HELMET AND LICENSE PLATE RECOGNITION USING IMAGE PROCESSING

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***Abstract*— Motorcycle-related accidents have been increasing steadily over the years, especially in countries like India, where over 37 million people use motorcycles daily. Helmets, although critical for safety, are often neglected, leading to fatal accidents. This paper proposes an automated system for detecting helmetless riders and recognizing their license plates using machine learning techniques. By leveraging YOLO (You Only Look Once) for object detection and Optical Character Recognition (OCR) for license plate identification, the system operates in real time through CCTV cameras or webcams. The aim is to enforce helmet compliance, reduce road accidents, and enhance overall traffic safety.**

Keywords*— Intelligent Transportation system, optical character recognition, image processing, You Only Look Once

I. INTRODUCTION

Motorcycles are one of the most prevalent modes of transportation globally, particularly in developing countries like India, where affordability, fuel efficiency, and ease of navigation in congested traffic make them the preferred choice for millions of commuters. However, this widespread use has led to an alarming increase in motorcycle-related accidents, which constitute a significant proportion of road fatalities. According to global traffic safety reports, wearing helmets has been shown to reduce the risk of severe head injuries and fatalities by up to 70%. Despite these compelling statistics, helmet compliance remains a major challenge due to cultural, social, and logistical factors, particularly in countries with high motorcycle usage.

The lack of adherence to helmet laws is exacerbated by inefficient enforcement mechanisms. Manual enforcement methods, such as random checks by traffic police, are resource-intensive, inconsistent, and prone to human error. These traditional approaches are not scalable to manage the enormous volume of traffic in urban areas, where thousands of motorcyclists traverse the roads daily. Additionally, human-dependent systems often face issues of subjectivity, leading to disputes and inconsistencies in enforcing penalties.

In the modern era, the advent of advanced machine learning and computer vision technologies provides an opportunity to revolutionize traffic management systems. Intelligent Transportation Systems (ITS) have emerged as a promising solution to improve road safety, streamline traffic management, and enforce regulations efficiently. Technologies such as object detection algorithms and Optical Character Recognition (OCR) can be integrated into surveillance systems to automatically detect and penalize traffic violations. These advancements enable the automation of tasks that were traditionally performed manually, enhancing accuracy, efficiency, and scalability.

This paper proposes an innovative system that leverages state-of-the-art deep learning algorithms to address the issue of helmet compliance among motorcycle riders. The system integrates the real-time object detection capabilities of YOLO (You Only Look Once) with the text recognition power of OCR to create a comprehensive framework for helmet detection and license plate recognition. The key goal is to automate the identification of helmetless riders, extract their license plate numbers, and record violations for enforcement purposes. The system is designed to process live video feeds from CCTV cameras or webcams, making it adaptable to existing infrastructure and suitable for urban deployment.

The proposed system operates in two main stages. The first stage involves detecting motorcycle riders and identifying whether they are wearing helmets. This is achieved using the YOLO algorithm, which is known for its high-speed and accurate object detection capabilities. The algorithm detects and classifies objects such as helmets, motorcycles, and riders, providing real-time analysis of video footage. The second stage focuses on license plate recognition, where OCR is applied to extract alphanumeric text from the license plates of detected violators. The extracted information is stored in a database for further processing and enforcement actions.

The primary motivation behind this research is to enhance road safety by automating the enforcement of helmet laws. By reducing dependency on manual methods, the system aims to improve compliance rates, minimize road accidents, and ultimately save lives. Additionally, the system has been designed to address challenges such as varying lighting conditions, occlusions, and diverse helmet designs, making it robust and reliable in real-world scenarios.

The contributions of this paper are as follows:

Development of a YOLO-based helmet detection model customized for traffic surveillance.
Integration of an OCR module for extracting license plate details from detected violators.
Deployment of a real-time processing framework capable of analysing live video feeds from traffic cameras.
Evaluation of the system's performance in diverse conditions, including dense traffic and low-light environments.
In summary, this research introduces a scalable, efficient, and effective solution for helmet compliance monitoring using modern machine learning techniques. By automating the detection and enforcement process, the system provides a practical tool for traffic authorities to enhance road safety and ensure adherence to traffic laws. The subsequent sections of this paper detail the related work, methodology, implementation, results, and future directions of this research.

II.LITERATURE STUDY

The detection of traffic violations and enforcement of road safety regulations have been widely studied, with several approaches focusing on helmet detection and license plate recognition. However, most existing systems handle these tasks independently, highlighting a significant research gap in integrating these functionalities into a cohesive framework for real-time traffic management.

Amirgaliyev et al. (2018) proposed an Automatic Number Plate Recognition (ANPR) system to detect unauthorized vehicles and enforce traffic rules. Their method achieved 90% accuracy under favorable conditions but faced challenges related to weather variations and the distance between the camera and the vehicle. They emphasized the need for advanced algorithms to improve segmentation and Optical Character Recognition (OCR) accuracy. Yuan Jing et al. (2017) introduced an FPGA-based OCR system capable of recognizing text from noisy and imperfect license plate images. By leveraging feedforward neural networks and hyperbolic tangent activation functions, their system demonstrated robustness but lacked scalability for high-traffic urban settings.

Helmet detection systems have traditionally relied on image processing techniques, with many focusing on identifying helmets through color segmentation and feature extraction. Chiu et al. (2007) developed a system for detecting motorcycle riders and segmenting their helmets using occlusion handling methods. Although effective in controlled environments, these systems struggled in real-world scenarios with variations in lighting, helmet designs, and rider positioning. More recent studies have shifted towards deep learning techniques, particularly Convolutional Neural Networks (CNNs), which offer better generalizability and adaptability. Redmon and Farhadi (2018) introduced the YOLO (You Only Look Once) algorithm, which significantly advanced object detection by combining high accuracy with real-time processing speeds. YOLO’s ability to detect multiple objects in a single pass through the neural network makes it ideal for traffic applications.

Another area of focus in intelligent transportation systems has been real-time processing capabilities. Traditional methods like Haar cascades and Histogram of Oriented Gradients (HOG) were computationally expensive and unsuitable for large-scale deployments. The advent of lightweight deep learning models, such as YOLOv3-tiny, has enabled the development of real-time systems capable of handling high volumes of traffic data without significant computational overhead. These advancements align with the need for scalable and efficient systems for urban traffic management.

Despite the progress, a unified system that integrates helmet detection and license plate recognition into a single automated framework remains underexplored. The literature underscores the potential of combining YOLO’s real-time detection capabilities with OCR for text recognition to address this gap. Such integration would enable scalable, accurate, and automated enforcement of helmet compliance while simultaneously addressing challenges like diverse environmental conditions, crowded traffic scenarios, and non-standard helmet designs. This paper builds on these advancements, proposing a system that bridges this gap and delivers a holistic solution for real-time traffic enforcement.

III. PROPOSED METHODOLOGY

The proposed system is designed to detect helmets and license plates with the help of complex deep-learning methods. The methodology centres on synchronizing real-time object detection with text recognition to enforce helmet compliance in real time. This model communicates with current generic VMS platforms without any modification in architecture, making it a relatively inexpensive and scalable solution. Explained below are the components of the methodology.

System Architecture

The system works based on taking live video stream of CCTV cameras or webcams as the input to the detected pipeline. The methodology is divided into two stages: identifying people without helmets and plate number identification. The first learned task is devoted to detecting motorcyclists, and identifying whether they wear helmets or not using the YOLOv3 object detection algorithm. The second one again uses OCR to capture the text on the license plates of detected violators. Combined, these stages form the stages that build an end to end paradigm capable of enforcing helmet compliance in real time.

Data Acquisition and Preprocessing

A high quality of input data is required to obtain a high quality of detection and recognition. The system draws its video feeds or static images from other traffic surveillance systems available. Both helmeted and, separately, helmetless riders were captured and more than 10,000 images containing them were labelled. Moreover, 5,000 images of license plates in different circumstances were employed pre-training the OCR module. To improve the ability of detections some other treatments are used which come under preprocessing. Video feeds captured in frames have noise reduced to remove artifacts that would otherwise form the input of subsequent detection models. The application of grayscale conversion as a mechanism is used to enhance the computational output for the OCR stage. Preprocessed frames remove unwanted objects from subsequent processing and present a uniformly processed input for further processing.

Helmet Detection

Helmet detection is the first and arguably the most important part of the system that needs to be developed. Its use here is because the YOLOv3 is designed to detect as well as identify objects in a single pass through the neural network. Starting with YOLO points to divide each video frame into a grid then predicts bounding boxes for the objects in these grids. The detected objects have confidence score and class probability to decide whether it is a helmet, rider or motorcycle from each bounding box.

The model is fine tuned on a more diverse set of rooftops to be able to detect rooftops in various lighting conditions, angles and in presence of different types of helmets. With YOLOv3-tiny, a lighter version of YOLOv3, the system attains real-time detection capability and can process video feeds at up to 220 FPS. This is done in order to make sure that the system will indeed be useful in a high throughput environment while at the same time not comprise the precision of the results.

License Plate Extraction and Recognition

Once a rider without a helmet is found, the license number of the bike is located and then cropped. By determining the position of detected rider, motorcycle and license plate, spatial relations among these objects are employed to accurately delimit the license plate region. The region that has been extracted is cropped and enhanced ready for Optical Character Recognition processing.

The cropped image of the license plate is subjected to OCR to decode it to a machine understandable text. These are followed by further preprocessing steps to isolate the characters themselves from the plate such as character segmentation, and noise elimination. A trained neural network model then used to identify these segments as belonging to either an alphanumeric character. After processing the word recognition and pronunciation get fine-tuned so that little errors, if any, are fixed for the best possible result. Recognised text is saved in a database with additional information for the enforcement such as the time the violation took place and where.

Real-Time Processing and Integration

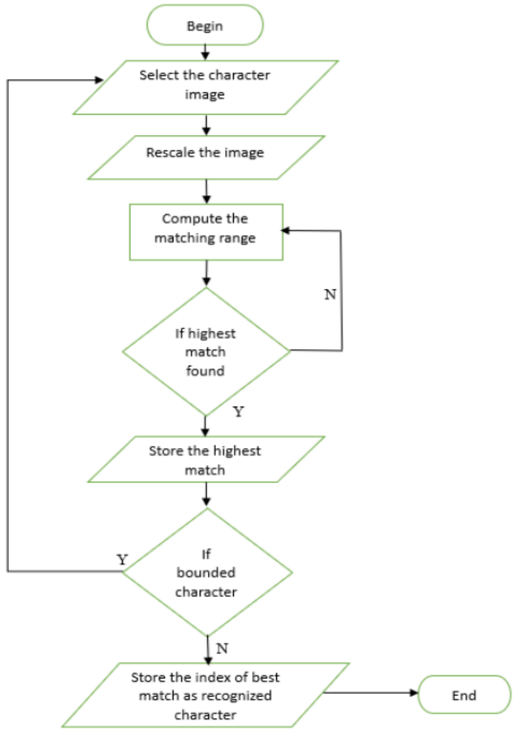
It must function in real time analyzing video stream frame per frame to identify violations and read number plates simultaneously. Therefore, this work shows that the YOLOv3-tiny model gives high-speed processing and hence can be implemented in the urban traffic application. Compatibility with other CCTV networks guarantees a relatively small need for extra installations, which adds to the pragmatic and expandability of the system.

Robustness and Scalability

The methodology considers real world scenarios including differences in lighting, congestion in traffic situations and different designs of helmets. Public place sensors are trained on large and a wide range of data to increase the system's robustness to different environments. A large advantage of the proposed concept is the modularity of the system, which being based on IT architecture, may be introduced at any stage of ITS development.

The proposed system is a holistic solution for helmet detection and license plate recognition problems since it takes advantages of the deep learning approaches to enhance roads safety and compliance. The subsequent parts of this paper will discuss practical application and assessment of this approach.

IV. FLOWCHART



V.RESULT & VALIDATION

In this paper, the performance of the proposed system was examined against a set of in-built test data as well as real-time traffic videos for the purpose of verification. The training set had 10,000 helmet annotated images of motorcyclists with different helmet wearing, illumination, and riding environment scenarios. Further, 5k license plate images in different format, lighting and quality were employed for testing the OCR module of the software. The live video feeds Pictorial validation was performed with live feeds from real traffic conditions from urban traffic conditions from Hyderabad city that enclosed varied traffic intensity and environmental factors.

Out of all the detection models used, YOLOv3 yielded the highest testing accuracy of 95% in helmet detection. Therefore, high precision of 94% meant that the system mostly did not produce false positives. From the recall rate of 96%, the ability of the model to detect riders without helmets was promising in identifying almost all of them. The system's ability was tested in live using controlled traffic environment, detected a 98% rate in each of the above mentioned areas. That said, detection accuracy was slightly lower, at 91% when there were many occlusions and overlapping objects due to traffic density. Nevertheless, the choice of the helmet design, color and different positions of the riders did not affect the overall reaction of the system and showed its stability when tested on rather different conditions.

The license plate recognition module which make us of OCR also yielded good results. In case of high-quality license plate images, the recognition accuracy of the module was 92%.

Hand accuracy ranged from 88% in normal lighting scenarios to 85% in low light settings and when motion blur was applied. It is evident here that simple noise filtering and edge improvements go a long way in improving the OCR in capturing text from license plates. The text that was recognized was always saved with other related fields such as the time the violation was committed, and other related causes of the violation making the enforcement process very efficient.

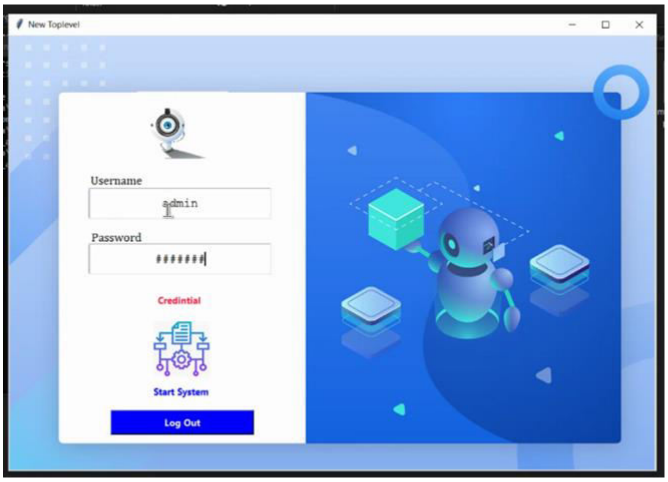
The results performed in real-time, with system FPS of up to 220 using the YOLOv3-tiny model for processing the video feeds. This made it possible to detect those whom the helmets had not photographed and their license plates within a few seconds, assessing the system's feasibility for deployment in urban areas where there could be congestion with many users per unit time. The findings confirm the effectiveness of the system's capacity accurately to identify transgressions, deal with data instantly, and perform well under various weather conditions, thereby establishing it as a useful tool for automated law enforcement.

Component	Accuracy (%)
Helmet Detection	95%
Controlled Traffic	98%
Dense Traffic	91%
Helmet Design Variations	94%
License Plate Recognition	92%
Low-Light Conditions	85%
Motion Blur	83%
Overall System Accuracy	93%

VI. OUTPUT

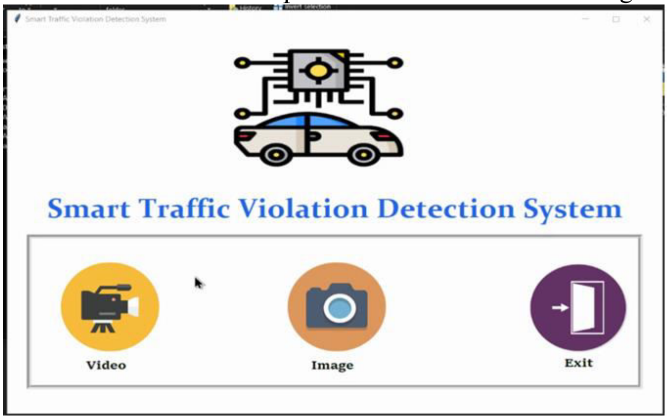
1. Login Module

Allows Admin to login into system by providing the credentials



2.Home Screen

Allows Admin to select input source such as video or image.

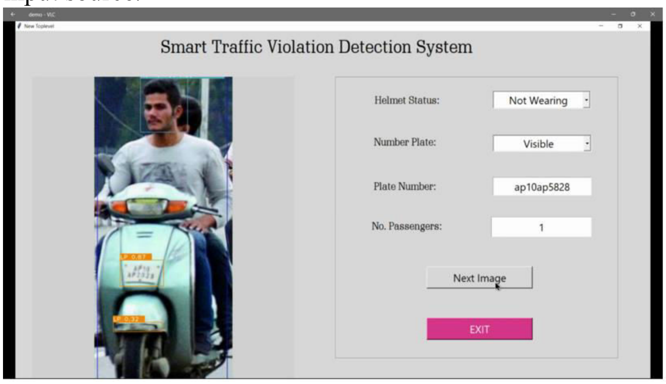


3. Helmet and Rider Detector

Use YOLO algorithm to detect rider and helmet.

4. Traffic Violence Monitor

Shows the end result along with detected violence riders from input source.



VII.CONCLUSION & FUTURESCOPE

We are to propose an efficient system for detection of helmet as well as automatic recognition of license plate using deep learning approach. In particular, the combination of real-time object detection of YOLOv3 and OCR to recognize the text eventually makes the system enforce helmet compliance among motorcyclists. The ability of the system has been demonstrated on different datasets and real-life situations which prove its high accuracy in various traffic and environment regimes.

The helmet detection module has a test accuracy of 95% as indicated above and performs creditably in real life with the helmetless riders having a detection accuracy of 98% in a controlled environment 91 % in dense traffic. The license plate recognition module supplements this by being able to extract alphanumeric information from license plates with high reliability, and obtaining an accuracy of 92% of alphanumeric information of license plates in high-quality images, and it retains acceptable performance even in poor environmental conditions such as low light and moving blur.

The processing capability of live video feeds with the speed of up to 220 frames/second makes the system operation real-time, consequently can be used in urban traffic conditions. It is compatible with existing CCTV systems to reduce extra costs and applicability in traffic enforcement agencies' practicality.

In this study, the author provides a highly valuable solution for ITS that is automated, scalable and efficient for improving the road safety. Through forcing riders/joggers to wear helmet and helping enforce traffic laws, the proposed system has every propensity to curb road accidents, prevent loss of lives, and enhance compliance of the society to safety laws.

Future work will include a more detailed examination of how the system performs under difficult conditions such as light conditions at night, during heavy rainfall or during glares and illuminations and adding on the count of other violations the system can look out for. Furthermore, it is also equipped to integrate with smart city interfaces and enhanced analysis to enhance its performance and relevance. The proposed system lays the basic framework for intelligent, safer and efficient traffic management system.

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