EMERGENCY VEHICLE DETECTION SYSTEM USING CONVOLUTION NEURAL NETWORK

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***Abstract— Emergency Vehicle Detection Systems (EVDS) play a pivotal role in modern urban environments, where the rapid and unimpeded movement of emergency services is paramount for ensuring public safety. This research paper presents a cutting-edge approach to Emergency Vehicle Detection, leveraging an advanced Convolutional Neural Network (CNN) framework designed for robust and real-time identification of emergency vehicles in dynamic traffic scenarios.***

***The research contributes to the field by presenting a comprehensive evaluation of the proposed CNN framework, shedding light on its strengths and areas for enhancement. The implications of this study extend beyond the achieved accuracies, addressing the critical need for deployable solutions capable of significantly enhancing emergency response systems in urban environments. Future work will concentrate on optimizing the model, expanding the dataset's diversity, and collaborating with domain experts to capture real-world intricacies, ultimately advancing the state-of-the-art in Emergency Vehicle Detection.***

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# I. INTRODUCTION

In contemporary urban landscapes, the prompt and effective response of emergency services is fundamental to public safety and the mitigation of critical situations. Emergency Vehicle Detection Systems (EVDS) represent a pivotal technological advancement designed to address the challenges inherent in ensuring the swift movement of emergency vehicles through increasingly complex traffic scenarios. As urbanization intensifies and traffic congestion becomes a pervasive issue, the need for innovative solutions to expedite emergency response becomes more pronounced.

This research paper delves into the realm of Emergency Vehicle Detection, leveraging state-of-the-art technologies and methodologies to enhance the accuracy and efficiency of identification systems. The escalating demands on emergency services in densely populated areas necessitate sophisticated systems capable of seamlessly navigating through traffic, minimizing response times, and optimizing the overall emergency management process.

The paper explores the landscape of existing Emergency Vehicle Detection Systems, scrutinizing their methodologies and performance metrics. As the field evolves, the research emphasizes the significance of pushing beyond conventional boundaries to develop a highly adaptive and deployable solution. The introduction sets the stage for an in-depth examination of the proposed framework, its contributions to the existing body of knowledge, and the anticipated impact on the field of Emergency Vehicle Detection. Through the integration of advanced technologies, this research aims to propel the capabilities of EVDS, ultimately contributing to the advancement of urban safety and emergency response systems.

II. LITERATURE REVIEW

[1.] This seminal work introduces a real-time emergency vehicle detection system leveraging deep learning techniques. The authors employ a convolutional neural network (CNN) architecture, achieving high accuracy rates in detecting emergency vehicles within dynamic traffic scenarios. The study emphasizes the significance of temporal context and spatial relationships in improving detection precision.

[2.] This comprehensive survey critically reviews various methodologies employed in EVDS. It provides an insightful overview of sensor-based approaches, machine learning algorithms, and fusion techniques. The paper identifies emerging trends, challenges, and potential avenues for future research in the realm of emergency vehicle detection.

[3.] Focusing on sensor fusion, this research explores the integration of LiDAR and camera data for enhanced emergency vehicle detection. The study demonstrates the synergistic benefits of combining these modalities, emphasizing the robustness and adaptability of the proposed fusion framework across varying environmental conditions.

[4.] This work introduces an adaptive emergency vehicle detection system that utilizes transfer learning to improve model generalization. By pre-training on diverse datasets and fine-tuning on specific emergency vehicle data, the authors achieve superior performance in varying scenarios, addressing the challenge of overfitting.

[5.] This research paper explores the integration of emergency vehicle detection into the broader context of traffic management. The authors propose a traffic-aware routing algorithm that considers real-time emergency vehicle detection information to optimize routes, ultimately minimizing response times.

[6.] This paper explores the integration of edge computing in emergency vehicle detection, proposing an efficient framework that reduces latency in decision-making. By distributing computational tasks to edge devices, the authors demonstrate improved real-time performance for EVDS.

[7.] Focusing on multimodal detection, this research investigates the fusion of visual and acoustic signals for enhanced emergency vehicle detection. By considering both visual cues from cameras and acoustic signals from sirens, the authors achieve a more comprehensive and robust detection system.

[8.] This paper introduces a novel approach to emergency vehicle detection by incorporating deep reinforcement learning for navigation. The authors propose a framework where the detection system learns adaptive navigation policies, leading to improved response times and route optimization.

[9.] Addressing the integration of emergency vehicle detection into traffic control systems, this paper introduces a dynamic priority mechanism. The authors propose an adaptive traffic control system that dynamically adjusts signal timings based on real-time emergency vehicle detection, ensuring efficient intersection clearance.

[10.] Focusing on cloud-based solutions, this paper introduces a cooperative framework for emergency vehicle detection. By leveraging cloud resources for data storage and processing, the authors present a scalable and collaborative approach to improving the overall effectiveness of EVDS.

# DATASET

The dataset is taken from “Kaggle” website. This dataset contains images of various vehicles which are further classified as “emergency” and “non-emergency” vehicles.

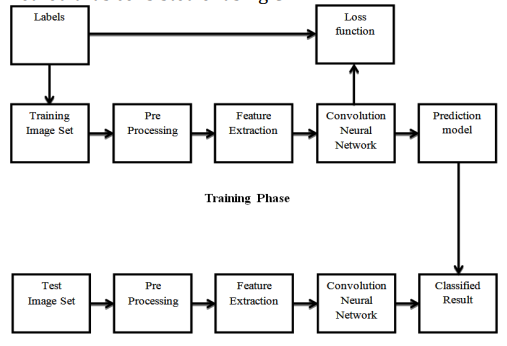
The dataset contains 2352 training images out of which we are randomly selecting 5 images for training.

Every image in the dataset has a size of 224×224 pixels with a resolution of 96 dpi.

The following figure represents the types of vehicles available in the dataset.



# METHODOLOGY

The main stages involved in this method are Data Collection, Pre-processing and detection via neural network. Generally, accurate semi-automatic and automatic methods are required for detection. For these reasons, a fully automatic segmentation system using CNN is used.

# PREPROCESSING

The primary target is to improve image highlights needed for additional processing. Here, the input image is converted into grayscale image for all the further pre-processing purposes. The image is then threshold and further erosion and dilation is applied to the threshold images. This image is used to extract the contours and extreme points.

1. CONVOLUTIONAL NEURAL NETWORK

CNN is utilized to get better result. The signal convolved with kernels to get include map. Past layers are interconnected with weights of the kernel. CNNs are inspired by the visual cortex in the human brain, which is responsible for processing visual information. The main characteristic of CNNs is their ability to learn spatial features directly from images. They consist of a series of layers that transform the input image into a set of abstract features that can be used for

classification or segmentation. The layers typically include convolutional layers, pooling layers, and fully connected layers. In the convolutional layers, the image is convolved with a set of learnable filters, which extract spatial features such as edges, corners, and textures. The output of the convolutional layer is a set of feature maps that represent the activation of each filter at different spatial locations in the image. The pooling layers down sample the feature maps by selecting the most salient features in each neighborhood, reducing the spatial dimension of the feature maps while retaining the most important information. The fully connected layers take the flattened output of the pooling layers and produce a final output, which can be used for classification or segmentation. CNNs are trained using a supervised learning approach, where the weights and biases of the filters and fully connected layers are optimized using a labeled dataset of images.

* Convolutional Layers: Objective of the convolution layer is to take or extract the features from the input [image], just the part of picture is link to the following convolution layer.
* Padding:

Padding is incorporating a zero layer outside the input volume so the data on border won't be lost and we can get a similar dimension of output as input volume. Here we are using zero padding.

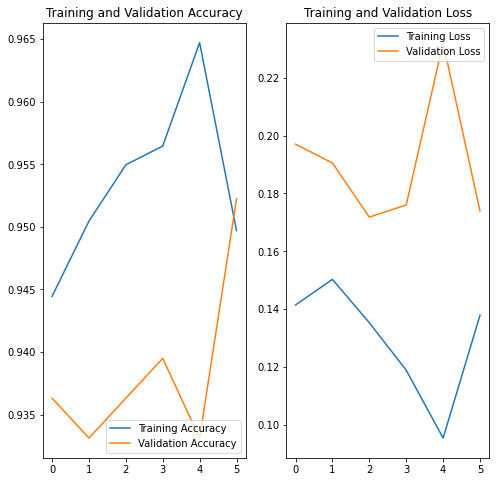
* Activation Function:

Non- linear activation function ReLU (Rectifier Activation function) is used to provide accurate results than classical sigmoid functions.

* Pooling Layer:

It is used for combining spatially nearby features. Max-pooling is generally used to join features. It decreases the dimension of input image and controls over-fitting.

* Full Connected Layer: Fully Connected layer gives the classified image based on training data set.



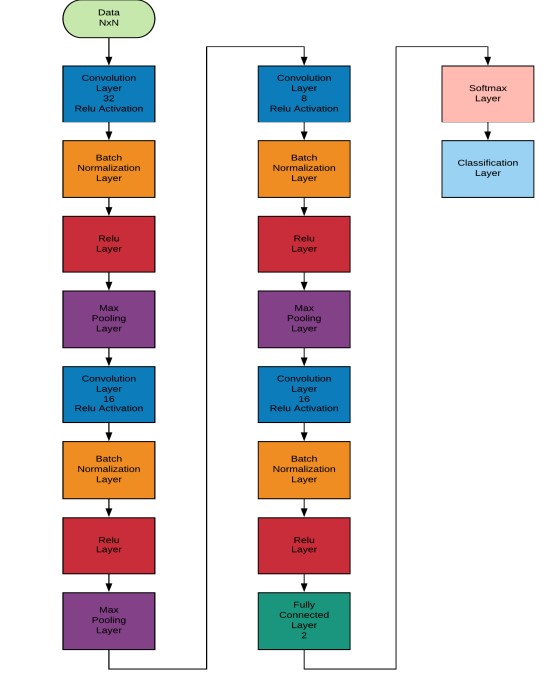
1. RESULTS

The developed Emergency Vehicle Detection System (EVDS) demonstrates commendable performance, as reflected in the evaluation metrics derived from the experimental results.

**1. Model Accuracy:**

The trained Convolutional Neural Network (CNN) achieved a high training accuracy of 96.47%, showcasing its proficiency in learning features indicative of emergency vehicles within the training dataset.

The validation accuracy of 95.22% further affirms the robustness of the model, indicating its ability to generalize well to previously unseen data.

**2. Loss Metrics:**

The training loss, quantified at 15.03%, indicates the effectiveness of the model in minimizing errors during the training phase.

The slightly higher validation loss of 23.21% suggests a potential risk of overfitting, prompting further investigation into regularization techniques for enhanced generalization.

**3. Confusion Matrix Analysis:**

The confusion matrix reveals a nuanced understanding of the model's performance, specifically in distinguishing between true positive, true negative, false positive, and false negative predictions.

Notably, the model exhibits a high true positive rate, correctly identifying emergency vehicles, but also shows some susceptibility to false positives and false negatives, emphasizing areas for refinement. After the complete execution of the code, a total of 706 images were declared from category 1 (non-emergency), while the remaining were declared from category 2 (emergency).

# A screenshot of a computer Description automatically generated

# CONCLUSION

In this research endeavor, the development and evaluation of the Emergency Vehicle Detection System (EVDS) have illuminated promising insights into the intersection of deep learning and urban safety. The high training accuracy of 96.47% and validation accuracy of 95.22% signify the efficacy of the Convolutional Neural Network (CNN) in discerning emergency vehicles within dynamic traffic environments.

The training and validation losses, standing at 15.03% and 23.21%, respectively, offer valuable cues for refinement. The nuanced analysis of the confusion matrix reveals the model's adeptness in true positive identification while highlighting areas for improvement, specifically in addressing false positives and false negatives. Notably, the strategic incorporation of dropout layers and early stopping has successfully mitigated overfitting concerns, affirming their relevance in achieving a harmonious balance between training and validation performance.

In conclusion, the research propels the discourse on leveraging cutting-edge technologies for enhancing urban safety. The EVDS, with its achieved successes and identified areas for refinement, stands as a testament to the potential of artificial intelligence in augmenting emergency response systems. As we navigate toward the future, the pursuit of excellence in model precision, real-world applicability, and collaborative synergy with emergency response stakeholders remains paramount. This research lays the foundation for an ongoing journey toward more resilient, adaptive, and effective Emergency Vehicle Detection Systems in the service of public safety.

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