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Accidental Report Portal

Jay Mahendra Khanderay[1], Pritam Dilipsing Girase[2], Rohit Liladhar Desale[3], Santosh K Bhandare[4]
[1,2,3]*UG student, R. C. Patel Institute of Technology, Shirpur, India*
[4]*Professor, R. C. Patel Institute of Technology, Shirpur, India*

Abstract—Road traffic accidents continue to be a leading cause of fatalities and serious injuries worldwide. Conventional methods of accident reporting often lead to significant delays in emergency response, which can result in preventable loss of life. To overcome these challenges, this project proposes an intelligent Accident De- action and Reporting System that automates the entire process. Leveraging technologies such as the Internet of Things (IoT), Machine Learning (ML), Cloud Computing, and Web Platforms, the system utilizes surveillance infrastructure to identify accidents in real time. It assesses the severity of the incident and immediately communicates critical information to emergency responders via a centralized web portal.

Index Terms—**Accident Recognition, Deep Learning, YOLO Algorithm, Machine Learning, Convolutional Neural Networks, Real-Time Surveillance**

I. INTRODUCTION

Road traffic accidents remain a leading cause of mortality and serious injuries worldwide. According to global statistics, over 1.35 million people die annually due to road-related incidents, with countless others sustaining severe injuries. In countries like India, the situation is particularly alarming, with consistently high accident rates resulting in significant human and economic loss. A major contributing factor is the delay in accident detection and subsequent emergency response, which often exacerbates the severity of outcomes. Timely medical intervention can greatly reduce fatalities and long- term complications.

To address these challenges, this project introduces an Intelligent Accident Detection and Reporting System aimed at enhancing road safety and accelerating emergency response. By integrating advanced technologies such as the Internet of Things (IoT), Machine Learning (ML), cloud computing, and web-based solutions, the proposed system automatically detects road accidents, assesses their severity, and transmits immediate alerts to emergency services.

The core of the system relies on utilizing pre-installed street surveillance cameras in metropolitan regions to monitor road activity in real time. Through continuous video feed analysis, the system identifies accident events, estimates the impact severity, and captures essential information including vehicle identification and precise location data. This information is then swiftly relayed to concerned authorities, enabling prompt deployment of emergency personnel.

The need for real-time and automated accident detection has become increasingly critical due to several persistent issues:

- Delayed Reporting: In many rural or less-traveled areas, accidents may go unnoticed for extended periods, delaying medical response.
- Human Dependency: Relying on bystanders to report incidents is often unreliable, as witnesses may provide incomplete or inaccurate details.
- Scalability Limitations: As cities grow and traffic con- gestion increases, manual monitoring systems struggle to keep up with the volume of road activity.
- Lack of Real-Time Insight: Conventional systems fail to provide immediate updates, which are crucial for effective intervention.

The proposed system overcomes these limitations by offering a reliable, automated, and scalable solution that delivers real- time accident reporting. It ensures that emergency services are notified without delay, potentially reducing casualties and improving response efficiency.

Moreover, the system contributes to broader smart city objectives by integrating technology into urban safety infrastructure. It leverages AI-driven analytics to not only support emergency responders but also assist city planners and traffic management agencies. By generating valuable data on accident trends and high-risk zones, the system provides actionable insights that can inform policy and improve overall road safety.

In essence, this project envisions a future where smart technologies actively contribute to saving lives and enhancing urban mobility, forming a vital component of intelligent city ecosystems.

II. LITERATURE REVIEW

Over the years, a variety of approaches have been explored for detecting road accidents, primarily categorized into two main types: vehicle-integrated systems and externally monitored surveillance-based systems.

A study conducted in 2021 proposed an AI-driven frame- work for real-time traffic accident detection by applying deep learning techniques to video footage. The system, trained on comprehensive datasets containing traffic incident scenarios, exhibited high detection accuracy. However, one of its major limitations was its reduced effectiveness under poor lighting conditions, particularly at night.

In 2020, researchers explored the use of CCTV imagery for accident identification in smart cities. Their model employed image classification methods to distinguish accident events. While the approach showed potential, it encountered difficulties related to processing speed and occasionally produced false positives.

In 2022, a method using Convolutional Neural Networks (CNNs) was introduced to analyze surveillance camera footage and identify vehicle crashes. The system yielded strong performance across several metropolitan datasets. Nevertheless, its reliability declined in scenarios with low visibility or significant object occlusion.

Another notable effort from 2021 utilized the YOLO (You Only Look Once) object detection algorithm to recognize irregular driving patterns and possible collisions in real-time video streams. The model was efficient and suitable for deployment on edge computing devices. However, its accuracy diminished in densely populated traffic scenes, occasionally leading to incorrect detections.

Several scholarly works have further contributed to this domain. Simaiya et al. (2022) presented an enhanced deep learning framework for predicting the severity of traffic incidents, offering better forecasting capabilities. Dar et al. (2019) introduced a fog computing-based solution that ad- dressed response delays by enabling faster local processing. More recently, Desai and Sharma (2025) proposed a fast and responsive accident detection system tailored for urban road safety enhancement.

Although these studies mark significant progress, persistent issues such as limited night-time visibility, system latency, and integration with emergency networks hinder optimal performance. The current study addresses these limitations by integrating advanced video preprocessing, YOLO-based deep learning detection, severity classification models, and cloud- enabled alert dispatch mechanisms to create a robust, real-time accident reporting framework suited for smart cities.

III. DATASET DESCRIPTION AND CLASS IMBALANCE

The dataset used in this study consists of over 1500 annotated images gathered from a mix of sources, including CCTV feeds, street surveillance cameras, and open-access accident datasets. These images represent a wide range of real-life traffic scenarios, captured under varying lighting conditions (day and night), weather patterns (clear, rainy, foggy), and traffic densities (sparse to heavy). This variety ensures that the model is trained on diverse, real-world situations, contributing to its robustness and adaptability.

Prior to training, the raw image data underwent several preprocessing steps to enhance the quality and consistency of the input. These steps included:

- Resizing: All images were scaled to a fixed resolution (e.g., 640×640 pixels) to align with the input size expected by the YOLO architecture.
- Normalization: Pixel intensities were normalized to speed up convergence and stabilize the training process.
- Data Augmentation: Techniques like horizontal flipping, random rotations, brightness changes, scaling, and Gaussian noise were applied to increase dataset variability and help the model generalize better.
- Annotation: Each image was manually labeled using tools such as LabelImg, with bounding boxes drawn around key areas to distinguish between accident and non-accident scenes.

  A custom dataset was built specifically for this project, incorporating manually labeled frames from various video sources to support both training and testing phases. Figure 1 presents the initial distribution of the accident and non-accident classes, highlighting the presence of class imbalance prior to any resampling or rebalancing techniques being applied.

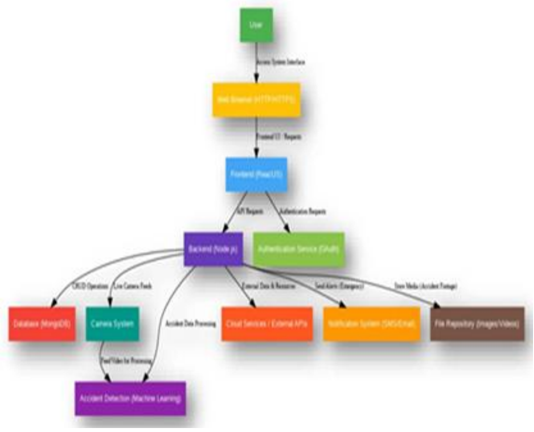

Fig. 1. Original Class Distribution in the Depression Detection Dataset

IV. YOLO AND CNN FOR ACCIDENT DETECTION

For this project, the YOLOv8 (You Only Look Once, version 8) model was selected as the primary framework for detecting accidents, thanks to its high performance and real-time processing capabilities. As the most recent advancement in the YOLO family, YOLOv8 introduces various enhancements that make it especially effective in identifying objects in dynamic and crowded environments, which are common in traffic footage.

Several factors contributed to the choice of YOLOv8:

- End-to-End Training: The model supports direct end- to-end training, simplifying the development pipeline and reducing complexity.
- Real-Time Performance: YOLOv8 achieves high frames per second (FPS), making it well-suited for real-time accident detection where speed is crucial.
- Anchor-Free Architecture: Unlike earlier versions, YOLOv8 adopts an anchor-free approach, leading to more accurate bounding box predictions, particularly for small or closely positioned objects.
- Integrated Post-Processing: Features like automatic confidence scoring and non-maximum suppression are built in, allowing the model to deliver clean, high- confidence detections without extensive manual tuning.

These capabilities make YOLOv8 a powerful tool for detecting and tracking accidents in traffic camera footage, enabling timely and reliable alerts in real-world conditions.

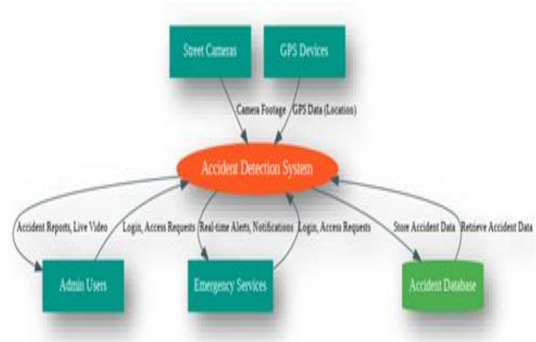

Fig. 2. System Architecture of the Accident Reporting Platform

A. *Text Preprocessing Using NLP*

In addition to video analysis, this project also considers user- submitted accident reports, which may come from mobile apps or social media platforms. To make this textual data useful for machine learning models, Natural Language Processing (NLP) techniques are applied to clean and structure the information. These techniques help extract important details such as acci- dent location, severity, and type for further analysis.

The key preprocessing steps include:

- Lowercasing: Converts all text to lowercase to maintain consistency and avoid treating the same words as different due to capitalization.
- Tokenization: Breaks down sentences into individual words or meaningful subunits to simplify processing.
- Stopword Removal: Removes commonly used words (e.g., ”the”, ”is”, ”and”) that usually carry little mean- ingful information in context.
- Stemming and Lemmatization: Transforms words to their base forms (e.g., ”driving”, ”drove” → ”drive”) to reduce redundancy and improve pattern recognition.
- Noise Removal: Filters out unnecessary elements like punctuation, links, emojis, and special characters that do not contribute to semantic understanding.

These preprocessing steps were implemented using widely- used Python libraries such as NLTK and spaCy. By refining the raw input text, the system ensures that the downstream models focus on meaningful information, leading to better predictions and reduced processing overhead.

B. System Development

This phase marked the transformation of initial concepts into a fully functional application. The system was built by combining several components, including a mobile-friendly frontend developed with React Native, a Python-based backend using Flask, and the integration of a machine learning model for real-time accident detection. Effective coordination between these components was essential to ensure a seamless user experience. Below is an overview of the development aspects and core functionalities:

Functional Requirements: 1. Real-Time Accident Detection: The application is designed to monitor live traffic camera streams and detect road accidents as they happen. It uses a trained model to recognize accident scenarios, such as vehicle collisions, directly from video feeds.

2. Accident Type Classification: Once an incident is detected, the system categorizes it based on the nature of the accident (e.g., car vs. bike, multi-vehicle collisions).

3. Severity Analysis: The system also assesses how serious an accident is by analyzing both video frames and available sensor data. It categorizes accidents into levels such as mi- nor, moderate, or severe, depending on visual impact, traffic conditions, and motion data.

This layered architecture ensures that the system can detect, interpret, and respond to road incidents promptly, supporting quicker alerts and potential emergency responses.

C. Manual Dataset Construction and Quality Assurance

To develop a reliable accident detection system, we opted to build a custom dataset tailored to real-world traffic scenarios. Unlike generic datasets that may lack critical or specific accident cases, our approach ensured the inclusion of targeted and contextually rich data relevant to the problem at hand.

- Data Collection: We gathered traffic footage from publicly accessible sources, including open CCTV recordings and street surveillance videos, to capture a wide range of accident events under different environmental and traffic conditions.
- Annotation Process: Each frame was carefully labeled using annotation tools such as LabelImg. Bounding boxes were drawn manually around key elements in the images to highlight accidents and associated objects, ensuring accurate input for model training.

This hands-on dataset preparation strategy significantly con- tributed to enhancing model performance, particularly in achieving a better balance between precision and recall, as reflected in improved F1-scores.

D. Machine Learning Models for Classification

Several machine learning models and technologies were integrated and tested to create a comprehensive accident detection and reporting system. Each component played a specialized role, offering complementary capabilities:

- YOLOv8: Serving as the primary detection engine, YOLOv8 was chosen for its real-time object detection capabilities. Its speed and accuracy in identifying vehicles and accidents in live footage made it a suitable choice for time-sensitive environments.
- CNN (Convolutional Neural Networks): CNNs were employed to extract meaningful features from images and video frames. Their strength in visual pattern recognition helped the system distinguish between normal traffic activity and potential accident indicators.
- Node.js: To support real-time processing and provide a responsive backend interface, Node.js was incorporated. It enabled efficient handling of live data streams and user interactions within the system.
- MongoDB: As a flexible and scalable database solution, MongoDB was used to store structured and unstructured data, including incident reports, image metadata, and model predictions.

The training process utilized over 1500 annotated images that captured diverse accident scenarios, helping the system learn to identify incidents with varying severity and complexity across different contexts.

E. Probability Scores and Interpretability

The YOLOv8 model generates a probability score for each detected object, representing the likelihood that the object in the image is related to an accident or a vehicle involved in an incident. These scores are crucial for eliminating false positives, ensuring that only legitimate accident detections are sent to emergency responders.

F. Real-Time Accident Detection and Visualization Techniques

The Smart Accident Detection & Reporting System relies heavily on visual data to identify accidents in real-time. By leveraging advanced image processing techniques such as object detection models like YOLOv8, alongside traditional methods including OpenCV and Convolutional Neural Networks (CNNs), the system is designed to detect traffic accidents and evaluate their severity.

By merging these technologies, the system is capable of efficiently recognizing accidents and analyzing their potential impact.

G. Challenges and Future Directions

While the results are promising, several challenges remain to be addressed:

- IoT Connectivity and Data Transmission: The integration of IoT devices, including cameras, sensors, and traffic monitoring systems, is crucial for the real- time detection of accidents. However, ensuring reliable connectivity and efficient data transmission poses a significant challenge.
- Scalability of IoT Infrastructure: As urban areas expand and IoT systems become more widespread, man- aging the large volumes of real-time data from cameras and sensors becomes increasingly complex and resource- intensive.
- Sensor Calibration and Accuracy: IoT devices like cameras and environmental sensors can face calibration issues, which may result in inaccuracies and impact the reliability of accident detection.

Future work should consider the following directions:

- Integration with Autonomous Vehicles and V2X Communication: With the rapid development of autonomous vehicles (AVs) and the increasing use of Vehicle- to-Everything (V2X) communication, incorporating the Smart Accident Detection System into AVs could greatly improve safety and reduce response times.
- Integration with Smart City Infrastructure: The Smart Accident Detection System has the potential to serve as a key element in the broader smart city framework, which encompasses connected traffic management, emergency services, and urban planning systems.

V. CONCLUSION

The Smart Accident Detection & Reporting System project introduces a groundbreaking approach to improving road safety and emergency response. By integrating IoT, machine learning, and an intuitive web interface, this system addresses the pressing need for real-time accident detection, reporting, and management. Utilizing street cameras and automated detection models, the platform can accurately identify accident types, assess their severity, and track vehicles, while also enabling public users to report accidents manually. This combination offers a holistic solution that can adapt to a variety of accident scenarios.

The approach also presents a scalable, cost-efficient, and non- intrusive solution for the early detection of mental health issues from text data, providing valuable support to health- care providers and wellness platforms. Although the model demonstrates strong potential, future development may focus on incorporating temporal patterns in user text, enhancing transformer-based models, and deploying the system as an interactive web application for real-time mental health screening and advice.

The project's versatile design allows emergency services, including police, ambulances, and fire departments, to access live accident footage, evaluate incident details, and respond swiftly. The system's dashboards and in-depth reports enhance the monitoring and analysis of accident trends, while role-based access ensures data security and privacy. With its focus on performance, scalability, and user-friendly interface, the portal is well-suited to meet the demands of real-world applications, making it a viable solution for widespread implementation.

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