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Detection and Classification of Emergency Vehicles using Deep Learning

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***Abstract*—Emergency vehicle detection plays a critical role in ensuring safe, efficient, and sustainable transportation within modern urban environments. Unfortunately, delays in their response times can have significant consequences. This project proposes a novel approach to address this challenge by leveraging state-of-the-art deep learning techniques for emergency vehicle detection within an Intelligent Transportation Management System (ITMS) framework. The proposed system utilizes a two-step approach. First, it employs the You Only Look Once (YOLO) algorithm, a real-time object detection system, to identify and localize vehicles captured by traffic surveillance cameras. This allows the system to isolate vehicles within the image data for further analysis. Following vehicle detection, the system performs classification using three deep learning architectures: MobileNet, EfficientNet, and ResNet. Each of these models will be evaluated to determine its effectiveness in accurately and efficiently classifying vehicle types, with a particular focus on identifying emergency vehicles. By comparing the performance of these models, the project will identify the optimal choice for real-world implementation within the ITMS. Finally, to further enhance the chosen classification model's performance, the project will utilize the Adam optimizer. This optimizer offers improved convergence behavior and robustness compared to traditional methods, leading to a more accurate and reliable system.**

***Index Terms*—ITMS, YOLO, MobileNet, EfficientNet, ResNet, Adam optimizer.**

I. INTRODUCTION

In today's increasingly crowded urban areas, effectively managing emergency vehicles is crucial for public safety and quick response to critical situations. However, accurately detecting and prioritizing these vehicles amidst modern traffic complexities is a significant challenge. To tackle this issue, our project focuses on utilizing advanced technology to create a reliable system for detecting and classifying emergency vehicles.

Our approach centers on transfer learning, a powerful technique that allows us to adapt cutting - edge deep learning models like YOLO (You Only Look Once) for the specific task of identifying emergency vehicles. By enhancing pre-trained models with our annotated dataset containing various vehicle images, we can fine-tune the models to recognize emergency vehicles with high precision.

The impact of this project goes beyond simple vehicle recognition. By seamlessly integrating our system into existing traffic management systems, we can transform how emergency vehicles navigate through city streets. Traffic signals can adjust dynamically to clear the path for approaching emergency vehicles, reducing response times and potentially saving lives.

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Additionally, our system provides crucial support to law enforcement agencies by offering real-time insights into vehicle movements. This enables proactive measures for enhancing public safety, including advanced surveillance capabilities and efficient suspect tracking. With these tools, law enforcement can address security concerns more effectively and maintain order in urban areas.

II. RELATED WORKS

[1] introduces a model designed to efficiently detect sirens on vehicles using the YOLO architecture, thereby enhancing the identification of emergency vehicles regardless of their shape. This approach effectively reduces false positives and false negatives that often occur when non-emergency vehicles closely resemble emergency ones. The model is trained on the COCO dataset, which consists of 6,776 original images expanded to 17,288 through augmentation. [1] aims to minimize false positives and false negatives in emergency vehicle detection, achieving a training accuracy of 77.1% and a mAP 50:95 of 0.42.

In [2], a model using YOLO-v3 is designed for vehicle detection, categorizing vehicles within images as Cars, Bikes, or Trucks while noting accuracy for each class. Additionally, the model calculates the speed of each detected vehicle and its proximity to nearby vehicles.

This information is used to alert the driver and nearby traffic police to potentially reduce speed. Trained on the Vehicle Detection dataset from Kaggle, which includes 7,036 training images and 1,760 testing images, the model achieves an average accuracy of 82.5%.

[3]presents a vehicle detection model designed to identify a wide variety of vehicle types specific to Indian roads, including ambulances, auto-rickshaws, bicycles, buses, cars, garbage vans, human haulers, minibuses, minivans, motorbikes, pickups, army vehicles, police cars, rickshaws, scooters, SUVs, taxis, three-wheelers (CNG), trucks, vans, and wheelbarrows. The purpose of the model is to detect these vehicles, compile traffic counts, and assist in making decisions at traffic signals.

[4]presents a Traffic Control System integrating Internet of Things (IoT) technology and computer vision. Its aim is to optimize traffic signal durations to minimize vehicle waiting times and, subsequently, decrease greenhouse gas emissions. The mean Average Precision (mAP) values of both the standard YOLOv3-tiny model and a custom detector are compared across all classes, including the Car class and Emergency class. The proposed algorithm reduces signal wait times by 50%, leading to enhanced throughput.

In [5], the implementation is divided into two stages. Initially, YOLOv4 is utilized to detect vehicles in the image. Subsequently, these detected vehicles serve as regions of interest, which are then classified into emergency and non- emergency categories by a CNN. The model achieves an average accuracy of 82.03% on the Emergency Vehicle Identification v1 dataset.

In [6], a classification model is developed to distinguish between emergency and non-emergency vehicles using vehicle color. It employs a CNN based on the VGG-16 architecture. The model is trained on a dataset of 1,400 images, divided equally among four classes—Ambulance, Firetruck, Standard Car, and Police Car—with each category having 350 images. The model reports an accuracy of 95%. [7]presents a comparative analysis of three CNN classifiers: MobileNet, ResNet, and InceptionNet. The study uses the Indian Driving Data, developed collaboratively by IIIT Hyderabad and Intel Bangalore, focusing on a subset of 13,000 images that capture various perspectives including front far, front near, rear near, side left, and side right. The performance of each model is assessed in terms of Mean Average Precision and Classification Time Complexity, with detailed tabular comparisons for different versions of each classifier. The results demonstrate that the Faster RCNN ResNet50 model excels in both mAP and computational efficiency, outperforming the other models.

III. PROPOSED MODEL

The model is designed to fulfill a crucial role in an Intelligent Transportation Management System, focusing on vehicle detection and classification. It specifically aims to precisely identify emergency vehicles while ensuring minimal computation time. Ambulances and Firetrucks are considered as emergency vehicles.

Tailored to monitor vehicles approaching a traffic signal or intersection, the model employs YOLOV8 for vehicle detection. It distinguishes between emergency and non-emergency vehicles using three separate CNN models: ResNET, EfficientNET, and MobileNET. The performance of these models is evaluated by comparing their Mean Average Precision values and the computation times required for each [7].

A. YOLOV8

Vehicle detection in our system is conducted using a YOLO model [1][5] due to its high accuracy and reasonable speed.

Given the constant computation demands of real-time traffic management, the YOLOv8n model, the smallest variant of YOLOv8, is particularly suitable for our needs. This model has only 3.2 million parameters, significantly fewer than the
25.9 million parameters of the full YOLOv8, making it more efficient for our application [1]. The architecture of YOLOv8 utilizes a deeper and wider network compared to earlier versions, enabling it to detect objects with higher precision across various scales.
In our system, the model is trained to recognize a diverse range of vehicle classes including cars, buses, motorcycles, bicycles, trucks, ambulances, police cars, and fire trucks. This breadth in classification allows the system to process complex urban traffic scenarios effectively.

B. Convolutional Neural Networks

The proposed system uses the following Convolutional Neural Network models for classification of emergency vehicles

ResNet
ResNet50 is a 50-layer version of the ResNet architecture that uses residual learning to prevent vanishing gradients, enabling deeper network training. It balances complexity and performance, offering higher accuracy than ResNet34 and being less demanding than ResNet101 or ResNet152, making it popular for diverse applications.

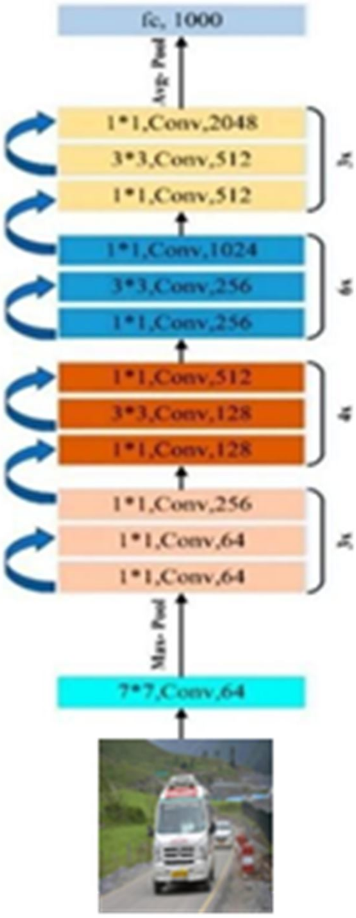

Fig. 2. ResNet50 Model Architecture

EfficientNet
EfficientNetB0 is the baseline model of the EfficientNet family, featuring 5.3 million parameters and using a compound scaling method to balance network depth, width, and resolution. It offers a good trade-off between accuracy and computational efficiency, making it ideal for various applications without the high resource requirements of larger models like EfficientNetB7.

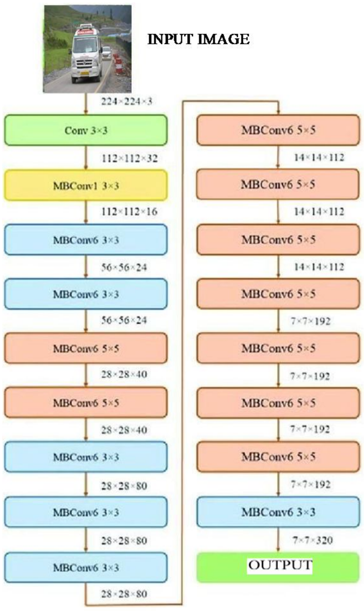

Fig. 3. EfficientNetB0 Model Architecture

MobileNet

MobileNetV2 is a lightweight deep learning model with 3.4 million parameters, optimized for mobile and embedded vision tasks. It incorporates inverted residuals and linear bottlenecks, boosting performance and efficiency compared to MobileNetV1. This design provides a better balance of accuracy and speed, making MobileNetV2 superior for resource-constrained environments compared to its predecessors.

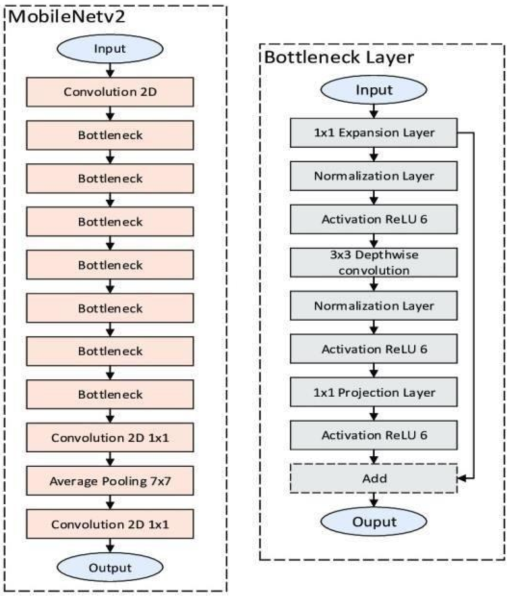

Fig. 4. MobileNetV2 Model Architecture

IV. DATASET COLLECTION

The dataset is sourced from various projects on Roboflow, specifically focusing on vehicles approaching a traffic signal. To match this scenario, images from several Roboflow projects were selected and labeled. The dataset includes multiple vehicle classes: AMBULANCE, AUTO_B, AUTO_F, BICYCLE_B, BICYCLE_F, BUS_B, BUS_F, CAR_B, CAR_F, FIRETRUCK, MOTORBIKE_B, MOTORBIKE_F, POLICECAR, SIREN [1], TRUCK_B, TRUCK_F, and person. Each vehicle class's front and back profiles are distinctly annotated as “vehicle name_F” and “vehicle name_B” respectively. The system's focus will be solely on vehicles facing forward.

Fig. 1. Images for Ambulance, Police car, Fire truck and Regular Vehicles from Collected Dataset

V. IMPLEMENTATION

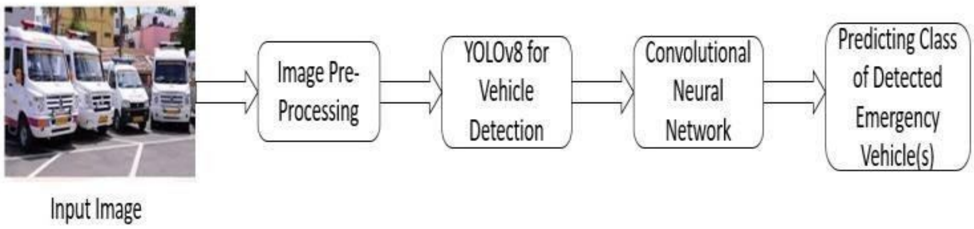

Fig. 5. Proposed Workflow

A. Vehicle Detection

Utilizing the highly accurate YOLOv8 algorithm, vehicles in a traffic scenario image are detected, focusing specifically on their front profiles. If the front profile of a truck, "TRUCK_F" or an ambulance is detected during this process, the corresponding image section is cropped along its bounding box and processed in the second phase of implementation.

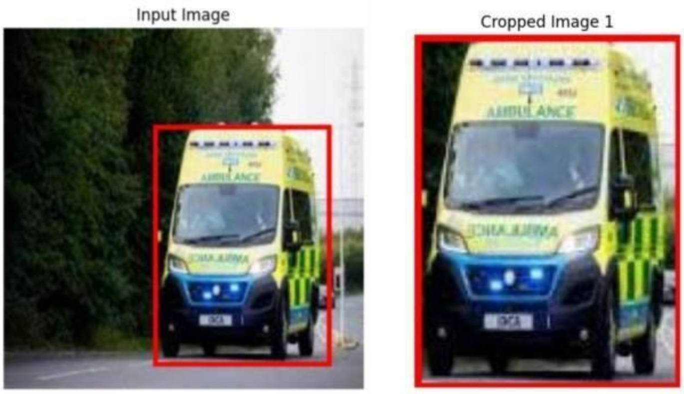

Fig. 6. Emergency Vehicle Cropped after Object Detection, Fed into CNN for Further Classification

B. Emergency Vehicle Classification

In this phase, the vehicle in the cropped image is classified to determine its specific emergency class. This workflow aims to enhance the accuracy of classifying vehicles by correctly identifying their actual class and avoiding misclassification of non-emergency vehicles like police cars. If neither a truck nor an ambulance is detected, no further action is taken. In real- time applications, detecting an emergency vehicle can trigger a response in the Intelligent Transportation Management System.

VI. RESULTS AND DISCUSSIONS

The training for YOLOV8n model resulted in 67.9% mAP, precision of 81.5% and recall score of 60.4%.

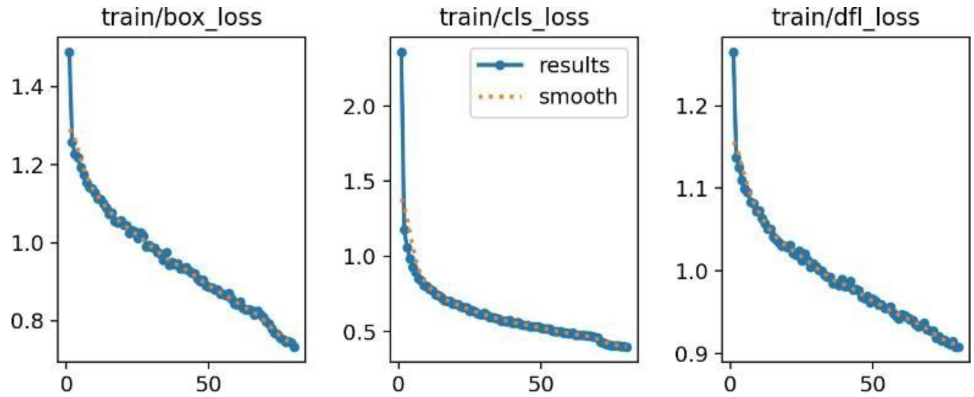

Fig. 7. Evolution of Training Loss vs. Epochs

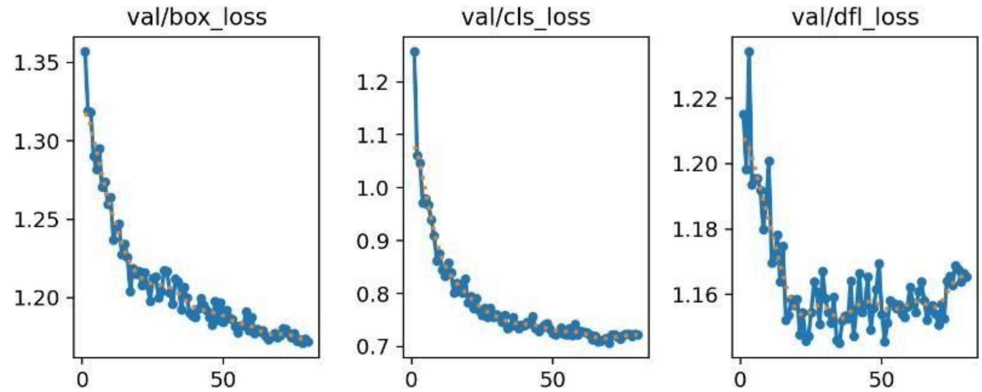

Fig. 4. Evolution of Validation Set Loss vs, Epochs

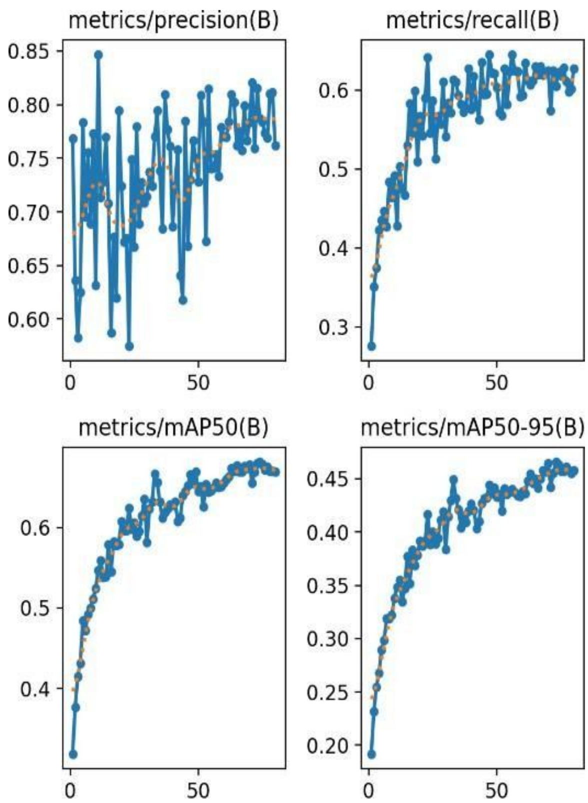

Fig. 5. Evolution of Precision, Recall and mAP vs. Epochs

Fig. 6. Different Classes of Vehicles Detected by Yolov8

In the second stage the following results are observed on implementing the classifiers on the dataset,

TABLE I. CLASSIFICATION METRICS, MAP AND TIME TAKEN BY MODELS

Model	Average Precision	Average Recall	Average F1 score	Mean average precision (mAP)	Classification Time (in sec)
ResNet	65	65	65	54	2.09
Efficient Net	70	70	70	60	2.18
Mobile Net	62	62	62	51	0.94

VII. CONCLUSION

In conclusion, our proposed model successfully detects emergency vehicles in traffic scene images, achieving satisfactory accuracy levels. However, as the model requires cropping the vehicle of interest during the transition from vehicle detection to vehicle classification, the quality of the images is crucial for the model's optimal performance.

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