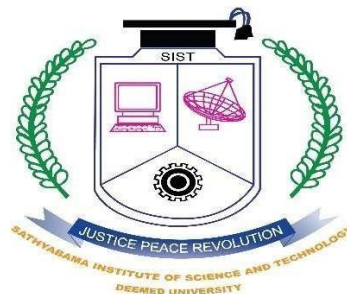


AUTOMATIC TOLL COLLECTION USING VEHICLE CLASSIFICATION IN TOLL BOOTH

Submitted in Partial Fulfilment of the Requirements For
The Award Of
Bachelor of Engineering Degree in Computer Science and Engineering
By

POTHININDI SHANKAR CHANDRA (Reg. No. 37110575)



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade “A” by NAAC

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MARCH – 2021



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BONAFIDE CERTIFICATE

This is to certify that this project report is the bonafide work of POTHININDI SHANKAR CHANDRA (Reg. No. 37110575) who carried out the project entitled "AUTOMATIC TOLL COLLECTION USING VEHICLE CLASSIFICATION IN TOLL BOOTH" under my supervision from November-2020 to April – 2021.

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I, POTHININDI SHANKAR CHANDRA (Reg. No. 37110575) hereby declare that the projectreport entitled “AUTOMATIC TOLL COLLECTION USING VEHICLE CLASSIFICATION IN TOLL BOOTH” done by me under the guidance of Dr. A. Pravin , is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

DATE:

PLACE: CHENNAI.

SIGNATURE OF THE CANDIDATE

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ABSTRACT

Toll Vehicle Classification is an important task. Indeed, it has many uses in traffic management and toll collection systems. In this paper, Vinci Auto-roads group Networks (the biggest French Highways concession) are considered, where every year, millions of vehicles are classified in real time. Then, a small decrease in classification performance can have serious economic losses. Therefore, the accuracy and the time complexity become critical for the toll collection system. The current classification algorithm uses the scene features to detect vehicles classes. However, it requires a large labelled dataset, and has a limitation when multiple vehicles are in the scene. Herein, we propose a novel context-aware vehicle classification method that takes profit from the semantic spatial relationship of the objects. The experiments show that our method is performing as accurately as the existing model with significantly lower labelled datasets (74 times smaller). Moreover, the obtained accuracy of the proposed method is 99.97% compared to 99.79% achieved by the current method when using the same training set. We apply Haar Cascade algorithm to detect the vehicle classification.

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LIST OF ABBREVIATION

S.NO	ABBREVIATION	EXPANSION
1	AI	ARTIFICIAL INTELLIGENCE
2	GPS	GLOBAL POSITIONING SYSTEM
3	UML	UNIFIED MODELLING LANGUAGE

CHAPTER 1

INTRODUCTION

OUTLINE OF THE PROJECT

Transportation nowadays is a primary need for every person in finding to most suitable daily transportation. However, there is an existing huge problem. The uncontrolled personal vehicle growth has become one of serious transportation problems. According to the previously conducted research by Indonesia Ministry of Transportation, Indonesian vehicle growth exhibits surprising results, 12% for motorcycle, 8.89% for car, and 2.2% for bus. In addition, the research proves that the need of transportation is increasing every year with many factors triggering this increment exemplified by geography, technology, social and economy. The vehicle detection is essential in intelligent systems that aims to detect potentially dangerous situations with vehicles in advance to warn the driver. Thus, the cameras are adapted to detect the automobiles because they are similar to the human visual perception system and provide rich information for applying machine learning techniques.

MOTIVATION

Classification and detection of objects have been the state-of-art approach for many areas in computer vision. In the domain of video surveillance classification of objects have been a major breakthrough. The Haar classifier is able to detect vehicles and showed that the vehicle detection performance was greatly improved with higher accuracy and robustness.

PROBLEM STATEMENT

This paper presents a real-time vision framework that detects and tracks vehicles. The framework consists of three main stages. Vehicles are first detected using Haar cascade algorithm. In the second phase, an adaptive appearance-based model is built to dynamically keep track of the detected vehicles and the third phase of data association to fuse the detection and tracking results.

CHAPTER 2

LITERATURE SURVEY

1. A. Hasnat, N. Shvai, A. Meicler, P. Maarek, A. Nakib, "New vehicle classification method based on hybrid classifiers" in IEEE Int. Conf on Image Processing, IEEE, pp. 3084-3088, 2018.

In this work, a real-world problem of the vehicle type classification for automatic toll collection is considered. This problem is very challenging because any loss of accuracy even of the order of 1% quickly turns into a significant economic loss. To deal with such problem, many companies currently use Optical Sensors (OS) and human observers to correct the classification errors. Herein, a novel vehicle classification method is proposed. It consists in regularizing the problem using one camera to obtain vehicle class probabilities using a set of Convolutional Neural Network (CNNs) models, followed by the Gradient Boosting based classifier to fuse the continuous class probabilities with the discrete class labels obtained from optical sensors. We evaluate our method using a challenging dataset collected from the cameras of the toll collection points of the VINCI Autoroutes French network. Results show that our method performs significantly better than the existing automatic toll collection system and, hence will vastly reduce the workload of human operators.

2. N. Shvai, A. Meicler, A. Hasnat, E. Machover, P. Maarek, S. Loquet, A. Nakib, "Optimal ensemble classifiers-based classification for automatic vehicle type recognition", 2018 IEEE Congress on Evolutionary Computation (CEC), pp. 1-8, 2018.

In this work, a challenging vehicle type classification problem for automatic toll collection task is considered, which is currently accomplished with an Optical Sensors (OS) and corrected manually. Indeed, the human operators are engaged to manually correct the OS misclassified vehicles by observing the images obtained from the camera. In this paper, we propose a novel vehicle classification algorithm, which first uses the camera images to obtain the vehicle class probabilities using several Convolutional Neural Networks (CNNs) models and then uses the Gradient Boosting based classifier to fuse the continuous class probabilities with the discrete

class labels obtained from two optical sensors. We train and evaluate our method using a challenging dataset collected from the cameras of the toll collection points. Results show that our method performs significantly (98.22% compared to 75.11%) better than the existing automatic toll collection system and, hence will vastly reduce the workload of the human operators. Moreover, we provide an in-depth analysis w.r.t. the learning strategies., choice of the optimization algorithm of the CNN model. Our results and analysis highlight interesting perspectives and challenges for the future work.

3. J. Fang, Y. Zhou, Y. Yu, S. Du, "Fine-grained vehicle model recognition using a coarse-to-fine convolutional neural network architecture", IEEE Trans. Intell. Transp. Syst., vol. 18, no. 7, pp. 1782-1792, 2017.

Fine-grained vehicle model recognition is a challenging problem in intelligent transportation systems due to the subtle intra-category appearance variation. In this paper, we demonstrate that this problem can be addressed by locating discriminative parts, where the most significant appearance variation appears, based on the large-scale training set. We also propose a corresponding coarse-to-fine method to achieve this, in which these discriminative regions are detected automatically based on feature maps extracted by convolutional neural network. A mapping from feature maps to the input image is established to locate the regions, and these regions are repeatedly refined until there are no more qualified ones. The global and local features are then extracted from the whole vehicle images and the detected regions, respectively. Based upon the holistic cues and the subordinate-level variation within these global and local features, an one-versus-all support vector machine classifier is applied for classification. The experimental results show that our framework outperforms most of the state-of-the-art approaches, achieving 98.29% accuracy over 281 vehicle makes and models.

4. L. Jiang, J. Li, L. Zhuo, Z. Zhu, "Robust vehicle classification based on the combination of deep features and handcrafted features" in Trustcom/BigDataSE/ICSS 2017 IEEE, IEEE, pp. 859-865, 2017.

Vehicle classification plays an important part in Intelligent Transport System. Recently, deep learning has showed outstanding performance in image classification. However, numerous parameters of the deep network need to be

optimized which is time-consuming. PCANet is a light-weight deep learning network that is easy to train. In this paper, a new robust vehicle classification method is proposed, in which the deep features of PCANet, handcrafted features of HOG (Histogram of Oriented Gradient) and HU moments are extracted to describe the content property of vehicles. In addition, the spatial location information is introduced to HU moments to improve its distinguishing ability. The combined features are input to SVM (Support Vector Machine) to train the classification model. The vehicles are classified into six categories, i.e. large bus, car, motorcycle, minibuss, truck and van. We construct a Vehicle Dataset including 13700 vehicle images extracted from real surveillance videos to carry out the experiments. The average classification accuracy can achieve 98.34%, which is 4.49% higher than that obtained from the conventional methods based on "Feature + Classifier" and is also slightly higher than that from Google Net (98.26%). The proposed method doesn't need GPU and has much greater convenience than Google Net. The experimental results have demonstrated that for a specific task, the combination of the deep features obtained from light-weight deep learning network and the handcrafted features can achieve comparable or even higher performance compared to the deeper neural network.

5. M. Biglari, A. Soleimani, H. Hassanpour, "A cascaded part-based system for fine-grained vehicle classification", IEEE Trans. Intell. Transp. Syst., vol. 19, no. 1, pp. 273-283, 2018.

Vehicle make and model recognition (VMMR) has become an important part of intelligent transportation systems. VMMR can be useful when license plate recognition is not feasible or fake number plates are used. VMMR is a hard, fine-grained classification problem, due to the large number of classes, substantial inner-class, and small inter-class distance. A novel cascaded part-based system has been proposed in this paper for VMMR. This system uses latent support vector machine formulation for automatically finding the discriminative parts of each vehicle category. At the same time, it learns a part-based model for each category. Our approach employs a new training procedure, a novel greedy parts localization, and a practical multi-class data mining algorithm. In order to speed up the system processing time, a novel cascading scheme has been proposed. This cascading scheme applies

classifiers to the input image in a sequential manner, based on the two proposed criteria: confidence and frequency. The cascaded system can run up to 80% faster with analogous accuracy in comparison with the non-cascaded system. The extensive experiments on our data set and the Comp Cars data set indicate the outstanding performance of our approach. The proposed approach achieves an average accuracy of 97.01% on our challenging data set and an average accuracy of 95.55% on Comp Cars data set.

6.Varsha,Amit Kumar Mishra, Binita Pareek "Automated Aproach for Toll Detection Using Circular Hough Transform and Scalar Sharpness Index"2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)

Automated Toll accounting is super concerning its usage in unique government projects, and in vehicle identity, it's manner mandatory to raise alert at any suspicious diversion. To locate any automotive, we would really like to extract its talents. Machine imaginative and prescient can also be aware of eliminating the ones skills. The cars and automobiles can be modeled as some functions with the intention to be specific, e.g., color, type so forth. Still, the registration code is a completely precise identity of an automotive that could spot its owner. The preparation of toll detection exploitation registration code system is wastage of large data, networking, system and server efforts. Therefore, we generally tend to advocate a cutting-edge version so that you can integrate automatic toll detection using system vision based totally strategies ordinarily focused to wheel detection for SUV, LUV, MCV, and HCV. During this painting, the Hough domain transformation is tailored to account the wheel size. Additionally, to it, the importance of the planned module is even for clattery and rainy seasons using discrete wavelet transform and Scalar Sharpness Index based totally more often than not picture smoothening approach.

7.Debkumar Chowdhury ; Souraneel Mandal ; Dona Das ; Soumya Banerjee ; Sourath Shome ; Devlina Choudhary"An Adaptive Technique for Computer Vision Based Vehicles License Plate Detection System"2019 International Conference on Opto-Electronics and Applied Optics (Optronix)

Automatic license plate recognition (ALPR) is a process of identification of the license plate from an image taken at any signal stop or parking station. The Identified information or the number plate can be used for keeping a check on signal stops or for monetary settlements at parking lots or toll stations. It can also be used around the world for law and administrative works like checking a vehicle if it is registered or not. It also finds its use in safety supervision system. The ALPR can be used upon various types of pictures like color images, black and white images and etc. ALPR may fail a number of times if the quality of the picture is not up to the mark. So, ALPR depend a lot in the image quality, and hence the challenges in its real-life application. It may be used both indoors and outdoors but it must be able to process the images both quickly and successfully in all sorts of environments, be it daytime or night time, sunny or rainy. Our proposed method mainly has three modules: 1) Detection of license plate 2) Segmentation of Characters 3) Text Box Generation. The number plates sometimes may be unclear for the cameras. It may sometimes have dirt and scratches on it and thus increasing the complexities of the ALPR system. Today nationwide ALPR has been adopted by several law and governmental agencies for its efficiency and usefulness. Public safety agencies are using the ALPR system to gather and store relevant information about people and to keep a check on the vehicular activities. It is becoming a significant tool for the Law Enforcement Agencies.

8.Akshay Bhavke ; Sadhana Pai”Smart weight based toll collection & vehicle detection during collision using RFID”2017 International conference on Microelectronic Devices, Circuits and Systems (ICMDCS)

“Smart Weight Based Toll Collection & Vehicle Detection During Collision using RFID” addresses the problems faced at the toll plaza. The system also identifies the vehicles against which stolen and accident cases are registered using RFID. Initially user has to create an account and register his RFID number at central database using the mobile application. When a vehicle with RFID tag passes through Toll Collection Unit (TCU) it is classified as a passenger carrying vehicle or goods carrying vehicle based on its RFID Number. If a vehicle is detected as goods carrying vehicle it is weighed and if it is overloaded then charged with extra toll. RFID Number is then passed to Central Server Unit (CSU) where a balance is deducted from user account after which CSU indicate TCU to open barricade and

allow the vehicle to pass. If the vehicle is identified as stolen vehicle by CSU, it will indicate TCU not to open the barricade. In order to identify the culprit in hit and run case collision detection mechanism is implemented using vibration sensor.

9.Mochamad Vicky Ghani Aziz ; Hilwadi Hindersah ; Ary Setijadi Prihatmanto“Implementation of vehicle detection algorithm for self-driving car on toll road cipularang using Python language” 2017 4th International Conference on Electric Vehicular Technology (ICEVT)

Self-Driving Car research problem requires several sub-topics that need to be discussed more deeply. Such as Deep Learning, Computer Vision, Fusion Sensor, Localization, Control, until Path Planning. All of them are fusion of several fields of study. This paper discusses the results of implementation of vehicle detection algorithm on toll road Cilvaringz as parts of self-driving car system. Video image taken using action camera mounted on top of the vehicle, with 1280×720 resolution. Average speed of the vehicle is 100 km per hour. Programming language of image processing using Python 3. Image processing method are a combination of methods of object detection, feature intuition, color spaces, and HOG (histogram of oriented gradient). The result shows this algorithm needed to be add some method that can changing the parameters during day and night adaptively. Because constant parameters can only be used in the same lighting conditions. Overall, the implementation method in Python Language can be successfully detect the vehicle with an accuracy above 90 percent.

10.Akhil Soin,Manisha Chahande,”Moving vehicle detection using deep neural network”2017 International Conference on Emerging Trends in Computing and Communication Technologies (ICETCCT)

In recent years, vehicle recognition has become one of the most important applications in the field of intelligent traffic monitoring and management. Vehicles detection on road is a necessary component in many intelligent applications, such as driver assistance systems, automatic toll collection, intelligent parking systems, self-guided vehicles and traffic statistics such as speed, flow and vehicle count.

CHAPTER 3

METHODOLOGY

AIM

There are two toll collection system are existing: All vehicle has to stop at toll plaza along the highway to pay the toll, one person collects the money and issue a receipt, after which gate is opened either mechanically or electronically for the driver to get through the toll plaza. Another is smart card system in which driver show a smart card to access the data to the system installed on toll plaza to pass.

SCOPE

Detection and classification of the vehicles and other objects of interest (e.g., toll payment box). Predicting the scene class based on the spatial relationships among the vehicles of interest and contextually important objects. This uses machine learning techniques to get a high degree of accuracy from what is called “training data”. Haar Cascades use the Adaboost learning algorithm which selects a small number of important features from a large set to give an efficient result of classifiers.

Drawback of Existing System

The above system for collecting toll tax is time consuming method; there is long queue of vehicle at toll plaza chances of escaping the payment of toll tax.

HARDWARE REQUIREMENTS

The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware. A hardware requirements list is often accompanied by a hardware compatibility list, especially in case of operating systems. The minimal hardware requirements are as follows,

- | | |
|-----------------|------------|
| 1. Processor: | Pentium IV |
| 2. RAM: | 8 GB |
| 3. Processor: | 2.4 GHZ |
| 4. Main Memory: | 8GB RAM |

- 5. Processing Speed: 600 MHZ
- 6. Hard Disk Drive: 1TB
- 7. Keyboard: 104 Keys

SOFTWARE REQUIREMENTS

Software requirements deals with defining resource requirements and prerequisites that needs to be installed on a computer to provide functioning of an application. These requirements are need to be installed separately before the software is installed. The minimal software requirements are as follows,

- 1. Front End: Python
- 2. IDE: Anaconda
- 3. OS: Windows 10

SYSTEM DESIGN

Architecture

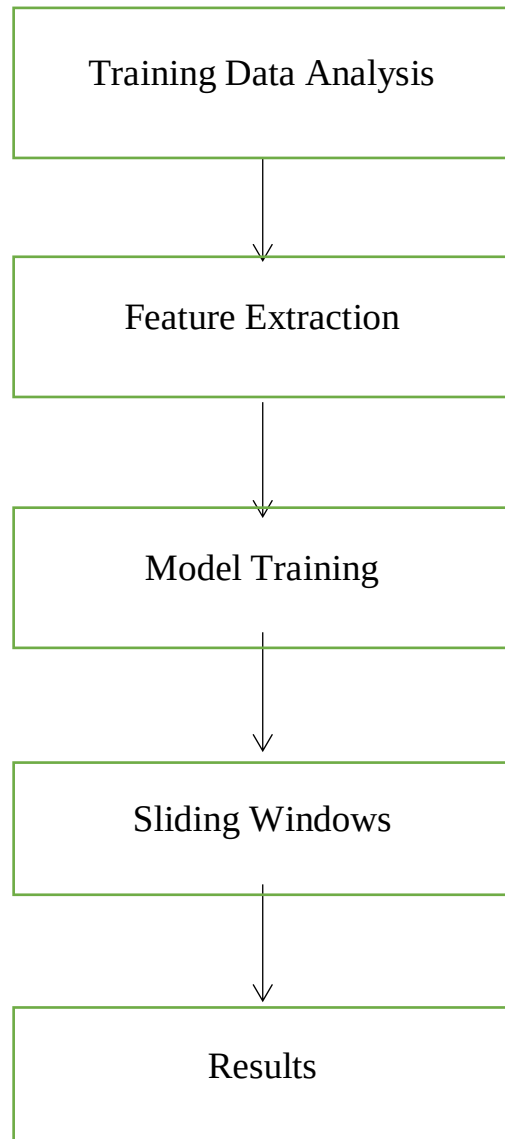


Fig 3.1: Proposed Architecture

MODULE IMPLEMENTATION

Data Pre-processing

It is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.

Feature extraction

It is the process of transforming the raw pixel values from an image, to a more meaningful and useful information that can be used in other techniques, such as point matching or machine learning.

Sliding Windows

Object detection using sliding window machine learning algorithm, first requirement of sliding window algorithm is to prepare labeled training set. Sliding window is a problem-solving technique for problems involves arrays/lists. Window Sliding Technique

The technique can be best understood with the window pane in bus, consider a window of length n and the pane which is fixed in it of length k . Consider, initially the pane is at extreme left i.e., at 0 units from the left. Now, co-relate the window with array arr of size n and pane with current sum of size k elements. Now, if we apply force on the window such that it moves a unit distance ahead. The pane will cover next k consecutive elements. Consider an array $arr = \{5, 2, -1, 0, 3\}$ and value of $k = 3$ and $n = 5$

Applying sliding window technique:

1. We compute the sum of first k elements out of n terms using a linear loop and store the sum in variable window sum.
2. Then we will graze linearly over the array till it reaches the end and simultaneously keep track of maximum sum.
3. To get the current sum of block of k elements just subtract the first element from the previous block and add the last element of the current block. The below representation will make it clear how the window slides over the array. This is the initial phase where we have calculated the initial window sum starting from index 0 . At this stage the window sum is 6. Now, we set the maximum sum as

current window 8 i.e.

HAAR CASCADE ALGORITHM

Haar Cascade is a machine learning object detection algorithm used to identify objects in an image or video and based on the concept of features proposed by

Paul Viola and Michael Jones in their paper "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001.

It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images.

The algorithm has four stages:

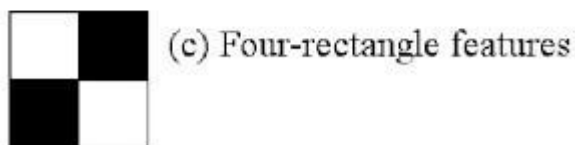
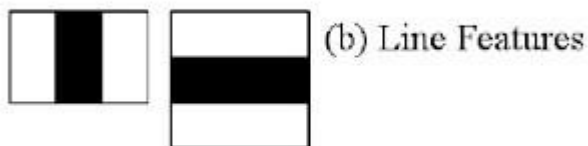
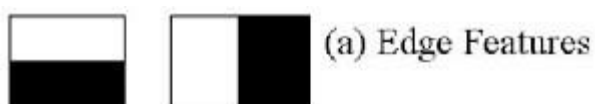
1. Haar Feature Selection
2. Creating Integral Images
3. Adaboost Training
4. Cascading Classifiers

It is well known for being able to detect faces and body parts in an image, but can be trained to identify almost any object.

Let's take face detection as an example. Initially, the algorithm needs a lot of positive images of faces and negative images without faces to train the classifier. Then we need to extract features from it.

Haar Feature Selection

First step is to collect the Haar Features. A Haar feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums.



Creating Integral Images

Integral Images are used to make this super-fast. But among all these features we calculated, most of them are irrelevant. For example, consider the image below. Top row shows two good features. The first feature selected seems to focus on the property that the region of the eyes is often darker than the region of the nose and cheeks. The second feature selected relies on the property that the eyes are darker than the bridge of the nose. But the same windows applying on cheeks or any other place is irrelevant.

Adaboost Training

So how do we select the best features out of 160000+ features? This is accomplished using a concept called Adaboost which both selects the best features and trains the classifiers that use them. This algorithm constructs a “strong” classifier as a linear combination of weighted simple “weak” classifiers. The process is as follows.

During the detection phase, a window of the target size is moved over the input image, and for each subsection of the image and Haar features are calculated. You can see this in action in the video below. This difference is then compared to a learned threshold that separates non-objects from objects. Because each Haar feature is only a “weak classifier” (its detection quality is slightly better than random guessing) a large number of Haar features are necessary to describe an object with sufficient accuracy and are therefore organized into *cascade classifiers* to form a strong classifier.

Cascading Classifiers

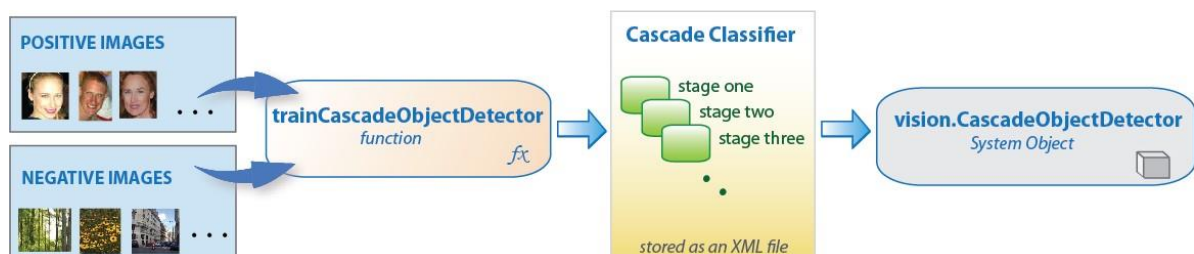


Fig 3.2 Cascade Classifier

The cascade classifier consists of a collection of stages, where each stage is an ensemble of weak learners. The weak learners are simple classifiers called *decision stumps*. Each stage is trained using a technique called *boosting*. *Boosting* provides the ability to train a highly accurate classifier by taking a weighted average of the decisions made by the weak learners.

Each stage of the classifier labels the region defined by the current location of the sliding window as either positive or negative. *Positive* indicates that an object was found and *negative* indicates no objects were found. If the label is negative, the classification of this region is complete, and the detector slides the window to the next location. If the label is positive, the classifier passes the region to the next stage. The detector reports an object found at the current window location when the final stage classifies the region as positive.

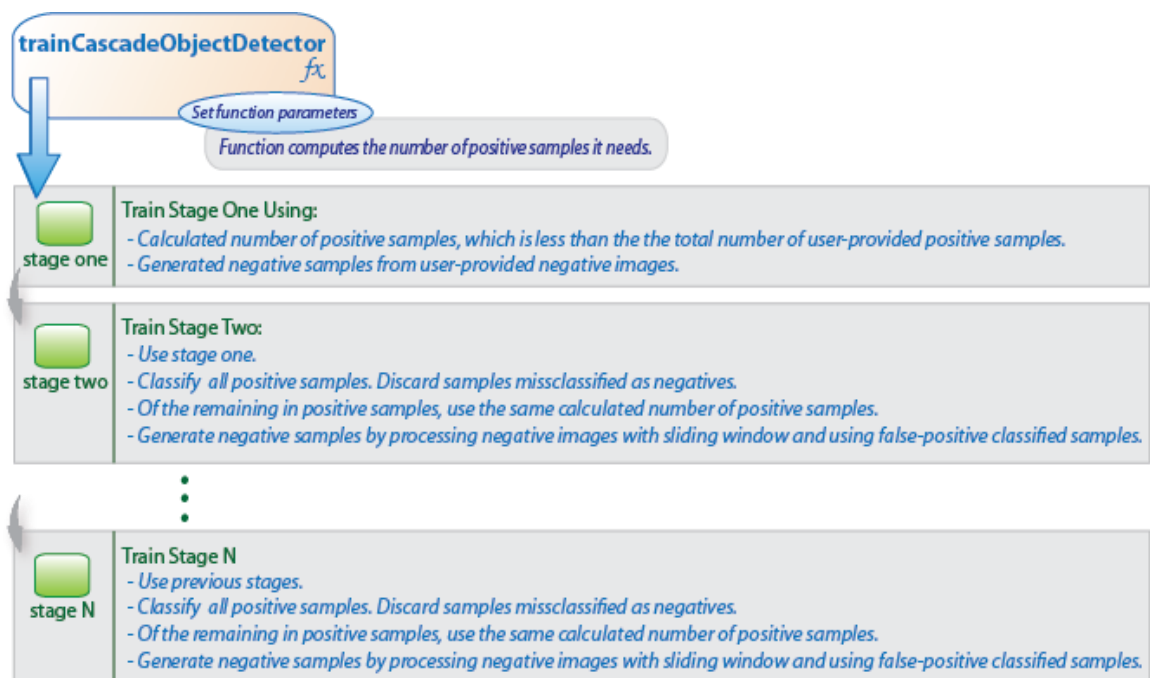


Fig 3.3 train cascade object detector

APPLICATIONS

Virtual Personal Assistants

Siri, Alexa, Google Now are some of the popular examples of virtual personal assistants. As the name suggests, they assist in finding information, when asked

over voice. All you need to do is activate them and ask “What is my schedule for today?”, “What are the flights from Germany to London”, or similar questions. For answering, your personal assistant looks out for the information, recalls your related queries, or send a command to other resources (like phone apps) to collect info. You can even instruct assistants for certain tasks like “Set an alarm for 6 AM next morning”, “Remind me to visit Visa Office day after tomorrow”. Machine learning is an important part of these personal assistants as they collect and refine the information on the basis of your previous involvement with them. Later, this set of data is utilized to render results that are tailored to your preferences. Virtual Assistants are integrated to a variety of platforms. For example: Smart Speakers: Amazon Echo and Google Home Smartphones: Samsung Bixby on Samsung S8 Mobile Apps: Google All

Traffic Predictions

We all have been using GPS navigation services. While we do that, our current locations and velocities are being saved at a central server for managing traffic. This data is then used to build a map of current traffic. While this helps in preventing the traffic and does congestion analysis, the underlying problem is that there are a smaller number of cars that are equipped with GPS. Machine learning in such scenarios helps to estimate the regions where congestion can be found on the basis of daily experiences. When booking a cab, the app estimates the price of the ride. When sharing these services, how do they minimize the detours? The answer is machine learning. Jeff Schneider, the engineering lead at Uber ATC reveals in an interview that they use ML to define price surge hours by predicting the rider demand. In the entire cycle of the services, ML is playing a major role.

Videos Surveillance

Imagine a single person monitoring multiple video cameras! Certainly, a difficult job to do and boring as well. This is why the idea of training computers to do this job makes sense. The video surveillance system nowadays is powered by AI that makes it possible to detect crime before they happen. They track unusual behaviour of people like standing motionless for a long time, stumbling, or napping on benches

etc. The system can thus give an alert to human attendants, which can ultimately help to avoid mishaps.

PROPOSED SYSTEM

1. Detection and classification of the vehicles and other objects of interest (e.g., toll payment box).
2. Predicting the scene class based on the spatial relationships among the vehicles of interest and contextually important objects.

This uses machine learning techniques to get a high degree of accuracy from what is called “training data”. Haar Cascades use the Adaboost learning algorithm which selects a small number of important features from a large set to give an efficient result of classifiers.

CHAPTER 4

RESULTS AND DISCUSSION

The Results obtained are based on the live and continues inputs given to it. The below figures represent a sample image of the result obtained in which it signifies the description of vehicle classified as bus/car/cycle e.c.t along with the amount associated with it. The results obtained can be reliable since it also differentiates between vehicles and others moving bodies.

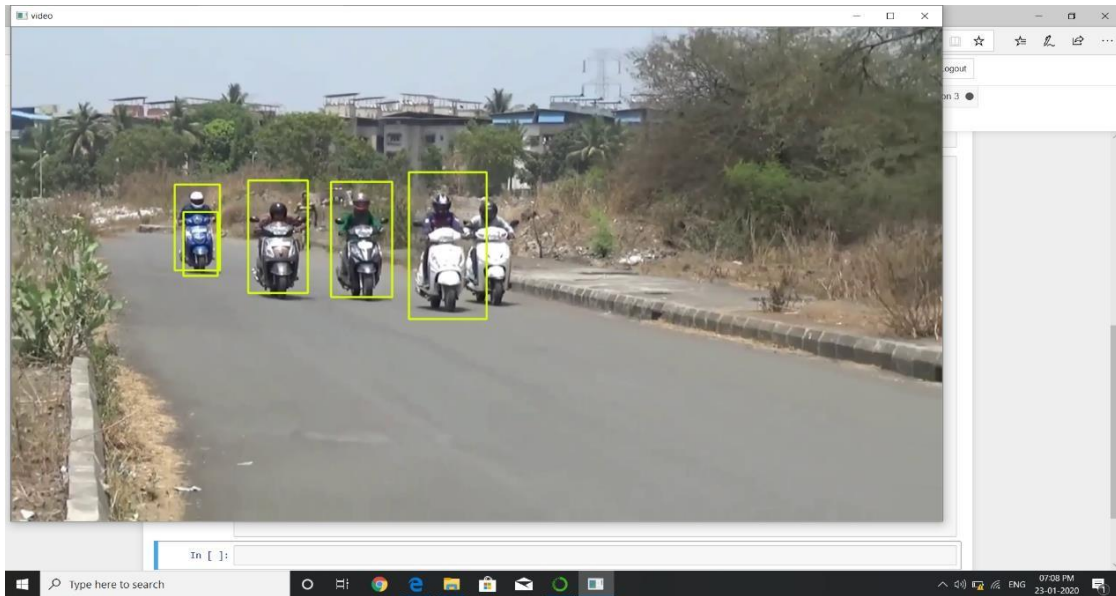


Fig 4.1 Detection of motor cycles

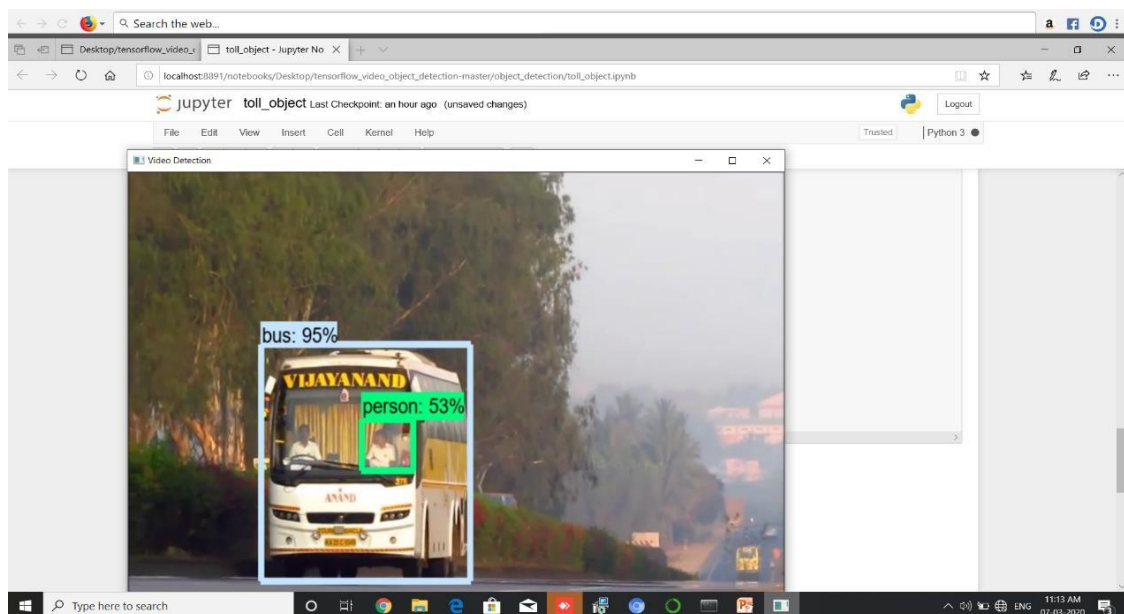


Fig 4.2 Detection of bus

CHAPTER 5

CONCLUSION AND FUTURE WORK

CONCLUSION

This research designs a classification system to determine object as specific type of vehicle. Haar Cascade Classifier proposed to detect an object. The experimental results, gave satisfactory and which makes the proposed rapid and robust system for the detection of vehicles.'

FUTURE WORK

In the future, we will combine discriminative loss with classification loss for network training to get better features. However, several improvements can be made to this single object detection system to allow it multi object detection (vehicle, pistons. etc) usable in real applications of road safety. These improvements will be the objective of future works.

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APPENDIX

A. SOURCE CODE

```
import cv2

cascade_src = 'Bus_front.xml'

video_src = 'bus1.mp4'

cap = cv2.VideoCapture(video_src)

car_cascade = cv2.CascadeClassifier(cascade_src)

while True:

    ret, img = cap.read()

    if (type(img) == type (None)):

        break

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    cars = car_cascade.detectMultiScale(gray, 1.16, 1)

    for (x,y,w,h) in cars:

        cv2.rectangle(img,(x,y),(x+w,y+h),(0,0,255),2)

    cv2.imshow('video', img)

    if cv2.waitKey(33) == 27:

        break

cv2.destroyAllWindows()

import cv2

cascade_src = 'two_wheeler.xml'

video_src = 'two_wheeler2.mp4'

cap = cv2.VideoCapture(video_src)
```

```
car_cascade = cv2.CascadeClassifier(cascade_src)

while True:

    ret, img = cap.read()

    if (type(img) == type(None)):

        break

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    cars = car_cascade.detectMultiScale(gray,1.01, 1)

    for (x,y,w,h) in cars:

        cv2.rectangle(img,(x,y),(x+w,y+h),(0,255,215),2)

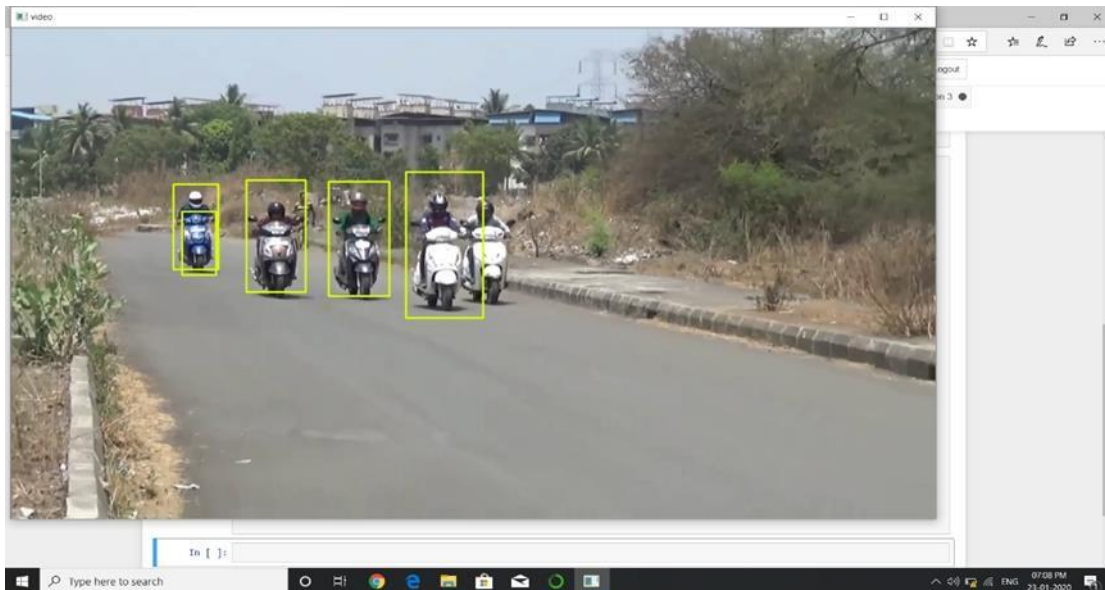
    cv2.imshow('video', img)

    if cv2.waitKey(33) == 27:

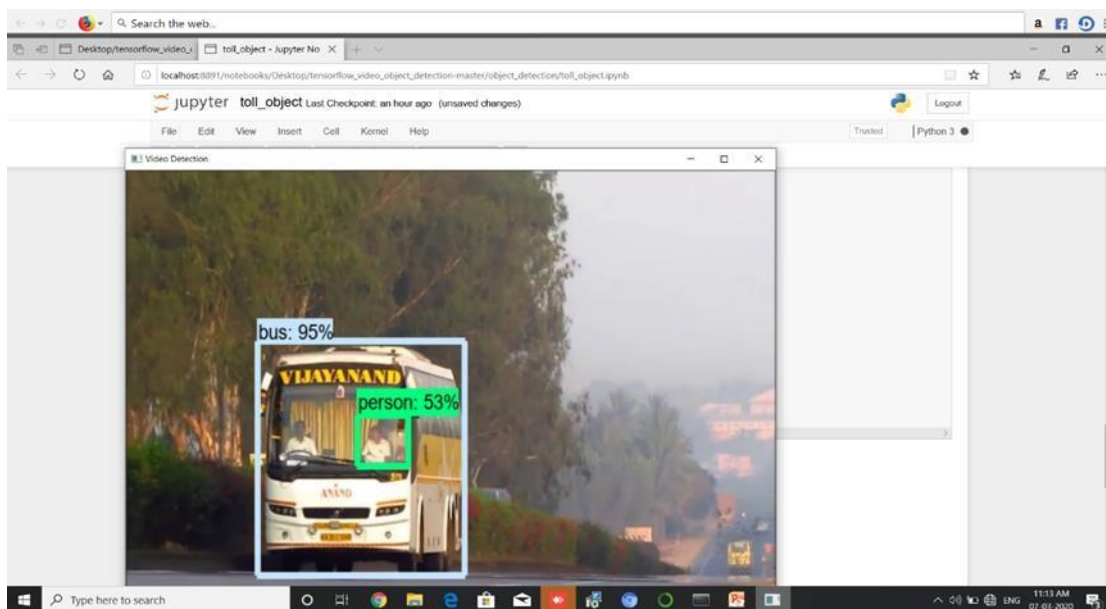
        break

cv2.destroyAllWindows()
```

B. SCREEN SHOTS



Detection of motor cycles



Detection of bus

C. PUBLICATION WITH REPORT

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AUTOMATIC TOLL COLLECTION USING VEHICLE CLASSIFICATION IN TOLL BOOTH ABSTRACT: - Toll Vehicle Classification is a significant undertaking. Without a doubt, it has numerous utilizations in rush hour gridlock the board and toll assortment frameworks. Right now, Auto-courses bunch Networks (the greatest French Highways concession) are considered, where consistently, a large number of vehicles are arranged progressively. At that point, a little diminishing in order execution can have genuine financial misfortunes. Along these lines, the exactness and the time unpredictability become basic for the toll assortment framework. The present arrangement calculation utilizes the scene highlights to recognize vehicles classes. Whatever it may be, it requires a huge named dataset, and when different vehicles are in the picture, it has an impediment. Therefore, we suggest a novel environment that takes advantage of the papers ' semantic spatial relationship in mindful vehicle characterization strategy. The analyzes [show that our methodology is progressing just as reliably as the current model with relatively lower named datasets](#) (littler several [times](#)). In addition, the acquired [accuracy of the proposed technique is 99.97 percent compared with 99.79 percent obtained by the present method when using a similar set of preparations](#). We apply Haar Cascade calculation to distinguish the vehicle arrangement. I INTRODUCTION Automated toll collection is a development enabling the electronic aggregation of toll Payments. It has been inspected by examiners and associated in various freeways, platforms, and entries requiring such a method. It is furthermore a methodology by which to control complaints from drivers concerning the weights drew in with genuinely making portions at the fee collection counters. Other than this obvious good position, applying ATC [5,6] could moreover benefit the toll overseers. Right now, ATC