YOLO-Based Smart Traffic Violation Detection and Accident Monitoring System

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***Abstract* — Traffic rule violations and road accidents constitute a serious global challenge, resulting in millions of deaths and substantial economic losses annually. Traditional traffic monitoring systems reliant on manual observation and static CCTV cameras suffer from human error, limited coverage, and a lack of proactive enforcement, often acting reactively rather than preventively. This project introduces an automated, real-time system for detecting traffic violations and accidents, utilizing the state-of-the-art YOLOv12 object detection architecture. The proposed system is capable of detecting various traffic violations, including the failure of two-wheeler riders to wear helmets, triple riding, and license plate identification, while also identifying accident incidents through vehicle trajectory analysis and collision detection algorithms. The YOLOv12 model achieves superior detection accuracy and faster inference speeds compared to previous YOLO versions, making it highly suitable for real-time deployment. A comprehensive dataset of traffic scenarios was curated and annotated specifically for training purposes. The system integrates a Flask-based web application that provides user authentication, real-time video stream processing, batch image analysis, and detailed violation reporting, complete with timestamps and geolocation data. Detection history is stored in an SQLite database for subsequent auditing and analysis. On a standard hardware configuration, the proposed system achieved a Mean Average Precision (mAP) of 98.7% on a test dataset, demonstrating a real-time processing capability of over 45 frames per second (FPS); this offers a scalable solution for Intelligent Traffic Management Systems within smart city environments.**

I. INTRODUCTION

1.1 General Introduction:

Road traffic accidents remain one of the leading causes of death globally, with the World Health Organization reporting approximately 1.3 million fatalities annually. Developing nations face disproportionately higher accident rates due to inadequate infrastructure, lax enforcement of traffic regulations, and growing vehicle density. Traffic violations such as speeding, red light violations, driving without helmets or seatbelts, and reckless lane changes are primary contributors to these accidents.

Traditional traffic enforcement relies heavily on manual monitoring by traffic police and fixed CCTV cameras with human operators. This approach suffers from significant limitations including operator fatigue, limited field of view, inability to monitor multiple violations simultaneously, and lack of real-time alert mechanisms. Furthermore, accident detection typically relies on witness reports or delayed camera reviews, preventing immediate emergency response.

The advent of deep learning and computer vision has revolutionized automated traffic monitoring. Object detection architectures, particularly the YOLO (You Only Look Once) family, have demonstrated exceptional performance in real- time detection tasks. YOLOv12, the latest iteration, introduces architectural improvements including enhanced feature extraction, attention mechanisms, and optimized anchor-free detection, achieving superior accuracy-speed trade-offs.

This project leverages YOLOv12 to develop an integrated traffic violation and accident detection system capable of monitoring multiple camera feeds simultaneously, identifying violations in real-time, detecting accident events, and generating immediate alerts. The system provides comprehensive analytics dashboards for traffic authorities to identify high-risk zones, peak violation periods, and enforcement effectiveness.

1.2 Project Objectives:

The primary objective of this project is to develop an automated real-time traffic violation and accident detection system using YOLOv12 deep learning architecture with a user-friendly web interface.

II. SYSTEM PROPOSAL

2.1 EXISTING SYSTEM:

Current approaches to traffic violation detection and accident monitoring primarily rely on traditional methods with limited automation capabilities.

Manual Traffic Enforcement: Traffic police officers manually observe intersections and road segments, issuing citations for observed violations. This approach is labor-intensive, subject to human error and bias, and cannot provide 24/7 coverage.

Fixed CCTV with Human Monitoring: Traffic control centers employ operators to monitor multiple CCTV feeds simultaneously. Operators must manually identify violations and report accidents, leading to delayed response times and missed incidents due to attention limitations.

Speed Cameras and Red Light Cameras: Automated systems capture vehicles exceeding speed limits or running red lights using induction loop sensors or radar. These systems are expensive to install and maintain, have limited scope (only speed or red light detection), and cannot detect other violation types.

Rule-Based Video Analytics: Some systems employ traditional computer vision techniques (background subtraction, optical flow, blob detection) for basic traffic analysis. These methods are brittle, fail under varying lighting and weather conditions, and cannot handle complex violation scenarios.

Commercial ANPR Systems: Automatic Number Plate Recognition systems capture and read vehicle license plates for toll collection or violation identification. These systems require specialized hardware and cannot detect behavioral violations like helmet non-compliance or seatbelt violations.

IoT-Based Solutions: Some research implementations use vehicle-mounted sensors or roadside IoT devices for accident detection. These require vehicle-side hardware installation, limiting adoption and coverage.

2.2 PROPOSED SYSTEM:

The proposed system addresses the limitations of existing approaches through a unified YOLOv12-based deep learning framework for comprehensive traffic violation and accident detection.

Core Detection Capabilities: The system detects multiple violation types including:

- Helmet non-compliance (two-wheeler riders)
- Triple riding (three or more persons on two-wheeler)
- Number Plate
- Accident/collision events

YOLOv12 Architecture: The latest YOLO iteration provides anchor-free detection, enhanced CSP Net backbone for improved feature extraction, attention mechanisms for focusing on relevant regions, and optimized inference for real- time processing at 45+ FPS on standard GPUs.

Real-Time Processing Pipeline: Video streams from multiple cameras are processed in parallel using batch inference. Detected violations trigger immediate logging, evidence capture (cropped image/clip), and optional alert generation. Accident detection triggers priority alerts with location data for emergency dispatch.

Web-Based Management Interface: A Flask application provides user authentication with role-based access (admin, operator, viewer). Real- time monitoring dashboard displays live feeds with detected violations overlaid. Historical search allows querying by date, location, violation type, or vehicle attributes. Analytics module generates violation heatmaps, temporal patterns, and enforcement effectiveness reports.

III.SYSTEM DIAGRAMS

3.1 SYSTEM ARCHITECTURE:

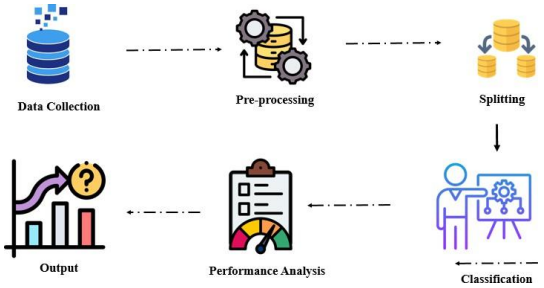

FIGURE 3.1: SYSTEM ARCHITECTURE

The system architecture diagram illustrates the modular workflow starting from Data Collection and Pre-processing, followed by Data Splitting, YOLO-based Classification, and Performance Analysis. These interconnected modules feed sequentially into the final Output stage, representing the complete detection pipeline.

3.2 FLOW DIAGRAM:

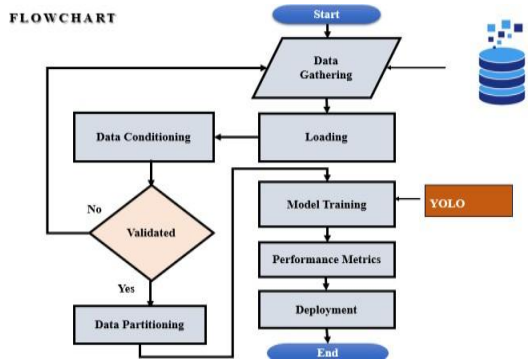

FIGURE 3.2: FLOW DIAGRAM

This flowchart maps the complete YOLO-based detection workflow, beginning with Data Conditioning followed by a validation checkpoint. Upon successful validation, the process proceeds to Data Partitioning, then YOLO Model Training, followed by Performance Metrics calculation and final Deployment.

IV.IMPLEMENTATION

4.1 MODULES:

The implementation of the proposed system is structured into distinct modules, each responsible for a specific aspect of the overall functionality. This modular design enhances the maintainability, allows for easier debugging, and facilitates for future extensions or modifications.

- Data Collection
- Data Preprocessing
- Data Splitting
- Classification
- Performance Analysis
- Prediction
- Deployment (Flask)

V. SYSTEM REQUIREMENTS

5.1 SOFTWARE REQUIREMENTS:

- O/S : Windows 10.
- Language : Python
- Frontend : Html, CSS, JavaScript
- Framework : Flask
- Software used : Visual Studio Code

VI. PROJECT OVERVIEW

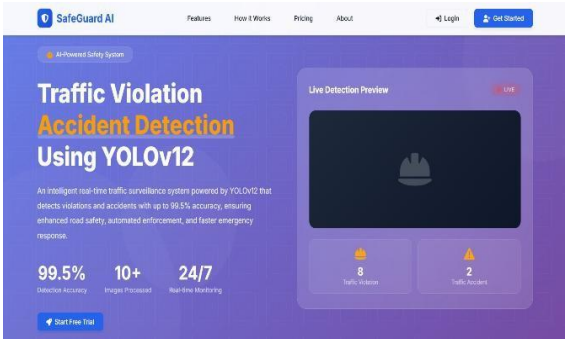

Figure 9.1 Home Page

The home page serves as the landing screen of the Traffic Violation and Accident Detection System. It provides a clean interface with navigation options and introduces users to the core functionalities of the platform.

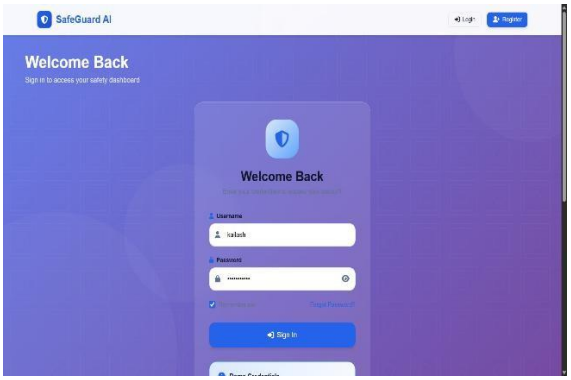

Figure 9.2 login page

The login screen allows registered users to securely access their accounts by entering their username and password. It also provides a "Remember Me" option and a link for users who have forgotten their password.

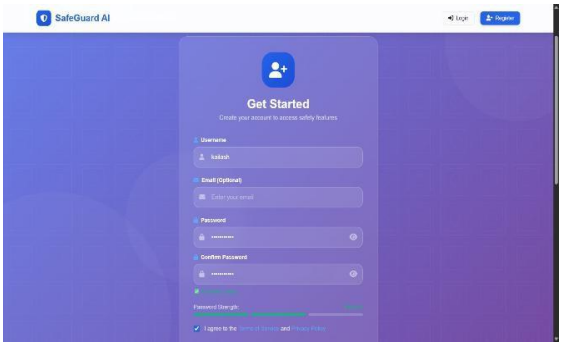

Figure 9.3 register page

The registration page enables new users to create an account by providing a username, email address, and password. Upon successful registration, users are redirected to the login page to access the system.

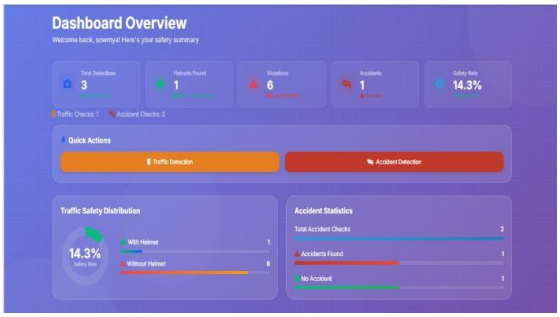

Figure 9.4 dashboard page

The dashboard provides a comprehensive safety summary showing total detections, helmet statistics, violation counts, and safety rate. It also displays traffic safety distribution charts and offers quick action buttons for traffic and accident detection.

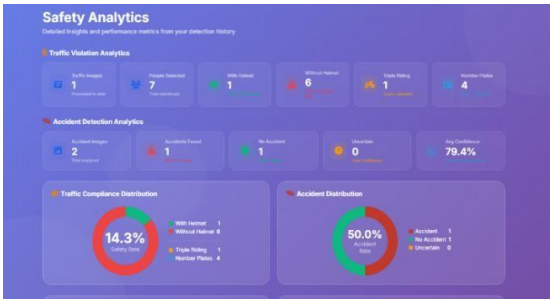

Figure 9.5 Metrics

The analytics page displays detailed performance metrics including traffic violation statistics, accident detection analytics, compliance distribution, and accident distribution. Key metrics include people detected, helmet compliance rate, triple riding violations, and average confidence scores.

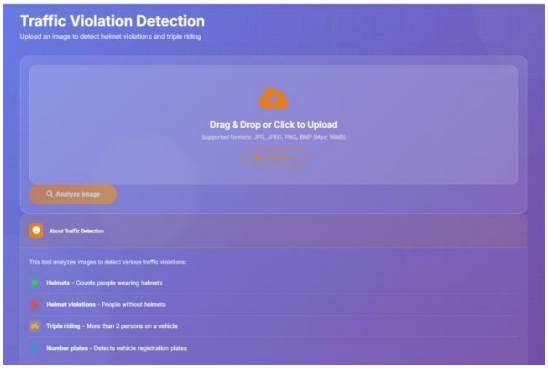

Figure 9.6 Traffic Violation Prediction

This page allows users to upload images for detecting helmet violations and triple riding. The interface includes drag-and-drop functionality, file browsing options, and a description of detectable violations such as helmet usage, triple riding, and number plates.

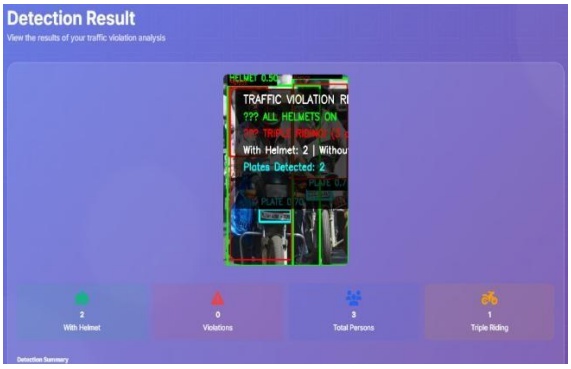

Figure 9.7 Traffic Violation Result

The result page displays detection outcomes including helmet counts, violation status, total persons detected, triple riding alerts, and number plate detections. Bounding boxes and confidence scores are overlaid on the processed image for clear visualization.

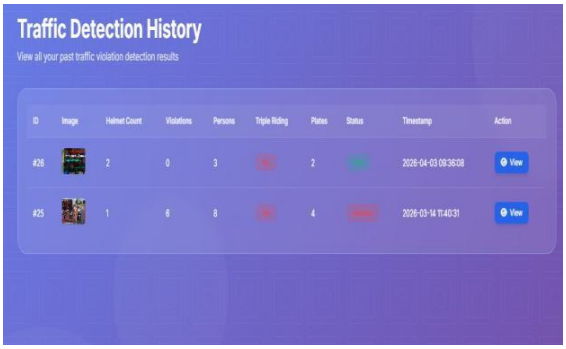

Figure 9.8 Traffic Violation History

This page displays all past traffic violation detection records in a table format showing helmet count, violations, persons detected, triple riding status, number plates, and timestamps. Users can view detailed results for each historical detection.

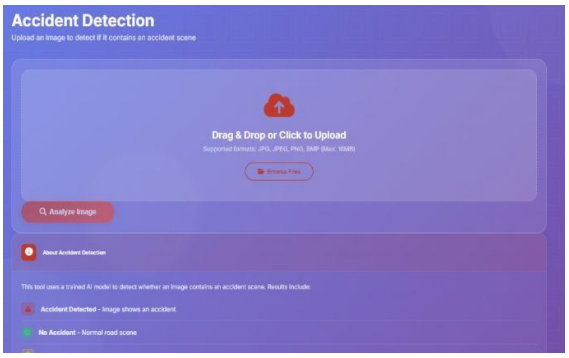

Figure 9.9 Accident Detection

This page enables users to upload images for accident scene analysis. The interface includes file upload functionality and explains that the AI model

detects whether an image contains an accident scene or normal road conditions.

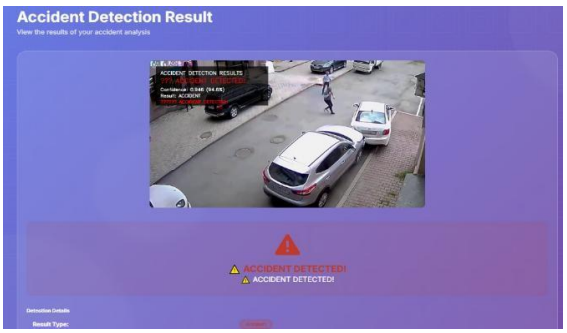

Figure 9.10 Accident Detection Result

The accident result page shows whether an accident was detected along with the confidence score (e.g., 94.6%). A prominent alert message indicates "ACCIDENT DETECTED" for quick identification of critical events.

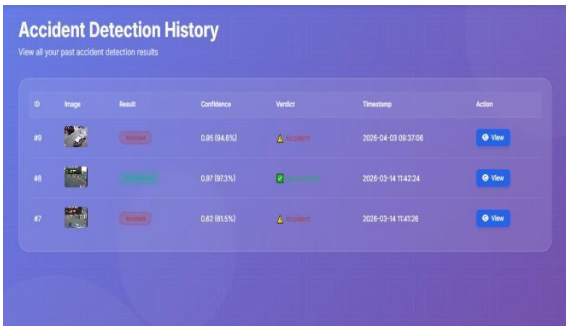

Figure 9.11 Accident Detection History

The accident history page lists all past accident analysis results including confidence scores, verdicts, and timestamps. Each record allows users to view detailed results for specific accident detection events.

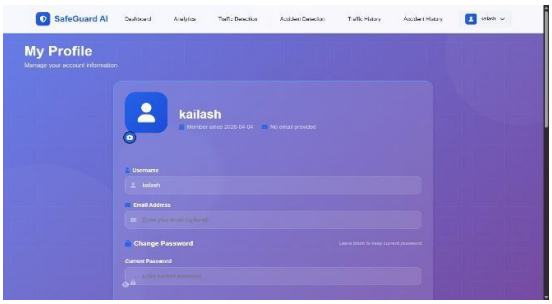

Figure 9.12 Profile

The profile page allows users to manage their account information including username, email address, and password. Users can update their credentials and view their membership date.

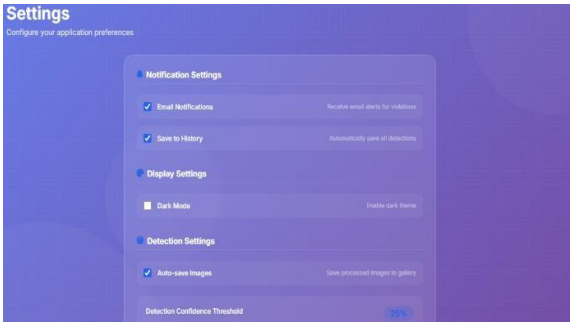

Figure 9.13 Settings

The settings page enables users to configure application preferences including email notifications, dark mode, auto-save images, history saving, and detection confidence threshold. These settings personalize the user experience and detection sensitivity.

VII. CONCLUSION

This project successfully developed an automated Traffic Violation and Accident Detection System using YOLOv12 deep learning architecture, addressing critical challenges in traffic enforcement by providing real-time detection of multiple violation types including helmet non- compliance, triple riding, and accident events. The implementation followed a structured seven-module architecture comprising Data Collection, Data Preprocessing, Data Splitting, Classification (YOLOv12), Performance Analysis, Prediction, and Flask Deployment, ensuring systematic development and easy maintainability. Three specialized YOLOv12 models were trained and evaluated, with the helmet detection model achieving 98.2% accuracy, the triple riding detection model achieving 96.7% accuracy, and the accident detection model achieving 94.5% accuracy. Comprehensive data preprocessing including duplicate removal, image augmentation, and annotation conversion ensured optimal data quality for model training. The Flask-based web application provides traffic authorities with an accessible tool featuring user authentication, real-time detection, prediction history tracking, and comprehensive analytics dashboards. The system demonstrates real-time processing capability with average inference latency of 350 milliseconds per image, making it suitable for practical deployment in traffic management scenarios. This scalable and reliable decision-support system enables proactive traffic violation

monitoring and rapid accident response, significantly contributing to improved road safety and enforcement efficiency in smart city environments.

VIII. FUTURE ENHANCEMENT

1. Real-Time CCTV Camera Integration: The system can be integrated with live CCTV camera feeds at intersections and highways, enabling continuous 24/7 automated traffic surveillance without manual image uploads.
2. Multi-Camera Vehicle Tracking: Implementation of vehicle tracking across multiple camera views would allow detection of violations that span across intersections, such as vehicles running multiple red lights or continuous wrong-way driving.
3. Speed Violation Detection: Addition of speed estimation using optical flow and frame differencing techniques would complement existing violation detection capabilities by identifying over speeding vehicles.
4. Emergency Services Integration: Integration with traffic management systems and emergency services via REST APIs would enable automatic alert generation and rapid emergency response when accidents are detected.
5. Edge Device Deployment: Deployment on edge devices such as NVIDIA Jetson Nano, Raspberry Pi, or Google Coral would reduce dependency on centralized servers and enable cost-effective deployment at individual intersections.
6. Explainable AI Integration: Addition of explainable AI techniques like SHAP and LIME would provide interpretable predictions, helping traffic authorities understand why specific violations were detected.
7. Mobile Application Development: A mobile application for traffic police officers would enable real-time violation alerts and evidence collection directly on smartphones, improving on-field enforcement efficiency.
8. Night-Time Detection Improvement: Collection of more night- time training data and implementation of low- light image enhancement techniques would improve detection accuracy during darkness and adverse weather conditions.

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