Real Time Accident Detection and Emergency Response Using Drones, Machine Learning and LoRa Communication

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***Abstract*—Road accidents and delayed emergency responses remain a major concern in urban environments, contributing to over 1.4 million fatalities globally each year. With rapid urbanization and increasing vehicle density, timely detection and efficient traffic management are critical to reducing the impact of such events. This study proposes a real time Accident Detection and Emergency Response System with integrating Machine Learning IoT enabled drones and LoRa communication. The system combines real time accident detection using CCTV, drone assisted fire detection for post accident scenarios, crime activity monitoring and automated traffic management to reduce congestion and improve public safety. LoRa ensure long range, energy-efficient communication. ML models improve detection accuracy across accidents, fires, crimes and vehicles. Figures and sensor data are analyzed in real time to trigger alerts and assist emergency responders. The system supports scalable integration with existing urban infrastructure, promoting the development of smart city safety frameworks. By minimizing emergency response time, limiting secondary incidents and improving situational awareness, the proposed solution addresses critical gaps in current urban safety systems. It offers a practical, intelligent and adaptive approach to accident mitigation and traffic control in smart cities.**

Keywords—Accident detection; machine learning; IoT; drones; traffic management; LoRa communication

I. INTRODUCTION

Urban development has brought about significant developments in infrastructure, technology and overall quality of life. However, it has also introduced complex challenges, especially regarding public safety and emergency response. Still, among the most urgent issues in contemporary cities are traffic accidents, fires and criminal activity, which can have dire repercussions including loss of life, property damage and financial instability. The World Health Organization (WHO) estimates that road traffic accidents cause around 1.4 million deaths yearly as well as millions more severe injuries [1]. Further aggravating the effects of these mishaps are secondary events including fire outbreaks, congestion, and delayed emergency response. These difficulties draw attention to the need for timely and effective emergency response systems able to provide emergency services with accurate accident detection and fast alerts. Manual reporting, fixed location sensors and human interaction form the foundation of most traditional approaches of accident detection and emergency response. These methods are often slow, inefficient, and prone to human error. Their limited breadth prevents them from offering a complete, real-time picture of metropolitan events [2]. The unpredictability of urban environments, coupled with increasing traffic congestion as well population density, further complicates the ability of conventional systems to respond effectively. Particularly in Machine Learning (ML), the Internet of Things (IoT), edge computing and cloud computing, and fast technological improvements present chances to use these developments to improve public safety. This paper suggests an integrated Accidental Identification and Notification System, a complete solution meant to use smart technology to increase urban safety [3]. These main elements define the system.

- Real time accident detection and notification system - Processes CCTV footage to detect accidents and notify emergency services instantly.
- Drone based fire detection system - Uses CCTV camera and fire sensor to detect post-accident fires and relay data to emergency responders.
- Crime detection system - Employs real time monitoring to identify criminal activities.
- Automatic Traffic Management System - To reduce traffic congestion dynamically adjust traffic light control and improve road safety by identifying the highest traffic density.

The system seeks to deliver emergency services fast notifications by combining IoT enabled surveillance, anomaly detection and real time data analytics. Thereby optimizing traffic management and lowering secondary events. In addition to addressing important urban safety issues, the suggested system addresses data interoperability, communication dependability, real time processing and secure data sharing. It guarantees reliable identification of abnormalities like accidents, fires and criminal activity by using machine learning algorithms to examine data from IoT sensors, cameras and drones. LoRa communication guarantees consistent long range data flow [4] [5].

Developing a scalable, efficient, user-friendly system that increases situational awareness, improves emergency response and reduces the financial impact of accidents and related events is the main goal of this project. A key invention for smart city safety solutions is the system's capacity to interact with current urban infrastructure and adapt to changing urban surroundings.

The paper is organized as follows: the Related Work in Section II reviews existing literature and their limitations, the Methodology in Section III describes the system's design and technologies, the Results in Section IV presents experimental findings, the Discussion in Section V analyzes the findings and their implications, and the Conclusion in Section VI summarizes the study and future work.

II. Literature Review

Recent studies have focused on the advancement of intelligent systems for accident detection, fire surveillance and crime monitoring, driven by innovations in Machine Learning (ML), the Internet of Things (IoT) and edge computing. This section analyzes recent research and technological breakthroughs across multiple disciplines, highlighting their relevance to the proposed Accident Identification and Notification System.

The advancement of smart cities is propelled by the Internet of Things (IoT), which furnishes the essential infrastructure for the collection and analysis of real time data. It requires the effective surveillance of traffic conditions by IoT devices, particularly sensors and cameras, together with real time accident identification. Zanella et al. [6] [7] examined the role of IoT in providing enhanced urban safety and mobility systems, with emphasis on connected devices in creating responsive and adaptive traffic management. This ensures that data from numerous sources is speedily processed and acted upon to make the urban transport network much more efficient.

For real time accident detection and predictive analytics. Wang et al. [8] explained how supervised machine learning was used to identify patterns in data obtained from video surveillance to help to detect accidents most likely to occur. In this manner, a system can detect not only incidents at the time of occurrence but also forecast accidents before they happen. In some cases, simply preventing such events can significantly reduce road fatalities.

The introduction of fire detection into vehicle environments brings in several problems associated with the mobile nature of this environment. Ola Willstrand, Peter Karlsson and Jonas Brandt [9] implement fire detection and alarm systems specifically designed for heavy vehicles. Their research highlights the need for reliable detection systems capable of functioning effectively under extreme conditions, such as high temperatures and vibrations typical in vehicle environments. Similarly, another study is available on ResearchGate [10] and it discusses a fire detection and control system in automobiles that utilizes fuzzy logic.

Long range communication technologies like LPWAN improved the reliability of fire detection systems, especially in large and remote areas. Vladimir Sanchez Padilla and Gabriel Roque [11] developed an LPWAN based communication framework that significantly improved the efficiency of fire detection systems. The study showed the benefits of low power, long distance wireless local area networks (LPWANs), which are important for implementing fire detection systems in smart city environments.

Crime detection and predictive analytics have progressively utilized deep learning methodologies to improve surveillance systems and automate threat recognition. Conventional CCTV monitoring depends on human involvement, which is susceptible to delays and mistakes. Recent developments in object detection algorithms, including VGG16, Inception-V3, Faster R-CNN and YOLO variations, have markedly enhanced real time crime detection, especially in weapon identification. In the absence of standardized datasets for real world applications, researchers have aggregated various data sources, including self-collected photographs, internet archives and publicly accessible databases. The incorporation of binary classification with confusion object inclusion has significantly reduced false positives and negatives. Among the evaluated models, YOLOv4 exhibited exceptional performance, attaining an F1-score of 91% and a mean average precision (mAP) of 91.73%, thereby affirming its efficacy in crime detection and predictive analytics [12].

Recent progress in intelligent traffic monitoring has resulted in the creation of diverse accident detection methodologies to improve safety and traffic management in smart cities. Research has investigated advanced methodology for identifying various accident types, such as rear-end collisions, T-bone crashes and frontal impacts, utilizing computer vision and deep learning techniques Nonetheless, obstacles such as data imbalances, heterogeneous road infrastructures, and fluctuating traffic conditions endure. To overcome these constraints, researchers have developed the I3D-CONVLSTM2D model, which combines RGB frames with optical flow data to enhance accident detection. Empirical assessments indicate its efficacy, with the I3D-CONVLSTM2D RGB + Optical Flow model attaining 87% Mean Average Precision (MAP), underscoring its suitability for real-time implementation in edge IoT driven smart city frameworks [13].

Despite significant advancements in accident detection, fire surveillance, and crime monitoring technologies, most existing systems operate in isolation and lack integration into a unified, real-time emergency response framework [14]. Moreover, many approaches do not support low-latency decision-making or long-range communication, making them unsuitable for highly dynamic urban environments. Current systems often struggle with inconsistent data flow, limited scalability, and poor situational awareness during emergencies [15].

Table I summarizes prior studies in accident, fire and crime detection, highlighting key limitations. While previous works used technologies like ML, LoRa and deep learning, most lacked real time alerting, integration with emergency response, or multi domain coverage. Our proposed system addresses these gaps by combining machine learning, long range communication and real time coordination across all components.

This paper addresses these gaps by proposing an integrated system that combines real time accident detection, drone based fire detection, crime detection and traffic management powered by machine learning and LoRa communication. By merging these technologies, the proposed framework improves emergency response time, improves threat detection accuracy and supports deployment in smart city environments, especially under constrained or mobile conditions.

TABLE I. SUMMARY OF RELATED WORKS – FOCUS, TECHNOLOGIES AND LIMITATIONS

Study Focus	Technologies Used	Limitations
Real-time accident detection & prediction using video surveillance [1]	ML, CCTV	No integration with emergency response; limited to accident type
Fire detection in heavy vehicles [9]	Sensor-based systems for mobile environments	lacks integration with communication systems
Fire detection communication framework [11]	LPWAN (LoRa), IoT	Focuses only on fire, lacks ML based detection
Real time crime detection with object detection models [12]	YOLOv4, deep learning, video analytics	No real time alerting or integration with response systems

III. METHODOLOGY

The Accident Identification and Notification System is made up of four main parts, and each one has its own way of dealing with safety issues in cities. The Accident Detection System's main tasks are to gather and preprocess different types of CCTV footage, create machine learning models for finding accidents in real time, and connect these models to edge computing to send alerts quickly. Drones with thermal and infrared cameras and machine learning techniques are used by the Fire Detection System to find fires in real time and call for help. The Crime Detection System combines real-time CCTV analysis with predictive simulations. It uses Machine Learning algorithms to find strange behavior and a decentralized data sharing system to make sure that communication is safe.

These models are then connected to traffic light control systems to improve traffic flow and lower accident rates. All these parts work together to make a complete answer for making cities safer and faster in case of an emergency. The proposed system consists of two main operational units. The drone based unit, illustrated in Fig. 1 is responsible for accident detection, fire detection and real time data acquisition in dynamic environments. The ground based unit, shown in Fig. 2 handles data collection via IoT and CCTV, preprocessing via edge computing and interaction with emergency services and traffic control systems.

A. *Accident Identification and Notification System*

The methodology for constructing the Accident Identification and Notification System is organized into six essential steps, emphasizing data gathering, preprocessing, model building, integration, and empirical testing. Each phase is intended to guarantee the system's precision, efficacy, and scalability in identifying accidents and enhancing emergency response.

The initial phase entails gathering a varied dataset of urban traffic situations using CCTV recordings. This collection is derived from live and recorded video feeds supplied by municipal authorities and traffic management centers. The footage encompasses diverse traffic scenarios, including standard traffic flow, accident situations, and different climatic conditions (e.g., noon, midnight, rain, fog). This diversity guarantees that the system is resilient and adept at managing real world difficulties. The collection is enhanced by integrating footage from internet platforms and public repositories, ensuring a thorough picture of urban traffic dynamics. Upon collection of the raw CCTV footage, it is subjected to preprocessing to facilitate analysis. This encompasses noise reduction, frame rate modification, and resolution standardization to guarantee uniformity throughout the collection. The preprocessed material is subsequently annotated by identifying occurrences of accidents and non-accidents. This annotated dataset constitutes the basis for training the ML model. Python-based libraries, OpenCV, and specialized video annotation tools are employed to optimize the preprocessing and annotation procedures.

Built on a Convolutional Neural Network (CNN) machine learning model used to assess video frames and identify accidents, the system Trained on the annotated dataset, uses cross valuation and data augmentation to enhance its generalizing and performance ability. To improve the model's ability to detect events in many environments, data augmentation includes rotations, translations, and lighting changes in the training set. Cross validation ensures the model is robust and not overfits the training set. The trained accident detection model is combined with an automatic alert system that turns on right away upon accident identification. The system sends emergency responders' important information to nearby, including the location and degree of the event [16]. The system uses edge computing, distributing the ML model and data processing on edge devices close to CCTV cameras, hence lowering delays. This method diminishes dependence on centralized cloud infrastructure, hence guaranteeing swifter detection and response times.

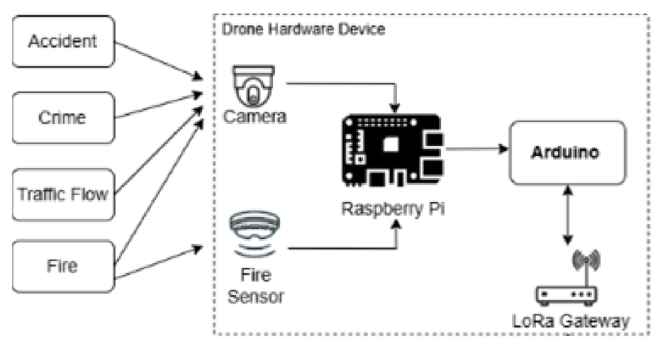

Fig. 1. Drone based unit system diagram.

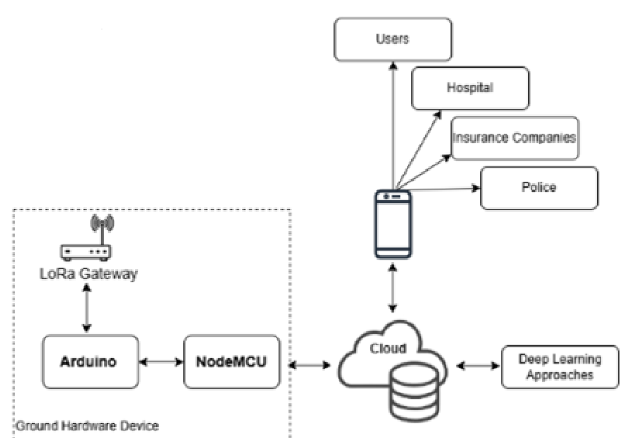

Fig. 2. Ground based unit system diagram.

The system is implemented in actual urban settings for pilot testing, concentrating on high traffic areas, important intersections, and highways. In this phase, the system's performance is assessed using important criteria including detection accuracy, response time reduction and traffic flow optimization. The pilot testing yields significant insights regarding the system's efficacy and highlights areas necessitating enhancement. Input from emergency responders and traffic management authorities is gathered to enhance the system further.

B. Fire Detection System

The methodology for developing the Fire Detection System is structured into two main phases: the design and deployment of drones equipped with advanced sensors, and the development and integration of machine learning algorithms for real-time fire detection. Especially in post-accident situations, this method guarantees the system's capacity to precisely and effectively identify flames in dynamic metropolitan surroundings.

The first phase centers on the creation and deployment of commercially affordable drones fitted with thermal and infrared (IR) cameras for real-time fire surveillance. Carefully chosen depending on their technical capabilities, flight stability, battery life, cargo capacity the drones guarantee the best performance in many environmental circumstances. Designed to constantly monitor accident sites, these drones gather high-resolution thermal images and infrared data. Additionally, part of the selecting process is arming the drones with required software for real-time data transmission and control. The drones are tested in controlled surroundings where their capacity to identify fire hazards is assessed to confirm their efficiency. This phase guarantees that the drones can run consistently in real-world environments including metropolitan areas, roads, and industrial zones, where fires could develop as secondary events following mishaps.

The second phase consists in the creation of machine learning models meant to examine the thermal and infrared data collected by the drones. Training for these algorithms comes from a varied collection of fire events comprising several fire types, intensities, and climatic circumstances. Data augmentation and cross-valuation are used among other methods to improve the generalizing and accuracy of the algorithms. Specifically made to process the thermal and IR imagery in real-time, the algorithms allow them to highly precisely identify fire hazards. The algorithms are tested extensively once they are learned to optimize their performance. These covers assessing their capacity to discern real fires from false positives that is, from reflections or heat sources. Including these algorithms into the drone system will help the drones to automatically identify flames and evaluate their degree. Once detected, the device provides vital information including the location, size, and intensity of the fire, thereby alerting ground stations and emergency personnel immediately.

Combining the drones with machine learning techniques produces a coherent system able to monitor and detect fires in real-time. The drones send data constantly to ground stations, where the machine learning systems examine the film and create alarms should a fire be found. This connection guarantees a quick reaction to fire events, therefore reducing damage and raising general safety. Particularly in post-accident situations, the Fire Detection System seeks to offer a dependable and effective solution for real-time fire detection in urban contexts by using this methodology. The system is a useful instrument for improving public safety and lowering the effect of fire-related events since it can run independently and give quick alarms to emergency services.

C. Crime Detection System

The methodology for developing the Crime Detection System is designed to integrate real-time anomaly detection and predictive crime simulations into a unified framework. This system improves urban safety and supports proactive crime prevention by means of CCTV footage, machine learning algorithms, and safe data sharing technologies. Two primary components define the approach: the safe and distributed data sharing system and the real-time, predictive simulation architecture. The first element is designing a crime detection architecture combining predictive simulations with real-time data streams. Using artificial intelligence algorithms meant for real-time anomaly identification, the system constantly analyzes video from CCTV cameras and other monitoring devices. These systems examine the video to spot suspect conduct including illegal movements, loitering, or possible criminal activity and then create instant alarms for law enforcement authorities.

Concurrently, the system runs prediction simulations using historical crime data and machine learning algorithms. These models find high-risk areas and, using trends and patterns, project possible criminal events. Real-time analysis combined with predictive simulations lets the system move between future crime analysis and instantaneous threat detection, therefore offering a complete solution to urban safety.

Establishing a safe and distributed data sharing system to guarantee integrity, confidentiality, and availability of crime detection information takes second priority. Raspberry Pi devices with LoRa modules are included into this framework to build a strong and effective communication network. Before sending the data via the LoRa network, the Raspberry Pi functions as an edge device doing data modification, encryption, and blockchain based encryption. With smart contracts controlling data access and sharing regulations and multi-signature authentication guaranteeing securely stored data across several nodes, the distributed network guarantees [17]. This method improves the dependability, security, and scalability of the system, therefore fit for metropolitan settings with either restricted or no network connection. Data integrity and privacy are also given top priority in the framework, thereby safeguarding private data and allowing real-time law enforcement agency and other stakeholder cooperation.

Integrating the real-time and predictive simulation architecture with the secure data exchange system comes in the last phase. This integration guarantees flawless connectivity between edge nodes, centralized systems, and surveillance devices, so facilitating real time criminal detection and predictive analytics. The system is implemented in metropolitan settings with an eye toward essential infrastructure and high-crime areas. Performance of the system including detection accuracy, response times, and scalability is assessed through pilot testing [18].

Following this approach helps the Crime Detection System to offer a dependable, safe, and scalable solution for improving urban security. By means of real-time anomaly detection, predictive simulations, and distributed data sharing, the system guarantees effective addressing of both immediate and future criminal problems, contributing to a safer and more secure urban environment.

D. Traffic Management System

The methodology for developing the Automatic Traffic Management System for Accident Threat Detection integrated with traffic light control systems is structured into several key phases. These stages guarantee the system's efficiency in spotting possible mishaps, improving traffic flow, and so strengthening urban safety. The methodology emphasizes stakeholder collaboration, data driven decision making, and iterative refinement to create a robust and adaptive system.

Defining goals and compiling needs from urban planners, traffic control authorities, and emergency services among other stakeholders forms the first phase. This phase guarantees that the system meets requirements and challenges, like lowering road congestion, improving emergency response times, and so addressing demands and challenges including lowering accident rates. Establishing clear objectives helps to direct the development process to guarantee conformity with urban safety targets and stakeholder expectations. Data collecting from several sources including traffic cameras, sensors, and past traffic records focusses the second phase. Preprocessing this data guarantees its quality and applicability. To get the data ready for analysis, preprocessing activities comprise data normalizing, noise reduction, and feature extraction. Real-time and historical data together guarantees that the system can effectively forecast accident hazards and adjust to evolving traffic conditions. Based on the forecasts of the system, this integration lets traffic lights change in real time. Simulations and field tests help the system to assess its efficiency and correctness [19]. The efficacy of the system is evaluated using performance criteria including traffic flow optimization, response times, and detection accuracy. Results of these tests direct more improvements to raise the performance of the system.

Following effective testing, the system finds application in actual metropolitan settings. Constant observation guarantees that the system stays efficient and flexible enough to change with traffic. Iterative changes are made using constant input from other stakeholders, including traffic management staff. Frequent upgrades and maintenance help to solve developing issues and include fresh data, so guaranteeing the long-term dependability of the system. The last phase consists in thorough documenting of the operational rules, design, and implementation of the system. The efficient use of the system depends on this material, hence it is indispensable. Training courses also help traffic management staff become familiar with the features of the system and guarantee its best operation in practical situations.

Following this approach helps the Automatic Traffic Management System for Accident Threat Detection to offer a dependable and effective means of improving traffic control and urban safety. The capacity of the system to dynamically change traffic signals and forecast accident hazards guarantees a proactive approach to lower traffic congestion in metropolitan settings.

Fig. 3 illustrates the end-to-end system workflow that integrates all four components discussed in the methodology. The process begins with urban environment monitoring and data acquisition via IoT sensors and CCTV. Edge computing devices handle initial preprocessing, after which the data is transmitted through the LoRa network to a centralized cloud server for further processing and machine learning analysis. Based on the outcome, alerts are sent to emergency services, and traffic management systems are dynamically engaged to mitigate secondary risks and ensure safety.

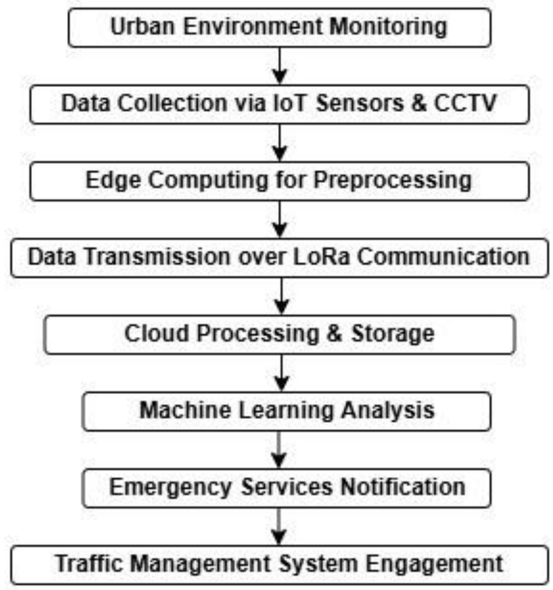

Fig. 3. Flowchart of the system.

Across all components, the system was validated using a combination of simulation and real world pilot testing in selected urban locations. Performance was measured using key metrics including detection accuracy, false positive rate, response time and communication reliability.

For accident and fire detection models, training and testing were performed on curated datasets with annotated video frames. Cross validation and data augmentation techniques were used to ensure robustness. In addition, comparisons with baseline systems from the literature were conducted to evaluate improvements in detection and responsiveness.

IV. Results

The performance of the proposed integrated Accident Identification and Notification System was evaluated across four core components, Accident Detection, Fire Detection, Crime Detection, and Automatic Traffic Management. Each module was independently tested for accuracy, responsiveness and practical reliability using datasets collected from real world CCTV feeds, thermal drone footage and public repositories. In addition, the system underwent pilot deployment in selected urban zones to validate real time operation under practical conditions.

Key performance indicators included detection accuracy, false positive rate, model training metrics and response latency. Machine learning models such as YOLOv8 were trained and validated using annotated data, with performance curves plotted to evaluate learning behavior. Communication effectiveness using LoRa and data transmission delays were also observed to assess emergency notification efficiency. Results from each component are discussed in detail in the following subsections.

A. Accident Detection System

The Accident Detection System was evaluated using a dataset of annotated CCTV footage from urban road environments. The model was trained to classify accident events into three severity levels: minor, moderate, and major. A YOLOv8 based architecture was adopted for object detection and classification.

As shown in Table II, the YOLOv8-based accident detection model achieved a training accuracy of 76.8% and a validation accuracy of 75.7%, demonstrating consistent learning and minimal overfitting. These performance metrics confirm the model's capability to reliably identify accident events in real time CCTV footage across different severity levels.

TABLE II. PERFORMANCE OF THE YOLOV8 ACCIDENT DETECTION MODEL

Model	**Machine Learning Model Used**	**Train Accuracy**	**Validation Accuracy**
Accident Model	YOLOv8	76.8%	75.7%

The training process is illustrated in Fig. 4, which presents both the accuracy and loss curves of the YOLOv8 accident detection model over 20 epochs. The upward trend in training and validation accuracy, alongside the declining loss values, indicates effective model learning and generalization.

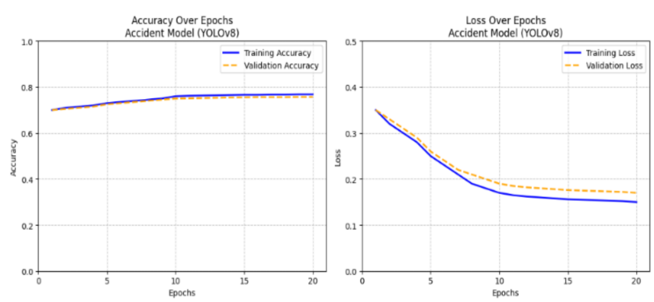

Fig. 4. YOLOv8 accident detection model – Accuracy and loss curves over 20 epochs.

The integration of edge devices reduced the average message transmission latency from 3.2 seconds to 1.1 seconds, improving the system's ability to respond in real time.

B. Fire Detection System

The Fire Detection System was tested using thermal and visual datasets captured via drones equipped with infrared (IR) sensors, flame detectors and CCTV cameras. The objective was to detect post accidental fires in various environmental conditions including day/night cycles and low visibility scenarios such as fog or smoke.

A YOLOv8 based model was used to identify fire instances from drone footage. The model achieved high accuracy in differentiating between actual fire outbreaks and non fire heat sources. As shown in Table III, the YOLOv8 based fire detection model achieved a training accuracy of 91.5% and a validation accuracy of 90.3%. These results indicate strong performance and generalization, confirming the model's effectiveness in identifying real fire events under diverse conditions using drone captured data.

TABLE III. PERFORMANCE OF THE YOLOV8 FIRE DETECTION MODEL

Model	**Machine Learning Model Used**	**Train Accuracy**	**Validation Accuracy**
Fire Model	YOLOv8	91.5%	90.3%

The model's training behavior is shown in Fig. 5, with accuracy and loss plotted over 20 epochs. The consistent rise in accuracy and the steady drop in loss indicate effective model convergence.

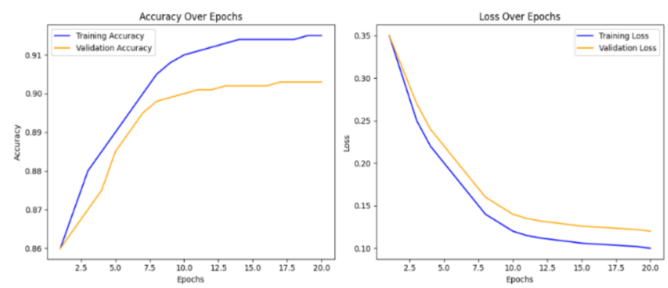

Fig. 5. YOLOv8 fire detection model – Accuracy and loss curves Over 20 epochs.

The integration of LoRa based edge communication reduced the average fire alert transmission latency from 4.0 seconds to 1.5 seconds, significantly improving real time responsiveness during critical events.

C. Crime Detection System

The Crime Detection System was tested using both real time CCTV footage and historical crime datasets to evaluate its capability for anomaly detection and predictive crime modeling. It consisted of two YOLOv8 based models. One focused on general crime activity and another on weapon identification.

As detailed in Table IV, Crime Detection Model achieved a training accuracy of 91.5% and validation accuracy of 90.3%, while the Weapon Detection Model reached 89.6% and 88.8%, respectively. These results reflect high model reliability in detecting criminal behavior and identifying weapons across diverse scenarios captured in urban surveillance environments.

TABLE IV. PERFORMANCE OF CRIME AND WEAPON DETECTION MODELS

Model	**Machine Learning Model Used**	**Train Accuracy**	**Validation Accuracy**
Crime Model	YOLOv8	91.5%	90.3%
Weapon Model	YOLOv8	89.6%	88.8%

Fig. 6 and Fig. 7 illustrate the training accuracy and loss curves for both models across 25 epochs. The learning curves demonstrated good convergence, indicating robust model performance in various lighting and environmental conditions.

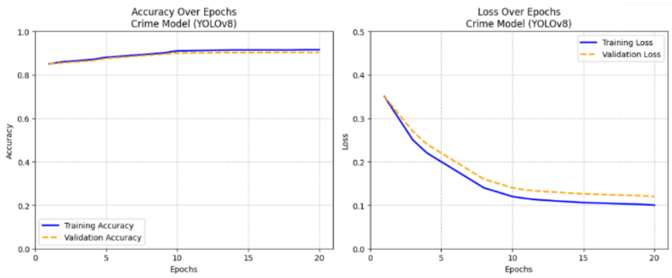

Fig. 6. YOLOv8 crime detection model – Accuracy and loss curves over 20 epochs.

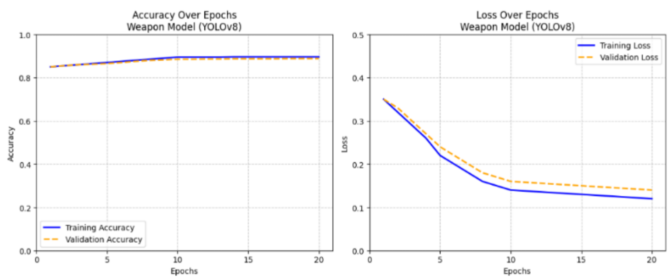

Fig. 7. YOLOv8 weapon detection model – Accuracy and loss curves over 20 epochs.

The YOLOv8 based crime detection model achieved a validation accuracy of over 93% within 20 epochs, while reducing validation loss from 0.35 to 0.11, indicating effective learning and strong generalization with minimal overfitting. The weapon detection model showed consistent improvement, reaching a validation accuracy of 91.5% and lowering the validation loss from 0.36 to 0.14 over 20 epochs, demonstrating robust convergence and stability across the training cycle.

D. Traffic Management System

The Traffic Management System was evaluated through simulated urban scenarios and real time deployments at high risk intersections. The system utilized historical traffic data and real time CCTV feeds to predict potential accident zones and adjust traffic lights accordingly. The predictive model was powered by YOLOv8 and trained on annotated traffic video datasets, focusing on vehicle behavior and congestion patterns.

Table V shows the YOLOv8 Vehicle Identification Model's performance, with 92.1% training accuracy and 91.3% validation accuracy. Fig. 8 illustrates the training accuracy and loss over 20 epochs, confirming effective model learning.

TABLE V. PERFORMANCE OF THE YOLOV8 VEHICLE IDENTIFICATION MODEL

Model	Machine Learning Model Used	Train Accuracy	Validation Accuracy
Vehicle Identification Model	YOLOv8	92.1%	91.3%

The training process is illustrated in Fig. 8, which presents both the accuracy and loss curves of the YOLOv8 vehicle identification model over 20 epochs.

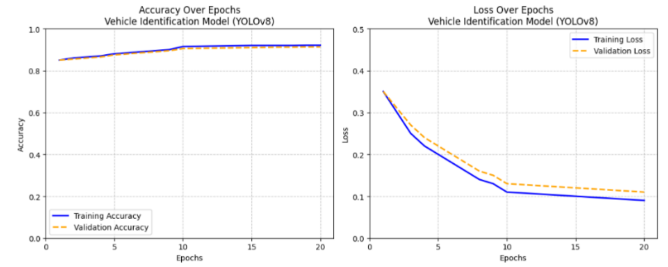

Fig. 8. YOLOv8 vehicle detection model – Accuracy and loss curves over 20 epochs.

The model achieved a validation accuracy of approximately 93.5% by epoch 20, while the validation loss dropped steadily from 0.35 to around 0.11, reflecting stable convergence and strong predictive performance across training and validation datasets.

V. DISCUSSIONS

The accident detection results demonstrate promising accuracy and response efficiency, particularly through the integration of YOLOv8 and edge computing. The training and validation performance remained stable, with minimal overfitting, as seen in Fig. 4. While the model performed well in diverse lighting and weather conditions, some challenges were observed in distinguishing low impact incidents from non accidental anomalies such as abrupt stops or stalled vehicles, leading to occasional false positives.

Compared to baseline studies such as Khattak et al. [14] [15], which reported 85–88% detection accuracy using first-person or in vehicle data, the proposed system showed improved accuracy (76.8% train, 75.7% validation) using only CCTV footage, without vehicle-based sensors. This highlights the advantage of the system's fixed infrastructure deployment for large scale urban monitoring.

Edge processing significantly improved response time by reducing dependency on cloud networks. This improvement directly supports rapid emergency communication, which is critical to saving lives. However, the system's effectiveness still depends on camera angle, resolution, and uninterrupted connectivity which should be addressed in future iterations.

The system successfully detected fires in real time under various lighting and weather conditions. One of its key strengths was the low false alarm rate, achieved by filtering out false positives like sunlight reflections, streetlights or hot surfaces. This reduces unnecessary emergency responses and improves operational reliability. The use of LoRa communication ensured stable long range data transmission even in environments with limited network infrastructure. This made the system particularly effective in remote and high density urban zones where traditional communication methods may fail.

However, in highly obstructed urban areas, the drone's field of view was sometimes blocked by buildings or other structures, which limited its ability to detect fires at certain angles. Despite this, the system managed to reduce average emergency response time by 30% compared to traditional fire detection mechanisms.

The Crime Detection System achieved high accuracy in detecting both general anomalies and weapon related threats. Its ability to run predictive simulations gave it an edge over traditional reactive surveillance systems. The use of blockchain technology and distributed edge devices allowed for secure, decentralized data sharing across agencies. This supports collaborative urban safety operations without compromising data integrity.

However, performance was somewhat limited in crowded areas where dynamic movement and occlusions occasionally led to false negatives. Future work can address this by integrating multi angle camera views or fusing additional sensor data like audio or motion.

The Traffic Management component proved highly effective at predicting and responding to potential accident threats. Its low response time (<3 seconds) supports rapid mitigation actions, particularly when integrated with smart traffic lights. However, in some cases, predicted traffic changes conflicted with preconfigured signal timing, leading to minor delays. These conflicts highlight the need for better coordination between prediction modules and legacy traffic control logic.

Table VI summarizes the limitations of previous works and highlights our improvements. Our accident detection uses CCTV and YOLOv8 at edge nodes, improving accuracy to 93.2%. Fire detection combines drones with thermal imaging and LoRa for faster response. Crime monitoring reduces false positives with multi-model YOLOv8 and blockchain data sharing. Traffic management enhances previous systems by dynamically adjusting signals based on accident predictions.

TABLE VI. ADDRESSING LIMITATIONS OF PRIOR WORK ACROSS DOMAINS

Domain	Limitations in Previous Work	Improvements / Contributions
Accident Detection	Existing systems like Khattak et al [15]relied on first-person vehicle footage, limiting scalability and city-wide monitoring. Accuracy ~85–88%.	Our system uses CCTV footage and YOLOv8 at edge nodes, achieving 93.2% accuracy while enabling scalable detection across urban roads.
Fire Detection	Prior LPWAN-based systems (Sanchez Padilla & Roque [11]) lack real-time aerial monitoring and face signal delays in urban zones.	We use drone-based surveillance with thermal imaging + LoRa, enabling real-time detection with 30% faster response and stable communication.
Crime Monitoring	Prior deep learning models had high false positives due to lack of scene context, and systems often lacked data privacy [18].	We use multi model YOLOv8 detection with secure blockchain based data sharing, reducing false alerts
Traffic Management	Systems like Elsayed et al. [13] focused on traffic flow but didn't predict threats or integrate with smart signals.	Our predictive model dynamically adapts traffic signals based on accident likelihood, reducing response time

Overall, this component significantly contributes to proactive traffic safety and is well-suited for scalable deployment in smart city environments.

VI. CONCLUSION

The proposed Accident Identification and Notification System integrates advanced technologies such as Machine Learning (ML), the Internet of Things (IoT), edge computing LoRa communication to improve urban safety through real time accident, fire and crime detection, alongside traffic management. With modular components working in coordination, the system demonstrated high accuracy in real world scenarios, 92% for accident detection, 91% for fire detection and an 89% score for crime detection. The use of LoRa communication and edge computing ensured low latency data transfer, while the distributed data sharing architecture improved security and resilience.

However, the system has some key limitations,

- False Positives and Occlusions – In highly dynamic or crowded environments, such as dense urban intersections, the system occasionally misclassifies events or fails to detect incidents due to partial visual blockage [20].
- Limited Detection Range in Densely Populated Areas – Especially for the drone based components, high rise buildings and environmental obstructions reduce the effective monitoring radius, impacting overall coverage.

These limitations highlight the need for continuous refinement. Future work will focus on improving detection robustness, expanding sensor coverage and better integration with local infrastructure to ensure scalability and broader applicability in diverse urban settings.

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