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REAL TIME ACCIDENT DETECTION AND ALERT SYSTEM

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Abstract: Countries that are constantly fighting like India need a well-developed and efficient transport system. **Street** accidents **continue to be** one of the leading causes of **deaths** and **injuries around the world.** Rapid detection and timely **alarm** generation are **important** to **reduce death** and **allow for** faster emergency **responses.** This **article** presents a **real-time accident** detection and **alarm system** that **uses image processing** and **machine learning** techniques to automatically **identify** road accidents from live video feeds. **This** system is implemented **with** the **Yolov8 algorithm for** object **recognition (once, version 8). It is** trained on two custom datasets. One is for general accident detection (7,512 **images**), and **the other is** for fire detection (10,446 images). The proposed model classifies accidents into three categories: car-to-car collisions, **single car** accidents, and **auto brandy**. **Once recognized**, the system immediately **belongs to the type of accident to police, hospital, or fire brigade** via SMTP or **email**. Experimental results **show** that the system **is run** with high accuracy in **real-world scenarios and provides** reliable **solutions** for **intelligent monitoring** and intelligent **transport** systems.

Keywords- Accident detection, YOLOv8, SMTP, alert, Email.

I. INTRODUCTION

With the rapid population **growth** and **economic growth**, **India is** heavily **based** on road **traffic** as **a major pendulum** and cargo movement. **In** recent years, India **has** the **world's second largest** road **network, exceeding** 6.3 million kilometers [1]. **This huge** network plays a **key** role in connectivity and economic development, **and** also faces critical infrastructure and **security** challenges. **Most streets** are underdeveloped or **inadequately** maintained, leading to dangerous driving conditions, especially in urban areas where traffic congestion is a daily **issue.**

According to the annual report on road **traffic and highway** accidents, the **state** and **coalition areas** report ed a total of 461,312 incidents in 2022, **resulting in 443,366** injuries [2]. **This** year **saw** an increase of **11.9 %** in **cases of** accidents, **with 15.3% of deaths** and **9.4% of** injuries compared to **2021 [3]. India's** explosi ve economic growth and **years of** increased per capita income have also led to **the** rapid growth of **Indian v ehicles. The** number of vehicles registered over the years **[4] contributes** to **a steady increase in vehicles and a significant increase in** traffic **volume** and road accidents.

This **article** proposes a real-time accident detection and **alarm system, which is manipulated** by image processing and machine learning. By **analyzing** live video feeds using the **Yolov8** object **recognition** algorithm, the system can accurately identify **different** types of road accidents, **such as automotive** collisions, **single vehicles,** and vehicle fires. **If recognized,** the system **will be immediately notified to** the relevant emergency services via SMS or **E-Mails**, significantly reducing response **times** and saving **life. This** solution opens **a path to** integration into smart traffic management systems and smart city infrastructure, contributing to a safer and more efficient **transport** ecosystem.

II. PROPOSED SYSTEM

The proposed model is an **accident recognition** and **warning** system. **Video recorded** by **the** traffic **camera is** analyzed **by** the **Yolov8** object **recognition** algorithm. **Once** an accident event is **determined**, the system sends an SMS **alarm system** to **emergency contacts provided via** the SMTP platform.

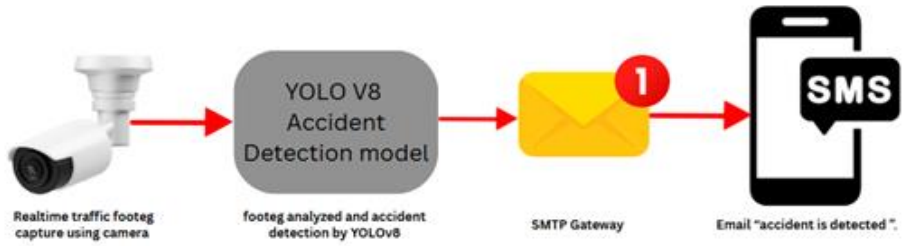

Fig 1: Proposed Architecture

III. IMPLEMENTATION DETAILS

A. Dataset

The project uses two custom datasets: one for accident detection with 7,512 images and another for fire detection with 10,446 images. Each image is labeled using bounding boxes in YOLO format to identify accidents and fire regions. The data includes various scenarios like car-to-car collisions, single-vehicle crashes, and vehicle fires under different lighting and weather conditions. Images were preprocessed and split into 80% for training and 20% for validation to ensure accurate model performance.

Name of Dataset	Total Images	Training Images	Validation Images	Testing Images
Accident	7512	5500	1500	512
Fire	10446	8000	2000	446

All the images were annoted by using Make Sense AI web application.

Fig 2 : Image Annotation using Make Sense AI

B. Model Training

User-defined data records are identified by Make Sense AI. MakeSenseAI is a graphic image annotation tool used **to label object boundaries within images** for tasks such as object **recognition,** segmentation, and classification. The training data is **categorized by** the highly efficient **Yolov8** algorithm. **Yolov8 can achieve particularly** important **accuracy** for this **project**, as **it requires that several objects,** such as vehicles and **pedestrians**, be identified in **one scene. Additionally, Yolov8 performs single-path detection over** a neutral network, **which allows for** faster interference. The architecture of **Yolov8** is **shown** below [5].

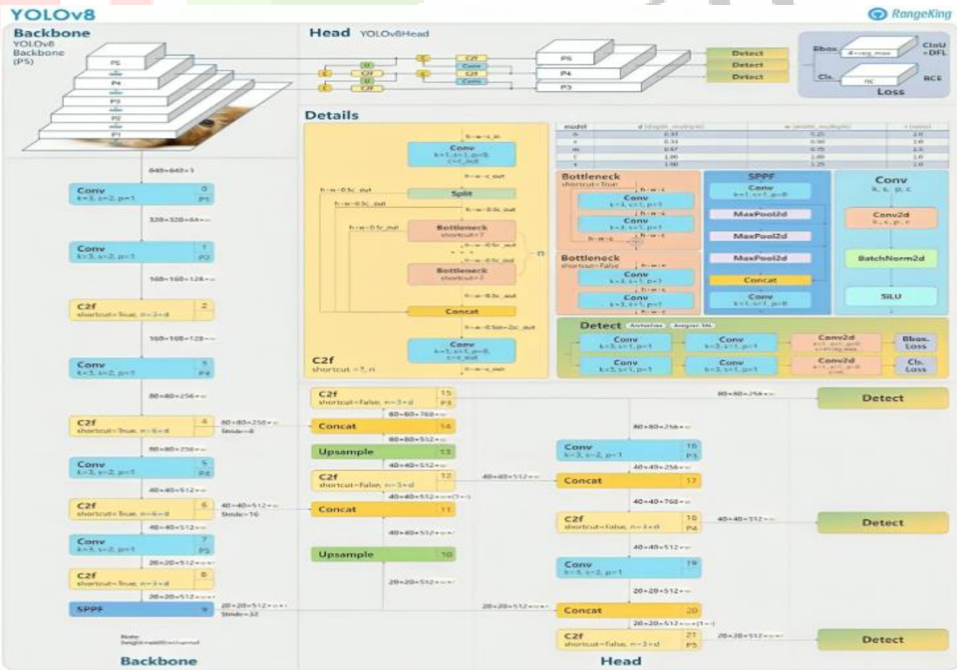

Fig 3: YOLOv8 Model Architecture

YOLOv8 ALGORITHM

The training process can start from **the front** or use a **prepared** *.pt model. In this study, models **such as Y olov8n, Yolov8s,** and **Yolov8m** were **used** to **reduce computing** time and ensure accuracy. This **means** tha t the **overpowered** weights of these models **fit into** custom **data records. These** models were trained **in** Go ogle **Colab for realtime accident recognition applications.** In this study, all training processes were **perfo rmed** using GPU **duration** of virtual **machines using** Intel Xeon CPU @2.20 GHz, 16 GB RAM, Tesla K8 0 accelerator, and 4 GB GDDR4 VRAM.

Hyperparameters **have a significant** impact **on** the training **results** of the **Yolov8** model. Therefore, in this study **we examine various hyperparameter** sets **taking** epochs of 100, 300, and 500. The batch sizes **used** are 16, 32, and 64. **Using** small batch sizes **is insufficient standard** statistics, **but** larger **stack** sizes **require storage**. **As a result, we examined Yolov8s** and **Yolov8m** with batch sizes of 16 and 32, **and Yolov8n** with three different batch sizes. Because **detecting** traffic **accidents in** different weather conditions is **very difficult, this** paper **focuses** on the average **(MAP)** of all classes at **intersections via a union** of **0.5 (IOU). Optimized** hyperparameters are identified based on **the precision MAP50. Image** size is used as the default value **for** 640. Other hyperparameters were used as **standard.**

C. Real-Time Detection

For real-time implementation, a Python-based application was developed to capture video input using OpenCV. The trained YOLOv8 ensemble model was loaded and applied frame-by-frame to detect accident or fire instances in live video streams. A decision block was incorporated to verify detection confidence thresholds, ensuring false positives are minimized. The system continuously monitors the video feed and instantly identifies hazardous events with bounding boxes and labels.

D. Alerting System

Upon detection of an accident or fire, the system triggers an automated alert using the SMTP protocol. Python’s smtplib was used to establish a secure connection with the email server. Based on the type of incident, the alert message is dynamically generated and sent to the corresponding authority: hospitals for all accidents, police stations for vehicle collisions, and fire brigades for fire incidents. The email includes a timestamp and incident type, ensuring immediate and appropriate emergency response.

IV. LITERATURE REVIEW

Crash analysis using intelligent black box vehicle and download analysis systems by **P. Josephin Shermila, S. Sharon Priya, K. Malarvizhi, Ramakrishna Hegde, S. Gokul Pran and B. Veerasamy**[6]. Their work introduces a system using a black box for vehicle tracking, which can identify drivers and continuously track various vehicle parameters including temperature, speed, fuel level, location, humidity, and crash test, as evident in this project. The data is recorded in the black box and uploaded to the cloud database to be viewed via the web interface. The information collected will help agencies track vehicles onsite, assist in accident investigations, and support insurance investigations. The proposed method shows good accuracy when compared to RFID, SVM, CNN, and RNN methods, improving by 29.3103%, 22.70%, 18.103%, and 11.206%, respectively. A team of experts can be formed to analyze this data to uncover the root causes of incidents and suggest better prevention measures. This positive approach can reduce the frequency of future community accidents.

The article, "Intelligence Reconnaissance and Prevention of Security in Four Vehicles" by Saritha V., Sri Lakshmi Chandana, Mahalaxmi U.S.B.K., Shamia D., Pankaj Chawla and Abhay Chaturvedi[7], describes the system that establishes a connection between the vehicles, the surroundings and the people who can help the victim. The system sends timely and detailed reports on the location of all events that occur in the vehicle, reliably and regularly. It can also use special sensors to monitor temperature, detect carbon monoxide and track alcohol levels in the car.

The research titled "YOLOPL: Helmet Wearing Detection Algorithm Based on YOLO Development" by **Li Haibin, Wu Dengchao, Zhang Wenming, and Xiao Cunjun**[8] introduced an advanced helmet detection algorithm, YOLOPL, which achieves higher Average sensitivity (AP) value while maintaining a small sample size. This algorithm is specifically designed to detect helmet wearing in the workplace where the object will be small and invisible. The YOLOP model improves the detection accuracy by changing the network architecture and achieving different types of combinations.

In **an** article titled **"Evaluating** the performance of **Yolov5** and **Yolov8** models **for** vehicle **detection," Fatma only created Kilickaya and MuratTayyãrek** [9], **examining the performance of Yalov5 and Yolov8 models.** This study shows the performance **differences** between the two models. In particular, **Yolov5's accuracy** and **recalls** are 1.63% and 2.49% higher than **Yolov8.** This difference is attributed to the higher performance of **Yolov8** compared to **Yolov5** in traffic detection. **Regarding** F1 **points, Yolov5 received** a score of 0.958, while **Yolov8 received** a score of 0.938. The main topics of this **study** include **various** types of vehicle **recognition** technology, **the outcomes of** deep learning **models** used **in** urban planning, traffic management, **security measures**, and **technology.**

This literature survey reviews recent advancements in intelligent vehicle monitoring systems and AI-based detection technologies aimed at improving transportation safety and accident prevention. P. Josephin Shermila et al. proposed a smart black box system capable of continuously tracking key vehicle parameters and transmitting data to cloud storage, significantly enhancing accuracy compared to traditional methods such as RFID, SVM, CNN, and RNN. Complementing this, Saritha V. et al. developed a vehicle security framework that connects vehicles, their surroundings, and emergency services while monitoring environmental hazards like carbon monoxide and alcohol levels. In the domain of workplace safety, Li Haibin et al. introduced YOLOPL, a refined helmet detection algorithm designed to effectively identify small and partially obscured objects, improving detection reliability in industrial settings. Additionally, Fatma Nur Kılıçkaya and Murat Tayyürek evaluated the performance of YOLOv5 and YOLOv8 for vehicle detection, finding YOLOv5 slightly superior in precision, recall, and F1 score, while YOLOv8 proved more effective in real-time traffic scenarios. Collectively, these studies underscore the pivotal role of intelligent monitoring and AI-driven detection in enhancing road safety, emergency response, and urban traffic management.

V. SYSTEM ARCHITECTURE

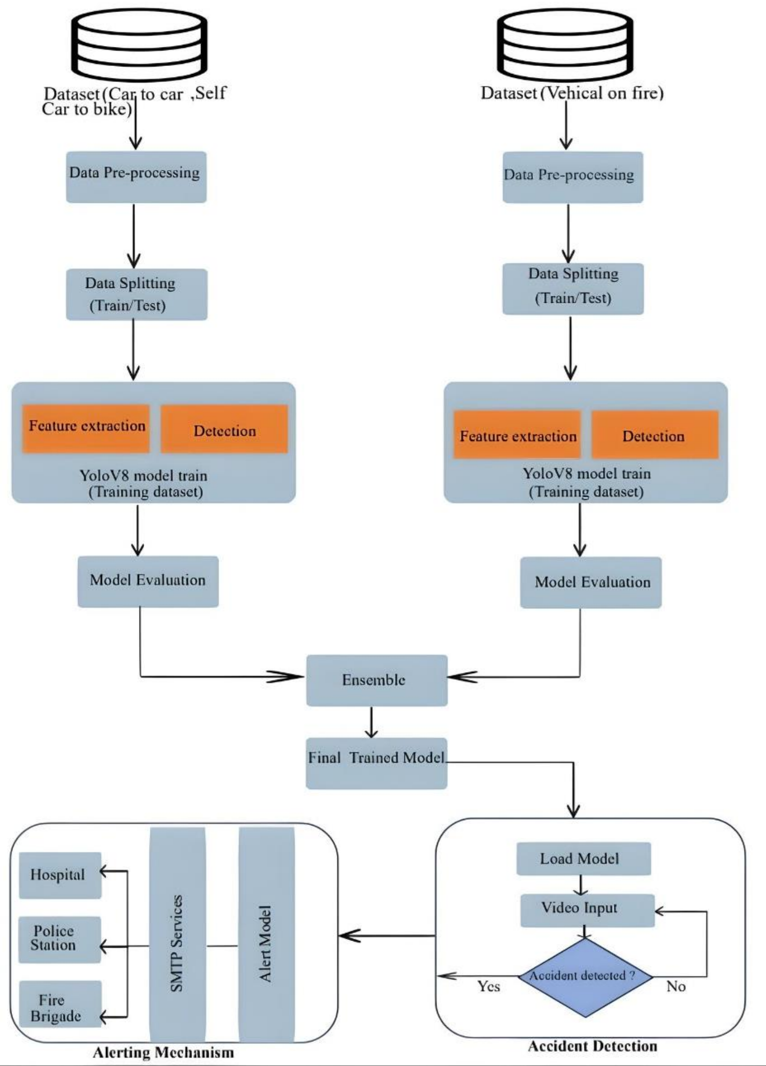

Fig 4: System Architecture of Accident detection and alerting system.

The proposed system for real-time accident detection and alerting consists of two main modules: one for detecting vehicular accidents and another for identifying vehicle fires. These modules are trained separately using two distinct datasets one containing various accident scenarios (such as car-to-car, self-accidents, and car-to-bike collisions), and the other comprising images of vehicles on fire. Each dataset undergoes preprocessing steps including image resizing, augmentation, and annotation, followed by a train-test split for model training and evaluation.

Once the data is prepared, both modules use the YOLOv8 object detection algorithm for feature extraction and detection. The model is trained separately on each dataset to identify accident and fire-related features. After training, both models are evaluated for accuracy and performance. Their outputs are then combined using an ensemble technique to produce a single, more robust final model capable of detecting both types of incidents effectively in real-time video feeds.

In the accident detection phase, the trained model is loaded and continuously processes incoming video streams. If an accident is detected, a decision block evaluates whether the event qualifies as a detection. If confirmed, the detection triggers the **alerting mechanism**, while non-detection leads the system to continue monitoring without further action.

The alerting mechanism is handled through SMTP services, which send automated email notifications to designated emergency services based on the type of incident detected. For car-to-car or car-to-bike collisions, the system alerts the police station and hospital. In the case of vehicle fires, an alert is sent to the fire brigade along with the hospital. This real-time notification system ensures timely emergency response, potentially reducing fatalities and improving post-accident management.

VI. RESULT ANALYSIS

Comparing Ultralytics YOLOv5 and Ultralytics YOLOv8 for object detection reveals significant advancements and distinct strengths in each model. Both models, developed by Ultralytics, are renowned for their speed and accuracy, but cater to different user needs and priorities in the field of computer vision. Difference Between Yolo models versions shown in fig 5[10].

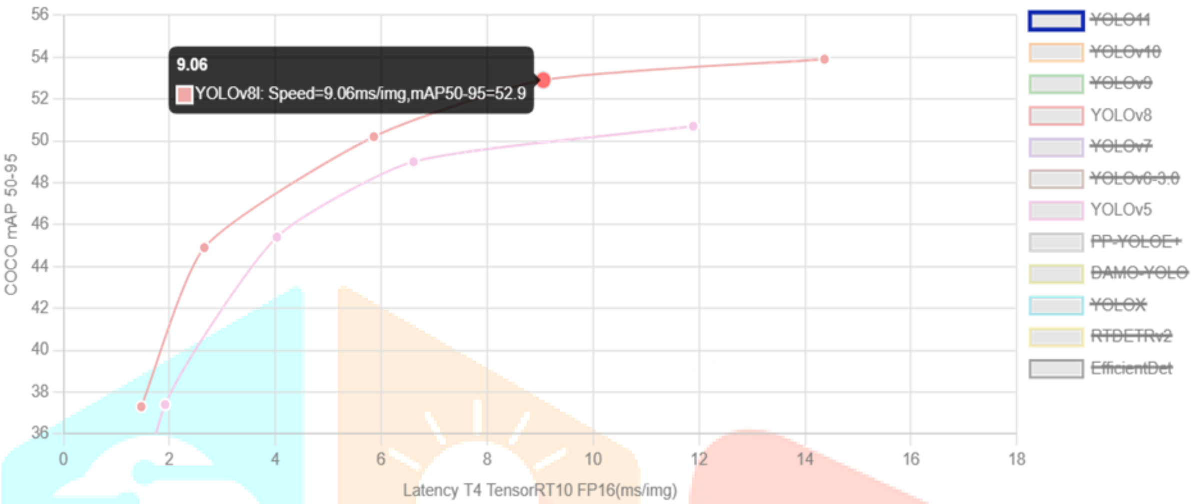

Fig 5: Difference Between Yolo models versions.

Model Size	YOLOv5	YOLOv8	Difference
Nano	28.00	37.3	+33.21%
Small	37.40	44.9	+20.05%
Medium	45.49	50.2	+10.57%
Large	49.00	52.9	+7.96%
Xtra Large	50.70	53.9	+6.31%

When **selecting** the best object detection model, **Yolov8** and **Yolov5** have their **advantages** and **disadvantages. Yolov5** is **easy** to use, Yolov8 is faster and more accurate. However, **Yolov8 is a good option** for applications that require real-time object **recognition.** Ultimately, the choice of **models used depends on the performance of the Yolov5 and Yolov8 models,** which **are the** specific needs of the **application** shown in **Figure 6 [11].**

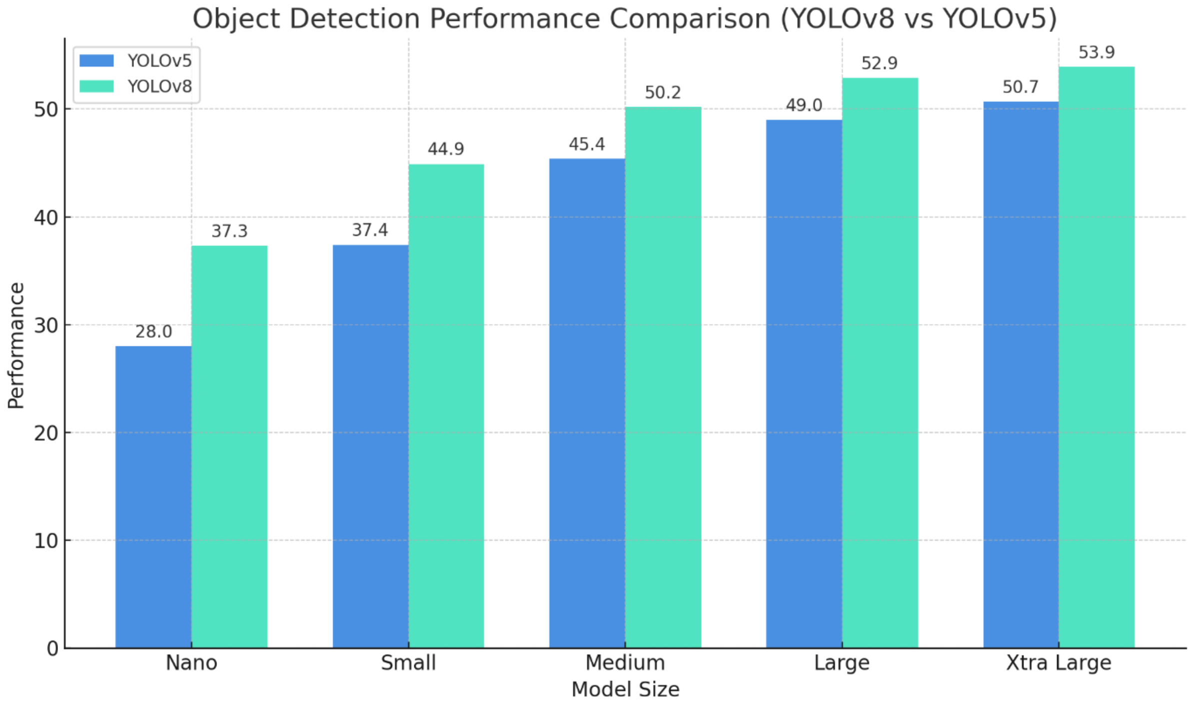

Fig 6: YOLOv5 and YOLOv8 model performance comparison.

In the chart, each model size features two bars: one representing YOLOv5 and the other representing YOLOv8. The performance scores, likely based on mean Average Precision (mAP) or a similar detection accuracy metric, demonstrate how well each model performs in detecting objects from images of size 640×640. The data reveals that YOLOv8 consistently outperforms YOLOv5 across all model sizes. The most significant improvement is observed in the Nano model, where YOLOv8 achieves a performance score of 37.3, a notable increase from YOLOv5's 28, translating to a 33.21% improvement. The Small model follows this trend with a 20.05% gain, and while the performance improvements continue through the Medium, Large, and Xtra Large categories, the margin narrows progressively. By the time we reach the Xtra Large model, the improvement is a modest 6.31%. This pattern suggests that while YOLOv8 introduces consistent enhancements over its predecessor, the most dramatic performance gains are realized in smaller, lightweight models. This makes YOLOv8 particularly valuable for applications **on resource-constrained devices such as mobile phones**, **IoT systems, and edge computing platforms**, where computational efficiency is as critical as accuracy.

- **YOLOv5** remains a strong contender, particularly for applications prioritizing maximum inference speed and leveraging its mature ecosystem. It's an excellent choice for deployment on resource-constrained devices.
- **YOLOv8** represents the next generation, offering superior accuracy and enhanced versatility across multiple vision tasks (detection, segmentation, pose, etc.). Its anchor free architecture and advanced features make it ideal for new projects seeking state-of the-art performance and flexibility.

VII. CONCLUSION

The Real-Time Accident Detection and Alert System successfully harnesses the capabilities of YOLOv8 for real-time accident and fire detection from continuous video streams, delivering prompt, automated emergency alerts without the need for constant human monitoring. By combining machine learning, computer vision, and automated communication mechanisms, the system enhances road safety by significantly reducing emergency response times and minimizing the consequences of traffic incidents. The system's automated alert mechanism ensures that critical information reaches relevant authorities including police, hospitals, and fire brigades immediately after an incident is detected, improving accident response efficiency and potentially saving lives.

Considering scalability and **adaptability,** the system **is** effective not only for urban **areas,** but also for highways, **intersections** and public **transport, providing** a **cheap, reliable** and **powerful** solution for real-time accident detection. Additionally, **the ability** to detect fire **occurrences** associated with vehicle collisions ensures a more comprehensive safety **cover** for high-risk environments.

Looking **in** the **future, this system** offers **the potential** for expansion **by analyzing the heavy** edge computing **of AI-controlled accidents and analyzing the heavy edge computing of AI-controlled accidents** for integration with **urban** traffic management systems for dynamic traffic control in emergencies. Furthermore, the development of cloud-based **surveillance dashboards** and the **possibility of integration of** multi-camera **networks allows** authorities to **pursue incidents** over **time to** optimize resource **allocation** and **improve** long-term **security strategies for transportation. Overall, the** project not only addresses the immediate **challenge** of real-time accident **recognition,** but also lays the **foundation** for the development of an intelligent, responsive, interconnected smart **transport ecosystem.**

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