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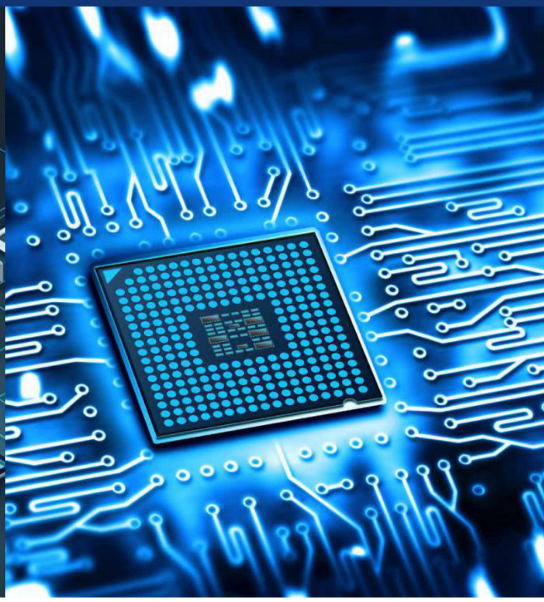


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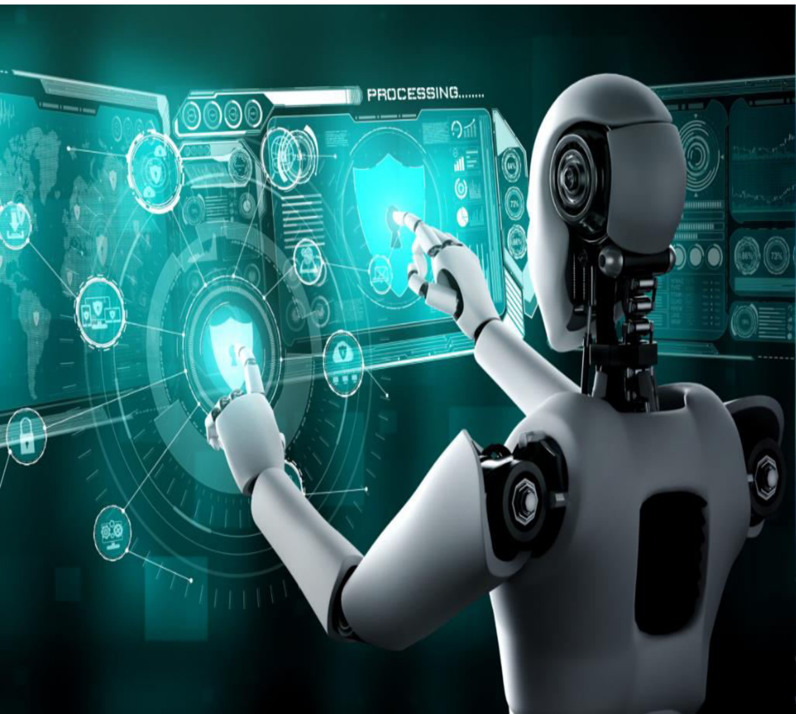

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Accident Eye: AI-Based Real-Time Accident Detection and Multi-Model Surveillance System

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ABSTRACT: "Accident Eye" is a comprehensive system designed to enhance road safety by detecting accidents in real time and monitoring critical aspects such as helmet usage, vehicle types, license plate recognition, and speed detection. This study introduces an AI-powered framework that employs deep learning—primarily using Yolov11—for accurate detection across multiple modules. By integrating advanced computer vision techniques with IoT-enabled alert mechanisms, the system processes live traffic data and autonomously notifies emergency responders, reducing response delays and potentially saving lives. In our experiments, the accident detection module achieved a precision of 93.8%, a recall of 98%, and a mean Average Precision (mAP) of 96.1% [3]. The helmet, vehicle, and license plate detection modules demonstrated similarly robust performance, while the speed detection module estimated vehicle speeds with an average error of approximately 3 km/h and 90% accuracy [5].

KEYWORDS: Energy efficient algorithm; Manets; total transmission energy; maximum number of hops; network lifetime

I. INTRODUCTION

Road traffic accidents and traffic violations are major concerns in India and worldwide, resulting in significant loss of life, economic damage, and reduced compliance with safety regulations such as helmet use and speed limits [8]. Traditional detection methods, which rely on manual reporting, often result in critical delays that can exacerbate accident outcomes.

Recent advances in artificial intelligence, particularly deep learning models like Yolov11, have enabled real-time processing of video streams for a range of detection tasks [1], [3]. This research aims to develop an efficient, AI-driven system that supports multi-modal detection—including accident, helmet, license plate, vehicle, and speed detection—to facilitate prompt emergency responses and comprehensive traffic monitoring.

Recent advances in artificial intelligence have transformed road safety and traffic management. The seminal work by Redmon and Farhadi [1] introduced the YOLO (You Only Look Once) framework, which revolutionised real-time object detection by employing a single-stage approach that balances speed and accuracy. In their experiments, YOLO was reported to operate at around 45 frames per second on standard GPUs while achieving competitive accuracy on benchmark datasets [1]. Building on this, Bochkovskiy et al. [2] developed YOLOv4 by incorporating CSPDarknet53 and PANet, which improved detection performance significantly. More recently, Yolov11 [3] has further advanced real-time detection capabilities by optimising the network architecture and training strategies, resulting in higher mAP values and lower latency.

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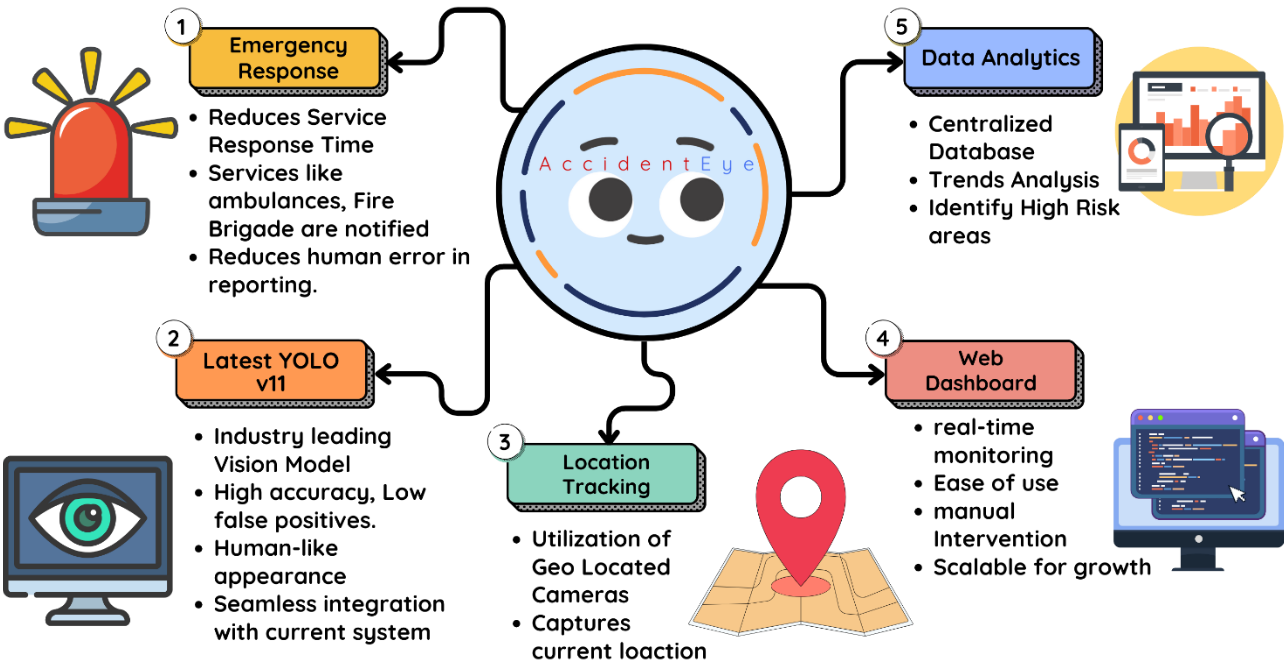

FIGURE 1: SYSTEM ARCHITECTURE DIAGRAM ILLUSTRATING THE OVERALL FRAMEWORK AND MODULE INTERACTIONS

YOLO-based models have been widely applied in various domains, such as vehicle detection, pedestrian monitoring, and hazard recognition in complex traffic scenes [1], [2]. Specialized applications have emerged to address critical safety concerns. For instance, helmet detection systems, as explored by Patel et al. [4], use deep learning to monitor compliance with safety regulations, thereby reducing the risk of head injuries during accidents.Similarly, license plate recognition systems have evolved using convolutional neural networks integrated with YOLO-based architectures to accurately capture vehicle registration details, enhancing law enforcement and traffic management [5]. In addition, video analysis for speed detection, which correlates motion between consecutive frames with spatial references, has shown promise in enforcing speed limits with an accuracy close to 90% [5].

II. METHODOLOGY

i. The multi-modal detection pipeline follows these stages:

1. **Data Acquisition**: Collecting and labelling images and video sequences for accidents, helmet usage, license plates, vehicle types, and vehicle speeds from open datasets and real-world footage [6], [7].
2. **Model Training**: Fine-tuning separate Yolov11 models for each detection task. For the speed detection module, a dedicated script estimates vehicle speeds by analysing consecutive video frames against known spatial references [5].
3. **Inference and Real-Time Processing**: Deploying each trained model on edge computing devices (e.g., Jetson Nano) to process live footage with minimal latency, ensuring real-time performance [3].
4. **Automated Emergency Response**: When any module detects an anomaly (such as an accident, helmet non-compliance, over speeding, or other violations), the system triggers alerts via SMS, mobile notifications, or cloud-based APIs to enable rapid response [8].

ii. The "Accident Eye" system has been architected as a modular system with the following systems:

- **Surveillance Cameras**: High-definition CCTV cameras are used to record live streams of traffic at select locations [8].
- Accident Detection Module: Utilises the Yolov11 model to interpret video streams and accurately identify accidents [3].

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- **Helmet Detection Module:** Monitors helmet usage among riders, ensuring that riders are doing all that they can to mitigate the risk of head injury [4].
- **License Plate Detection Module:** Detects the license plates of vehicles to both record traffic events and for enforcement purposes, assisting police and enforcing authorities [5].
- **Vehicle Detection Module:** Utilises computer vision to detect and classify various vehicles to facilitate a more complete analysis of traffic.
- **Speed Detection Module**: A special script estimates the speed of vehicle movements by analysing vehicle movement across frames and extrapolating this motion to known distances. Evaluation of these types of methods has indicated, on average, an error of approximately 3km/h and the measuring method adopted [5].
- **Cloud-Based Alert System:** Automated alerts to emergency service and local authorities are created when anomaly detection occurs.
- **User Interface**: A Computer application developed using Customtkinter and python provides real-time alerts and intuitive visualisation of all detected events, to ensure officials and citizens are kept up-to-date and informed.

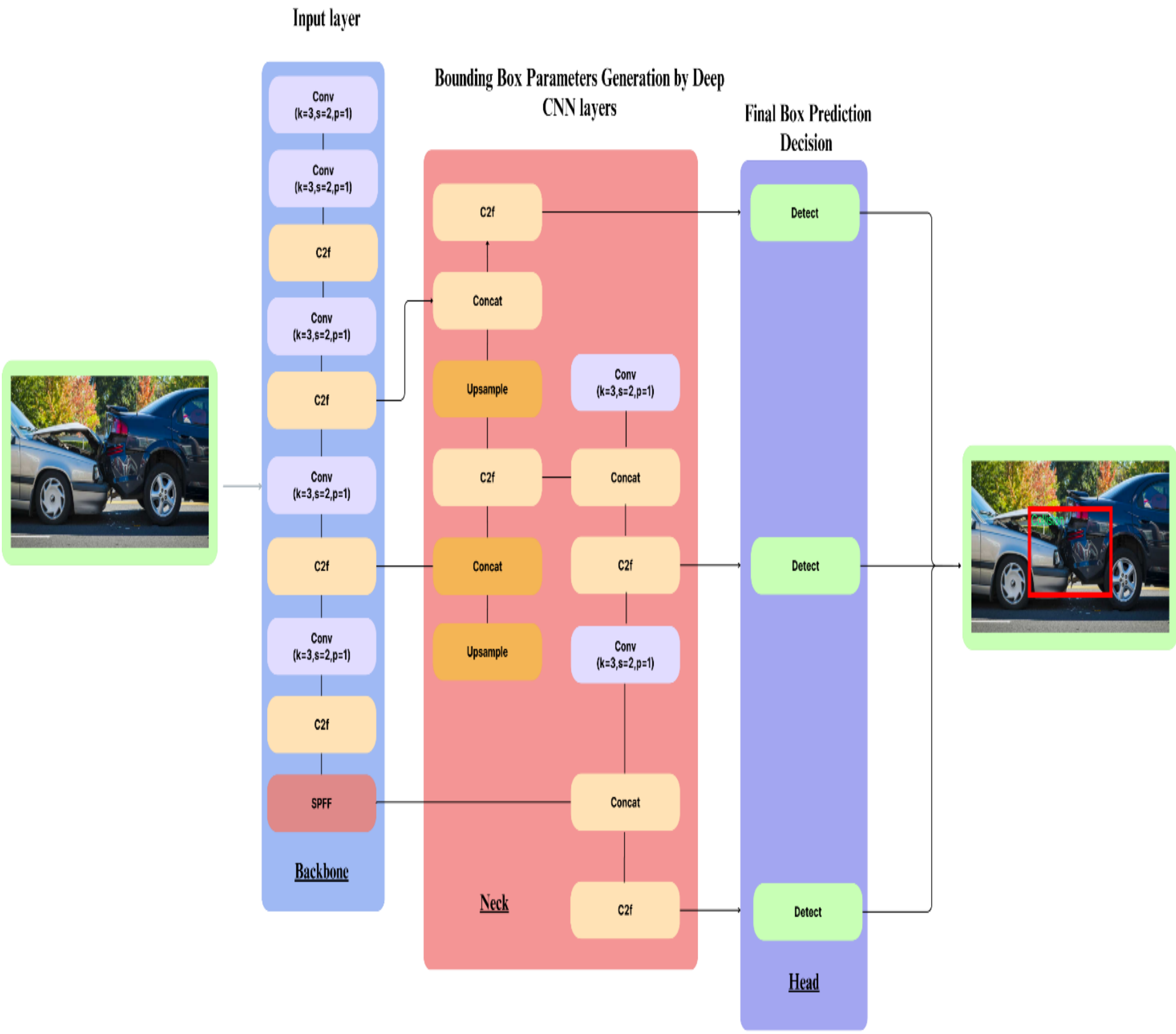

FIGURE 1: YOLOV11 SYSTEM ARCHITECTURE AND WORKING

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SIMULATION RESULTS

The performance of each detection module is summarised below based on CSV results from our experiments. Note that the helmet detection module was trained for 30 epochs, while all other modules were trained for 40 epochs.

III. RESULTS & DISCUSSION

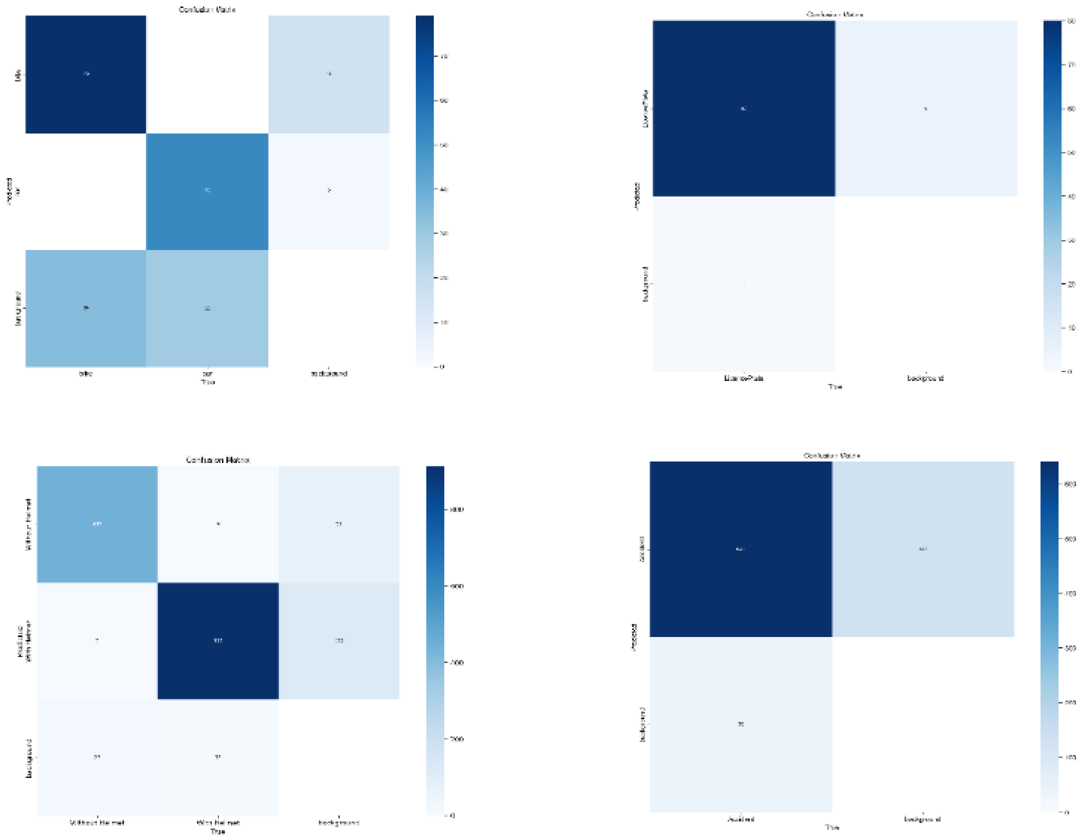
Datasets for each module were compiled from open repositories and real-world surveillance footage:

- **Accident Detection**: 5,000 images for training, 1,500 for validation, and 500 for testing [6].
- **Helmet Detection**: A similar split was applied; note that the helmet detection module was trained for **30 epochs** to balance performance and training time [4].

Module	*Epochs*	*Training Loss (Final)*	*mAP/ Accuracy*	*Precision*	*Recall*	*Additional Metrics*
Accident Detection	40	0.36	96.1% mAP	93.8%	98%	False Positive Rate: <4%; 30% faster alert dispatch [3]
Helmet Detection	30	0.40	94.5% mAP	92.0%	96%	False Positive Rate: <5% [4]
Vehicle (Car/Bike) Detection	40	0.34	95.0% mAP	94.0%	97%	False Positive Rate: <4% [2]
License Plate Detection	40	0.38	91.0% mAP	90.0%	94%	False Positive Rate: <5% [5]

- **License Plate Detection**: Data collected under diverse conditions to ensure robust performance [5].
- **Vehicle Detection**: A comprehensive dataset covering various vehicle types was used to train the vehicle detection module.
- **Speed Detection**: Annotated video sequences with known vehicle speeds were used for calibration [5].
- *Training Parameters (per module):*
- **Epochs**: 40 for all modules except Helmet Detection (30 epochs)
- **Batch Size**: 16
- **Initial Learning Rate**: 0.001
- **Hardware**: NVIDIA Tesla V100 GPU (or equivalent)
- **Training Duration**: Approximately 4 hours per module on average
- **Runs**: Multiple independent runs (typically 3) were conducted, with the reported metrics averaged over these runs [6], [7].

Advanced data augmentation techniques—such as contrast adjustments, noise addition, and simulated occlusion—were applied to further improve model robustness [6].



1. Helmet Detection (First Image):

- **Classes:** Without Helmet, With Helmet, Background
- **Observation:** The model correctly detects "With Helmet" (513 TPs) and "Without Helmet" (408 TPs) but misclassifies some helmets as background (112 FNs).
- **Insight:** Good helmet detection but with background confusion.
- **Focus:** Reduce background misclassification.

2. Accident Detection (Second Image):

- **Classes:** Accident, Background
- **Observation:** Accident class detected well (641 TPs), with some background falsely marked as accidents (127 FPs).
- **Insight:** Strong accident detection with minor background noise.
- **Focus:** Improve background filtering.

3. License Plate Detection (Third Image):

- **Classes:** License Plate, Background
- **Observation:** High accuracy with 59 correct license plate detections and very few errors.
- **Insight:** Excellent performance on license plate detection.
- **Focus:** Nearly optimal, minimal adjustments needed.

4. Vehicle Type Detection (Fourth Image):

- **Classes:** Bike, Car, Background
- **Observation:** Correct detections for bike (70 TPs) and car (52 TPs) with some background confusion (28 FNs for each).
- **Insight:** Effective vehicle detection but needs improvement in background differentiation.

- **Focus:** Minimize background classification errors.

IV. CONCLUSION AND FUTURE WORK

The simulation results showed that the proposed algorithm performs better with the total transmission energy metric than the maximum number of hops metric. The proposed algorithm provides energy efficient path for data transmission and maximizes the lifetime of entire network. As the performance of the proposed algorithm is analyzed between two metrics in future with some modifications in design considerations the performance of the proposed algorithm can be compared with other energy efficient algorithm. We have used very small network of 5 nodes, as number of nodes increases the complexity will increase. We can increase the number of nodes and analyze the performance.
Future work will focus on:

- Integrating additional sensors (e.g., accelerometers and LiDAR) to enhance contextual understanding and improve detection accuracy [8].
- Refining detection algorithms to further reduce false positives, especially in complex traffic scenarios [6].
- Development of mobile application to provide features that may improve public safety through a distributed community based social platform which may provide more detailed real-time analytics.
- Expanding deployment to smart city frameworks for broader impact on urban traffic management [8].
- Development of real time Indian traffic dataset like movement, flow of traffic, management for further research and infrastructure improvements.
- High Risk Area Identification: Highlights areas with high accident frequency to help authorities implement preventive measures.

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