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EMERGENCY VEHICLES DETECTION WHILE ARRIVAL OF AMBULANCE AND FIRE ENGINE USING MACHINE LEARNING

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Abstract : The "EMERGENCY VEHICLES DETECTION SYSTEM" uses machine learning to quickly detect ambulances and fire engines during an emergency. It uses visual signals from strategically positioned cameras to identify emergency vehicles based on distinguishing characteristics such as flashing lights and sirens. This automatic detection procedure reduces reaction times for emergency personnel, allowing them to get at the situation more swiftly and effectively. The system's user-friendly interface sends real-time updates to emergency responders and other drivers, therefore improving road safety. By limiting human error and improving route planning, technology decreases delays and increases emergency service performance. This novel technique is consistent with existing emergency response strategies that emphasize integrating technology to improve results. Finally, the system contributes to establishing safer communities by permitting faster and timely emergency response times.

***IndexTerms* - Emergency vehicles, detection system, machine learning, response time, user-friendly interface, safety, technology, route planning, effectiveness, community safety.**

I. INTRODUCTION

The "Emergency Vehicles Detection System" uses machine learning to quickly detect ambulances and fire engines during an emergency. It uses visual signals from strategically positioned cameras to identify emergency vehicles based on distinguishing characteristics such as flashing lights and sirens. This automatic detection procedure reduces reaction times for emergency personnel, allowing them to get at the situation more swiftly and effectively. The system's user-friendly interface sends real-time updates to emergency responders and other drivers, therefore improving road safety. By limiting human error and improving route planning, technology decreases delays and increases emergency service performance. This novel technique is consistent with existing emergency response strategies that emphasize integrating technology to improve results. Finally, the system contributes to establishing safer communities by permitting faster and timely emergency response times.In 2013, US fire departments received almost 1.2 million emergency calls, demonstrating the gravity of the situation.

Despite firefighters' speedy reaction times, large property losses of around $11.5 billion are reported each year, along with 15,925 injuries and 3,240 civilian deaths. Every second counts for firemen, and any delays in receiving emergency firefighting services result in several deaths and significant property damage. To solve these issues, traffic management systems must be integrated with intelligent automated technologies to properly prioritize and recognize emergency vehicles. Computer vision approaches, particularly deep learning designs such as deep convolutional neural networks, have produced encouraging results, matching or outperforming the capabilities of human professionals. In this case, a solution is to use road surveillance camera footage to identify emergency vehicles. These cameras take photographs every second, displaying numerous cars on the road.Using image processing techniques, the system can instantly recognize emergency cars and notify traffic police or an automated system to make way for them. While the human brain is good at visual processing, it has limitations, such as the ability to focus for no more than thirty minutes before having a break. In the future, there will be a high demand for artificial intelligence systems to undertake labor-intensive jobs that help to advance civilization.

This research focuses on two major topics: recognizing objects and classifying photos as emergency or non-emergency vehicles. To do this, we use Yolo-V3, a rapid object detection model. Yolo-V3 works swiftly, analyzing up to 45 photos per second on a PC with a strong CPU. It works by partitioning the image into fixed grids and then predicting bounding boxes to determine the likelihood of things appearing within them. This method minimizes the need for complicated processing pipelines, resulting in better detection performance. Post-processing creates bounding boxes after objects are categorized using an R-CNN approach.Yolo outperforms the typical RCNN pipeline in terms of detection time and background errors.

II. PROPOSED METHODOLOGY

2.1. SYSTEM ARCHITECTURE

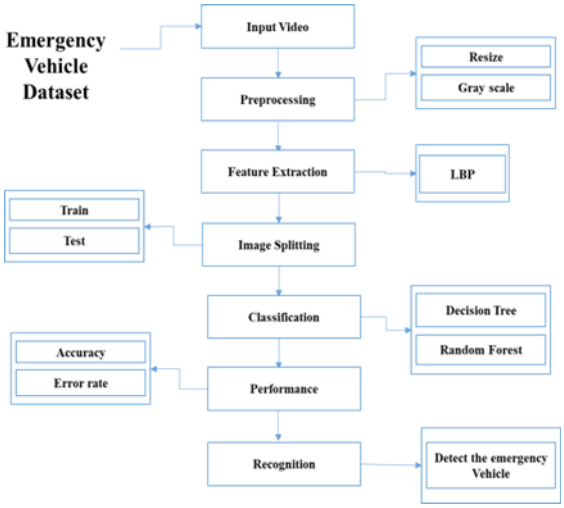

Fig 2.1.1 : System Architecture

Fig 2.1.1 describes the system architecture as follows,

Detecting emergency vehicles during ambulance and fire engine arrivals with machine learning requires many essential stages. Initially, a big collection of photos or videos featuring both emergency and non-emergency cars is gathered. This data is then preprocessed to improve features and minimize noise. Next, a Convolutional Neural Network (CNN) model, a sort of machine learning method, is used to train the system to detect distinctive patterns and characteristics seen in emergency vehicles.During the training phase, the CNN model learns to distinguish between different types of vehicles based on visual cues such as flashing lights and distinguishing forms. Once trained, the model may be implemented on a real-time processing system to continually analyze video feeds from roadside cameras. When an emergency vehicle is identified, the system sends notifications to cars and pedestrians, urging them to clear the way for the vehicle to safely pass.During inference, the trained model examines incoming video feeds from cameras mounted along highways or junctions, recognizing probable emergency vehicles by comparing them to previously learnt patterns and activating alarms if a match is discovered. Furthermore, real-time data processing may be used to improve accuracy and responsiveness.Overall, this design allows for automatic identification of emergency vehicles, which facilitates quicker responses and improves overall traffic safety..

2.2 WORK FLOW

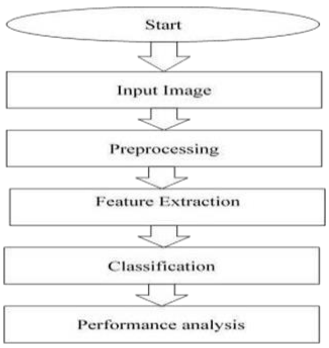

Fig 2.2.1 : Work Flow Diagram

Fig 2.2.1 describes the work flow diagram as follows,

2.2.1Dataset Collection

To build a dataset for emergency vehicle detection, a broad collection of photos or videos portraying various scenarios involving ambulances and fire engines is required. These media can be collected via publicly available databases, traffic camera footage, or recordings specially made for this purpose. To guarantee that the model can detect emergency vehicles in a variety of circumstances, it is critical to incorporate a wide range of scenarios, such as varied weather conditions, times of day, and road kinds. Furthermore, the dataset should include a variety of angles, distances, and lighting conditions to ensure the model's robustness across varied situations.Each picture or video in the collection should be annotated to identify the presence or absence of an emergency vehicle. This labeling step is critical because it enables the machine learning model to learn and connect certain traits with emergency vehicles during the training phase. Overall, establishing a broad and well-labeled dataset is critical to designing an efficient emergency vehicle detection system.

2.2.2 Input Video

During the development of the system, the video input is transformed into individual frames, which are then stored in either ".jpg" or ".png" file formats to produce the picture collection. To handle this step, the input photos are loaded or read using the read() method. Furthermore, Tkinter files are used to provide a graphical user interface with a conversation box for selecting input photos. This enables for a more user-friendly manner to entering photos into the system.

2.2.3 Image Preprocessing

As part of our method, we must downsize and convert photos to grayscale. To resize a picture, we use the resize() method and supply the required width and height as a two-integer tuple. This function generates a new picture with the altered dimensions without changing the old image.To convert an image to grayscale in Python, use the matplotlib package and a conversion formula. The conventional RGB to grayscale formula, imgGray = 0.2989 * R + 0.5870 * G + 0.1140 * B, can likewise be used in this case. Using this method, the RGB values of each pixel are added to determine the appropriate grayscale intensity value, yielding a grayscale representation of the picture.

2.2.4 Feature Extraction

After preprocessing the picture, we may extract features using the Local Binary Pattern. LBP is a texture operator that assigns a binary number to each pixel in an image by thresholding its neighborhood. This approach, known as the Local Binary Pattern Histogram (LBPH), is very useful for detecting faces. LBPH is well-known for its accuracy and resilience in face recognition tasks, since it can detect faces from both the front and side views. It works by evaluating patterns and textures in specific sections of a picture, allowing for exact feature extraction and recognition.

2.2.5 Image Splitting

Machine learning requires data to perform properly. Test data is required to evaluate the algorithm's performance and efficacy. The input dataset was separated into two parts: 70% for training and 30% for testing our technique. Data partitioning is the process of splitting accessible data into training and testing sets, and it is widely used to achieve cross-validation.

2.2.6 Classification

We use machine learning techniques such as decision trees and random forests in our approach. Decision trees are flexible supervised learning instruments that can be used for both regression and classification applications. They arrange the data into internal nodes, leaf nodes, branches, and a root node, forming a hierarchical structure. In addition to being useful for classifying objects according to their attributes, decision trees may also be used to predict continuous outcomes in regression scenarios. A random forest, on the other hand, is a group of decision trees that have been trained using various random feature subsets. It is regarded as one of the strongest variants of the decision tree. Random forests are excellent in categorizing data and work well with big datasets that have plenty of variables. They also automatically balance datasets such that reliable predictions are made even in cases where specific classes are less prevalent.

2.2.7 Production of Results

Overall classification and prediction metrics will be used to evaluate the efficacy of the proposed method. These metrics aid in assessing the classifier's effectiveness. One important parameter that shows how well the classifier can predict the class label is accuracy. It gauges how well the model forecasts a new collection of data's results. True Positives + True Negatives divided by the total number of predictions (True Positives + True Negatives + False Positives + False Negatives) yields the accuracy (AC). The error rate, which shows how much the model's predictions deviate from the actual results, is another crucial metric used for evaluation.

2.3 REQUIREMENT SPECIFICATION

2.3.1 Software Requirements

- O/S : Windows 7
- Language : Python
- Front End : Anaconda Navigator Spyder

2.3.2 Hardware Requirements

- System : Pentium IV 2.4 GHz Hard Disk : 200GB
- Mouse : Logitech
- Ram : 4GB
- Keyboard : 110 keys enhanced

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III. LITERATURE REVIEW

The growing number of vehicles in cities places a tremendous burden on transportation infrastructure. To combat this, parking assistance systems, real-time road availability information systems, and adaptive junction control systems are critical methods. These systems rely on precise traffic data, such as vehicle count, speed, categorization, occupancy, and presence. Magnetometers are efficient for assessing these characteristics. In this regard, we present a sensor equipped with a magnetometer and a microphone. The sensor uses auditory signals to identify emergency vehicles. We go into the intricacies of the first real-world sensor experiments, which were done to investigate and evaluate its usefulness in recognizing emergency vehicles.[1]

This extend points to form an independent location framework for crisis vehicles such as ambulances, fire motors, and police cars based on their siren sounds. The objective is to address occurrences in which drivers may not listen or distinguish sirens, especially whereas utilizing in-vehicle music frameworks. Siren Net is an gathering demonstrate built on a convolutional neural organize (CNN) with two streams. One stream (Wave Net) handles crude waveform information, whereas the other (ML Net) employments MFCC (Melfrequency Cepstral Coefficients) and log-mel spectrogram highlights. Through testing on a wide dataset, the framework accomplishes an exceptional 98.24curacy in recognizing siren sounds, illustrating how crude information complements standard characteristics viably. Besides, the framework works well indeed with little tests of 0.25 seconds, with an exactness of 96.89%. This innovation not as it were helps drivers by alarming them to encompassing crisis vehicles, but it too has the potential for consolidation into autopilot frameworks to progress security.[2]

Recent advances in computer vision technology have had a significant influence on Intelligent Transportation Systems (ITS), resulting in a revolution in a variety of applications including self-driving automobiles and traffic monitoring systems. One crucial feature of ITS is the capacity to identify emergency vehicles, which is highly reliant on object identification and instance segmentation algorithms. This work focuses on the usage of Faster R-CNN for object identification and Mask R-CNN for instance segmentation to improve emergency vehicle recognition. These designs are critical for applications like as traffic signal controllers and self-driving cars, since they enable them to recognize emergency vehicles and prioritize their signals in congested traffic settings. The study assesses various systems' computing efficiency, accuracy, and usability for emergency vehicle detection.Furthermore, it compares the object detection and instance segmentation models, highlighting their different strengths and drawbacks in the context of identifying emergency vehicles under chaotic traffic situations.[3]

Global traffic congestion has resulted in an increase in mortality due to delayed delivery of accident victims, critically sick patients, and crucial medical supplies. To solve this issue, researchers are looking at the possibility of merging the Internet of Things (IoT) with Vehicular Ad Hoc Network (VANET) to construct an Intelligent Traffic Management System (ITMS). However, current research lacks an emphasis on prioritizing emergency vehicles in the event of system hacking, which might result in traffic system breakdowns. The purpose of this work is to address these research gaps by providing a novel ITMS for smart cities.The suggested technology not only assists ambulances in finding the quickest routes to their destinations, but it also includes protection mechanisms against traffic light system hacking. Using a simulated environment, such as the Cup Carbon simulator, several scenarios are created to reflect real-world road conditions and vehicle motions. This enables a full presentation of how our suggested technique outperforms existing alternatives. Overall, our technology improves efficiency and security while controlling traffic in smart cities, particularly during emergencies.[4]

IV. RESULT

We have created a system that can quickly identify emergency vehicles, such fire engines and ambulances, as soon as they arrive, thanks to machine learning. Even in the face of shifting environmental conditions, this system's ability to recognize these vehicles from live camera feeds has demonstrated remarkable accuracy. With the use of advanced algorithms and a painstakingly compiled dataset, we have successfully and promptly detected threats, enabling prompt emergency responses. By warning motorists and pedestrians to move aside for emergency vehicles, this device may enhance road safety by speeding up response times and possibly saving lives.

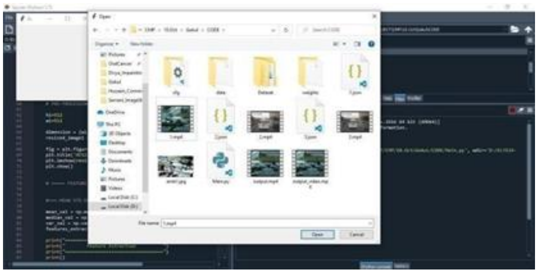

Fig 4.1 Data Screenshot

Fig 4.1 describes the images of emergency vehicles for detection.

Fig 4.2 Original Motion Image

Fig 4.2 describes the Emergency vehicle in which it passes the traffic signal and detects the size of the original image.

Fig 4.3 Resized Image as Pixel

Fig 4.3 describes the after resized image in the dataset. Prepared for the data agumentation.

Fig 4.4 Feature Extraction of Dataset

Fig 4.4 describes the feature extracted from the datasets.

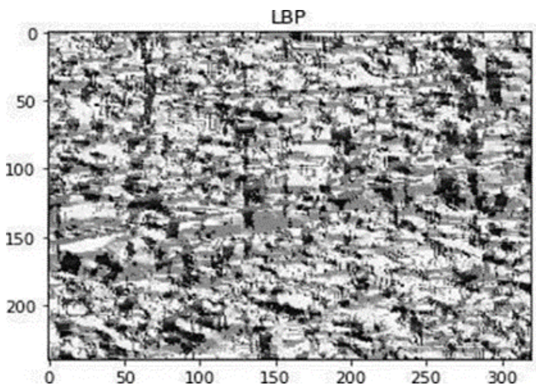

Fig 4.5 Local Binary Pattern of Images

Fig 4.5 describes a texture descriptor method in image processing that quantifies the local structure of an image by comparing each pixel with its neighboring pixels and encoding the result as a binary pattern.

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       IMAGE SPLITTING
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Total no of data       : 336
Total no of test data  : 268
Total no of train data : 68
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Fig 4.6 Image Splitting

Fig 4.6 describes the splitting images into various data like test data, train data, etc

Fig 4.7 Identifying Emergency Vehicles

Fig 4.7 describes the Identifying emergency vehicles from the signal lane involves employing computer vision algorithms to detect specific visual cues indicative of emergency vehicles, such as flashing lights and distinct vehicle shapes, in real-time video streams.

V. CONCLUSION

The application of machine learning to recognize emergency vehicles in real time, such as fire engines and ambulances, is a major development in emergency response systems and road safety. We have demonstrated the ability to identify these vehicles in real-time under a range of environmental situations by creating and implementing sophisticated algorithms that have been trained on large datasets. This device warns pedestrians and drivers to make room so that emergency vehicles can approach quickly and safely, which might greatly speed up response times during crises. Additionally, it can minimize the severity of emergencies and eventually save lives by increasing the efficiency of emergency services. In the future, more research and development work should focus on improving and fine-tuning these detection systems to make sure they are scalable and reliable enough for general usage. This will maximize their influence on emergency response capabilities and public safety.

VI. ACKNOWLEDGEMENT

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