Image and Video Processing based Expressway Reverse Violation Detection System

PROJECT ID: 2021-238

Final Report

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B.Sc. (Hons) Degree in Information Technology

Specialized in Information Technology

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Sri Lanka

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Declaration

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Signature of the supervisor: Date

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Signature of the co-supervisor: Date

ABSTRACT

This research it is described a solution to detect reverse violation detection in expressways. The concept of this reverse violation system is to detect such vehicles as soon as they enter an area covered by a single closed-circuit television (CCTV) camera. The application notifies and sends a violation notification to the monitoring center. The created system is a video-based tracking system and includes three aspects: detection, tracking, and validation. We utilize a deep learning approach known as you only look once version 3 to find a vehicle in a video frame (YOLOv3). As a result, we construct a deep learning model using a video-based dataset for training. Following the estimate of a vehicle's position, we use linear quadratic estimation (also known as Kalman filtering) to follow the identified vehicle through time. Finally, we use an "entry-exit" method to determine the car's trajectory, attaining accuracy of 96.98 percent in wrong-way driving identification.

Keywords: convolutional neural networks (CNNs); reverse violation detection; kalman filter; you only look once version 3 (YOLOv3);

ACKNOWLEDGEMENT

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1. INTRODUCTION

The function of the traffic rules violation system is becoming increasingly important as the fourth industrial revolution progresses, guaranteeing the safety and efficiency of drivers. The goal of this system is to collect relevant and precise traffic data while maximizing the usage of surveillance technology. According to the National Information, Sri Lanka has more than two thousand closed-circuit television (CCTV) cameras installed by the year 2018 in expressways. There is no way that CCTV footage can be a perfect answer for all traffic offenses. However, combined with facts, witnesses, and records, it is routinely and increasingly utilized by government authorities to detect significant breaches. Driving the wrong way along a road occurs for a variety of causes, including driver distraction or confusion, failure to see pavement markings or traffic signs, willful violation of the laws, and so on. Even while new pavement markings and signage are creative, they may not be adequate to warn vehicles of wrong-way travels, resulting in vehicle accidents. Despite the fact that it is nearly impossible to govern human driving behavior, it is critical to identify and analyze irregular activity in everyday traffic settings in order to avoid catastrophic vehicle accidents. Until now, the duty of identification has been handled by persons who work for monitoring firms. Nonetheless, as the number of camera devices grows, so does the requirement for intelligent software that is automated. Intelligent software that is automated is in high demand. Sensor-based detection, radar-based detection, and video imaging-based detection are the three primary kinds of wrong-direction detection methods. The goal of this study is to automate the detection of moving infractions so that less human contact is required, as well as to identify them (using a single video camera)

While our suggested system is based on video imaging-based detection, it also takes into account three major computer vision difficulties, including vehicle localization, tracking, and direction determination. Vision-based learning is one of the most cost-effective techniques since it saves people's time while also reducing expenses by employing fewer equipment and eliminating defective goods.

1.1 Background

In order to establish a car's direction, it must first be detected, therefore detection is the first stage in our investigation. We describe and implement different techniques in computer vision to compare different detection and tracking algorithms for vehicles in this section. Wrong direction estimation is not a recent problem, and in this section, we describe and implement different techniques in computer vision to compare different detection and tracking algorithms for vehicles. Well-known machine learning and deep learning methods are among these approaches.

1.2 Literature Survey

Vehicles are clearly an important mode of transportation now and into the. They have revolutionized our way of life, and we can no longer imagine a world without motor vehicles. Even if you already own one or more, their costs continue to fall, and the comfort they provide makes it all the more appealing to purchase new ones. As a result, the amount of cars on the expressway is steadily growing year after year. Simultaneously, the amount of people killed or injured is increasing at an alarming rate.

One of the globs most pressing health and patient care issues is traffic crashes. According to the World Health Organization [1] [2], more than a million people die every year on the world's roads. In 2010, there were over one thousand car accidents in Sri Lanka. Over $ 23 thousand was wasted as a result of these blunders. Over 45,000 people were killed, and over 2 million people were injured. Every 12 minutes, someone in the country dies in a car accident, equating to around 100 deaths per day [3].

Exceeding the posted speed limit is the leading cause of fatalities, accounting for 34.25 percent of all collisions. The red-light signal is responsible for 5.25 percent of all incidents. It is now clear that being above the posted speed limit and failing to obey traffic lights account for about 40% of all crashes. Around 21% of crashes are caused by traffic laws like wrong way driving, overtaking on the right side of the road or failing to keep a safe distance between vehicles.

After reviewing this data, it is clear that these issues are the result of non-compliance with road safety regulations. The number of crashes reduces considerably if all drivers obey the rules. Despite governments' best attempts to reduce incidents, there are certain problems that result in an increase in the number of traffic violations. The most significant problem is the lack of traffic patrols or cameras, as well as the growing number of roads and highways with a low percentage of patrols or cameras on roads and streets. We believe that the true number of unreported traffic violations is much higher than what the 2police report.

"The City of Intifton installed an automatic speed camera in early 2007," according to the Georgia City newspaper website [4]. In 2007, there were 793 accidents, up from 793 in 2006. The number of Tifton deaths dropped by 27% after crossing the bridge. Installation of a camera Only at intersections are cameras fitted. If, on the other hand, cameras are placed on all highways and streets, ensure that the number of incidents is decreased or eliminated. It is backed up by the fact that [6].

Given these facts, it's safe to presume that traffic enforcement has the same number of cops as vehicles, that each of these cops is a trained professional capable of detecting all types of traffic violations, and that they are heartless men who record every crime, even if it's committed by their fathers or loved ones. Every vehicle on the road has a driver and one or more police officers whose job it is to watch the driver and register traffic violations without speaking to him. In this situation, no conscious driver is committing a traffic violation.

The primary aim of this article is to create a system that functions similarly to that of this policeman. This means that each driver is tracked individually for traffic violations in real time, wherever and at any moment. If the driver commits a traffic violation, the location and time are also documented.

The concept is to have a system integrated into the car. The system will detect the above-mentioned traffic violations in real time, which caused the accident. When a traffic violation happens, the system remembers the location, time, and type of violation. The traffic authorities should read the data on the embedded system at any time. Another aim is to suggest a system that automates wireless traffic violation reading and sends data to a central server in the traffic and patrol division, making violation data collection simple. GPS (Global Positioning System) and DGPS (Digital Global Positioning System) are two of the reasons why this system should be realized (Differential GPS, more accurate than GPS). These can be used to define the real-time position, velocity, direction, and acceleration. Furthermore, one of the system's key components is Car-2-The term "car" refers to a wireless ad hoc communication system that is used to determine the distance between two cars. Smart traffic lights are also recommended because they allow the on-board device to identify to keep track of the red-light violations. The following is how the remainder of this white paper is packaged: The second section covers associated new developments and innovations to the first. The system architecture and comprehensive system features are outlined. Finally, the findings and future study directions are reviewed.

Connecting the CCTV surveillance to the central server, so that data collected by one of them is forwarded to that server, is the most expensive network infrastructure. This solution's other side effect is outlined in [4]. "The goal of speed cameras and traffic lights," according to the author, "is to prevent collisions." Residents on Long Avenue, on the other hand, believe that traffic light camera collisions are to blame. They risk losing control of their car or colliding with other cars as a result.

1.3 Research Gap

When we contemplate Sri Lanka's expressway. There are certain traffic laws to obey when driving on the expressway, such as maintaining a safe distance from the vehicle in front, the outer lane is for driving, while the inner lane is only for overtaking, not attempting to reverse a car, or turning back and driving in the opposite direction, and so on. However, all of these violation notifications have been viewed as the exception rather than the rule so far, with no one taking action. There isn't a more intelligent solution for that.

Here, we mainly focusing on some specific type of violations. The first is finding a signal violation as a car approaches an overtake (change outer lane to inner lane). When entering through the wrong ramp and passing the toll gate or missing the exit ramp, the second violation is a reverse violation or a turn back. So, in order to detect those violations, we proposed a smarter solution i.e., without the help of human beings, and informed the monitoring center through a CCTV caption by using image processing techniques. So, they can take necessary actions at the exit ramp. This will reduce the risk of accidents as I have already mentioned.

Table 1.3.1: COMPARISON OF PREVIOUS RESEARCH

Research	Wrong way drive violation detection	Proposed methodology with greater accuracy
[4]	✓	✗
[5]	✓	✓
[6]	✓	✗
[7]	✓	✗
Proposed system	✓	✓

1.4 Research Problem

To meet our daily needs, vehicles are also necessary. People, on the other hand, do not know how to follow the laws of the road while driving. Some individuals do not consciously follow it correctly,

Perhaps more so, if you take the express route, carelessness can be seen as minimal by drivers. The explanation is that the penalty offered in the normal path will not be given in the expressway. That causes more accidents. According to available data, 38,000 accidents occur on average each year, resulting in approximately 3,000 fatalities and 8,000 serious injuries. Sri Lanka has the highest fatality rate among its immediate South Asian neighbors.

1.5 Research Objectives

1.5.1 Main Objective

The primary goal of putting this system in place is to decrease the number of incidents by adding a monitoring mechanism to identify breaches on expressways. Vehicles are, without a doubt, necessary to satisfy our daily needs. However, as previously stated, traffic violations are causing an increasing number of accidents every day. As a result, the primary goal is to protect people from such mishaps.

1.5.2 Specific Objectives

The special goals that must be met in order to achieve the primary objectives are as follows:

- Detect the vehicles captured from the CCTV and divided into single frames.
- Track the vehicles by drawing a trajectory point on vehicles' way and verified the vehicle position.
- Predict the vehicle current position and the previous position according to the detection threshold, duration, direction, and standard deviation given by the system.
- Check if vehicles' have reached the previous position that will be violated as a reverse violation
- Check the accuracy measures of the generated results.
- The detected violations are passed through the CCTV to the monitoring center with specific information of violated vehicles.

2. METHODOLOGY

2.1 Methodology

This section explains the methods and procedures we intend to use to build our system. Violations are detected using Faster R-CNN Deep Learning methods by collecting video footage from CCTV cameras. R-CNN and Fast R-CNN use an area proposal algorithm as a pre-processing step before running the CNN. The suggested algorithms are standard methods that are not reliant on CNN, such as Edge Boxes [5] or Selective Search [6]. In Fast R-CNN, the use of these tools becomes the processing bottleneck when compared to running the CNN. By incorporating the region proposal mechanism into the CNN training and prediction steps, faster R-CNN solves this problem.

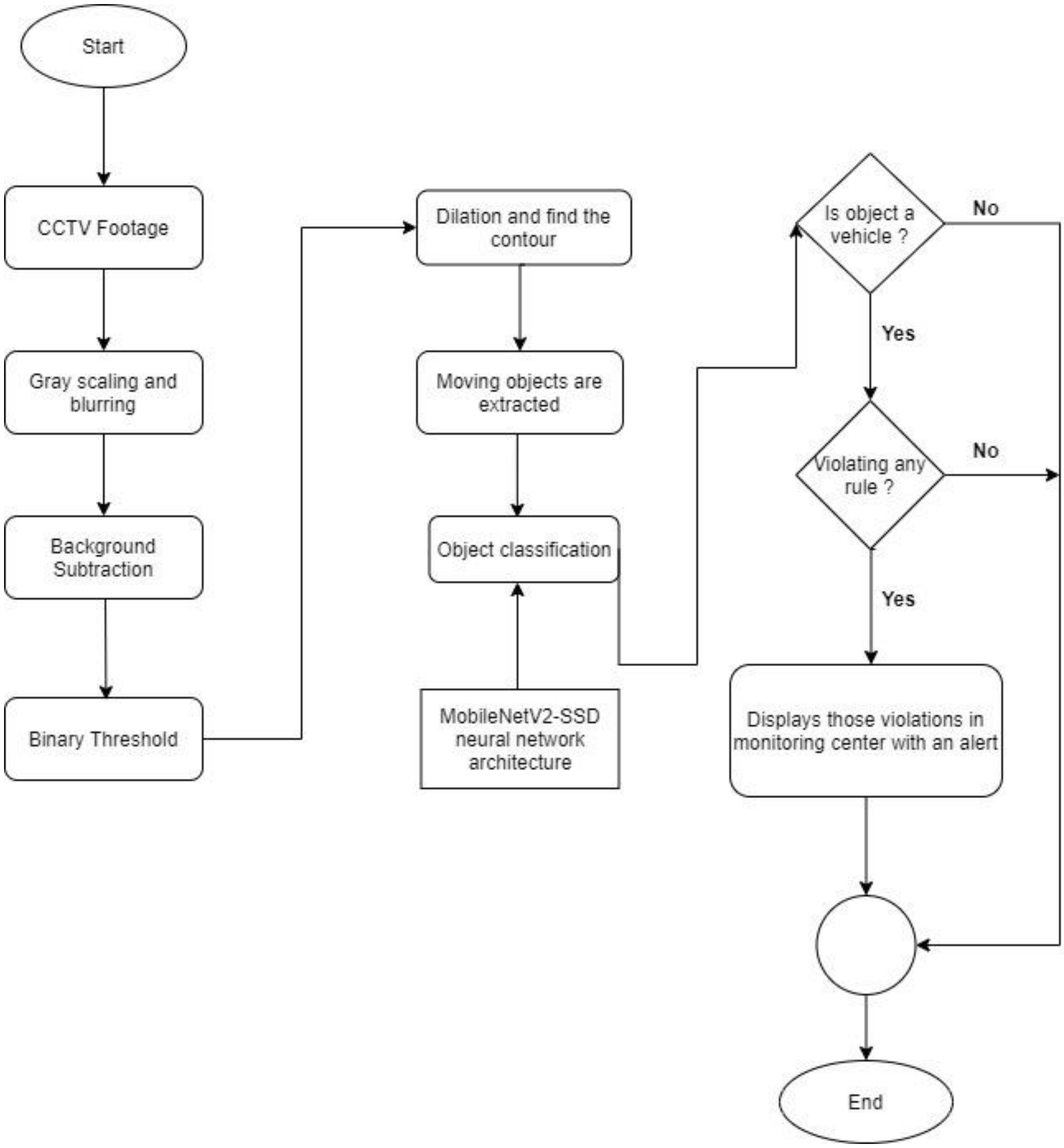

Figure 2.1.1: Flowchart of violation detection of vehicles

2.1.1 Image and Video Processing

- **Gray scaling and blurring:** As the part of preprocessing the input frame got from the CCTV footage, the image is gray scaled and blurred with Gaussian Blur method.

- **Background subtraction:** Background subtraction method is used to subtract the current frame from the reference frame to get the desired object's area.

- **Binary threshold:** Binarization method is used to remove all the holes and noises from the frame and get the desired object area accurately.

- **Dilation and find the contour:** After getting the thresholded image, it is dilated to fill the holes and the contour is found from the image. Drawing points over the contours desired moving objects are taken.

- **Reverse violation detection:** When a vehicle comes from a wrong direction (reverse way), it is detected by tracking the vehicle. The direction of the vehicle is determined using its current position and previous few positions.

The input of the prediction module

This system consists of two main components-:

- Vehicle violation detection model
- A Graphical User Interface (GUI)

First video footage that is captured from CCTV is sent to the system. Vehicles are detected from the footage. Tracking the activity of vehicles, systems determine if there is any violation or not.

The Graphical User Interface (GUI) makes the system interactive for the user to use.

can monitor the traffic footage and get the alert of violation with the detected license plate of a vehicle. Authority can take further action using the GUI.

- **Reverse violation detection**

Same as when we consider the reverse violation in an expressway, you should not attempt to reverse your vehicle or turn back and drive against the traffic direction when you entered through a wrong ramp and had passed the toll gate or if you missed the exit ramp. In those situations, CCTV detects those violating vehicles as well as detects a license plate and that will display the GUI. Then appropriate actions will be done by the authority. Those monitored video sequences are separated into frames.

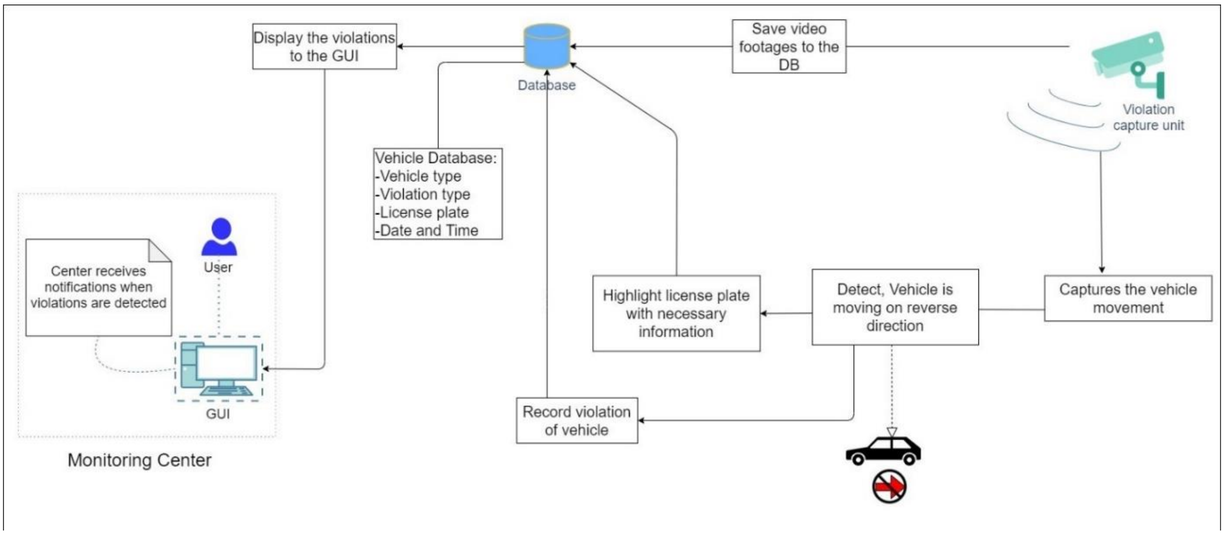

Figure 2.1.2: Wrong-way detection module high-level overview

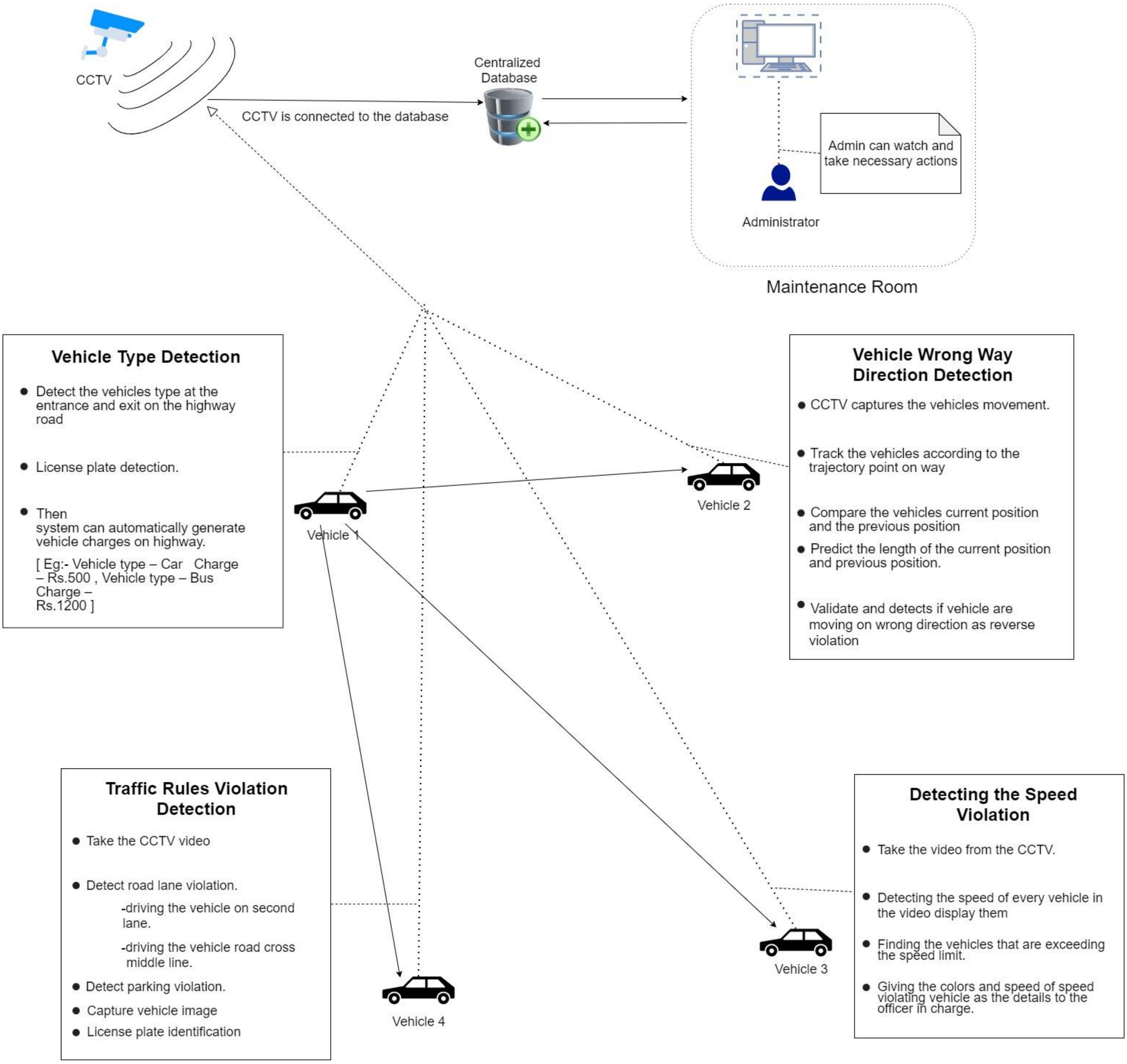

Figure 2.1.3: System overview of diagram of detection and tracking

MobileNetv2-SSD model

MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices as well as GUI-based applications. It is based on an inverted residual structure where the residual connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity. As a whole, the architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.

In MobileNetV2, there are two types of blocks. One is the residual block with a stride of 1. Another one is blocked with the stride of 2 for downsizing. There are 3 layers for both types of blocks. This time, the first layer is 1×1 convolution with ReLU6. The second layer is the depth-wise convolution. The third layer is another 1×1 convolution but without any non-linearity. It is claimed that if ReLU is used again, the deep networks only have the power of a linear classifier on the non-zero volume part of the output domain.

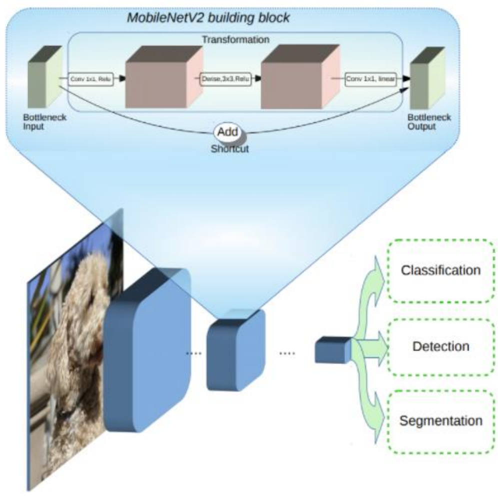

Figure 2.1.4: Detection hierarchy of MobileNetV2 SSD model

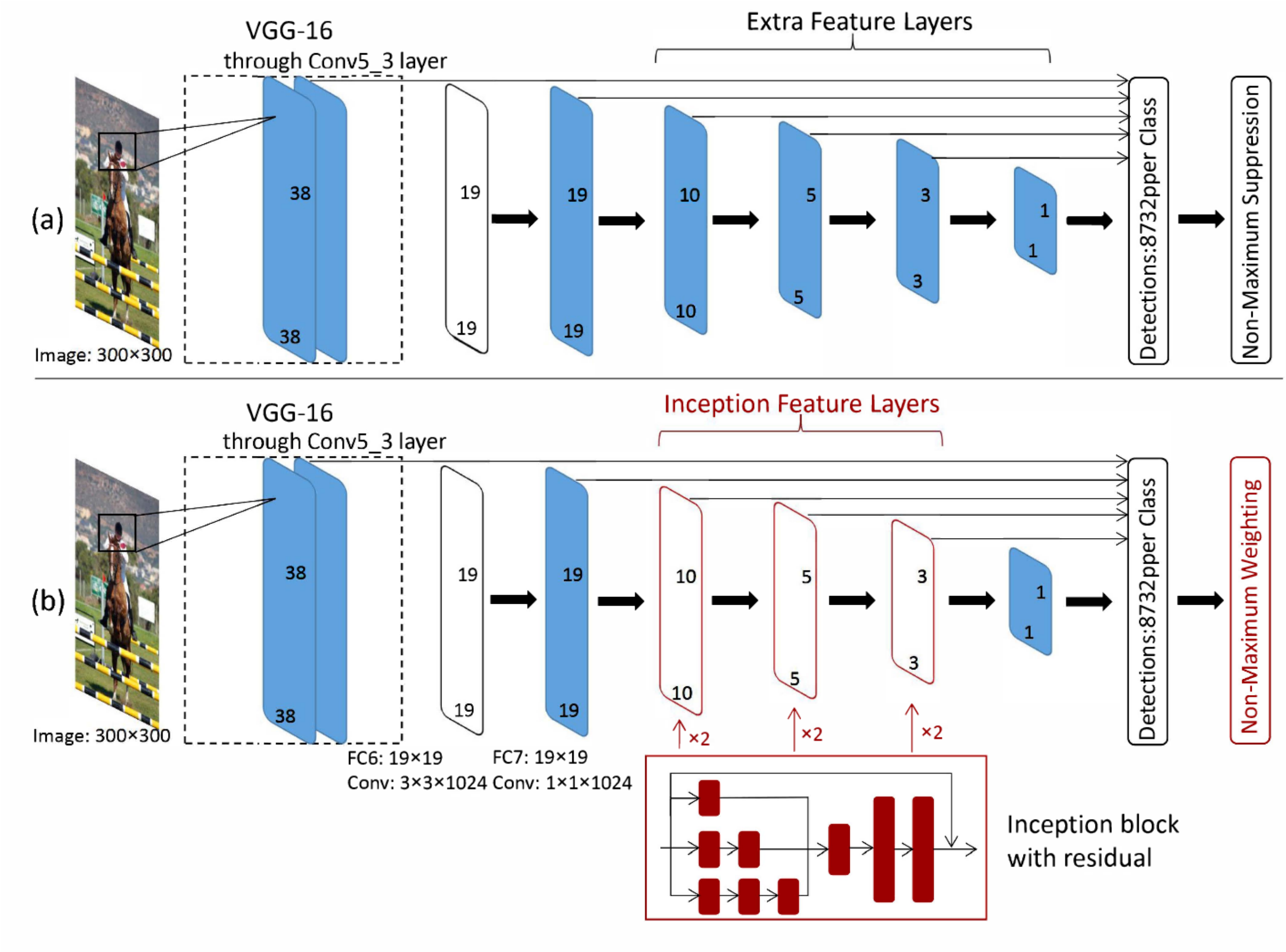

Figure 2.1.5: *mobileNet-SSD-network-architecture*

Unsupervised Learning

Unsupervised learning is a branch of machine learning that is used to find underlying patterns in data and is often used in exploratory data analysis. Unsupervised learning does not use labeled data like supervised learning but instead focuses on the data's features. Labeled training data has a corresponding output for each input. When using unsupervised learning, we are not concerned with the targeted outputs because the goal of the algorithm is to find relationships within the data and group data points based on the input data alone. Supervised learning is concerned with labeled data in order to make predictions, but unsupervised learning is not.

Kalman filter

Kalman filtering is an algorithm that provides estimates of some unknown variables given the measurements observed over time. Kalman filters have been demonstrating its usefulness in various applications. Kalman filters have relatively simple forms and require small computational power. However, it is still not easy for people who are not familiar with estimation theory to understand and implement the Kalman filters. Whereas there exist some excellent kinds of literature such as [1] addressing derivation and theory behind the Kalman filter, this chapter focuses on a more practical perspective.

Process of Prediction

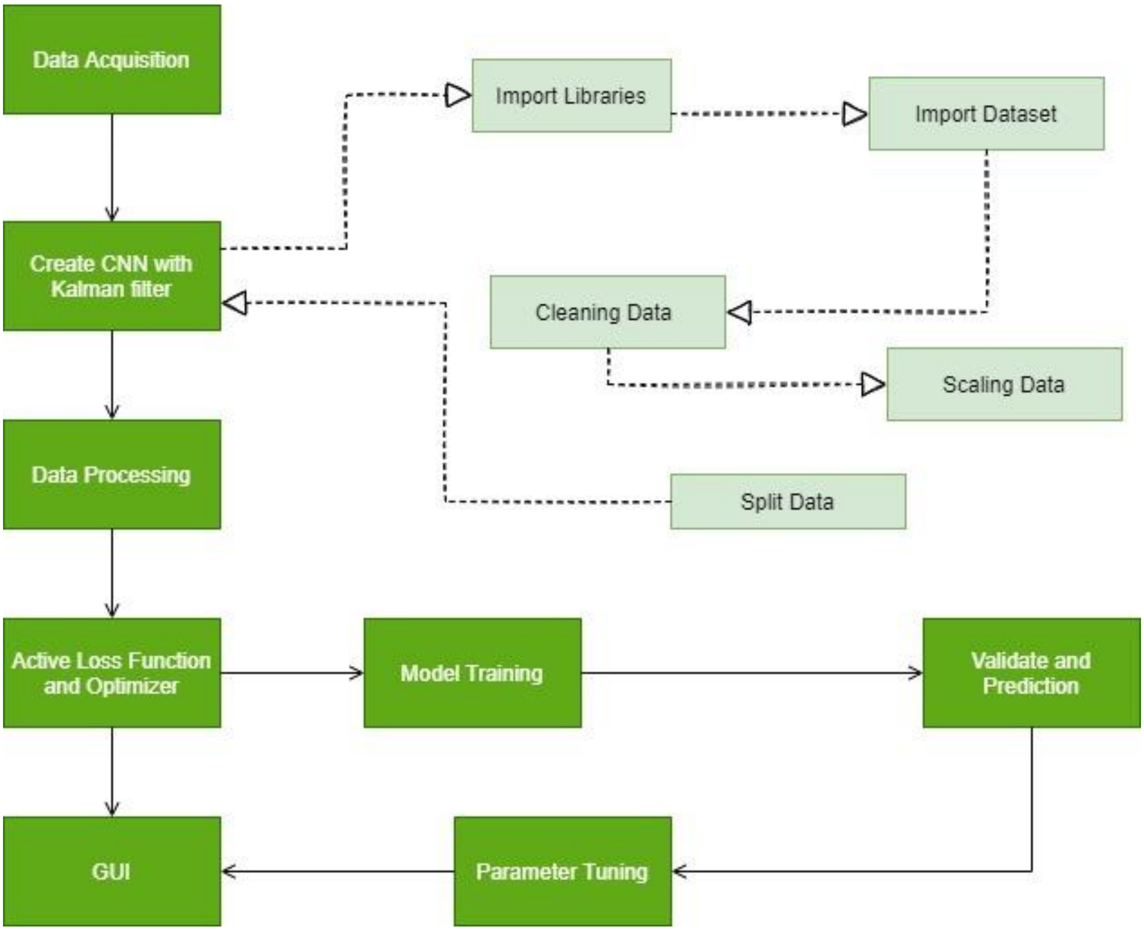

Figure 2.1.11: Process of the prediction module

Step 1.0: Data Acquisition

All the necessary data have been collected from the expressway in several locations. Those datasets can be accessed in both jpeg image format and the mp4 video format.

Step 2.0: Data Processing

All collected data are analyzed using various data analysis techniques such as prescriptive analysis, descriptive analysis methods used in qualitative data analysis.

Step 2.1: Import Libraries

All the necessary Python libraries are imported during this step. Pandas, Numpy, Seaborn, Keras, Tensorflow libraries are imported for data analysis, visualization, and CNN model building processes.

Step 2.2: Import Dataset

The collected video-based dataset is imported at this stage.

Step 2.3: Data Preprocessing

In this step imported video datasets, it is, preprocessed to understand the true positive and false positive of available data. We put on video sequence and expect our machine learning and deep learning model to get trained.

Step 3.0: Create the CNN with Kalman filter

The CNN is created on top of a specific library. The main components of tracking are defined as follows.

- Number of inputs of each detection
- Number of time steps of each detection

- Number of divided frames
- Number of layers
- Number of outputs
- Learning rates
- Batch size
- Number of epochs

Once all these parameters are defined, the layers of the Kalman Filter are created.

Step 4.0: Training the model

In this step, the model is trained batch-wise, up to the number of epochs defined earlier. For each and every iteration, a loss is generated and it is gradually decreased.

Step 5.0: Validate the model and Prediction

The test data are passed to the trained model and the necessary plots are taken and a comparison is done between the test observations vs. predicted output.

Step 6.0: Parameter tuning

At this stage, several parameters are changed by considering the outputs and the quality metric values obtained. Therefore, the model is retrained and reevaluated until it produces the most accurate result. Finally, the model is saved in .xml format.

Step 7.0: Creating a User Experienced GUI

As the final step, Front-end was created using python, TKinter, and WxPython frameworks which used kivy as the open-source python library.

Used Tools and Technologies

This process mainly used python as the programming language and specific python libraries which are mainly used for prediction such as certifi, cycler, filterpy, Keras, Numpy, scipy, and Pandas.

Also, TensorFlow and Kalman filters are used to run the Keras library which is used for the MobileNetv2-SSD model. All the testing is done using Jupyter notebook in Anaconda Navigator with Windowsplatform. Also, the OpenVINO toolkit provided by Intel to facilitate faster inference of deep learning models is used to create cost-effective and robust computer vision applications, it supports a large number of deep learning models out of the box.

2.1 Implementation and Testing

2.1.1 Implementation

- **Requirement Gathering and analysis**

  At the beginning of the research project, data gathering was a challenging task with the technology of the country in order to obtain real-time video-based data of the expressway.

  At first, a study has been done in order to get a clear understanding of the existing systems. There are many traffic rule violation applications developed in other countries. Therefore, those applications helped to gain a clear idea for thismodule and they helped to identify the improvements and the requirements neededfor the project.

In the meantime, reviewing previously done researches also helped to identify the suitable approaches, machine learning algorithms that can be used, and methodologies that need to be followed in order to make this module a success.

- **Design**

In this phase of development, the design of the violation detection system was prepared. The system design assisted to build an overall architectural design using the system requirements. This stage is very important for a strong foundation of the system since it is the medium where the proposed features and functionalities areintroduced for the users. According to the reverse violation prediction module, real-time violation detection updates and the predicted reverse violations are identified as the main features and functionalities of the application. Using the high-level architecture of the module, the feasibility of transforming the requirements for proper methods was considered. Data sources, storage platforms, and visualizationmethods are concerned well in this process.

- **Implementation**

All the specifications related to reverse violation prediction were implemented at this stage. After completion of the prediction model development, real-time object detection with rules violations connected the CCTV database in order to output prediction results from the trainedmodel. The generated results were passed using a MobileNetv2-SSD model to the GUI.

GUI of the proposed desktop application

- **Trajectory point view for reverse violation detection**

Figure 2.2.1.1: Interface- Trajectory point view for violation detection

- **Vehicle reverse violation detection**

Figure 2.2.1.2: Interface- Vehicle reverse violation detection

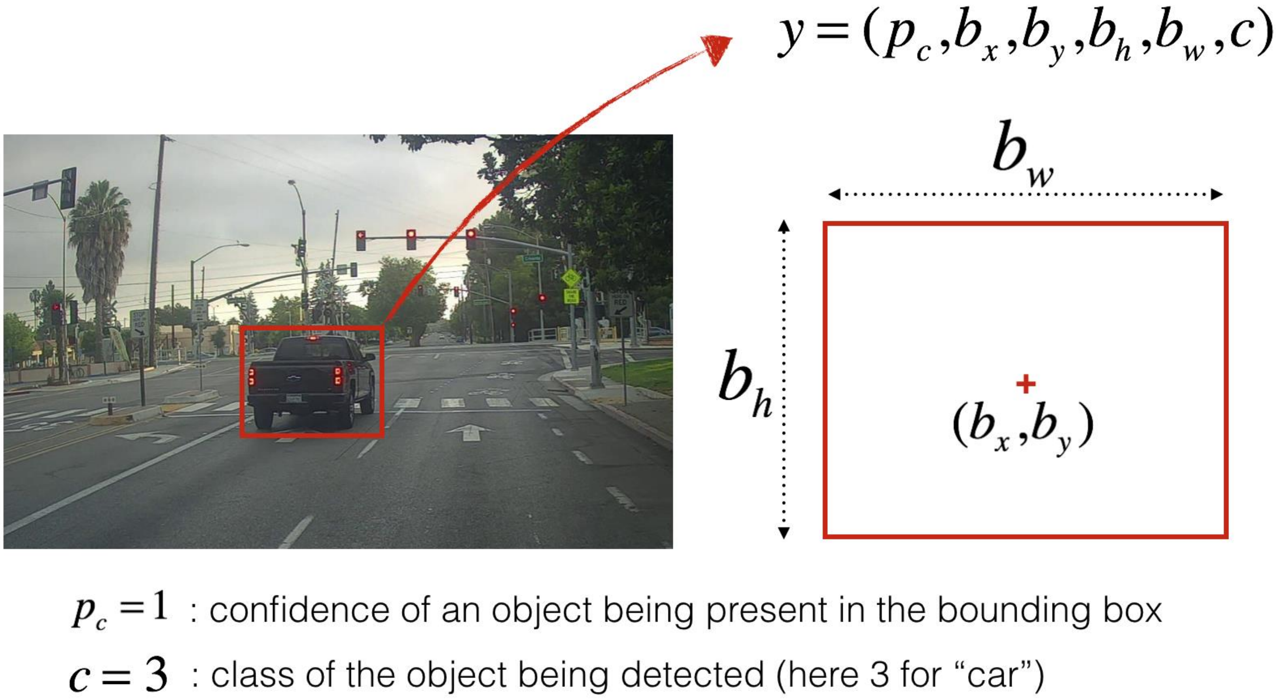

Figure 2.2.1.3: Object tracking with YOLOv3 module

2.1.2 Testing

- **Testing**

Since, this module has been a prediction model, done with the use of a machine learning algorithm, black-box testing was performed. Therefore, out of black-box testing techniques to machine learning models, model performance testing was done. Following are the most significant test cases out of several test cases performed.

Test Case 01:

Here, the batch size and the number of epochs were taken as 40.

Table 2.1.2.1: TEST CASE 01 PARAMETER VALUES

Parameter	Keyword used	Value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	12
No of iterations	epochs	40
Learning Rate	lr	0.01
Batch size	batch_size	40

- Accuracy gained by the model: 96.34 %
- Overall CNNs value: 0.1492

Test Case 02:

Keeping the batch size value constant, the number of epochs was changed to 200.

Table 2.1.2.2: TEST CASE 02 PARAMETER VALUES

Parameter	Keyword used	Value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	12
No of iterations	epochs	200
Learning Rate	lr	0.01
Batch size	batch_size	40

- Accuracy gained by the model: 91.52 %
- Overall CNNs value: 0.1659

Test Case 03:

Since, the results of the above test cases were not able to provide a satisfactory accuracy, in this test case number of epochs and the batch size were changed as 100 and 30 respectively, keeping other parameter values constant.

Table 2.1.2.3: TEST CASE 03 PARAMETER VALUES

Parameter	Keyword used	Value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	12

No of iterations	epochs	100
Learning Rate	lr	0.01
Batch size	batch_size	30

- Accuracy gained by the model: 92.24 %
- Overall CNNs value: 0.1622

<u>Test Case 04:</u>

The number of epochs was changed to 100 and other values remained constant.

Table 2.1.2.4: TEST CASE 04 PARAMETER VALUES

Parameter	Keyword used	Value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	12
No of iterations	epochs	100
Learning Rate	lr	0.01
Batch size	batch_size	30

- Accuracy gained by the model: 96.34 %
- Overall CNNs value: 0.053

Test Case 05:

Since the results provided by Test Case 04 were at a satisfied level, a slight change was made to the number of epochs changing it from 100 to 500.

Table 2.1.2.5: TEST CASE 05 PARAMETER VALUES

Parameter	Keyword used	Value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	12
No of iterations	epochs	500
Learning Rate	lr	0.01
Batch size	batch_size	10

- Accuracy gained by the model: 88.4 %
- Overall CNNs value: 0.045

- **Maintenance**

In this phase, the system will be maintained properly to keep the maximum uptime and availability for users and keep the system from error-free and crashes up to date.

3. RESULTS AND DISCUSSION

3.1 Results

- **Prediction Module**

This section mainly focuses on the experiments conducted in order to find the best parameters of the designed model. Some of the experiments discussed in this document aredone using the data in the "Kaduwela" expressway, ideally which predicts the reverse violation of daytime. The data used for the experiments are based on daytime between the intervals of (8.00 am) to (4.00 pm). The following setup is used to run the experiment related to the reverse violation predictionmodule.

```
# Convolutional network building
network = input_data(shape=[None, 32, 32, 3],
                     data_preprocessing=img_prep,
                     data_augmentation=img_aug)
network = conv_2d(network, 32, 3, activation='relu')
network = max_pool_2d(network, 2)
network = conv_2d(network, 64, 3, activation='relu')
network = conv_2d(network, 64, 3, activation='relu')
network = max_pool_2d(network, 2)
network = fully_connected(network, 512, activation='relu')
network = dropout(network, 0.5)
network = fully_connected(network, 10, activation='softmax')
network = regression(network, optimizer='adam',
                     loss='categorical_crossentropy',
                     learning_rate=0.001)
```

Figure 3.1.1: Code relevant to the CNN model building

Table 3.1.1: VALUES USED FOR THE PARAMETERS IN THE NETWORK

Parameter	Keyword used	Default value
No of inputs	n_input	1
No of outputs	n_output	1
No of time steps	n_timesteps	100
No of iterations	epochs	400
Batch size	batch_size	10

3.2 Experimental Setup

The performed experiments are done using a Lenovo ideapad (2018) with processor power 2.2 GHz, Intel Core i3, Memory 8GB, Intel(R) HD Graphics 5500, and the operating system used is Windows 10 Home. The model is trained using the CPU of the above-mentioned machine.

Experiment 1: This experiment was done in order to find the model accuracy by changing the number of epochs.

Table 3.2.1: MODEL PERFORMANCE WITH TRAINING EPOCHS COUNT

Training Epochs	100	400
Best Fit %	86.7	84.8

The graphs shown below are the graphical output of the predicted results over actual data.

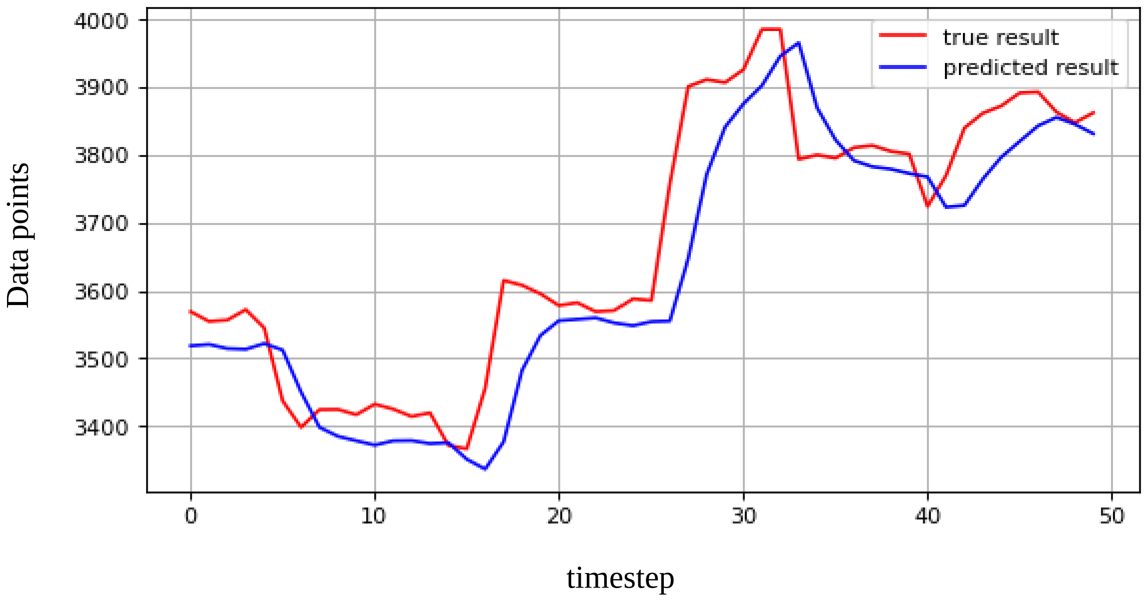

Figure 3.2.1: Predicted results over actual data with 100 training epochs

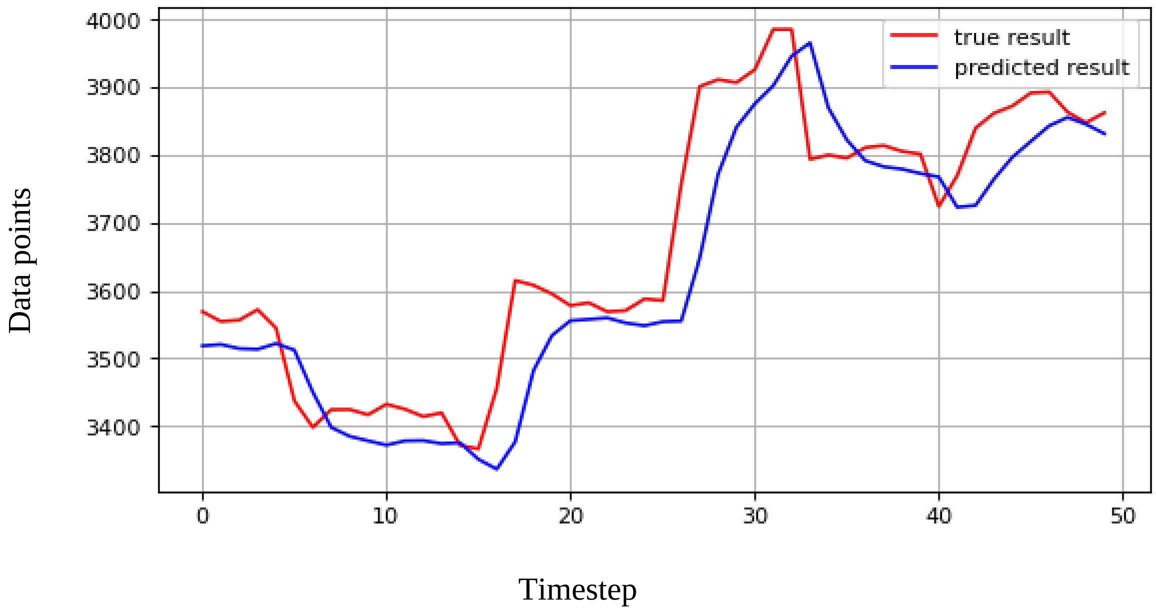

Figure 3.2.2: Predicted results over test data with 400 training epochs

Therefore, it is clear that increasing the number of training epochs increased the model accuracy. By changing the number of epochs, it takes more time to train the model.

4. CONCLUSION

For automatic detection of traffic rule violations, the proposed approach makes use of concepts such as YOLO, CNN, Mask R-CNN, and OCR. It achieves the desired result with precision and ease, but it requires a large amount of computational power due to the use of concepts such as image analysis and object detection. The proposed system has the advantage of being able to detect more violations than the human-intervened system. Furthermore, the proposed methodology will provide an end-to-end autonomous system that, if implemented, would provide an advantage in detecting violations. This software can be improved to detect the rules violation at different weather conditions and nighttime.

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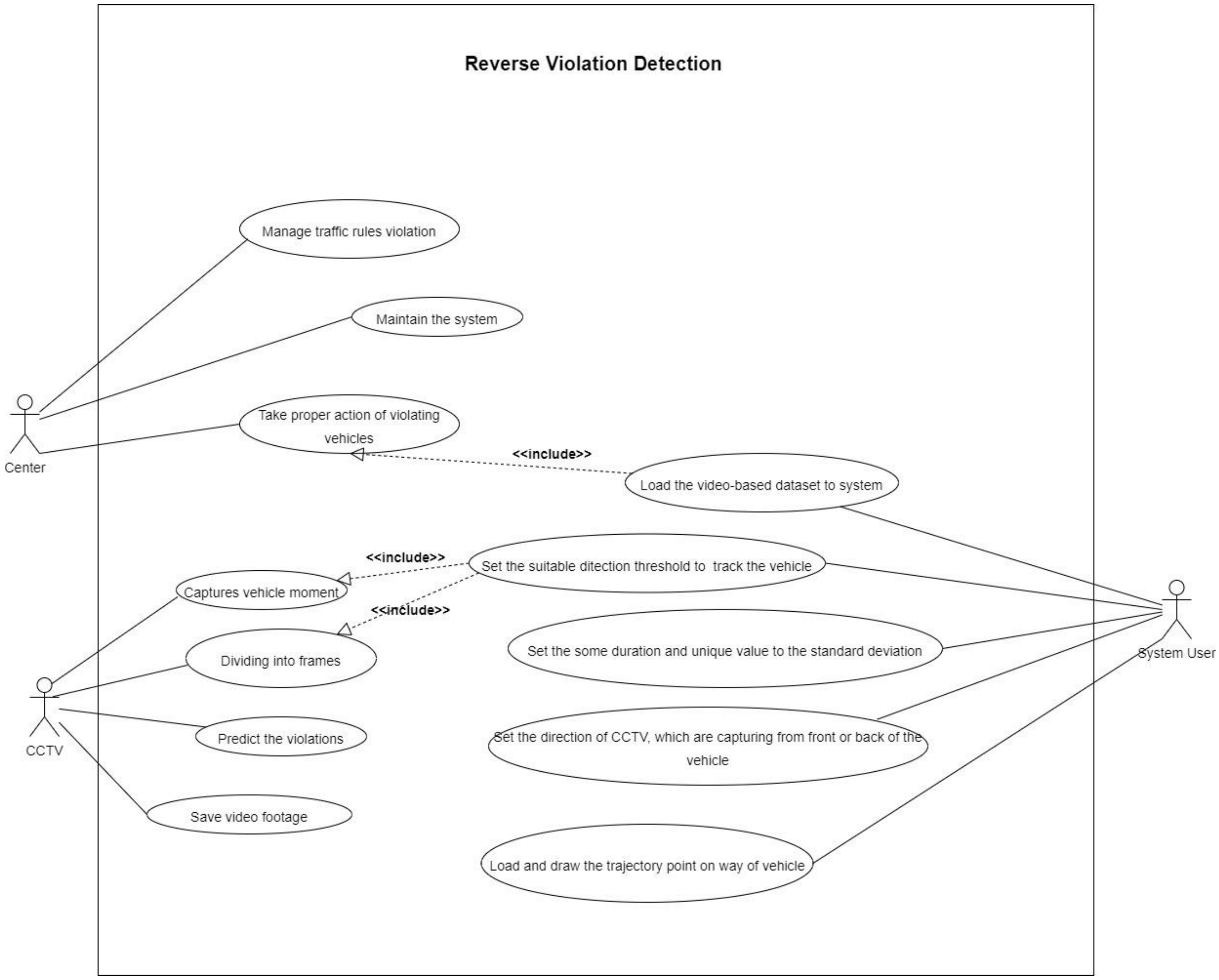
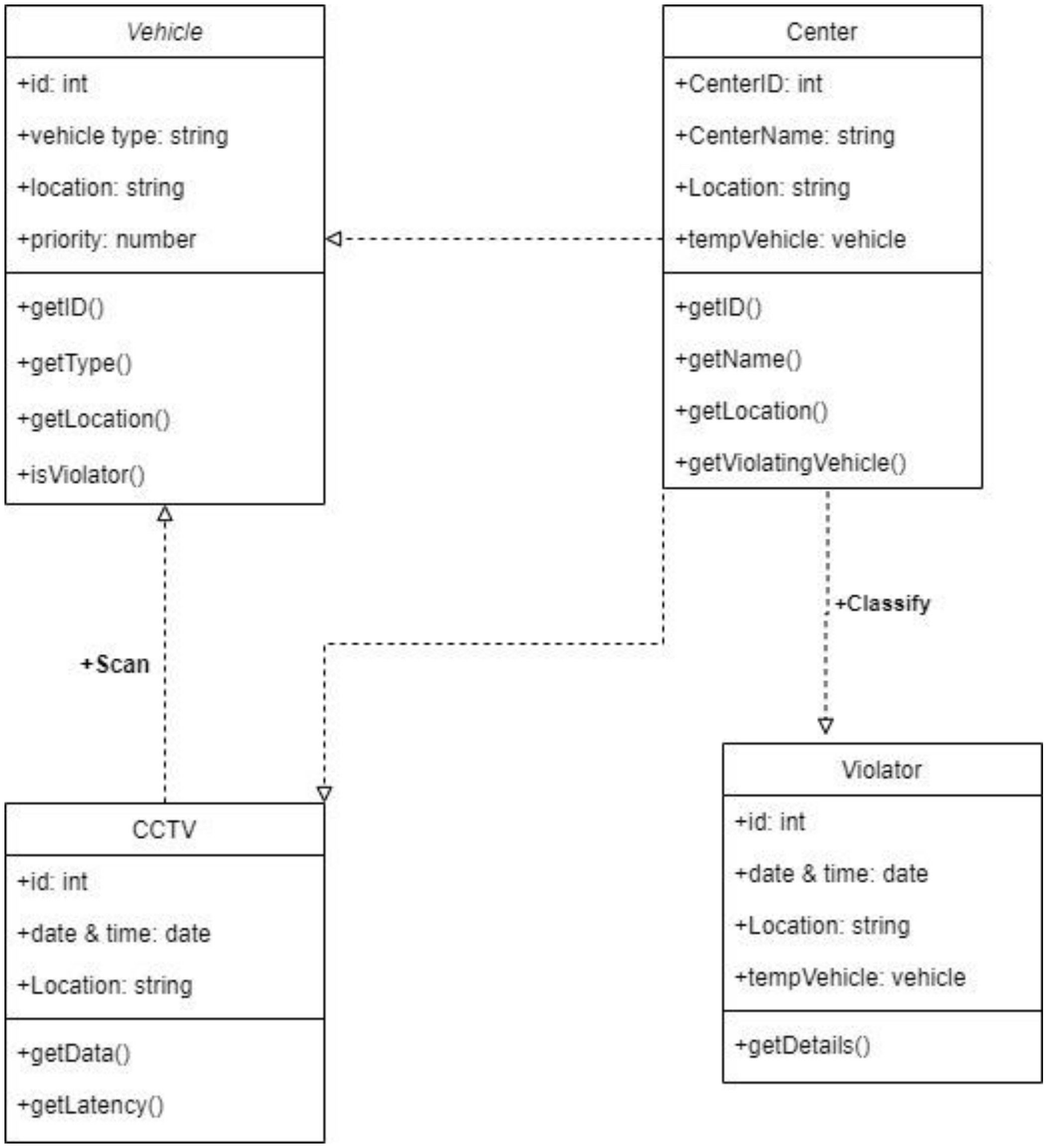
6. APPENDICES

6.1 Appendix A: Use case Diagram reverse violation detection module



6.2 Appendix B: Class Diagram of Reverse violation detection module



6.3 Appendix C: Activity Diagram of violation detection