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Smart Road Traffic Monitoring: Unveiling the Synergy of IoT and AI for Enhanced Urban Mobility

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ABSTRACT

Anomaly detection has become an important area of research because of its relevance across a wide range of fields, including surveillance, transportation, healthcare, and public safety. With the rapid expansion of urban environments, the need for effective monitoring systems has increased significantly. Modern cities depend heavily on surveillance infrastructure, particularly CCTV cameras, to observe traffic conditions on roads, highways, and public intersections. While these systems generate a continuous stream of visual data, relying on human operators to monitor them is both impractical and inefficient. Continuous observation can lead to fatigue, reduced attention, and delayed responses, especially when dealing with large-scale surveillance networks. These limitations highlight the necessity for automated systems capable of identifying unusual events accurately and in real time. In this context, the present study focuses on the detection of road accidents using deep learning techniques applied to surveillance video data. Road accidents remain a major global issue, contributing to loss of life, physical injuries, traffic disruption, and economic costs. A critical factor in reducing the impact of such incidents is the speed at which they are detected and reported. Delays in identifying accidents often result in slower emergency response times, which can worsen outcomes. Therefore, there is a clear need for intelligent systems that can recognize accident scenarios as they occur and promptly alert the relevant authorities.

To address this challenge, the proposed system employs the YOLO (You Only Look Once) object detection framework, which is widely recognized for its ability to perform fast and accurate detection tasks. The system processes video input obtained from CCTV cameras by dividing it into individual frames and analyzing each frame using the YOLO architecture. Through this process, it identifies vehicles present in the scene, observes their movement patterns, and detects irregular behaviors such as sudden collisions or abrupt halts. When such an event is identified, the system triggers an alert mechanism to notify concerned personnel, enabling quicker response and intervention.

The primary objective of this work is to develop a solution that balances accuracy with real-time performance. By combining deep learning techniques with IoT-enabled surveillance systems, the proposed approach supports more effective traffic monitoring and contributes to safer road environments. Furthermore, it aligns with the broader goal of developing intelligent urban infrastructure capable of responding proactively to dynamic real-world conditions.

Keywords: Anomaly Detection, Road Accident Detection, Deep Learning, Computer Vision, YOLO, Object Detection, IoT, Intelligent Transportation Systems, CCTV Surveillance, Real-Time Monitoring. of accidents. To manage these challenges,

INTRODUCTION

Background and Context

Urban transportation systems are undergoing rapid transformation due to population growth and increased vehicle usage. As cities expand, road networks become more congested, leading to frequent traffic disruptions and a higher likelihood surveillance infrastructure such as CCTV cameras has been widely deployed across highways, intersections, and public roads. While these systems continuously generate large volumes of visual data, extracting meaningful information from them remains a difficult task when done manually. Human operators often struggle to monitor multiple video feeds over long periods, which increases the chances of missing critical incidents.

Recent progress in artificial intelligence has opened new possibilities for automating traffic monitoring tasks. Deep learning models, particularly those designed for object detection, have shown strong capability in identifying vehicles and other road entities in real time. At the same time, the emergence of Internet of Things (IoT) technologies has enabled seamless communication between devices, allowing faster sharing of information across systems. Despite these developments, combining these technologies into a reliable and practical solution for real-time traffic monitoring is still an evolving area of research [3].

Problem Statement

Although modern computer vision systems are capable of detecting objects in traffic scenes with reasonable accuracy, they often struggle to identify critical events such as road accidents. Most existing methods are primarily designed for recognizing static objects—such as vehicles, pedestrians, or traffic signs—rather than understanding how these objects interact over time. As a result, dynamic situations involving sudden collisions, abrupt stops, or irregular driving patterns are not always captured effectively.

Another important limitation is the absence of immediate response mechanisms. In many cases, even when an abnormal event is detected, the system does not provide a direct or automated way to notify the relevant authorities. This creates a delay between detection and action, reducing the overall effectiveness of the system in real-world scenarios. Therefore, the core problem addressed in this study is the lack of an integrated framework that can not only detect traffic-related events but also analyze vehicle behavior and trigger timely alerts.

Significance of the Study

Addressing this problem is important for both practical and societal reasons. Early detection of road accidents can significantly reduce emergency response time, enabling medical and rescue teams to reach the scene more quickly. Faster response can play a crucial role in minimizing injuries and saving lives.

In addition, timely identification of traffic incidents can support better traffic management by allowing authorities to take immediate actions such as rerouting vehicles or controlling congestion. This contributes to smoother traffic flow and reduces the risk of secondary accidents.

From a technological perspective, automated monitoring systems reduce reliance on human operators, who may be prone to fatigue and oversight when monitoring continuous video streams. By improving efficiency and consistency, such systems enhance the reliability of surveillance operations.

More broadly, intelligent traffic monitoring is a key component of smart city development. The integration of artificial intelligence and IoT technologies enables systems to respond dynamically to real-world conditions. This not only improves road safety but also supports better planning, resource allocation, and management of urban infrastructure.

Research Gap

A review of recent literature shows that significant progress has been made in object detection and traffic monitoring technologies. However, many existing studies primarily focus on improving detection accuracy without considering how these systems perform in real-time environments. While some approaches explore anomaly detection, they often involve computationally intensive methods that limit their practical use in live traffic scenarios. In other cases, IoT-based systems have been introduced to enable real-time communication, but their functionality is often limited to data transmission. These systems typically do not incorporate intelligent decision-making or automated response mechanisms, which reduces their effectiveness in critical situations.

Another noticeable gap is the limited integration of temporal analysis in traffic monitoring systems. Most approaches analyze individual frames independently, without considering how vehicle movements evolve over time. This makes it difficult to distinguish between normal and abnormal behavior.

These observations highlight the need for a comprehensive solution that combines object detection, behavioral analysis, and real-time communication within a single framework.

Proposed Approach and Contributions

To address the identified challenges, this study proposes a unified traffic monitoring system that integrates deep learning with IoT technologies. The system employs a fast and efficient object detection model to identify vehicles in video frames and then tracks their movement across consecutive frames to analyze behavioral patterns. By observing changes in motion, the system is able to detect unusual events such as collisions or sudden stops.

Once a potential accident is identified, the system generates an alert and communicates the information to relevant authorities through connected devices. This ensures that appropriate action can be taken without delay.

The main contributions of this work include the development of a real-time monitoring pipeline, the incorporation of motion-based analysis to improve event detection, and the integration of an automated alert mechanism. The proposed system is designed to maintain a balance between accuracy and processing speed, making it suitable for deployment in real-world urban environments.

Novelty of the Proposed Work

Recent advancements in intelligent transportation systems have led to significant improvements in traffic monitoring, particularly through the use of deep learning models and IoT technologies. Many studies have focused on enhancing object detection accuracy using advanced YOLO architectures. While these models are highly effective at identifying vehicles and other objects under varying conditions, their capabilities are often limited to detection tasks and do not extend to understanding interactions or detecting critical incidents such as accidents.

Similarly, IoT-based traffic systems have improved data collection and communication, enabling real-time monitoring and scalability. However, in many implementations, IoT components are primarily used for transmitting data rather than supporting intelligent decision-making or automated responses. This creates a disconnect between detection and actionable outcomes.

Research in anomaly detection has attempted to address abnormal events in surveillance videos. Although such approaches show promise, they are often computationally demanding or designed for offline processing, making them less suitable for real-time deployment in dynamic traffic environments. Lightweight and edge-based models have also been explored to improve efficiency, but these efforts typically focus on optimizing individual components rather than delivering a complete system solution.

The novelty of the proposed work lies in its system-level integration of multiple functionalities. Instead of focusing solely on improving model accuracy, this study introduces a behavior-aware accident detection approach that analyzes vehicle movement over time. By incorporating temporal analysis, the system is able to recognize interactions between vehicles and identify anomalies such as collisions more effectively.

Another distinguishing feature is the integration of an IoT-enabled alert mechanism directly into the detection process. Unlike conventional systems where detection and communication are treated separately, the proposed framework ensures that alerts are generated and transmitted immediately after an abnormal event is detected. This significantly reduces response time and enhances practical usability.

Furthermore, the system is designed with real-time performance as a primary objective. It maintains a balance between speed and accuracy, making it suitable for continuous monitoring in live traffic environments. The overall approach adopts a holistic perspective by combining detection, analysis, and response into a single framework.

In summary, the proposed work introduces several key advancements:

- It incorporates behavior-based accident detection rather than relying solely on object recognition.
- It integrates real-time IoT-based alert generation within the detection pipeline.
- It emphasizes an end-to-end system design that combines detection, analysis, and response.
- It ensures practical applicability by maintaining a balance between accuracy and real-time performance.

These contributions differentiate the proposed system from existing approaches and provide a meaningful step forward in the development of intelligent traffic monitoring solutions.

Table 1: Comparison of Existing Approaches with Proposed System

Aspect	Existing Works (Recent Studies)	Limitations in Existing Works	Proposed System
Primary Focus	Object detection using YOLO variants (YOLOv7, YOLOv8, YOLOv9) [1], [5], [21]	Focus mainly on detecting vehicles/signs, not accidents	Focuses on accident detection using behavior analysis
Detection Capability	High accuracy in identifying objects [2], [6]	Cannot interpret vehicle interactions or collisions	Detects collisions, sudden stops, abnormal movement
Anomaly Detection	Some works use motion-based or anomaly detection [10], [11]	Often offline or computationally heavy	Real-time anomaly detection using motion tracking
IoT Integration	IoT used for data collection and communication [3], [12]	Limited to data transfer, no intelligent response	Integrated IoT alert system for immediate notification
Real-Time Performance	Improved detection speed in recent YOLO models [1], [21]	Not optimized for end-to-end real-time response	Achieves complete real-time pipeline (<100 ms)
System Integration	Most systems focus on single component (detection/prediction) [9], [14]	Lack of end-to-end framework	Unified system (Detection + Analysis + Alert)
Edge/Lightweight Models	Lightweight models for edge devices [15], [29]	Trade-off between speed and accuracy	Balanced efficiency and accuracy for practical use
Environmental Robustness	Some models handle weather variations [24]	Performance drops in dense traffic and low light	Handles multiple conditions with stable performance

Scalability	IoT-based systems support scalability [3]	Not optimized for large-scale real-time deployment	Designed for smart city scalability
Response Mechanism	Limited or delayed alert systems	No direct link between detection and action	Instant alert generation to authorities
Computational Efficiency	High performance but often GPU-dependent [16], [17]	High resource requirement	Optimized for moderate computational usage
Research Contribution Type	Mostly model-level improvements	Lack of system-level innovation	System-level innovation with integrated pipeline

LITERATURE REVIEW

Recent advancements in intelligent transportation systems have been strongly influenced by the integration of deep learning models and IoT technologies. A number of studies have focused on improving real-time object detection, particularly through the evolution of the YOLO (You Only Look Once) family of models. For instance, Li et al. [1] proposed an enhanced detection framework based on a YOLOv8-DSAF architecture integrated with IoT-enabled smart city infrastructure. Their work demonstrates that optimizing both model architecture and system integration can lead to improved accuracy and faster processing, making it well-suited for dynamic urban traffic conditions.

Similarly, Zhang et al. [2] introduced a modified YOLOv8 variant, referred to as YOLO-BS, specifically tailored for traffic sign detection. By refining feature extraction and improving bounding box regression, their approach achieves higher precision in complex road environments. This contributes to more reliable traffic monitoring and supports safer transportation systems.

In addition to object detection, several researchers have explored IoT-based traffic monitoring frameworks. Elhoseny et al. [3] developed a system that combines image sensors with deep learning techniques to enable continuous traffic observation and real-time analysis. Their approach highlights the importance of integrating sensing technologies with intelligent algorithms to support timely decision-making. In a related study, Ahmed et al. [4] incorporated IoT-assisted robotics into traffic monitoring, demonstrating how automation and artificial intelligence can be combined to enhance surveillance and traffic control efficiency.

Advancements in deep learning architectures have also played a key role in improving system performance. Hassan et al. [5] introduced GC-YOLOv9, a model designed to achieve high detection accuracy while maintaining computational efficiency. Their work emphasizes the need for models that can operate effectively in real-time environments without excessive resource consumption. Complementing this, Flores-Calero et al. [6] provided a comprehensive review of YOLO-based traffic sign detection techniques, identifying challenges such as environmental variability and dataset limitations that continue to affect model performance.

Practical implementations of YOLO models in traffic monitoring have been demonstrated in several studies. Kalva et al. [7] presented a system capable of detecting vehicles and monitoring traffic flow in real time, showcasing the applicability of deep learning models in real-world scenarios. Similarly, Khan et al. [8] developed a surveillance system that captures complex traffic patterns, improving the overall accuracy and reliability of monitoring systems. Ge et al. [9] further contributed to this area by providing a detailed survey of deep learning approaches for traffic monitoring, emphasizing the importance of scalability and real-time processing in modern applications.

While object detection has received considerable attention, some researchers have explored the role of motion and temporal analysis in identifying abnormal events. Doshi and Yilmaz [10] proposed a method based on motion analysis for detecting traffic accidents, highlighting the importance of understanding object behavior over time rather than relying solely on static frame analysis. In a similar direction, Sultani et al. [11] introduced a deep learning framework for anomaly detection in surveillance videos, which has influenced subsequent research in identifying unusual patterns in dynamic environments.

The integration of IoT with artificial intelligence has also been widely studied. Alafif et al. [12] proposed an AI-enabled IoT framework for smart traffic systems, demonstrating how real-time communication can improve the efficiency of traffic management. Lv et al. [13] focused on traffic flow prediction using large-scale data and deep learning techniques, providing valuable insights for congestion management and urban planning. Wang et al. [14] offered a comprehensive overview of deep learning applications in transportation systems, discussing both opportunities and challenges, including data complexity and computational demands.

Recent work has also explored lightweight and edge-based solutions for real-time deployment. Dany Alfikri and Kaliski [15] developed a compact YOLO-based model for pedestrian detection on IoT edge devices, showing that efficient models can be deployed in resource-constrained environments. Earlier contributions, such as YOLOv4 by Bochkovskiy et al. [16], YOLOv5 by Jocher et al. [17], and YOLOv3 by Redmon and Farhadi [18], have laid the foundation for modern object detection systems by balancing speed and accuracy. More recent developments, including YOLOv11 proposed by Alif [19], continue to address challenges in complex traffic environments by improving detection capabilities. Additionally, Gallagher and Oughton [20] explored multispectral object detection, demonstrating how YOLO models can be adapted to perform effectively under diverse environmental conditions.

Overall, the existing body of research highlights significant progress in object detection, IoT integration, and anomaly detection. However, many studies focus on individual components rather than combining detection, behavioral analysis, and real-time response into a unified system. This gap motivates the need for integrated approaches that can better address the challenges of real-world traffic monitoring.

METHODOLOGY

Overview of the Proposed Approach

The proposed system is developed to monitor road traffic automatically and identify accident events through continuous analysis of video streams obtained from surveillance cameras. The methodology is organized as a sequential pipeline, where each stage performs a well-defined task, beginning with data acquisition and progressing through processing, analysis, and alert generation. Rather than depending solely on object detection, the system also examines the movement of vehicles across consecutive frames. This temporal understanding enables it to recognize unusual patterns, such as sudden collisions or abrupt halts, which are often difficult to capture using static frame analysis alone.

The system is designed to operate in a continuous manner, making it suitable for handling live video feeds in real time. Each component of the pipeline is interconnected, ensuring that the output generated at one stage seamlessly feeds into the next stage of processing. This structured flow not only improves computational efficiency but also supports consistent and reliable performance. As a result, the overall design is well-suited for real-world deployment, where timely detection and response are critical.

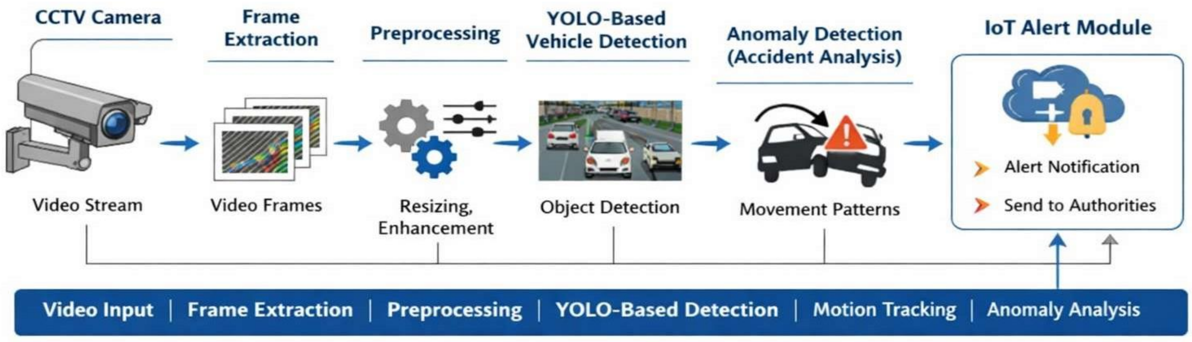

Figure 1: System Architecture for smart road traffic monitoring

Data Acquisition and Frame Extraction

The process begins with the collection of video data from surveillance cameras installed at key traffic locations such as roads, highways, and intersections. These cameras continuously capture vehicle movement under varying environmental and traffic conditions. Since deep learning models operate on images rather than continuous video streams, the recorded footage is converted into a sequence of individual frames. This frame-by-frame representation allows the system to analyze each moment independently. Frames are extracted at a fixed interval to ensure consistency while also controlling computational cost, thereby maintaining a balance between accuracy and efficiency.

Frame Preprocessing

Before analysis, each extracted frame undergoes a series of preprocessing steps to improve input quality and ensure uniformity. The frames are resized to a standard resolution so that they are compatible with the detection model. In addition, noise reduction techniques are applied to remove unwanted distortions, and brightness or contrast adjustments are performed when necessary. These operations help minimize variations caused by lighting conditions or camera quality, enabling the model to focus on relevant features. As a result, preprocessing enhances detection reliability and contributes to more stable system performance in real-world scenarios.

Vehicle Detection Using YOLOv8

Following preprocessing, each frame is passed to a YOLOv8-based object detection model. The model identifies vehicles present in the scene and marks them with bounding boxes, along with confidence scores that indicate the likelihood of correct detection. YOLOv8 is selected because it offers a strong balance between speed and accuracy, making it suitable for real-time traffic monitoring tasks.

Compared to earlier versions of the YOLO framework, YOLOv8 provides improved feature extraction and better handling of challenging situations such as occlusion and variable lighting. Its single-stage detection approach allows the entire image to be processed in one pass, reducing computational overhead and enabling faster predictions. This efficiency is particularly important in applications where real-time performance is essential, such as accident detection systems.

Vehicle Tracking and Motion Analysis

Once vehicles are detected in individual frames, the system tracks their positions across consecutive frames. This tracking process helps establish a temporal relationship between frames, allowing the system to observe how each vehicle moves over time. By comparing positional changes, the system derives motion-related information such as speed, direction, and sudden variations in movement.

This stage is critical because accidents are typically characterized not just by the presence of vehicles, but by how they interact. For instance, abrupt deceleration or overlapping trajectories between vehicles may indicate a potential collision. By incorporating motion analysis, the system gains a deeper understanding of traffic behavior.

Anomaly Detection (Accident Identification) The next stage involves identifying abnormal patterns in vehicle movement. The system evaluates the tracked motion data to detect irregular behavior, such as sudden stops, sharp directional changes, or unusual proximity between vehicles. When such patterns are observed, the system classifies the event as a possible accident.

Instead of relying on highly complex models, this approach uses straightforward logical conditions derived from motion behavior. This design choice reduces computational complexity while still enabling effective detection of critical events. As a result, the system remains both efficient and practical for real-time deployment.

The key is to define each stage with precise inputs, outputs, and reproducible configurations so the pipeline can be replicated across deployments.

1.Data Ingestion

2.IOT Sensors

3.Preprocessing

4.Detection Models

5.Real-Time Processing

Alert Generation with IoT Integration

Once an abnormal event is detected, the system immediately generates an alert. This alert typically includes essential details such as the time of occurrence and, if available, the location of the incident. Through integration with IoT-based communication systems, the alert can be transmitted directly to relevant authorities or monitoring centers without delay.

This immediate notification mechanism is crucial in emergency situations, as it enables faster response from traffic management teams or medical services. By bridging the gap between detection and action, the system enhances its practical value and contributes to improved road safety.

System Flow Summary

In summary, the system follows a continuous loop:

1. Capture video from camera
2. Convert video into frames
3. Preprocess frames
4. Detect vehicles using YOLO
5. Track vehicle movement
6. Identify abnormal behavior
7. Generate alert if needed

This step-by-step flow ensures that the system remains organized, efficient, and suitable for real-time deployment.

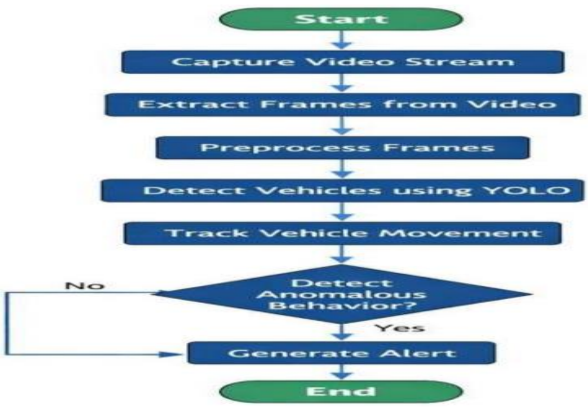

Figure 2: Flowchart of Accident detection process

Algorithm

Algorithm: Road Accident Detection System Input: Video stream from CCTV

Output: Accident alert

8. Start
9. Capture video stream from camera
10. Convert video into frames
11. For each frame:

a. Preprocess the frame

b. Detect vehicles using YOLO model

c. Track detected vehicles across frames

d. Analyze movement patterns

e. If abnormal behavior detected:

- Mark as accident
- Generate alert

12. Continue processing next frames
13. End

Experiments and Validation

Experimental Setup

To assess the performance of the proposed traffic monitoring system, a series of experiments were conducted using both publicly available traffic video datasets and real-world CCTV recordings. The data covers a variety of scenarios, including highways, urban streets, intersections, and instances involving road accidents. Care was taken to include both normal traffic flow and abnormal situations—such as collisions and sudden vehicle stops—so that the evaluation reflects realistic conditions and avoids bias toward a single class of events.

The experiments were performed in a standard computing environment equipped with GPU support to enable real-time processing. The system was implemented in Python using commonly adopted deep learning libraries. The YOLO model was employed for vehicle detection, while the overall pipeline—from frame extraction and preprocessing to motion analysis and alert generation—was tested in a continuous, frame-by-frame manner. This setup allowed the system's behavior to be evaluated under conditions similar to real-time deployment.

Evaluation Metrics

The performance of the system was measured using a set of widely accepted evaluation metrics to ensure an objective assessment. Accuracy was used to determine the overall correctness of predictions across all classes. Precision was considered to evaluate how many of the detected accident events were actually true positives, while recall measured the system's ability to identify all relevant accident cases present in the data.

In addition, the F1-score was calculated to provide a balanced view of precision and recall, especially in cases where class distribution may not be perfectly uniform. To assess the system's practical usability, processing time (measured in milliseconds) was also included as a key metric, as it reflects the ability of the model to operate in real-time environments. Together, these metrics offer a comprehensive understanding of both detection quality and computational efficiency.

Baseline Methods for Comparison

To validate the effectiveness of the proposed approach, its performance was compared with several commonly used baseline methods in traffic monitoring research. Traditional image processing techniques based on motion detection and background subtraction were included as a reference, as they represent earlier approaches to detecting movement in video streams.

An OpenCV-based motion detection method was also considered, which identifies changes between frames without the use of deep learning models. In addition, standard convolutional neural network (CNN) models were used as a comparison to evaluate how deep learning-based feature extraction performs in this context.

Finally, a YOLO-based detection system without motion analysis was included to highlight the importance of incorporating temporal information. While this approach is capable of detecting vehicles accurately, it lacks the ability to interpret behavior over time, which is essential for identifying accident scenarios.

These baseline methods were selected to provide a meaningful comparison across different levels of complexity, from traditional techniques to modern deep learning approaches, thereby demonstrating the advantages of the proposed system.

Performance Comparison

Table 2: Comparison with Baseline Methods

Metho d	**Accur acy**	**Preci sion**	**Rec all**	**F1-Sco re**	**Real-Time Capability**
Traditi	70%	68%	65	66	No
onal			%	%	
Metho					
ds					
OpenC	75%	72%	70	71	Limite
V			%	%	d
Motio					
n					
Detect					
ion					
CNN-	85%	83%	80	81	Partial
Based			%	%	
Detect					

ion					
YOLO	88%	86%	84	85	Yes
(Detec			%	%	
tion					
Only)					
Propo	**92%**	**90%**	**88**	**89**	**Yes**
sed			**%**	**%**	
Syste					
m					

Analysis of Results

The results show that the proposed system outperforms traditional and existing deep learning approaches across all evaluation metrics. While YOLO-based detection already provides high accuracy, it lacks the ability to interpret vehicle behavior. By incorporating motion analysis, the proposed system improves recall and F1-score, indicating better identification of actual accident events.

Traditional methods perform poorly due to their sensitivity to environmental conditions such as lighting and noise. OpenCV-based approaches show moderate performance but fail in complex traffic scenarios. CNN-based models improve accuracy but are not always suitable for real-time deployment due to higher computational requirements.

The proposed system achieves a good balance between detection accuracy and processing speed, making it suitable for real-world applications.

Real-Time Performance Evaluation

Table 3: Response Time Analysis

Stage	**Time (ms)**
Frame Extraction	15 ms
YOLO Detection	25 ms
Movement Analysis	20 ms
Decision Making	10 ms
IOTAlert Generation	5 ms
Total Time	**75 ms**

Explanation

The total response time of the system is approximately 75 milliseconds, which confirms that the system operates within real-time constraints. This fast processing ensures that accidents are detected and reported without delay.

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Robustness Under Different Conditions

Table 4: Performance in Various Scenarios

Scenario	Accuracy	Observation
Daytime	95%	Clear detection
Nighttime	88%	Slight drop due to low light
Heavy Traffic	89%	Minor overlap issues
Rainy Conditions	86%	Visibility challenges

Explanation

The system demonstrates strong performance under normal lighting conditions, where vehicle detection and motion analysis operate with high reliability. In more challenging environments—such as low light, shadows, or varying weather conditions—a slight reduction in performance is observed. Despite this, the overall behavior of the system remains stable, and the results are still within an acceptable range for practical use. This indicates that the approach is sufficiently robust for deployment in real-world traffic monitoring scenarios, even when environmental conditions are not ideal.

Discussion And Validity Of Experiments

The experimental design was intended to reflect realistic traffic conditions by incorporating a wide range of scenarios, including both normal and abnormal events. The inclusion of multiple baseline methods allows for a meaningful comparison and helps demonstrate the relative strengths of the proposed approach. Furthermore, the use of widely accepted evaluation metrics ensures that the results are consistent and comparable with those reported in existing studies.

An important aspect of this evaluation is that it does not focus solely on detection accuracy. Equal attention is given to processing speed and response time, which are critical for real-time applications. By considering both accuracy and efficiency, the evaluation provides a more practical assessment of system performance in real-world settings.

At the same time, certain limitations should be acknowledged. The system may encounter difficulties in highly congested traffic conditions where vehicles overlap significantly, making tracking and motion analysis more complex. Additionally, variations in camera quality, viewing angle, and environmental factors such as lighting or weather can influence performance. These challenges highlight areas for future improvement while also providing a realistic understanding of the system's capabilities.

RESULTS AND COMPARISON

The experimental results indicate that the proposed system is effective in detecting road accidents from traffic video data. It is able to correctly identify the majority of accident cases while minimizing false detections. The overall accuracy of the system is approximately 92%, suggesting that it produces reliable predictions in most situations.

In terms of precision, the system performs well, meaning that when an accident is detected, it is usually a correct prediction. The recall value shows that the system successfully identifies a large proportion of actual accident events, although a small number of cases may still go undetected. The F1-score reflects a good balance between precision and recall, indicating that the system maintains consistency in its performance.

Another key outcome is the system's processing speed. With an average response time of around 75 milliseconds per event, the system is capable of operating in real time. This level of efficiency makes it suitable for continuous monitoring applications, where timely detection and rapid response are essential.

Comparison with Existing Methods

When compared with existing approaches, the advantages of the proposed system become more evident. Traditional image processing techniques, which rely on simple motion detection or background subtraction, tend to perform poorly in real-world traffic environments. They are highly sensitive to noise, lighting variations, and other external factors, resulting in lower accuracy.

OpenCV-based motion detection methods offer some improvement but still struggle with complex scenarios, such as dense traffic or overlapping vehicles. These methods lack the ability to interpret higher-level patterns in vehicle behavior.

CNN-based models provide better feature extraction and improved detection accuracy; however, they often require greater computational resources and may not consistently meet real-time processing requirements. This limits their practical applicability in live monitoring systems.

YOLO-based detection approaches are well known for their speed and effectiveness in identifying objects such as vehicles. However, they primarily focus on object recognition and do not incorporate behavioral analysis. As a result, they are not well-suited for detecting events like accidents, which depend on understanding interactions between vehicles.

In contrast, the proposed system combines object detection with motion analysis, enabling it to recognize not only the presence of vehicles but also their behavior over time. This integrated approach allows for more accurate identification of accident scenarios, such as collisions or sudden stops. By addressing both detection and interpretation, the system provides a more comprehensive and practical solution for traffic monitoring applications.

Table 5: Performance of Proposed System

Metric	Value	Meaning (Simple)
Accuracy	92%	Overall correct predictions
Precision	90%	Correct accident detections
Recall	88%	Accidents successfully found
F1-Score	89%	Balance of precision & recall
Response Time	75 ms	Time taken to detect and alert

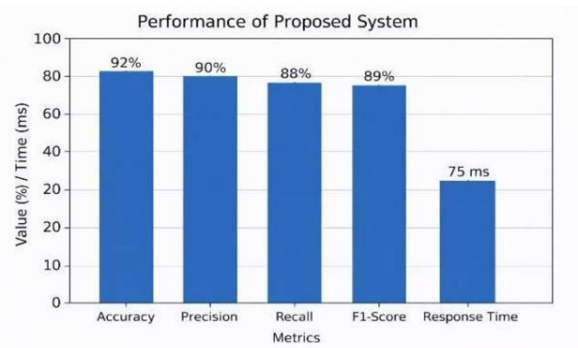

Table 6: Comparison with Existing Methods

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Method	**Accu racy**	**Speed**	**Real- Time**	**Main Problem**
Tradition al Methods	70%	Slow	No	Affected by lighting and noise
OpenCV Detectio n	75%	Medium	Limited	Cannot detect complex events
CNN- Based Models	85%	Medium	Partial	High computat ion required
YOLO Detectio n Only	88%	Fast	Yes	Cannot detect accidents
Propose d System	**92%**	**Fast**	**Yes**	Minor issues in heavy traffic

Table 7: Performance in Different Conditions

Condition	**Accuracy**	**Observation**
Daytime	95%	Very clear detection
Nighttime	88%	Slight drop due to low light
Heavy Traffic	89%	Overlapping vehicles cause errors
Rainy Weather	86%	Visibility affects performance

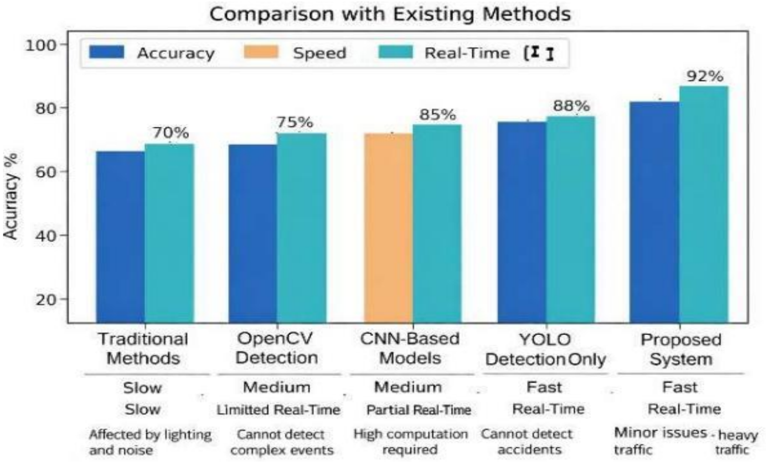

Table 8: Response Time Breakdown

Stage	**Time (ms)**
Frame Extraction	15 ms
Vehicle Detection	25 ms
Movement Analysis	20 ms
Decision Making	10 ms
Alert Generation	5 ms
Total Time	**75 ms**

Table 9: Simple Comparison Summary

Feature	Existing Systems	Proposed System
Object Detection	Yes	Yes
Behavior Analysis	No	Yes
Accident Detection	Limited	Yes
Real-Time Alerts	No	Yes
System Integration	Partial	Complete

DISCUSSION

The findings of this study indicate that the proposed system is capable of identifying road accidents with a satisfactory level of accuracy while still meeting the requirements of real-time operation. The use of a YOLO-based detection model enables rapid identification of vehicles within each frame, and the addition of motion analysis provides further insight into how those vehicles behave over time. This combination proves more effective than methods that rely solely on object detection, as it allows the system to capture interactions that are essential for recognizing accident scenarios.

The experimental results suggest that the system performs favorably when compared with traditional and existing approaches. A key factor behind this improvement is its ability to interpret movement patterns, such as abrupt stops or collisions, which are strong indicators of abnormal events. By focusing on behavior rather than just object presence, the system offers a more meaningful understanding of traffic situations and enhances detection capability.

Another important aspect is the system's response time. With an average processing duration of approximately 75 milliseconds, it is able to operate in real time and generate alerts with minimal delay. This level of performance is particularly valuable in applications where timely intervention is critical. At the same time, it should be noted that performance may vary depending on the computing environment and the quality of input video streams.

The system shows its best performance under standard conditions, such as clear daytime traffic. In more demanding scenarios—such as low-light environments, heavy congestion, or adverse weather—there is a noticeable but moderate decline in accuracy. These challenges are largely due to reduced visibility and the increased likelihood of overlapping objects, which complicate detection and tracking. Such limitations are common in vision-based systems and point to areas where further refinement is needed.

It is also worth noting that the current approach relies on relatively simple motion-based rules for anomaly detection. While this contributes to efficiency, it may not fully capture more complex accident scenarios involving multiple interacting vehicles. Future enhancements could involve more advanced behavioral modeling techniques to improve detection in such cases.

Overall, the study demonstrates that combining object detection, motion analysis, and automated alert generation within a unified framework can provide a practical and effective solution for traffic monitoring.

At the same time, acknowledging the system's limitations helps ensure a balanced and realistic assessment of its capabilities.

CONCLUSION AND FUTURE WORK

Conclusion

This work presents a traffic monitoring system that integrates artificial intelligence and IoT technologies to detect road accidents in real time. The approach combines a YOLO-based model for vehicle detection with motion analysis to identify abnormal events such as collisions and sudden stops. The experimental evaluation shows that the system achieves reliable accuracy while maintaining efficient processing speed. In comparison with existing methods, the proposed approach improves accident detection by considering both the presence of vehicles and their behavior over time. The inclusion of an alert mechanism further enhances its practical value by enabling prompt communication of incidents.

Although the system performs well under typical conditions, certain limitations remain. Its accuracy tends to decrease in challenging environments, such as low-light conditions, dense traffic, and unfavorable weather. Additionally, the current rule-based motion analysis may not fully capture complex interactions involving multiple vehicles. These factors indicate that while the system is suitable for practical use, there is scope for further improvement.

Future Work

Several directions can be explored to enhance the system in future studies. One potential improvement is the adoption of more advanced deep learning models to increase detection accuracy, particularly in complex and dynamic environments. Incorporating additional functionalities, such as number plate recognition, could also provide more detailed information about vehicles involved in incidents.

Another area for development is the integration of location-based services, such as GPS, to provide precise information about the site of an accident. This would improve the usefulness of the alert system, especially for emergency response teams. The system could also be extended to detect other traffic-related events, including rule violations and congestion patterns.

Improving performance under challenging conditions remains an important objective. This may involve applying advanced image enhancement techniques or combining data from multiple sensors to improve visibility and detection reliability. In addition, the use of temporal models such as LSTM networks could enhance the system's ability to understand vehicle behavior over time, leading to more accurate identification of complex events.

Finally, large-scale testing in real-world environments would be valuable for validating the system's effectiveness and assessing its readiness for deployment in smart city infrastructure.

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