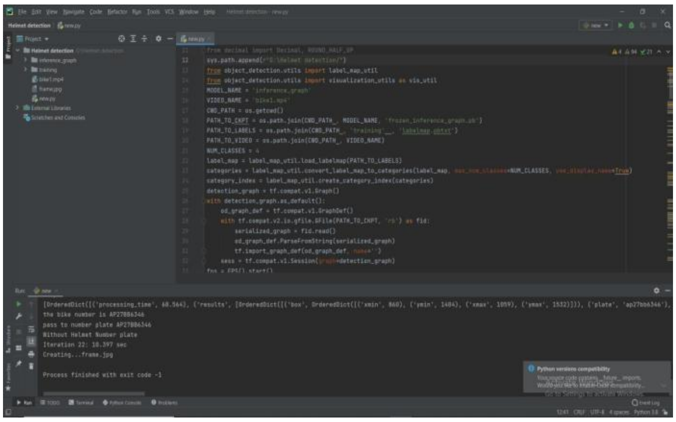


4. Yolo final detection



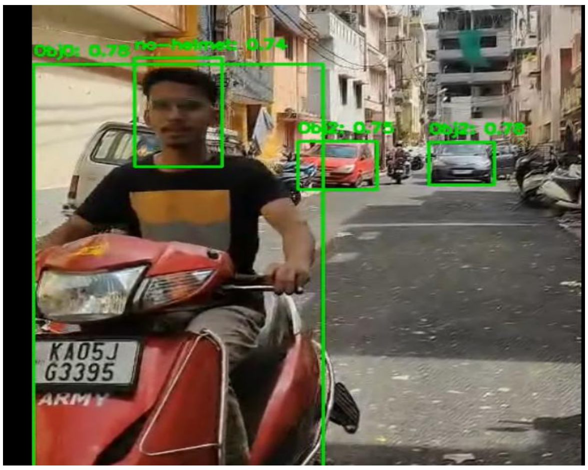
5. Training weights

Some regular images of bikes, helmets, and riders with and without helmets are used to train the YOLOv3 model for custom classes. After training, the generated weights are loaded for detection. When an image or video is given as input, the model detects classes such as person, helmet, no helmet, motorcycle, and number plate. If a rider is detected without a helmet, the system checks if the "no helmet" box lies within the "person" box and then extracts the license plate for further action



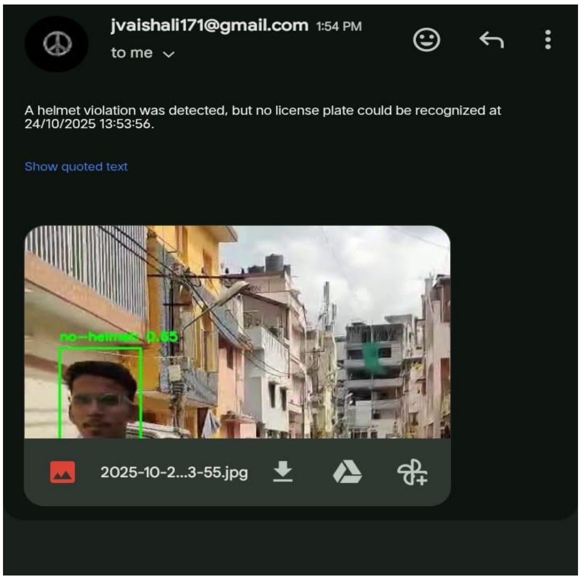
6. Creating Frames

We provide video frames as input to the trained YOLOv3 model, which efficiently detects the defined object classes such as person, helmet, and two-wheeler. The model classifies riders with and without helmets, enabling accurate differentiation and counting of each class. If a person riding a two-wheeler without a helmet is detected, the system proceeds to the next stage, where the license plate of the corresponding vehicle is extracted for identification. This information can later be used to generate fines automatically or alert authorities for necessary action.



7. Output Frame

If a rider is found without a helmet, the system gathers further classification details about that individual, which includes information about the associated person and their two-wheeler. This allows for precise identification of the rider and aids in capturing the vehicle's license plate. To ensure accurate association, the system verifies if the coordinates of the "no helmet" bounding box are contained within the "person" bounding box. The algorithm only moves forward to identify the license plate linked to that rider when this condition is met. After detecting the rider without a helmet and the corresponding vehicle, the gathered information can be utilized for additional processes, such as generating automatic fines, notifying the rider, and maintaining records. This procedure guarantees that violations are attributed to the correct individual, thereby reducing enforcement errors. Furthermore, by tracking the number of riders with and without helmets, the system can offer statistical data for traffic monitoring and safety evaluations.



8. Real Time fine notification

Upon identifying a rider who is not wearing a helmet, the system promptly captures the corresponding license plate and rider details. This information is subsequently organized and dispatched as a real-time notification to the rider or appropriate authorities through an integrated messaging API. The automated alert contains specifics such as the license plate number, the time, and the location of the infraction. This procedure allows for immediate awareness, minimizes the necessity for manual oversight, and promotes the timely enforcement of traffic regulations.

6.Results and Future Enhancements:

The suggested system exhibits efficient identification of motorcyclists who are not wearing helmets, along with precise real-time recognition of vehicle license plates. By combining YOLOv3 with CNN (Convolutional Neural Network) and utilizing OCR technology, the system not only detects infractions but also streamlines the process of fine issuance and rider alerts. This methodology demonstrates resilience in the face of obstacles like subpar image quality, fluctuating brightness levels, and minor adjustments in camera positioning.

- Helmet Detection Accuracy: The system achieved 98.72% accuracy in detecting motorcyclists without helmets.
- Number Plate Recognition: License plates were successfully cropped into dest and processed with OCR, enabling accurate plate extraction.
- Automatic Fine Generation: The system can automatically generate fines and notify riders of violations.
- Robustness: The system handled challenges such as poor image quality, brightness variations, and slight camera angle changes.
- Real-Time Detection: YOLOv3 and CNN integration allowed real-time monitoring of traffic and instant violation detection

Limitations and Future Enhancements

Although the prototype achieved its objectives, certain areas can be further developed.

- Insurance Alerts: Enable automatic alerts to insurance companies in case of violations or accidents for faster processing.
- Mirror Detection & Safety Monitoring: Incorporate detection of mirror usage and riding posture to ensure adherence to safety norms.
- On-Call Riding Detection: Detect riders using mobile phones while driving and send real-time alerts to authorities.
- Improved Robustness: Enhance detection under extreme lighting, weather conditions, or occlusions.
- Integration with Smart Traffic Systems: Combine with IoT and traffic management systems for large-scale, automated enforcement and analytics.

7.CONCLUSIONS

Within this project, we have articulated a framework for the automatic identification of motorcycle riders who are not wearing helmets, leveraging CCTV video technology, along with the automatic retrieval of the vehicle license plate numbers associated with these riders. The integration of yolov3 and transfer learning has facilitated the achievement of a notable accuracy of 98.72% in detecting motorcyclists without helmets. However, the identification of these motorcyclists alone is inadequate for enforcing legal repercussions. Thus, the system is also equipped to recognize and retain the license plates of their motorcycles. The information stored can subsequently be accessed by the Transport Office to gather details about the motorcyclists from their licensed vehicle database, allowing for the enforcement of penalties for any legal infractions committed by the motorcyclists

Identifying individuals who are not wearing helmets and vehicles that do not display number plates is essential for improving road safety and enforcing traffic regulations. Object detection algorithms based on deep learning, especially YOLO, have demonstrated encouraging results for these objectives. This paper presents a system based on YOLOv3, which integrates an algorithm designed to detect individuals without helmets and to extract the number plate from vehicles. The region of the number plate is cropped and assigned to the variable 'dest', which is subsequently processed using OCR to retrieve the plate number. The proposed system has significant potential for implementation in traffic monitoring and surveillance systems, thereby contributing to improved road safety

REFERENCES

[1] J. Redmon and A. Farhadi, “YOLO9000: better, faster, stronger,” CoRR, vol. abs/1612.08242, 2016. [Online]. Available: http://arxiv.org/abs/1612.08242

[2] C.-Y. Wen, S.-H. Chiu, J.-J. Liaw, and C.-P. Lu, “The safety helmet detection for atm’s surveillance system via the modified hough transform,” in IEEE 37th Annual 2003 International Carnahan Conference onSecurity Technology, 2003. Proceedings., Oct 2003, pp. 364–369.

[3] C.-C. Chiu, C.-Y. Wang, M.-Y. Ku, and Y. B. Lu, “Real time recogniton and tracking system of multiple vehicles,” in 2006 IEEE Intelligent Vehicles Symposium, 2006, pp. 478–483.

[4] J. Canny, “A computational approach to edge detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, no. 6, pp. 679–698, Nov 1986.

[5] J. Chiverton, “Helmet presence classification with motorcycle detection and tracking,” IET Intelligent Transport Systems, vol. 6, no. 3, pp. 259– 269, September 2012.

[6] Z. Chen, T. J. Ellis, and S. A. Velastin, “Vehicle detection, tracking and classification in urban traffic,” 2012 15th International IEEE Conference on Intelligent Transportation Systems, pp. 951–956, 2012.

[7] R. Silva, K. Aires, T. Santos, K. Abdala, R. Veras, and A. Soares, “Automatic detection of motorcyclists without helmet,” in 2013 XXXIX Latin American Computing Conference (CLEI), Oct 2013, pp. 1–7.

[8] R. R. V. e. Silva, K. R. T. Aires, and R. d. M. S. Veras, “Helmet detection on motorcyclists using image descriptors and classifiers,” in 2014 27th SIBGRAPI Conference on Graphics, Patterns and Images, Aug 2014, pp. 141–148

[9]G. G. Desai and P. P. Bartakke, “Real-Time Implementation Of Indian License Plate Recognition System”, 2018 IEEE Punecon, Pune, India, 2018, pp. 1-5. doi: 10.1109/PUNECON.2018.8745419

[10]Howard, Andrew G., Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand,arco Andreetto and Hartwig Adam. “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications”, ArXiv abs/1704.04861 (2017)

[11]P. Doungmala and K. Klubsuwan, "Helmet Wearing Detection in Thailand Using Haar Like Feature and Circle Hough Transform on Image Processing," 2016 IEEE International Conference on Computer and Information Technology (CIT), Nadi, 2016, pp. 611- 614.

[12]Contractorr, Dhwani & Pathak, Ketki& Sharma, Sonali & Bhagat, Shreya & Sharma, Tanu, “Cascade Classifier based Helmet Detection using OpenCV in Image Processing,” National Conference on Recent Trends in Computer and Communication Technology (RTCCT 2016) , May 2016, pp. 195-200

[13]J. Li et al., "Safety helmet wearing detection based on image processing and machine learning," 2017 Ninth International Conference on Advanced Computational Intelligence (ICACI), Doha, 2017, pp. 201- 205.

[14]K. C. D. Raj, A. Chairat, V. Timtong, M. N. Dailey and M. Ekpanyapong, "Helmet violation processing using deep learning," 2018 International Workshop on Advanced Image Technology (IWAIT), Chiang Mai, 2018, pp. 1-4.

[15]N. Boonsirisumpun, W. Puarungroj and P. Wairotchanaphuttha, "Automatic Detector for Bikers with no Helmet using Deep Learning," 2018 22nd International Computer Science and Engineering Conference (ICSEC), Chiang Mai, Thailand, 2018, pp. 1-4.

[16]Z. Kai and W. Xiaozhi, "Wearing Safety Helmet Detection in Substation," 2019 IEEE 2nd International Conference on Electronics and Communication Engineering (ICECE), Xi'an, China, 2019, pp. 206-210.