Project Report

On

"Hybrid Traffic Safety System"

IS SUBMITTED TO

SANT GADGE BABA AMRAVATI UNIVERSITY

IN THE PARTIAL FULFILLMENT OF THE DEGREE OF

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

BY

Mr. Jagrut M. Thakare **Mr. Yogesh P. Bawankar**

Mr. Atharva R. Bhuyar **Mr. Sarang V. Khode**

Ms. Tanuja M. Deshpande

GUIDED BY

Prof. A. P. Ghatol

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

(ACCREDITED BY NBA)

SIPNA COLLEGE OF ENGINEERING AND TECHNOLOGY, AMRAVATI

(AN ISO 9001:2015 CERTIFIED INSTITUTE & NAAC ACCREDITED)

SANT GADGE BABA AMRAVATI UNIVERSITY, AMRAVATI

2024-2025

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Sipna College of Engineering & Technology,

Amravati

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that **Mr. Jagrut M. Thakare, Mr. Yogesh P. Bawankar, Mr. Atharva R. Bhuyar, Mr. Sarang V. Khode, Ms. Tanuja M. Deshpande** has satisfactorily completed the project work towards the **Bachelor of Engineering** Degree of Sant Gadge Baba Amravati University, Amravati in **Computer Science and Engineering** discipline on the topic entitled **"Hybrid Traffic Safety System",** during the academic year 2024-2025 under my supervision and guidance.

Date:

Prof. A. P. Ghatol	**Dr. V. K. Shandilya**
Guide	**Head of Department**

Dr. S M. Kherde

Principal

Project Approval Sheet

Project Entitled

“Hybrid Traffic Safety System”

by

Mr. Jagrut M. Thakare **Mr. Yogesh P. Bawankar**

Mr. Atharva R. Bhuyar **Mr. Sarang V. Khode**

Ms. Tanuja M. Deshpande

is approved for the degree of

Bachelor of Engineering

in

Computer Science & Engineering

of

Sant Gadge Baba Amravati University, Amravati

Internal Examiner:	**External Examiner:**
Name:	**Name:**
Date:	**Date**

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Mr. Jagrut M. Thakare
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ABSTRACT

The Hybrid Traffic Safety System presents an integrated approach to enhancing urban traffic law enforcement by combining Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection technologies. With the rapid pace of urbanization and the resulting surge in vehicular traffic, traditional monitoring systems are increasingly challenged in their ability to ensure adherence to traffic regulations, particularly concerning helmet usage and restrictions on the number of riders on two-wheelers. This project aims to bridge these gaps by leveraging recent advancements in computer vision and deep learning to create a more robust, automated solution for traffic safety enforcement.

The proposed system employs YOLOv12, a high-speed object detection algorithm, to identify motorcycles, riders, helmets, and instances of triple riding. Complementing this, TrOCR is utilized for accurate license plate recognition, even under challenging lighting or environmental conditions. The integration of these technologies allows for seamless data extraction and cross-referencing, enabling law enforcement agencies to rapidly detect and document violations. The system's architecture is designed to handle variability in real-world scenarios, including occlusions, motion blur, and diverse weather conditions, thereby improving overall detection reliability.

This comprehensive review of the system's components and their integration highlights the significant potential of hybrid approaches in traffic monitoring. Furthermore, the report discusses implementation challenges, such as computational overhead and scalability issues, and proposes potential solutions including model optimization and edge computing. By improving the accuracy, speed, and adaptability of traffic violation detection, the Hybrid Traffic Safety System contributes to reducing accident rates and promoting safer road behaviour. Future research directions are also explored to enhance the system’s performance and facilitate widespread deployment across diverse urban environments.

1. INTRODUCTION

The rapid and continuous rise in the number of vehicles, driven by accelerated urbanization and population growth, has led to increasingly complex traffic scenarios in metropolitan areas. This surge in vehicle population places immense strain on existing traffic infrastructure and challenges the efficiency of conventional traffic management systems. Traditional traffic enforcement methods—primarily dependent on manual monitoring and on-ground personnel—are becoming increasingly inadequate to deal with the volume and diversity of violations. As a result, there has been a noticeable increase in road accidents, congestion, and non-compliance with traffic laws, ultimately compromising public safety and urban mobility. One of the major issues contributing to road safety violations includes the failure to wear helmets, particularly among two-wheeler riders. In addition, riding with more than the allowed number of passengers on motorcycles (commonly referred to as triple riding) remains a frequent offense in many urban and semi-urban areas. These behaviours significantly increase the risk of fatal injuries during accidents. Meanwhile, identifying and tracking offenders through manual inspection is time-consuming, prone to human error, and not scalable. To address these limitations, the integration of intelligent, automated traffic surveillance systems has become a critical need for modern cities aiming to improve road safety and enforcement efficiency.

This project introduces a Hybrid Traffic Safety System, an intelligent, automated solution that integrates three vital traffic monitoring functionalities: Automatic Number Plate Recognition (ANPR), Helmet Detection, and Triple Ride Detection. By employing state-of-the-art deep learning and computer vision algorithms, this system is capable of detecting traffic violations, thereby aiding traffic enforcement agencies in automating the process of monitoring, identifying, and recording violations without human intervention.

At the core of this system are robust object detection models, including YOLOv12 (You Only Look Once) for fast and accurate localization of objects such as motorcycles, helmets, and riders. The system also incorporates TrOCR, an efficient Optical Character Recognition (OCR) tool used to extract vehicle registration numbers from license plates. The combination of these technologies ensures that both the presence of safety gear and the legality of the ride (in terms of rider count and vehicle identification) can be verified automatically, even under challenging environmental conditions like poor lighting, occlusions, or varying camera angles. The system architecture is implemented using the Python programming language, with the Stream lit framework providing an interactive, web-based user interface for visualization and interaction. Detection results, including images and violation data, are stored securely in a SQLite database along with relevant metadata such as timestamps, vehicle numbers, and violation type. Administrative functionalities, including user authentication and access control, are also integrated to ensure that the system is securely operated and managed by authorized personnel only.

In addition to facilitating traffic law enforcement, the system offers scalability and flexibility, making it a practical solution for integration into smart city infrastructure. It provides valuable data analytics capabilities that can be used to identify high-violation zones, support policy decisions, and optimize deployment of enforcement resources. The hybrid nature of the system ensures that multiple safety parameters are monitored concurrently, reducing the need for separate tools or manual inspections.

Overall, this project aims to contribute meaningfully to the broader goal of developing intelligent traffic management systems that are efficient, scalable, and effective in promoting compliance with traffic rules, thereby improving road safety and reducing the incidence of traffic-related injuries and fatalities.

2. LITERATURE REVIEW

Sr. No.	Title	Author	Main Objective
1	Relevance of Automatic Number Plate Recognition Systems in Vehicle Theft Detection.	Kumawat, Jain, and Tiwari	To evaluate the effectiveness of ANPR systems in vehicle theft detection and identify challenges
2	Helmet Detection for Safety Compliance Using Deep Learning.	Wang and Zhang	To develop a helmet detection system using YOLOv8 and CNNs and evaluate its performance.
3	Triple Ride Detection on Motorcycles Using Object Detection Techniques.	Patel and Rao	To explore the use of YOLOv8 for detecting triple riding on motorcycles and assess its accuracy.
4	Triple Riding and No-Helmet Detection.	N. Kumar, G. K. Sahu, M. Ravi, S. Kumar, V. Sukruth, and A. N. Mukunda Rao	To enhance the accuracy of helmet use and rider number detection on motorcycles, especially in difficult conditions.

1. Relevance of Automatic Number Plate Recognition Systems in Vehicle Theft Detection.

Kumawat, Jain, and Tiwari, conducted a study titled "Relevance of Automatic Number Plate Recognition Systems in Vehicle Theft Detection" with the primary objective of evaluating the effectiveness of ANPR systems in detecting and preventing vehicle theft. Their analysis highlighted that while ANPR systems are crucial for vehicle identification, they face significant challenges in real-world applications. Poor image quality, often due to low-resolution cameras or adverse weather conditions, was identified as a major factor compromising the accuracy of these systems. Additionally, the study revealed difficulties in handling nonstandard license plates, which vary significantly in design across different regions. High-speed vehicles also presented challenges, as motion blur often prevented clear images of license plates from being captured. Despite these challenges, the authors emphasized the importance of ANPR systems in vehicle tracking and suggested adopting advanced image processing techniques to enhance robustness. However, the primary drawbacks noted were the significant drop in ANPR accuracy under suboptimal conditions and the system's struggle with nonstandard plates, indicating a need for further research to improve performance in real-world scenarios.[12]

2. Helmet Detection for Safety Compliance Using Deep Learning.

Wang and Zhang, through their study "Helmet Detection for Safety Compliance Using Deep Learning," sought to develop and evaluate a helmet detection system using YOLOv8 and Convolutional Neural Networks (CNNs). The objective was to ensure motorcyclist safety by accurately detecting helmet use in traffic environments. The system, trained on a dataset featuring various helmet styles and colors, demonstrated high accuracy under controlled conditions. However, when deployed in real-world scenarios, particularly in low-light conditions or heavily shaded areas, the system's reliability significantly decreased. The study also noted challenges in detecting helmets that blended with the background or were of certain styles that the system struggled to identify. The authors suggested expanding the training dataset to include more variations in lighting conditions and helmet styles and implementing advanced preprocessing techniques to improve the system’s robustness. The primary drawbacks of this study were the system's reduced effectiveness in low-light environments and its difficulty in detecting certain helmet styles, indicating the need for more comprehensive datasets and better preprocessing methods.[13]

3. Triple Ride Detection on Motorcycles Using Object Detection Techniques.

Patel and Rao, In their research "Triple Ride Detection on Motorcycles Using Object Detection Techniques," aimed to explore the application of YOLOv8 for detecting triple riding on motorcycles and assess its accuracy in various settings. The system was tested in controlled environments as well as in complex urban areas. While the system performed well in controlled conditions, it struggled with accuracy in more complex scenes, particularly in crowded urban environments where multiple riders were closely positioned. This often led to high false positive rates, where the system mistakenly identified groups of riders as instances of triple riding. Patel and Rao suggested refining the detection algorithm to better differentiate between closely positioned riders and incorporating additional contextual information, such as rider spacing, to enhance accuracy. They also emphasized the importance of further training the model on diverse real-world scenarios. The significant drawbacks of their approach include the high false positive rate in urban settings and the difficulty in distinguishing closely positioned riders, indicating a need for further research to improve the system's performance in real-world applications.[14]

4. Triple Riding and No-Helmet Detection.

N. Kumar, G. K. Sahu, M. Ravi, S. Kumar, V. Sukruth, and A. N. Mukunda Rao, in their paper "Triple Riding and No-Helmet Detection," presented at the 4th IEEE Global Conference for Advancement in Technology, focused on improving the accuracy of helmet use and rider number detection on motorcycles, particularly in challenging real-world conditions. The system employed deep learning models, specifically YOLOv8, for detection, trained on a diverse dataset that included various helmet types, rider positions, and lighting conditions. This approach aims to address common issues such as false positives in crowded environments and difficulties in detecting dark-colored helmets or unconventional headgear. The model showed high accuracy in both helmet detection and counting the number of riders, proving its feasibility for traffic law enforcement. However, challenges remained, especially in low-light environments, where helmets and rider outlines blended into the background, reducing detection reliability. Additionally, the system's computational requirements were high, limiting its application in resource-constrained settings. False positives with non-helmet objects, like bags, were also a noted limitation. Despite these drawbacks, the study demonstrated significant advancements in enhancing rider and helmet detection, paving the way for future improvements in real-world traffic monitoring.[15]

3. PROBLEM STATEMEMT

The rapid growth in urbanization and vehicular density has led to a surge in traffic violations, such as riding without helmets, triple riding on two-wheelers, and the operation of unauthorized vehicles. These violations are key contributors to road accidents and public safety hazards.

Conventional traffic monitoring still largely depends on manual inspection and surveillance, which is not only labour-intensive and time-consuming but also prone to human error and inconsistency. Automated systems, while emerging, are often limited to single-purpose tasks like number plate recognition or helmet detection. More importantly, many of these systems are designed for real-time deployment, which may not be feasible or necessary in all scenarios, especially during the development and prototyping stages. There is a growing need for an integrated, multi-functional system that can analyse recorded images or videos to identify traffic violations, rather than requiring live feed analysis. Such a solution must support accurate detection of key violations, offer structured storage of results, and include administrative tools for managing and reviewing data.

This project presents a Hybrid Traffic Safety System, which leverages artificial intelligence, deep learning, and computer vision to detect multiple types of traffic violations—including helmet absence, triple riding, and number plate recognition—from input media. While the current version is not real-time, it provides a scalable and modular foundation for offline analysis and has the potential for future integration into live traffic systems.

4. OBJECTIVE

The primary objective of this project is to design, develop, and deploy a Hybrid Traffic Safety System that harnesses the power of artificial intelligence, deep learning, and computer vision to automate the detection of critical traffic violations in real time. The system is intended to aid traffic enforcement agencies by offering a comprehensive, scalable, and efficient platform for improving road safety and compliance. The specific goals of the project are outlined below:

1. **Accurate Automatic Number Plate Recognition (ANPR):** To develop a reliable module that detects and recognizes vehicle number plates using advanced object detection algorithms and Optical Character Recognition (OCR) techniques. This ensures that violators can be accurately identified and documented, even under varying lighting and environmental conditions.
2. **Helmet Detection for Two-Wheeler Riders:** To implement a robust helmet detection system capable of distinguishing between helmeted and non-helmeted riders on motorcycles. The system helps ensure compliance with road safety regulations and aims to reduce the risk of fatal head injuries in accidents.
3. **Triple Ride Detection on Motorcycles:** To create a module that identifies instances of triple riding—where more than two individuals are present on a two-wheeler. This is a common yet hazardous violation, and detecting it effectively is critical to enforcing traffic laws and promoting rider safety.
4. **Unified Web Application Interface:** To integrate all three detection modules (ANPR, Helmet Detection, and Triple Ride Detection) into a single, user-friendly, interactive web application. The front-end is developed using the **Stream lit framework, allowing** real-time monitoring, visualization, and user interaction through a browser-based interface.
5. **Structured Data Storage and Management:** To ensure that all detection outcomes, including captured images, detected classes, confidence scores, timestamps, and other metadata, are systematically stored in an SQLite database. This structured storage enables efficient retrieval, analysis, and use of data for enforcement or policy planning.

6. **Secure User Access and Administrative Control:** To provide user authentication features, including secure login and signup, ensuring that only authorized personnel can access system functionalities. Additionally, an admin dashboard allows for the management of detection records, system configurations, and user roles, thereby improving operational control and data integrity.
7. **Scalability and Smart City Integration:** To design the system architecture in a modular and extensible manner so it can be easily scaled or integrated with larger smart city frameworks, including automated ticketing systems, centralized traffic databases, or municipal surveillance networks.

By meeting these objectives, the Hybrid Traffic Safety System aims to significantly reduce the burden on manual enforcement, improve road safety outcomes, and contribute to the advancement of intelligent urban traffic management solutions.

5. MOTIVATION

With the continuous rise in vehicular traffic, especially in urban and semi-urban regions, traffic safety has emerged as a critical public concern. The increasing number of road accidents, traffic violations, and inconsistent enforcement highlight the urgent need for effective monitoring systems. Among the most common and hazardous infractions are riding without helmets, triple riding on motorcycles, and the operation of vehicles with falsified or unregistered number plates.

These violations not only put the lives of the offenders at risk but also compromise the safety of other road users. Helmetless riding and triple riding drastically increase the chances of severe injuries or fatalities in the event of an accident. Simultaneously, vehicles with unreadable or fake number plates make it difficult for authorities to identify and take action against violators. Unfortunately, traditional manual surveillance methods struggle to keep pace with these issues—they are slow, prone to error, and not scalable in high-traffic environments.

While automated systems have been introduced, most are limited to solving isolated problems, such as only recognizing number plates or only detecting helmet usage. They lack integration and do not offer a unified solution for multiple violations. More importantly, many real-time systems require high computational resources or consistent video streams, which may not always be feasible in resource-constrained or offline scenarios.

The motivation behind this project is to develop a modular, AI-powered system capable of detecting multiple traffic violations using still images rather than real-time video, offering an affordable, accessible, and accurate alternative for traffic enforcement agencies. By leveraging deep learning, computer vision, and OCR techniques, the project aims to create a Hybrid Traffic Safety System that can perform:

- Automatic Number Plate Recognition (ANPR),
- Helmet Detection, and
- Triple Ride Detection,

all in one unified offline platform. The system's integration into a simple yet effective web application—complete with SQLite database storage, user authentication, and a friendly GUI—makes it practical for demonstrations, future research, and scalable deployment.

This project not only addresses the need for smarter, more efficient traffic violation detection but also aligns with the larger vision of building intelligent infrastructure for smart cities. By combining modern AI techniques with focused problem-solving, this project contributes towards a safer, more structured, and law-abiding transportation system.

6. METHODOLOGY

This project presents a hybrid traffic safety system that detects vehicle number plates using YOLOv12 and extracts their characters using TrOCR (Transformer-based OCR). The workflow includes dataset preparation, model training, detection, OCR, evaluation, and deployment.

1. Dataset Collection and Preparation

A custom dataset of vehicle images with visible number plates was created using Rob flow. This tool facilitated uploading, labelling, and preprocessing the dataset. Bounding boxes were annotated directly in Rob flow's online workspace, and augmentations like flipping, rotation, brightness adjustment, and blur were applied to diversify the dataset. The final annotated dataset was exported in YOLOv12-compatible format and used for training.

2. YOLOv12 Model Training

The YOLOv12 model—an advanced version of the YOLO family—was employed for number plate detection. The training environment was set up with PyTorch, OpenCV, and necessary dependencies. The model was trained on the pre-processed dataset, with performance tracked using key metrics such as precision, recall, and (mAP). Various augmentation strategies were applied during training to enhance the model's robustness under different conditions. The trained model was saved for subsequent inference.

3. Number Plate Detection Using YOLOv12

For inference, input images were resized and normalized before being passed into the trained YOLOv12 model. The model generated bounding boxes indicating the presence of number plates, with Non-Maximum Suppression (NMS) applied to refine detections. Detected regions were then cropped from the original image for OCR processing.

4. Text Recognition Using TrOCR

The cropped number plate images underwent preprocessing steps such as grayscale conversion, contrast enhancement, and thresholding to improve OCR accuracy. These processed images were then fed into TrOCR, a Transformer-based OCR model developed by Microsoft. TrOCR utilizes an image Transformer encoder and a text Transformer decoder to perform end-to-end text recognition. The model was fine-tuned on the SROIE dataset, making it well-suited for recognizing printed text in number plates. Post-processing techniques, such as regular expression filtering and basic correction, were applied to refine the extracted text.

5. Validation and Testing

The system's performance was evaluated using standard metrics like Intersection over Union (IoU), precision, and recall for detection accuracy. OCR results were compared against ground-truth values to assess text recognition performance. Although the system does not operate in real-time, it was tested on a variety of static images from traffic footage to validate its effectiveness in practical scenarios.

6. Optimization and Deployment

Given that real-time operation was not a requirement, the system was optimized for accuracy and usability. It was deployed as a Stream lit-based web application, allowing users to upload images and receive annotated results with extracted number plate text. Detection records and user data were securely stored using an SQLite database, with administrative features for monitoring usage and managing stored entries.

7. TOOLS USED

The development of the Hybrid Traffic Safety System employed a combination of essential tools and frameworks to ensure effective performance, user interaction, and data management. Python served as the primary programming language, enabling seamless integration of AI models and backend logic. The user interface was built using Stream lit, offering an interactive and real-time experience. For object detection, the project incorporated pre-trained models from Rob flow based on the YOLOv12 architecture, which were used for license plate, helmet, and triple ride detection. Text recognition from number plates was handled using TrOCR, a powerful Transformer-based OCR model from Hugging Face. Image processing and enhancement were carried out using OpenCV and PIL. Data generated during detection and user operations was stored in SQLite, a lightweight relational database.

Key Tools and Technologies Used:

Python – Core programming language

One of the most notable features of Python is its readable and simple syntax. The language uses indentation to define code blocks rather than braces, which enhances code clarity and reduces the chances of errors. Python is an interpreted language, meaning that code is executed line by line, simplifying debugging and improving development speed. Python also uses dynamic typing, meaning that variables do not require explicit type declarations. The interpreter determines the data type at runtime, providing flexibility and making the language easier to use. Python supports multiple programming paradigms, including object-oriented, procedural, and functional programming. This versatility allows developers to choose the approach that best suits their needs.

Another significant advantage of Python is its extensive standard library. It comes with pre-built modules for tasks such as file handling, regular expressions, data serialization, networking, and more, making it easier to implement complex functionality without writing code from scratch. Python's cross-platform compatibility ensures that code can run on different operating systems (Windows, macOS, Linux) with minimal modification, which is crucial for building portable applications.

Stream lit – Web application framework

Stream lit is an open-source Python library designed to create and share interactive web applications with minimal effort. It was developed to allow data scientists and machine learning engineers to turn their data scripts into interactive applications quickly, without needing extensive web development knowledge. First released in 2019, Stream lit has rapidly become popular for building applications for data visualization, machine learning models, and dashboards. Stream lit allows developers to build applications with real-time interactivity. It supports widgets like sliders, buttons, text inputs, and file uploads that can be used to control the flow of the application or modify visualizations dynamically. Any change in the user input automatically triggers the application to update, enabling a seamless and interactive experience.

Another key feature is Streamlet's automatic layout management. The framework intelligently arranges components like charts, graphs, tables, and text on the page, so developers don't need to worry about manually managing HTML/CSS layout. This greatly speeds up the development process.

Stream lit also integrates seamlessly with popular Python libraries like Matplotlib, Plotly, Pandas, and Altair, allowing developers to display visualizations, data frames, and interactive plots with minimal code. It also supports the deployment of machine learning models, enabling users to build and deploy models as web applications.

YOLOv12 (Rob flow models) – Object Detection

YOLOv12 (You Only Look Once) is an advanced, high-performance object detection model known for its exceptional speed and accuracy. Unlike traditional object detection techniques, which process each region of an image independently, YOLOv12 treats the task as a single regression problem. It divides an image into a grid and predicts bounding boxes along with class probabilities for each grid cell in a single pass through the network. This approach enables YOLOv12 to perform real-time object detection while maintaining high accuracy, making it suitable for applications that demand both speed and precision.

In this project, we used the YOLOv12 model trained through Rob flow, a widely used platform for creating, training, and deploying machine learning models. Rob flow simplifies the process of preparing data, training models, and deploying them for real-world use. By allowing users to upload their dataset, label images, and choose from various model architectures (including YOLOv12), Rob flow handles much of the complexity behind the scenes, enabling quick and efficient integration of object detection into applications.

Rob flow's version of YOLOv12 is fine-tuned for excellent performance across a wide range of scenarios, from smaller-scale applications to more complex real-world use cases. It supports the customization of YOLOv12 on specific datasets, enabling precise detection of objects such as license plates, helmets, and triple ride violations, as required in this project. Roboflow's platform allows for seamless adjustments to hyperparameters, real-time monitoring of training progress, and easy evaluation of model performance, ensuring optimal results for the specific detection tasks.

TrOCR (Hugging Face) – OCR for number plate recognition

TrOCR, developed by Microsoft and available on platforms like Hugging Face, is an advanced deep learning model for Optical Character Recognition (OCR). TrOCR, short for Transformer-based OCR, uses a transformer architecture to efficiently convert images of text into machine-readable text. The model leverages the capabilities of transformers, a type of neural network architecture that has shown remarkable success in a variety of natural language processing tasks, such as translation and text generation. By combining transformers with techniques specific to image processing, TrOCR is able to recognize text in images with a high degree of accuracy, handling a wide range of fonts, handwriting, and noisy backgrounds.

The strength of TrOCR lies in its ability to deal with complex OCR tasks that traditional models may struggle with. The model is trained on large datasets of scanned documents and images with text, allowing it to generalize well across different types of content. One of the most notable features of TrOCR is its end-to-end design. Unlike older OCR models that require separate stages for text detection, character recognition, and post-processing, TrOCR handles the entire process in a single step, simplifying the OCR pipeline. This results in faster processing and improved accuracy, especially in cases where text appears in irregular fonts, skewed orientations, or mixed languages. Hugging Face provides an easy-to-use interface for accessing and fine-tuning the TrOCR model, making it highly accessible to developers. Using Hugging Face's transformers library, users can quickly integrate TrOCR into their workflows. This integration allows for seamless application in various domains such as document digitization, data extraction from scanned forms, invoice processing, and historical text preservation. The platform also offers pre-trained versions of TrOCR, which can be used directly for text extraction tasks or further fine-tuned for specific datasets or use cases.

OpenCV & PIL – Image processing and annotation

OpenCV (Open-Source Computer Vision Library) and PIL (Python Imaging Library, now maintained as Pillow) are two of the most widely used libraries in Python for image processing and computer vision tasks. OpenCV, developed by Intel, provides a comprehensive set of tools for real-time computer vision, enabling developers to perform complex operations such as image manipulation, object detection, facial recognition, and video analysis. OpenCV is highly optimized for performance and can handle a wide range of image and video processing operations. It supports a variety of file formats and offers advanced functionalities like edge detection, image filtering, geometric transformations, and object tracking, making it an essential library for applications in robotics, surveillance, augmented reality, and machine learning.

PIL, on the other hand, focuses primarily on image processing and manipulation, providing easy-to-use functions for opening, editing, and saving images in different formats. The library allows users to perform a variety of tasks such as resizing, cropping, rotating, and applying filters to images. While OpenCV is more suited for complex computer vision tasks, PIL (or its modern fork, Pillow) is often used for simple image processing applications like handling image files, converting between formats, and applying basic transformations. Although both libraries have overlapping functionalities, OpenCV and PIL/Pillow serve different purposes and are often used in tandem. For example, a typical workflow might involve using OpenCV for tasks like object detection, feature matching, or video processing, followed by using Pillow for simpler tasks like saving the processed images or applying minor transformations. OpenCV can also work with Pillow images by converting between the two formats, enabling users to take advantage of the strengths of both libraries in a single pipeline.

SQLite – Local database for storing records

SQLite is a lightweight, serverless, self-contained relational database management system (RDBMS) that is widely used for local storage of data in applications. It is a file-based database, meaning the entire database is stored in a single file on disk, which makes it ideal for applications that require a simple, embedded database with minimal configuration. Unlike traditional client-server database systems like MySQL or PostgreSQL, SQLite does not require a separate server process. It is embedded directly into the application and interacts with the database through a simple file-based interface SQLite's design makes it particularly well-suited for local storage in desktop, mobile, and web applications. Its small footprint and ease of setup make it a popular choice for developers building applications that need a lightweight database to store records or configuration data without the overhead of a full database server. Despite its small size, SQLite supports a rich set of SQL features, including transactions, ACID compliance (Atomicity, Consistency, Isolation, Durability), and full-text search. This ensures that SQLite is capable of handling moderate-sized datasets and providing reliable storage for a wide range of applications.

One of the key advantages of SQLite is its simplicity. Setting up an SQLite database is as easy as creating a file, and it does not require complex server configurations or network connections. This makes SQLite an excellent choice for applications where ease of use and low maintenance are priorities. It can be used for storing records such as user preferences, session data, logs, or even entire datasets for smaller applications. Since SQLite operates as an embedded database, all the data is stored locally on the device, making it ideal for offline scenarios where network connectivity may be intermittent or unavailable.

8. DESIGN AND IMPLEMENTATION

The Hybrid Traffic Safety System is built as an integrated, modular web application that streamlines the process of detecting and documenting traffic violations, namely helmet non-compliance, triple riding, and unauthorized vehicles through number plate recognition. This system is implemented using a combination of deep learning models, a web interface powered by Stream lit, and efficient image processing techniques.

The following subsections describe the system architecture, user interface flow, core detection modules, and backend functionalities.

8.1 System Flow and Architecture

The architecture follows a role-based access model, where the system distinguishes between **Admin** users and **Normal Users**. The complete workflow is illustrated in the system flowchart below:

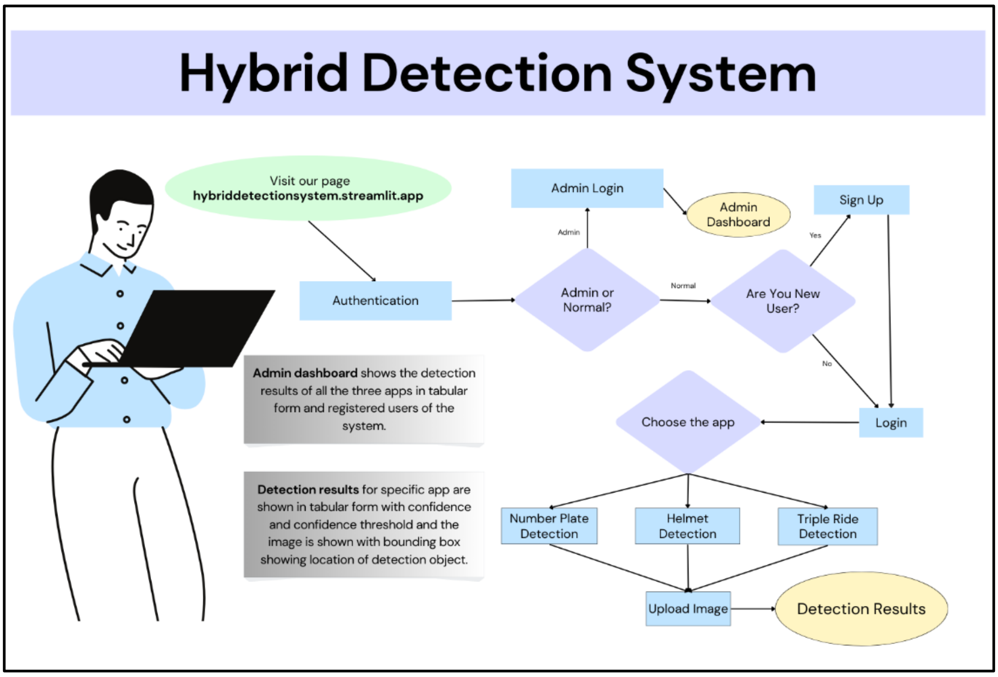

Figure 8.1: System Flowchart of the Hybrid Detection System

8.2 User Authentication and Access Control

Upon launching the application, the user is directed to the Authentication Page. The system prompts the user to choose between two roles:

- **Admin**

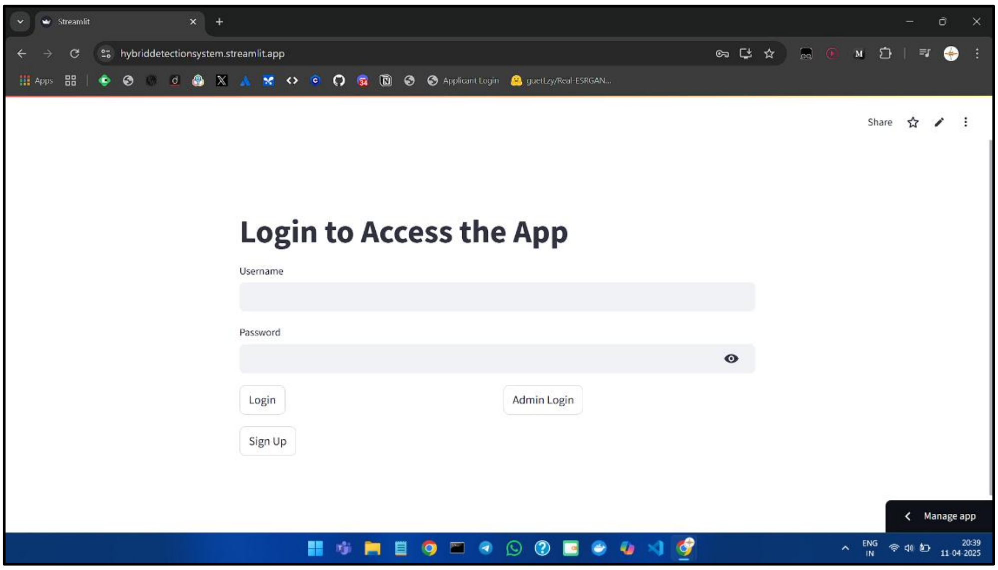

Figure 8.2: Login Page for User Authentication

- **Normal User**

For new users, a sign page is provided. Returning users can directly log in. After logging in:

- **Admins** are redirected to the Admin Login Page, followed by the Admin Dashboard upon successful authentication.
    - **Normal users** proceed to a detection selection page.

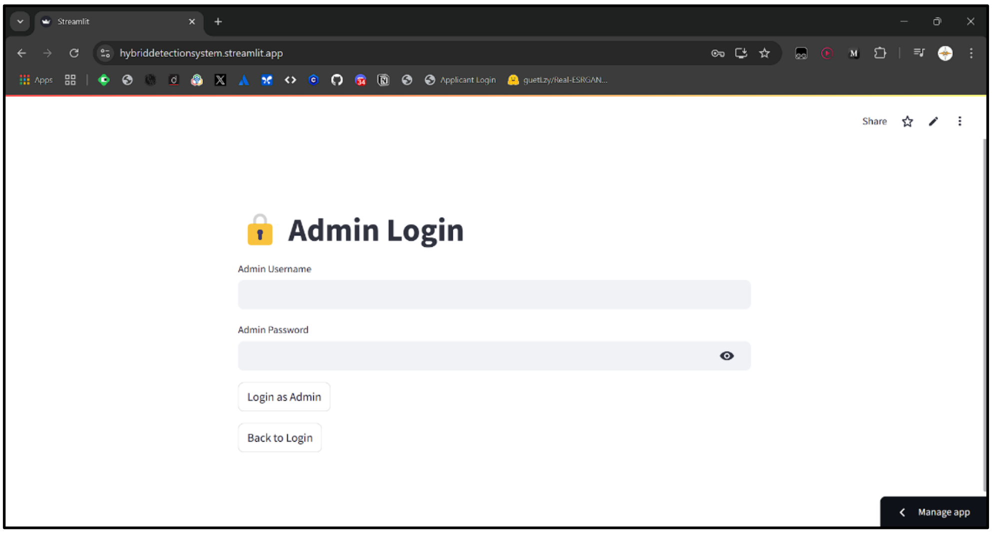

Figure 8.3: Admin Login Page

8.3 Admin Dashboard Features

The Admin Dashboard acts as a centralized control panel for reviewing system usage and detection results. Admins can view:

- A tabulated list of all registered users
- Detection logs from all three detection modules
- Timestamps and confidence levels for each detection
- Preview images with bounding boxes of the detected objects

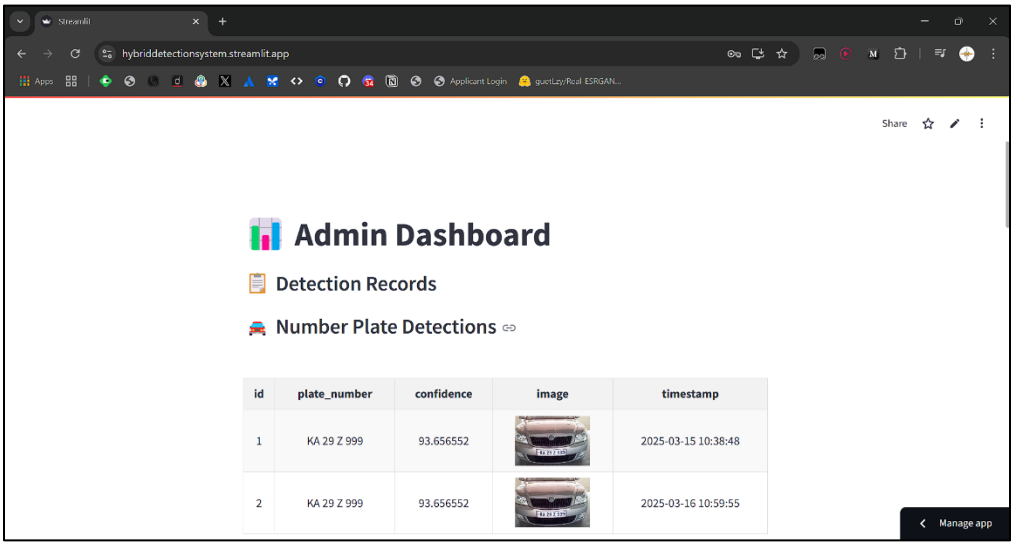

Figure 8.4: Admin Dashboard Showing Detection Logs and User Data

This ensures traceability and supports law enforcement by providing structured evidence.

8.4 Detection Module Interface

Once a normal user logs in, they are presented with three core options:

- **Helmet Detection**
- **Triple Ride Detection**
- **Number Plate Recognition**

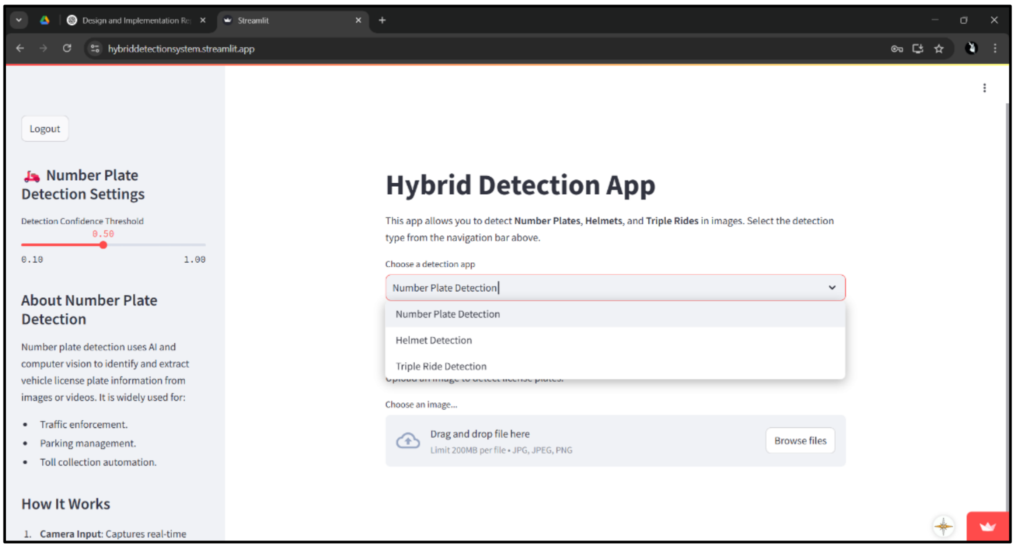

Figure 8.5: Detection Options Displayed After User Login

Upon selecting a module, the user is prompted to upload an image. This image is processed using deep learning models tailored for each detection type:

- YOLOv12 for helmet detection and triple ride detection
- TrOCR for number plate recognition

The models identify objects of interest and overlay bounding boxes with confidence scores on the image.

8.5 Detection Output

After image processing, the system displays the results to the user in an interactive format. Each output contains:

- The original image with visual annotations (bounding boxes)
- The type of violation detected
- The confidence score of the prediction

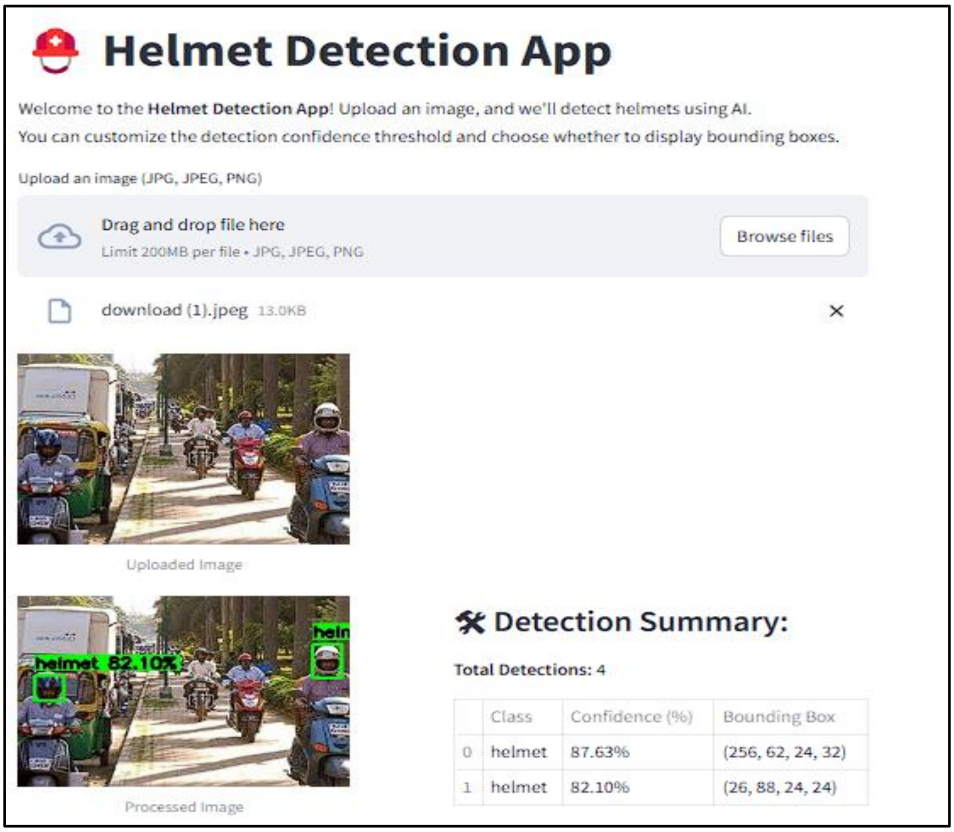

Figure 8.6: Sample Output - Helmet Detection

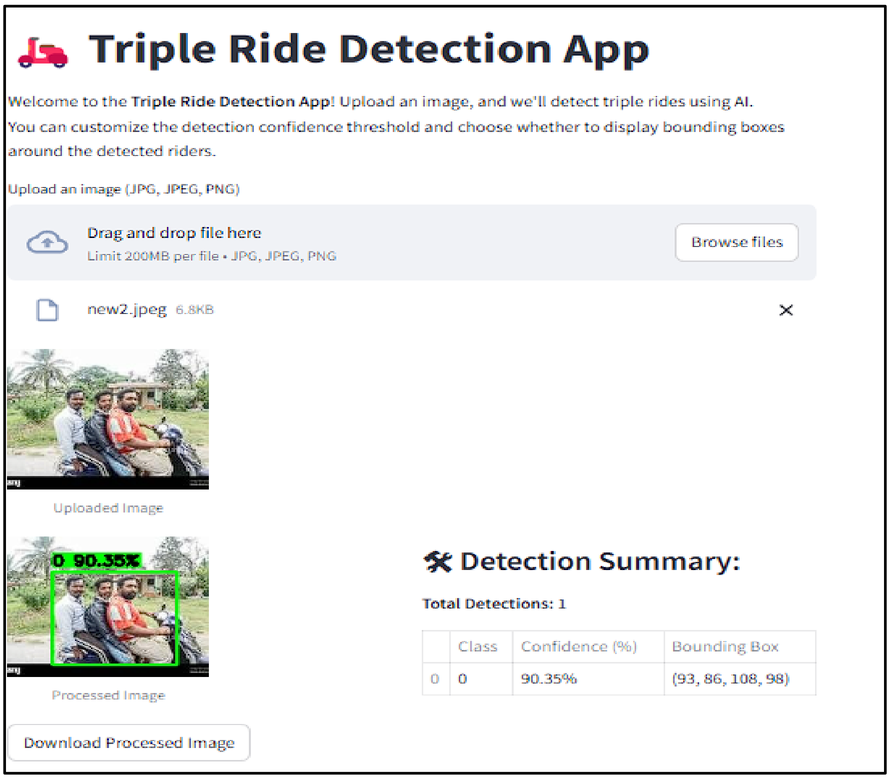

Figure 8.7: Sample Output - Triple Ride Detection

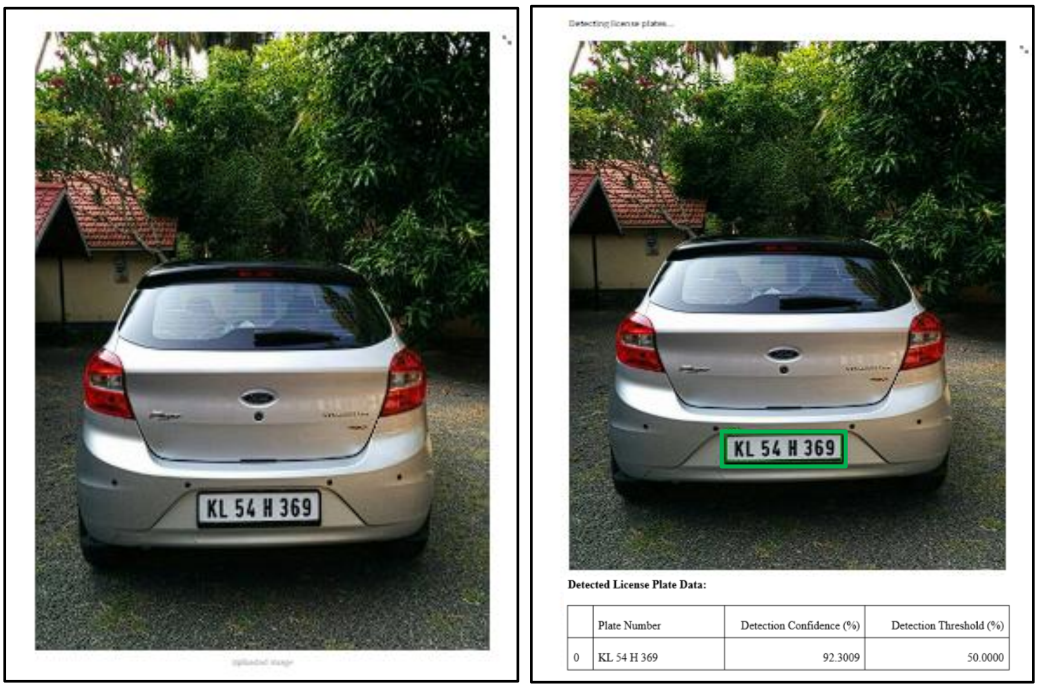

Figure 8.8: Sample Output - Number Plate Recognition

This interface provides immediate feedback to the user and can also be logged in the admin panel for review.

9. ADVANTAGES

The Hybrid Traffic Safety System offers several practical and technological advantages over traditional traffic monitoring and enforcement methods. By integrating deep learning, OCR, and image processing into a unified platform, the system provides a more efficient, accurate, and scalable approach to road safety.

Key Advantages:

- **Real-Time Detection**: Enables instant identification of traffic violations such as missing helmets, triple riding, and unauthorized number plates using AI models.
- **Multi-Violation Monitoring**: Unlike conventional systems that detect only a single type of violation, this system simultaneously supports three critical detections in one interface.
- **Automation and Efficiency**: Reduces manual workload for traffic authorities by automating the process of surveillance, detection, and logging of incidents.
- **High Accuracy**: Utilizes robust deep learning models (YOLOV12, TrOCR) to ensure accurate detection and recognition under various environmental conditions.
- **Visual Evidence and Logging**: Stores images along with metadata (confidence, bounding boxes, etc.) to provide concrete visual proof for future reference or legal enforcement.
- **User and Admin Control**: Offers a secure login system and an admin dashboard to manage user access, view detection history, and export records.
- **Cost-Effective Deployment**: Built with lightweight tools like Streamlit and SQLite, making the system ideal for deployment in resource-constrained environments or edge devices.
- **Scalable for Smart Cities**: Designed to support future expansion into real-time video feeds, IoT integration, and centralized traffic monitoring systems.

10.DISADVANTAGES

While the Hybrid Traffic Safety System presents numerous advantages, there are also certain limitations and challenges associated with its current implementation:

Key Disadvantages:

- **Limited to Static Images**: The current version processes uploaded images only and does not support real-time video stream analysis, which limits its application in continuous surveillance scenarios.
- **Dependence on Image Quality**: Detection accuracy can be significantly affected by low-resolution images, poor lighting conditions, motion blur, or partial occlusion of the target object (e.g., number plates or helmets).
- **Cloud Model Dependency**: The use of external APIs (Rob flow, Hugging Face) for model inference requires a stable internet connection and may introduce latency or API rate limits.
- **Resource Requirements for Local Processing**: Although lightweight for small-scale deployment, local execution of image preprocessing and OCR still requires moderate computational resources, especially for batch processing.
- **Limited Dataset Customization**: The performance of the pre-trained models may degrade when applied to region-specific data (e.g., non-standard number plates or local helmet styles) unless further training is done with localized datasets.
- **Security and Privacy Concerns**: Image data containing vehicle and personal information must be handled securely to ensure compliance with data protection regulations.

11.FUTURE SCOPE

The Hybrid Traffic Safety System demonstrates significant potential for further development and integration in real-world traffic management and smart city applications. The current implementation provides a strong foundation that can be enhanced and expanded in various directions:

Key Areas for Future Enhancement:

- **Real-Time Video Stream Processing**: Integration with live CCTV feeds to enable continuous, automated traffic monitoring without manual image uploads.
- **Edge Device Deployment**: Optimization of the system for deployment on low-power edge devices like Raspberry Pi or NVIDIA Jetson to allow decentralized processing at traffic signals or surveillance points.
- **Multi-Language OCR Support**: Enhancement of the OCR module to support license plates in regional languages and fonts for wider applicability across different geographic regions.
- **Integration with Government Databases**: Connecting the system with national or state-level vehicle and driver databases for automated verification, fine generation, and notification.
- **Enhanced Violation Detection**: Expansion of the system to detect other types of violations such as signal jumping, wrong-way driving, seatbelt non-compliance, and speeding using AI and sensor fusion.
- **Mobile Application Interface**: Development of a mobile app version for field officers to perform on-the-spot checks and access detection records on the go.
- **AI Model Retraining with Local Datasets**: Training the detection models with region-specific datasets to improve accuracy and reduce false positives in different traffic and environmental conditions.
- **Privacy and Security Enhancements**: Implementation of secure image encryption, anonymization techniques, and GDPR-compliant data handling protocols for public deployments.
- **Simultaneous Multi-Violation Detection in Crowded Frames:** Enable detection of multiple violations like triple riding, helmet issues, and number plates in dense, high-traffic frames or feeds.

12.CONCLUSION

The Hybrid Traffic Safety System successfully demonstrates the potential of integrating artificial intelligence and computer vision to automate the detection of critical traffic violations. By combining Number Plate Detection, Helmet Detection, and Triple Ride Detection into a unified platform, the system addresses multiple road safety challenges through a single, efficient interface. The application is built using Stream lit, with detection powered by YOLOV12-based models from Rob flow and OCR capabilities from Hugging Face's TrOCR. The use of SQLite for storing detection records and user data ensures lightweight, local data management The system enhances traffic law enforcement by reducing dependency on manual surveillance, improving detection accuracy, and offering visual evidence for validation. Although the current version is limited to static image processing, it lays a strong foundation for future expansion into real-time video analysis and integration with smart city infrastructure.

Overall, this project provides a scalable, modular, and practical solution to support traffic authorities in promoting road safety, enforcing compliance, and reducing violations using advanced AI-driven technologies.

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HYBRID TRAFFIC SAFETY SYSTEM: INTEGRATION OF ANPR, HELMET AND TRIPLE RIDE DETECTION

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ABSTRACT

This paper provides a comprehensive review of hybrid traffic safety systems that integrate Automatic Number Plate Recognition (ANPR) with Helmet Detection and Triple Ride Detection technologies. As urbanization increases, so does the complexity of traffic management, necessitating advanced solutions to ensure road safety. Traditional ANPR systems, while effective in vehicle identification, often fail to address critical safety issues such as helmet compliance and the detection of multiple riders on motorcycles. This review examines recent advancements in these integrated systems, highlighting their potential to enhance traffic law enforcement by ensuring compliance with safety regulations. The paper discusses the strengths and limitations of current methodologies, particularly in real-time processing and accuracy under varying conditions. Furthermore, it proposes a framework that leverages deep learning models, such as YOLOv2 and EasyOCR, to improve detection efficiency and reliability. The integration of these technologies offers a holistic approach to traffic monitoring, with the potential to significantly reduce traffic violations and accidents. Future research directions are also suggested to address existing challenges and enhance the scalability and effectiveness of these systems.

Keywords: Traffic Safety, ANPR, Helmet Detection, Triple Ride Detection, YOLOv2, EasyOCR, Image Processing, Deep Learning.

I. INTRODUCTION

The rapid urbanization witnessed globally has led to an increase in vehicle density, making road safety a critical issue. With more vehicles on the roads, especially in urban areas, traffic law enforcement agencies face the challenge of ensuring compliance with safety regulations, such as helmet use by motorcyclists and adherence to rider limits on motorcycles. Traditional traffic monitoring systems have predominantly relied on Automatic Number Plate Recognition (ANPR) to identify vehicles. While ANPR systems are effective in vehicle identification and law enforcement, they fall short in addressing other critical aspects of traffic safety, such as detecting helmet use and triple riding on motorcycles. This paper presents a comprehensive review of hybrid traffic safety systems that integrate ANPR with Helmet Detection and Triple Ride Detection technologies. These integrated systems provide a more holistic approach to traffic safety by not only identifying vehicles but also ensuring that motorcyclists adhere to safety regulations. This review paper examines recent developments in these technologies, identifies the limitations of existing systems, and proposes an integrated framework that addresses these challenges. The paper also explores future research directions aimed at improving the effectiveness and scalability of these systems.

II. LITERATURE REVIEW

1] K. Kumawat, A. Jain, N. Tiwari. Investigated the effectiveness of ANPR systems for vehicle theft detection. They found that ANPR systems, crucial for vehicle identification, often perform poorly in suboptimal conditions. Issues such as low-resolution cameras, adverse weather, and nonstandard license plates reduce accuracy. High-speed vehicles create motion blur, complicating image capture, while obstructions like dirt can further degrade performance. The study highlighted the need to improve ANPR technology for better reliability in tracking and enforcement. The authors recommended advanced image processing techniques and machine learning models to enhance system robustness, especially in varying environmental conditions.

2] J. Smith and H. Lee. Conducted a comparative analysis of OCR techniques in ANPR systems, focusing on traditional methods like template matching and edge detection. They found these methods struggled with varying lighting conditions, such as glare and shadows, which obscured parts of license plates and hindered text recognition. The variability in fonts and character styles further impacted accuracy, especially with nonstandard fonts. The authors proposed integrating deep learning-based OCR models to improve adaptability and accuracy. These models, trained on large datasets, better handle diverse lighting and font conditions. Their research demonstrated that machine learning approaches enhance recognition accuracy and system reliability across various environments, making them a more effective solution for modern ANPR systems.

3] Y. Wang and L. Zhang. Investigated YOLOv2 and CNNs for real-time helmet detection. They achieved high accuracy under controlled conditions but faced challenges with varying lighting and helmet styles. Their study suggested diversifying training datasets and exploring preprocessing techniques to enhance detection reliability in real-world scenarios with different lighting and helmet variations.

4] R. Kumar, P. Singh. advanced helmet detection using CNNs by emphasizing the need for diverse training datasets. They found that while CNNs effectively identify helmets in simple scenarios, performance drops in complex environments, particularly with partial obstructions like a rider's body or other vehicles. The study highlighted that training on varied datasets, including different angles and lighting, is crucial for improving model robustness. The authors also proposed using transfer learning to refine models on specific datasets for better accuracy in challenging conditions. They concluded that expanding datasets and exploring new model architectures are essential for handling real-world complexities in helmet detection.

5] M. Patel, S. Rao. Investigated triple-riding detection on motorcycles using YOLOv2. While their system effectively counted riders in controlled settings, it struggled in crowded urban environments where riders were closely positioned, leading to high false positive rates. They found that the system often misidentified groups of riders as a single instance of triple riding. To address this, Patel and Rao recommended refining the detection process with additional contextual information, such as rider spacing and positions. They also emphasized the need for further model training on diverse real-world datasets to enhance accuracy and reliability in complex scenarios.

6] A. Chaudhary, N. Gupta. Analyzed challenges in detecting triple riding in urban environments. They noted issues with varying rider postures and clothing leading to false positives. The authors proposed enhancing training datasets with diverse examples and developing sophisticated detection algorithms to improve accuracy and handle real-world variations in rider appearance.

7] M. Ali, T. Khan examined integrating ANPR with helmet detection for enhanced traffic safety. They found that while this integrated system could improve law enforcement by addressing multiple safety issues, it introduced challenges, particularly in processing multiple tasks simultaneously, which led to delays in real-time applications. The authors recommended optimizing the system's architecture and using efficient algorithms and hardware acceleration, such as GPUs, to improve performance. They emphasized the need for a scalable system adaptable to different environments and traffic conditions, concluding that further research is needed to tackle real-time processing and scalability challenges for effective deployment.

8] A. Hussain, S. Mehta. Developed a real-time traffic monitoring system combining license plate recognition with rider detection for vehicles and compliance monitoring. They found that while integration improved system effectiveness, it increased complexity, causing processing delays due to simultaneous task handling. The authors recommended optimizing algorithms and using parallel processing and distributed computing to enhance real-time performance. They emphasized the need for a system adaptable to various traffic conditions, from dense urban areas to rural settings. The study concluded that further work is needed to refine the system for real-time use and ensure effective deployment across diverse environments.

9] X. Zhao, J. Liu. Proposed an integrated traffic safety system combining ANPR with rider compliance checks for vehicle identification, helmet use, and rider limits. While effective in detecting violations, the system faced scalability issues in large deployments, particularly in high-traffic areas where processing large volumes of data degraded performance. The authors recommended optimizing scalability through cloud-based processing and distributed computing to manage increased data loads. They also suggested developing more robust algorithms to maintain accuracy and performance on a scale. The study concluded that while promising, further research is needed to ensure effective large-scale deployment.

10] Y. Chen, W. Zhang. Developed a unified framework combining ANPR with helmet and triple ride detection to address multiple traffic safety concerns. Their system was effective in detecting violations but faced challenges with real-time processing due to the complexity of handling multiple tasks, which increased computational demands and caused delays. The authors suggested optimizing the system's architecture and using efficient algorithms, along with hardware acceleration techniques like GPUs, to enhance processing speed. They concluded that while the framework shows promise, further work is needed to refine the system for real-time applications and ensure effective operation across varied traffic conditions.

III. METHODOLOGY

To address the limitations identified in the literature, this paper proposes a hybrid traffic safety system that integrates ANPR, Helmet Detection, and Triple Ride Detection using advanced deep learning models and image processing techniques. The proposed system is designed to operate in real time, ensuring immediate detection and response to traffic violations.

3.1 Automatic Number Plate Recognition (ANPR)

The ANPR component of the system uses EasyOCR, an open-source OCR tool, for text extraction from license plates. EasyOCR is chosen for its ability to handle various fonts and styles, making it suitable for use in diverse regions with different license plate designs. The images captured by traffic cameras are first preprocessed using OpenCV (cv2) to enhance image quality. This preprocessing includes resizing, normalization, and noise reduction to ensure that the images are of sufficient quality for OCR [21]. Once the images are preprocessed, EasyOCR is applied to recognize the characters on the license plates. The recognized text is then compared against a database of registered vehicles to identify the vehicle and check for any violations, such as expired registration or unpaid fines. The ANPR system operates in real-time, allowing law enforcement agencies to identify and respond to violations immediately.

3.2 Helmet Detection

For Helmet Detection, the proposed system employs YOLOv2, a deep-learning model optimized for real-time object detection. YOLOv2 is trained on a diverse dataset that includes images of motorcyclists with and without helmets, captured under various lighting conditions and from different angles. The model learns to detect helmets' presence by analyzing the riders' features and their headgear. The Helmet Detection module is designed to operate in real-time, continuously analyzing video feeds from traffic cameras. When a motorcycle is detected, the system checks whether the rider is wearing a helmet. If the rider is not wearing a helmet, the system flags the violation and sends an alert to law enforcement. The use of YOLOv2 allows the system to accurately detect helmets even in challenging scenarios, such as poor lighting or partial obstructions.

3.3 Triple Ride Detection

The Triple Ride Detection module also utilizes YOLOv2, with the model trained to detect and count the number of riders on a motorcycle. The model is trained on a dataset containing images of motorcycles with one, two, and three riders. By analyzing the spatial arrangement of the riders, the model can accurately identify instances of triple riding. In real-time applications, the system continuously monitors motorcycles for the presence of multiple riders. When the system detects three or more riders on a motorcycle, it flags the violation and sends an alert to law enforcement. The use of YOLOv2 ensures that the system can accurately detect triple riding even in complex scenes, such as crowded urban environments.

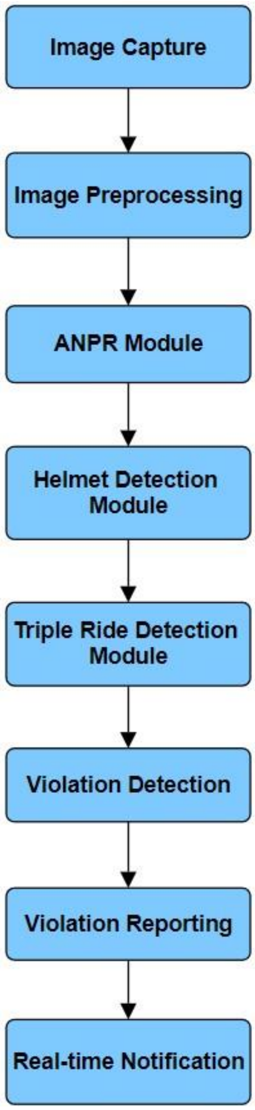
3.4 Integration and Real-Time Processing

The proposed system integrates the ANPR, Helmet Detection, and Triple Ride Detection modules into a unified framework. Images captured by the system's cameras are first processed by the ANPR module to recognize license plates. The images are then passed to the Helmet Detection and Triple Ride Detection modules, which analyze the images for helmet compliance and triple-riding violations. The results from each module are combined to generate a comprehensive traffic violation report. This report includes information on the vehicle's license plate, the presence or absence of a helmet, and the number of riders on the motorcycle. The system is designed to operate in real time, allowing law enforcement agencies to respond to violations immediately.

IV. SYSTEM REQUIREMENTS

The proposed hybrid traffic safety system requires a high-resolution camera setup capable of capturing clear images in various lighting conditions. The hardware should include Graphics Processing Units (GPUs) to handle the computational load associated with real-time image processing and deep learning model inference. The software components include Python libraries such as OpenCV for image processing, TensorFlow or PyTorch for model implementation and EasyOCR for license plate recognition.

FLOW CHART



V. CONCLUSION

The integration of Automatic Number Plate Recognition (ANPR) with Helmet Detection and Triple Ride Detection technologies offers a comprehensive solution for traffic law enforcement. This hybrid system addresses the limitations of traditional traffic monitoring systems by providing a more holistic approach to ensuring road safety. The use of advanced deep learning models, such as YOLOv2 and EasyOCR, allows the system to operate in real time, accurately detecting and responding to traffic violations. Despite the advancements made in recent years, several challenges remain, particularly in terms of scalability and the ability to handle diverse and complex traffic environments. Future research should focus on optimizing these systems for large-scale deployment, improving the robustness of the detection models, and exploring the use of additional technologies, such as AI-powered predictive analytics, to further enhance traffic safety.

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