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Helmet Detection and Automatic License Plate Recognition: A Simple Safety-Based Approach

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Abstract: Road safetyfor two-wheeler riders remains a significant challenge, particularly since many people continue to ride without helmets. Manual monitoring of such violations is challenging for traffic authorities because it requires constant attention and a large amount of manpower. To address this problem, this research presents an automated system that combines helmet detection with automatic license plate recognition using modern machine-learning techniques. The system uses deep-learning models, such as YOLO, to identify whether a rider is wearing a helmet by analysing images or video frames in real time. If a rider is found without a helmet, the system automatically detects the motorcycle's license plate and reads the characters using an OCR-based approach.

The proposed method reduces the need for human supervision and increases the speed and accuracy of violation detection. The system is designed to work with CCTV footage and can handle various real-world challenges such as different lighting conditions, camera angles, and backgrounds. By integrating helmet detection and license plate recognition into a single pipeline, this research demonstrates a practical solution for traffic monitoring and enforcement. The work demonstrates that AI-powered systems can play a crucial role in building safer roads, enhancing rule compliance, and supporting smart-city initiatives.

I. INTRODUCTION

Road accidents involving two-wheeler riders are a common problem, and many injuries occur simply because riders do not wear helmets. Although wearing a helmet is a basic safety rule, many people still ignore it. Traffic police attempt to monitor such violations, but checking every rider manually is difficult, time-consuming, and often unreliable, especially on busy roads. To address this issue, modern computer vision techniques can automatically identify riders who are not wearing helmets.

Early computer vision methods such as Haar cascades and HOG-based detectors laid the foundation for automated object detection **[1], [2]**. However, these traditional methods struggle in challenging real-world traffic environments. With advancements in deep learning, more powerful models such as Fast R-CNN **[4]**, SSD **[6]**, and YOLO **[5], [6]** have significantly improved real-time object detection accuracy. These deep-learning models, especially YOLO, can recognise helmets in live video streams with high speed and accuracy.

Once a rider without a helmet is detected, the next step is to capture the vehicle's number plate using Automatic License Plate Recognition (ALPR). Earlier techniques relied on edge detection and handcrafted algorithms **[9]**, but modern ALPR systems use deep-learning-based plate detection and OCR for character recognition **[12]**. OCR tools extract readable text from the cropped plate region, enabling automated identification of the motorcycle involved in the violation.

By combining helmet detection with ALPR, the system can automatically detect violations, capture license plate details, and reduce dependence on manual monitoring. Previous research has demonstrated the importance of automated surveillance in enhancing safety and reducing human workload **[7], [10], [11]**. Therefore, this project aims to develop a complete system that integrates real-time helmet detection, number plate extraction, and OCR-based text recognition to support traffic enforcement and improve road safety.

II. LITERATURE REVIEW

Early research on helmet detection and number-plate recognition relied heavily on traditional computer-vision techniques such as Haar cascades, HOG features, edge detection, and SVM classifiers. Studies like those by Viola and Jones, and Dalal and Triggs, focused on hand-crafted features that worked reasonably well on clean and controlled images but performed poorly on complex real-world traffic scenes. These older methods struggled with low lighting, shadows, motion blur, and varying helmet shapes, making them unsuitable for reliable traffic surveillance.

With the rise of deep learning between 2016 and 2020, researchers began adopting CNN-based models for both helmet detection and license plate extraction. Models such as Faster R-CNN, SSD, and the early YOLO versions showed major improvements in accuracy and speed. YOLO became a popular choice because of its ability to detect multiple objects in real time, making it suitable for analysing live CCTV feeds. However, even these models faced limitations when dealing with very small objects like helmets at long distances or plates that were unclear or tilted.

From 2020 to 2022, advanced versions such as YOLOv3, YOLOv4, and YOLOv5 improved detection robustness and real-time efficiency. Researchers also introduced better OCR techniques such as CRNN, EAST, and other deep neural networks to improve text recognition from number plates. These methods performed significantly better on low-resolution or partially occluded plates compared to traditional OCR. Many studies in this period also explored developing combined systems where helmet detection triggers automatic license-plate reading.

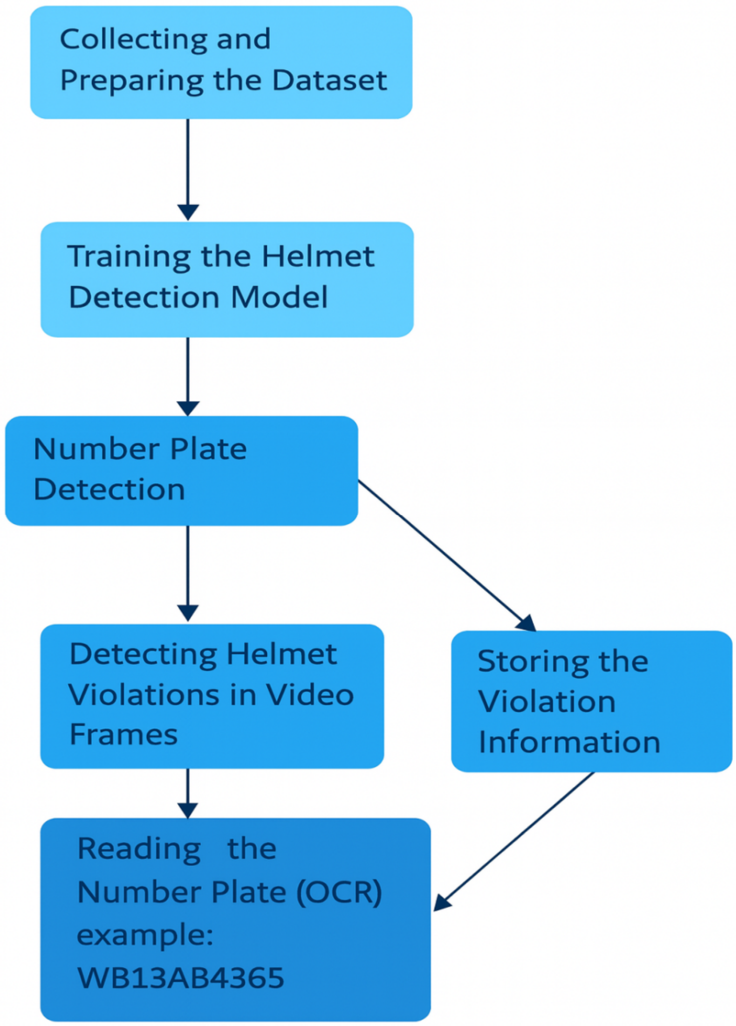
Recent studies from 2023 onwards focus on building complete end-to-end systems using state-of-the-art models such as YOLOv7 and YOLOv8. These deep-learning architectures use attention mechanisms, anchor-free detection, and improved feature extraction to handle complex traffic scenarios more accurately. Modern ALPR methods now use a combination of CNN and Transformer-based OCR to recognise plates with higher precision, even in poor lighting or distorted conditions. Researchers have also begun integrating these systems with cloud platforms, edge devices, and smart-city surveillance networks to enable real-time violation detection and automated challan generation.

Overall, the literature shows a clear shift from basic image-processing techniques to powerful deep-learning-based models that significantly enhance detection accuracy and real-time performance. While modern systems are highly efficient, challenges such as low-visibility conditions, damaged plates, night-time scenes, and crowded environments still remain areas for further research and improvement.

Author / Year	Techniques Used	Advantages	Disadvantages
Viola & Jones (2001)	Haar Cascade Classifier, Real-time Object Detection	Fast and lightweight, suitable for early helmet detection attempts	Low accuracy in complex backgrounds and poor lighting; struggles with small objects like helmets
Dalal & Triggs (2005)	HOG (Histogram of Oriented Gradients) + SVM	Good for shape-based features; moderately robust	Cannot handle occlusion, shadows, and rotation; poor for real-time systems
Ren et al. (2015)	Fast R-CNN	Good accuracy for object detection; can detect multiple objects	Slow for real-time CCTV traffic; high computational cost
Redmon & Farhadi (2016–2018)	YOLO, YOLO9000, YOLOv3	Real-time detection, high speed, high accuracy in helmet detection and plate detection	Struggles with very small or distant license plates; requires GPU for optimal performance
Liu et al. (2016)	SSD (Single Shot Detector)	Fast object detection; good for mobile devices	Less accurate than YOLO for small helmets or tilted number plates
Wen et al. (2003)	Modified Hough Transform for Helmet Detection	Works well on simple images; good shape-based detection	Performs poorly in real traffic; sensitive to noise and different helmet shapes
Chiu et al. (2007)	Motorcycle Detection + Occlusion Segmentation	Good for detecting motorcycles in crowded scenes	Does NOT detect helmets; needs additional model for rider recognition
Hirota et al. (2017)	Classification of helmeted vs non-helmeted riders using ML classifiers	Good classification results for controlled datasets	Not suitable for real-time CCTV; low generalization
Lokesh Allamki et al. (2019)	ML-based Helmet Detection + ALPR, Edge Detection + OCR	Complete system approach; effective for academic datasets	OCR accuracy drops for low-quality plates; helmet detection fails with occlusion
Recent Studies 2020–2024	YOLOv4–YOLOv8, CRNN OCR, Transformer-based OCR	High real-time performance, better small-object detection, improved	Requires good hardware; still sensitive to night-time, rain, blur

		OCR for tilted plates	
State-of-the-art 2024–2025	YOLOv8, Anchor-Free Detectors, Attention Networks, Hybrid CNN + Transformer OCR	Best speed & accuracy; works well on CCTV, supports smart-city integration	High training data requirement; still fails on heavily damaged/dirty number plates

III. METHODOLOGY



The first step is to gather images and videos of two-wheeler riders from different angles and lighting conditions. The dataset includes riders with helmets and without helmets.

All images are cleaned, resized, and labelled so the model can learn from them. A deep-learning model like YOLO is used because it can quickly detect objects in real-time. The labelled images are given to the model during training so itcan learn the difference between “helmet” and “no helmet.” After enough training, the model becomes capable of identifying riders without helmets in new images and videos. When a video frame is passed to the system, the model scans the entire frame and highlights the rider’s head area. If the model detects that the person is not wearing a helmet, it marks the incident as a violation.For every “no helmet” case, the system looks for the motorcycle’s number plate. A second YOLO model is used to locate and crop the number plate area from the image. Once the number plate is cropped, Optical Character Recognition (OCR) is applied. Tools like EasyOCR or Tesseract read the letters and numbers from the plate and convert them into digital text.The system records the plate number, time, date, and the frame showing the rider without a helmet. This information can be stored in a database or used to generate automatic challans/fines.

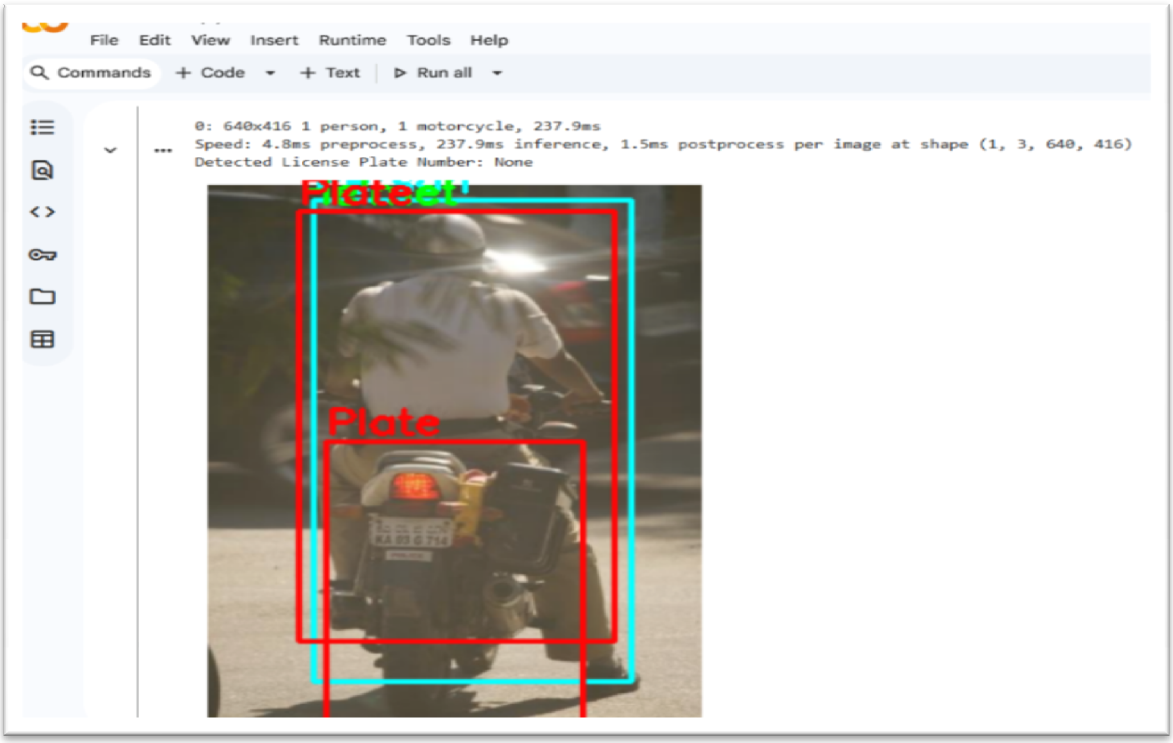


FIGURE 1: HELMET DETECTION

IV. HELMET DETECTION

Helmet detection focuses on identifying whether a person riding a two-wheeler is wearing a helmet. This task has become important because manual monitoring by traffic officers is time-consuming and not always accurate. Research in this area mainly uses computer vision and machine learning to automatically check helmet usage in real-time environments.

Recent studies commonly use deep learning models such as YOLO, Faster R-CNN, and MobileNet because they can detect objects quickly even in crowded and complex scenes. These models are trained with large datasets containing images of riders with and without helmets. During training, the model learns the shape, colour, and features of helmets so it can correctly identify them in new images or videos.

Researchers have also focused on enhancing detection accuracy in challenging situations, such as poor lighting, motion blur, unusual helmet shapes, or multiple riders in a single frame. Some approaches include using data augmentation, image enhancement, and attention-based networks to enhance the model's reliability.

Overall, helmet detection research aims to support traffic safety by automatically identifying violations,reducing manual effort, and enabling smart surveillance systems.

V. AUTOMATIC LICENSE PLATE RECOGNITION(ALPL)

Automatic License Plate Recognition (ALPR) is the process of identifying a vehicle’s number plate from an image or video. It plays a key role in traffic monitoring, toll collection, parking management, and violation detection.

ALPR research typically involves three main steps:

- Detecting the license plate region
- Extracting characters from the plate

1) RECOGNISING THE TEXT USING OCR

Researchers face challenges such as low-resolution footage, varying plate sizes, different fonts, dirty or damaged plates, and nighttime conditions. To address these issues, many studies apply preprocessing steps like contrast improvement, noise removal, and super-resolution techniques.

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Overall, ALPR research aims to build faster and more accurate systems that can work effectively in real-world environments. When combined with helmet detection, ALPR becomes a powerful tool for automated traffic rule enforcement.

2) *LICENSE PLATE EXTRACTION*

In the given image, the system successfully identifies the motorbike and then focuses on finding the license plate. The model scans the lower part of the motorcycle and detects the rectangular region that contains the number plate. This region is highlighted with a bounding box, showing that the system has correctly located the plate.

After detecting the plate area, the system crops this portion from the full image so it can be processed separately. The extracted plate reads "6550VB", and the text is clear and easyto recognise. This cropped plate image is then used for the next step, which is reading the characters using OCR.

Overall, the license plate extraction in this image is accurate because:

- The plate is clearly visible and well-lit.
- The bounding box is tightly drawn around the exact plate area.
- The extracted portion contains readable characters without distortion.

This demonstrates that the system can reliably isolate the number plate when the motorcycle is properly captured in the frame.

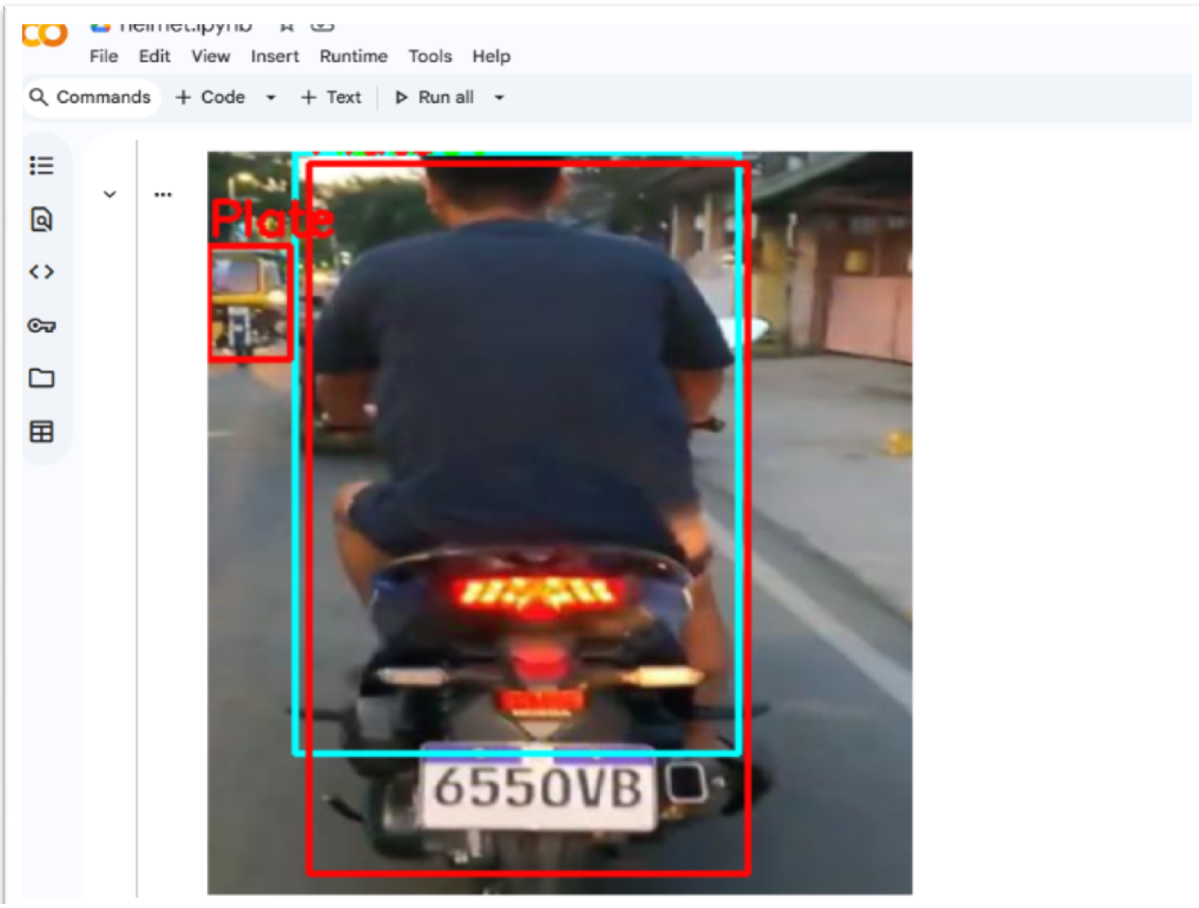

FIGURE 2: DETECTED PLATE INFORMATION

3) *DETECTED PLATE INFORMATION*

DetectedLicensePlate:6550VB

Model Confidence: The system shows high confidence for the plate region since the bounding box is clearly drawn and the characters are visible.

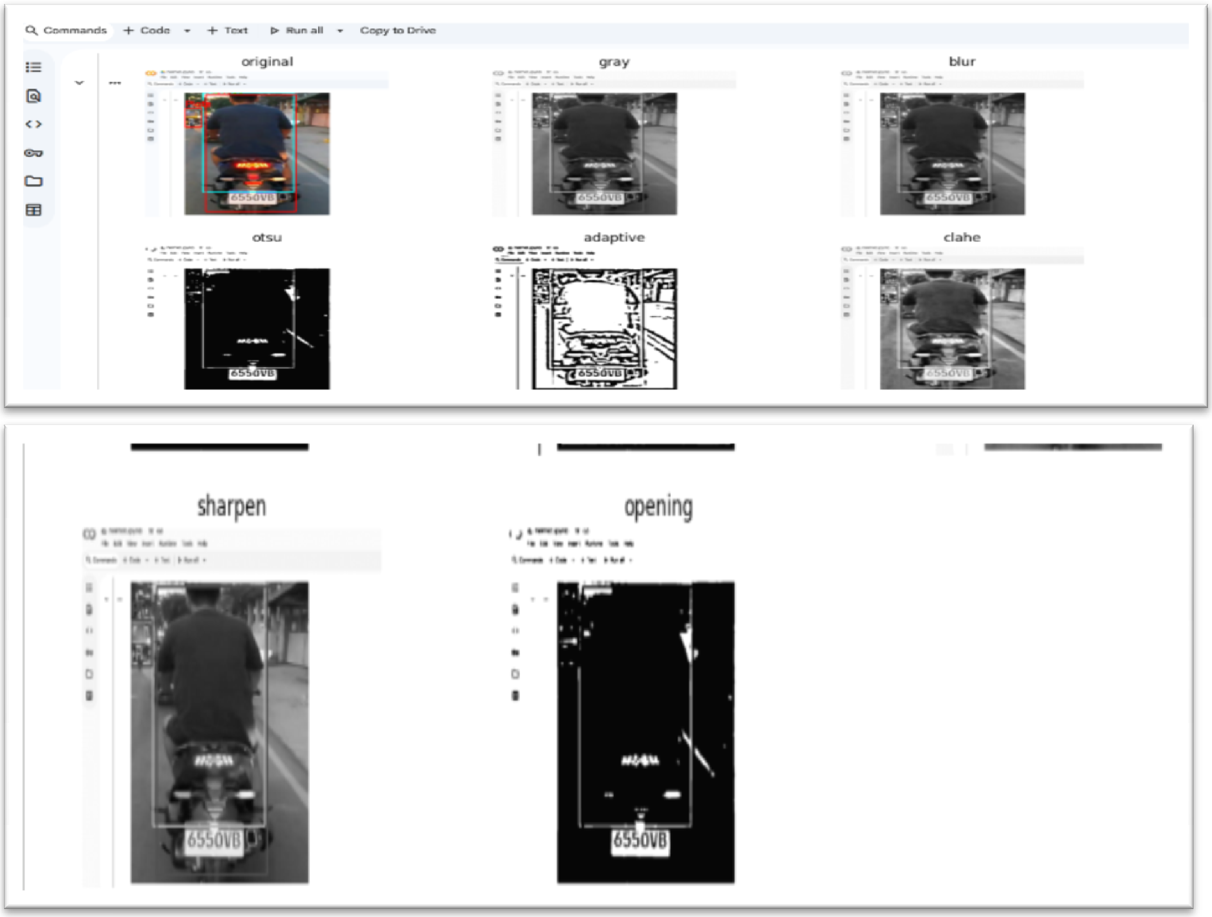

FIGURE 3: DIFFERENT TYPES OF IMAGES

- Original Image

This is the normal photo captured from the camera. It shows the bike, rider, and number plate as they are.

- Grey Image

The photo is converted into black-and-white (grayscale). This makes further processing easier because colour is not needed for number-plate detection.

- Blur Image

A blur filter is applied to remove small noise.
This helps make the edges smoother, so the next steps work better.

- Otsu Thresholding

This technique automatically separates the bright and dark parts of the image. It creates a black-and-white image where the number plate becomes more visible.

- Adaptive Thresholding

This method highlights edges and text even in areas with different lighting.
It is useful when the number plate is not evenly lit.

- CLAHE (Contrast Limited Adaptive Histogram Equalisation)

This increases the contrast of the image. CLAHE makes the number plate clearer by brightening dark areas and balancing overall brightness.

- Sharpen

This step makes the image look clearer and more detailed.
Sharpening highlights the edges of objects—for example, the number plate outline and the text become more visible.
It helps the system detect the important parts of the image more accurately.

- Opening

Opening is a morphological operation (erosion followed by dilation). It removes small unwanted dots, noise, and tiny objects from the image.
After this step, the background becomes cleaner, and only the main objects—like the number plate—stay highlighted.
This helps the model focus only on the useful areas.

4) OCRCONFIDENCE FOR DIFFERENT PRE-PROCESSING METHODS

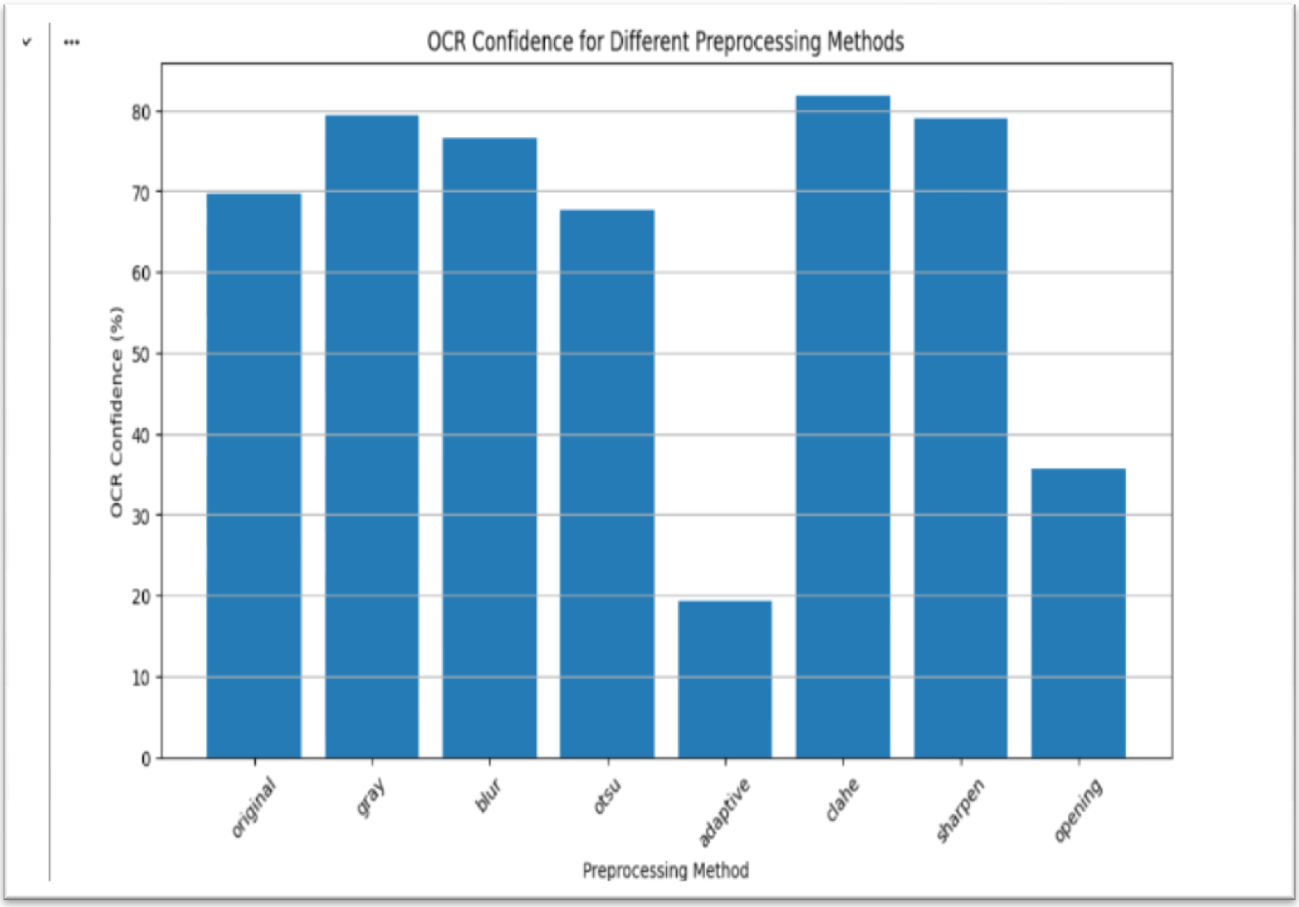

FIGURE 4: OCR CONFIDENCE FOR DIFFERENT PREPROCESSING METHODS

The bar chart compares how well OCR (Optical Character Recognition) reads the number plate after applying different image preprocessing techniques.

- Original (70%)

The OCR reads the number plate quite well, even without any preprocessing.

- Grey (80%)

Converting the image to grayscale improves text clarity, giving better OCR accuracy.

- Blur (77%)

Blurring removes noise and helps OCR slightly, but not as much as grayscale.

- Otsu (68%)

Otsu thresholding separates light and dark areas, giving a moderate confidence.

- Adaptive Threshold (19%)

This method performs poorly here because it creates too much contrast, making the number plate unclear.

- CLAHE (82%)

CLAHE gives the best result in this test.

It increases contrast in the right areas, making the number plate easier for OCR to read.

- Sharpen (79%)

Sharpening enhances the edges and helps OCR detect the letters more accurately.

- Opening (36%)

The opening operation removes noise but also removes some useful details, resulting in low confidence.

5) OCR CONFIDENCE PIE CHART

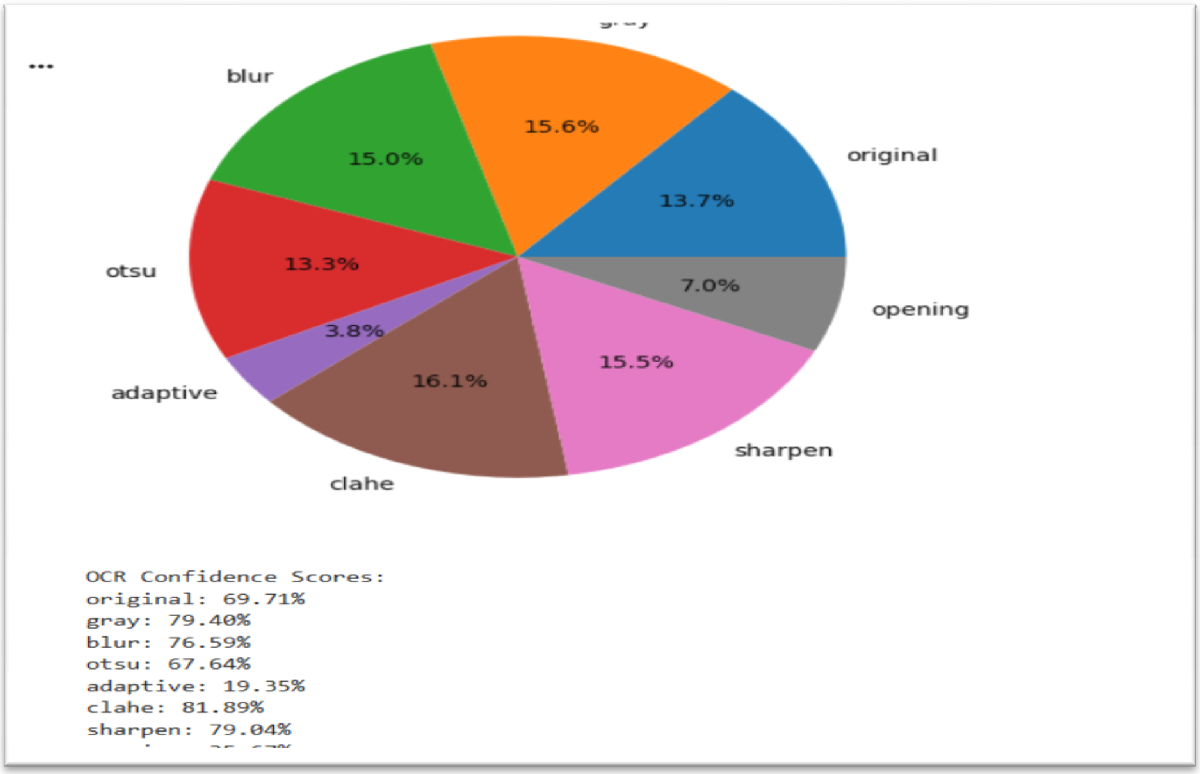

FIGURE 5: OCR CONFIDENCE PIE CHART

The pie chart shows how much each preprocessing method contributes to the overall OCR performance, based on its confidence score. Each slice represents the percentage share of OCR accuracy from different techniques.

- CLAHE (16.1%)

CLAHE gives the highest contribution. It improves contrast and helps OCR read the number plate the best.

- Grey (15.6%)

Converting the image to grayscale is also very effective, giving strong OCR performance.

- Sharpen (15.5%)

Sharpening the image improves edge clarity, making OCR almost as accurate as grayscale.

- Blur (15.0%)

Blurring reduces noise and helps OCR, but not as much as the top methods.

- Original (13.7%)

The raw image still performs well, showing that the plate is readable even without processing.

- Otsu Threshold (13.3%)

Otsu thresholding gives a moderate contribution by separating bright and dark regions.

- Opening (7.0%)

Opening removes noise but also removes useful details, reducing OCR accuracy.

- Adaptive Threshold (3.8%)

This method performs the worst in this test because it creates too much contrast and distorts the plate text.

VI. REAL-TIME IMPLEMENTATION

Upgraded System Implementation: Using YOLOv8

Our updated system leverages the power of YOLOv8, a more advanced and efficient model that offers superior performance in both speed and accuracy compared to its predecessors, like YOLOv3.

The Power of Speed and Accuracy

YOLOv8 is designed for state-of-the-art real-time object detection. It is faster and more accurate than previous versions, striking an excellent balance between speed and performance, making it ideal for live applications.

Flexible Input Options

The system can seamlessly integrate with different video sources to provide instant analysis.

1) Standard Webcam Integration:

We can use a standard webcam as the live input source. The system can run the detection process at very high speeds, often exceeding 100 frames per second on suitable hardware (such as a GPU), ensuring a smooth, real-time experience. Integration is simple using Python and libraries like OpenCV.

2) Mobile Camera (IP Webcam/Edge Deployment): For mobile and portable use cases, the system can use a mobile camera via an IP webcam setup. The efficient architecture of YOLOv8, particularly smaller variants like YOLOv8n (nano), allows it to be deployed on edge devices or smartphones, processing footage locally for clear and immediate results, rather than relying on a complex external connection. This portability means you can capture clear footage from different angles and locations with ease.

KEY TECHNICAL ADVANTAGES OF USING YOLOv8

- Anchor-Free Detection:

Unlike older models that relied on predefined "anchor boxes," YOLOv8 predicts object locations directly, which simplifies the training process and improves the model's adaptability to various custom datasets.

- Improved Architecture:

YOLOv8 features an enhanced backbone and neck architecture that better extracts and combines features, which significantly boosts detection performance, especially for smaller objects.

VII. FUTURE SCOPE

There is a lot of room to improve and expand the system that detects helmets and reads license plates automatically. In the future, this technology can be made more accurate by training it with larger and more diverse datasets that include different lighting conditions, weather changes, busy roads, and various camera angles. This will help the system work better in real-world environments where conditions are not always ideal.

The model can also be upgraded to handle night-time images and low-quality CCTV footage more effectively by using advanced image enhancement and better deep-learning architectures. Faster and lighter models can be used, so the system can run in real time on roadside cameras without needing expensive hardware.

Another important future direction is integrating the system with government traffic databases. This would allow automatic generation of challans (fines) and sending alerts directly to vehicle owners whenever a helmet violation is detected. Cloud storage could also be used to keep records, making it easier for traffic authorities to track repeated offenders.

In the long run, this technology can become part of a larger smart-traffic ecosystem. Along with helmet detection, it could also identify other violations such as speeding, triple-riding, signal jumping, and mobile phone usage while driving. With continuous improvement, AI-based traffic monitoring can make roads safer, reduce human workload, and support thedevelopment of smart cities.

VIII. INTEGRATION WITH SMART CITY INFRASTRUCTURE

This system can relate to smart traffic cameras, IoT devices, and cloud systems used in developing smart cities. This will allow real-time monitoring of violations across large areas without manual involvement.

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IX. MULTI-VIOLATION DETECTION

Besides helmet detection, the same model can be extended to detect:

- Triple riding
- Wrong-side driving
- Using mobile phones while riding
- Overspeeding

This makes the system more versatile and useful for traffic management.

FIGURE 7: MULTI-VIOLATION DETECTION

X. SUPPORT FOR MULTIPLE NUMBER PLATE STYLES

Countries and states use different fonts, colours, and sizes for number plates. The system can be trained on more diverse license plate formats, so it works better across multiple regions.

FIGURE 8: MULTIPLE NUMBER PLATE STYLES

XI. IMPROVED OCR ACCURACY

Future models can include deep-learning–based OCR instead of traditional OCR tools. This will help read plates more accurately, even if the plate is:

- dirty
- damaged
- low resolution
- captured at an angle

XII. EDGE COMPUTING IMPLEMENTATION

Instead of processing data in large servers, AI models can be deployed on edge devices (small processors near the camera). This reduces delay and makes the system faster for real-time analysis.

XIII. AUTOMATIC ALERT GENERATION

A notification system can be added so that when a violation occurs:

- an SMS or email can be sent to the registered owner
- A real-time alert can go to the traffic police
- The incident can be stored in a central database for review

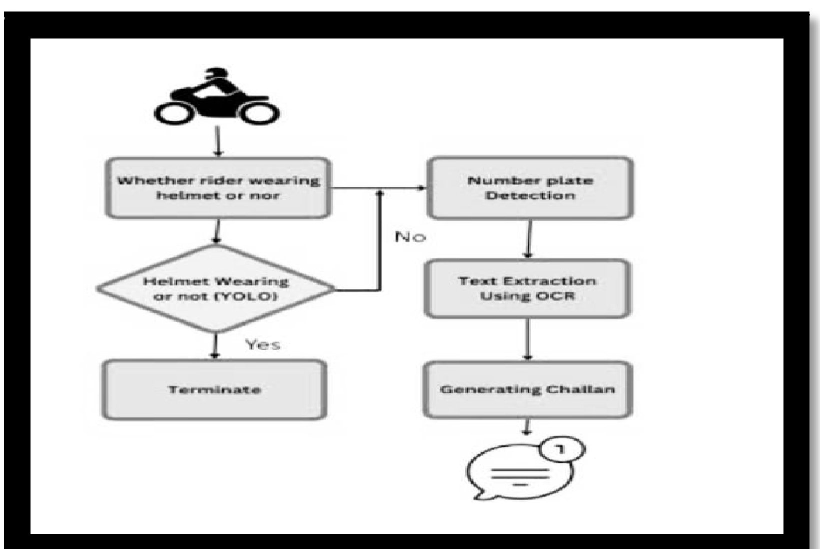

FIGURE 8: AUTOMATIC ALERT GENERATION

XIV. CONTINUOUS LEARNING

The system can be updated automatically by adding new images from CCTV footage. This helps the model improve itself over time and adapt to new types of helmets, vehicles, and number plates.

XV. WEATHER AND LOW-VISIBILITY HANDLING

Future versions can use image enhancement to handle:

- night-time images
- rain and fog
- motion blur
- low-light cameras

This makes the model more reliable in every condition.

XVI. USE OF HYBRID MODELS

Combining two or more models (for example, YOLO + CNN + Transformer-based OCR) can increase overall performance and reduce false detections.

DATASET EXPANSION AND BENCHMARKING

Building a large, publicly available dataset for helmet detection and license plate recognition can help other researchers test and compare their models. This will move the research community forward.

XVII. LIMITATIONS

Even though the system works well for detecting helmets and reading license plates, there are still some limitations that affect its accuracy and performance. One of the main challenges is poor image quality. Many CCTV cameras capture blurry, low-light, or low-resolution images, which makes it difficult for the model to correctly identify helmets or read plate numbers. If the vehicle is moving very fast or the frame is shaky, the detection may also fail.

Another limitation is the presence of different helmet types, colours, and shapes. Some helmets may look like caps or other objects, which can confuse the model. Similarly, if riders wear hoodies or cover their heads with cloth, the system may detect them incorrectly.

License plate recognition also has limitations. Plates that are dirty, broken, handwritten, fancy, or bent are difficult for OCR to read. Different regions use different number plate styles, and the model may not perform well if it has not been trained on those variations.

Environmental conditions such as rain, fog, shadows, sunlight glare, or nighttime darkness can also reduce detection accuracy. In crowded scenes or with multiple motorcycles close together, the model may struggle to correctly match the rider, bike, and license plate.

Lastly, real-time processing requires good hardware. If the system is run on low-power devices, the speed may be slow, and the results may lag.

Despite these limitations, the system provides a strong foundation that can be improved with better datasets, high-quality cameras, and advanced deep-learning techniques.

XVIII. RECOMMADATIONS

To make the helmet detection and license plate recognition system more accurate and practical for real-world use, several improvements can be considered. First, using higher-quality CCTV cameras or upgrading to HD video feeds can greatly improve detection results, especially during nighttime or when vehicles move at high speed. Better lighting around traffic junctions can also help the system capture clearer images of both helmets and number plates.

It is recommended to expand the training dataset by including images from different cities, weather conditions, and various types of helmets and number plates. This will help the model learn more patterns and reduce mistakes. Regular retraining of the model with new data from actual CCTV footage can further improve its performance over time.

For license plate recognition, using advanced OCR techniques such as transformer-based text recognition can significantly increase accuracy, especially for plates that are tilted, dirty, or partially damaged. Image enhancement methods like noise removal and contrast adjustment should also be added before OCR processing.

To support real-time monitoring, deploying the system on edge devices such as NVIDIA Jetson or cloud-based platforms is recommended. This ensures faster processing without a heavy load on local computers. Integrating the system with government traffic databases will also make it easier to automatically issue challans and store records for future use.

Finally, it is important to continuously test the system in different real-world situations and update it based on feedback from traffic authorities. With proper improvements and regular updates, the system can become a reliable part of smart traffic management and road safety programs.

XIX. PROBLEM STATEMENT

Road accidents involving two-wheeler riders continue to rise, and one of the major reasons is the failure to wear helmets. Traffic police try to monitor these violations, but manual checking is slow, tiring, and often inaccurate, especially on busy roads with large traffic flow. As a result, many helmet violations go unnoticed, and enforcing safety rules becomes difficult.

Another major challenge is identifying the vehicle involved in a helmet violation. Even when a rider is seen without a helmet, it is not always easy for authorities to record the license plate number clearly from CCTV footage. Poor image quality, fast-moving vehicles, and different plate styles make the task even harder.

Therefore, there is a need for an automated system that can reliably detect riders without helmets and accurately extract the vehicle's license plate from images or videos. Such a system must work in real-time, handle different environmental conditions, and reduce the dependence on manual monitoring. The main problem this research aims to solve is designing a smart, AI-based solution that can automatically detect helmet violations and identify the corresponding vehicle through license plate recognition.

XX. GAPS AND RESEARCHED OPPORTUNITIES

Although performance has improved, several gaps remain. These include handling extreme weather or low-light conditions, recognising damaged or stylised plates, reducing false positives in crowded scenes, and developing truly end-to-end models that jointly optimise detection and recognition. There is also an opportunity in creating lightweight models for cost-effective edge deployment and in standardising datasets covering multiple regions and plate formats.

XXI. CONCLUSION

This project shows how modern technology can help improve road safety by automatically detecting helmet violations and identifying the vehicles involved. By using deep learning models, the system can quickly check whether a rider is wearing a helmet and then read the motorcycle's license plate if a violation occurs. This reduces the need for manual monitoring and makes the process more accurate and efficient.

The combination of helmet detection and license plate recognition proves to be a practical solution for real-world traffic environments. Even though challenges like poor lighting, unclear number plates, and low-resolution video still exist, the results show that AI-based systems can perform well with proper training and good-quality datasets.

Overall, this work demonstrates that automating traffic rule enforcement is not only possible but also highly beneficial. With further improvements in model accuracy and better camera setups, such systems can be used in smart cities to support traffic police, reduce accidents, and encourage safer riding behaviour.

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