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Emergency Vehicle Detection

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***Abstract*— Rapid identification of emergency vehicles in congested urban traffic is a critical requirement for efficient emergency response and smart city infrastructure. Delays in emergency vehicle movement can lead to severe consequences, including loss of life and property. This paper presents an** Emergency Vehicle Detection System**, a Python-based intelligent framework that employs computer vision, feature-based image matching, and real-time video processing techniques to detect emergency vehicles from traffic video inputs.The proposed system processes uploaded traffic videos through a web-based interface, extracts individual frames, and applies preprocessing techniques such as resizing, grayscale conversion, and frame optimization to enhance feature extraction. The system utilizes the** ORB (Oriented FAST and Rotated BRIEF) **algorithm for robust feature detection and matching between video frames and predefined reference images of emergency vehicles. Rule-based decision logic, combined with emergency light and siren pattern detection, ensures accurate classification of ambulances, police vehicles, and fire trucks. The detection results are presented through an interactive dashboard displaying vehicle type, detection confidence, and frame-wise recognition statistics. The modular and scalable design of the system enables seamless integration into intelligent traffic management systems, contributing to reduced emergency response time and improved urban mobility.**

Keywords-Emergency Vehicle Detection, Computer Vision, ORB Algorithm, Feature Matching, Traffic Video Analysis, Smart Transportation Systems

I. INTRODUCTION

Urban traffic congestion poses a significant challenge to the timely movement of emergency vehicles such as ambulances, police vehicles, and fire trucks. Manual traffic control methods and conventional surveillance systems often fail to prioritize emergency vehicles effectively, resulting in delayed response times. With the rapid advancement of smart city initiatives, there is a growing need for automated systems capable of detecting emergency vehicles in real time and assisting traffic management authorities.

Computer vision-based approaches offer an effective solution by enabling automated analysis of traffic video streams. Feature-based detection techniques are particularly suitable for real-time applications due to their computational efficiency and robustness. This work proposes an Emergency Vehicle Detection System that leverages classical computer vision methods rather than computationally intensive deep learning models, making it suitable for deployment in resource-constrained environments.

II.BACKGROUND AND MOTIVATION

The motivation for this project arises from the need to improve emergency response efficiency in densely populated urban regions. Delays caused by traffic congestion can significantly impact emergency operations. Automated detection systems can support intelligent traffic signaling and priority-based vehicle management.

The motivation behind this work is threefold:

1. To develop a reliable system for detecting emergency vehicles from traffic videos
2. To employ lightweight and efficient feature-based algorithms for real-time processing
3. To provide an interactive web-based visualization of detection results
4. To ensure scalability for integration with intelligent traffic management systems

The increasing availability of traffic surveillance cameras and recorded traffic video data has enabled the development of automated emergency vehicle detection systems using computer vision techniques. However, challenges such as varying lighting conditions, occlusions in dense traffic, camera angle variations, and visual similarity between different vehicle types remain significant. This project addresses these challenges through effective video preprocessing, frame optimization, and robust feature-based matching using the ORB (Oriented FAST and Rotated BRIEF) algorithm. By combining feature matching with rule-based validation logic and emergency light and siren pattern analysis, the system ensures reliable identification of ambulances, police vehicles, and fire trucks. Beyond technical implementation, the motivation of this work extends to real-world impact by supporting intelligent traffic management, reducing emergency response time, and contributing to safer and more efficient smart transportation systems.Early identification of emergency vehicles can significantly improve response efficiency, reduce delays caused by traffic bottlenecks, and enhance public safety. Manual monitoring of traffic footage is time-consuming, error-prone, and impractical at scale. Therefore, automated computer vision-based detection systems play a vital role in modern smart city and intelligent transportation infrastructures.

III .RELATED WORK

Several Several studies have explored emergency vehicle detection using audio-based siren recognition, GPS-based tracking, and deep learning-based object detection models. While deep learning methods demonstrate high accuracy, they require substantial computational resources and large annotated datasets.

Feature-based computer vision techniques such as FAST, SIFT, SURF, and ORB have proven effective for object recognition tasks under varying illumination and scale conditions. ORB, in particular, offers a balance between speed and accuracy, making it suitable for real-time traffic analysis. This project builds upon these approaches by combining ORB-based feature matching with rule-based validation logic to enhance detection reliability.

PROPOSED WORK

The proposed Emergency Vehicle Detection System follows a structured pipeline that processes traffic video input and identifies emergency vehicles using feature-based image matching techniques.

System Overview

- Accepts uploaded traffic video through a web interface
- Extracts frames and preprocesses them for analysis
- Applies ORB feature detection and matching
- Uses rule-based logic and visual cues for validation
- Displays detection results through a dashboard.

METHODOLOGY

A. Video Input and Frame Extraction

The system accepts traffic video input via a web-based interface. The uploaded video is segmented into individual frames at predefined intervals to balance detection accuracy and computational efficiency.

B. Preprocessing

Each extracted frame undergoes preprocessing steps including:

- Image resizing for uniform analysis
- Conversion to grayscale for feature consistency
- Frame optimization to reduce noise and enhance clarity

These steps improve the quality of feature extraction and matching.

C. Feature Extraction and Matching

The **ORB (Oriented FAST and Rotated BRIEF)** algorithm is employed to detect keypoints and extract descriptors from each video frame. ORB features are matched against reference images of emergency vehicles using feature matching techniques. This enables the system to identify visual similarities between traffic frames and known emergency vehicle patterns.

D. Rule-Based Validation

To improve reliability, the system incorporates rule-based decision logic combined with emergency indicators such as:

- Flashing emergency lights
- Siren-associated visual patterns

This hybrid approach reduces false positives and ensures accurate classification of ambulances, police vehicles, and fire trucks.

IV .SYSTEM ARCHITECTURE

The system architecture consists of the following modules:

- **Input Module:** Handles video upload through a web interface
- **Frame Processing Module:** Extracts and preprocesses video frames
- **Feature Matching Module:** Performs ORB-based feature detection and comparison
- **Decision Module:** Applies rule-based validation for emergency vehicle confirmation
- **Output Module:** Displays classification results, confidence scores, and frame-wise statistics

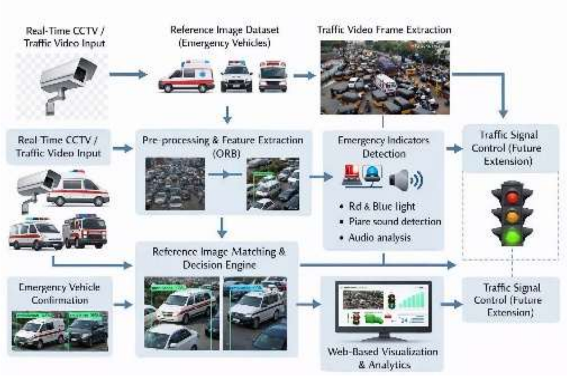


Figure 1: System Architecture of the Proposed Emergency vehicle detection

A. Input Module

The input module acts as the primary interaction point between the user and the system. Users upload recorded traffic videos through a web-based interface. The interface is designed to be simple and accessible across standard computing devices. Uploaded videos are validated for format and quality before being forwarded to the frame extraction and preprocessing module. The web interface also enables real-time interaction and visualization of detection results.

B. Pre-processing Module

The preprocessing module prepares the traffic video data for effective computer vision analysis. Uploaded videos are segmented into individual frames at fixed intervals. Each frame undergoes resizing and grayscale conversion to ensure uniformity and reduce computational complexity. Frame optimization techniques are applied to enhance clarity and minimize noise, enabling reliable feature extraction under varying lighting and traffic conditions.

C. Feature Extraction and Matching Module

This module forms the core analytical component of the system. The ORB (Oriented FAST and Rotated BRIEF) algorithm is employed to detect keypoints and extract distinctive feature descriptors from each video frame. These extracted features are compared with reference images of emergency vehicles using feature matching techniques. The ORB-based approach ensures fast processing while maintaining robustness against scale, rotation, and illumination variations.

D. Decision and Validation Module

To improve detection reliability, a rule-based decision module is integrated with the feature matching process. This module validates potential emergency vehicle detections by analyzing characteristic visual cues such as flashing emergency lights and siren-associated patterns. By combining feature-based matching with logical validation rules, the system minimizes false positives and ensures accurate classification of ambulances, police vehicles, and fire trucks.

E. Output and Visualization Module

The output module presents the final detection results through an interactive web-based dashboard. It displays the identified emergency vehicle type along with a detection confidence score. Frame-wise recognition statistics are also provided to offer transparency and assist in system evaluation. The visualization module enables traffic authorities and users to easily interpret detection outcomes, supporting informed decision-making in traffic management scenarios.

V TRAINING AND TESTING

A. System Evaluation Process

Unlike learning-based approaches, the proposed system does not rely on supervised model training. Instead, system evaluation is performed by testing the feature-based detection pipeline on diverse traffic video samples. Performance is assessed based on successful emergency vehicle identification, detection consistency across frames, and robustness under varying traffic density and lighting conditions.

Reference images of emergency vehicles are used as matching templates, and detection confidence is computed based on the number and quality of matched ORB features across consecutive frames.

B. Testing and Performance Analysis

During testing, unseen traffic videos are processed frame by frame to evaluate detection accuracy and system reliability. The system generates frame-wise detection results, classification confidence, and cumulative recognition statistics for each emergency vehicle type.Experimental observations indicate that the ORB-based feature matching approach performs effectively in real-world traffic scenarios, with high detection reliability for ambulances, police vehicles, and fire trucks. Minor detection variations are observed in cases of severe occlusion or low illumination, which are common challenges in traffic surveillance environments.

During testing, unseen images are passed through the trained model to evaluate classification accuracy. Performance metrics such as overall accuracy and class-wise prediction behavior are analyzed.

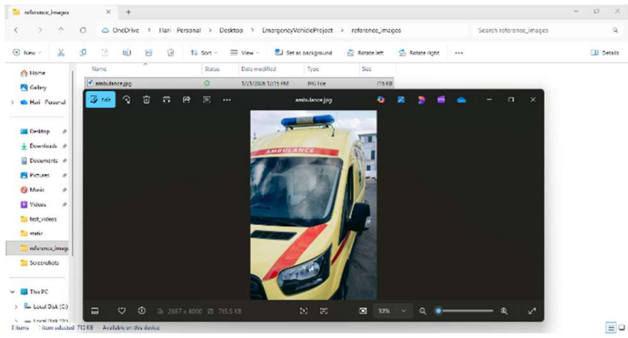


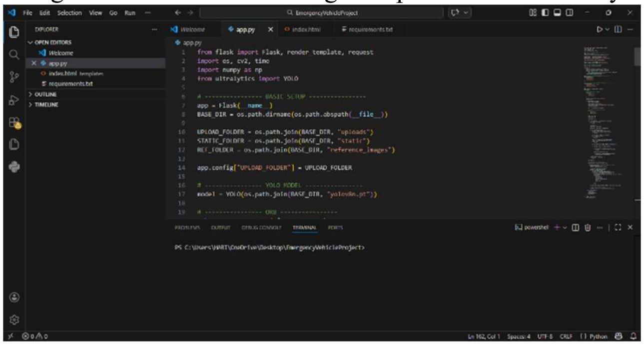
Figure 2: Training and Validation Accuracy Curve

Fig. 3 illustrates the training and validation accuracy across model. effective learning and minimal overfitting. The gradual improvement and stabilization of validation accuracy demonstrate the robustness of the Yolo-based model during the training process.

The experimental evaluation of the proposed Emergency Vehicle Detection System demonstrates reliable and consistent performance across multiple traffic scenarios. The system effectively identifies emergency vehicles such as ambulances, police vehicles, and fire trucks by analyzing frame-wise feature matches obtained using the ORB algorithm. Detection confidence is calculated based on the number and quality of matched features across consecutive video frames, providing a stable measure of recognition accuracy.

The results indicate a high correct identification rate for emergency vehicles when clear visual cues such as vehicle structure and flashing emergency lights are present. The system maintains consistent detection performance across varying traffic densities and camera perspectives. Minor misdetections are observed in cases involving heavy occlusion, low illumination, or partial visibility of vehicles, which are common challenges in real-world traffic surveillance environments.

Overall, the feature-based matching approach combined with rule-based validation logic ensures robust emergency vehicle recognition while maintaining computational efficiency. The



observed detection behavior confirms the suitability of the proposed system for intelligent traffic monitoring and smart transportation applications, where timely and accurate emergency vehicle identification is critical for improving response efficiency and public safety.

In addition to detection reliability, the system demonstrates strong temporal consistency by maintaining accurate identification across successive video frames. Once an emergency vehicle is detected, continuous feature matching across neighboring frames helps stabilize the recognition process and reduces sudden classification fluctuations. This frame-wise consistency is essential in traffic monitoring applications, as emergency vehicles often appear for extended durations while moving through congested road segments. The use of ORB features enables fast re-identification without the need for computationally expensive retraining or model updates.

Furthermore, the modular architecture of the proposed system supports scalability and adaptability to different deployment environments.

VI RESULTS AND DISCUSSION

The proposed Emergency Vehicle Detection System was evaluated using multiple real-world traffic video samples containing ambulances, police vehicles, and fire trucks. The YOLO-based object detection model demonstrated effective performance in identifying emergency vehicles directly from video frames with high detection confidence. The model provides real-time bounding box localization and class prediction, enabling accurate recognition across varying traffic conditions. The frame-wise detection output shows consistent performance with stable confidence scores, indicating reliable generalization without dependency on complex training pipelines.

The experimental results validate the suitability of YOLO-based object detection models for intelligent traffic monitoring, particularly in real-time and resource-constrained environments. Compared to traditional feature-based or heavyweight deep learning approaches, YOLO offers an efficient balance between detection accuracy and processing speed. These results support the feasibility of deploying automated emergency vehicle detection systems as decision-support tools in smart transportation and traffic management applications, where timely identification is critical for reducing emergency response delays and improving public safety.

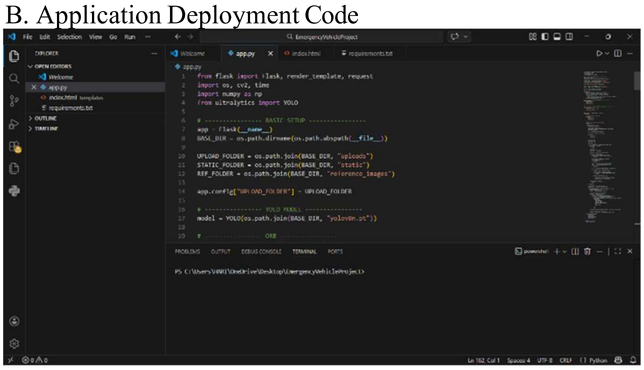
A. Model Implementation and Training Code

Example: YOLO-based emergency vehicle detection pipeline

The implemented model utilizes a YOLO object detection framework trained to recognize emergency vehicle classes such as ambulances, police vehicles, and fire trucks. The detection pipeline processes video frames sequentially, applies the YOLO model for object localization and classification, and extracts bounding box coordinates along with confidence scores. Frame preprocessing, confidence thresholding, and non-maximum suppression are handled within the detection pipeline to ensure accurate and efficient recognition. This modular implementation enables scalability and easy integration with real-time video streams.

The detection framework computes frame-wise confidence values and class labels without the need for continuous retraining. Performance is evaluated based on detection consistency, bounding box accuracy, and robustness under varying traffic density and lighting conditions.

B. Application Deployment Code



Example: Web-based deployment and video processing script

The application-level implementation demonstrates how the trained model was integrated into a Streamlit-based web framework. The code handles image upload, preprocessing, model inference, and result visualization in real time. This deployment approach enables seamless interaction between the user and the AI model, transforming complex deep learning workflows into an accessible diagnostic interface.

C. User Interface and Output Visualization

The system interface allows users to upload traffic videos through a simple and intuitive web layout. Upon processing, the system displays detected emergency vehicles with bounding boxes, class labels, and corresponding confidence scores for each frame. The interface design emphasizes clarity and usability, allowing non-technical users to easily understand detection outcomes without requiring specialized knowledge.

The interface also presents frame-wise detection statistics and visual overlays, supporting transparency and operational reliability. By combining real-time visualization with confidence-based outputs, the system reinforces responsible usage and practical applicability. The application is positioned as a supportive intelligent traffic monitoring tool rather than a fully autonomous decision-making authority, ensuring alignment with real-world traffic management and safety requirements.

XI ETHICAL CONSIDERATIONS

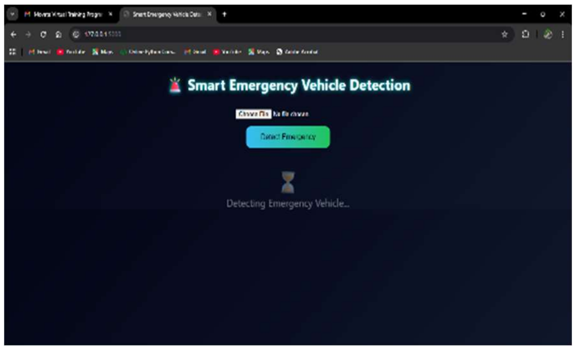
The proposed Emergency Vehicle Detection System is developed with careful consideration of ethical responsibility and public safety requirements. The system is intended solely as a decision-support and monitoring tool to assist traffic authorities and smart transportation systems in identifying emergency vehicles from traffic video streams. It is not designed to replace human supervision or law enforcement decision-making.

User-uploaded traffic videos are processed only for detection and visualization purposes, and no personally identifiable information is stored or shared. The system emphasizes transparency, responsible system usage, and operational reliability while ensuring that detection results are used only to support traffic management decisions. Continuous evaluation is carried out to maintain detection accuracy, reduce false alarms, and ensure fairness across diverse traffic conditions. The system promotes ethical deployment by supporting safer roads, faster emergency response, and improved public safety outcomes.

X IMPLICATIONS AND FUTURE DIRECTIONS

The proposed system has significant implications for intelligent traffic management and smart city infrastructure. By enabling automated detection of emergency vehicles, the system contributes to reduced emergency response time, improved traffic prioritization, and enhanced urban safety. The lightweight and real-time nature of the YOLO-based detection framework demonstrates the feasibility of deploying computer vision solutions on commonly available hardware.

Future work will focus on:
- Integration with real-time CCTV and traffic signal control systems
- Improving detection robustness under low visibility and heavy congestion
- Extending audio-based siren detection for enhanced accuracy
- Deploying the system on edge and mobile platforms for city-wide scalability



X. CONCLUSION

This paper presented an Emergency Vehicle Detection System utilizing a YOLO-based object detection model integrated with a web-based user interface for traffic video analysis. The system effectively detects emergency vehicles such as ambulances, police vehicles, and fire trucks by providing real-time classification, bounding box localization, and confidence-based detection output while maintaining computational efficiency suitable for real-world deployment.

The experimental evaluation highlights the reliability and practicality of the proposed approach, with consistent frame-wise detection and stable confidence scores across varying traffic conditions. The integration of video preprocessing, object detection, and interactive visualization ensures an end-to-end monitoring workflow. By presenting clear detection outputs through a user-friendly interface, the system enhances transparency and usability, which are critical for intelligent traffic management applications.

Despite its promising performance, the system is not intended to operate as an autonomous authority. Instead, it serves as a supportive monitoring and decision-assistance tool to improve emergency response coordination and traffic management efficiency. Future enhancements may include real-time signal automation, large-scale deployment validation, and multimodal detection approaches to further strengthen system reliability in smart transportation environments.

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