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Dual Detection of License Plates and Helmets Using Optimised Yolo and Neural Networks

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Abstract: The growing incidence of traffic infractions particularly helmet less riding and unregistered vehicles has underscored the urgent need for automated road safety surveillance. This work presents a unified, real-time detection framework that simultaneously identifies helmet compliance and localises vehicle license plates by leveraging a fine-tuned YOLOv10 architecture integrated with deep neural network processing. Input traffic footage is analysed frame-by-frame to classify rider behaviour and precisely locate plate regions, which are subsequently passed through an OCR pipeline to extract registration numbers programmatically. Robustness under adverse conditions including poor illumination, motion-induced blur, and partial occlusion is addressed through a combination of augmented training data, transfer learning from pretrained models, and targeted feature refinement. Crucially, the architecture is optimised for edge deployment on existing CCTV networks and smart roadside units, eliminating the dependency on high-performance computing hardware. Evaluations confirmstrong detection accuracy alongside real-time throughput, validating the system's readiness for deployment within intelligent transport ecosystems and broader smart city initiatives. The framework substantially reducesthe burden on human traffic personnel, enhances enforcement consistency, and is architected for seamless, scalable integration with cloud-native traffic management platforms.
Keywords: YOLOv10, Helmet Detection, License Plate Recognition, Optical Character Recognition(OCR), Traffic Violation Detection, Real-Time Surveillance, Deep Learning.

I. INTRODUCTION

Rising traffic violations, particularly the non-use of helmets by two-wheeler riders, have made automated road safety monitoring an urgent priority in urban environments. Manual surveillance methods are inherently limited they are labor-intensive, inconsistent, and unable to scale across dense road networks. This paper presents a computer vision-based system that addresses these limitations by performing simultaneous helmet compliance detection and license plate recognition within a single inference pipeline, powered by a fine-tuned YOLOv10 model. Unlike conventional approaches that treat each detection task independently, the proposed framework processes both objectives in a unified pass over each video frame, reducing computational overhead while improving response time. Detected license plate regions are forwarded to a neural network-based OCR module that accurately decodes alphanumeric registration text for vehicle identification. The system is specifically engineered to handle small objects helmets and plates under challenging real-world conditions including low illumination, partial occlusion, and varying camera perspectives. Its modular architecture supports integration with existing CCTV infrastructure and cloud-connected traffic management platforms, offering a scalable and practical solution for intelligent road safety enforcement.

A. Objective

The primary objective of this project is to design and implement an automated detection system capable of identifying helmet non-compliance and extracting vehicle registration numbers from two-wheeler traffic in real time. The system leverages an optimised YOLO-based detection model in conjunction with an OCR pipeline to analyse both static images and live video input with high speed and accuracy. By automating the identification of helmet less riders and linking each violation to a specific vehicle through license plate recognition, the system reduces dependence on human monitoring and enables consistent, unbiased enforcement of road safety regulations.

The architecture is designed with scalability as a core requirement, supporting seamless deployment across smart city surveillance networks, roadside monitoring units, and urban traffic management infrastructure.

B. Problem Statement

The rapid expansion of urban traffic has exposed the limitations of conventional road safety enforcement, which relies heavily on human supervision and is therefore inconsistent and resource-intensive. A significant gap persists in the reliable, automated detection of helmet violations among two-wheeler riders and the concurrent identification of their vehicles through license plate recognition. Existing automated systems frequently under perform in real-world conditions degraded visibility, motion blur, partial obstruction of riders or plates, and regional variation in plate formats all contribute to reduced detection reliability. This project proposes a unified deep learning pipeline that integrates an optimised YOLO model with OCR-based text extraction to simultaneously detect riders, classify helmet usage, and retrieve plate numbers from live traffic feeds prioritising high accuracy, low latency, and robustness under operational conditions.

C. Scope of the Project

The scope of this project encompasses the end-to-end development of a real-time helmet and license plate detection system for two-wheeler traffic, designed to operate reliably across varying environmental conditions including fluctuating lighting, traffic density, and camera orientations. The system targets practical deployment in traffic monitoring stations, roadside surveillance setups, and smart city environments where continuous automated oversight is required. License plate recognition via OCR extends the system's utility to include vehicle identification, digital record maintenance, and automated violation logging. The underlying architecture is light weight and compatible with edge devices and CCTV-integrated platforms, ensuring low operational cost and ease of deployment. The system is further extensible future iterations may incorporate real-time alert generation, vehicle tracking across frames, and centralised cloud-based analytics, positioning it as a foundational component for next-generation intelligent traffic management solutions.

II. LITERATURE SURVEY

1. **Zhou et al. (2023**) SG-YOLOv5 is introduced as a computationally lean detection model tailored for simultaneous helmet and license plate identification within live traffic feeds. Rather than conventional convolution operations, the architecture integrates ShuffleNetv2 and GhostNet blocks, achieving a marked reduction in parameter count without sacrificing detection quality. Additional enhancements including refined multi-scale feature aggregation and channel-wise attention bolster the model's sensitivity to small, densely packed objects under visually degraded conditions such as nighttime scenes and congested roadways. Benchmarking against the baseline YOLOv5 confirms measurable gains across precision, recall, and frame-rate throughput, positioning the model as a strong candidate for resource-constrained edge deployments.
2. **Reddy et al. (2024)** through a systematic survey of existing helmet and license plate detection pipelines, this work exposes a fundamental inefficiency in conventional approaches: treating both recognition tasks as independent processes inflates computational demand and limits deployment practicality. Multi-task learning paradigms are examined as a particularly effective design philosophy, with shared representational layers enabling the network to generalise better across both tasks simultaneously. The survey concludes that co-trained, integrated systems consistently outperform disjoint solutions in the throughput and latency demands of real-world smart city traffic monitoring.
3. **Singh et al. (2022)** this work investigates a composite deep learning strategy for flagging traffic rule violations, coupling object detection with dedicated classification and text recognition stages. A YOLO-based front-end handles the spatial localization of riders, protective head gear, and registration plates, while downstream OCR components built on CRNN and LSTM architectures decode the extracted plate imagery into readable character strings. Practical obstacles inherent to on-road footage, including motion smear, inconsistent illumination, and partial occlusion, are mitigated through carefully selected CNN design choices. Across diverse real-world test scenarios, the hybrid pipeline demonstrates substantially stronger accuracy and resilience than conventional rule-based or single-stage detection alternatives.
4. **Kulkarni et al. (2022)** conducted a comparative analysis of multiple YOLO variants spanning YOLOv3 throughYOLOv8 evaluating their suitability for helmet detection tasks across dimensions of precision, inference speed, and computational efficiency. Their findings indicate that while larger models such as YOLOv4 and YOLOv5 deliver stronger detection accuracy, nano-scale variants like YOLOv5n and YOLOv8n offer a more practical trade-off for edge device deployment due to their reduced resource footprint. The study further examines end-to-end traffic enforcement pipelines that couple helmet detection with automated license plate localization and OCR-based character recognition.
5. **Rahman et al. (2023)** surveyed the evolution of Automatic Number Plate Recognition (ANPR) systems, contrasting conventional image processing pipelines against contemporary deep learning architectures. The authors demonstrate that detectors such as YOLO and Faster R-CNN substantially outperform legacy techniques in both recognition accuracy and real-time responsiveness. For the character extraction stage, sequence-based models like CRNN and LSTM were found to surpass rule-based OCR approaches in handling diverse and challenging plate formats. The study ultimately advocates for a fully integrated pipeline pairing YOLO-based plate detection with neural OCR as the most viable architecture for scalable, real-world ANPR deployment. At the heart of the proposed framework lies a fine-tuned YOLOv10 model engineered for low-latency visual recognition. Incoming RGB frames are first channeled through the backbone (C1–C11), which builds a layered representational hierarchy from raw pixel data. The neck (C12–C17) then reconciles feature maps across multiple spatial scales through up sampling and lateral merging, substantially improving localisation of compact targets such as registration plates and protective headgear. Final outputs region proposals, category labels, and detection confidence values are produced by the prediction head (C18–C23) in a single, uninterrupted forward pass.

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III. SYSTEM DESIGN

A. System Architecture

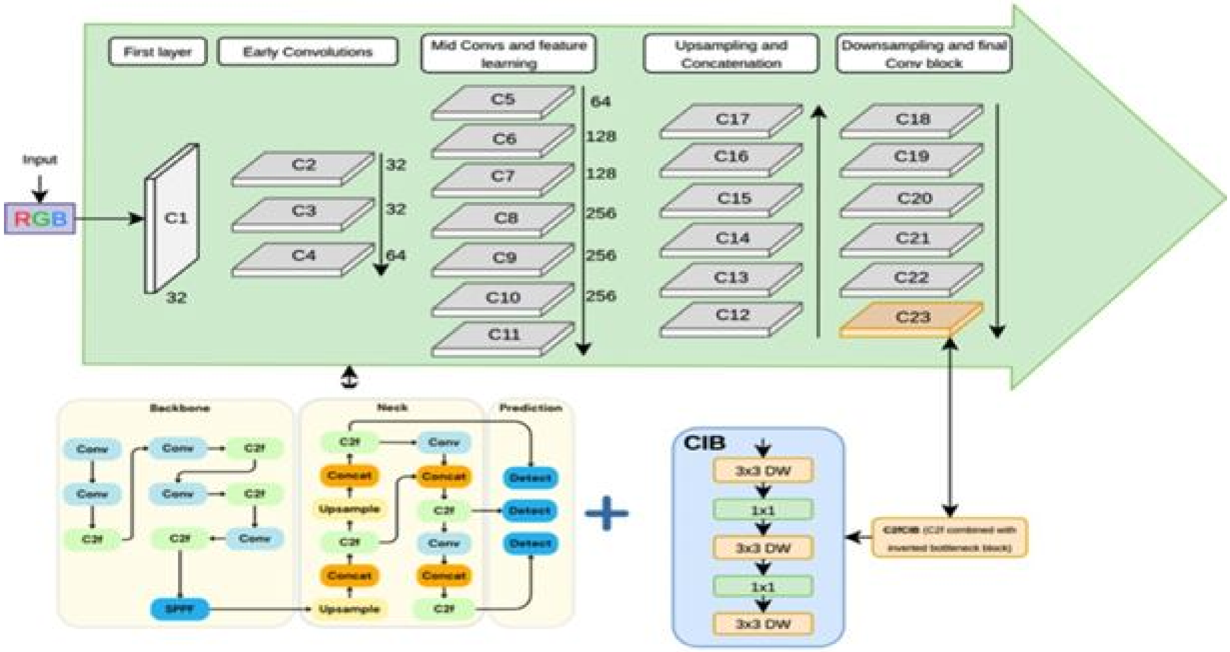

Fig1: System Architecture

Structural efficiency is maintained through three key components: C2f modules that encourage cross-layer feature reuse, an SPPF block that widens contextual receptive coverage, and a CIB block that constrains parameter overhead without degrading representational quality. The net result is a streamlined inference pipeline capable of sustaining the speed and precision required for continuous roadway surveillance.

B. Methodology Modules Name:

1. Data collection and Dataset Preparation
2. Data Preprocessing
3. Model Optimisation
4. Dual Detection
5. License Plate recognition using OCR
6. System Implementation and Real Time Testing
7. Result Evaluation and Optimisation

1. **Data collection and Dataset Preparation:** A diverse dataset of traffic images and videos is collectedunder varying real-world conditions such as lighting, weather, and camera angles. Data is sourced from public datasets, CCTV footage, and manual collection. Each image is annotated with bounding boxes for helmets, riders, and license plates to ensure robust and accurate model training.
2. **Data Preprocessing:** Raw data is processed by resizing and normalizing images to maintain consistency and reduce computational load. Data augmentation techniques like rotation, flipping, and brightness adjustment are applied to improve diversity. Trained on 4,800 annotated images across 3 classes for 120 epochs at 640×640 resolution. Noise reduction, image enhancement, and class balancing are used to increase clarity and prevent model bias.
3. **Model Optimisation:** An optimized YOLO model (e.g.,YOLOv10) is selected for its real-time detection capabilities and high accuracy. The model is trained using annotated datasets with fine-tuned hyper parameters and optimised backbone for better feature extraction. Performance is evaluated using metrics such as precision, recall, and mAP.
4. **Dual Detection:** The trained YOLO model performs simultaneous detection of helmets and license plates with in a single frame. It identifies riders and classifies helmet usage while localizing license plates using bounding boxes. This unified approach improves efficiency and enables real-time detection of multiple violations.
5. **License Plate Recognition using OCR:** Detected license plate regions are cropped and enhanced using preprocessing techniques like thresholding and contrast adjustment. OCR confidence threshold set at 0.6; plates below threshold flagged for manual review. A neural network-based OCR system is used to extract alphanumeric characters accurately. The recognised text is converted into a digital format for vehicle identification.
6. **Violation identification:** The system automatically detects violations such as riders without helmets based on detection results. The corresponding license plate number is linked to each violation instance. Relevant details like image, time stamp, and vehicle number are recorded and stored securely for further use.
7. **Result Evaluation and Optimisation:** System performance is evaluated using real-world data by comparing predictions with ground truth values. Error analysis identifies false positives and negatives to improve accuracy. Optimisation techniques such as pruning, quantisation, and batch normalisation enhance efficiency and scalability.

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IV. EXISTING SYSTEM VS PROPOSED SYSTEM

A. Existing System

Existing traffic monitoring systems mainly depend on CCTV surveillance, speed sensors, and manual supervision, which are inefficient and prone to human error, especially in busy environments. Some automated approaches use traditional image processing and basic machine learning, but they rely on handcrafted features and perform poorly under real-world conditions such as low lighting, motion blur, occlusion, and varying camera angles. Additionally, differences in license plate formats further reduce accuracy. Most systems focus on a single task, like license plate detection, and do not support combined analysis such as helmet detection. They also struggle with real-time processing and scalability, making them unsuitable for large-scales mart city applications. These limitations highlight the need for an advanced, integrated deep learning-based solution.

Existing System Disadvantages:

- Limited Accuracy For Small Objects
- Cannot handle Complex Environments
- Lack of Combined System
- High computation + slow processing

B. Proposed System

The YOLO v10 builds upon the YOLO v8 foundation with targeted architectural refinements aimed at resolving long standing weaknesses in real-time detection namely poor sensitivity to small objects, class imbalance, and cluttered backgrounds. Two core training-side improvements drive this: Focal Loss, which steers the optimizer toward harder, under represented samples rather than easy dominant ones, and Hard Negative Mining, which filters out uninformative false positives to sharpen the boundary between genuine and spurious detections. On the architectural side, upgraded FPN and PAN structures with in the backbone and neck enable richer multi-scale feature aggregation, extending reliable recognition across varying object sizes, lighting conditions, and partial occlusions. Trained on diverse, richly annotated datasets spanning multiple helmet styles and vehicle categories, the model generalizes effectively to deployment scenarios ranging from roadside license plate capture on moving vehicles to helmet compliance checks in visually degraded environments.

Proposed System Advantages:

- Dual Detection in single model
- Real-time processing
- High Accuracy using deep learning
- Works in complex Environments

V. IMPLEMENTATION

A. General

The implementation focuses on developing a real-time Helmet and License Plate Detection System using an optimized YOLO model and OCR techniques. The system is built using Python with libraries such as OpenCV, NumPy, and Flask, and is trained on annotated datasets of riders with helmet and license plate labels. Preprocessing techniques like resizing, normalisation, and image enhancement are applied to improve detection accuracy. The YOLO model performs multi-class detection (helmet, no-helmet, license plate), while OCR extracts license plate text.

B. Develop Environment

The system is developed using Python with support from libraries such as OpenCV and deep learning frameworks for implementing the YOLO-based model. Development is carried out on platforms like Jupyter Notebook or Spyder in Windows or Mac environments. Training can utilise GPU support for faster processing, while deployment can be done on local systems or edge devices. The use of open-source tools makes the system cost-effective, flexible, and easy to maintain. Additionally, the environment supports efficient testing, debugging, and future enhancements, along with smooth integration with other technologies.

C. System implementation and Deployment

The system is organised into modules including data acquisition, preprocessing, detection, OCR, and display. It supports real-time processing using live or recorded video and can be deployed on local or edge devices. Integration with CCTV systems enables practical monitoring applications. The model is evaluated using metrics such as precision, recall, and mAP to ensure accuracy and efficiency. Overall, the system provides a scalable and automated solution for intelligent traffic monitoring.

VI. EXPERIMENTAL RESULTS

The home page of the Helmet and License Plate Detection System acts as the main interface, providing a simple and user-friendly entry point for interaction. It includes a navigation bar with options like Home and Register, along with clear instructions such as “Upload Photo for Detection” to guide users. The clean layout, background visuals, and call-to-action button make the system easy to understand and use for all users. The User Registration page provides a clean and simple interface for new users to sign up easily. It includes a navigation bar with options like Home, Register, and Login, along with a well-structured “Sign Up” form containing fields for username, email, and password. The minimal design, clear input fields, and prominent Register button ensure a smooth and user-friendly on boarding experience. The User Login page provides a clean and simple interface for users to access the system easily. It includes a navigation bar with options like Home, Register, and Login, along with a well-designed login form containing fields for username/email and password. The minimal layout and prominent Login button ensure a smooth, user-friendly, and secure authentication experience.

A. Home Page

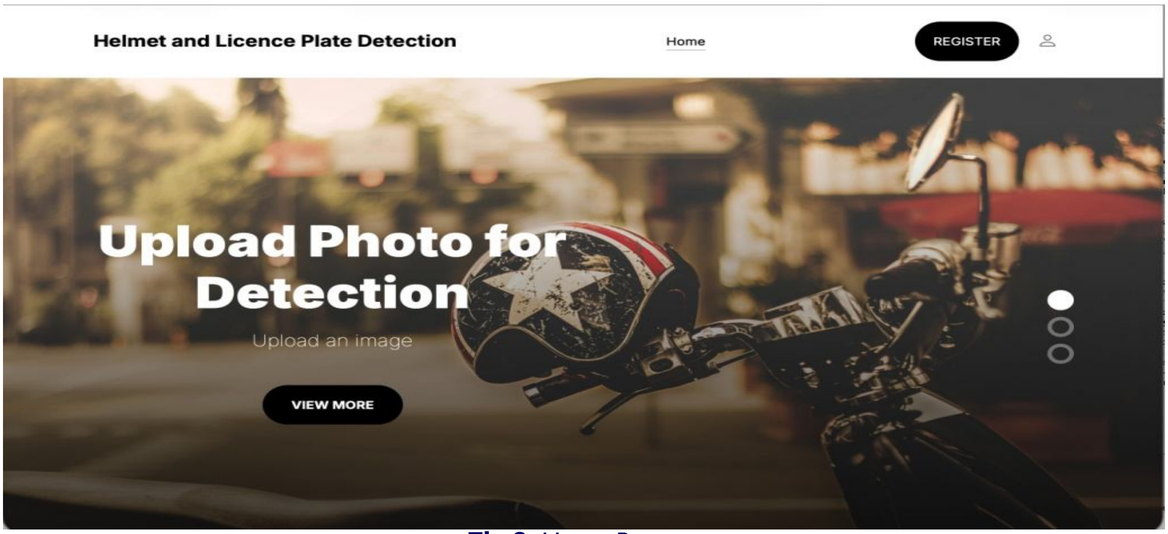

Fig 2: Home Page

B. Registration Page

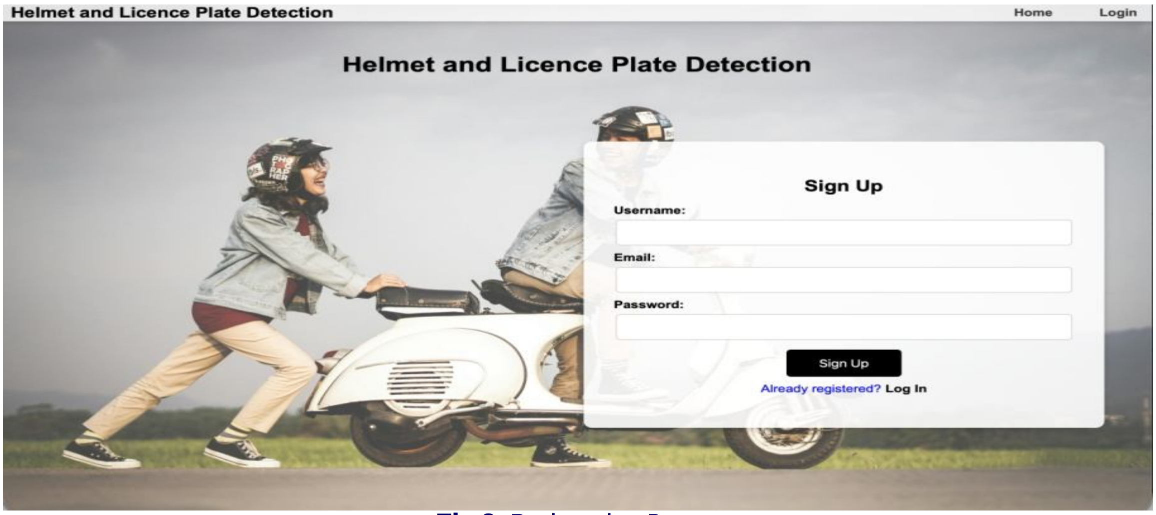

Fig 3: Registration Page

C. Login Page

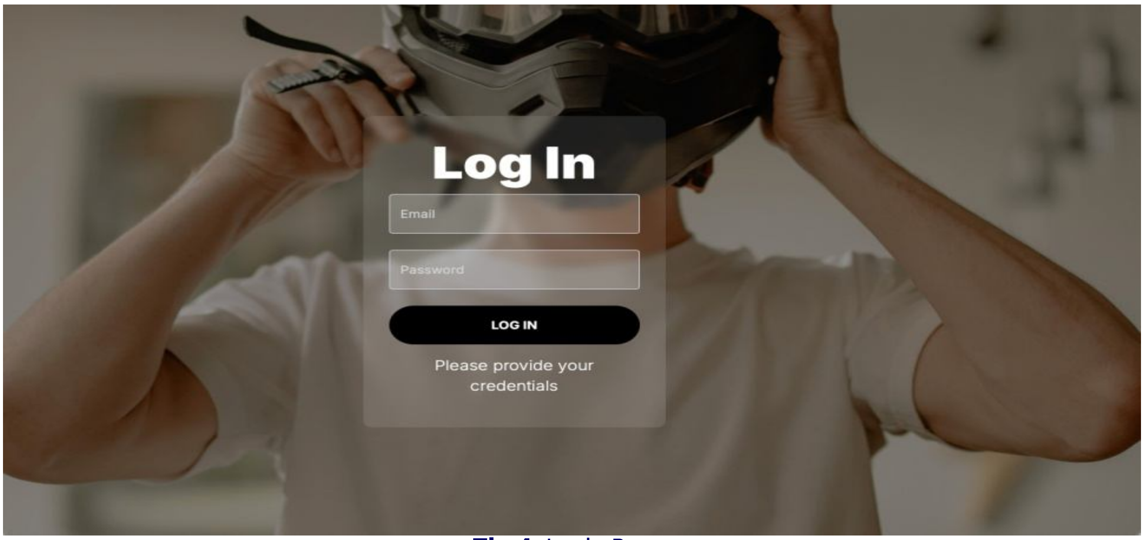

Fig 4: Login Page

The Detection Interface allows users to upload images or videos for helmet and license plate detection using the YOLO model. It features a navigation bar with options like Home, Register, Login, and Main for easy access. The clean layout with an upload panel (Choose File and Upload) ensures a simple and user-friendly detection process.

D. Data uploading Page

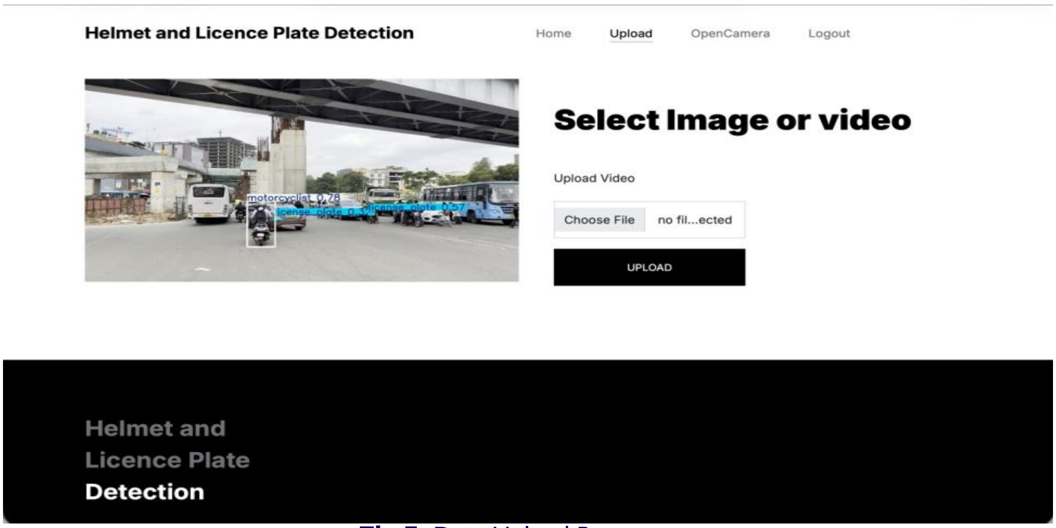

Fig 5: Data Upload Page

E. Detection Page

Fig 6: License Plate and Helmet Detection with bounding boxes

The Results page displays both the uploaded image and the processed output generated by the detection system. The resultant image highlights detected objects such as helmets and license plates using bounding boxes and labels. This side-by-side comparison helps users easily understand the model's detection performance and accuracy.

F. Real Time Object Detection

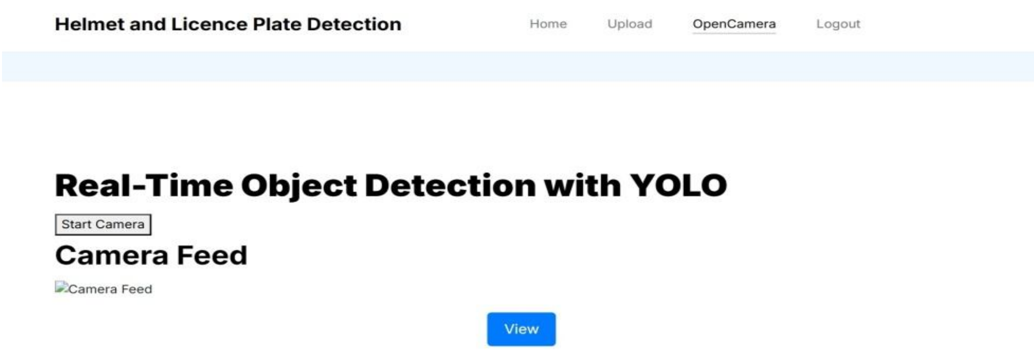

Fig7: Real-Time Object Detection Interface

The Real-Time Detection page enables users to perform live object detection using the system's camera. It includes options like "Start Camera" to initiate the feed and displays real-time detection results powered by the YOLO model. The simple layout and navigation bar make it easy for users to access live monitoring and interact with the system efficiently. The figure shows real-time detection results where the YOLO model identifies motorcyclists, helmets, and license plates using bounding boxes and confidence scores in a live traffic environment. The figure shows real-time detection results where the YOLO model identifies motorcyclists and license plates in a traffic environment using bounding boxes and confidence scores, demonstrating the system's effectiveness in multi-object detection.

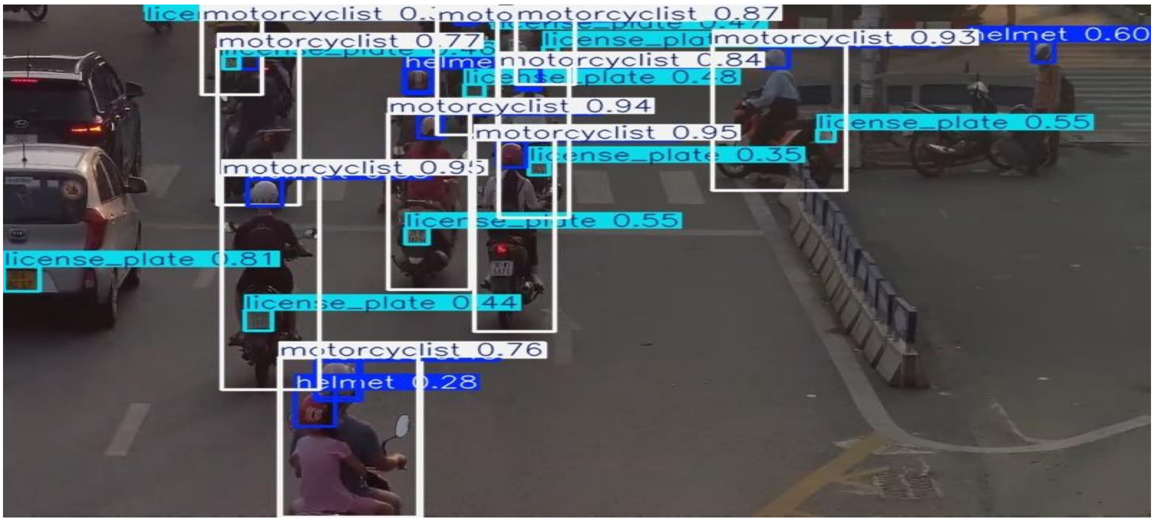

Fig 8.1: Live Camera Detection Output with Bounding Boxes

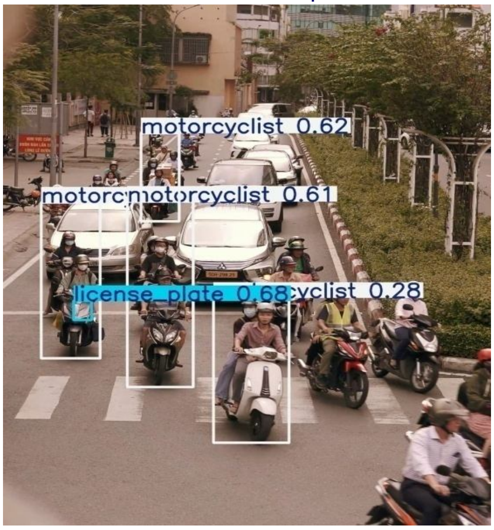

Fig 8.2: YOLO-Based Multi-Object Detection in Traffic Scene

VII. CONCLUSION

This project establishes a compelling proof-of-concept for deploying fine-tuned deep learning within live traffic enforcement, with a YOLOv10-based pipeline demonstrating that helmet compliance checks and license plate identification can be unified into a single, high-throughput inference system. The architecture handles the practical difficulties inherent to on-road footage diminutive target sizes, fluctuating illumination, partial obstruction, and visually noisy backgrounds without sacrificing recognition reliability. Co-locating both detection objectives within one forward pass not only reduces redundant computation but confirms the model's capacity for genuine multi-target recognition at scale. Operational utility is further reinforced by the OCR integration, which converts extracted plate crops into query able text strings, extending the system's reach into vehicle tracking, access governance, and automated penalty workflows. The underlying YOLO architecture strikes a deliberate balance between inferential accuracy and resource consumption, making edge and embedded deployment viable without hardware upgrades. Its modular construction additionally ensures that capability expansions whether through broader training corpora, refined weight tuning, or the addition of object tracking can be absorbed without architectural overhaul. Collectively, the system lays substantive groundwork for next-generation intelligent surveillance infrastructure, offering a scalable, adaptable, and minimally supervised monitoring solution well-aligned with the evolving demands of smart urban environments.

VIII. FUTURE ENHANCEMENT

Several avenues exist for extending the current framework into a more comprehensive enforcement platform. An event-driven notification layer could be embedded to flag violation incidents as they occur, enabling immediate response without continuous manual oversight. Plate text extraction could be further sharpened by pairing advanced preprocessing pipelines targeting degraded inputs such as motion-smeared or poorly lit frames with more expressive deep learning OCR backbones. Persistent cloud infrastructure would consolidate detection logs into a centralized repository, supporting retrospective analysis, visual dash boarding, and remote accessibility while naturally accommodating growth in deployment scale. Complementing this, a dedicated mobile interface would extend the system's reach beyond fixed installations, empowering field personnel to submit footage directly from handheld devices for either on-device or cloud-offloaded inference.

Collectively, these extensions would transition the system from a capable detection engine into a fully integrated, operationally mature traffic intelligence platform.

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