Emergency Vehicle Detection using Deep Learning

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Abstract

Emergency vehicle detection in heavy traffic can be challenging due to the presence of multiple vehicles and occlusions. However, using deep learning and computer vision techniques, we can develop an effective solution to this problem. The traffic congestion leads to high impact for emergency vehicles to pass by the particular road. The congestion can be deleted by many ways where in the video analytics-based detection and give more accuracy and able to count the type of vehicle in the particular traffic signals. The early detection of emergency vehicle in the particular signal can be avoid delay in transition. To overcome this problem, the proposed model that detects the emergency vehicle in the signal and pass the information to the signal regulating authorities to green corridor can be generated have on the information extracted from the video signals. One approach is to use a deep Convolutional Neural Network (CNN) to classify emergency vehicles in the video feed. CNNs are well-suited for image-based classification tasks and have shown promising results in object detection and recognition. To implement this approach, we can start by collecting a dataset of images or videos containing emergency vehicles in heavy traffic. The dataset should include a variety of scenarios with different lighting conditions, vehicle types, and traffic densities. The dataset is gathered and the model constructed with the cnn xception architecture. The RMSprop optimizer is used which is similar to the gradient descent algorithm with momentum. The RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase our learning rate and our algorithm could take larger steps in the

horizontal direction converging faster. For object recognition with a CNN, we freeze the early convolutional layers of the network and only train the last few layers which make a prediction with transfer learning. Finally, using Flask framework and CNN Xception architecture with RMSprop optimizer and transfer learning, we can develop a model that can detect emergency vehicles in traffic signals and generate green corridors for them, thus reducing the delay in transition and improving the efficiency of emergency services.

Keywords: *Vehicle detection, Xception model, Heavy Traffic analysis , Vehicle Datasets, Deep learning.*

INTRODUCTION

Emergency vehicle detection in heavy traffic is a critical problem in public safety. When emergency vehicles such as ambulances, fire trucks, or police cars need to navigate through busy roads, it can be challenging for drivers to notice them quickly, potentially leading to delays in response times and endangering lives. In recent years, deep ConvNets and computer vision have shown tremendous success in detecting objects in images and videos. These technologies can be leveraged to create an automated emergency vehicle detection system that can quickly and accurately identify emergency vehicles in heavy traffic scenarios. The system would require a dataset of images and videos that includes emergency vehicles in different traffic conditions. Deep ConvNets could be trained on this dataset to learn features that distinguish emergency vehicles from other objects in the scene. Computer vision algorithms could then be used to track the detected vehicles across frames and alert drivers in real-time. An emergency vehicle detection system based on deep ConvNets and computer vision could significantly improve the response times of emergency vehicles and reduce the risk of accidents in heavy traffic scenarios. Deep Convolutional Neural Networks (ConvNets) are a type of deep learning model that has revolutionized object detection in computer vision. ConvNets learn to recognize features of objects in an image by analyzing the image at different levels of abstraction, from simple edges and textures to more complex shapes and patterns. In emergency vehicle detection, ConvNets can be trained on a large dataset of images and videos that include emergency vehicles in different traffic conditions. The ConvNet can learn to recognize the unique features of emergency vehicles, such as their shape, color, and flashing lights. Once the ConvNet is trained, it can be used to detect emergency vehicles in real-time videos. The system can analyze each frame of the video and identify the location of emergency vehicles using bounding boxes. Computer vision algorithms can then be used to track the detected vehicles across frames and alert drivers in real-time. Overall, deep learning-based emergency vehicle detection systems have the potential to significantly improve response times for emergency vehicles and reduce the risk of accidents in heavy traffic scenarios.

1.1 Research Challenges

In a scenario consisting of more than one object, there are multiple objects moving at different speeds, in different directions, and with different sizes. These objects can include other vehicles, pedestrians, and cyclists, making it challenging to distinguish emergency vehicles from other objects. Emergency vehicle detection needs to work in low visibility conditions, such as fog, rain, or at night. This requires the use of advanced sensors and algorithms that can operate in such conditions.

1.2 Objective

The objective of this project is to identify emergency vehicles such as ambulances, firetrucks, and police cars in real-time is crucial for ensuring public safety and enabling emergency responders to arrive quickly at the scene of an emergency. One effective way to achieve this is by using computer vision techniques and deep learning algorithms.An emergency vehicle detection system based on deep ConvNets and computer vision could significantly improve the response times of emergency vehicles and reduce the risk of accidents in heavy traffic scenarios. Deep Convolutional Neural Networks (ConvNets) are a type of deep learning model that has revolutionized object detection in computer vision. ConvNets learn to recognize features of objects in an image by analyzing the image at different levels of abstraction, from simple edges and textures to more complex shapes and patterns.

Once the ConvNet is trained, it can be used to detect emergency vehicles in real-time videos. The system can analyze each frame of the video and identify the location of emergency vehicles using bounding boxes. Computer vision algorithms can then be used to track the detected vehicles across frames and alert drivers in real-time. The system should operate in real-time with low latency, to enable timely responses to emergency situations.

Overall, deep learning-based emergency vehicle detection systems have the potential to significantly improve response times for emergency vehicles and reduce the risk of accidents in heavy traffic scenarios. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

1.3 Scope of the project

The proposed system monitors a specific area and captures images at regular intervals. The image that has been captured is segmented so that all objects in a given frame are extracted, the extracted image is then fed into the deep learning model that identifies the object and returns the label of the object being identified ensuring the safety of drivers and pedestrians on the road. Deep learning models have shown promising results in identifying and detecting emergency vehicles from video footage. Deep learning models, such as Convolutional Neural Networks (CNNs), can learn features from images and videos that help them distinguish between emergency vehicles and other types of vehicles. These models can be trained on large datasets of labeled images and videos of emergency vehicles to improve their accuracy.

I. EXISTING SYSTEM

This work investigates how to detect emergency vehicles such as ambulances, fire engines, and police cars based on their siren sounds. Recognizing that car drivers may sometimes be unaware of the siren warnings from the emergency vehicles, especially when in-vehicle audio systems are used, we propose to develop an automatic detection system that determines whether there are siren sounds from emergency vehicles nearby to alert other vehicles' drivers to pay attention.

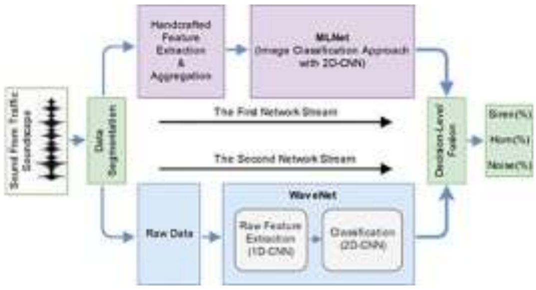


Fig 2.1

A convolutional neural network (CNN)-based ensemble model (SirenNet) with

two network streams is designed to classify sounds of traffic soundscape to siren sounds, vehicle horns, and noise, in which the first stream (WaveNet) directly processes raw waveform, and the second one (MLNet) works with a combined feature formed by MFCC (Mel-frequency cepstral coefficients) and log-mel spectrogram. The experiments conducted on a diverse dataset show that the raw data can complement the MFCC and log-mel features to achieve a promising accuracy of 98.24%.

The primary method applied to this work is audio recognition based on convolutional neural networks (CNN). In terms of data processing, we can roughly divide the techniques used in audio recognition into two broad categories: the first one generally applies audio feature engineering techniques to extract useful features in time-domain and/or frequency-domain before performing the recognition task, the second one is to take full advantage of deep neural networks to build an end-to-end recognition system which learns features directly from raw waveforms rather than extracting handcrafted features.

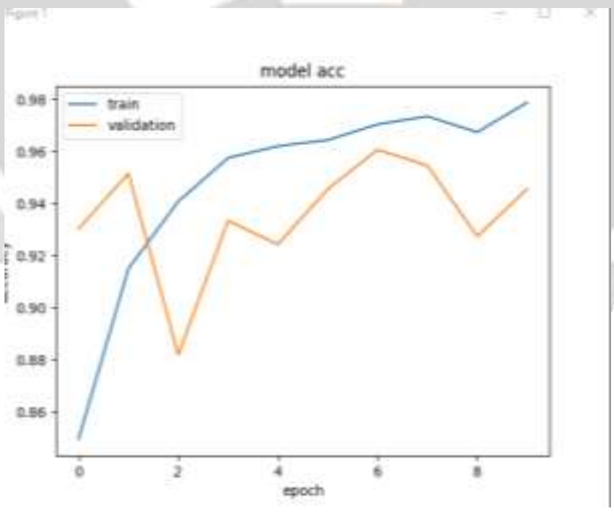
In this work, the idea is to apply both approaches and examine if it is possible to boost the system accuracy by aggregating models of these two approaches, in other words, we also examine if the features extracted by the deep neural network itself can complement the handcrafted features in dealing recognition task or not.

II. PROPOSED SYSTEM

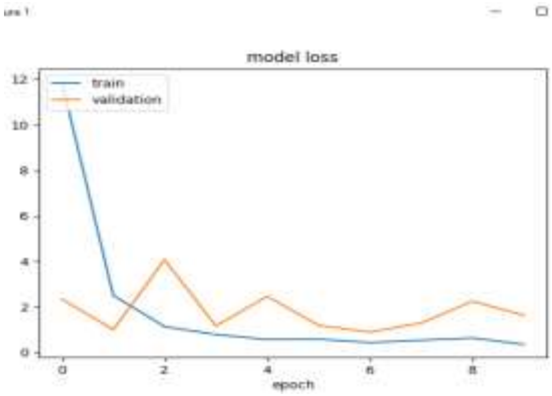
In proposed system, the first step is to collect a dataset of images containing emergency vehicles, such as ambulances, police cars, and fire trucks. This dataset should be diverse and representative of different scenarios and lighting conditions. The next step is to preprocess the data by resizing the images to a uniform size, normalizing the pixel values, and splitting the dataset into training and testing sets. Data augmentation techniques, such as rotation, scaling, and flipping, can also be applied to increase the diversity of the training data and prevent overfitting. The Xception model, which is a deep convolutional neural network designed for image classification, can be used as a pre-trained model for emergency vehicle identification. Transfer learning involves reusing the weights and architecture of a pre-trained model and fine-tuning them on a new task. In this case, the Xception model can be fine-tuned on the emergency vehicle identification task by replacing the final classification layer with a new one that outputs the probability of each class.

Fig 2.1

Once the model is trained, it can be tested on the held-out testing set to evaluate its performance. The testing set should contain images that are not seen during the training process to ensure that the model can generalize to new data. After testing, the model can be used to make predictions on new images of emergency vehicles. The input image is fed into the model, which outputs the probability of each class. The class with the highest probability is considered the predicted class of the image. The dataset should include a variety of scenarios with different lighting conditions, vehicle types, and traffic densities. The dataset is gathered and the model constructed with the CNN xception architecture. The RMSprop optimizer is used which is similar to the gradient descent algorithm with momentum. The RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase our learning rate and our algorithm could take larger steps in the horizontal direction converging faster.For object recognition with a CNN, we freeze the early convolutional layers of the network and only train the last few layers which make a prediction with transfer learning. Finally, using Flask framework and CNN Xception architecture with RMSprop optimizer and transfer learning, we can develop a model that can detect emergency vehicles in traffic signals and generate green corridors for them, thus reducing the delay in transition and improving the efficiency of emergency services.



The above accuracy plot described shows that the model has a high training accuracy and a slightly lower validation accuracy. This suggests that the model may be overfitting to some extent, but it is still able to generalize well to new data. The above accuracy plot described shows that the model has a high training accuracy and a slightly lower validation accuracy. This suggests that the model may be overfitting to some extent, but it is still able to generalize well to new data.



The above figure shows the training loss is very low at 0.3, while the validation loss is relatively high at 1.5%, the model has a low training loss but a high validation loss, indicating that the model is overfitting to some extent. The plot can be used to monitor the performance of the model during training and to make decisions about whether to adjust the model's architecture or training parameters to improve its performance on new data.

Implementation Details-Prerequisites

Environment	Anaconda-Jupyter Notebook
Languages	Python 3
Packages	**Numpy, Tensorflow, Pandas, Matplotlib, Sklearn, Tdqm, Flask,OS, Librosa, Cv2**
Dataset	Emergency Vehicles - Kaggle

III. RESULTS AND DISCUSSION

The upgraded model with image segmentation performs multiple object detection overcoming the issue of the existing model which works effectively only in the cases of single object detection. Flexibility to identify all the objects and detection percentage are improved significantly.

IV. IMPLEMENTATION & SCREENSHOT

Fig 4.1

The figure 4.1 above is the output prediction figure would be a visual representation of the results of the model's predictions. The figure shows an image captured by a camera, which has been submitted by a user to the system for prediction. The system has identified the image as containing an emergency vehicle. The label "Emergency Vehicle" is also displayed above indicating the type of object that has been detected.

Fig 4.2

The figure 4.2 is the output prediction figure would be a visual representation of the results of the model's predictions. The figure shows an image captured by a camera, which has been submitted by a user to the system for prediction. The system has identified the image as containing an emergency vehicle. The label "Non Emergency Vehicle" is also displayed above indicating the type of object that has been detected.

V.CONCLUSION AND FUTURE WORK

5.1 Conclusion

In conclusion, using the Xception model for emergency vehicle detection in combination with the Flask framework provides a powerful and user-friendly system for quickly and accurately detecting emergency vehicles from images. The Xception model is a state-of-the-art deep learning model that has been shown to be effective in detecting objects in images, including emergency vehicles.

5.2 Future Work

By integrating the Xception model with the Flask framework, we can create a web application that allows users to submit images and receive near-instant feedback on whether the image contains an emergency vehicle. This can be particularly useful in emergency situations, where a quick response time is crucial. The Flask framework provides a lightweight and flexible web application framework that is easy to use and deploy. By using Flask, we can create a web application that is user-friendly, responsive, and scalable. This allows us to easily deploy the system to multiple locations and handle large volumes of traffic.

VI. REFERENCES

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