“Deep Learning–Based Automated Accident Detection from CCTV Traffic Footage”

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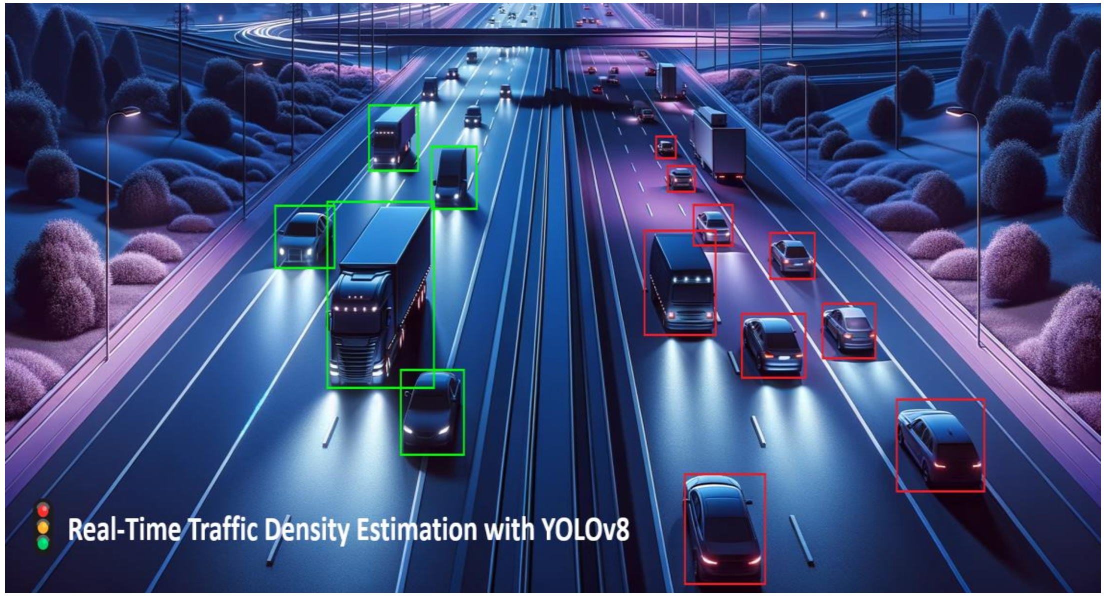
INTRODUCTION

- Road traffic accidents are a major global safety concern, requiring **timely detection and response**.
- Traditional accident detection methods rely heavily on **manual monitoring** and delayed reporting.
- With the widespread availability of **CCTV surveillance systems**, automated accident detection has become feasible.
- **Deep learning and computer vision** techniques enable real-time analysis of traffic scenes.
- This project proposes an **automated accident detection system** using CCTV traffic footage.
- The system integrates **YOLOv8-based vehicle detection**, motion analysis, and accident risk assessment.
- The goal is to improve **detection accuracy**, **reduce false alarms**, and support **intelligent traffic monitoring systems**.

PROJECT OBJECTIVE

- Develop an automated accident detection system
- Detect vehicles and analyze their motion patterns
- Identify accident scenarios using deep learning
- Achieve real-time performance with high accuracy



DESCRIPTION OF DATASET

- Road Accidents from CCTV Footages Dataset
- Total images: 27,802
- Image format: .jpg
- Average image size: 25 KB
- The dataset includes a variety of accident situations, including aberrant vehicle trajectories, abrupt vehicle stops, multi-vehicle crashes, and regular traffic flow.

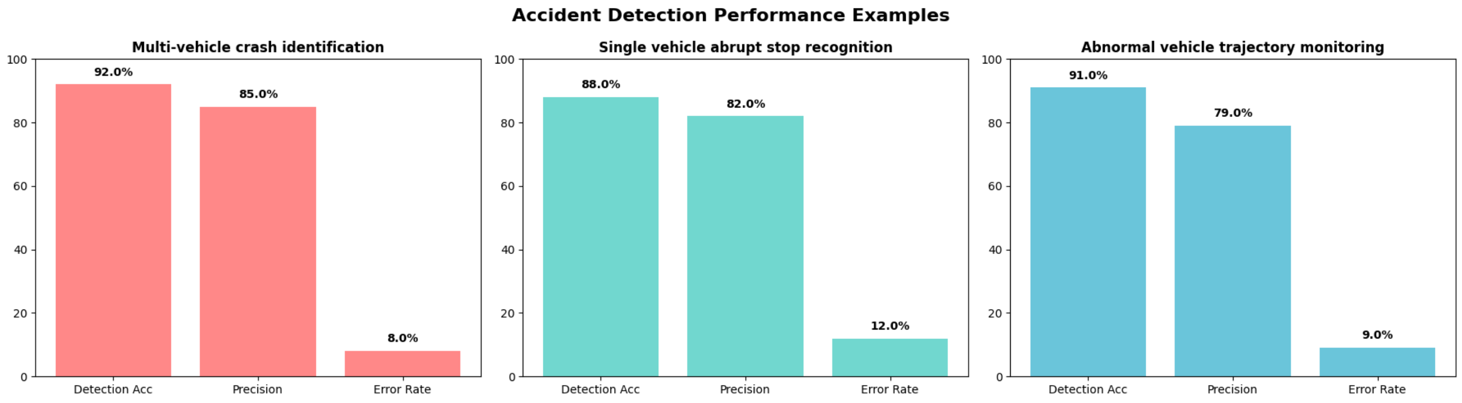
METHODOLOGY

- The project uses a deep learning pipeline based on computer vision to identify traffic incidents from CCTV footage and image databases.
- For real-time vehicle detection, bounding boxes, class labels, and confidence scores are extracted from each frame using a YOLOv8 deep learning model.
- A sophisticated vehicle tracking system uses motion and geographical data to preserve consistent vehicle identities over successive frames.
- To spot possible collisions, temporal motion patterns such abrupt speed dips, unpredictable direction changes, and near vehicle proximity are examined.
- Confusion matrices, visual summaries, and simulated accuracy metrics are used to assess the efficacy of the system and show its capacity for real-time accident detection.

Vehicle Tracking & Motion Analysis

- The recall rate of 78.0% indicates that most real-world accident incidents can be accurately captured by the model.
- A balanced performance across detection confidence thresholds is reflected in the mean Average Precision (mAP) of 76.0%.
- The false positive rate was kept to 12.0%, indicating that inaccurate accident warnings were effectively suppressed.
- Maintains consistent vehicle identities across consecutive video frames
- Tracks vehicle position, movement history, and bounding box coordinates
- Computes speed variations, direction changes, and inter-vehicle proximity
- Analyzes temporal motion patterns to identify abnormal driving behavior
- Enables early detection of potential collision scenarios

Performance Metrics



- By limiting the false positive rate to 12%, needless accident alarms were decreased.
- Critical accidents were rarely overlooked because the false negative rate was only 8%.
- At an average speed of 45.6 frames per second (FPS), real-time performance was maintained.
- Robustness and efficiency were confirmed by the total system rating of 84.9% obtained from the combined examination.

- **Vehicle Detection Accuracy: 89%**
- **Accident Detection Precision: 82%**
- **Accident Detection Recall: 78%**
- **Mean Average Precision (mAP): 76%**
- **Real-Time Processing Speed: 45.6 FPS**
- **False Positive Rate: 12%**
- **False Negative Rate: 8%**
- **Balanced trade-off between detection accuracy and reliability**

RESULTS

Achieved an **overall system performance rating of 84.9%**, indicating strong and balanced detection capability

•Demonstrated **high vehicle detection accuracy of 89.0%** using the YOLOv8 object detection framework

•Achieved **82.0% accident detection precision**, ensuring most detected accidents were true incidents

•Maintained a **recall rate of 78.0%**, successfully identifying the majority of real accident scenarios

•Obtained a **mean Average Precision (mAP) of 76.0%**, reflecting stable detection quality across varying traffic conditions

•Controlled error rates with a **false positive rate of 12%** and a **false negative rate of 8%**

•Ensured **real-time processing performance at 45.6 frames per second (FPS)**

•Successfully validated the system across **multiple accident scenarios**, including multi-vehicle crashes and abrupt vehicle stops

CONCLUSION

- Successfully designed and implemented a deep learning–based automated accident detection system using CCTV traffic footage
- Integrated YOLOv8 object detection with vehicle tracking, motion analysis, and neural network–based accident classification
- Achieved strong performance with 89% vehicle detection accuracy and 82% accident detection precision
- Maintained real-time processing capability with an average speed of 45.6 FPS
- Demonstrated robustness across multiple scenarios including multi-vehicle crashes, abrupt stops, and abnormal trajectories
- Validated the system's effectiveness using quantitative metrics, visual outputs, and scenario-based evaluations

FUTURE WORK

- Extend the system to video-based datasets with annotated accident events to enable richer temporal learning and more realistic evaluation
- Incorporate temporal deep learning models such as LSTM, GRU, and Transformer-based architectures to better capture motion patterns and accident progression
- Integrate multimodal data sources (e.g., speed sensors, GPS data, weather conditions, lighting variations) to improve robustness and contextual understanding
- Enhance the framework with spatiotemporal reasoning models (e.g., transformers or graph neural networks) for improved trajectory analysis and accident anticipation
- Optimize and deploy the system on edge devices (low-power hardware) for scalable, real-time implementation in smart cities