AI-Powered Real-Time Accident Detection via CCTV with Severity-Based Emergency Response Optimization

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Abstract: Road traffic accidents remain a major public safety challenge, where delays in detection, verification, and emergency response significantly impact survival outcomes. Existing accident detection systems often lack real-time severity classification and reliable post-impact validation, resulting in false alarms and inefficient allocation of emergency resources. This project proposes an integrated, real-time accident detection and severity-aware emergency response framework that leverages deep learning and existing CCTV infrastructure. The system utilizes YOLOv11 for high-speed object detection and ByteTrack for multi-object tracking to analyze vehicle and pedestrian motion patterns. A multi-layer verification pipeline combines visual signals, kinematic motion metrics, and audio cues to confirm accident events and minimize false positives. Following verification, a hybrid decision engine incorporating multimodal reasoning and rule-based scoring classifies incident severity into actionable categories. Based on this classification, the system automatically initiates an intelligent emergency response workflow, including optimal hospital selection using multi-criteria decision-making, real-time ambulance dispatch, and traffic-aware route optimization. Additionally, the framework integrates real-time communication mechanisms, paramedic field data input, and centralized dashboards for hospitals and authorities, ensuring coordinated and informed response execution. By utilizing existing surveillance networks and introducing an end-to-end automated response pipeline, the proposed system provides a cost-effective, scalable, and immediately deployable solution for enhancing urban road safety and reducing emergency response time.

Keywords: *Real-Time Accident Detection, Severity-Aware Emergency Response, YOLOv11, ByteTrack, Multimodal Verification, CCTV-Based Monitoring, Multi-Criteria Decision-Making, Route Optimization.*

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I. INTRODUCTION

The proposed system is designed as a modular and automated pipeline for real-time accident detection and emergency response using CCTV surveillance. It begins with data ingestion, where live video streams are captured from RTSP-enabled cameras and converted into standardized frames. This is followed by preprocessing and normalization to ensure consistent and reliable input for AI-based analysis.

The system then performs real-time accident detection using deep learning models, supported by temporal filtering and heuristic signal scoring to reduce false positives and improve detection accuracy. A multimodal verification layer integrates visual, motion, and audio cues to confirm accident events, ensuring higher reliability compared to traditional approaches.

Once verified, the system carries out severity classification, categorizing incidents into different levels based on impact and contextual factors. This enables the activation of an intelligent decision-making module, which performs hospital selection using multi-criteria evaluation and optimizes ambulance routing based on real-time traffic conditions.

Additionally, the system includes an automated communication and monitoring layer, which disseminates alerts to relevant authorities and provides real-time updates through dashboards. An integrated data management and logging mechanism ensures complete tracking of the incident lifecycle.

Overall, the proposed system transforms traditional CCTV infrastructure into an intelligent, proactive emergency response framework, addressing key limitations such as delayed detection, lack of severity awareness, and inefficient resource coordination.

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II. RELATED WORKS

The literature survey focuses on major components of accident detection and emergency response systems, including real-time video analysis, object detection, multi-object tracking, severity estimation, and emergency response optimization.

Accident detection using deep learning has gained significant attention in recent years. N. Prakash et al. [1] proposed a hybrid RTSP–WebRTC architecture integrated with YOLOv11 for low-latency surveillance. Their work improves real-time video streaming performance but mainly focuses on efficient transmission rather than accurate accident verification. Similarly, Q. N. H. Minh et al. [2] developed a YOLOv8-based accident detection system that achieves good detection accuracy. However, the system performs only basic detection and does not include severity classification or temporal analysis, which may result in false positives in complex traffic scenarios.

To improve object-level understanding, multi-object tracking techniques are widely used. Y. Wang and V. Y. Mariano [3] proposed a tracking framework combining YOLOv8s and ByteTrack for maintaining object identities across frames. While effective for tracking, the approach does not analyze motion patterns such as sudden speed changes or trajectory deviation for accident verification. In another study, T. Singh et al. [4] proposed a deep learning-based method for accident detection using transformer architectures. Although the model provides improved performance, it relies on offline data and is not suitable for real-time CCTV-based systems.

In the area of emergency response, several studies focus on ambulance routing and optimization. M. Almalki et al. [5] proposed an ambulance routing optimization system based on emergency medical service availability. The system improves response efficiency by considering resource availability, but it does not include real-time accident detection or severity-based decision-making. Similarly, C. Selvan et al. [6] developed a deep learning-based ambulance routing system, but it does not integrate hospital resource status or dynamic coordination with emergency services.

Hospital selection and resource allocation have been studied using multi-criteria decision-making techniques. H. Bouraghi et al. [7] applied the TOPSIS method for evaluating hospital performance based on multiple factors. Likewise, A. Mosaffa and A. Baghbanian [8] used fuzzy AHP and TOPSIS methods for healthcare planning. However, these approaches are mainly designed for planning purposes and are not suitable for real-time emergency situations.

In terms of communication and system integration, IoT-based solutions have been proposed. H. Li et al. [9] developed an emergency alert system using WebSocket communication for low-latency data transmission. M. Sahraei and A. Al-Kheder [10] reviewed IoT-based accident detection systems and emphasized the need for integrated and scalable frameworks.

Overall, existing works address individual aspects such as detection, tracking, routing, hospital selection, or communication. However, they lack a unified system that integrates real-time accident detection, motion-based verification, severity classification, emergency decision-making, and coordinated response.

The proposed system addresses these limitations by providing a complete and integrated framework that combines detection, tracking, multimodal verification, severity classification, hospital selection, and emergency response into a single real-time pipeline.

III. PROPOSED WORK

Fig. 1 shows the architecture of the proposed system. The proposed system focuses on the design and implementation of an automated real-time accident detection and emergency response system using CCTV video data. It is developed as a complete pipeline that connects accident detection, verification, severity analysis, and emergency response into a single framework. The system converts continuous video streams into meaningful information for faster and accurate emergency handling.

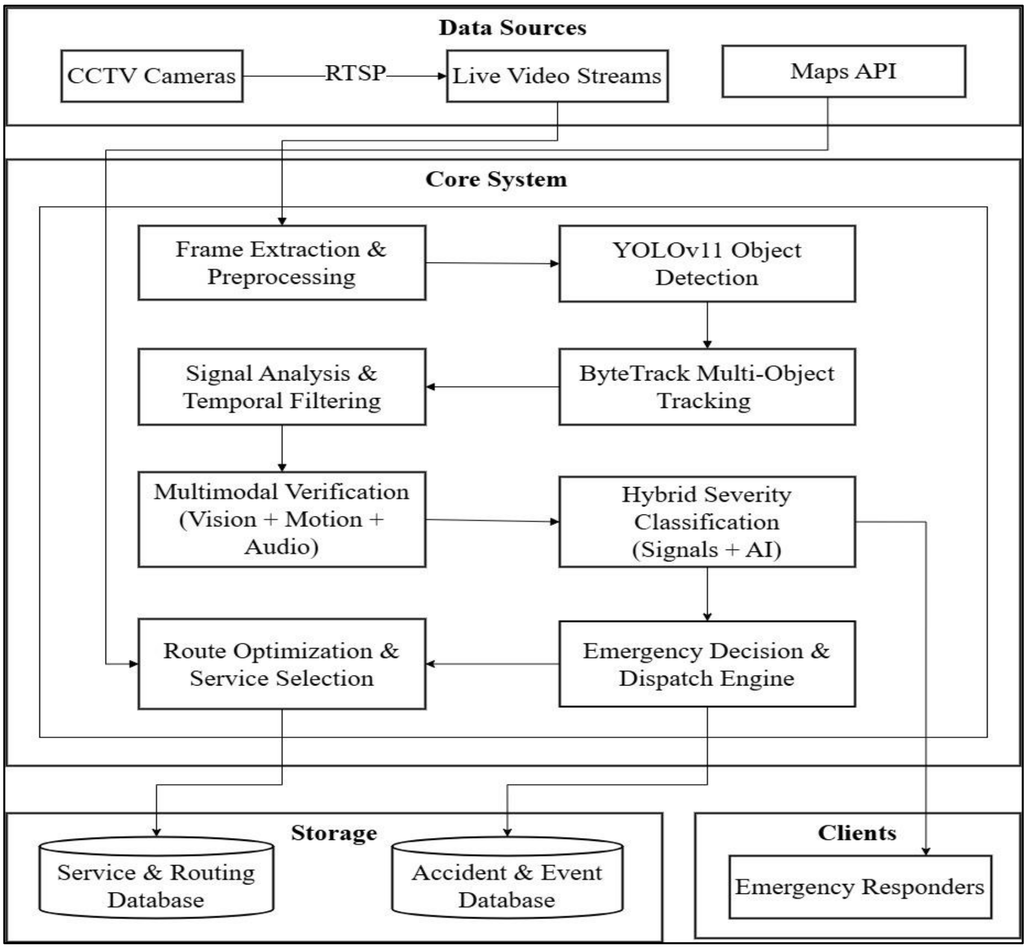

Fig 1 Architecture Diagram of the Proposed Model

The system is divided into multiple modules, where each module performs a specific stage in the overall workflow. This modular structure improves scalability, maintainability, and processing efficiency.

- ➢ *Module – I: Accident Detection and Analysis*

This module, represented in Fig. 2, is responsible for continuously monitoring CCTV video streams, detecting potential accidents, and verifying them using multiple data sources. It converts raw video input into structured accident-related information for further processing.

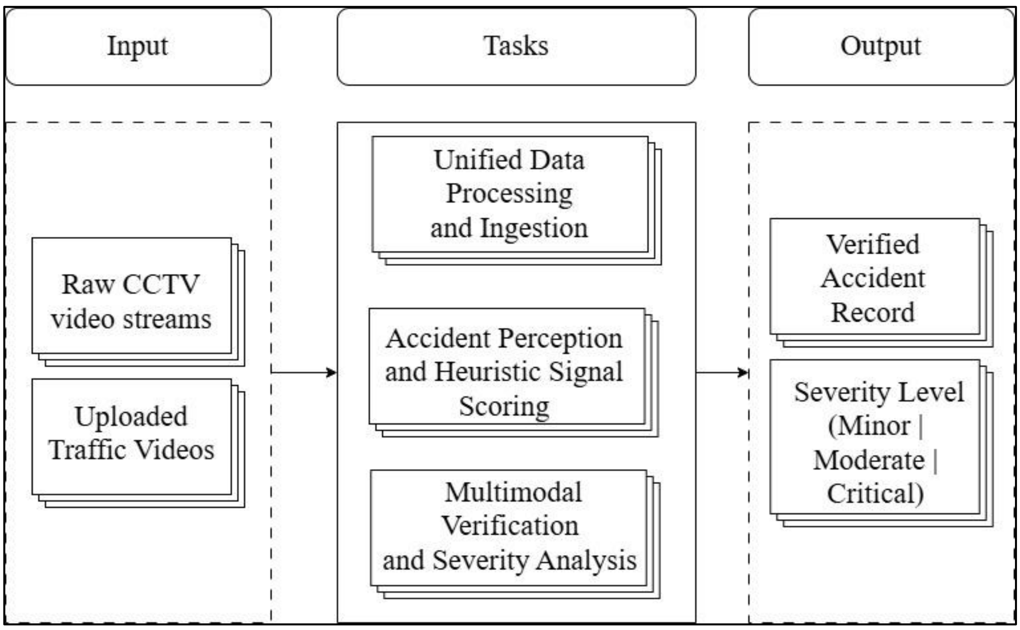

Fig 2 Module Diagram of Accident Detection and Analysis

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- *Data Ingestion (RTSP Streaming)*

The system captures live video streams from CCTV cameras using the RTSP protocol. A streaming server is used to handle multiple camera feeds simultaneously while maintaining low latency. In addition to live streaming, the system also supports uploaded video files for offline analysis and testing. All incoming video data is converted into a standard format to ensure compatibility with downstream processing modules.

- *Frame Extraction and Preprocessing*

The continuous video stream is divided into frames at a fixed frame rate to enable real-time analysis. Each frame undergoes preprocessing steps such as resizing to a fixed resolution, normalization of pixel values, and noise reduction. These steps ensure uniform input quality and improve the performance and stability of the detection model. Frame buffering is also applied to maintain temporal continuity between consecutive frames for motion analysis.

- *Object Detection (YOLO Model)*

A real-time object detection model (YOLOv11) is applied to each frame to identify vehicles, pedestrians, and other relevant road entities. The model generates bounding boxes, class labels, and confidence scores for each detected object. This step provides a detailed understanding of the scene and forms the basis for further motion and interaction analysis.

- *Multi-Object Tracking (ByteTrack)*

After detection, objects are tracked across consecutive frames using the ByteTrack algorithm. Each object is assigned a unique tracking ID, allowing the system to monitor its movement over time. Tracking enables the extraction of motion-related features such as speed, direction, trajectory deviation, and interaction between objects.

- *Signal Scoring and Temporal Filtering*

The system analyzes motion patterns to detect accident-related signals such as sudden deceleration, abnormal trajectory changes, collision proximity, and object overlap. These signals are evaluated across multiple frames using temporal filtering instead of relying on a single frame. A scoring mechanism is applied to determine the likelihood of an accident. This reduces false positives caused by normal traffic behavior, occlusions, or camera noise.

- *Multimodal Verification (Vision + Motion + Audio)*

To confirm the occurrence of an accident, the system combines multiple sources of information:

✓ Visual detection results from the object detection model
✓ Motion patterns obtained from tracking
✓ Audio signals such as collision sounds or abrupt noise

This multimodal verification ensures that an accident is confirmed only when multiple indicators are present, thereby improving detection reliability and reducing incorrect alerts.

- *Severity Classification*

Once an accident is verified, the system performs severity classification using a hybrid approach. Initially, accident signals derived from motion analysis and object interactions are used to determine a base severity level. This level is further refined using visual, motion, and audio features such as collision intensity, speed variation, object displacement, and duration of impact.

The system also applies rule-based conditions to prioritize critical scenarios such as pedestrian involvement, fire or smoke, and multi-vehicle collisions. Based on this analysis, the accident is categorized into minor, moderate, or critical levels, which directly influences the type of emergency response initiated in the next module.

➢ *Module– II: Emergency Decision and Routing*

This module, represented in Fig. 3, is responsible for selecting the appropriate emergency response based on the detected accident and ensuring efficient coordination between hospitals, ambulances, and routing systems. It converts accident information into actionable decisions for real-time response.

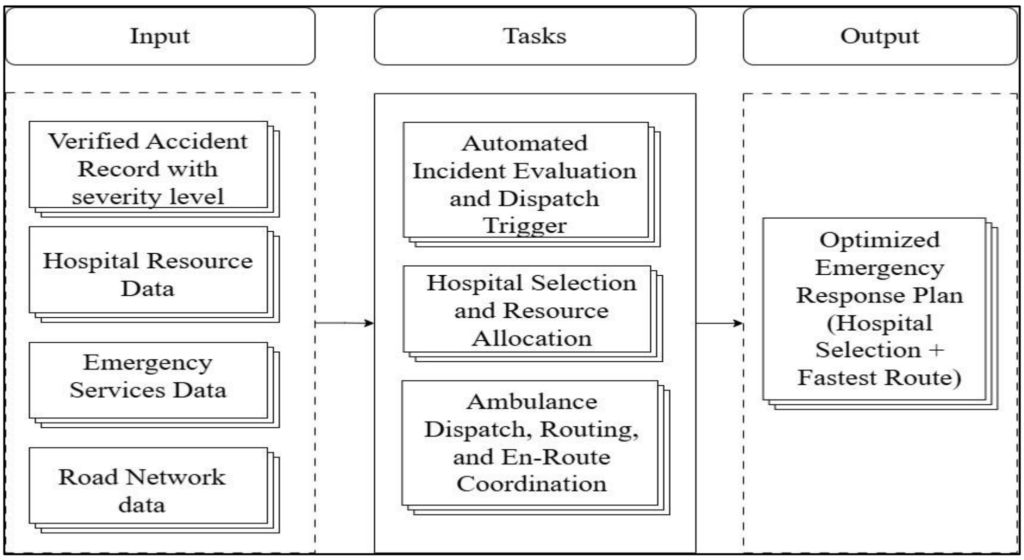

Fig 3 Module Diagram of Emergency Decision and Routing

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- *Incident Evaluation*

The system first evaluates the detected accident using the severity level and verification results obtained from the previous module. Each incident is categorized as minor, moderate, or critical. Based on this Classification, the System Applies Response Gating Logic:

- ✓ Minor → Monitoring only (no ambulance dispatch)
- ✓ Moderate → Short operator review window before dispatch
- ✓ Critical → Immediate emergency response

Only verified and high-confidence incidents are allowed to proceed further. This prevents unnecessary alerts and ensures that system resources are used efficiently.

- *Hospital Selection (Multi-Criteria Decision Making)*

The system selects the most suitable hospital using a multi-criteria decision-making approach. Instead of choosing only the nearest hospital, multiple factors are considered:

- ✓ Distance from accident location
- ✓ Estimated travel time (ETA)
- ✓ Availability of ICU beds and emergency facilities
- ✓ Trauma care level and specialization
- ✓ Current hospital resource load

A ranking method such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is used to evaluate hospitals. Each hospital is scored based on its closeness to an ideal solution (minimum cost and maximum resources), and the best-ranked hospital is selected for the emergency case.

- *Resource Availability Check*

After selecting a hospital, the system verifies whether the hospital has sufficient resources to handle the emergency. This includes:

- ✓ Availability of ICU beds and emergency beds
- ✓ Presence of trauma teams and medical staff
- ✓ Availability of critical equipment (ventilators, operation theatres)

If the selected hospital does not meet the required conditions, the system automatically selects the next best hospital from the ranked list. This ensures that patients are not directed to under-equipped facilities.

- *Ambulance Allocation and Dispatch*

The system identifies and assigns the most suitable ambulance based on:

- ✓ Proximity to the accident location
- ✓ Availability status
- ✓ Readiness for dispatch

Ambulance dispatch follows a tier-based selection strategy, where nearby ambulances are prioritized. The system sends a dispatch request to one ambulance at a time, and if no response is received within a specified time, the request is reassigned to the next available ambulance.

Once an ambulance accepts the mission, it is locked for that incident, preventing multiple assignments and ensuring coordinated response.

- *Route Optimization (Traffic-Aware Routing)*

The system calculates the most efficient route in two phases:

- ✓ Ambulance → Accident location
- ✓ Accident location → Selected hospital

Real-time traffic data is used to estimate travel time and avoid congestion. The routing system supports:

- ✓ Traffic-aware path selection
- ✓ Dynamic rerouting in case of delays or roadblocks
- ✓ Continuous route updates during transit

The system also provides estimated arrival times (ETA) to hospitals and control centers, enabling better preparation for incoming patients.

➢ *Module– III: Notification and System Management*

This module, represented in Fig. 4, manages communication, monitoring, and overall coordination between different system components.

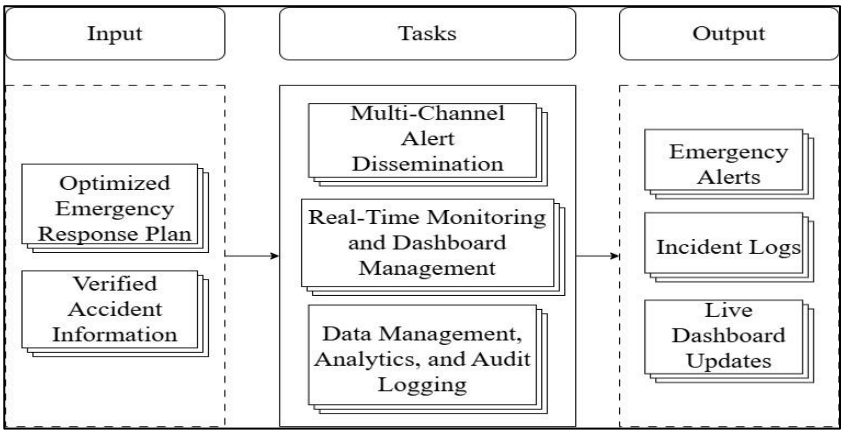

Fig 4 Module Diagram of Notification and System Management

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- *Alert Generation and Notification*

Once an accident is confirmed and the response decision is made, the system generates alerts containing critical information such as:

- ✓ Accident location (GPS coordinates)
- ✓ Severity level (minor, moderate, critical)
- ✓ Selected hospital details
- ✓ Assigned ambulance information

These alerts are sent in real time to relevant stakeholders, including hospitals, ambulance drivers, and control centers. Notification channels may include mobile alerts, dashboard updates, or messaging services. This ensures quick awareness and immediate action.

- *Centralized Monitoring Dashboard*

The system provides a centralized dashboard for monitoring all ongoing incidents. The dashboard displays:

- ✓ Live CCTV feeds
- ✓ Detected accident details
- ✓ Severity classification
- ✓ Ambulance status and location
- ✓ Hospital allocation

This interface allows authorities to track events in real time and take manual control if required. It improves situational awareness and supports decision-making during emergencies.

- *Real-Time Status Tracking*

After dispatch, the system continuously tracks the progress of the emergency response. This includes:

- ✓ Ambulance movement from source to accident location
- ✓ Travel from accident site to hospital
- ✓ Current status (dispatched, en route, arrived)

The system updates this information dynamically, allowing all stakeholders to stay informed throughout the response process.

- *Logging and Data Management*

All system activities are recorded for future analysis and auditing. The system maintains logs for:

- ✓ Detected incidents and timestamps
- ✓ Severity classification results
- ✓ Ambulance dispatch records
- ✓ Routing and travel details

This data can be used for performance evaluation, system improvement, and reporting purposes.

- *System Reliability and Fail-Safe Handling*

To ensure continuous operation, the system includes mechanisms for handling failures and unexpected conditions. These include:

- ✓ Fallback actions when communication fails
- ✓ Default decision-making in case of missing data
- ✓ Retry mechanisms for alert delivery
- ✓ Backup logging for critical events

These features improve system robustness and ensure that emergency response is not interrupted.

IV. RESULTS ANALYSIS

The proposed system is evaluated based on its performance in real-time accident detection, severity classification, and emergency response. The evaluation is carried out using sample CCTV video streams and controlled testing scenarios to observe system behavior under different conditions.

The system processes live video input and detects accidents using object detection and tracking techniques. By incorporating multi-frame temporal analysis and signal-based filtering, the system improves detection reliability compared to traditional single-frame approaches. The observed detection accuracy is approximately in the range of 88% to 92% under controlled testing conditions, indicating that the system can correctly identify most accident events.

The performance is further analyzed using precision and recall metrics. The precision is observed to be around 85% to 90%, while recall is slightly higher at 90% to 94%. This indicates that the system prioritizes detecting accident events even if a small number of false positives occur, which is acceptable in safety-critical applications.

The false positive rate is observed to be relatively low, approximately 5% to 8%, due to the use of temporal filtering and multimodal verification. These techniques combine visual, motion, and contextual information to confirm accidents, thereby reducing incorrect detections caused by noise or normal traffic movements.

The severity classification module categorizes accidents into minor, moderate, and critical levels based on factors such as motion patterns, collision intensity, and object interaction. The observed classification accuracy is approximately 85% to 90%, demonstrating the effectiveness of the hybrid severity classification approach.

The system also shows efficient performance in terms of response time. The average response time, including detection, processing, and dispatch, is observed to be around 4 to 6 seconds, which enables quick emergency response. In addition, the routing module selects near-optimal paths using real-time traffic information, improving the efficiency of emergency services. This helps in reducing travel delays and ensures faster arrival of emergency responders.

Overall, the proposed system demonstrates reliable performance in accident detection and emergency response. The integration of detection, tracking, signal analysis, and decision-making into a unified pipeline enhances accuracy, reduces false alarms, and improves response efficiency compared to existing methods. These results indicate that the

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proposed system performs effectively in real-time environments and can support timely emergency response in practical scenarios.

V. CONCLUSION AND FUTURE ENHANCEMENTS

The proposed system presents an effective solution for real-time accident detection and emergency response using CCTV video streams. By integrating object detection, multi-object tracking, signal analysis, and severity classification, the system is able to accurately identify accident events and assess their impact. Unlike traditional approaches that rely on single-frame analysis, the system uses multi-frame temporal filtering and multimodal verification to improve detection reliability and reduce false alarms.

A key contribution of the system is the severity-based classification, which categorizes accidents into minor, moderate, and critical levels. This enables the system to make informed decisions regarding emergency response, ensuring that appropriate actions are taken based on the seriousness of the situation. The integration of an automated decision engine further enhances the system by enabling quick ambulance dispatch and efficient hospital selection.

The system also incorporates traffic-aware route optimization, which helps emergency responders reach the accident location and hospital in minimal time. Overall, the proposed approach provides a unified pipeline that combines detection, verification, classification, and response, making it suitable for real-time applications in smart traffic management and public safety systems.

While the system demonstrates promising performance, there are several areas for future improvement. The system can be enhanced by training on larger and more diverse datasets to improve accuracy under different environmental conditions such as low lighting, rain, and occlusions. The integration of advanced deep learning models can further improve detection and classification performance.

Future work can also focus on incorporating additional data sources such as IoT sensors and vehicle communication systems to improve reliability. The system can be extended to support cloud-based or distributed deployment for large-scale city-wide monitoring. Additionally, the inclusion of real-time dashboards and human-in-the-loop validation can further improve system transparency and control. Overall, the proposed system provides a strong foundation for developing intelligent and automated accident detection and emergency response solutions, with the potential for further enhancements in real-world deployments.

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Bathmasri A A B.Tech Information Technology student at Puducherry Technological University with a strong interest in full-stack application development. Skilled in Python, C, and C++, along with frameworks and technologies such as Flask, React, and SQL, with a focus on designing scalable software systems and structured architectures. Focused on developing efficient applications that combine robust backend processing with smooth and interactive user interfaces.

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