Experimental Design and Implementation of Real Time Priority Management of Ambulances at Traffic Intersections using Visual Detection and Audio Tagging

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Abstract* – The second wave of the Covid-19 pandemic has wreaked havoc in India. Patients infected by the virus are losing their lives mainly due to the de-saturation of their SPO2 levels. For these critical patients every minute counts. Hence, transporting them to the hospitals in the least possible time is of utmost importance. In this work, the authors have come up with a unique solution to reduce the transport time of patients to hospitals by reducing the average waiting time at traffic intersections. In the metro cities of India, the minimum average waiting time in a traffic intersection is 15s. The authors propose a deep learning solution to tackle this problem. Wi-Fi enabled CCTV cameras at the traffic intersections will detect an incoming ambulance using the You Only Look Once (YOLO) v3 object detection algorithm. Once, an ambulance is detected the next part of the model is triggered which is audio classification and tagging. The ambulance siren is tagged and classified from the regular traffic noises. Immediately the police inspector is made aware of the situation. As a prototype, the authors have built a hardware model which can be easily installed in traffic intersections to make the other drivers aware of the incoming ambulance through an LCD display and a buzzer. Immediately the traffic signal corresponding to this path will be made green while shutting down the traffic signals of the remaining directions – to allow safe and quick passage of the ambulance through the traffic intersection. Statistical analysis of this work shows 2/3rd of the waiting time can be reduced if the country can adopt to this system. This prototype will surely add a positive note in saving the lives of critical patients.

***Index terms:* Ambulance detection, audio tagging and classification, COVID-19, deep learning, object detection, SPO2 level, traffic intersection, YOLO-v3**

I. INTRODUCTION

Emergency vehicles like ambulance are the first pillar of the health infrastructure of any country. Ambulances play an essential role when it comes to life threatening situations. They quickly transport patients to hospitals requiring serious medical attention. This noble work carried out by the ambulance drivers and concerned authorities are greatly hampered by traffic congestions. Traffic congestions counts for almost 20% deaths caused due to unavailability of proper medical help. Traffic congestions act as the last nail in the coffin for a person fighting for his/her life. Patients having a serious heart attack or Covid 19 patients requiring immediate oxygen supply and proper medical attention must not be stuck in any kind of traffic congestion. Covid 19 patients stuck in traffic congestion further increases the transmissibility of the virus and spreads the disease. It takes away the last glimpse of hope for these patients. Every second matters for these patients. These traffic congestions are prevalent in each and every country and they impair the health infrastructure [1].

This work tries to address this problem in an innovative way by using sophisticated deep learning and machine learning tools [2]. In most cases, the traffic in crossroads is managed by policemen. So, it is impossible for them to know beforehand whether there is an ambulance in this road or not. They can only see them when they are almost in front of the road. Moreover, a human brain has its own limitations and is bound to make some mistakes after some time. So, to eliminate even the slightest of the mistakes, the traffic management system must be equipped with artificial neural network which can work in unison with policemen to efficient identify the essential medical vehicles and provide a clear and fast passage avoiding the traffic congestion [3][4].

In this work, the images from the CCTV installed along the roads is taken along with audio. The images are taken continuously each second and are analyzed to detect different classes of vehicles. The audio further simplifies the process of detecting ambulances and increases the overall accuracy. Whenever an ambulance is detected, it will immediately notify the policemen as well as other drivers near the crossroads.

This work uses YOLO-v3 algorithm for detecting the presence of ambulance in the traffic. This algorithm is very fast and gives highly accurate values both in terms of IoU (Intersection over Union) and mAP (mean Average Precision) when compared with other object detection algorithms. The audio tagging and classification is done by generating the frequency Power Spectrum images of the incoming sound signals and feeding it to the Convolutional Neural Network for classification. Finally, for alerting policemen and other people, the authors have provided a low-cost hardware implementation of the prototype using Raspberry Pi3 Model B+, Buzzer and LCD as a proof of concept.

Unlike most western countries, Indian cities face traffic mismanagement caused due to a lack of enough road space and poor planning of road infrastructure. In most cases, there are no separate lanes for emergency vehicles like ambulances. In this work, the authors have implemented a low-cost prototype that will help the traffic police and concerned personals to provide a clear and safe passage to the ambulances so that the patients can be speedily transported to the hospitals. The addition of deep learning tools to traffic management makes it think like a human and it acts like an artificial brain helping in reducing traffic congestion and providing an alternative solution to essential medical vehicles.

II. LITERATURE SURVEY

There is no denying that with the advancement of time and technology, the roads are becoming more and more busy with increasing number of vehicles and numerous traffic problems are taking place every day. These result in more severe problem like accidents involving emergency vehicles such as ambulances, firefighter truck, police cars etc. A few systems and notable researches have been done detecting an emergency vehicle. The problem is approached by developing an automatic traffic control system which detects and clear the path of the emergency vehicles. This is accomplished by applying deep learning architecture i.e., deep convolutional neural networks along with computer vision. For object detection, Yolo -V3 architecture is used which can evaluate up to maximum 45 images per second and it processes the image dividing it in fixed segments, and it checks the probability of the occurrence of the essential vehicle being in the particular segment. YOLO detection is faster and more reliable than R-CNN pipelining. For the next part, a deep earning technique called transfer-learning is employed, which uses the model previously trained with huge dataset. For example, VGG_16 is used as CNN which is trained with ImageNet dataset [5].

Unawareness of drivers has been a big concern when it comes to traffic control which leads to accidents and delay management of emergency vehicle. The frequent observation of such incidents urges the need to reduce such incidents urgently. Loud music inside vehicles and conversation with fellow passenger are one of the prime reasons. The authors addressed this problem by developing a siren detection system which primarily detects the presence of emergency vehicle's siren sound and thereby alerts the driver. The detection system uses audio tagging and classification, to differentiate sounds of normal traffic with and without the presence of siren sounds from emergency vehicle. The working of the model is based on two network streams for classification. In first stream, raw data is directly proposed using WaveNet whereas in the second one MLNet is being used which works a 2D representation of audio formed using Mel spectrogram and Mel-Frequency Cepstral Coefficients (MFCC) [6].

A mobile automated model is developed for intersections to analyze the one-of-a-kind traits of automobiles in environments irrespective of their inter-connection. This prototype considers the rate outcomes of main automobiles, the impact of traffic signals and any other traffic rules and regulations prevalent in that particular road intersection in order to reproduce the same traffic flow. An assessment of various parameters like automobile velocity, traffic glide, and average tour time are estimated through this model for the above-mentioned scenarios. The obtained results indicate a better traffic flow and a reduction in the amount of time wasted on the traffic intersection along with significant improvement in fuel consumption and pollution reduction [7].

The vehicles in the roads doesn't always know about the traffic conditions which leads to unending traffic congestions. A new mechanism is proposed where each vehicle is connected in a single system and are constantly and automatically updated with real time traffic conditions in that road or of the upcoming roads intersection. An alternate route can be provided by this centralized system to the vehicles depending upon the traffic conditions. This system is efficient in handling traffic automatically in small areas by providing dynamic routing options to the vehicles. This system reduces the time wasted on the roads due to the traffic congestion and overall increase the average speed of the vehicles on that area [8].

The authors have developed a smart traffic system using embedded systems tools. Traffic signals at the intersections depend on detecting emergency vehicles along with recognizing the density of traffic in a particular lane. This method improves upon previous systems which used to find the density of traffic in a lane by the use of IR sensors that were installed along the side of the road. A real-time video stream is used for image acquisition and then the algorithm is processed. Frames are taken from the video stream for processing. The amount of time for which the green signal will be on for a particular direction of the road depends on the density of the vehicles in that particular lane. Object detecting and counting algorithm is used to determine the quantity of traffic from the frames of the video stream. When an emergency vehicle i.e., a fire truck or an ambulance is detected in a lane the former gets higher priority than all other directions in the traffic intersection. Immediately the surrounding traffic is made aware of the emergency vehicle and after a few seconds the signal in the lane which has the ambulance is switched to green allowing a seamless flow of traffic for that particular lane [9].

The WIFI-enabled CCTV cameras installed along the roads are incorporated with some software to calculate the distance of essential vehicles like ambulance from the traffic signal and this information is delivered to concerned traffic personnels. The images obtained from the cameras are converted from RGB to equivalent gray level image. These grayscale images' resolution is processed to their threshold level and the images are enhanced using morphological processing techniques. In the next step, the distance between the CCTV camera and the essential vehicle is calculated using the Euclidean formula using MATLAB software. Along with this, other essential parameters like the speed of the vehicle and the number of essential vehicles present in the road at a particular time are forwarded to the traffic policemen and the concerned personals to effectively control the traffic flow at the intersections. This will allow an easy passage for the essential vehicles [10].

III. SYSTEM ARCHITECTURE

A. Flowchart

The entire system architecture is described by the flowchart given in **Fig. 1**.

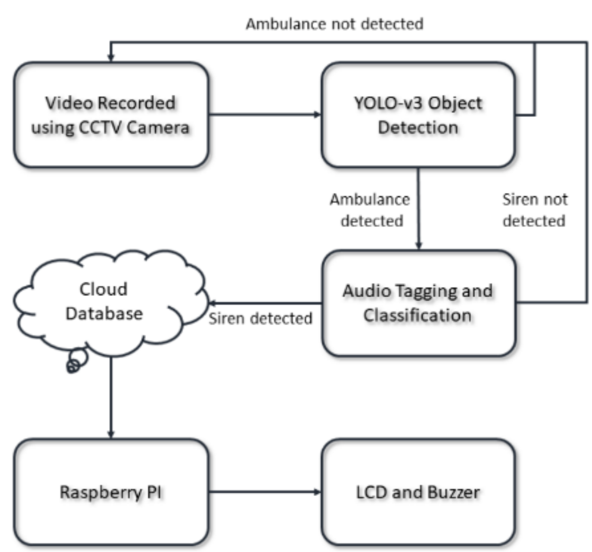

Fig. 1. Flowchart of the proposed system

Fig. 2. Ambulance detected in traffic using YOLO-v3 algorithm

B. Audio Tagging Dataset

The dataset – *Emergency Vehicle Siren Sounds* – available as an open-source dataset in the Kaggle platform is used to train the deep learning model for audio tagging and classification. The dataset has 200 samples of ambulance siren and 201 samples of regular traffic noise. Each audio sample ranges between 3-5 seconds.

C. Visual Ambulance Detection

Visual detection of ambulance in a traffic congestion, is the first step in priority management in a road crossing. The detection of ambulance from a road full of cars, requires computer vision solutions which uses heavy Deep Learning algorithms for accurate detection and localization. Some of the algorithms used are Convolutional Neural Networks (CNN), Faster Region-based Convolutional Neural Networks (Faster R-CNN) and Single Shot Multi-box Detector (SSD). These algorithms successfully detect any type of vehicles, pedestrians, traffic signs and other objects on the road. These algorithms contain some number of limitations. For example, of Faster R-CNN which overcomes the high computational time requirement of R-CNN and Fast R-CNN limits itself in interference time. Similarly, SSD was developed which outperformed existing algorithms compromised its accuracy.

YOLO was first introduced in 2015 which revolutionized object detection in all aspects of accuracy and interference time. The author has used YOLO-v3 which is the third version of the algorithm [11]. This algorithm is very fast and gives highly accurate values both in terms of IoU (Intersection over Union) and mAP (mean Average Precision) when compared with other object detection algorithms which fits perfectly for real time object detection, which is in the proposed case – vehicle detection. It was implemented using a deep convolutional neural network called Darknet-53 which contains 53-layer network, trained on ImageNet. 53 more layers is being used for detection making it 106 layers deep [11].

The proposed model in based on a traffic crossing having a camera placed with traffic lights for each direction. The purpose of the camera is to record video from which image frame at a rate of 45 frames/sec is being processed by YOLO-v3 algorithm. The algorithm detects the objects present in the road like car, buses, trucks, ambulances, persons, etc. For each detected object the algorithm draws an anchor box around it and shows the name of the class it belongs to. If the algorithm detects the presence of an ambulance on that particular road, it transmits a message regarding the presence of it. The presence of an ambulance activates the next part of the model which is audio tagging and classification, used to confirm that the ambulance is on emergency service.

The resultant images from the object detection module are visualized in **Fig. 2**.

D. Audio Tagging and Classification

Ambulance detection using only image may not be enough to efficiently detect them. There can be a scenario where an ambulance is not using the siren indicating that it is not transporting any patients to hospital but this can't be understood by the deep learning model unless the audio, that is, the siren is added and processed by deep learning model. If the system allows each and every ambulance which are not essential or not transporting any type of patients, then it will create more traffic congestion and it will nullify the whole effort of adding the artificial brain to the traffic management system.

Audio Classification of various traffic sounds and ambulance sirens are discussed in this work. This audio classification increases the efficiency of the proposed prototype. The authors have used the Mel Scale to classify and separate the ambulance siren from rest of the traffic noises. Each and every sound has a definite frequency and power which creates a unique spectrogram. Using python and librosa library, the authors have created a spectrogram using Mel Scale to easily classify and segregate traffic noise from the ambulance sirens and this spectrogram is known as Mel Spectrogram [12]. Mel Spectrogram is significantly different from normal audio spectrogram. It uses Mel-Frequency in place of frequency on the y-axis and Decibel in place of Amplitude on the x-axis. **Fig. 3** represents a normal audio spectrogram while **Fig. 4** represents a Mel-Frequency Spectrogram.

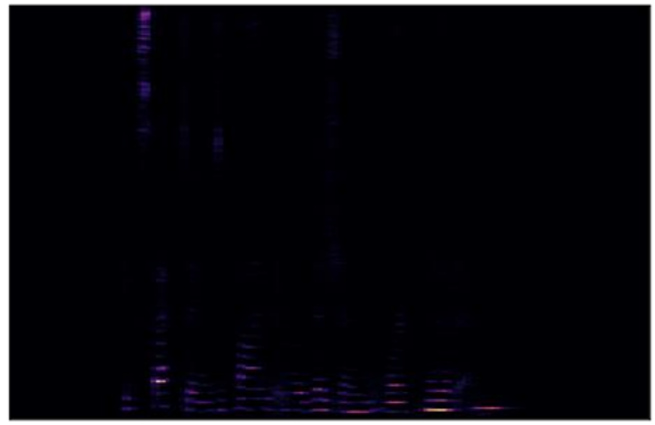

Fig. 3. Normal Audio Spectrogram

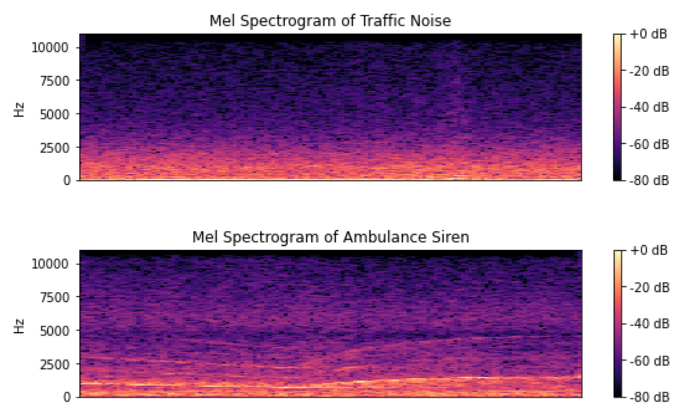

Fig. 4. Mel Spectrogram

MFCC represent the Mel Spectrogram. The human ear can detect diverse frequencies due to its non-linear nature. A human ear can easily differentiate between sound of frequencies 100 Hz and 200 Hz while 15000 Hz and 15100 Hz sounds are barely indistinguishable. Moreover, the human ear perceives loudness of the audio signal logarithmically rather than linearly. The loudness of the sound is represented in Decibel scale. The 0dB is total silence while 120 dB is totally unbearable to human beings. With an increase of 10dB, the loudness increases ten times. To mimic the same result, the MFCC can be used in the deep learning model to separate the ambulance siren from the rest of the traffic noise. **Eq. (1)** is the mathematical formulation to convert frequency to Mel-frequency scale.

$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \tag{1}$$

where f represents the frequency and m represents mels.

To calculate MFCC, the first step includes the preprocessing of the incoming audio signal which includes splitting the audio signals in short frames and applying window. In the second step, each frame is then subjected to NN-point Fast Fourier Transform (FFT) to calculate the frequency spectrum which is known as the Short-Time Fourier Transform (STFT). Then it is passed through Mel scaled Filter Banks which are triangular shaped filters. The output energy spectrum is then operated using logarithmic operations to get logarithmic energy spectrum. These logarithmic energy coefficients are highly correlated. So, to prevent any chances of overfitting and to optimize for much better performance, Discrete Cosine Transform (DCT) is applied to decorrelate the coefficients. The Mel Spectrogram images generated after these operations by the librosa library are fed as input to the CNN model – which classifies between the different traffic noises and ambulance siren [13].

D.1 Deep Learning Architecture

The authors have proposed an effective deep learning neural network architecture which will classify and tag the corresponding ambulance siren from traffic noises. The deep learning model has 8 layers. The first layer of the architecture is a 2D convolution layer with 64 output kernels. The convolution matrix used as a dimension of 3x3. The second 2D convolution layer has 128 output kernels. Both the convolution layers are activated using a ReLU activation layer and are followed by the 2D max pooling layers which have a stride size of 2x2. The convolution layers extract features from the input mel-frequency spectrogram images. A dropout layer with a rate of 0.1 is added to control regularization. The extracted features from the CNN layers are flattened into a one-dimensional input vector as input to the fully connected layer. A hidden layer is added with 1028 output neurons. The output layer has 2 neurons for classification into the 2 classes and is activated by the 'Softmax' activation function. The entire deep learning architecture is shown in **Fig. 5**.

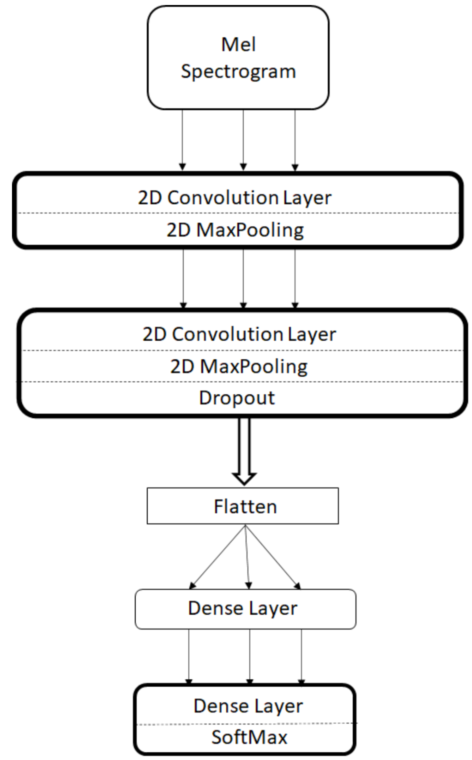

Fig. 5. Deep Learning Architecture

E. Cloud Infrastructure

In this work, the authors have used an online cloud infrastructure – Firebase – to store data and this acts as an intermediatory between deep learning model and the Raspberry Pi. The Firebase is a cloud infrastructure developed by Google. It is user-friendly and can be integrated with the deep learning model as well as Raspberry Pi through python programming. The data obtained after classification using YOLO-v3 is transferred to Firebase – shown in **Fig. 6** – which is then retrieved by the Raspberry Pi for further processing.

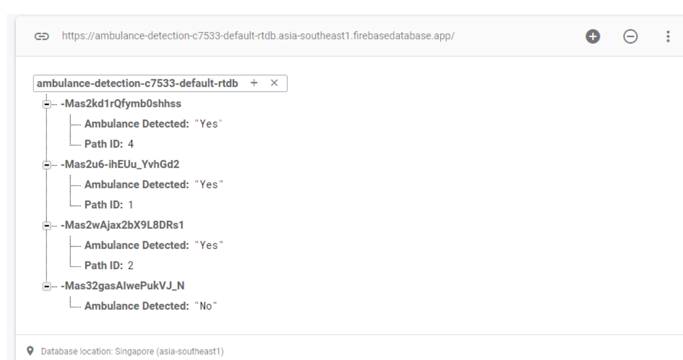

Fig. 6. Realtime online database

F. Hardware Implementation

The hardware equipment employed in this prototype are Raspberry Pi 3 Model B+, LCD and Buzzer. The Raspberry Pi 3 acts the controlling unit and provides the necessary processing power to the prototype. The LCD acts like electric hoarding and the Buzzer is used to send out alerting signal to the people and policemen. In place of LCD and Buzzer, OLED displays and Speakers can be used to provide much better visibility and warning but overall cost will increase. The authors have also used 4 pairs of LED lights consisting of a red and green light which indicates the traffic light in the cross section of four roads. The Raspberry Pi is connected to the laptop and VNC viewer is used to interface and remote control the Raspberry Pi from the laptop. The whole hardware implementation is shown in **Fig. 7** and the GUI Interface of Raspberry Pi 3 is shown in **Fig. 8.**

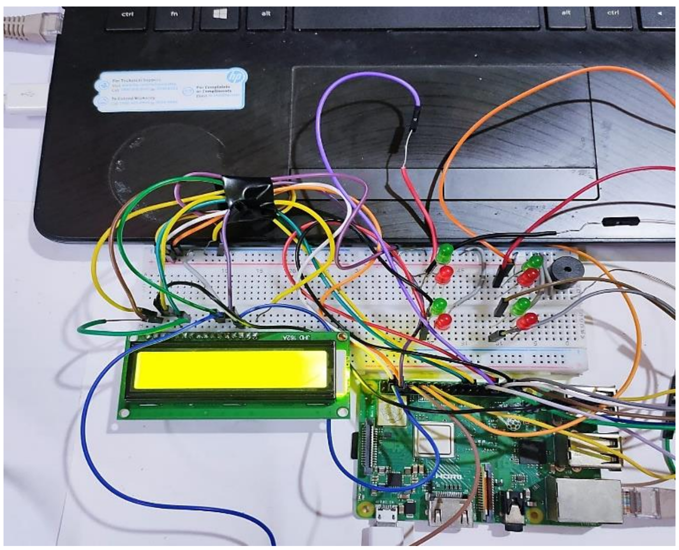

Fig. 7. Hardware Implementation

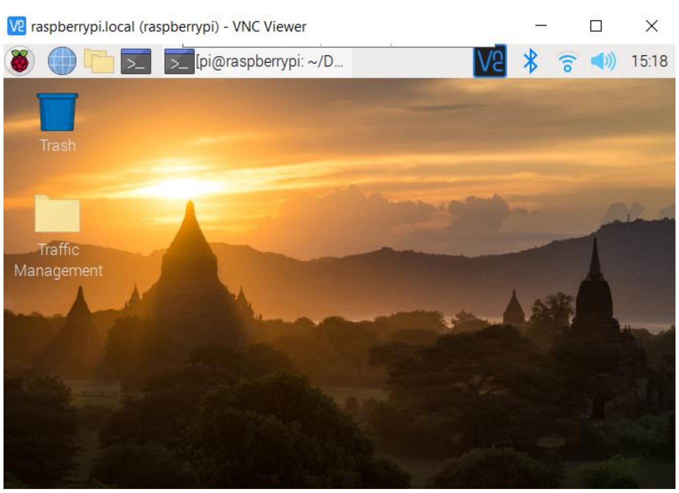

Fig. 8. GUI Interface of Raspberry Pi 3

IV. RESULTS

The YOLO-v3 object detection algorithm runs at 45fps with real time speed and has a mAP of 63.4%.

The deep learning model for audio tagging and classification is trained on 90% of the dataset. The remaining 10% of the audio samples are used evaluating the test accuracy. The model is trained for 50 epochs. The training accuracy of the model is 92.37% and the test accuracy on the validation set is 88.72%. The F_1 score is 0.89. The result is compiled and sent to the real-time online database.

The data is stored in the firebase cloud infrastructure and it is retrieved by the Raspberry Pi controller. In the beginning, there is no ambulance in any of the intersecting roads. There is no input of ambulance image through the camera as well as the microphone. So, there is no need to change the traffic signal in any of the path as it is shown in **Fig. 9.** In **Fig. 9,** since there is no ambulance, Path 1 and Path 3 traffic signals are turned green and similarly, Path 2 and Path 4 traffic signals are turned red indicating normal traffic conditions at the cross section. The phrase “Ambulance Not Detected” is displayed through LCD and the Buzzer is off as shown in **Fig. 10.**

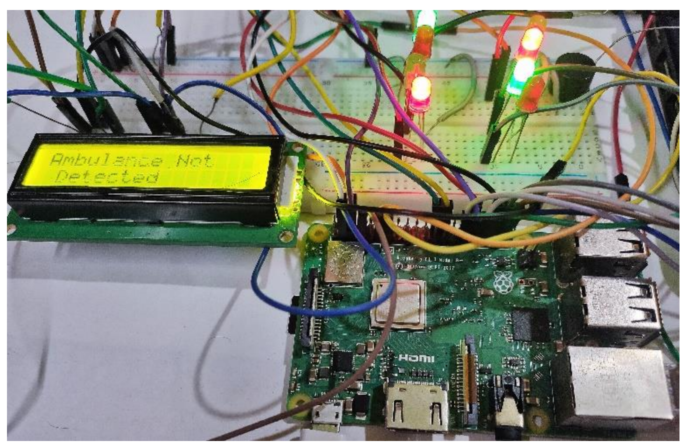

Fig. 9. Ambulance is not detected and the traffic lights are not changed

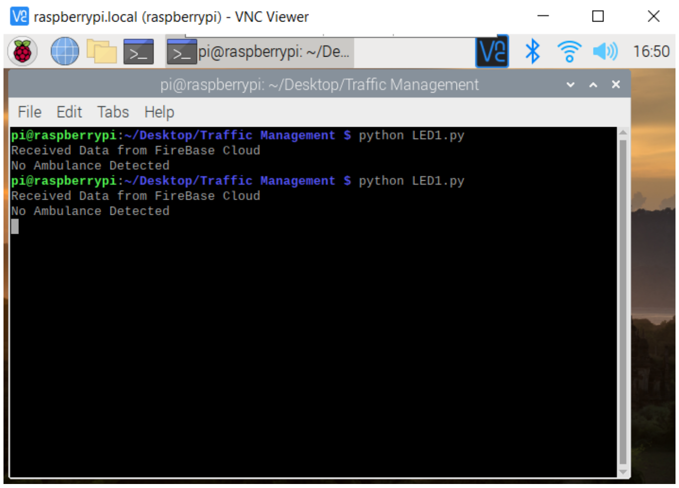

Fig. 10. Data is retrieved and no ambulance is detected

In another scenario, an ambulance is detected and the data along with the road or path number is sent to Firebase cloud infrastructure and the same is then transferred to the Raspberry Pi controller from the cloud. The traffic signal on Path 4 turns green while on other paths the traffic signal is turned to red as shown in **Fig. 11**. Moreover, the LCD which acts as an electric hoarding board and the Buzzer which acts a speaker in the prototype are displaying the message "Ambulance on Path 4" and emitting warning sound respectively as shown in **Fig. 12**. This will alert the police and concerned traffic personals. This will reduce the traffic in cross section before the ambulance reaches there and thus it will have a clear, safe and fast passage to the hospital. This will prevent infection if it is carrying any patient infected with Covid 19 or any other kind of infectious diseases.

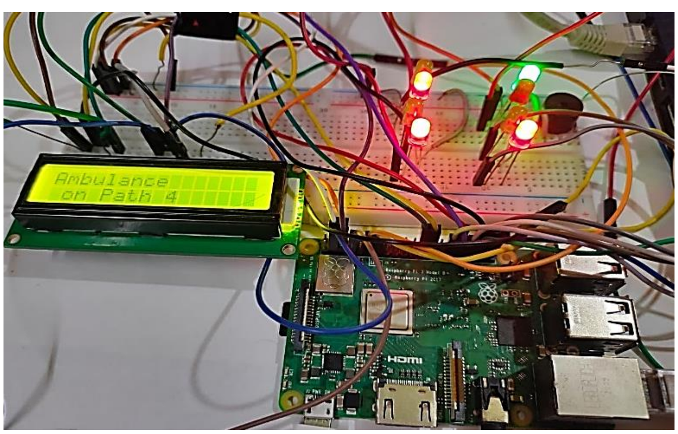

Fig. 11. Ambulance on Path 4 and the traffic lights are changed accordingly

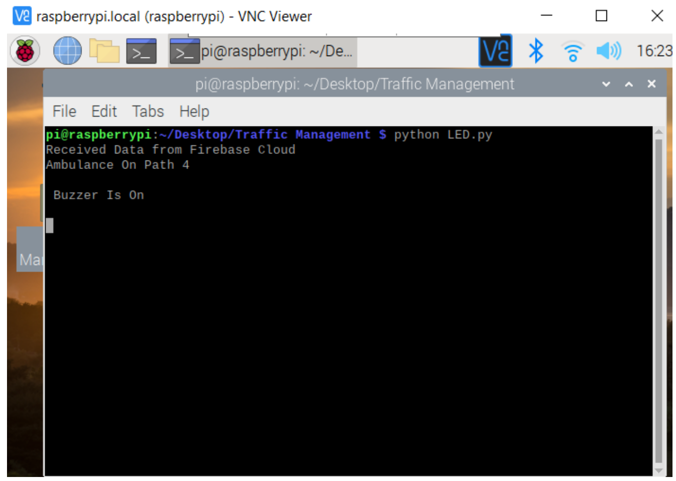

Fig. 12. Data retrieved from cloud and the Buzzer is on upon detection of ambulance

This action is same on all the paths. Whenever an ambulance is successfully detected by camera and microphone, the data will be sent to cloud along with the road/path number. The same data will be retrieved by the Raspberry Pi and the corresponding traffic light of that path will be turned green while rest of the signals on all other path will be turned red. The LCD and the buzzer will simultaneously display the same result.

The traffic signals will not be changed abruptly upon detecting an ambulance as it will lead to some serious accidents. The cameras and the microphones along the roads must be installed much before the cross section to facilitate early detection of ambulance. This will give enough time to change the signals slowly and steadily alerting the police as well as other drivers and people. In this way, the prototype can run smoothly with high effectiveness facilitating easy movement of the ambulances on the roads and thereby reducing early fatalities due to non-availability of health personals.

V. SOCIAL IMPACT FOR COVID-19

Covid-19 is a β corona virus causing severe acute respiratory syndrome, which results in hypoxemia. In India, hardly ambulances are equipped with oxygen support which means the patients' needs to reach to the hospital as quick as possible in order to get oxygen support [14]. According to a survey, the average waiting time of ambulance per traffic signal ranges around from 15 s to 200 and number of traffic signals per km ranges somewhere around 2 to 5. In metro cities, the average ambulance response time is nearly 15 mins. Taking all this delays in traffic, maximum permissible speed on road and ambulance response time, it can be said that it takes roughly around 30 mins to 200 mins to reach hospital. Being devoid of oxygen, for patients having SPO2 less than 90 is a serious issue. Patients who severely and critically infected with Covid-19, experiences drop in oxygen level faster as oxygen desaturates [15]. The proposed model aims in reducing the average waiting time in signal by two-third, which has an overall impact on the time required for reaching hospital. The reduction in travel time ensures faster arrival in hospital and faster access to oxygen and medical support thereafter. These will result in saving valuable lives which are lost due to delayed access to medical treatment and oxygen.

VI. CONCLUSION

A real time traffic management system has been implemented in this work which will detect the presence of ambulance on road from the video captured using CCTV present over the traffic lights. Audio tagging and classification has been used to confirm that the ambulance is on emergency service. Therefore, the authors have successfully built a prototype using YOLO-v3 for visual detection of ambulance. For audio tagging, Mel spectrogram of the surrounding sounds have been feed to deep learning model to classify whether the ambulance is in emergency service or not. The positive output from the visual detection and audio tagging, generates an interrupt which is communicated to the hardware prototype in order to provide priority to the ambulance by stopping the ongoing traffic on other roads. Thus, the whole system allows faster arrival in hospital which means faster access to medical treatment and oxygen. This faster mode of travel facilitates an average decrease in waiting time at the intersection thereby increasing the chances of survival of the Covid 19 patients and moreover it facilitates a safe and secure way to transport the patient without compromising any safety measures of either the patient or the normal commuters.

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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