Visvesvaraya Technological University, Belagavi.

PROJECT REPORT

on

"INTELLIGENT SURVEILLANCE SYSTEM FOR RIDERS WITHOUT HELMET AND TRIPLE RIDING DETECTION ON TWO WHEELERS"

Project Report submitted in partial fulfillment of the requirement for the award of the degree of

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CERTIFICATE

This is to certify that the internship work entitled **"Intelligent Surveillance System For Riders Without Helmet And Triple Riding Detection On Two Wheelers"** is carried out by **Apoorva Saumya, Gayathri V, Sarthak kale** bearing USN 1CR16EC020, 1CR16EC042, 1CR16EC153 bonafide students of **CMR INSTITUTE OF TECHNOLOGY** in partial fulfillment for the award of **Bachelor of Engineering** in **Electronics and Communication Engineering** from **Visvesvaraya Technological University, Belagavi** during the academic year **2019-2020**. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the department library. The Internship Report has been approved and satisfies the academic requirements with respect to internship work prescribed for the said degree.

Signature of Guide	Signature of HOD	Signature of Principal
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ABSTRACT

The rate at which the number of two wheelers in India is rising is 20 times the rate at which human population is growing. The risk of death is 2.5 times more among riders not wearing a helmet compared with those wearing a helmet. The existing video surveillance-based system is effective but it requires significant human assistance whose efficiency decreases with time and human biasing also comes into the picture. This project aims to solve this problem by automating the process of detecting the riders who are riding without helmets. The system takes a video of traffic on public roads as the input and detects moving objects in the scene. A machine learning classifier is applied to the moving object to identify if the moving object is a two-wheeler. If it is a two-wheeler, then another classifier is used to detect whether the rider is wearing a helmet. So, wearing headgear is critical to decrease the danger of injuries in the event that mishap happens. This work proposes a system for location of individual or different riders taking a trip on bikes with no helmets. Inside the proposed approach, from the beginning stage, bike riders are recognized with the use of YOLOv3 model which is a consistent type of YOLO model, the forefront methodology for object distinguishing helps as such in distinguishing the riders with and without helmet. The vertical projection of binary image is used for counting the number of riders if it exceeds two.

Chapter 1

INTRODUCTION

Two-wheeler is a very popular mode of transportation in almost every country. However, there is a high risk involved because of less protection. To reduce the involved risk, it is highly desirable for bike-riders to use a helmet.

Two-Wheelers account for the greatest number of road accidents. Though careless and rash driving is the main cause of these accidents, head injuries form a single largest reason for the road accident deaths. Study shows that more than one- third who died in road accidents could have survived if they would have worn a helmet, the usage of helmet can save accident deaths by 30 to 40%.

Number of road accidents due to bike riders without helmets has been alarming. A Delhi Police annual report (released in 2017) revealed that of the total number of fatal accidents in the city in 2016, 35-40 percent of the deaths were due to riders “not wearing helmets" or “poor quality helmets”. It is compulsory for two-wheeler riders to wear safety helmets under Section 129 of the Motor Vehicles Act, 1988. The rule also says that a helmet should have a thickness of 20-25 mm, with quality foam. It should also have an ISI mark and follow the Bureau of Indian Standards.

But unfortunately, no one seems to follow these rules, at least not for the pillion riders. These days video Surveillance based systems have turned into a significant gear to remain a track on any very crook or hostile to law movement in current human advancement. There are existing methods which use specialized sensors in the ergonomics of the motorbike to check the presence of a helmet. But it is impossible to convince every user to install sensors on the already existing bikes. Also, the accuracy and integrity of these sensors is questionable. Apart from this, systems that use video processing have very high computational costs. The technologies that were used to build the system were very expensive hence making it an economically non-viable choice.

Considering this present, there's an expanding request to build up a solid and convenient proficient system for identifying helmet utilization of motorbike riders that doesn't accept an individual's spectator. A promising strategy for accomplishing this mechanized recognition of motorbike helmet use is AI. AI has been applied to an assortment of street wellbeing related discovery undertakings, and has accomplished high precision for the general recognition. To date several researchers have tried to tackle the problem of detection of motorcyclists without helmets by using different methods but have not been able to accurately identify motorcyclists without helmets under challenging conditions such as occlusion, illumination, poor quality of video, varying weather conditions, etc. One major reason for the poor performance of existing methods is the use of less discriminative representation for object classification as well as the consideration of irrelevant objects against the objective of detection of motorcyclists without helmets. Also, the existing approaches make use of handcrafted features only. Deep networks have gained much attention with state-of-the-art results in complicated tasks such as image classification, object recognition, tracking detection and segmentation due to their ability to learn features directly from raw data without resorting to manual tweaking.

Nowadays video surveillance-based systems have become an essential equipment to keep a track on any kind of criminal or anti law activity in modern civilization.

Over the past decades, some artificial intelligent techniques like computer vision and machine learning with growing progress have been widely applied in intelligent surveillance in power substations. It can not only avoid time consuming labor intensive tasks, but also point out the power equipment fault and worker illegal operation in time and accurately against accidents.

However, the existing video surveillance-based methods are passive and require significant human assistance. In general, such systems are infeasible due to involvement of humans, whose efficiency decreases over long duration. Automation of this process is highly desirable for reliable and robust monitoring of these violations as well as it also significantly reduces the amount of human resources needed. Also, many countries are adopting systems involving surveillance cameras at public places. So, the solution for detecting violators using the existing infrastructure is also cost-effective.

However effective automatic surveillance systems generally involve following tasks: environment modelling, detection, tracking and classification of moving objects.

In order to adopt such automatic solutions certain challenges, need to be addressed:

1) Real-time Implementation: Processing significant amounts of information in a time Constraint manner is a challenging task. As such applications involve tasks like segmentation, feature extraction, classification and tracking, in which a significant amount of information needs to be processed in short duration to achieve the goal of real-time implementation.

2) Occlusion: In real life scenarios, the dynamic objects usually occlude each other due to which object of interest may only be partially visible. Segmentation and classification become difficult for these partially visible objects.

3) Direction of Motion: 3-dimensional objects in general have different appearance from different angles. It is well known that accuracy of classifiers depends on features used which in turn depends on angle to some extent. A reasonable example is to consider the appearance of a bike-rider from front view and side view.

4) Temporal Changes in Conditions: Over time, there are many changes in environment conditions such as illumination, shadows, etc. There may be subtle or immediate changes which increase complexity of tasks like background modelling.

5) Quality of Video Feed: Generally, CCTV cameras capture low resolution video.Also, conditions such as low light, bad weather complicate it further. Due to such limitations, tasks such as segmentation, classification and tracking become even more difficult. As stated in , a successful framework for surveillance application should have useful properties such as real-time performance, fine tuning, robust to sudden changes and predictive. Keeping these challenges and desired properties in mind, we propose a method for automatic detection of bike-riders without helmets using feed from existing security cameras, which works in real time.

The prevailing video statement primarily based on strategies is passive and wants important human help. Automation of this procedure is exceedingly appealing for energetic commentary of this infringement and additionally it likewise altogether lessens the measure of human resource required. Available strategies utilize particular sensors inside the ergonomics of the motorbike to see the existence of a helmet. Be that as it may, it's unrealistic to persuade each individual to place sensors on the effectively present motorbikes. Likewise, the exactness and honesty of those sensors may be flawed. Aside from this, structures that use video processing have very excessive computational prices. The technology that had been wont to build the device is very high-priced consequently building that with inexpensively infeasible preference.

1.1 Challenges Faced

1.1.1 Real-time Implementation: Processing critical measure of data in a period imperative way is a test undertaking. All things considered applications include assignments like segmentation, feature extraction, classification and tracking, in which a lot of data should be prepared in a brief term to accomplish the objective of ongoing usage.

1.1.2 Occlusion: In real life scenarios, the dynamic objects usually occlude each other due to which object of interest may only be partially visible.

1.1.3 Temporal Changes in Conditions: Over time, there are numerous progressions in environmental conditions, for example, light, shadows, and so forth.

1.1.4 Quality of Video Feed: Generally, CCTV cameras catch low resolution video input. Likewise, environmental conditions such as low light, hazy climate may deteriorate it further.

1.2 YOLO (You Only Look Once)

YOLO is an effective real-time object recognition algorithm. Image classification is one of the many exciting applications of convolutional neural networks. Aside from simple image classification, there are plenty of fascinating problems in computer vision, with object detection being one of the most interesting. It is commonly associated with self-driving cars where systems blend computer vision, LIDAR and other technologies to generate a multidimensional representation of the road with all its participants. Object detection is also commonly used in video surveillance, especially in crowd monitoring to prevent terrorist attacks, count people for general statistics or analyse customer experience with walking paths within shopping centres.

YOLO trains on full images and directly optimizes detection performance. This unified model has several benefits over traditional methods of object detection. First, YOLO is extremely fast. Since we frame detection as a regression problem we don't need a complex pipeline. We simply run our neural network on a new image at test time to predict detections.

Two types of YOLO algorithm

1. Algorithms based on classification: They are implemented in two stages. First, they select regions of interest in an image. Second, they classify these regions using convolutional neural networks. This solution can be slow because we have to run predictions for every selected region. A widely known example of this type of algorithm is the Region-based convolutional neural network (RCNN) and its cousins Fast-RCNN, Faster-RCNN and the latest addition to the family: Mask-R CNN. Another example is Retina Net.

2. Algorithms are based on regression: instead of selecting interesting parts of an image, they predict classes and bounding boxes for the whole image in one run of the algorithm. The two best known examples from this group are the YOLO (You Only Look Once) family algorithms and SSD (Single Shot Multibox Detector). They are commonly used for real-time object detection as; in general, they trade a bit of accuracy for large improvements in speed.

How does YOLO work?

1. Objects are detected by a combination of **object locator** and an **object recognizer.**
2. YOLO approaches the object detection problem in a completely different way. It forwards the whole image **only once** through the network.
3. First, it divides the image into a 13×13 grid of cells. The size of these 169 cells vary depending on the size of the input.
4. For each bounding box, the network also predicts the confidence that the bounding box actually encloses an object, and the probability of the enclosed object being a particular class.
5. Most of these bounding boxes are eliminated because their confidence is low or because they are enclosing the same object as another bounding box with a very high confidence score. This technique is called non-maximum suppression.

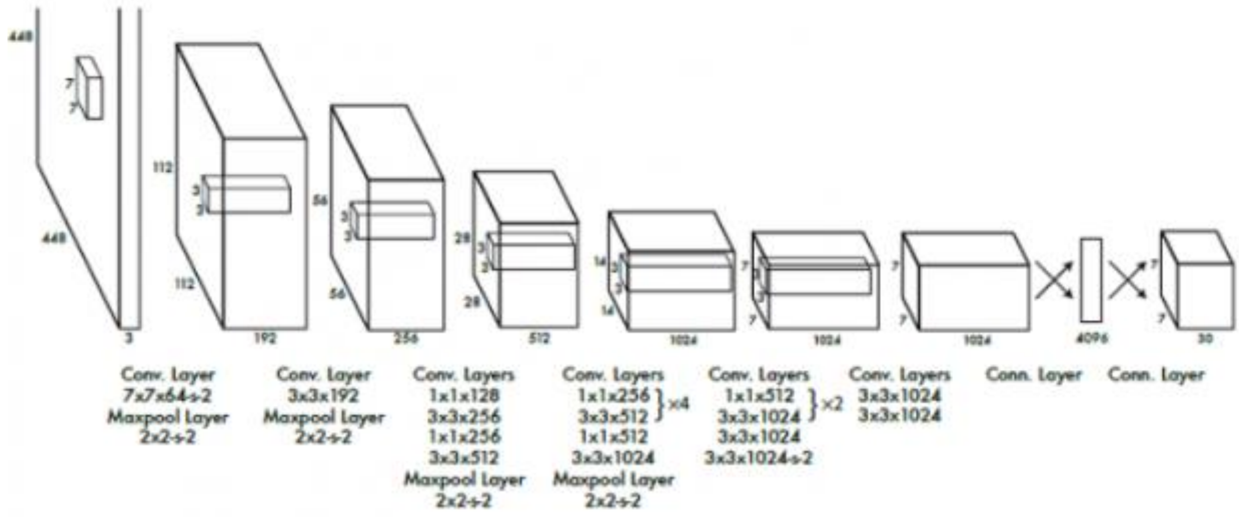


Figure 1 Working of YOLO algorithm

1.3 MACHINE LEARNING

The basic process of machine learning is to give training data to a learning algorithm. The learning algorithm then generates a new set of rules, based on inferences from the data. This is in essence generating a new algorithm, formally referred to as the machine learning model.

Instead of programming the computer every step of the way, this approach gives the computer instructions that allow it to learn from data without new step-by-step instructions by the programmer. This means computers can be used for new, complicated tasks that could not be manually programmed Machine learning, a particular approach to AI and the driving force behind recent developments. Instead of programming the computer every step of the way, machine learning makes use of learning algorithms that make inferences from data to learn new tasks.

As machine learning is used more often in products and services, there are some significant considerations when it comes to users' trust in the Internet. Several issues must be considered when addressing AI, including, socio-economic impacts; issues of transparency, bias, and accountability; new uses for data, considerations of security and safety, ethical issues; and, how AI facilitates the creation of new ecosystems.

At the same time, in this complex field, there are specific challenges facing AI, which include: a lack of transparency and interpretability in decision-making; issues of data quality and potential bias; safety and security implications; considerations regarding accountability; and, its potentially disruptive impacts on social and economic structures. Machine Learning is simply making a computer perform a task without explicitly programming it. In today's world every system that does well has a machine learning algorithm at its heart. Take for example Google Search engine, Amazon Product recommendations, LinkedIn, Facebook etc, all these systems have machine learning algo rithms embedded in their systems in one form or the other. They are efficiently utilising data collected from various channels which helps them get a bigger picture of what they are doing and what they should do.

1.4 PYTHON

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.

Python's simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse.
Advantages:

1. easy to learn and use
2. python is broadly adopted and supported
3. python is not a toy language
4. open source with vibrant community
5. extensive support libraries

Python offers concise and readable code. While complex algorithms and versatile workflows stand behind machine learning and AI, Python's simplicity allows developers to write reliable systems. Python code is understandable by humans, which makes it easier to build models for machine learning.

Python is a widely used high-level programming language for general-purpose programming. Apart from being an open source programming language, python is a great object-oriented, interpreted, and interactive programming language. Python combines remarkable power with very clear syntax. It has modules, classes, exceptions, very high-level dynamic data types, and dynamic typing. There are interfaces to many systems calls and libraries, as well as to various windowing systems. New built-in modules are easily written in C or C++ (or other languages, depending on the chosen implementation). Python is also usable as an extension language for applications written in other languages that need easy-to-use scripting or automation interfaces.

Python is widely considered as the preferred language for teaching and learning Ml (Machine Learning). Few simple reasons are:

- It’s simple to learn. As compared to c, c++ and Java the syntax is simpler and Python also consists of a lot of code libraries for ease of use.
- Though it is slower than some of the other languages, the data handling capacity is great.
- Open Source! – Python along with R is gaining momentum and popularity in the Analytics domain since both of these languages are open source.
- Capability of interacting with almost all the third party languages and platforms.

OpenCV is used for all sorts of image and video analysis, like facial recognition and detection, license plate reading, photo editing, advanced robotic vision, optical character recognition, and a whole lot more. All this under one library of Python making python fan favourite.

Compared to other languages like C/C++, Python is slower. But another important feature of Python is that it can be easily extended with C/C++. This feature helps us to write computationally intensive codes in C/C++ and create a Python wrapper for it so that we can use these wrappers as Python modules. This gives us two advantages: first, our code is as fast as original C/C++ code (since it is the actual C++ code working in the background) and second, it is very easy to code in Python. This is how OpenCV-Python works, it is a Python wrapper around original C++ implementation.

Chapter 2

LITERATURE SURVEY

Automatic identification of bicycle riders without headgear falls under general class of anomaly recognition in video recordings. Effective detection system framework include following errands: environmental modeling, detection, tracking and classification of moving objects. Chiverton proposed an approach which utilizes geometrical state of headgear and illumination difference at various bits of the headgear. It utilizes circle arc discovery strategy in view of the Hough transform. The major constraint of this approach is that it tries to find headgear in the full frame which is computationally costly and furthermore it might frequently confound other comparable modeled objects as headgear. Additionally, it manages the reality that headgear is applicable just if there should arise an occurrence of bicycle riders. Chen et al. proposed an effective way to distinguish and track vehicles in urban rush hour gridlock. It utilizes Gaussian mixture model along with a system to refine foreground blob keeping in mind the end goal to remove foreground. It tracks a vehicle utilizing Kalman filter and refines classification utilizing dominant part voting. There is a proposed circular arc detection method based on the modified Hough transform. This transformation has been applied to detect a helmet by an ATM surveillance system.

Comprehensively, there are two noteworthy constraints in the current work discussed above. Firstly, recommended approaches are either computationally extremely costly or passive in nature which are not reasonable for ongoing execution. Furthermore, the relationship between the frames is underutilized for final decisions , as the outcomes from back to back frames can be joined to raise more reliable cautions for infringement. The proposed approach overcomes the above examined constraints by giving an effective solution which is suitable for real time application.

Automatic identity of motorbike-riders without helmets in surveillance videos comes underneath the specific category of anomaly detection. As described in [15], powerful automated surveillance generally consists of the subsequent responsibilities: modeling, identity, tracking and type of transferring items within the environment. Chiverton recommended a technique in [16] that uses the geometric form of the helmet and the variant of lights at various parts of the helmet. This uses a way for detecting circle arcs primarily based on the transformation of the Hough. By this strategy the exactness was exceptionally high anyway the quantity of test pictures taken was extremely less so it wasn't a lot dependable.

The greatest weakness of this methodology is that it endeavors to find the helmet in the entire picture, which is computationally expensive, and it can also confuse more fashionable gadgets like helmets. It additionally supervises the fact that helmets are best appropriate only for cyclists.

Doughmala et al.[8] provides a half and full helmet spotting recognition through Haar with abilities like nose, ear, mouth, left eye, appropriate eye and roundabout Hough rebuild to run over helmet presence. In any case, all through this paper it is chipped away to fix resolution of the pictures.
In Dahiya et al. [2], detection of two-wheeler riders without helmet has been developed using real time videos and applied (HOG) Histogram of Oriented Gradients, (SIFT) Scale invariant feature transform, (LBP) Local binary pattern. Through this technique, the detection accuracy was 93.80% however the time interval needed was not speedy at the rate of 11.58 per frame [2]. It affords the method for actual-time detection of motorbike-

riders having no helmets which works in two levels. In the first section, a motorcycle-rider within the video frame is detected. In the second phase, the head of the motorbike-rider is detected and checks if the rider is with or without a helmet, so as to scale back false predictions. Even being less expensive than other previous works, this takes a lot of time implementing the pre-processing techniques as HOG, SIFT, SVM which makes the process slow.

[12] talks about a few systems which are fundamentally the same as the one proposed during this paper, distinguishes bike riders without helmets and catches the sum plate of the considerable number of guilty parties on a COCO database. It characterizes engine bikes and helmets utilizing YOLO and in this manner the innovation utilized for license plate recognition is Open ALPR. Both of those technologies charge monthly fees and hence aren't economically feasible. In rush hour gridlock video, division of motorbike riders utilizing a foundation deduction strategy followed classification using Support Vector Machine (SVM) is proposed by Chiverton et al. [16]. Li et al [3] have applied Histogram of Oriented Gradients (HOG) based absolutely including extraction finished SVM for security helmet discovery. Although operating with nice results, the accuracy and speed of detection was very slow. The classifier additionally gave wrong effects occasionally due to the one of a kind depth of light which had to be corrected.

A local Binary Pattern based cross breed descriptor for features extraction is proposed by Silva et al. [7]. They additionally utilized HOG and Hough Transform descriptors for robotized distinguishing proof of helmet-less motorcyclists. But comparative slower results were obtained. Over the previous decades, some counterfeit canny strategies like PC vision and AI with developing advancement are broadly applied in smart observation in power substations. It can't just maintain a strategic distance from tedious work escalated assignments, yet in addition implies the office gear issue and specialist unlawful activity in time and precisely against mishaps [3].

In rush hour traffic recordings as caught by observation cameras, rapid vehicles don't show up obviously in outlines. So location of rapid bikes in continuously observation video might be difficult work. Furthermore, various shapes, hues and size of bikes additionally make the identification procedure generally complex [1]. In this way a solid system is required to distinguish the defaulters.Above-mentioned researches mainly focus on the power equipment fault detection and state recognition. Aside from equipment safety, intelligent surveillance systems still need to monitor operator safety work. The real time safety helmet wearing detection for perambulatory workers, as a most common safe operation situation in power substation, is a considerably important task related to worker safety. Thus it is necessary to develop a system for automatic detection of safety helmet wearing power substation. Unfortunately, the related work is little and mostly has been made in the detection of motorcyclists with or without helmets.

Wen et al. [18] suggested a circle arc detection method based on Hough transform. They applied it to detect the presence of a helmet on the surveillance system of Automatic Teller Machine. But the drawback of this work was it has used only the geometric features to detect the presence of a helmet. Geometric features are not enough to detect the presence of a helmet; many times the head can be mistaken with the helmet. In Chiu et al. It has used a computer vision based system which aims to detect and segment motorcycles partly occluded by another vehicle. Helmet detection system was used in which the presence of a helmet simplifies that there is a motorcycle. In this paper to detect the helmet edges were computed of the possible helmet region.

Chiverton et al. [16] described and tested a system for automatic classification of motorcycles with and without helmets. It has used (SVM) Support Vector Machine which is trained on (HOG) Histogram of

Oriented Gradients which is derived from the head region of the static images and individual image frame from video data. By this method the accuracy rate was high but the number of testing images taken were very less.

Silva et al. proposed a system for detection of helmet which first starts with moving object segmentation using descriptors then detection of helmet tracing the (ROI) Region of interest which is the head region and then classifies between helmet and non- helmet.But the disadvantage was that it uses circle Hough transform to classify between helmet and non-helmet which also results in misclassification between head and helmet as both has similar shape.[4].

Dahiya et al. proposed a system for detection of two-wheeler riders without helmet using real time videos and has applied (HOG) Histogram of Oriented Gradients, (SIFT) Scale invariant feature transform, (LBP) Local binary pattern. By this method the detection accuracy was 93.80% but the time interval required was very slow at the rate of 11.58 ms per frame [5].

Doughmala et al.[8] presents a half and full helmet wearing detection by Haar with features like nose, ear, mouth, left eye, right eye and circular Hough transform to detect helmet presence. But during this time period project it's worked on fixed resolution images.

The algorithm(YOLO) is used to extract the foreground objects in the video which is then extracted as frames.The location where the helmet can be found is found by the bounding boxes. This area is extracted and the helmet is detected using a machine learning classifier, here YOLO. The driver of the vehicle(two wheeler) is involved in a high-speed accident without wearing a helmet. It is highly dangerous and can cause death. Wearing a helmet can reduce shock from the impact and may save a life. The aim of this research work is to identify the two wheelers riders' so that they can be penalised and to also detect traffic violations such as triple riding .Motorcycles being an obvious choice and a convenient transportation mode, it has a significant contribution to road accident casualties and injuries. Despite the Government traffic regulation, people still avoid using a helmet. The proposed system is an effort to create awareness in society by endorsing the use of helmets and leading people to safety. This project proposes effective enforcement of the use of a helmet by implementing helmet detection for a rider. A system very similar to the one proposed in this paper which identifies bike riders without helmets and captures the number plate of all the offenders on a COCO database. It classifies motor bikes and helmets using YOLO and the technology used for license plate recognition is Open ALPR. Both of these technologies charge monthly fees and hence are not economically feasible.

Based on the YOLO V3 full-regression deep neural network architecture, this paper utilizes the advantage of Densenet in model parameters and technical cost to replace the backbone of the YOLO V3 network for feature extraction, thus forming the so-called YOLO-Densebackbone convolutional neural network. The test results show that the improved model can effectively deal with situations where the helmet is stained, partially occluded, or there are many targets with a low image resolution. In the test set, compared with the traditional YOLO V3, the improved algorithm detection accuracy increased by 2.44% with the same detection rate. The establishment of this model has important practical significance for improving helmet detection and ensuring safe construction.

Over the past years, multiple approaches have been proposed to solve the problem of helmet detection. The authors in [7] use a background subtraction method to detect and differentiate between moving vehicles. And they used Support Vector Machines (SVM) to classify helmets and human heads without helmets. Silva et al.

in [9] proposed a hybrid descriptor model based on geometric shape and texture features to detect motorcyclists without helmets automatically. They used a Hough transform with SVM to detect the head of the motorcyclist. Additionally, they extend their work in [10] by multilayer perceptron models for classification of various objects.

Below are the few major papers, that were referred to during the making of this project:

1. Automated Helmet Detection for Multiple Motorcycle Riders using CNN
(M. Dasgupta, O. Bandyopadhyay and S. Chatterji)

- **Abstract**: Automated detection of traffic rule violators is an essential component of any smart traffic system. In a country like India with a high density of population in all big cities, motorcycles are one of the main modes of transport. Use of a helmet can reduce the risk of head and severe brain injury of the motorcyclists in most of the motorcycle accident cases. Today violation of most of the traffic and safety rules are detected by analysing the traffic videos captured by surveillance cameras. This paper proposes a framework for detection of single or multiple riders traveling on a motorcycle without wearing helmets. In the proposed approach, at first stage, motorcycle riders are detected using the YOLOv3 model which is an incremental version of YOLO model, the state-of-the-art method for object detection. In the second stage, a Convolutional Neural Network (CNN) based architecture has

  been proposed for helmet detection of motorcycle riders. The proposed model is evaluated on traffic videos and the obtained results are promising in comparison with other CNN based approaches

- **Conclusion:** The proposed approach is to detect single or multiple riders basically all riders of a motorcycle without wearing helmets from traffic surveillance videos. First YOLOv3 model has been used for motorcyclist detection. Then, the proposed lightweight convolutional neural network detects wearing of helmet or no helmet for all motorcycle riders. The proposed model works quite well for helmet detection in different scenarios with accuracy of 96.23%. Results of helmet detection for motorcycle riders using proposed approach 500 1000 1500 2000 2500 3000 3500 4000 4500 Iteration 0.4 0.5 0.6 0.7 0.8 0.9 Precision AP=Average Precision Average precision of helmet detection on iteration basis methods and can be extended in future to detect more complicated cases of multiple riders including child riders. Further this work can be extended to even more complex scenarios of bad weather for detection of helmetless motorcyclists.

2. Automatic detection of bike riders without helmets using surveillance videos in real-time
(K. Dahiya, D. Singh and C.K .Mohan)

- **Abstract:** This paper presents a framework for automatic detection of bike-riders without helmets using surveillance videos in real time. The proposed approach first detects bike riders from surveillance video using background subtraction and object segmentation. Then it determines whether the bike-rider is using a helmet or not using visual features and binary classifiers. Also, we present a consolidation approach for violation reporting which helps in improving reliability of the proposed approach. In order to evaluate our approach, we have provided a performance comparison of three various feature representations for classification. The experimental results show detection accuracy of 93.80% on the real world surveillance data. It has also been shown that the proposed approach is

computationally less expensive and performs in real-time with a processing time of 11.58 ms per frame.

- **Conclusion:** In this paper, we propose a framework for real-time detection of traffic rule violators who ride bikes without using a helmet. Proposed framework will also assist the traffic police for detecting such violators in odd environmental conditions viz; hot sun, etc. Experimental results demonstrate the accuracy of 98.88% and 93.80% for detection of bike-riders and detection of violators, respectively. Average time taken to process a frame is 11.58 ms, which is suitable for real time use. Also, the proposed framework automatically adapts to new scenarios if required, with slight tuning. This framework can be extended to detect and report number plates of violators.

3. Safety helmet wearing detection based on image processing and machine learning
(J. Li et al)

- **Abstract:** Safety helmet wearing detection is very essential in power substation. This paper proposed an innovative and practical safety helmet wearing detection method based on image processing and machine learning. At first, the ViBe background modelling algorithm is exploited to detect motion objects under a view of a fixed surveillant camera in power substation. After obtaining the motion region of interest, the Histogram of Oriented Gradient (HOG) feature is extracted to describe the inner human. And then, based on the result of HOG feature extraction, the Support Vector Machine (SVM) is trained to classify pedestrians. Finally, the safety helmet detection will be implemented by color feature recognition. Compelling experimental results demonstrated the correctness and effectiveness of our proposed method.

- **Conclusion:** In this paper, we have investigated a practical and novel method of safety helmets wearing detection in power substations which can real-time monitor the people whether wearing safety helmets or not. The image processing and machine learning techniques are employed in surveillance systems of power substation. Firstly, the ViBe background modelling algorithm was used to segment the moving objects under the view of the monitoring camera. This trick could filter a lot of static objects. Moveover, the histogram of oriented gradient (HOG) feature extraction and support vector machine (SVM) classifier training were implemented to achieve human location per frame. Finally, we utilized color features to recognize the safety helmet wearing situations. The overall method is verified by an amount of experiments on the surveillance video of power substation. The faster and excellent pedestrian detection algorithm and more accurate safety helmet detection strategy will be considered into our detection system frameworks.

4. YOLOv3: An Incremental Improvement
(Redmon J, Farhadi A)

- **Abstract:** We present some updates to YOLO! We made a bunch of little design changes to make it better. We also trained this new network that’s pretty swell. It’s a little bigger than last time but more accurate. It's still fast though, don't worry. At 320 × 320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as an SSD but three times faster. When we look at the old .5 IOU mAP detection metric

YOLOv3 is quite good. It achieves 57.9 AP50 in 51 ms on a Titan X, compared to 57.5 AP50 in 198 ms by RetinaNet, similar performance but 3.8× faster.

5. Detection of Motorcyclists without Helmet in Videos using Convolutional Neural Network
(C. Vishnu, Dinesh Singh, C. Krishna Mohan and Sobhan Babu)

- **Abstract:** In order to ensure the safety measures, the detection of traffic rule violators is a highly desirable but challenging task due to various difficulties such as occlusion, illumination, poor quality of surveillance video, varying weather conditions, etc. In this paper, we present a framework for automatic detection of motorcyclists driving without helmets in surveillance videos. In the proposed approach, first we use adaptive background subtraction on video frames to get moving objects. Later convolutional neural networks (CNN) is used to select motorcyclists among the moving objects. Again, we apply CNN on the upper one fourth part for further recognition of motorcyclists driving without a helmet. The performance of the proposed approach is evaluated on two datasets, IITH Helmet 1 contains sparse traffic and IITH Helmet 2 contains dense traffic, respectively. The experiments on real videos successfully detect 92.87% violators with a low false alarm rate of 0.5% on an average and thus shows the efficacy of the proposed approach.

- **Conclusion:** The proposed framework for automatic detection of motorcyclists driving without helmets makes use of adaptive background subtraction which is invariant to various challenges such as illumination, poor quality of video, etc. The use of deep learning for automatic learning of discriminative representations for classification tasks improves the detection rate and reduces the false

  alarms resulting in a more reliable system. The experiments on real videos successfully detect ≈ 92.87% violators with a low false alarm rate of ≈ 0.50% on two real video datasets and thus shows the efficiency of the proposed approach.

Chapter 3

PROPOSED TECHNIQUES

This segment presents the proposed approach for continuous recognition of no. of bike-riders and bike riders without helmets utilizing YOLO.

3.1 You Look Only Once

YOLO is a smart convolutional neural network (CNN) for performing object detection in actual-time. The technique uses one neural network on the entire image, later splits the photograph into different areas and predicts bounding containers along with possibilities for each region. The biggest advantage of using YOLO is its pace which could be very speedy and may process 45 frames according to second.

Beside simple image characterization, there are numerous captivating troubles in PC vision, with item identity being one some of the first fascinating. It's often recognized with self-riding vehicles where systems blend PC imaginative and prescient, LIDAR and one of a kind advances to get a multidimensional portrayal of the street with each one of its members. Item discovery is commonly used in video commentary, for instance, swarm controlling, visitors light, in shopping facilities and so on.

YOLO trains on various full pictures and legitimately expands discovery execution. This particular model has loads of greater advantages over standard strategies for object popularity. In the first vicinity, YOLO is extremely brief. Since area is outlined as a relapse issue, the system need not hassle with a luxurious pipeline. The neural system is run on a substitution photograph at test time to foresee discoveries.

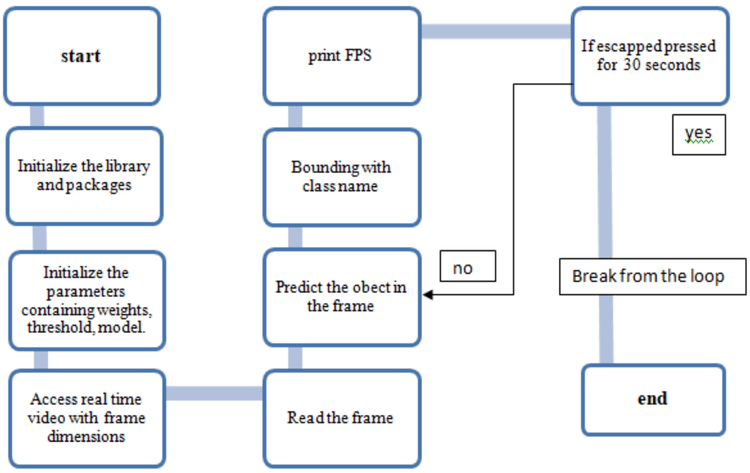


Figure 2. Workflow of YOLO scheme

Contrasted with other nearby proposition association structures (brief RCNN) which carry out place on extraordinary district hints and along those strains land up performing forecast on several occasions for one of a kind regions in a image, Yolo layout is an increasing number just like FCNN (fully convolutional neural gadget) and passes the picture (nxn) as soon as thru the FCNN and yield is (mxm) expectation. This design is parting the records image in mxm lattice and for every matrix age 2 bouncing boxes and sophistication probabilities for the ones leaping bins.

Calculations that depend on relapse, as opposed to choosing fascinating pieces of an image, they anticipate classes and leaping confines for the whole image one run of the calculation. The two most popular models from this gathering are the YOLO family calculations and SSD (Single Shot Multibox Detector). They're normally utilized for ongoing item identification as for the most part, they exchange a hint of exactness for monster enhancements in pace.

3.2 MACHINE LEARNING

The simple system of device studying is to give schooling facts to a learning algorithm. The learning algorithm then generates a brand new set of rules, primarily based on inferences from the facts. This is in essence producing a new algorithm, officially referred to as the machine mastering model.
Instead of programming the computer each step of the manner, this approach offers the device commands that allow it to study from facts without new step-with the aid-of-step commands via the programmer. This approach computer systems may be used for brand new, complex tasks that could not be manually programmed.

Instead of programming the pc every step of the way, machine learning makes use of getting to know algorithms that make inferences from facts to research new obligations.
As devices getting to know are used extra regularly in products and services, there are some vast issues when it comes to customers' agreement with the Internet. Several troubles need to be considered while addressing AI, including, socio-economic effects; troubles of transparency, bias, and accountability; new makes use of for information, considerations of protection and safety, ethical issues; and, how AI enables the advent of latest ecosystems.

At the same time, in this complicated field, there are specific demanding situations facing AI, which encompass: a loss of transparency and interpretability in selection-making; problems of information satisfactory and capability bias; protection and safety implications; concerns regarding responsibility; and, its doubtlessly disruptive effects on social and monetary structures. Here Machine learning is used with YOLO for the detection specifically of heads, vehicles - two wheelers.

3.3 Google Collab

Collaboratory, or "Colab" for short, allows you to write and execute Python in your browser, with

- Zero configuration required
- Free access to GPUs
- Easy sharing

Google is quite aggressive in AI research. Over many years, Google developed an AI framework called TensorFlow and a development tool called Collaboratory. Today TensorFlow is open-sourced and since 2017, Google made Collaboratory free for public use. Collaboratory is now known as Google Colab or simply Colab.

Another attractive feature that Google offers to the developers is the use of GPU. Colab supports GPU and it is totally free. The reasons for making it free for the public could be to make its software a standard in the academics for teaching machine learning and data science. It may also have a long term perspective of building a customer base for Google Cloud APIs which are sold per-use basis.
Irrespective of the reasons, the introduction of Colab has eased the learning and development of machine learning applications.

Colab notebooks allow you to combine executable code and rich text in a single document, along with images, HTML, LaTeX and more. When you create your own Colab notebooks, they are stored in your Google Drive account. With Colab you can import an image dataset, train an image classifier on it, and evaluate the model, all in just a few lines of code. Colab notebooks execute code on Google's cloud servers, meaning you can leverage the power of Google hardware, including GPU and CPU, regardless of the power of your machine.

Chapter 4

METHODOLOGY

In this paper, YOLOv3 calculates an attempt to do an image grouping to investigate the info dataset about motorcyclists with a helmet or without a helmet. Additionally, a profound learning technique for picture identification to attempt to discover a biker by not having helmet discovery from the video picture.

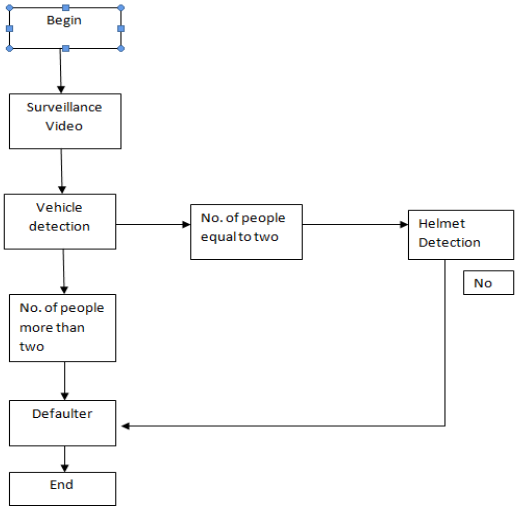
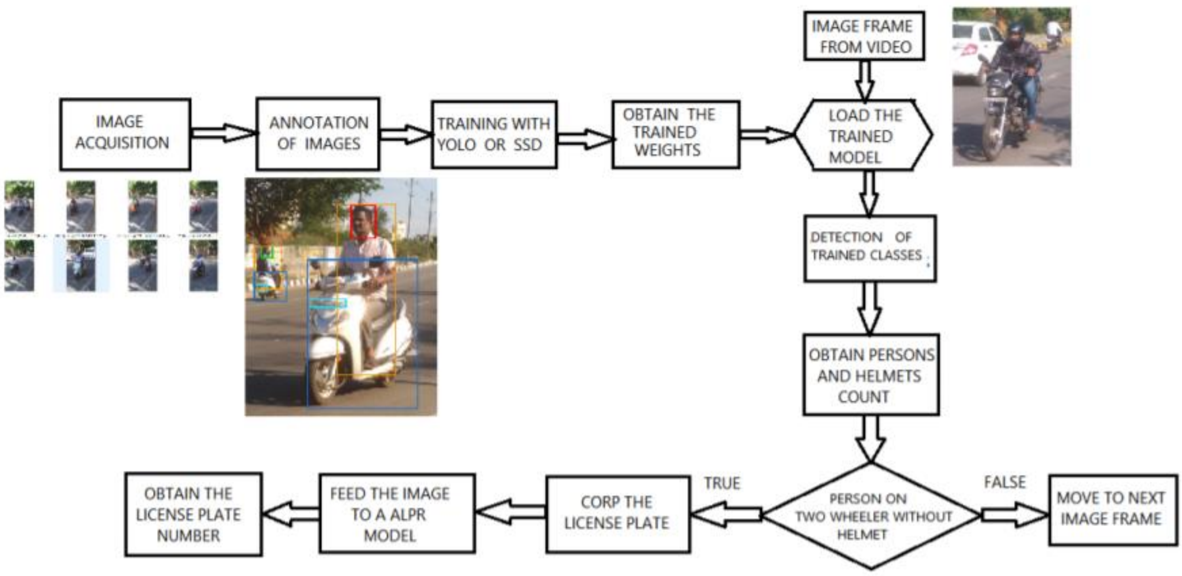


Figure 3. flow diagram of methodology

This exploration has upheld the five-advanced procedure: video and image gathering, image classification, vehicle detection and grouping, image detection examination, and interpretation of result.



1. Video and Image Gathering

The information datasets were gathered from the assets dataset of IIT Hyderabad. There are 3 unique recordings utilized. Video Dataset for Helmet Detection in Sparse Traffic from IITH Campus, in Crowded Traffic from Hyderabad City CCTV Network and Hyderabad City Video Dataset for Accident Detection from Hyderabad City CCTV Network. Images were also collected from different sources in different angles.
For training our custom object detection model, a lot of images of objects are needed which are supposed to be trained, nearly a few thousand because more number of images means more accuracy.

2. Image classification

The pictures were split into two classes in the wake of gathering 1000 pictures for the examination dataset, one for preparing information and another for test information to be utilized in grouping tests. The system has utilized a 10-crease cross approval analysis for the assessment, where a set up for various test information for 10 percent of the general picture. Preparing systems are prepared with the guide of the Python TensorFlow library; at that point exactness is measured and pick two appropriate models for use in picture recognition. Further it is processed with google collab to train the data.

For data preparation we need to use some tool to mark objects in the image. YOLO has its own format for training data.
Yolo format is:

```
<object-class> <x> <y> <width> <height>

<x_center> = ((X_end + X_start) / 2) / image_width

<y_center> = ((Y_end + Y_start) / 2) / image_height

<width> = (X_end - X_start) / image_width

<height> = (Y_end - Y_start) / image_height
```

Figure 4. Yolo format

This will help us in making the bounding boxes around the objects that we want as follows:

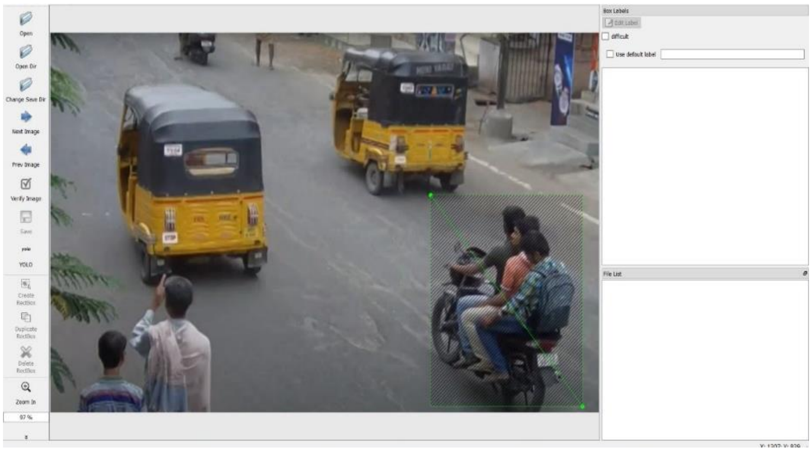


Figure 5. Labelimg tool to make bounding boxes

Setting up a platform for training data:

After having the data set, a platform is needed to train the models. There are a lot of techniques that can help in training which includes the GPU as well as CPU methods.
In this particular experiment, Cloud is used to train which is 15 times faster on GPU than CPU.
Google Colab is used in this project. Python scripts are uploaded which includes the configuration (.cfg) and object (.obj) files and the result is a trained dataset of different objects.

obj.names ✕ obj.data ✕

```
classes= 1
train  = data/train.txt
valid  = data/test.txt
names = data/obj.names
backup = /mydrive/yolov3

```

Figure 6. obj.data file format

train.txt ✕

```
data/obj/49.jpg
data/obj/26.jpg
data/obj/118.jpg
data/obj/157.jpg
data/obj/30.jpg
data/obj/20.jpg
data/obj/38.jpg
data/obj/74.jpg
data/obj/29.jpg
data/obj/92.jpg
data/obj/155.jpg
data/obj/131.jpg
```

Figure 7. train.txt that is generated

2) Configure yolov3.cfg file

```
[ ] # Make a copy of yolov3.cfg
    !cp cfg/yolov3.cfg cfg/yolov3_training.cfg
```

```
[ ] # Change lines in yolov3.cfg file
    !sed -i 's/batch=1/batch=64/' cfg/yolov3_training.cfg
    !sed -i 's/subdivisions=1/subdivisions=16/' cfg/yolov3_training.cfg
    !sed -i 's/max_batches = 500200/max_batches = 6000/' cfg/yolov3_training.cfg
    !sed -i '610 s@classes=80@classes=3@' cfg/yolov3_training.cfg
    !sed -i '696 s@classes=80@classes=3@' cfg/yolov3_training.cfg
    !sed -i '783 s@classes=80@classes=3@' cfg/yolov3_training.cfg
    !sed -i '603 s@filters=255@filters=24@' cfg/yolov3_training.cfg
    !sed -i '689 s@filters=255@filters=24@' cfg/yolov3_training.cfg
    !sed -i '776 s@filters=255@filters=24@' cfg/yolov3_training.cfg
```

3) Create .names and .data files

```
[ ] !echo -e 'Wearing Mask\n2nd item\n3rd item' > data/obj.names
    !echo -e 'classes= 3\ntrain  = data/train.txt\nvalid  = data/test.txt\nnames = data/obj.names\nbackup = /mydrive/yolov3' > data/obj.data
```

Figure 8. Google collab notebook

3. <u>Vehicle detection and grouping:</u>

A. Vehicle detection

From the beginning YOLOv3 [9] designing was used for two wheelers and individual revelation. YOLOv3 model is a continuous upgrading type of YOLO obtained by J. Redmon et al [11]. The model is in a circumstance to recognize a colossal game plan of classes, among them only two classes riders and person's head are taken for disclosure. The bouncing boxes are pulled in to confine the things. The framework predicts 4 headings; bx, by are the inside bearings and bw, bh are width, height independently of the ricocheting box of estimate. The covering zone among vehicles and individuals is taken from the bounding boxes to spot whether the individual is a bike rider or not.

B. Grouping (no. of people on bike)

At that point the Euclidean Distance between the center directions of two jumping boxes of an individual are determined and in this manner the cruiser. On the off chance that the space is inside the jumping box of the bike, at that point it may be inferred that the individual is the rider of that vehicle. Utilizing this procedure, all the number of riders on a motorbike is checked. Number of people is distinguished utilizing the directions from the jumping box. First the bike is identified and inside certain arrangements focuses if the quantity of people is surpassing three then violation comes into picture. For recognizing people and vehicles, the system is using a pre-prepared model.

Opencv implementation:

The darknet implementation for detecting objects takes a lot of time to detect the object. Therefore, simple OpenCV code is implemented for it. It is much faster than darknet and can also be used for finding specific classes and finding the coordinates of detected objects.

4. <u>Image detection experiment</u>

In this progression, 3 recordings were gathered and were used to attempt to do a picture recognition test utilizing the YOLOv3 calculation that browsed the past advance. All recordings tried and determined the

exactness of the biker with or without the helmet and number of people recognized on the bike inside the video. Likewise tallying the quantity of undetected motorcyclists to remember for the mistake percent.

5. Interpretation of the result

In the last advance, the performance is compared with two preceding stages and made the conclusion. The exactness of the investigations will show the exhibition of the procedure as far as in terms of image classification and image detection.

The OpenCV Libraries are used alongside the detection system which contains the predefined functions and data members used for processing images like background subtraction, morphological operations, feature extraction and classification.

Chapter 5

SOFTWARE

The code for the object detection is given as follows:

```
import cv2
import numpy as np

net = cv2.dnn.readNet('yolov3_training_last.weights', 'yolov3_testing.cfg')

classes = []
with open("classes.txt", "r") as f:
    classes = f.read().splitlines()

cap = cv2.VideoCapture('test1.mp4')
font = cv2.FONT_HERSHEY_PLAIN
colors = np.random.uniform(0, 255, size=(100, 3))

while True:
    _, img = cap.read()
    height, width, _ = img.shape

    blob = cv2.dnn.blobFromImage(img, 1/255, (416, 416), (0,0,0), swapRB=True, crop=False)
    net.setInput(blob)
    output_layers_names = net.getUnconnectedOutLayersNames()
    layerOutputs = net.forward(output_layers_names)

    boxes = []
    confidences = []
    class_ids = []

    for output in layerOutputs:
        for detection in output:
            scores = detection[5:]
            class_id = np.argmax(scores)
            confidence = scores[class_id]
            if confidence > 0.2:
                center_x = int(detection[0]*width)
                center_y = int(detection[1]*height)
                w = int(detection[2]*width)
                h = int(detection[3]*height)

                x = int(center_x - w/2)
                y = int(center_y - h/2)

                boxes.append([x, y, w, h])
                confidences.append((float(confidence)))
                class_ids.append(class_id)

    indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.2, 0.4)

    if len(indexes)>0:
        for i in indexes.flatten():
            x, y, w, h = boxes[i]
            label = str(classes[class_ids[i]])
            confidence = str(round(confidences[i],2))
            color = colors[i]
            cv2.rectangle(img, (x,y), (x+w, y+h), color, 2)
            cv2.putText(img, label + " " + confidence, (x, y+20), font, 2, (255,255,255), 2)

    cv2.imshow('Image', img)
    key = cv2.waitKey(1)
    if key==27:
        break

cap.release()
cv2.destroyAllWindows()
```

Chapter 6

DATA ANALYSIS AND RESULT

From prior stages, nearby outcomes for example regardless of whether a two-wheeler rider is using a helmet or not, at some stage in that aspect. Be that as it may, till now the association between consistent casings is dismissed. Along these lines, as to downsize bogus alerts, then merge nearby outcomes. This included first, the detection of a bike and afterwards, the individual. After the identification of the bike just the location of the helmet was done on the rider utilizing YOLO. The heads with and without helmets were separated and exhibited in various shaded bounding boxes.

In corresponding with the helmet location program, moreover the rider counter program is executed which utilizes the projection activities and lessen tasks to check the quantity of riders on the vehicle.

After calibration of the code, the outcomes acquired are shown in Fig.9, Fig.10 and Fig.11.
Objects are detected by a mixture of object locator and an object recognizer. YOLOv3 approaches the thing identification issue in a totally unique manner. It advances the whole picture only one event through the system.

In the first place, it isolates the photo into a 13×13 lattice of cells. The elements of those 169 cells shift depending on the components of the information. For each bouncing compartment, the system likewise predicts the pride that the jumping holder genuinely encases an object, and therefore the possibility of the encased thing being a specific class.

A large portion of those jumping boxes are disposed of due to their certainty which is low or in light of the fact that they're encasing a proportional item as another bouncing box with a very high certainty score. This system is named non-maximum suppression.

As it is visible from the video snippets, the algorithm used here gives a very accurate output percentage of helmet on bikers ranging from 70% - approx 90% and triple riders showcasing a very good percentage.

Figure 9 Annotation

Figure 10

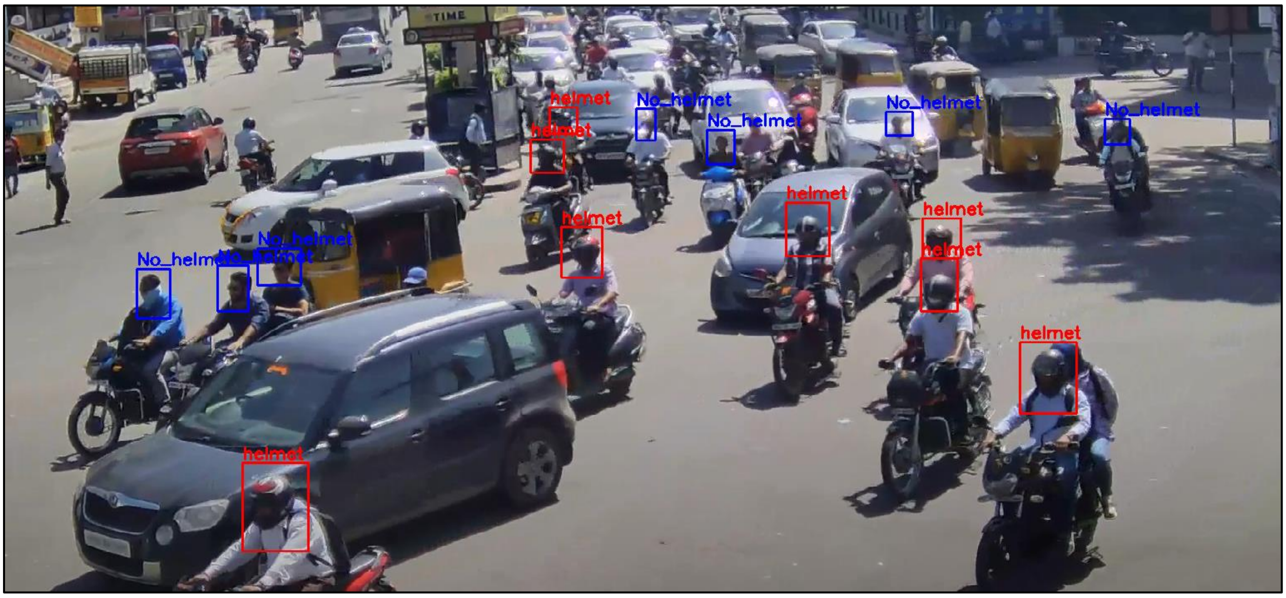


Figure 11 Detecting Helmet and Non helmet bike riders

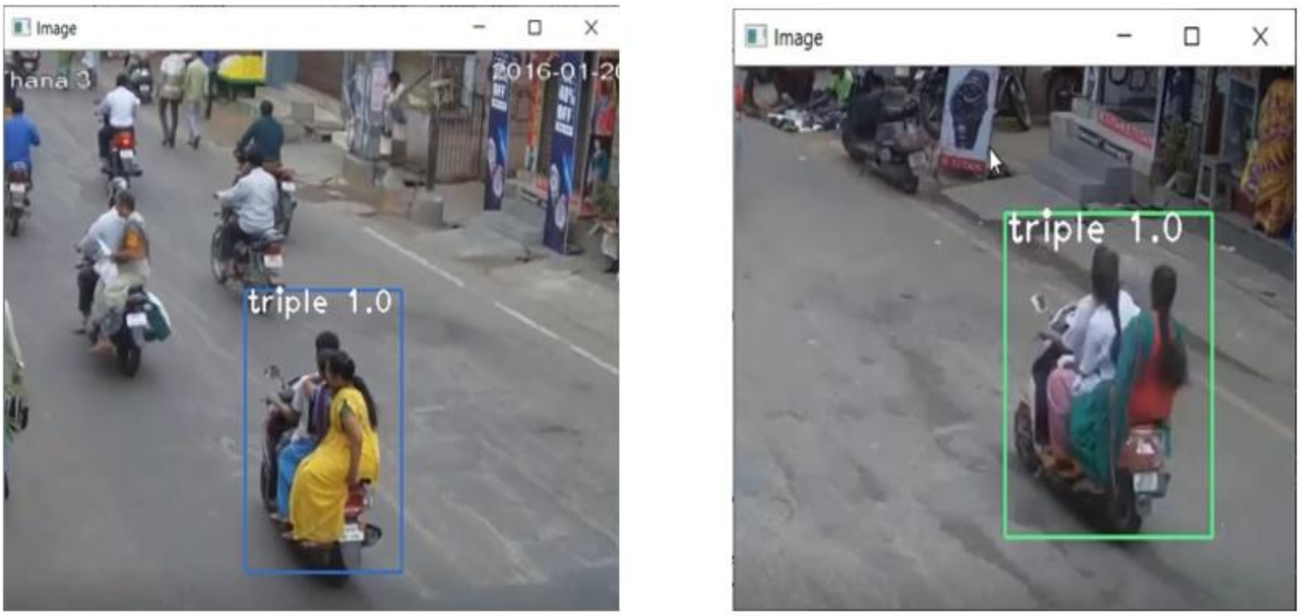


Figure 12. Detecting Triple rider

Figure 13 Detecting with different angle

Chapter 7

CONCLUSION

In this project, a system is proposed for ceaseless identification of traffic rule violators who ride motorbikes without using helmets and also defaulters, who triple ride on the vehicle. A PC vision framework that is isolated into modules like moving items division, moving articles arrangement and helmet use identification will help the traffic specialists to require activity contrary to managing violators. Proposed framework additionally will help the traffic police for such violators in odd ecological conditions like scorching sun, and so on. This framework is regularly stretched out to recognize and report number plates of violators by consolidating this method with programmed vehicle place acknowledgment frameworks by synchronizing various view cameras.

The annotated images are given as input to the YOLOv3 model to train for the custom classes. The weights generated after training are used to load the model. Once this is done, an image is given as input. The model detects all the five classes trained. From this we obtain the information regarding the person riding the motorbike. If the person is not wearing a helmet, then we can easily extract the other class information of the rider. This can further be used to extract the license plate.

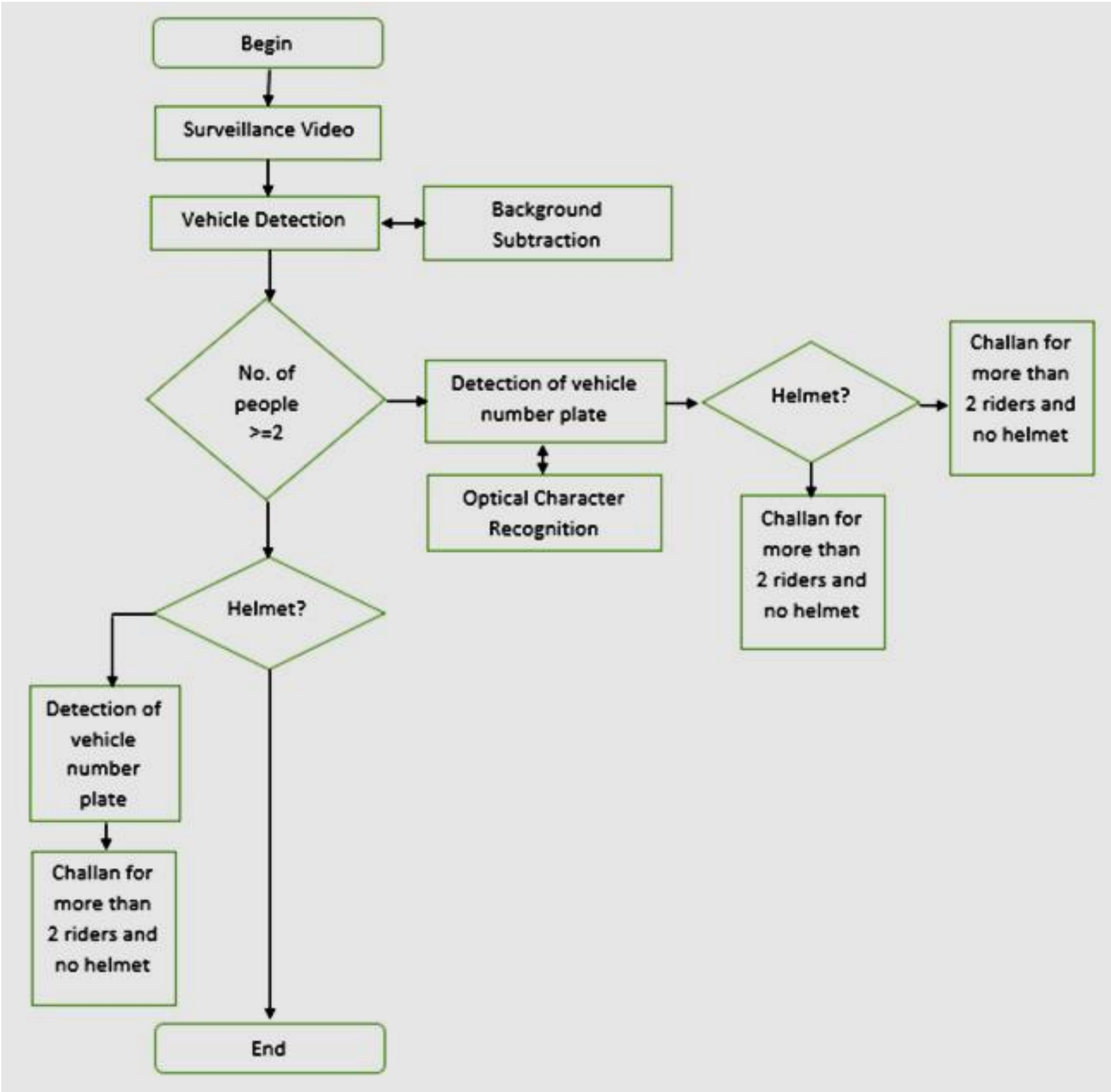
Likewise, propelled following calculations are regularly required to deal with impediment. Night-sight cameras are frequently used to utilize the location framework inside the nonattendance of light. In future, bigger quantities of positive and negative examples can be remembered for requests to expand the speculation capacity of the framework. Likewise work with front-end video catch modules.

The future work on this may include detection of license plates which will help the traffic police to automatically detect the defaulters thus sending an challan to them via SMS. This will not just ease the workload of the traffic police but also be more convenient in all aspects.

Chapter 8

FUTURE WORK

Following flow chart is proposed as a complete solution which can be implemented in future.



License plate recognition:

For the purpose of license plate recognition, we can use Automatic number-plate recognition (ANPR). It is a technology that uses optical character recognition on images to read vehicle registration plates to create vehicle location data. It can use existing closed-circuit television, road-rule enforcement cameras, or cameras specifically designed for the task. ANPR is used by police forces around the world for law enforcement purposes, including to check if a vehicle is registered or licensed. It is also used for electronic toll collection on pay-per-use roads and as a method of cataloguing the movements of traffic, for example by highways agencies.

Fine generation and text intimidation:

Once the license plate number is recognised and stored in a Data manager. The details regarding license plate can be accessed directly by cooperating with local traffic department. Once the details of the defaulter is obtained We can host an SQL based web application that can generate fine based upon the defaults and then it can generate a text and send directly to the defaulter.

When completely implemented, the solution proposed in this project can eliminate the human intervention in the process of detecting the traffic rule violators and imposing fine for their actions. It can further be delocalised by formulating an embedded system inside the surveillance cameras which will detect and directly send the fine amount to the traffic rule violators.

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