Feasible Real Time Helmet Detection Using Raspberry PI

A Project Software Requirements Specification submitted
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By

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Abstract

With the ever-increasing population of today’s world, the obvious outcome was an increase in the number of vehicles on road. Due to this increase in traffic and the increasing Fuel prices, Two-Wheelers have become the most popular mode of transport. Two-Wheelers have the significant disadvantage of safety, and therefore not surprisingly, the most common road accidents involve motorcycles and maximum cases result in fatal injuries.

To combat this issue, helmets were introduced which have been shown to be extremely effective in saving lives of riders. Witnessing the practicality of helmet, several state governments have made it a punishable offense to ride the bike without a helmet. The technique used to enforce the law includes Police Officers spending a significant proportion of their time spotting riders without helmets, stopping them and issuing them with traffic violation tickets. Besides the obvious time wastage, the incapability of catching each and every violator, and lack of police force, citizens are ignorant of the situation and a significant portion of the population avoid using the helmet. Even though in recent times the government has taken several steps such as increasing the fine amount, having more officers on road and so on, its efforts were futile and its effects only lasted for a short period.

This project is aimed at getting rid of all such disadvantages by automating the entire process and therefore freeing up the time of police officers, reducing traffic issues and ensuring the safety of citizens. The system will an object detection model for classifying riders not wearing helmets. The model once trained is converted to a TensorFlow Lite format to improve overall efficiency and effective cost. The proposed system will automatically detect bike riders not wearing helmets and transfer it to a website where it can be viewed by the law enforcement officers. It uses a Raspberry Pi 4 along with a web camera and processing is done on board and in real time.

Introduction

India has the worst road safety standards in the world, a fact repeatedly outlined in World Health Organization reports and backed up by the government’s own reports. The NCRB data shows that as many as 43,540 people were killed in accidents involving Two-Wheelers in a single year. More Indians die each and every year in road accidents than the total casualties suffered by India’s armed forces in all the wars fought since independence.

Most accidents that happen on National highways include Two-Wheelers. Reports reveal that the National Highways, which constitute approximately 2 percent of India's total road network of over 56 lakh kilometers, accounted for 30.4 percent of total road accidents and 36.0 percent of deaths in 2017, while accidents on State Highways and other roads constituted 25 percent and 44.6 percent respectively. In case of fatality, State Highways and other roads accounted for 26.9 percent and 37.1 percent, respectively.

What continues to be a huge concern is that among the vehicle categories involved in road accidents, Two-Wheelers, which is the most preferred and affordable mode of personal transport, account for the highest share (33.9%) in total accidents and fatalities (29.8%) in 2017. Additionally, in terms of road-user categories, the share of two-wheeler riders in total fatalities has been the highest (33%) in 2017, while pedestrian road-users comprise 13.8 percent of people killed in road accidents during 2017.

Unfortunately, a vast majority of the people involved in fatal road accidents largely constituted the young population in the productive age groups: young adults between 18 and 45 years old accounted for 72.1 percent of victims during 2017.

Steeper fines under the amended Motor Vehicles Act have been met with much opposition from the general public. With many states opposing the revised penalties, Union Road Transport and Highways Minister iterated that heavier fine were introduced to reduce road deaths and not for revenue generation. Analyzing statistics provided by the ministry, India Today Data Intelligence Unit (DIU) has found that of all the road accidents that took place in 2017, Two-Wheelers were the worst hit. In 2017, more than 48,746 two-wheeler users died in road mishaps. Incidentally, 73.8 per cent of them did not wear a helmet. This means that every hour, four two-wheeler users who died in a road accident did not wear a helmet. In 91 per cent cases of two-wheeler accidents, a non-helmet rider was hurt, i.e. they either died or were grievously injured or faced minor injuries. For every hundred two-wheeler accidents in Tamil Nadu, 126 people were hurt. Tamil Nadu is followed by Maharashtra, Rajasthan, West Bengal, Himachal Pradesh, Jharkhand and Karnataka where at least one two-wheeler rider who didn't wear a helmet faced at least one injury.

As clearly evident by the various aforementioned statistics, the need of the hour is a comprehensive and rigorous system that can reduce the number of casualties. The current system has too many problems. Trauma to the brain can occur as a result of an impact, which can cause a concussion or open skull fracture, or a jarring motion, such as a quick turn or sudden stop. Even seemingly mild head injuries, where you don't lose consciousness, can cause permanent behavioral and cognitive problems, such as memory loss, inability to concentrate, sleep disorders and, in some cases, permanent disability or death. Studies have shown that wearing a helmet can reduce your risk of a serious brain injury and death because during a fall or collision, most of the impact energy is absorbed by the helmet, rather than your head and brain.

Helmets were therefore introduced which have been shown to be extremely effective in saving lives of riders. Seeing the obvious use of the helmet, Governments have made it punishable offense to ride a bike without helmet.

Initially this was limited to national highways but now it has made its way (pun intended) to local roads as well. To enforce the law, Police Officers spend a significant proportion of their time spotting riders without helmets, stopping them and issuing them with traffic violation tickets.

This system obviously has several drawbacks. Besides the obvious time wastage, the incapability of catching each and every violator, and lack of police force, citizens are ignorant of the situation and a significant portion of the population avoid using the helmet. Besides that, catching hold of violators includes the cops usually causing a commotion by coming In between the road to stop the violator. The bikes in turn speed up and narrowly avoid accidents. This in turn causes traffic jams which is very ironic all things considered. In recent times the government has taken several steps to implement road such as increasing the fine amount, having more officers on road, having awareness programs and so on. But its efforts were futile and its effects only last for a short period.

Primary Objective

a) Efficient and low power usage.
b) Easy to use interface for Law enforcements officers
c) Truly feasible system due to small budget and energy requirements
d) Will reduce death rates drastically due to increased use of helmets.
e) Effectively make law enforcement officers free for better traffic management and flow.
f) Easy maintenance.
g) Can be made to work on solar power thus making it eco-friendly.
h) It’s extensible and thus new features can be added eventually.

Proposed System

The proposed system as its core is basically an automated surveillance system. It is made up of a surveillance cam and a Raspberry Pi. The Raspberry Pi was chosen because it had the necessary processing power, was relatively very efficient and was compatible with the libraries that were used. The surveillance cam can be replaced with any USB plug and play camera. The Raspberry Pi uses a TensorFlow Lite object detection model which will be been trained on a custom dataset that was photographed and tagged.

Related Work

In recent years, Convolutional Neural Network's (CNN's) performing both automatic feature extraction and classification have outperformed previously dominant methods in many problems. Advances in graphical processing units (GPUs), along with the availability of more training data for Neural Networks to learn, have recently enabled unprecedented accuracy in the fields of machine vision, natural language processing, and speech recognition. Nowadays, all state-of-the-art methods for object classification, object detection, character classification, and object segmentation are based on CNNs. See for example the methods used in the ImageNet large scale visual recognition challenge [7]. Below we will discuss several methods used for helmet detection.

In [1], Chiverton suggested a way which used the unique shape of a helmet and varied lighting conditions. It uses Hough transforms to identify the helmet in a video feed, it has very low accuracy. The major limitation of this approach is that it tries to locate helmet in the full frame which is computationally expensive and also it may often confuse other similar shaped objects as helmet. It ignored the fact that a helmet is valid only in case of bike-rider. This method will wrongfully label any round object near the rider as a helmet.

In [2], Duan et al. proposed an effective way to track vehicles in real time using just one camera. However, to achieve accelerated computation, it used an integrated memory array processor (IMAP). This wasn't an efficient solution due to its requirement of dedicated hardware.

Silva et al. [3], [4] proposed a system in which he tracks the vehicles using Kalman filter [5]. An important advantage of this Kalman tracking system [5] is the ability to continue to track objects even if they are lightly occluded but when there were more than two or three motorcyclists appear in a same frame, Kalman filter [5] fails because Kalman filter [5] mostly works well for linear state transitions (i.e. tracking single objects/one object at a time). Tracking multiple objects is only possible using nonlinear functions.

[6] J. Mistry et al. talks about a system very similar to the one proposed in this paper which identifies bike riders without helmet and captures the number plate of all the offenders on a COCO (Common Objects in Context) database. It classifies motor bike and helmet using YOLO (You only look once) and the technology used for license place recognition is Open ALPR (Automatic License Plate Recognition). Since Open ALPR is based on monthly charges it's not an economically feasible approach for the given objective.

Li and Shen [8] use a Deep Convolutional Neural Network and long-short term memory (LSTM) for the license plate recognition and character extraction process. They use a CNN for license plate detection. They use two methods for segmentation and recognition. The first is character segmentation-based recognition using image binarization, connected component analysis, and character recognition. The second is a sequence labelling based method using CNNs and recurrent Neural Networks (RNNs).

[9] K.C.D. Raj et al. have developed several different CNN models for the helmet/no-helmet classifier. Compared to an earlier version of the classifier incorporating a head/helmet detector and HOG descriptor classifier, the CNN for helmet/no-helmet classification improves accuracy from 80% to 98%. Though the more accurate classifier requires a high-performance GPU to run in real time. They have also developed a classifier that obtains 90% accuracy and runs in real time on a CPU. However, this approach is power hungry, slow and still uses more power than the suggested approach.

Recently, Dahiya et al. [10] proposed a system which first uses Gaussian mixture model to detect moving objects. The model was found to be effective even when there were slight alteration in the background. It uses two classifiers one after the other, one for the segregating bikers from moving objects and the other for separating those without helmets from the upper one fourth part of the bikers. However, it uses only hand engineered features such as SIFT (scale-invariant feature transform) [11], HOG (Histogram of Oriented Gradients) [12], LBP (Local Binary Patterns) [13] along with kernel SVM(Support Vector Machine) in both classifications. This approach was able to accurately classify bikers and non-bikers but wasn’t able to accurately label bikers wearing helmets and bikers not wearing helmets under unideal conditions.

[17] C. Vishnu et al. proposed a system in which they applied adaptive background subtraction to detect moving objects. These moving objects were then given to a CNN classifier as input which then classifies them into as bikers and non-biker. After that, only objects predicted as bikers were given to another CNN classifier where they determined whether the biker is wearing a helmet or not. This approach had a relatively long procedure and was again power hungry and wasn’t effective enough for real time detection. Most existent methods suffer from several problems such as occlusion of objects and varying illumination conditions. They tried to address it by using SVM [14], [15], [16] for classification between bikers and non-bikers and bikers wearing helmets and not, which made localization of occluded objects easier. But for any of that to work efficiently, we need to have good quality features from the bikers to classify accurately which is difficult using HOG [12] or LBP [13] or SIFT [11] on images with less pixels. Also, most of the Deep Learning-based approaches use CNNs but ultimately don’t work well real time detection and are computationally expensive.

Existing System

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Existing System Limitation

The proposed systems which do not use specialized hardware usually have low accuracy or work only under certain conditions. This places several constraints of the implementation of such systems. The systems which use modern machine learning techniques are power hungry and this creates a bottleneck on the feasibility of deploying such systems in large scale. Systems which use special hardware have better accuracy, performance and versatility. These systems are not implemented due to increased cost of customized hardware which is not economically possible considering the large-scale requirement. Most of the suggested methods also don't work in real time.

Software and Hardware Requirements

Software requirements

Operating System	Windows 10, Raspberry Pi OS, Android
Software Selection	Flutter, Firebase/Amazon web services, Visual Studio, Jupyter, Anaconda
Programming Languages	HTML, CSS, JAVASCRIPT, JAVA, XML, DART, PYTHON
Web Browser	Google chrome

Hardware Requirements

Sr No.	Requirement Name	Description
1	Processor	Quad-Core 64-bit Broadcom 2711, Cortex A72 Processor (Raspberry Pi), Cortex A-53 cores and above (Mobile app), Intel i7 core.
2	ROM	2 - 50 GB
3	RAM	1 - 16 GB
4	Processor Speed	1.3 GHz and above
5	System Type	64-bit Operating System.
6	Internet Connection	512kb/s

Module design

1. Registration:
   The public users will undergo the registration procedure by specifying the identity proof and obtain a username and password, which is used for authentication.

2. Login:
   This module contains the login. The admin can access his admin dashboard and perform all functionalities and also control user groups based on their access to the system. The user and can use the login module to access all the functionalities.

3. Object detection in Raspberry PI:
   Riders not wearing helmets are recognized by the object detection algorithm and their photos are sent to an online database using IOT.

4. View violators:
   Law enforcement authorities can view the violators in real time from different locations. Their time and date and relevant information will also be displayed.

5. Send Messages:

The main functionality of this module is to send a challan message to rider of the bike if approved by the law enforcement officer.

Functional requirements and Non-Functional Requirements

Functional requirements

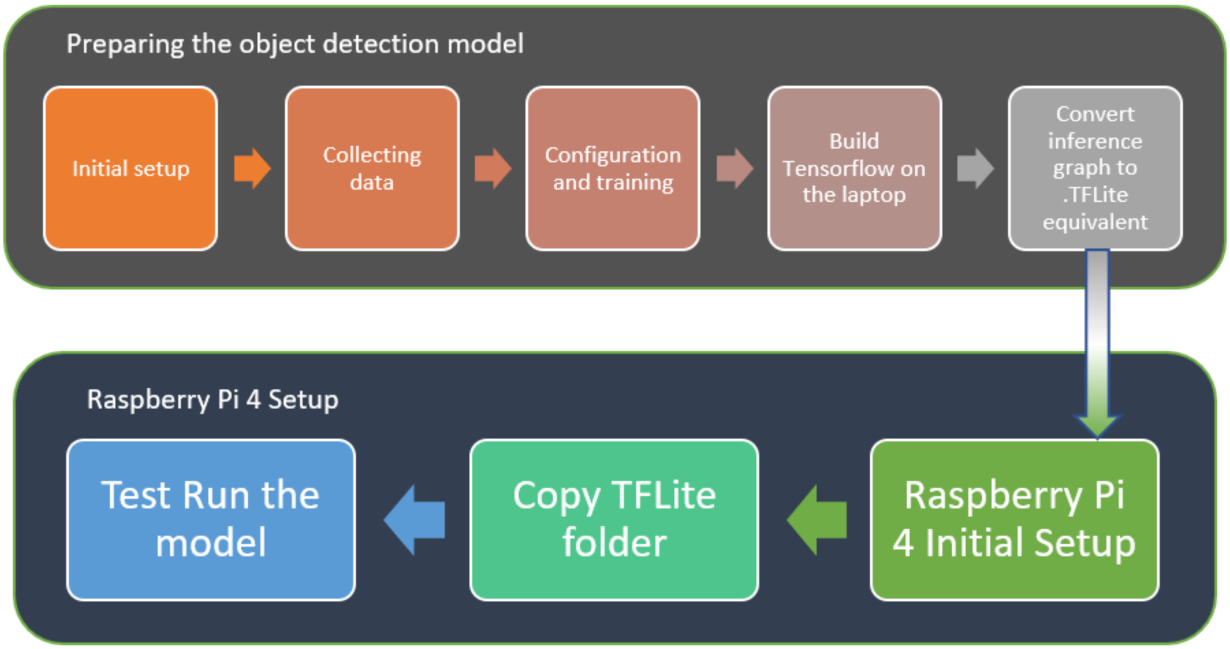
Requirement ID	Requirement name	Description
FR1	Login	Admin and User can log on to the system
FR2	Register	To be authenticated, first users have to be registered
FR3	Uploading Details	Users can upload their skill-set on the application
FR4	Model training	Train model so that it can be used for object detection
FR5	Message forwarding	Forward challan to violator
FR6	Optimizing Model	Optimize model for Microcomputer.

Non-functional requirements

Requirement ID	Requirement Name	Description
NFR1	Accuracy	The system should accurately provide real time information taking into consideration various concurrency issues
NFR2	Usability	The system shall allow the users to access the system from the internet using the application. The system is user friendly which makes the system easy.
NFR3	Secure	Data stored is highly secure. Any user who has access to the data only can access the system if they log in to the system. It does not allow an unauthorized person to enter into the system. Thus, this system is secure.

NFR4	Availability	The system is available 100% for the user and is used 24 hours a day and 365 days a year.

Block Diagram



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