IJIRAE::International Journal of Innovative Research in Advanced Engineering ISSN:2349-2163
Volume 13, Issue 04, April https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2026.v1304.09

A Comprehensive Benchmark Dataset for Traffic Accident Detection Using YOLOv8

SK.Pujitha
Assistant Professor, Department of CSE
Guru Nanak Institute of Technology, Hyderabad, Telangana, India
https://orcid.org/0000-0002-7740-0593
Tejavath Sravya, Thandu Pooja, Shaik Vaseem
UG Students, Department of CSE
Guru Nanak Institute of Technology, Hyderabad, Telangana, India

Publication History
https://www.ijirae.com/volumes/Vol13/iss-04/09.AEAP26.APAE10088.pdf
Manuscript Reference No: IJIRAE/RS/Vol.13/Issue04/AEAP26.APAE10088
Research Article | Open Access | Double-Blind Peer-Reviewed| Article ID: IJIRAE/RS/Vol.13/Issue04/AEAP26.APAE10188
Received:02,March 2026, Revised: 29, March 2026, Accepted: 10,April 2026,Published Online: 22, April 2026.
Article Citation:Pujitha,Tejavath,Thandu,Shaik(2026),A Comprehensive Benchmark Dataset for Traffic Accident Detection Using YOLOv8,IJIRAE: International Journal of Innovative Research in Advanced Engineering, Volume 13, Issue 04 of 2026 pages 785-792 **Doi:>** https://doi.org/10.26562/ijirae.2026.v1304.09
BibTeX Key: Pujitha@2026Comprehensive
IJIRAE papers should be cited as IJIRAE (International Journal of Innovative Research in Advanced Engineering, AM Publications, India 2025, ISSN 2349-2163, https://doi.org/10.26562/ijirae.2026.v1304.09 The journal's official abbreviation is IJIRAE. Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: The automatic detection of traffic accidents has become an essential focus area in computer vision, propelled by the rapid advancements in autonomous and intelligent transportation systems (ITS). To achieve reliable and real-time detection of accident scenarios, YOLOv8, the latest evolution in the YOLO family, offers a powerful and efficient framework for object detection in complex and dynamic traffic environments. Unlike traditional approaches that struggle with occlusions, varying lighting conditions, and high-speed vehicle motion, YOLOv8 provides superior detection accuracy through its optimized architecture, featuring re-parameterized convolutional layers, decoupled detection heads, and advanced feature fusion mechanisms. These enhancements enable the model to precisely identify accident-related events, such as collisions, overturned vehicles, or lane departures, from surveillance video streams.
Keywords:YOLOv8, Traffic Accident Detection, ComputerVision, Object Detection, Intelligent Transportation Systems (ITS), Deep Learning, Real-Time Video Analysis, Road Safety

I. INTRODUCTION

In recent years, the automatic detection of traffic accidents has emerged as a critical research domain within the field of computer vision, driven by the increasing demand for safer and more intelligent transportation systems. With the growth of autonomous and intelligent transportation systems (ITS), real-time and reliable accident detection has become indispensable for enhancing road safety, reducing emergency response time, and preventing secondary collisions. Traditional computer vision methods, however, often face limitations in handling challenges such as occlusions, varying illumination, camera vibrations, and high-speed vehicular motion, which significantly affect detection accuracy. To overcome these challenges, deep learning-based object detection models have gained prominence for their ability to learn complex visual patterns from large-scale data. Among them, YOLOv8, the latest iteration in the YOLO (You Only Look Once) family, represents a significant advancement in achieving fast and accurate detection in dynamic traffic scenes. Its enhanced architecture featuring re-parameterized convolutional layers, decoupled detection heads, and advanced feature fusion strategies enables robust identification of accident-related events such as vehicle collisions, rollovers, and lane departures from continuous surveillance video streams. This makes YOLOv8 a promising solution for developing intelligent systems capable of real-time accident monitoring and situational awareness in modern traffic environments.

II. LITERATURE SURVEY

D.Chen and L.Wang(2022) This study presents an intelligent traffic monitoring system that integrates object detection with a basic alert mechanism for accident detection. The system identifies vehicles and detects potential accidents, generating alerts to notify authorities. Although the system demonstrates the practical use of automation in traffic monitoring, it lacks advanced detection accuracy and detailed output representation. Features such as confidence scores, precise bounding boxes, and performance analysis are not fully developed. Additionally, the system provides limited user interaction and visualization capabilities, reducing its effectiveness for real-time decision-making.

A.Sharma and P.Singh (2022) This paper proposes a YOLOv5-based system for detecting vehicles and identifying accident scenarios from traffic images and videos. The model provides improved detection speed and accuracy compared to earlier YOLO versions and is capable of detecting multiple vehicle classes. However, the system still faces challenges in handling dense traffic conditions and complex scenarios involving overlapping vehicles. The detection performance is affected by variations in lighting, weather conditions, and camera angles. Additionally, the model has limitations in detecting small or partially visible objects, which can reduce its effectiveness in real-world accident detection.

Furthermore, the system lacks advanced performance visualization and user interaction features, making it less suitable for practical deployment in real-time web-based applications.

K.Lee and J.Park(2021) This work focuses on the creation of a dataset for training traffic accident detection models. The dataset is developed by collecting traffic images and video frames from various sources and annotating them with labels for vehicles and accident scenarios. While the dataset provides a foundation for training deep learning models, it lacks sufficient diversity in terms of environmental conditions, such as nighttime scenes, extreme weather, and different road types. The limited dataset size and variability affect the generalisation capability of trained models, leading to reduced performance when applied to real-world scenarios. Additionally, the dataset may suffer from class imbalance, where accident instances are fewer compared to normal traffic scenes, which impacts model learning. Inconsistent annotation quality and lack of standardisation can further reduce detection accuracy. Moreover, the absence of continuous video-based data limits the model's ability to capture temporal patterns of accidents, making it less effective in detecting dynamic traffic events.

S.Patel and M.Verma (2021) This research focuses on using convolutional neural networks (CNNs) to detect traffic accidents by analysing motion patterns and visual features from video data. The system is trained to recognise abnormal vehicle behaviour, such as sudden stops or collisions. Although CNN-based models improve detection compared to traditional image processing techniques, they require extensive training data and high computational resources. The approach also lacks real-time processing capabilities, making it less suitable for live traffic monitoring. Furthermore, the system is limited in detecting multiple objects simultaneously and struggles in highly dynamic traffic environments. Additionally, the model does not provide detailed output features such as bounding boxes, confidence scores, and clear object classification, which reduces its effectiveness for accurate analysis and interpretation.

III. EXISTING SYSTEM

In this project, **YOLOv5** is utilized as one of the existing state-of-the-art object detection algorithms for traffic accident detection from video surveillance. YOLOv5, part of the you Only Look Once (YOLO) family, is known for its real-time detection capabilities, combining high accuracy with fast inference speeds. Its architecture is designed to efficiently detect and localize multiple objects within a frame, making it highly suitable for complex and dynamic traffic scenes where quick and precise identification of vehicles and accident events is critical. By leveraging YOLOv5 on the TAD dataset, the project benefits from improved detection performance in challenging highway environments captured by surveillance cameras.

Existing System Disadvantages

- Difficulty detecting small or occluded objects
- Performance drops in low light or bad weather
- Requires large annotated datasets
- Can produce false detections in complex scenes
- Limited generalization to new environments

Proposed System The integration of YOLOv8 into traffic surveillance systems enables real-time accident detection, improving response time and situational awareness. Its ability to process multi-scale features allows effective detection in complex environments like highways. The model performs well under challenging conditions such as low light, rain, and motion blur. YOLOv8 provides accurate detection with precise bounding boxes and confidence scores. It can identify multiple vehicles and accident scenarios simultaneously. This makes it suitable for dynamic traffic conditions with high-speed movement. Overall, it enhances road safety and supports efficient traffic management systems.

Proposed System Advantages:

- High accuracy in detecting accident scenarios
- Strong real-time detection performance
- Better detection of small and complex objects
- Efficient and optimized architecture for improved results

IV. SYSTEM ARCHITECTURE

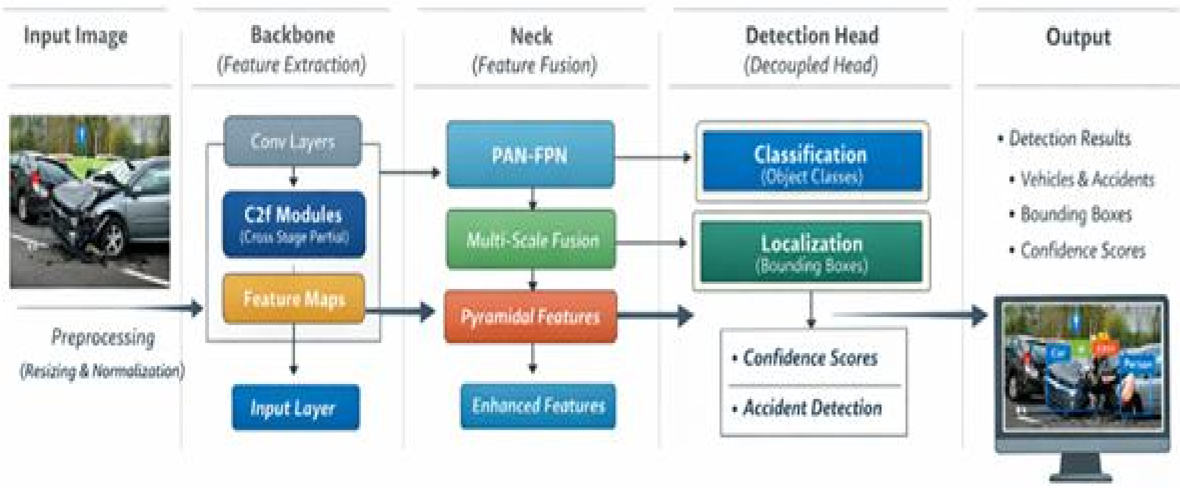

Fig 1.1 System Architecture

The proposed system utilizes the YOLOv8 (You Only Look Once version 8) architecture for efficient and real-time traffic accident detection. YOLOv8 is a one-stage object detection model designed to perform object localization and classification simultaneously with high accuracy and speed. The architecture is composed of three primary components: the Backbone, Neck, and Detection Head, along with input preprocessing and output generation.

Methodology & Modules Name:

- Data Acquisition and Preprocessing Module
- Object Detection Module (YOLOv8 Framework)
- Accident Detection and Classification Module
- Model Training and Evaluation Module
- Result Visualization and Interface Module

1) Data Acquisition and Preprocessing Module: The first module of the system deals with collecting and preparing the traffic data used for model training and testing. Videos are sourced from publicly available traffic accident datasets such as the Traffic Accident Dataset (TAD) or recorded surveillance footage. Each video is decomposed into individual frames, which are then resized and normalized to ensure consistent input dimensions for YOLOv8Noise reduction removes unwanted artifacts, while data augmentation techniques like rotation and brightness adjustment improve dataset diversity. This ensures clean and robust data for accurate deep learning-based detection.

2) Object Detection Module (YOLOv8 Framework): This is the core module of the project, responsible for detecting multiple objects within each frame of a video. The YOLOv8 model, known for its real-time detection speed and accuracy, is utilized to identify vehicles, pedestrians, and other traffic entities. The architecture of YOLOv8 includes enhanced transformer-based attention mechanisms, re-parameterized convolutional layers, and decoupled detection heads, all of which contribute to improved feature extraction and localization. When a video frame is processed, the model outputs bounding boxes around detected objects, along with their class labels and confidence scores. This enables the system to visually and quantitatively identify all relevant elements in a complex traffic environment, even under challenging conditions.

3) Accident Detection and Classification Module: After objects are detected, this module analyzes their motion and interactions over consecutive frames to determine if an accident has occurred. It studies the spatial and temporal relationships between vehicles, identifying unusual patterns such as abrupt stops, skidding, collisions, or overturned vehicles. By tracking vehicle trajectories and comparing motion vectors, the system can distinguish between normal driving behavior and accident scenarios. Frames where abnormal interactions occur are classified as “accident detected,” while normal sequences are labeled as “safe traffic.”This module plays a crucial role in filtering out false positives and ensuring that only genuine accident events are reported.

4) Model Training and Evaluation Module: This module focuses on training the YOLOv8 model using the processed dataset to achieve optimal detection performance. The dataset is divided into training, validation, and testing subsets, ensuring proper generalization and accuracy assessment. During the training process, the model learns to recognize accident-related patterns by adjusting parameters based on metrics such as precision, recall, F1-score, and mean Average Precision (mAP). Once trained, the model is evaluated using unseen data to measure its real-world effectiveness. The outcomes of this module ensure that YOLOv8 can efficiently detect accidents in diverse traffic environments with minimal error rates.

5) Result Visualization and Interface Module: This module provides a visual representation of the accident detection process and outcomes. Detected objects and accident events are displayed directly on the video feed with bounding boxes, class labels, and color-coded markers. A simple yet intuitive interface developed using Flask for web-based visualization or Tkinter for desktop-based applications allows users to observe real-time detection results. The interface may also include performance metrics and summary statistics for better interpretability. This visualization helps users easily monitor and verify the system’s performance without requiring deep technical expertise.

V. IMPLEMENTATION

The implementation phase involves transforming the designed system into a fully functional web-based Traffic Accident Detection application using YOLOv8. This phase includes setting up the development environment, coding the frontend and backend components, integrating the YOLOv8 deep learning model, and enabling real-time detection capabilities. The system is designed to allow users to register/login, upload traffic images, detect vehicles and accident scenarios, and visualize results with bounding boxes, class labels, confidence scores, and performance charts. The implementation ensures that all modules work together efficiently to provide accurate and user-friendly outputs.

Algorithm Used

Existing Algorithm

YOLOv5 (You Only Look Once version 5) is an advanced real-time object detection model developed by Ultralytics, representing a major improvement over earlier YOLO versions in terms of speed, accuracy, and efficiency. It is designed to perform object detection in a single forward pass, making it highly suitable for real-time applications such as traffic monitoring and surveillance systems. The model incorporates an optimized architecture with improved feature extraction, better object localization, and enhanced classification capabilities. A key advantage of YOLOv5 is its anchor-free detection mechanism, which allows it to detect objects of varying sizes more effectively without relying on predefined anchor boxes. It supports multiple computer vision tasks including object detection, instance segmentation, and image classification within a unified and flexible framework. The model is lightweight and computationally efficient, enabling deployment on a wide range of platforms, including edge devices and low-resource environments.

Proposed Algorithm

YOLOv8 represents the latest advancement in the You Only Look Once (YOLO) family of object detection models, designed to deliver state-of-the-art performance in both speed and accuracy. It builds upon the strengths of earlier versions by introducing several architectural innovations, such as re-parameterized convolutional blocks, lightweight decoupled heads, and improved feature fusion techniques.

These upgrades significantly enhance detection precision while maintaining real-time inference capabilities, making YOLOv8 ideal for critical applications like traffic accident detection, vehicle tracking, and intelligent transportation systems.

VI. EXPERIMENTAL RESULTS

Home Page:

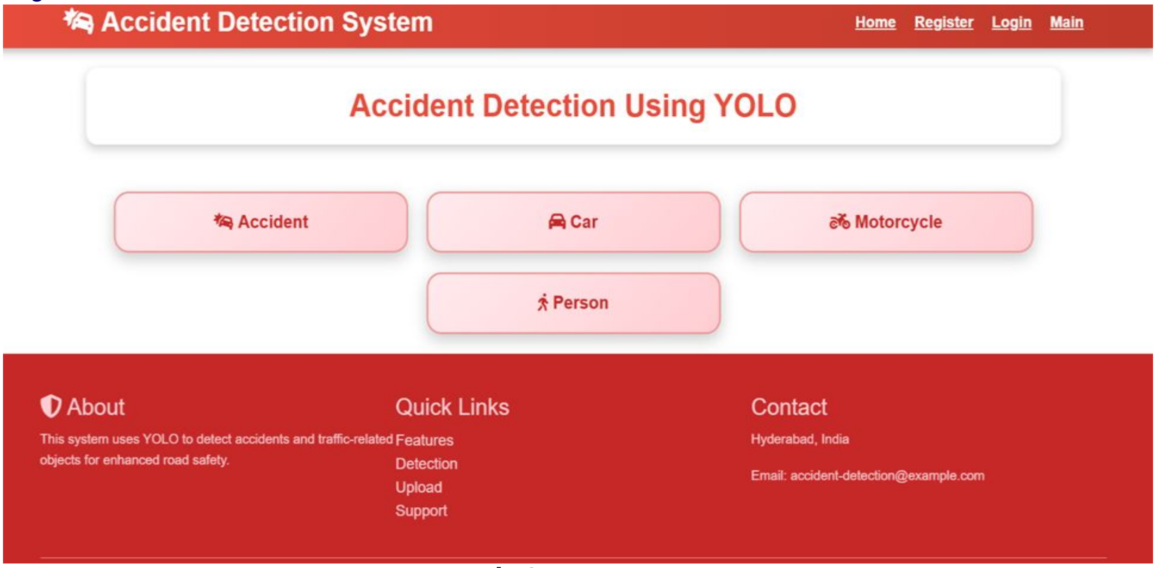

Fig 2: Home Page

This is the main dashboard of the Accident Detection System, where users can navigate different options like accident detection, car, motorcycle, and person recognition. It summarizes the system's capabilities using Computer Vision techniques and provides quick access to features, along with basic information and contact details for user support.

Registration Page:

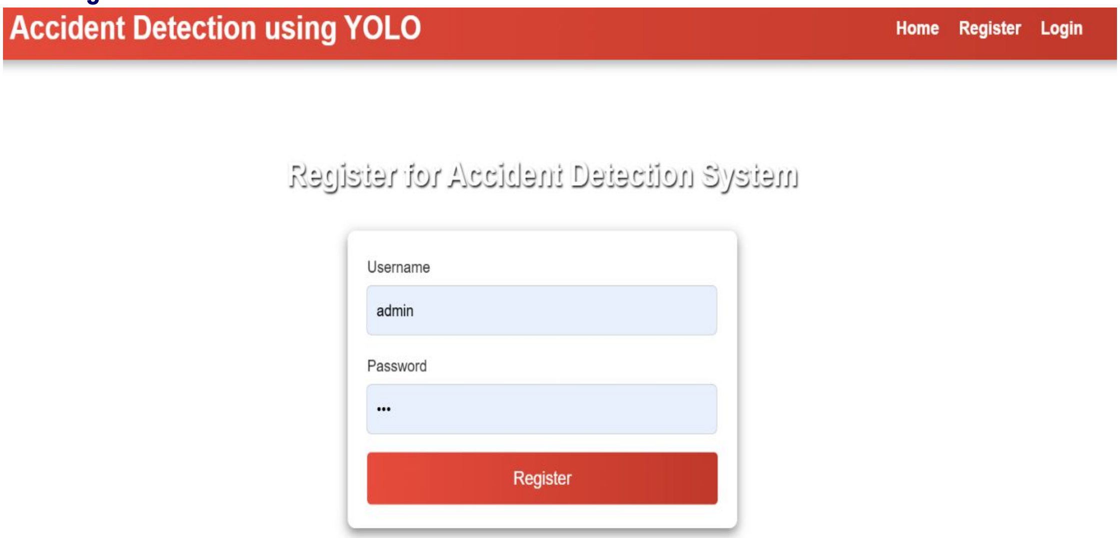

Fig 3: Registration Page

This screen shows the user registration page of an Accident Detection System built using YOLO. It provides a simple interface where users can create an account by entering a username and password, enabling secure access to the system's features such as uploading images and viewing detection results.

Login Page:

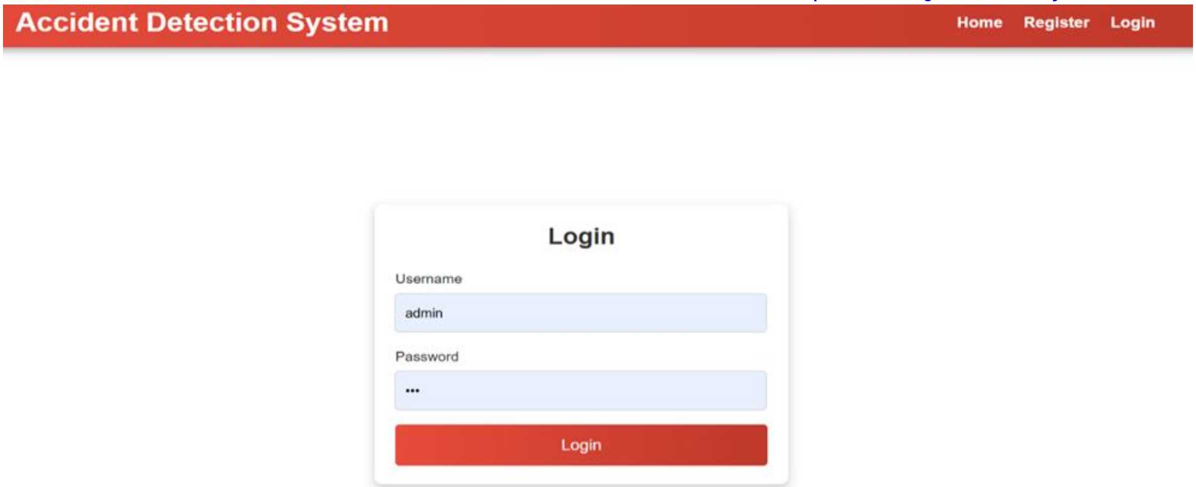

Fig 4: Login Page

This login page provides secure access to the accident detection system, allowing authorized users to analyze video surveillance data and evaluate different detection models for benchmarking performance.

Image Upload:

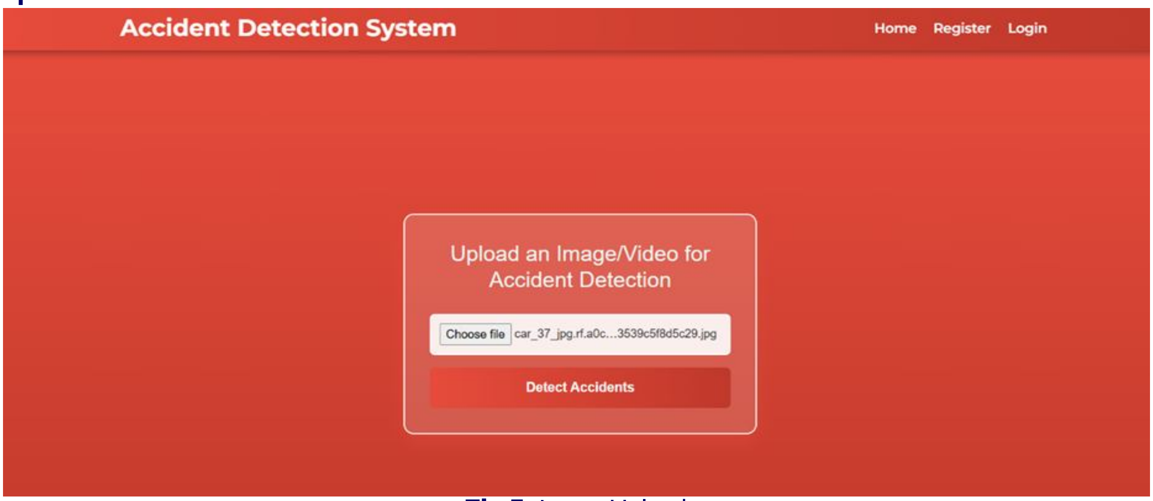

Fig 5: Image Upload

Through this interface, users can upload a new image or video sample, which may also belong to or resemble samples from the benchmark dataset. Upon clicking the "Detect Accidents" button, the trained model processes the input and predicts whether an accident has occurred. This helps in evaluating the model's performance, accuracy, and real-time applicability in detecting traffic accidents automatically.

Detection Result Page (Accident Detection):

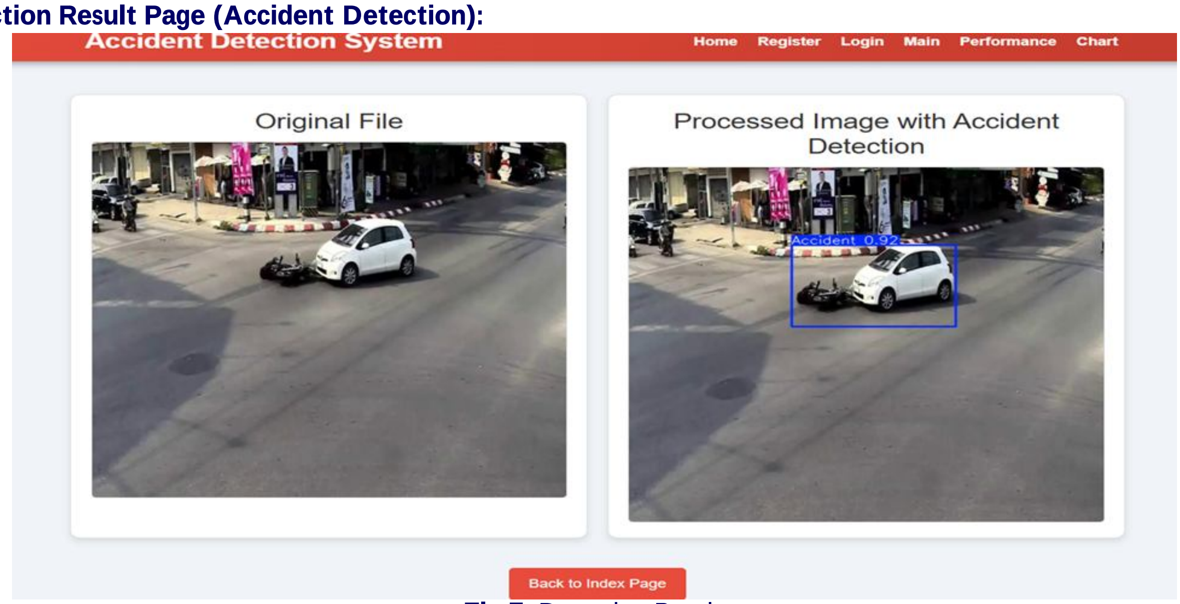

Fig 7: Detection Result

This interface demonstrates the core functionality of the system. On the left, the original traffic image is displayed, while on the right, the processed image highlights an accident detected using YOLO with a bounding box and confidence score (e.g., 0.92). This shows how the model identifies and localizes accidents in real-world road scenarios.

Performance Analysis Page:

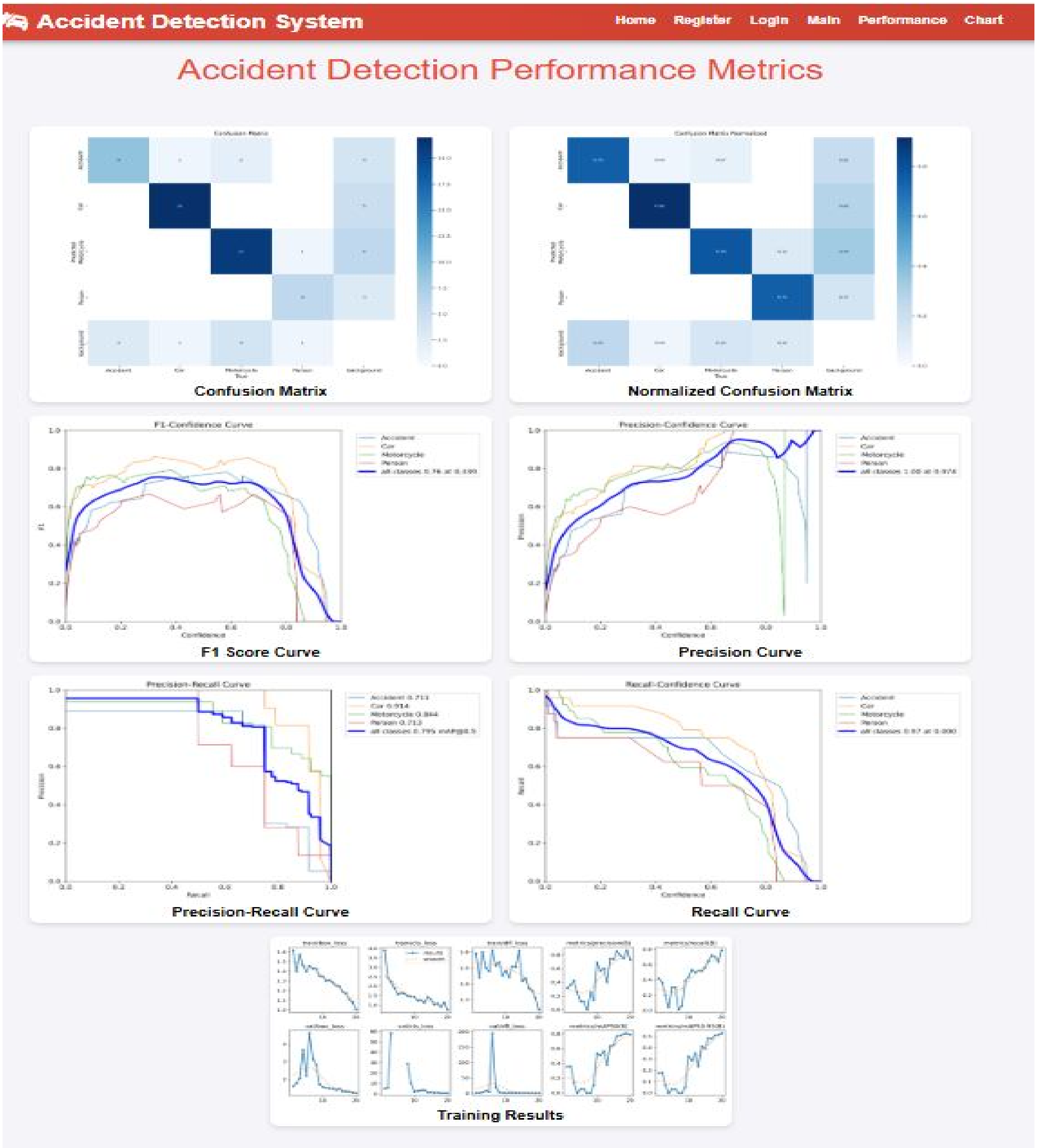

Fig 9: Performance Metrics

This image shows how well a traffic accident detection system performs using a video surveillance dataset. It includes charts like confusion matrices and curves for precision, recall, and F1 score, which together measure how accurately the model detects accidents and distinguishes them from other objects like cars, motorcycles, and people. The graphs also show how performance changes with confidence levels and how the model improves during training. Overall, it demonstrates that the dataset is useful for testing and comparing accident detection models in real-world conditions. The combined dashboards show traffic accident detection system evaluated on a realistic benchmark dataset in Computer Vision. The object distribution highlights cars as the most common class, with motorcycles and persons also present, while detection frequency confirms cars are detected most often. The confidence trend gradually declines, indicating the dataset includes both simple and challenging scenarios. The radar chart shows consistently strong performance across metrics, suggesting the model is robust overall but slightly challenged by complex cases.

Analytics Dashboard:

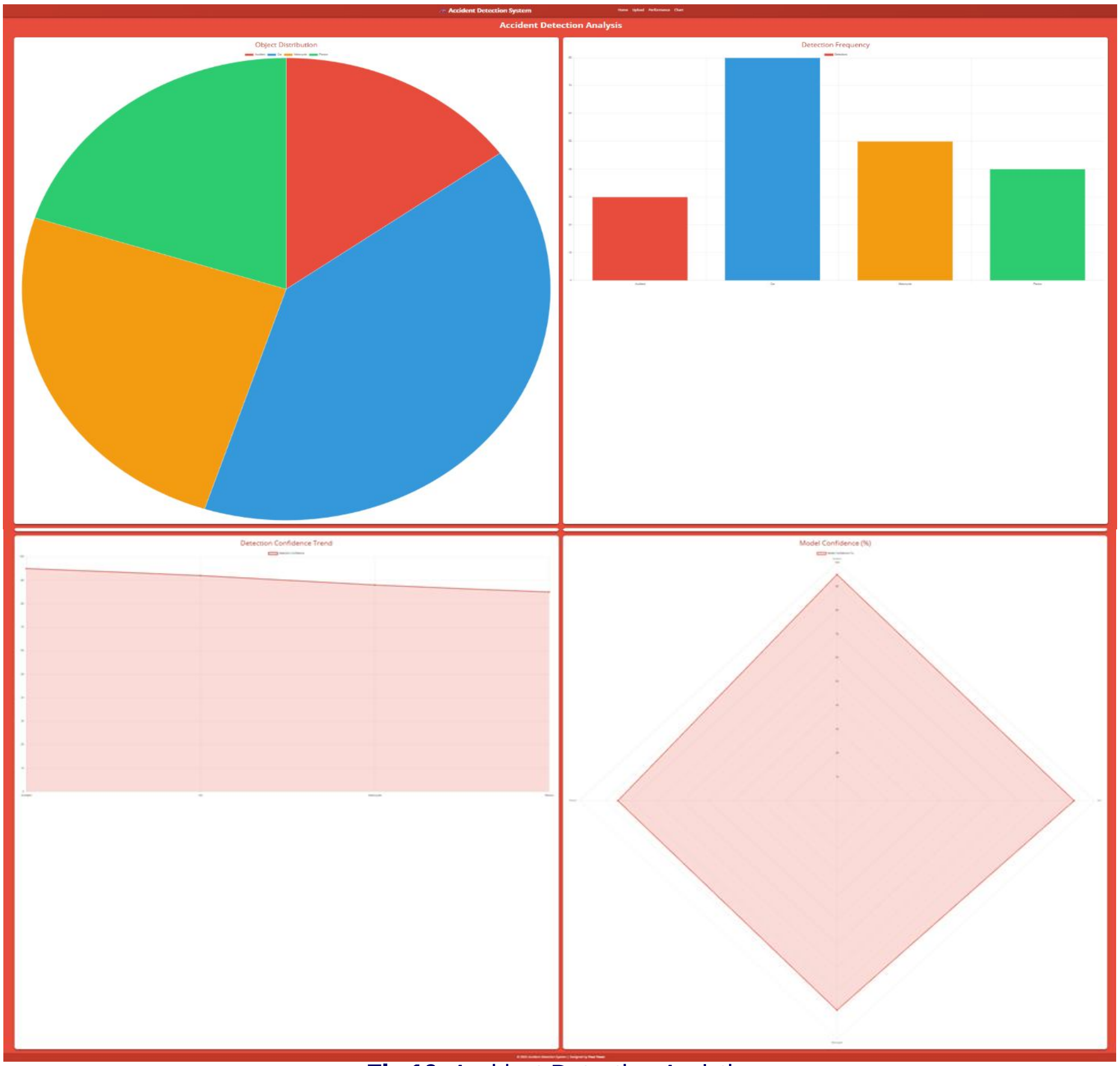

Fig 10: Accident Detection Analytics

VII. CONCLUSION

In conclusion, the proposed YOLOv8-based traffic accident detection system provides an effective and fully software-driven solution for identifying road accidents in real time using advanced computer vision and deep learning techniques. By leveraging YOLOv8's enhanced architecture—featuring transformer-based attention mechanisms, re-parameterized convolutional layers, and decoupled detection heads—the system achieves superior detection accuracy and speed even in complex traffic environments. The modular design ensures a smooth workflow from data preprocessing to visualization, enabling efficient analysis of traffic videos without the need for additional hardware or IoT devices. Experimental results and evaluations demonstrate that the model can successfully detect accident-related events such as collisions and overturned vehicles under diverse conditions. Overall, this project showcases the potential of artificial intelligence in promoting road safety, reducing emergency response times, and paving the way for the development of smarter and more reliable intelligent transportation systems in the future.

VIII. FUTURE ENHANCEMENT

In the future, this project can be further enhanced by integrating advanced deep learning techniques and hybrid architectures to improve the accuracy and efficiency of accident detection. One potential improvement is the incorporation of spatio-temporal models such as 3D Convolutional Neural Networks (3D-CNN) or Vision Transformers (ViTs) to better analyze motion patterns and temporal dependencies across video frames. Additionally, integrating multi-camera video fusion can help overcome occlusion and blind spot challenges by combining views from multiple surveillance angles for more reliable detection. Future versions may also include automatic accident severity estimation using visual cues and scene analysis, providing valuable insights for emergency management systems.

Enhancing the system's adaptability through real-time edge computing deployment and optimizing the model using lightweight versions of YOLO (e.g., YOLOv8n or YOLOv9-lite) can make the system suitable for large-scale implementation. Moreover, the integration of a user-friendly web-based dashboard for live visualization, logging, and analytics can make the system more interactive and accessible to traffic authorities. These enhancements will significantly contribute to building a more intelligent, scalable, and proactive traffic monitoring solution in the future.

REFERENCES

1. WHO road traffic deaths http://www.who.int/gho/road safety/mortality/en/
2. J.L.DSouza,Road Safety: A Critical Issue Requiring Government Attention. International Journal of Education and Science Research review, Volume-2, Issue-2, April, 2015.
3. J.Pang, I.Singh, Accelerometer Based Real-Time Remote Detection and Monitoring of Hand Motion. Proceedings of the World Congress on Engineering and Computer Science 2011 Vol II WCECS 2011, October 19-21, 2011, San Francisco, USA.
4. Author: Scott J. Weiner, Feasibility of a 802.11 VANET Based Car Accident Alert System.
5. halil, U., Javid, T., & Nasir, A. (2017). Automatic road accident detection techniques: A brief survey. 2017 International Symposium on Wireless Systems and Networks (ISWSN).
6. Faiz,A.B.,Imteaj,A.,& Chowdhury, M. (2015). Smart vehicle accident detection and alarming system using a smartphone. 2015 International Conference on Computer and Information Engineering (ICCIE).
7. Ozbayoglu, M., Kucukayan, G., &Dogdu, E. (2016). A real-time autonomous highway accident detection model based on big data processing and computational intelligence. 2016 IEEE International Conference on Big Data (Big Data).
8. Shailesh Bhavthankar, Prof. H.G.Sayyed, Wireless System for Vehicle Accident Detection and Reporting using Accelerometer and GPS. International Journal of Scientific & Engineering Research, Volume 6, Issue 8, August-2015.
9. Miao Chong, Ajith Abraham and Marcin Paprzycki, Traffic Accident Analysis Using Machine Learning Paradigms. Informatica 29 (2005) 8998.
10. Keiron OShea, Ryan Nash, An Introduction to Convolutional Neural Networks. arXiv:1511.08458v2 [cs.NE] 2 Dec 2015.
11. Pan, S. J., & Yang, Q. (2010). A Survey on Transfer Learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 13451359.
12. Dogru, N., & Subasi, A. (2018). Traffic accident detection using random forest classifier. 2018 15th Learning and Technology Conference (L&T).
13. Jayadeva, Khemchandani, R., & Chandra, S. (2007). Twin Support Vector Machines for Pattern Classification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(5), 905910.
14. Ding, S., Yu, J., Qi, B., & Huang, H. (2012). An overview on twin support vector machines. Artificial Intelligence Review, 42(2), 245252.
15. Tanveer2015application, title=Application of smoothing techniques for linear programming twin support vector machines, author=Tanveer, M, journal=Knowledge and Information Systems, volume=45, number=1, pages=191–214, year=2015, publisher=Springer.
16. Richhariya, B., & Tanveer, M. (2018). A robust fuzzy least squares twin support vector machine for class imbalance learning. Applied Soft Computing, 71, 418432.
17. Li,D., & Tian, Y. (2014). Twin Support Vector Machine in Linear Programs. Procedia Computer Science, 29, 17701778.
18. P.Kaliuga Lakshmi, C.Thangamani, AN EFFICIENT VEHICLE ACCIDENT DETECTION USING SENSOR TECHNOLOGY. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) Volume 5 Issue 3, March 2016.
19. Peddi Anudeep, K. Hari Babu, Wireless Reporting System for Accident Detection at Higher Speeds in Peddi Anudeep Int. Journal of Engineering Research and Applications.
20. Marek Dbrowski, Tomasz Michalik, How effective is Transfer Learning method for image classification. Position papers of the Federated Conference on Computer Science and Information Systems, pp. 39.
21. Xiaoling Xia, Cui Xu and Bing Nan, Inception-v3 for Flower Classification. 2017 2nd International Conference on Image, Vision and Computing.
22. Prajapati, S. A., Nagaraj, R., & Mitra, S. (2017). Classification of dental diseases using CNN and transfer learning. 2017 5th International Symposium on Computational and Business Intelligence (ISCBI).