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SmartFlow: A Machine Learning-Based Adaptive Traffic Signal Control System

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Abstract:
Traffic congestion in urban areas often causes delays for emergency vehicles such as ambulances, fire engines, and police vehicles. These delays can reduce the efficiency of emergency response and may lead to serious consequences in critical situations. Traditional traffic signal systems operate based on fixed timing schedules and do not provide priority to emergency vehicles. This research proposes an intelligent traffic light control system for automatic identification of emergency vehicles using computer vision and acoustic signals. The system uses the YOLO (You Only Look Once) deep learning model to detect ambulances from real-time traffic video captured by surveillance cameras. In addition, acoustic signal analysis is used to detect ambulance sirens. A Convolutional Neural Network (CNN) is used to improve detection accuracy and classification reliability. When an emergency vehicle is detected, the system automatically changes the traffic signal to green for the corresponding lane, allowing the vehicle to pass without delay. This approach reduces response time for emergency services and improves traffic management efficiency. The proposed system can be integrated into smart city traffic management infrastructure to enhance public safety and reduce traffic congestion.

Keywords: Emergency Vehicle Detection, Traffic Light Control System, YOLO Object Detection, Convolutional Neural Network, Computer Vision, Acoustic Signal Detection, Ambulance Detection, Smart Traffic Management.

I. INTRODUCTION

Traffic congestion has become one of the major problems in many urban and metropolitan areas due to the rapid increase in the number of vehicles on the road. Traditional traffic signal systems operate based on fixed time intervals that are pre-programmed without considering real-time traffic conditions. As a result, vehicles often have to wait at traffic signals even when the road on the other side has very little traffic. This leads to inefficient traffic management, increased travel time, fuel wastage, and environmental pollution. Intelligent transportation systems and adaptive signal control methods have been proposed in recent years to improve traffic flow and intersection management [4], [5].

Efficient traffic control is an important requirement for modern transportation systems. With the development of smart cities, it is necessary to implement intelligent solutions that can manage traffic dynamically. An adaptive traffic signal system can help in reducing congestion by adjusting signal timings according to the current traffic density. By analyzing real-time traffic conditions, such systems can improve road efficiency and reduce unnecessary waiting time for vehicles at intersections. Several studies have proposed adaptive traffic management techniques using IoT sensors and machine learning algorithms to monitor traffic flow and optimize signal control [3], [8].

Recent advancements in Artificial Intelligence (AI), Machine Learning, and Computer Vision have provided new opportunities for developing smart traffic management systems. These technologies enable computers to process images and videos captured from cameras and identify different types of vehicles such as cars, buses, trucks, and motorcycles. By analyzing these images, the system can determine the number of vehicles present on each lane and adjust the signal timing accordingly. Deep learning-based object detection methods have shown promising performance in detecting vehicles in complex environments [7], [9], [10].

In this project, SmartFlow: Adaptive Traffic Signal System is proposed to improve traffic management using intelligent techniques. The system uses cameras to capture real-time images of traffic at road intersections. The captured images are processed using the YOLOv5 object detection algorithm, which can accurately detect and count vehicles present in the traffic. Based on the detected traffic density, the system automatically adjusts the signal timing in order to allow smoother traffic flow.

Another important feature of the proposed system is providing priority to emergency vehicles such as ambulances. In many emergency situations, ambulances are delayed due to heavy traffic and fixed traffic signal patterns. These delays can result in serious consequences for patients who require immediate medical attention. Therefore, it is important to ensure that emergency vehicles are able to move quickly through traffic intersections. Several research works have explored intelligent systems for emergency vehicle priority in traffic networks [1], [2].

To address this issue, the proposed system integrates ambulance detection mechanisms using both visual and audio recognition techniques. The system can identify ambulances using object detection from camera images as well as through the recognition of ambulance siren sounds. A Convolutional Neural Network (CNN) is used to detect the siren sound of an ambulance. When an ambulance is detected, the system automatically changes the traffic signal to green in the direction of the ambulance, allowing it to pass through the intersection without delay.

II. METHODOLOGY

The proposed system is designed to automatically detect emergency vehicles such as ambulances in traffic and provide priority at intersections by controlling traffic signals. The system integrates computer vision techniques, deep learning models, and acoustic signal detection to improve the reliability and accuracy of emergency vehicle identification.

The methodology of the proposed system consists of several stages including video acquisition, image preprocessing, vehicle detection, emergency vehicle classification, siren detection, and traffic signal control. Each stage plays an important role in identifying the emergency vehicle and providing signal priority. The overall workflow of the system is illustrated as follows: Input Video Capture → Image Preprocessing → Vehicle Detection using YOLO → CNN-based Emergency Vehicle Classification → Acoustic Siren Detection → Traffic Signal Control

A. Problem Formulation

The main objective of the proposed system is to detect ambulances in traffic automatically and provide priority to them by controlling traffic signals.
Let:
X = Input image or video frame captured from the traffic camera
Y = Detection output of the system
The system learns a mapping function:
$f(X) \rightarrow Y$
where the output Y represents the classification of vehicles detected in the frame.
If the detected object belongs to the emergency vehicle category, the system triggers the traffic signal control module. The system also analyzes acoustic signals to confirm the presence of an ambulance siren. The final decision of emergency vehicle detection is based on both visual detection and acoustic confirmation.

B. Data Acquisition

The first step in the methodology is collecting traffic video data from surveillance cameras installed at road intersections. The cameras continuously capture real-time traffic footage containing different types of vehicles such as cars, buses, trucks, motorcycles, and ambulances. These video frames are used as input for the deep learning detection model. The dataset may include different traffic conditions such as daytime traffic, nighttime traffic, heavy congestion, and multiple lane intersections. The dataset is used for training, validation, and testing the emergency vehicle detection model.

C. Image Preprocessing

Before feeding the input images to the deep learning model, several preprocessing operations are performed to improve the quality and consistency of the data.
The preprocessing stage includes:
Image resizing to a fixed resolution suitable for the neural network
Noise removal to reduce distortions in the captured frames
Normalization to standardize pixel intensity values
Frame extraction from continuous video streams

These steps help the deep learning model process the images efficiently and improve detection performance.

D. Vehicle Detection using YOLO

The YOLO (You Only Look Once) algorithm is used for real-time object detection in the traffic video frames. YOLO is a deep learning-based object detection model that can identify multiple objects in a single image.
The YOLO model divides the input image into multiple grid cells and predicts bounding boxes for potential objects. Each bounding box contains information about the object's location and classification probability. In this system, the YOLO model is trained to detect different vehicle categories including cars, buses, trucks, and ambulances. The algorithm processes each frame of the video and detects vehicles present in the scene.
The output of the YOLO detection stage includes:
Bounding box coordinates
Vehicle class label
Confidence score
These outputs are passed to the next stage for further verification.

E. CNN-Based Emergency Vehicle Classification

Although YOLO detects vehicles in the frame, an additional classification step is required to accurately identify ambulances among other vehicles. For this purpose, a Convolutional Neural Network (CNN) is used.CNN models are widely used for image classification tasks because they can automatically learn visual features from images. In this system, the CNN analyzes the detected vehicle region and identifies whether it belongs to the ambulance category.
The CNN extracts important visual features such as:
Vehicle shape and structure
Emergency markings
Vehicle color patterns
Flashing lights
Based on these features, the CNN classifier confirms whether the detected object is an ambulance.

Acoustic Signal Detection

In addition to visual detection, the system also uses acoustic signal analysis to detect ambulance sirens. An audio sensor placed near the traffic intersection captures surrounding sounds. The captured audio signals are analyzed to identify frequency patterns corresponding to ambulance sirens. Ambulance sirens typically fall within a specific frequency range, which can be detected using signal processing techniques. If the detected sound matches the ambulance siren pattern, the system confirms the presence of an emergency vehicle. This audio confirmation improves the reliability of the system, especially in situations where the ambulance is partially blocked in the camera view.

Traffic Signal Control

Once the system confirms the presence of an emergency vehicle through both visual detection and siren detection, the traffic signal control module is activated. The system automatically changes the traffic signal to green for the lane in which the ambulance is approaching. Traffic signals for other lanes remain red to ensure a clear path for the emergency vehicle. After the ambulance crosses the intersection, the traffic signal returns to its normal timing cycle. This intelligent signal control mechanism helps reduce delays for emergency vehicles and improves the efficiency of traffic management.

Algorithm Steps

Capture real-time traffic video using a camera.
Extract frames and preprocess the images.
Apply YOLO to detect vehicles in the frame.
Use CNN to classify whether the detected vehicle is an ambulance.
Detect ambulance siren using acoustic signal analysis.
If ambulance is confirmed, change the traffic signal to green for that lane.
After the ambulance passes, return the signal to the normal cycle.

F. System Architecture

The system architecture consists of several components including a traffic camera, audio sensor, processing unit, deep learning model, and traffic signal controller. The traffic camera captures real-time video of vehicles approaching the intersection. The captured frames are processed using the YOLO object detection algorithm to identify vehicles in traffic.The detected vehicle region is further analyzed using a Convolutional Neural Network (CNN) to classify whether the vehicle is an ambulance.

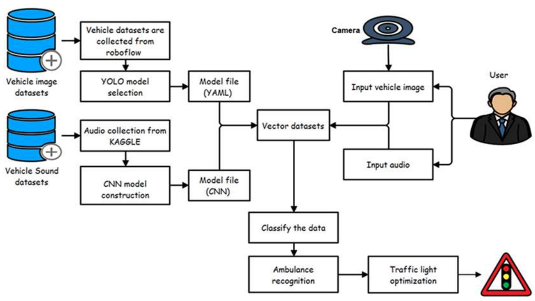

Fig. 1 System Architecture

At the same time, the audio sensor captures surrounding sounds and detects ambulance sirens using acoustic signal analysis. If both visual detection and siren detection confirm the presence of an emergency vehicle, the traffic signal controller automatically changes the signal to green for that lane to allow the ambulance to pass. After the emergency vehicle crosses the intersection, the traffic signal returns to the normal operation cycle.

1. Data Acquisition and Preprocessing

Traffic Data Collection: The system collects real-time traffic video using cameras installed at road intersections. The captured data includes vehicles moving in different lanes.

Reading Data: The captured video frames are given as input to the system for vehicle detection and analysis.
Data Formatting: The collected frames are converted into a suitable format so that they can be processed by deep learning models.
Data Preprocessing: Image preprocessing techniques such as resizing, noise removal, and frame extraction are applied to improve image quality and detection accuracy.

2. Vehicle Detection and Analysis

Vehicle Detection: The system uses the **YOLOv5 object detection algorithm** to identify vehicles such as cars, buses, trucks, and ambulances from the captured frames.
Vehicle Identification: The detected vehicle regions are further analyzed to identify whether the vehicle is an ambulance.

3. Model Processing and Traffic Control

Deep Learning Detection Model: The system uses YOLOv5 for real-time vehicle detection and CNN for ambulance classification.
Emergency Vehicle Detection: The system also detects ambulance siren sounds using acoustic signal analysis to confirm emergency vehicle presence.
Traffic Signal Control: When an ambulance is detected, the system automatically changes the traffic signal to **green** for that lane to allow the vehicle to pass quickly.

III. RESULT AND DISCUSSION

The proposed system was tested using traffic video samples containing various vehicles including ambulances. The YOLO object detection model successfully detected vehicles in real time with high accuracy. The CNN classification module improved the accuracy of identifying ambulances from other vehicles. The acoustic detection module effectively detected ambulance sirens and confirmed the presence of emergency vehicles. The experimental results showed that the system can quickly detect ambulances and change traffic signals accordingly. This significantly reduces waiting time at intersections and improves emergency response efficiency. Compared with traditional traffic signal systems, the proposed system provides faster response, better accuracy, and improved traffic management.

Output

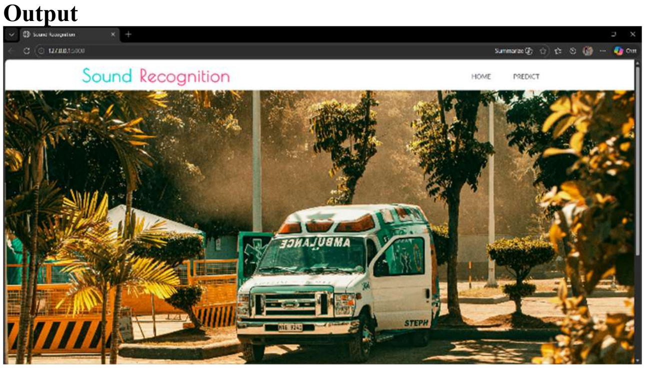

Fig. 2 System Web Interface for Ambulance Detection

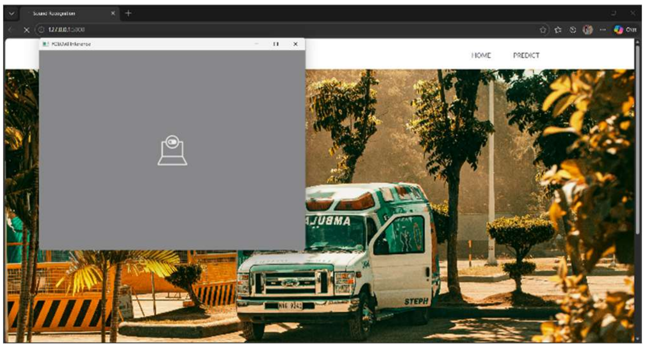
Fig. 3 Camera Initialization for Traffic Monitoring

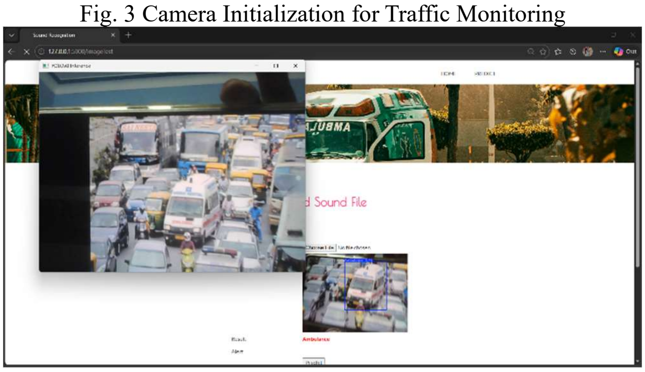
Fig. 4 Detecting Ambulance

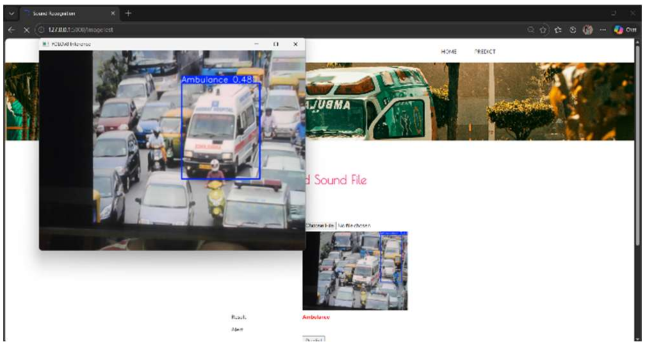
Fig. 5 Real-Time Ambulance Detection Using YOLO

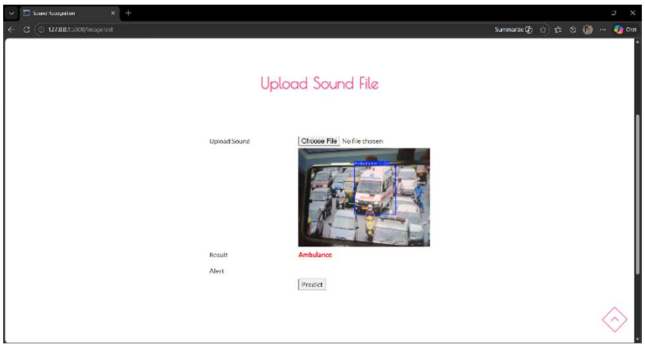

Fig. 6 YOLO Detection Window with Ambulance Identification

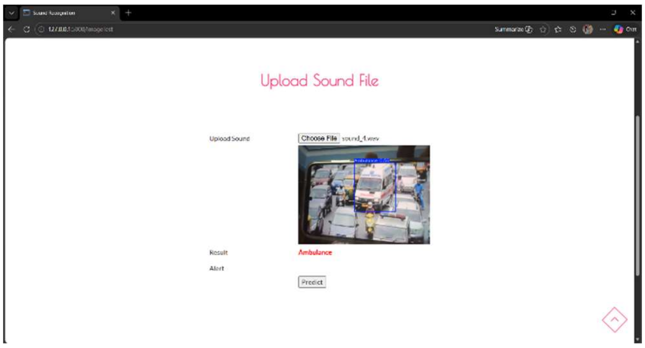

Fig. 7 Sound File Upload and Detection Result

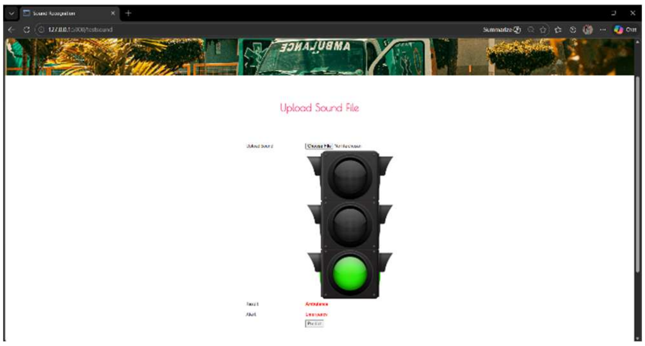

Fig. 8 Automatic Traffic Signal Control Output

Model Testing Performance

The YOLO object detection model was trained using the Python deep learning environment and the PyTorch framework. During training, the model learned important visual features such as vehicle shape, ambulance markings, and emergency vehicle patterns from traffic images. The model performance was evaluated using detection accuracy, precision, recall, and F1-score.

Testing Results

TABLE I
MODEL TESTING RESULTS

Metric	Value
mAP@0.5	0.85
Precision	0.94
Recall	0.74
F1 Score	0.83

Confusion Matrix

The confusion matrix presents the classification results of the ambulance detection model by comparing predicted labels with actual labels. It provides a clear visualization of correct detections and misclassifications. The matrix indicates that most ambulance instances were correctly identified by the model, while a smaller number of samples were misclassified as background objects. This analysis helps evaluate the reliability and effectiveness of the proposed detection system.

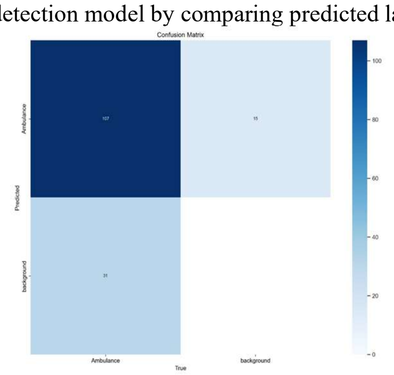

Fig. 9 Confusion Matrix of the Proposed Model

Dataset Distribution and Bounding Box Analysis

The dataset visualization illustrates the distribution of labeled ambulance instances used for training the detection model. The plots show the spatial distribution of bounding boxes in terms of object position (x and y coordinates) and size (width and height). The scatter plots indicate that ambulance objects appear in different positions and scales across the images, providing sufficient variation for model training. This diverse distribution helps the model learn generalized features and improves its ability to detect ambulances under different traffic conditions.

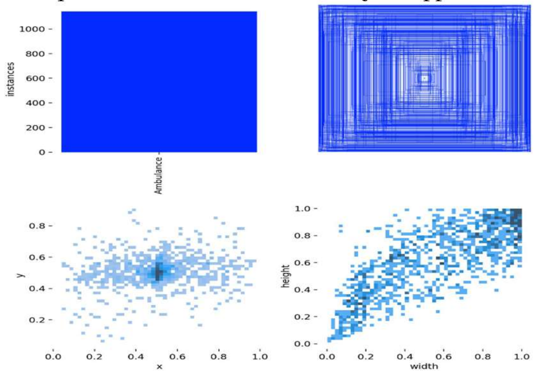

Fig. 10 Dataset Label Distribution and Bounding Box

Training Performance Metrics

The training results demonstrate a continuous improvement in the performance of the proposed ambulance detection model. As the training process progresses across multiple epochs, the loss values gradually decrease, indicating that the model is effectively learning important visual features from the dataset. These features include vehicle structure, ambulance markings, emergency lights, and other distinguishing characteristics present in traffic images. At the same time, the precision and recall metrics show steady improvement, which means the model becomes more accurate in detecting ambulance instances while reducing false detections. The increase in mean Average Precision (mAP) further confirms that the model achieves better object detection capability as training continues. Overall, the training graphs illustrate that the proposed deep learning model successfully learns meaningful patterns from the dataset and improves its detection accuracy and reliability over time.

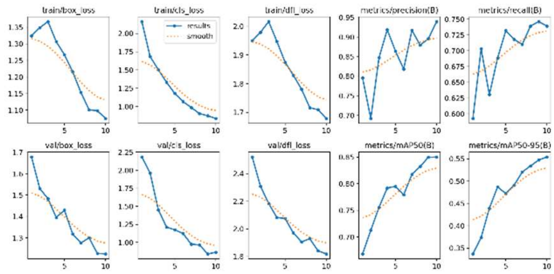

Fig. 11 Training Results of the Proposed YOLO Model

IV. CONCLUSION

This project presents an intelligent traffic light control system for emergency vehicle identification using computer vision and acoustic signal analysis. The system uses YOLO for real-time vehicle detection and CNN for accurate classification. In addition, acoustic signal detection is used to identify ambulance sirens.The proposed system can automatically provide priority to emergency vehicles by controlling traffic signals at intersections. This reduces delays for ambulances and improves emergency response time. The system can be integrated into smart city infrastructure for better traffic management and public safety.In the future, the system can be enhanced by using more advanced deep learning models and integrating it with IoT-based traffic monitoring systems.

V. FUTURE ENHANCEMENT

In the future, the proposed system can be improved by using a larger dataset to increase the accuracy of ambulance detection in different traffic conditions. Advanced deep learning models can also be implemented to enhance detection speed and performance. The system can be integrated with IoT-based smart traffic management systems to enable communication between multiple traffic signals in a city. Additionally, the system can be extended to detect other emergency vehicles such as fire trucks and police vehicles to improve overall emergency response and traffic management.

VI. REFERENCES

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