# Estimate the Minimum Quality of the Image to Recognize a Sri Lankan Vehicle Number from a CCTV Footage

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# Estimate the Minimum Quality of the Image to Recognize a Sri Lankan Vehicle Number from a CCTV Footage

**A dissertation submitted for the Degree of Master of Computer Science**

**A.M.N.D.Chandrawansa**
**University of Colombo School of Computing**
**2021**

# DECLARATION

I hereby declare that the thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis. This thesis has also not been submitted for any degree in any university previously.

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2021/11/28

Signature of the Student

Date

This is to certify that this thesis is based on the work of ~~Mr.~~ /Ms. A.M.N.D.Chandrawansa under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

Certified by,

Supervisor Name: Dr. A R Weerasinghe

2021/11/28

Signature of the Supervisor

Date

# DEDICATIONS

To my beloved parents……………………………

To my dearest teachers……………………………

To my dearest brothers and sisters………………..

To my dearest friends……………………………..

# ACKNOWLEDGEMENTS

First of all, I would like to acknowledge and give my warmest thanks to my supervisor Dr. A. R. Ranasinghe, who made this work encouraged. His guidance and advice carried me through all the stages of writing my project. Since there were a lot of troubles, occur his guidance always inspired me to reach goals.

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# ABSTRACT

Identifying vehicles by the number plate is widely using in forensic applications to investigate criminals. The most prominent approach is using computer vision embedded software and high-resolution cameras to detect and recognize vehicles in real-time. Due to the higher price of such systems, the widely using surveillance camera systems consist of low-resolution cameras. High-quality CCTV footage allows converting the blurred image into a clearly defined image in the society, which is beneficial for the development of the community. Trade experienced can be improved through using the CCTV conversion under the society development. The trade-off is the lack of pixel information stores for each image. Key issues related to image quality include blur, image aspects, camera positioning, light reflection, resolution, and night vision aspects. It has been negatively affected by forensic surveillance image analysis. The majority of the surveillance video footage received by the Government Analyst's Department in Sri Lanka is degraded considerably and quickly unusable. The major drawback of analyzing images to recognize vehicle number plates is that there is no proper quality standard for the video footage. Hence time, resources, and human resources wasting over unusable images is a significant issue. This research study introduces a systematic way to recognize vehicle numbers in surveillance camera images without wasting time and effort. The main objective of this research analysis is to predict the recognizability of a vehicle number plate, which can be recognized by the custom trained Convolution Neural Network.

Faster Region-Based Convolutional Neural Network (Faster-RCNN) trained with more than a hundred characters collected from surveillance camera footage of Sri Lankan vehicles have been used as the number recognition model. Based on the plate resolution, plate sharpness, and the recognized result received from the number recognition model, predictive analysis has conducted to determine the levels of resolution and sharpness that would support recognizing at least a single character of the number plate.

The Logistic Regression Model was able to predict images with 70% of accuracy. The predictive analysis showed that as the resolution increases, the recognizability also increases. The image resolution is the most important quality attribute than the sharpness to identify characters using the number recognition model. The analysis also showed that increasing the sharpness has no significant effect on increasing the recognizability. Hence, it is more important to focus on resolution enhancement techniques over sharpness enhancement when preprocessing the number plate.

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UCSC: University of Colombo School of Computing
CCTV: Closed-circuit television
DVR: Digital Video Recorder
NDVR: Network Digital Video Recorder
GAD: Government Analyst's Department
MSER: Maximally Stable Extreme Region
CSER: Class Specific Extremal Regions
BRISQUE: Blind/Reference Image Spatial Quality Evaluator
VQA: Video Quality Assessment
PEVQ: Perceptual Evaluation Video Quality
SIFT: Scale Invariant Feature Transform
SR: Super-resolution
ANPR: Automatic Number Plate Recognition
SRGAN: Super-Resolution Generative Adversarial Network
OAC: Optimal Adaptive Correlation
RBFNN: Radial Basis Function Neural Network
ALPR: Automated License Plate Recognition
DWT: Discrete wavelength transform
VEDA: Vertical Edge Detection algorithm
BLOB: Binary Large Objects
MLP: Multi-Layered Perceptron
OCS: Operator Context Scanning
SVM: Support Vector Machine
SSD: Single Shot Detector
MAP: Mean Average Precision
API: Application Programming Interface
LANN: Labeling and Artificial Neural Network
PWPLD: Periodic Walsh Piecewise-Linear Descriptors
ROI: Region Of Interest

# CHAPTER 1
# INTRODUCTION

In digital forensic, Closed-circuit television (CCTV) footage analysis is a significant task in identifying individual vehicles by the license plate number. Video streams from different cameras are saved in a Digital Video Recorder (DVR) or Network Digital Video Recorder (NDVR). The major problem in recognizing the number plate from the CCTV footage is the lack of video quality. According to the observations done during the analysis of CCTV footage, several factors were identified as causes for the quality loss of the image frame of the video when detecting vehicle numbers in the number plate and object detection. As (Jerian et al., 2007), (Porter, n.d.), and others have identified, the most widely affecting quality factors cause recognizing objects in CCTV images.

- Low Resolution
- Sharpness/Blur
- Light reflection (Mhou et al., 2017)
- Camera angle
- Low light condition (illumination) (Rio-Alvarez et al., 2019)
- Noise
- Compression artifact (Yang et al., 2018)

Government Analyst's Department (GAD) of Sri Lanka proves to be a service-providing institution in that it provides advisory, consultancy, and scientific service. The Government Analyst's Department issues analytical reports upon scientific and analytical testing on productions referred to it by the Law of Courts of the country, Department of Police, Department of Customs, Department of Excise, Ports, Local Government Institutions, Ministry of Health, and as well as other Government Departments and Statutory Bodies ("Department of Government Analyst," 2020). Forensic Science Division of the Government Analyst's Department of Sri Lanka involves various digital forensic activities according to the cases it receives for examination and reporting from Courts of Law, Police, other Government Departments, Statutory institutions, and from Private Sector ("Digital Forensic," 2020). Digital Image Analysis is one of the major activities that happen daily in the Digital Forensics Laboratory. This research is the study based on enhancing unclear CCTV footage and vehicle number plate detection.

## 1.1 Motivation

The current process in GAD of recognizing human unreadable license numbers is manually enhancing the video frame using photo editing software such as Photoshop and GIMP. After various image enhancement steps, number plates in some image frames become readable to some extent. In contrast, many images are not usable for license number recognition due to a lack of helpful pixel information. As an example, if there is a light reflection on the number plate, it doesn't have any useful information at the pixel level. It is identified that it is a very time-consuming task, and most of the license plates are still unreadable even after going through various enhancement steps. There are many numberplates recognition systems available. Most of the existing systems expect high-quality video/image to recognize the license number. Some forensic image enhancement software also responds only to high-quality videos, and they are costly. In digital forensics, the analyst/examiner needs to investigate many videos of different quality levels. Hence, it is highly useful that if there is a software that can take the CCTV footage as an input, analyses it, gives the number if it can recognize and otherwise the reason message (such as doesn't meet the required quality level of the input video) for the inability to recognize it. High-quality CCTV camera will be necessary for reducing the criminal activity in the area. A high-quality CCTV camera can provide a high-quality picture of the car number, car specification, license number, and owner's description, which is beneficial for policy to find key assessors in the incident and make steps effectively. Moreover, a higher quality CCTV camera effectively provides clear imgae, low light reflective image, high resolution, and high fraction artifact in the image effectively.

## 1.2 Statement of the problem

This research investigates how the blur/sharpness and the resolution of the number plate affect the possibility of recognizing the license number from CCTV footage and estimates the minimum required quality level that a video must meet to identify the vehicle number. It is important to determine the minimum quality measurement for the CCTV camera in Sri Lanka to verify the vehicle number through the CCTV footage. In the current environment, the corruption rate has increased dramatically in the country. As per the statistical survey outcome, the vehicle is often used for crime, and CCTV footage is beneficial to identify and recognize the vehicle effectively. CCTV footage is adequate to determine the vehicle number by verifying the number plate. However, current issues are regarding the quality of the camera or pixel measurement. Identification of the required pixel measurement for the CCTV camera to recognize the vehicle's number plate clearly in one of the major problems associated with this research topic. Pixel used to provide the higher graphic visual experience in the CCTV camera but the cost will also increase for the camera development. It is one of the major issues for the research to recognize the effective quality of graphics for CCTV in the operational and monitoring process for the whole area effectively in Sri Lanka. Estimating the cost and associates service along with the incremental procedure is essential before installing CCTV in the area. The design of the camera must be based on the graphical perspective that can be effective for the visualization of the number plate of the vehicle in Sri Lanka. This process will effectively reduce the country corruption rate and enhanced the efficiency in the criminal investigation detection process. It will be easy for the police of corps of the country to catch culprit through using CCTV camera.

## 1.3 Research Aims and Objectives

### 1.3.1 Aim

To estimate the minimum quality level of sharpness and plate resolution of a CCTV video should meet to recognize the vehicle number plate.

### 1.3.2 Objectives

- Building a predictive model to determine if a video image is of adequate sharpness and resolution for vehicle number identification.
- Building a predictive model to determine the vehicle number from video images that satisfy the identified quality attributes.

## 1.4 Scope

This research involves estimating the minimum quality attributes of CCTV footage to recognize the Sri Lankan vehicle number plates, regardless of the video format. That means this is not for a real-time system. Videos that are considering here have been compressed, processed, and stored in the DVR. Here this analysis only considers how the sharpness of the image and the resolution of the number plate affect the recognition of the number plate. Two thousand series (English number) of both front and rear Sri Lankan number plates will be considered only daylight. This research has higher scope in the future because of the increasing corruption rate in the country. Identification of the best fit CCTV camera graphic will effectively catch the main culprit by using the CCTV camera.

Visualization is an important factor in the CCTV installment and pixel process to store the vehicle number plate. Effectively higher visual and graphical aspects are necessary for CCTV camera visualization in the country operational process. CCTV installment will provide a higher scope in the future to catch large numbers of corrupted people and effectively reduce the rate of corruption. The higher pixel will be effective for the CCTV camera to identify different incidents more effectively and allow the corps to conclude more quickly. It is also beneficial to track the transaction during the time period effective through using the CCTV camera. A full coverage of the city can be done effectively by using a CCTV camera with higher pixel quality. This research is beneficial for the CCTV camera producers to reform the exact pixel number for the CCTV production that can effectively track the vehicle's number plate. Researchers are able to determine the impact of the CCTV camera quality on the development of society and policy effectively. It is important to develop the policy and efficiency of society and community by using higher camera quality in different areas of the city. In case of bank robbery, theft, scam, and other incidents, it will be very easy to track the owner and person details through monitoring the numbers in the number plate of the car or vehicle by using a CCTV camera. This process will create a new opportunity or scope for the community and business owner regarding the appropriate quality factors for CCTV.

## 1.5 Structure of the Thesis

Related work has been covered in chapter 2. The methodology has been separated into four sections within chapter 3. Data collection and data preparation have been described in section 1. Section 2 describes how the quality levels have been measured, and it is further divided into two sub-sections, measuring sharpness level and measuring number plate resolution. Number recognition has been covered in section 3. Predictive analysis (estimating the minimum quality) will be covered within section 4.

Chapter 2 is all about the literature review of the thesis where the activity of the work has been discussed through considering the thought of different authors. The literature review section will identify that the benefits and limitations of using or installing higher graphic CCTV cameras in the area. Additionally, it explains how the authors trying to extract number plates and characters using various techniques using CCTV camera videos will also be elaborated in this chapter of the thesis that can assist in recognizing the number or license of the vehicle. Chapter 3 is about the methodology which has been used to collect and analyzed the data regarding the thesis topic. Research philosophy, research strategy, and data collection methods have been identified in this thesis chapter to meet the objective effectively. Predictive analyses of the thesis have been seen under chapter 4. In this chapter, data analyses methods will be evaluated to achieve the research objective effectively.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Why are CCTV Footages Low in Quality?

When considering a video recorded by a smartphone and a video recorded by a surveillance camera, there is a massive gap between these two videos quality-wise. Someone can argue why one cannot replace a surveillance camera with a high-resolution camera to record 4k videos. When it comes to a surveillance camera, it is a must to consider many factors rather than just considering the quality of the video. The main factor that one must consider is the required memory capacity. According to (“Why Are CCTV Footages Always So Blurry And Low Quality? We Find Out! | News | Rojak Daily,” 2017), it takes the feed from many surveillance cameras to a single system to create the CCTV footage. The minimum hard disk space is 1TB to store a video recorded for a week. If the resolution is higher, it requires higher storage capacity. Video compression highly affects the quality of the final video. In Digital Video Recorder (DVR), video compression saves the hard drive space. Due to this compression, the frame rate (FPS) and the video's compression (H.264 etc). People can check these factors from the metadata of the video. Following, Figure 1 and Figure 2 on page 7 are well-known CCTV camera specifications widely available in Sri Lanka.

| TurboHD Analog Camera - 1080p | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Outdoor Bullet | Outdoor Dome | Outdoor Bullet | Outdoor Dome | | Outdoor Bullet | Outdoor Turret | Outdoor Bullet | Outdoor Turret |
| Model | DS-2CE16D1T-IR | DS-2CE56D1T-VPIR | DS-2CE16D1T-AVFIR3 | DS-2CE56D1T-AVPIR3 | DS-2CE56D5T-AVPIR3 | DS-2CE16D5T-IT3 | DS-2CE56D5T-IT3 | DS-2CE16D5T-AVFIT3 | DS-2CE56D5T-VFIT3 |
| Video Out | HD-TVI | HD-TVI | HD-TVI | HD-TVI | HD-TVI/CVBS-(Dual) | HD-TVI/CVBS (Dual) | HDTVI/CVBS (Dual) | HD-TVI/CVBS (Dual) | HD-TVI/CVBS (Dual) |
| Image Sensor | 1/2.7" progressive scan CMOS 1/3" progressive scan CMOS (only 2.8 mm) | 1/2.7" progressive scan CMOS 1/3" progressive scan CMOS (only 2.8mm) | 1/2.7" progressive scan CMOS | 1/2.7" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS |
| Min. Illumination (lux) | Color: 0.01 @ ƒ/1.2 0 with IR | Color: 0.01 @ ƒ/1.2 0 with IR | Color: 0.14 @ ƒ/1.2 0 with IR | Color: 0.01 @ ƒ/1.2 0 with IR | Color: 0.014 @ ƒ/1.4 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.014 @ ƒ/1.4 B/W: 0 with IR | Color: 0.014 @ ƒ/1.4 B/W: 0 with IR |
| Lens | 2.8 mm, 3.6 mm, 6 mm option | 2.8 mm, 3.6 mm, 6 mm option | 2.8 to 12 mm @ ƒ/1.4 | 2.8 to 12 mm @ ƒ/1.4 | 2.8 to 12 mm @ ƒ/1.4 | 3.6 mm @ ƒ/2.5 (2.8 mm, 6 mm, 12 mm option) | 3.6 mm @ ƒ/2.5 2.8 mm, 6 mm, 12 mm, option) | 2.8 to 12 mm @ ƒ/1.4 | 2.8 to 12 mm @ ƒ/1.4 |
| Horizontal Angle of View | 105.8° (2.8 mm), 84.3° (3.6 mm), 55.4° (6 mm) | 105.8° (2.8 mm), 84.3° (3.6 mm), 55.4° (6 mm) | 105.2° to 32.8° | 105.2° to 32.8° | 103° to 32.1° | 82.6° (3.6 mm), 103.5° (2.8 mm), 54.3° (6 mm), 24.4° (12 mm) | 82.6° (3.6 mm), 103.5° (2.8 mm), 54.3° (6 mm), 24.4° (12 mm) | 103° to 32.1° | 103° to 32.1° |
| Pan/Tilt/Rotation | 0° to 360°/ 0° to 90°/0° to 360° | 0° to 360°/ 0° to 90°/0° to 360° | 0° to 360°/ 0° to 90°/0° to 360° | 0° to 355°/ 0° to 90°/0° to 355° | 0° to 355°/ 0° to 80°/±90° | --- | 0° to 360°/ 0° to 90°/0° to 360° | 3-Axis Positioning | 0° to 360°/ 0° to 90°/0° to 360° |
| Day/Night | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE |
| BLC/WDR | Yes/No | Yes/No | Yes/No | Yes/No | No/120 dB | Yes/120 dB | Yes/120 dB | Yes/120 dB | Yes/120 dB |
| IR Range (meters) | 20 | 20 | 40 | 40 | Up to 40 | 40 | 40 | 50 | 50 |
| Max. Image Resolution (pixels) | 1920 x 1080 | 1930 x 1088 | 1930 x 1088 | 1930 x 1088 | 1920 x 1080 | 1920 x 1080 | 1920 x 1080 | 1920 x 1080 | 1920 x 1080 |
| Vertical Synchronization | Internal | Internal | Internal | Internal | Internal | Internal | Internal | Internal | Internal |
| OSD Menu via Up-the-Coax (UTC) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other features | IP66 | IP66 | IP66 | IP66/IK10 | IP66/IK10 | IP66 | IP66 | IP66 | IP66 |
| Operating Conditions (max.) | -40° C to 60° C, humidity 90% (non-condensing) | -40° C to 60° C, humidity 90% (non-condensing) | -40° C to 60° C, humidity 90% (non-condensing) | -40° C to 60° C, humidity 90% (non-condensing) | -30° C to 60° C, humidity 90% (non-condensing) | -30° C to 60° C, humidity 90% (non-condensing) | -30° C to 60° C, humidity 90% (non-condensing) | -30° C to 60° C, humidity 90% (non-condensing) | -30° C to 60° C, humidity 90% (non-condensing) |
| Power Requirements (max.) | 12 VDC, 3 W | 12 VDC, 3 W | 12 VDC, 6W | 12 VDC, 24 VAC, 4 W | 12 VDC, 4 W 24 VAC, 5 W | 12 VDC, 5 W | 12 VDC, 5 W | 12 VDC, 7 W 24 VAC, 8.5 W | 12 VDC, 7 W |

Figure 1: Analog Camera Specifications ("Hikvision Global English Site," 2021)


| Network Camera - Value Series | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Outdoor Bullet Fixed Focal | | | Indoor Dome Fixed Focal | | | | |
| Model | DS-2CD2012-I | DS-2CD2020F-I | DS-2CD2032-I | DS-2CD2112F-I | DS-2CD2120F-I | DS-2CD2122F-IWS | DS-2CD2132F-I | DS-2CD2132F-IWS |
| Image Sensor | 1/3" progressive scan CMOS | 1/2.8" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS | 1/2.8" progressive scan CMOS | 1/2.8" progressive scan CMOS | 1/3" progressive scan CMOS | 1/3" progressive scan CMOS |
| Min. Illumination (lux) | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.07 @ ƒ/1.2 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.01 @ ƒ/1.2 B/W: 0 with IR | Color: 0.07 @ ƒ/1.2 B/W: 0 with IR | Color: 0.07 @ ƒ/1.2 B/W: 0 with IR |
| Lens | 4 mm @ ƒ/2.0 (6 mm option) | 4 mm @ ƒ/2.0 | 4 mm @ ƒ/2.0 (6 mm option) | 2.8 mm@ ƒ/2.0 (4 mm option) | 2.8 mm@ ƒ/2.0 (4 mm option) | 2.8 mm@ ƒ/2.0 (4 mm, 6 mm option) | 2.8 mm@ ƒ/2.0 (4 mm, 6 mm option) | 2.8 mm@ ƒ/2.0 |
| Horizontal Angle of View | 73.1°(4 mm), 46° (6 mm) | 85° (4 mm) | 70° (4 mm), 43.3° (6 mm) | 92.5° (2.8 mm), 73.1° (4 mm) | 106° (2.8 mm), 85° (4 mm), 52 ° (6 mm) | 106° (2.8 mm), 85° (4 mm), 52 ° (6 mm) | 98.5° (2.8mm), 79° (4mm), 49° (6mm) | 98.5° (2.8mm), 79° (4mm), 49° (6mm) |
| Pan/Tilt/Rotation | 3-Axis Positioning | 3-Axis Positioning | 3-Axis Positioning | 0° to 355°/ 0° to 75°/0° to 355° | 0° to 355°/ 0° to 75°/0° to 355° | 0° to 355°/ 0° to 75°/0° to 355° | 0° to 355°/ 0° to 75°/0° to 355° | 0° to 355°/ 0° to 75°/0° to 355° |
| Day/Night | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE | TRUE |
| BLC/WDR | Yes/Digital | Yes/Digital | Yes/Digital | Yes/Digital | Yes/Digital | Yes/Digital | Yes/Digital | Yes/Digital |
| IR Range (meters) | up to 30 | up to 30 | up to 30 | up to 30 | up to 30 | up to 30 | up to 30 | up to 30 |
| Video Compression | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG | H.264/MJPEG |
| Max. Image Resolution (pixels) | 1280 x 960 | 1920 x 1080 | 2048 x 1536 | 1280 x 960 | 1920 x 1080 | 1920 x 1080 | 2048 x 1536 | 2048 x 1536 |
| Frame Rate (fps) | 25 @ 1280 × 960, 704 × 576, 640 × 480 | 25 @ 1920 × 1080, 1280 × 960, 1280 × 720 | 20 @ 2048 x 1536 25 @ 1920 × 1080, 1280 × 720 | 25 @ 1280 x 960, 1280 × 720, 704 x 576 | 25 @ 1920 × 1080, 1280 × 960, 1280 × 720 | 25 @ 1920 × 1080, 1280 × 960, 1280 × 720 | 20 @ 2048 x 1536 25 @ 1920 × 1080, 1280 × 720 | 20 @ 2048 x 1536 25 @ 1920 × 1080, 1280 × 720 |
| Multi-Streaming | Dual | Dual | Dual | Dual | Dual | Dual | Dual | Dual |
| Motion Detection | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Audio Input/Output | --- | --- | --- | --- | --- | IN: 1 line OUT: 1 line | --- | IN: 1 line OUT: 1 line |
| Alarm Input/Output | --- | --- | --- | --- | --- | 1/1 | --- | 1/1 |
| Local Storage | --- | MicroSD, 128 GB max.[3] | --- | MicroSD, 128 GB max. | MicroSD, 128 GB max. | MicroSD, 128 GB max. | MicroSD, 128 GB max. | MicroSD, 128 GB max. |
| Smart Features | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] | Basic Smart Suite[2] |
| Other features | IP66 | IP66 | IP66 | IP66/IK10 | IP66/IK10 | WiFi / IP66 / IK10 | IP66/IK10 | WiFi / IP66 / IK10 |
| Operating Conditions (max.) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) | -30° C to 60° C, humidity 95% (non-condensing) |
| Power Requirements (max.) | 12 VDC, PoE (802.3af), 7 W | 12 VDC, PoE (802.3af), 7 W | 12 VDC, PoE (802.3af), 7 W | 12 VDC, PoE (802.3af), 5 W | 12 VDC, PoE (802.3af), 5 W | 12 VDC, PoE (802.3af), 5 W | 12 VDC, PoE (802.3af), 5 W | 12 VDC, PoE (802.3af), 5 W |

Figure 2: Network Camera Specifications ("Hikvision Global English Site," 2021)

The number plate recognition of CCTV footage can be done in two different ways. They are:

- Manual method
- Automated method

## 2.2 Manual Method

In this method, the analyst plays the required video using an available video playing software and selects the most suitable image frame to further the enhancement process. If the vehicle number is not readable, the selected image frame will be enhanced by removing noise of the image, scaling, sharpening, increasing resolution, etc, using image editing software such as Photoshop and GIMP. Analysts may continue the enhancement process until the number become visible and more precise to a human-readable level.

## 2.3 Automated Method

There are many types of automatic number plate recognition systems (ANPR) available which use various techniques. Most of the solutions proposed by multiple researchers depend on high-quality videos, and they are real-time. (Matas and Zimmermann, 2005) proposed machine learning techniques for detecting extremal regions based on local threshold distinguishable detector, which is defined newly by those researchers. This technique is robust to the skewness of the license plate, viewpoint variation (from seven pixel character height to one hundred fifty pixel character height), plate occlusion, illumination, and even for damaged license plates. This research method focuses on the text area of the license plate and does character segmentation. This method still uses human-readable license plates. They used the standard Optical Character Recognition (OCR) method to recognize the character after using the Class-Specific Extremal Regions (CSER) method text detection and character segmentation. Even a part of the license plate is occluded with some other objects like another vehicle. This method can realize the remaining characters since it is not affecting the plate detection.

Research (Chen and Hsieh, 2007) used a morphological-based operation suggested by Viola and Jones to detect the number plate. That research has proposed a novel two-pass segmentation algorithm for number recognition to extract various text characters from a license plate. The first stage uses a vertical projection to extract multiple characters from a license plate roughly. Then, a “segmentation after recognition” scheme was suggested for finding all correct characters.

Research (Ajanthan et al., 2013) has suggested recognizing number plates using a supported vector machine. The framework proposed by Viola and Jones (Viola and Jones, 2004) was used for license plate localization. Then those researchers have applied connected component analysis and Support Vector Machine-based classifier to recognize the number plate. This approach is for a real-time ANPR system and does not consider any relationship between quality level and identifying the number plate.

License plate recognition for low-resolution number plates by enhancing the number plate details is done by (Seibel et al., 2017). The super-resolution technique has been used in this by combining five consecutive frames into a super-resolved image.

Research conducted by (Silva and Jung, 2018) has proposed a method to recognize a number plate in an unconstrained environment. Here they have only considered high-resolution images, which have orientation changed number plates. (Vaˇsek, 2018) has been proposed a solution to recognize number plates from low-resolution images using Convolution Neural Network (CNN). They have employed around 1.4M of images as the training set created by 24K synthetic images.

Faster-RCNN has been used by (Albahli et al., 2021) to recognize handwritten characters and found Faster-RCNN very robust to various artifacts, i.e., noise, blurring, chrominance changes, variations in light, digit size, rotational and scale variations, and the presence of distortion.

## 2.4 Quality Measuring

(Mittal et al., 2012) introduced a model called Blind/Reference Image Spatial Quality Evaluator (BRISQUE), which is available for public access. This research is not estimating the level of the degraded factor. It gives an overall quality level of the image as a value, and they are doing it for natural scene images. Since the proposed analysis work wants to measure the level of the quality attribute, it cannot use this model as the quality measuring module. (Kumar et al., 2012) used a local grayscale-based method that effectively measures the sharpness of images composed primarily of text which also performs well on natural scenes. (Shahid et al., 2014) has done some reviews about the recent approaches for quality assessment. This research was beneficial when understanding quality assessment. (Rajchel and Oszust, 2020) also very similar to BRISQUE model. It gives an overall quality of the image. Not in quality factor wise. They also have considered natural scene images. Quality measurement is a significant part of the designing of the CCTV camera for society. Quality measurement allows determining the CCTV camera current quality and future predicted camera quality to recognize the differences. It is essential to identify the difference to improve total professional aspects and recognize the image pixel-wise more clearly. In accordance with (Ehrlinger et al., 2019), quality measurement is the part of the development of the society which leads towards the success of the society. As it is identified that quality measurement is effective for identifying technological aspects in society and improve different factors of the community. Technological advancement is essential for the development of the society which can leads the community towards the progress. It is also effective for the strategic development regarding CCTV videos to reduce the corruption rate in the country properly.

## 2.5 Quality Estimation

(Janowski et al., 2014) have mentioned that the first group of distortions can be introduced at image/video acquisition. They are noise, lack of focus, or improper exposure. The second group of distortions appeared when compress and further processing the video/image. The third group of distortions occurs when transferring the video over the network. The fourth group of distortions may arise related to the equipment used to present the video. The proposed analysis considers the first group here, and lack of focus also causes blur and sharpness of the image. Here they have compared two algorithms for number plate recognition. They are:

- Labeling and Artificial Neural Networks - LANN
- Periodic Walsh Piecewise-Linear Descriptors – PWPLD

Then they have compared the probability of the correctly recognized number plates with the human model. Then they realized the human model is more accurate than the automated algorithms. So as the recognition model, they have used the human model. But they haven't done a predictive analysis. They just have taken the probability of the detection when the above quality factors change. In this research work, it is essential to know precisely will this image be recognized or not. Hence predictive analysis is necessary as it is one of the objectives of this research study.

Using an artificial neural network, further research (Menor et al., 2016) has introduced a new objective metric, Video Quality Assessment (VQA). The neural network has been trained by using degraded video extracted features. They have been using software called PEXQ, which OPTICOM develops to extract the features from each video. The Perceptual Evaluation Video Quality (PEVQ) algorithm has been used to evaluate the video quality under its license. The study has used the proposed method (Pech-Pacheco et al., 2000), which simply takes a single channel of an image and convolves it with the *3 x 3* kernel. It is a single line of code.

## 2.6 Super Resolution

The proposed area is working on very low-resolution images. Hence most of the object detection APIs fail due to a lack of enough pixels. The primary image enhancement technique used super-resolution suggested by (Wang et al., 2018). This research improves the original single image Super-Resolution (SR) technique using a Generative Adversarial Network proposed by (Ledig et al., 2017). Super-resolution image techniques can categorize in two ways.

- Single Image Super-Resolution
- Multi-Frame Image Super-Resolution

### 2.6.1 Single Image Super-Resolution

Reconstructing high-resolution images using a single low-resolution image. This technique is more practical than a multi-frame mechanism since this proposed study needs to depend on multiple images on the same scene. Single image super-resolution effectively converts the lower resolution image to higher resolution, which allows the visionary to get a higher graphical image from a lower graphic image. It can be effective for the development of the image graphical aspects effective in the business operation. According to (Ledig et al., 2017), single image super-resolution can effectively develop the graphical interface of the image. In the case of CCTV cameras, single image super-resolution can be used to detect the vehicle license number effectively, solving different issues in operation.

### 2.6.2 Multi-Frame Image Super-Resolution

Reconstructing a high-resolution image using multiple low-resolution image frames taken of the same scene. Multiple frame image super-resolution can be effective for getting higher quality images as the CCTV footage. Multi-frame image super-resolution has been worked as the visionary process of the images where the different small frame of lower resolution image has been constructed through the coding for developing a higher resolution image. In order to get higher quality and higher graphical image effectively, multi-frame image super-resolution can be used.

The main problem original research looked into is, recovering finer texture details when upscaling images significant factors. Super-Resolution Generative Adversarial Network (SRGAN) is capable of generating super-resolution images using a single image. Although the SRGAN performed well in creating super-resolution images, there is still a gap here since it introduces some unpleasant artefacts on its details. By analysing three components of SRGAN, network architecture, adversarial loss, and perceptual loss, (Wang et al., 2018) proposed and enhanced SRGAN (ESRGAN) to improve the overall perceptual quality of the super-resolution image. It is a deep learning technique. Super-Resolution Generative Adversarial Network is effective for the image resolution and construction performance development in operation.

## 2.7 CCTV Footage with High-Resolution and Low-Resolution Image

There are two types of resolution in the CCTV camera image quality: high resolution and low resolution. High-resolution image used to provide an effective quality image to the visionary. High-resolution images allow to make the decision more effectively for the visionary and corps as well. High-resolution CCTV footage is effective for getting higher quality assurance in the decision-making process. Multi-frame super image resolution is adequate for getting the higher quality assurance about the CCTV footage and provides HQ and HD quality pictures effectively. (Powale et al., 2020) stated that high resolution is effective for the camera that improve the night vision of the camera and quality of the image effectively. Night vision can be improved through the multiple low-resolution image visionary process. This process can allow recognizing the number plate of the vehicle effectively in daylight or night light. On the other hand, a low-resolution image directly impacts the graphical interface of the number plate of the vehicle, which is not beneficial to recognize the number effectively.

A plethora of techniques and algorithms have been developed in order to solve the plate detection problem of vehicles in CCTV footage. Various license plate detection techniques are reported in the literature review chapter. As per (Singh et al., 2021), Radial Basis Function Neural Network (RBFNN) is used to detect the vehicle number plate. Otsu's thresholding method is used to detect the plate region. This method can recognize the plates under different illumination conditions. Potential plate regions are found on the basis of features, such as aspect ratios and the number of pixels. The Connected Component Analysis is a widely used method for license plate detection. (Tomar et al., 2018) studied "Connected Component Analysis" to localize and extract the plate from an image of the vehicle, and authors used edges as a feature to detect plates. They proposed edge clustering using the Expectation-Maximization algorithm for detection. This method is very effective for the purpose of visualizing digits. The technique Sobel edge detector is used to locate the four corners of the vehicle plate with canny edge detection method to find the edges and Hough transformation is used to detect the plate.

According to (Kadambari and Nimmalapudi, 2020), AdaBoost algorithm with convolutional feature and cascade classifier to localize the license plates. Sobel edge detector, morphological algorithm, and dilation are used to find rectangles in the vehicle image. All the rectangles are compared with plate dimensions to extract the vehicle plate. The authors found connected components to detect the number plate. Authors used connected component property, area, aspect ratio, and the license plate's white/black pixels ratio to detect the plate. Top-hat transformation method is used for plate localization from the image. The area and aspect ratio is used to detect the plate. Authors presented a simple, fast and efficient technique using SIFT (Scale Invariant Feature Transform) features. In this technique, SIFT-based template corresponding is applied to find special symbols in the license plate. Based on these marks, the plate is segmented out from the image of the vehicle.

(Vinay et al., 2021) used mathematical morphology and color positioning for plate recognition. Mathematical morphology method uses the elements with a certain form to extract and measure the consistent figure from the image. The license plate is located by the Optimal Adaptive Correlation (OAC) technique. OAC algorithm gives a high overall pace to the process of license plate localization. Plate localization is performed by adaptive thresholding and edge detection. Thresholding is a technique where pixels are separated depending on the value of the threshold. The accuracy of the result depends on the appropriate selection of threshold values. Wavelength transform and RBFNN are used for license plate recognition. According to (Krishnamoorthy and Manickam, 2018), decomposition of the image in different layers is done by Wavelength transform, and the license plate is recognized by RBFNN. Authors used Principal component analysis and artificial neural networks to detect the vehicle plate. The algorithm for detecting vehicles plate firstly examinations the CCTV footage for numerical digits as in the character features process and then sets them and further analyzes them to determine a license plate. This method identifies the location of the plate even while the plate covers pictures in the background. Binary jump and image differencing techniques are used to determine the location of vehicle plate in the image. Binary jump method is used to detect top/down boundaries of the license plate and left/right boundaries are detected by image differencing technique.

As per (Pan and Wang, 2021), the algorithm is used in the canny edge detection operator to get the transition between white and black colors of the plate. Vertical Edge Detection algorithm

(VEDA) is used to localize the plate region, and it can work on blurry images and is grounded on the difference between greyscale standards. This algorithm is better than the Sobel operator for extracting vertical edges, and the morphological operator is used for plate extraction. It is a method of image processing grounded on shapes. Morphological operations and color information of the plate is used to locate the plate. Morphology is a technique which is used for shape analysis. Besides that, fuzzy logic is introduced for color recognition of the plate. HSV color space is used for color feature extraction. (Chawdhary et al., 2018) proposed Operator Context Scanning (OCS) algorithm for license plate detection. A region based license plate detection method is presented. Candidate regions are extracted using mean shift firstly. Vertical edge detection and morphology are used to determine the area of interest from the image of the car by using Local Binary Pattern and histogram matching technique for license plate localization.

Plate segmentation carries out an important role in an ANPR system and it is responsible to split the number plate into desired characters regions. If these characters are correctly segmented, they would be a valuable source for character recognition stage. The features like size, color and position of the characters are considered into account while extracting the characters. The input to this phase is license plate of vehicle and productivity is the alpha-numeric characters present on the vehicle plate. As per (Gondhalekar et al., 2021), the Maximally Stable Extreme Region (MSER) based character segmentation technique is used for horizontal projection to find starting and endpoints of characters. Horizontal Projection is used to extract the characters from the image of CCTV footage. Local Otsu's method is used to segment the characters. (Lee et al., 2021) presented an algorithm based on pixel projection and morphological operations. They introduced two optional morphological operations in the proposed algorithm to minimize the effect of noise. In this algorithm horizontal projection step is replaced by height optimization step. Horizontal projection is performed to calibrate the license plate. The position of each character is found by calculating the projection. The characters are segmented by edge detection methodology. A two-stage segmentation technique is proposed for extracting characters from the plate with a grey-level quantization and morphology analysis algorithm to obtain characters from the plate. The local binarization method is combined with this algorithm to improve the performance of segmentation with shift filtering technique for extracting the characters from the vehicle plate and segmentation.

Various character recognition methods are proposed by (Prabhu et al., 2017) and the neural network is a widely used character recognition technique. The probabilistic neural network is used to recognize the characters and Artificial Neural Network that is used and trained for feature extraction and character recognition. The Digital board method is discussed (Singh et al., 2021) for computing feature vector for each character uniquely. They used a Genetic Algorithm for recognizing the characters at the second level. Pre-processed the localized plate for noise exclusion and edge improvement. Afterward pre-processing, characters are separated by using Minimum Boundary Rectangle. Then characters are classified using the nearest neighbor classifier. Template matching is a modest and upfront technique for character recognition. Template toning is applied to recognize the characters. In template matching, segmented characters are matched with the database templates. The best match is the recognized character. This method is called OCR which is an electronic and mechanical conversion of images of text to machine-encoded text.

(Singh et al., 2021) proposed a dilation operation is used to enhance the image and MLP (Multi-Layered Perceptron) is used for character recognition. OCR based multi-layer neural network can recognize the characters present on the vehicle plate. Normalized cross-correlation template matching is used to distinguish the numbers. Normalized cross correlation is a template matching technique which is used to find the degree of similarity between characters and templates. Statistical correlation method was used in matching the characters. Then, Artificial Neural Networks were designed and trained for features extraction. OCR approach based on convolutional neural network for feature extraction and linear support vector machines for classification is used by (Tomar et al., 2018). Good results were achieved by training linear support vector machines on the resulting convolutional neural network features. The cross-correlation based approach is used for classification and this method computes the similarity between the character and its matching template. The D-isomap based method is used for final character recognition, which yields a higher recognition rate that detects pre-processed plates. Then, the extracted features are used to a trained neural network for recognition.

(Kadambari and Nimmalapudi, 2020) used MUNL shape descriptor for extracting the outer contour of characters and Partial Point Matching Algorithm to match the characters against templates. MUNL is modified normalized parametric polar transform which is used to extract characters. The maximal similarity measure is used to indicate the recognized character. This algorithm was used to recognize Polish car license plates. A feed-forward neural network based OCR algorithm is proposed to translate scanned character images into machine-encoded text. In this algorithm, (Vinay et al., 2021) stated noise added training process works on a neural network for better performance. Binary Large Objects (BLOB) analysis is used for character recognition. In this method, characteristics of characters like location, aspect ratio, and dimension are used to identify the characters. MLP (Multi-Layered Perceptron) ANN model are used for the classification of the characters. Two separate ANN were used by authors to increase the success rate of the character recognition. (Krishnamoorthy and Manickam, 2018) analysed data sets for MLP with three hidden layers using sigmoid functions. Convolution neural networks are used to recognize the extracted characters.

(Pan and Wang, 2021) designed a system to recognize automatically the characters written on the rear side of motor vehicles pass through a tollgate. This paper has proposed three-phased detection algorithm. First, a segmentation phase locates the vehicle plate in the CCTV footage. Then, characters are normalized by feature projection procedure. Finally, the matching the template technique is used to identify the fonts of license plate. (Chawdhary et al., 2018) proposed automatic car plate recognition system for automatic parking system. The proposed study developed a method based on four layers backpropagation neural networks with supervised learning. The candidate regions are regulated consistent with car license plate regulation such as shape of car plate and the color.

(Gondhalekar et al., 2021) proposed an algorithm for character segmentation using Hough transformations. In this work, the authors used a new object enhancement algorithm for image pre-processing. This algorithm was tested on six hundred ninety-seven vehicle plate images. Experiments showed that the proposed algorithm could deal the images with disturbance of noise and illumination variance. They used edge statistics, color analysis, and morphological operations to find license plate locations. Then, features of license plates are used to remove the incorrect candidate locations.

(Lee et al., 2021) proposed an efficient LPR algorithm for License Plates and the algorithm on images acquired under various conditions and achieved satisfactory results. An efficient License plate localization method based on discrete wavelength transform (DWT). The experiments are performed on images of vehicles captured under complex environments. Experimental results showed that the proposed technique can quickly detect the location of the license plate in different environments with high accuracy. (Prabhu et al., 2017) proposed an end-to-end ANPR system for license plates of Abu Dhabi. Background subtraction is used to segmenting moving vehicle. Color space and level set techniques are used to locate license plates from the image of the vehicle. Then, the neural network is trained for final classification.

# CHAPTER 3
# METHODOLOGY

## 3.1 Hardware and Software

Following Table 1 shows the hardware and software used for this research.

Table 1: Hardware and Software

| *Hardware* | *Software* | *Frameworks* |
|---|---|---|
| 8MP Hikvision cameras x 2 | python 3.9.6 running on Windows 10 Home edition | OpenCV |
| 5MP Hikvision camera x 1 | PyCharm 2021.1.3 community edition as IDE for python | Tkinter |
| Laptop with<br>Processor-10$^{th}$ generation Intel Core i7-10750H CPU @ 2.60GHz 2.59GHz<br>RAM – 16GB<br>GPU – CUDA enabled NVIDIA Geforce GTX 1650 | LabelImg for image annotation | Tensorflow 2and Object-detection API |
| | R statistical Software | |

## 3.2 Data Collection

About one thousand one hundred ninety four images have been collected using two cameras in two different resolutions, 5MP and 8MP separately. 8MP camera is for reference purposes of the low-resolution images. So, one thousand one hundred ninety four images of low resolution and their high-resolution versions have collected for the number recognition process. Images were collected from 8:00 AM to 4:00 PM. The time slot has been chosen by testing several video footage and identifying the video footage with the maximum recognizable number plates in 8MP resolution.

Both front and rear number plates have been captured using 8MP cameras to improve the accuracy of labeling. Three images have been collected when the vehicle is in three different positions.

- When the vehicle enters the camera view - the resolution of the number plate area is significantly low.
- When the vehicle is well focused - sometimes the number plate becomes human readable.
- When the vehicle is too close to the camera, it becomes out of focus and distorted with the gaussian blur.

## 3.3 Data Preparation

Low-resolution number plates are divided into two sets as training set and the test set. 90% of the images have been randomly selected as the training set, and 10% have been chosen as the test set. Number plates are cropped out from the original image, and preprocessing techniques have been applied to each cropped-out image. Number plates are scaled to six hundred forty pixel width, converted into grayscale first, and weights have been added. Then thresholding followed by morphological closing has been added.

## 3.4 Training Number Recognition Model

First, this proposed study selected Single Shot Detector (SSD) by comparing the Mean Average Precision (MAP) in the TensorFlow 2 model zoo, and found out in the (Huang et al., 2017) that most accurate model is the Faster-RCNN. Although it has lower performance, in this research, the most important fact is the accuracy. Hence, this proposed investigation selected Faster-RCNN, trained on the data set to build optical character recognition (OCR) model. The study tested low-resolution images with well-known OCR models such as EasyOCR and Tesseract, but they cannot recognize low-quality images. The proposed model can recognize some low-quality number plates that couldn't be recognized by general OCR models but need to train with more characters to increase the recognition accuracy.
To train the number recognition model, selected Object-detection Application Programming Interface (API) provided by the TensorFlow 2 machine learning platform in Graphical Processing Unit (GPU). Character recognition is still challenging for low-quality images due to varying character actual shapes due to blurring, distortion, light, and size variations in the input

sample. The research conducted by (Albahli et al., 2021) presented an effective and efficient HDR system and introduced a customized, faster regional convolutional neural network (Faster-RCNN). Following Figure 3 represents the high-level diagram of Faster- RCNN model.

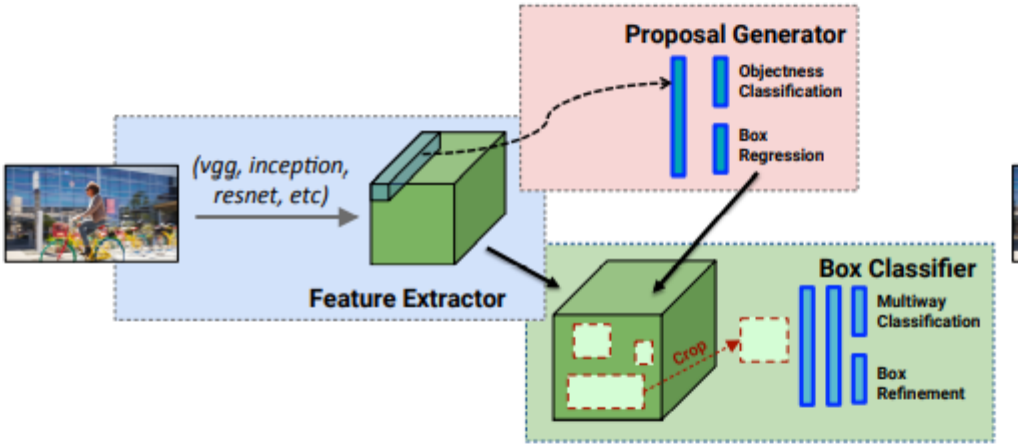


Figure 3: High-Level Diagrams of the Faster-RCNN (Huang et al., 2017)

Residual Network with fifty proposals (ResNet50) has been chosen for this model.

## 3.5 Quality Estimation

Two types of quality attributes have been collected to estimate the minimum quality. The proposed analysis has considered the sharpness level of the image and the resolution of the number plate. How far the vehicle is to the camera determines the resolution of the number plate.

### 3.5.1 Sharpness Measuring

To measure the sharpness of the image used the Laplace filter proposed by (Pech-Pacheco et al, 2000). The Laplacian with the convolutional kernel has been used here.

$$L = \frac{1}{6}\begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

The method is based on computing the absolute value of the Laplacian operator. Laplacian uses the gradient of images and calls internally the Sobel operator to perform its computation.

### 3.5.2 Number Plate Resolution Measuring

To measure the resolution of the number plate, taken minimum X, minimum Y, maximum X, and maximum Y positions of the bounding box drawn by the analyst to select the preferred number plate. Height and width are calculated by using these values and then the resolution is calculated.

*Height of the plate = maximum Y – minimum Y*

*Width of the plate = maximum X – minimum Y*

*Plate Resolution =Height of the plate X Width of the plate*

## 3.6 Proposed Research Design

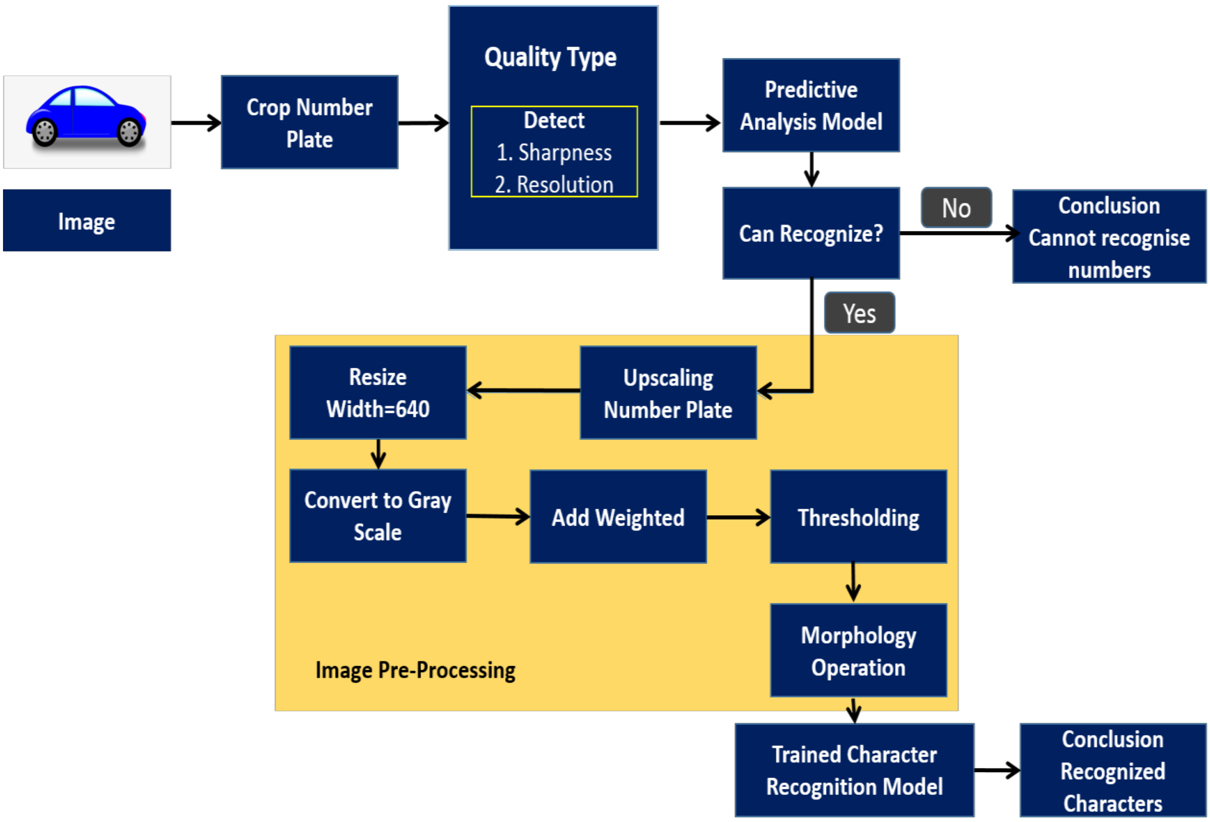


Figure 4: High-Level Diagram of Research Design

Figure 4 above shows a high-level diagram of how the proposed system works. A suitable image will be given as input into the system. When the investigator selects a number plate region, it will calculate sharpness and resolution while detecting the number plate. Based on the computed sharpness and resolution, the predictive analysis model will predict whether numbers can be recognized within that area. If the predictive analysis model cannot predict, it can conclude the registration number cannot be recognized within the selected region. Therefore it is not necessary to go for further enhancements.

If the predictive analysis model recognizes that it can detect the number, it can proceed to the enhancement procedure. As a further enhancement, it will pre-process the number plate. After that, the preprocessed number plate will be passed into the trained number recognition model. Finally the trained number recognition model will display identified characters with an accuracy rate as a result.

## 3.7 Building Predictive Module for Number Recognition

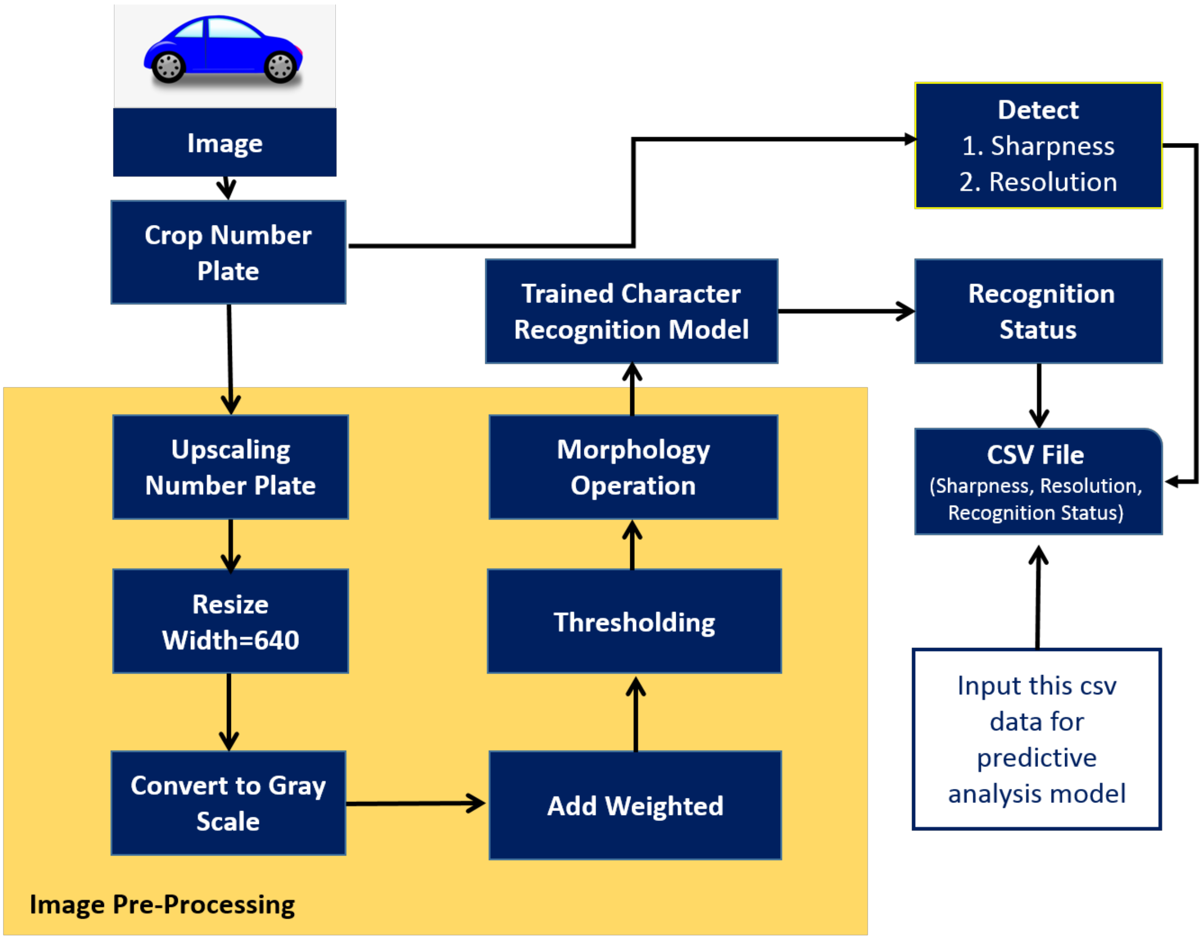


Figure 5: High-Level Diagram of Predictive Analysis Module

Figure 5 above shows the workflow that is followed to collect data for the predictive analysis model. A simple software is developed to apply various image processing techniques on the image frame and perform number recognition. A suitable image will be given as input into the system. The sharpness and resolution are calculated while choosing a number plate. The cropped number plate region will be forwarded to the pre-processing steps such as upscaling, resizing, converting to grayscale, adding weighted, thresholding, and morphology opening and closing operation. The pre-processed number plate region will be passed into custom trained number recognition model. If the number recognition model can identify at least one character, the recognition status, sharpness and resolution will be saved in a CSV file. Predictive analysis is done using R statistical computing software with data collected in a CSV file.

The standard python interface package "Tkinter" has been used to develop the software. Functionalities and features of the designed software to collect data for the predictive analysis as shown in Figure 6 below.

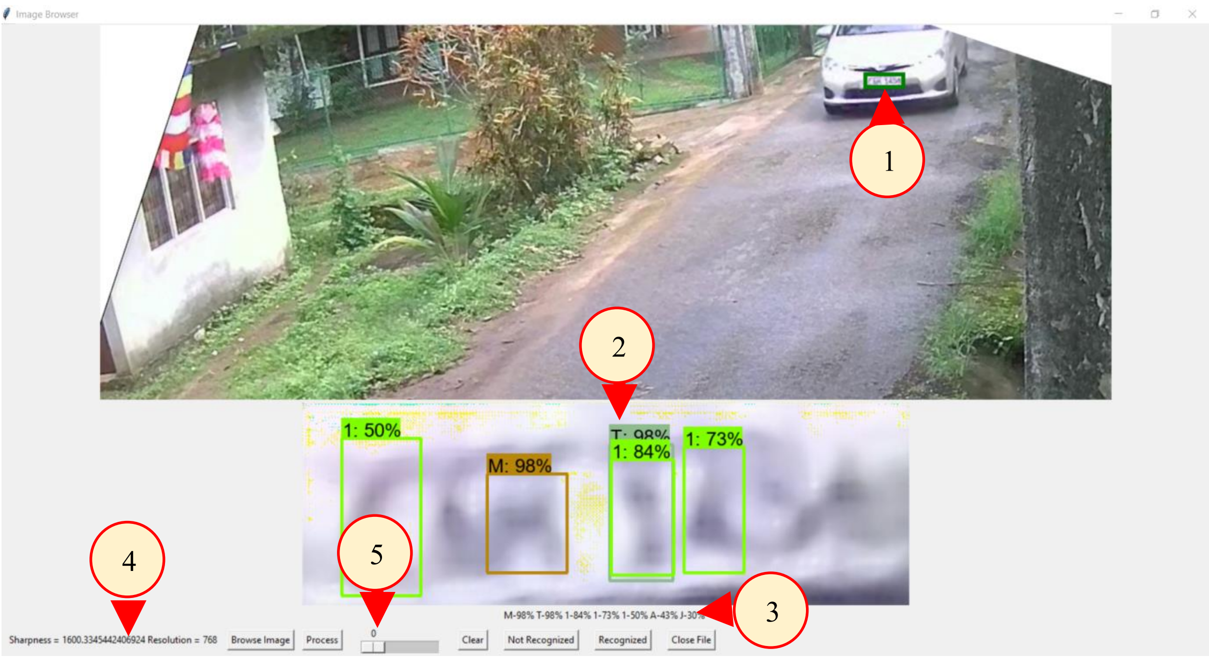

Figure 6: Main Interface of the Designed Software

- 1 – Bounding box to select ROI
- 2 – Cropped out, upscaled number plate with some recognized character bounding boxes
- 3 – Recognized characters display in a label with the detection score. It is for better visualization by overcoming hidden bounding boxes drawn underneath another.
- 4 – Plate resolution and plate sharpness
- 5 – Sharpness adjustment slider

### 3.7.1 Crop Number Plate

As a first step, videos have been split into frames in one second using the python program. Then the required image frames have been chosen manually by checking the extracted images carefully. At least three versions of frames have selected for a single-vehicle. Then the preferred image load into a Tkinter canvas for visualization purposes. By drawing a bounding box on the outline of the number plate, can tell the system this is the region of interest. Then the number plate has been cropped using the bounding box's starting and ending X, Y values. The following steps are used to preprocess the selected number plate region.

### 3.7.2 Upscaling Numberplate

The proposed study used the super-resolution technique suggested by (Wang et al., 2018) to reconstruct a high-resolution number plate image for low-resolution number plates gathered. This technique can reconstruct a high-resolution image four times higher resolution than the original image.

### 3.7.3 Resizing

Since the proposed examination worked with low-resolution images, further resized images to width = 640 to improves the recognized models.

### 3.7.4 Convert to Gray Scale

The proposed exploration of work focuses on applying thresholding on images to binarize the image. This technique increases the speed of the process as well as the accuracy. A grayscale image is given for thresholding. Hence vision has been converted into grayscale using Open CV.

### 3.7.5 Add Weighted

For further enhancement, the grayscaled image has been sharpened using OpenCV and combined with the grayscale image again.

### 3.7.6 Thresholding

The sharpened grayscale image has been converted into a binary image using "OTSU" and "BINARY INVARIENT" methods. Since there have dark characters in the light background used 0 as the thresholding value.

### 3.7.7 Morphological Operations

The opening operation is applied on the binary image to remove the noise, and closing operation is used to close the small holes in the foreground object if it is the character.

### 3.7.8 Character Recognition

Finally, each character is identified by the proposed pre-trained object detection Faster-RCNN model.

## 3.8 Predictive Analysis

Finally, predictive analysis has been conducted using the multiple logistic regression model. Collected sharpness level and the number plate resolution in the .csv file have been used as the input data, and the category is "is_recognized" by the number recognition model. Collected data in the csv file has been used as the training data of the predictive analysis model. Suppose the proposed OCR model recognizes a single character correctly. It is taken as "is_recognized =YES". First, considered the relationship between each quality attribute to the character recognizability. The following Figure 6 visualizes the relationship among sharpness, resolution, and recognizability.

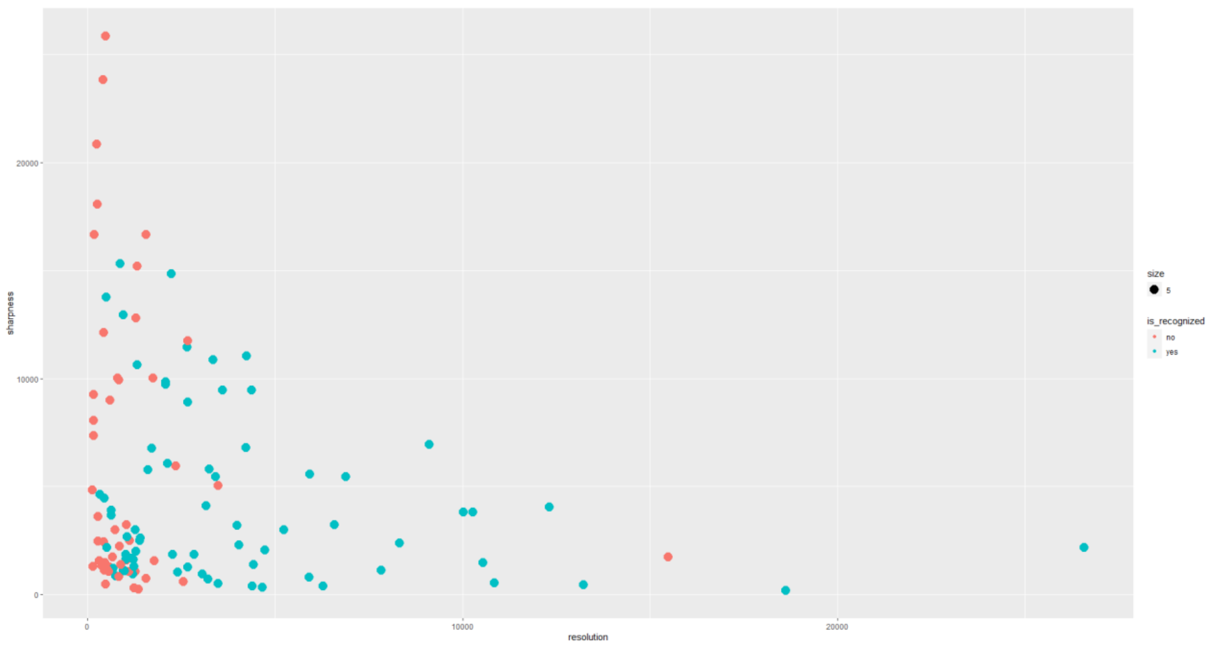


Figure 7: Relationships among Sharpness, Resolution, and the Recognizability

The above Figure 7 plot implies that most non-recognized images are clustered under low resolution and low sharpness values. It is clearly shown that increasing the image sharpness and the resolution increases the recognizability of the model.

The collected data set has been split into the training set and test set. 90% of the records were chosen as the training set, and 10% were chosen as the test set. As the sharpness and resolution variables are independent,  the categorical variable is selected asis_recognized as the Y-axis and applied binomial distribution as the family of the logistic regression model. Following Figure 8 on page 26 is the summary of the predictive analysis model fitting.

```
glm(formula = is_recognized.yes ~ resolution + sharpness, family = binomial,
    data = training)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.4518  -1.0603   0.3350   0.9903   1.4532

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.811e-01  4.611e-01  -1.043  0.29679
resolution   4.187e-04  1.549e-04   2.704  0.00686 **
sharpness   -2.568e-05  4.475e-05  -0.574  0.56607
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 114.104  on 83  degrees of freedom
Residual deviance:  97.853  on 81  degrees of freedom
AIC: 103.85

Number of Fisher Scoring iterations: 6
```

Figure 8: Logistic Regression Model Fitting

### 3.8.1 Relationship Between Resolution and Recognizability

Used the “is_recognized” variable as the categorical data, and “resolution” as continuous variable. The coefficient table received as the output of the logistic regression model shows that image resolution is the most significant predictor in determining the recognizability. It implies giving the lowest P-value and the highest Z value. The suggested hypothesis is as below:

$H_0 = There\ is\ no\ relationship\ between\ resolution\ and\ recognizability$
$H_1 = There\ is\ a\ relationship\ between\ resolution\ and\ recognizability$

$p - value\ =\ 0.00686$
$alternative\ hypothesis: true$
Null hypothesis can be rejected at 95% confidence.

### 3.8.2 Relationship Between Sharpness and Recognizability

Sharpness is a continuous variable. To determine the relationship between sharpness and the recognizability a Point-Biserial Correlation has been conducted on R to test the relationship between sharpness and recognizability. The suggested hypothesis is shown on page 27.

$H_0 = There\ is\ no\ relationship\ between\ sharpness\ and\ recognizability$

$H_1 = There\ is\ a\ relationship\ between\ sharpness\ and\ recognizability$

p-value = 0.56607

Accept null hypothesis at 95% confidence

Hence, it is identified that sharpness in determining the recognizability is not significant and resolution quality attributes have a significant relationship with the recognizability of the plate characters. The study for predictive analysis has collected data from one hundred and twenty images so far, and most of them are in the resolution under five thousand and sharpness under fifteen thousand.

.

# CHAPTER 4

# EVALUATION AND RESULTS

The logistic regression model is evaluated using model evaluation metrics such as accuracy, precision, and recall. The proposed model has 52% of accuracy with the collected records so far. The number of correct and incorrect predictions are summed up class-wise.

- Accuracy **-** the proportion of the total number of correct predictions
- Precision – the proportion of positive cases that were correctly identified
- Recall **-** the proportion of actual positive cases which are correctly identified
- F1 Score – the weighted average of Precision and Recall.

A confusion matrix has been used to evaluate the model. Following Figure 9 shows 2x2 matrix diagram use to evaluate the model. Figure 10 shows the values get as a result of the confusion matrix obtained from R studio.

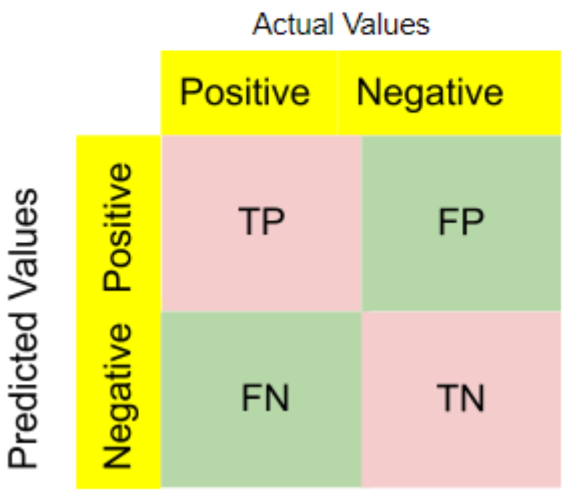


Figure 9: 2x2 Confusion Matrix has been Used to Evaluate the Model

$$Positive = recognized$$

$$Negative = not\ recognized$$

```
data.pred no yes
      no  16  21
      yes 19  28
```

Figure 10: Confusion Matrix obtained from R Studio

The below Table 2 is shown a classified version of confusion matix asTP, TN, FP and FN.

Table 2: Confusion Matrix Results

| | |
|---|---|
| *Number of records correctly classified as recognized (TP)* | 16 |
| *Number of records correctly classified as not recognized (TN)* | 28 |
| *Number of records incorrectly classified as recognized (FP)* | 21 |
| *Number of records incorrectly classified as not-recognized (FN)* | 19 |

## 4.1 Compute Success Rate

Mean is calculated to obtain the success rate of the model. The study got 52% accuracy rate while it gives 48% of error rate. Since the proposed research have above 50% of accuracy, it is an excellent model to predict the,

- The precision is the ratio of TP / (TP + FP) = 0.432
- The recall is the ratio of TP / (TP + FN) =0.4571
- The Accuracy is the ratio of TP+TN/TP+FP+FN+TN = 0.523
- The F1 score is the ratio of 2*(Recall * Precision) / (Recall + Precision) = 0.4441

## 4.2 Compute ROC Curve

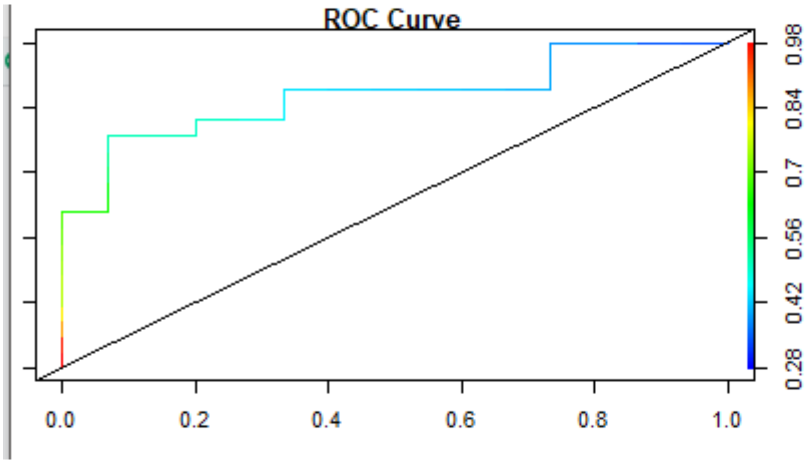


Figure 11: The Receiver Operating Characteristic Curve (ROC) Y axis – True positive rate, X-axis – False positive rate

The receiver operating characteristic (ROC) curve is another common tool used with binary classifiers. The dotted line represents the ROC curve of a purely random classifier; a good class classifier stays as far away from that line as possible (toward the top-left corner) (Li, 2019).

## 4.3 Results


Figure 12: Results of Recognition Model

The above Figure 12 on page 30 shows the result of the number recognition model with a precision value identified by the model. The data from the number recognition model was used for training the predictive analysis results.

Table 3: Predictive Analysis Results

| *Resolution* | *Sharpness* | *Predictive analysis result* | *Actual recognition model result* |
|---|---|---|---|
| 2077 | 1261 | 0.586003 - Recognized | Recognized |
| 594 | 746 | 0.429027 – Not recognized | Not recognized |
| 576 | 722 | 0.4272567 – Not recognized | Not recognized |
| 378 | 1314 | 0.4026159 - Not recognized | Not recognized |
| 472 | 1481 | 0.4114710 - Not recognized | Not recognized |
| 540 | 1135 | 0.4208329 - Not recognized | Not recognized |
| 884 | 1378 | 0.4562051 - Not recognized | Not recognized |
| 1350 | 251 | 0.5141142 - Recognized | Not recognized |
| 336 | 4623 | 0.3780385 - Not recognized | Recognized |
| 450 | 4457 | 0.3908073 - Not recognized | Recognized |

According to the predictive analysis results shown in Table 3, it has shown that the proposed solution can obtain 70% of the accuracy on the performed testing data.

Table 4: Minimum Average Resolution

| *Image* | *Resolution* |
|---|---|
| Image 1 with seven samples | 893 |
| Image 2 with seven samples | 712 |
| Image 3 with seven samples | 610 |
| Image 4 with seven samples | 468 |
| Image 5 with seven samples | 785 |
| Image 6 with seven samples | 598 |
| Image 7 with seven samples | 803 |
| Image 8 with seven samples | 503 |
| Image 9 with seven samples | 691 |
| Image 10 with seven samples | 625 |
| Minimum average resolution threshold value | 668.8 |

Table 5: Minimum Average Sharpness

| *Image* | *Sharpness* |
|---|---|
| Image 1 with seven samples | 14609 |
| Image 2 with seven samples | 13270 |
| Image 3 with seven samples | 4065 |
| Image 4 with seven samples | 10948 |
| Image 5 with seven samples | 8408 |
| Image 6 with seven samples | 7937 |
| Image 7 with seven samples | 12101 |
| Image 8 with seven samples | 7976 |
| Image 9 with seven samples | 6842 |
| Image 10 with seven samples | 12956 |
| Minimum average sharpness threshold value | 9911.2 |

As shown in Table 4, the minimum average resolution has been obtained as six hundred sixty-eight and eight-tenths using ten different images, each with seven samples by changing resolution only. And the minimum average sharpness has been received as nine thousand nine hundred eleven and two-tenths using ten additional images, each with seven samples by different sharpness values is shown in Table 5.

# CHAPTER 5
# CONCLUSION AND FUTURE WORK

The proposed research solution outperforms well-known character recognition models like "EasyOCR" and "Tesseract" on low-quality images.  According to the predictive analysis, the resolution of the number plate significantly affects the recognizability of the characters than the sharpness of the images. Most of the well-known optical character recognition models work on high-resolution images or when the background and foreground characters have significant contrast. Low-quality images are hard to recognize. But when it comes to forensic, especially when working with the court, it is better to give an acceptable and scientific reason why one cannot recognize a particular number plate. The character segmentation is a tedious task; hence it is time-consuming. In this work, the used a better object enhancement procedure for image preprocessing.

The proposed system has worked with more than a thousand images. Experiments showed that the proposed algorithm could deal with noise and daylight images except overexposed and underexpose images. Several image preprocessing techniques have been used in this system operation, such as bounding box region of number plates, upscaling number plate, resizing, converting grayscale, weighted images, thresholding, and morphological operations. The custom-trained character recognition model using Faster-RCNN to identify the number plate used to train the predictive analysis model, which performs to find out whether the number can be recognized or not based on sharpness and image resolution. The developed predictive model successfully sensed images with 70% accuracy.

It has shown that resolution is the most significant factor than sharpness. Therefore, increasing sharpness has not significantly affected recognizing number plates compared to increasing image resolution. As a result of the predictive analysis, data collected shows that more than two thousand plate resolution is required to recognize at least a single character from the number plate correctly. And this is a beneficial study for the current workstation where it is easy to identify whether the number can recognize or not without manually doing image enhancement.

It is evident that a high-resolution image is beneficial for the CCTV camera footage, clearly showing the different actions. Higher resolution can also be effective for the decision-making process more effectively. This study has identified a minimum of six hundred sixty-eight pixels needed to find at least one character of the number plate. A minimum of nine thousand nine hundred eleven sharpness would help identify the number from the number plate. It founds that it is necessary to develop the pixel quality of the CCTV camera from 2MP to upwards to improve the quality of the picture. This study has determined that quality measurement is effective for enhancing different factors of CCTV. Technological advancement is essential for the development of society which can lead the community towards progress.

## 5.1 Further Improvements

It is required to improve the character recognition model since some characters are incorrectly identified. Model is confused with identifying,

H,N, M

1, T

S,5,E


Figure 13: Wrongly Identified Character

The above Figure 13 identified as T but should be recognized as number 1.

To overcome the above matters, improving the preprocessing of the number plate using image processing techniques is required. It identified that collecting some more data will improve the accuracy of the number recognition and the predictive analysis models. In order to improve the quality of the CCTV camera it is necessary focus on the pixel size of the camera which directly impact on the size and quality of the CCTV footage.

## 5.2 Future Work

Improve and train the model with more images and create the final software that can predict the recognition ability of number plate in an image before sending it to the most time and resource-consuming number recognition model. Hence the analyst would be able to identify the images which don't meet the expected quality level. In the future, the research can be improved by identifying required level of pixel size need in the image for identifying vehicle number plates. It is beneficial for the CCTV camera producers to reform the exact pixel number for the CCTV production to effectively track the vehicle number plate. And it will enhance the efficiency of the forensic criminal investigation detection operations in Sri Lanka.

# APPENDICES

## APPENDIX A: CHARACTER RECOGNITION

```python
from tkinter import *
from tkinter import filedialog
import os
import io

import numpy as np
import cv2
import tkinter as tk
import csv
from PIL import Image, ImageTk, ImageEnhance
from matplotlib import cm
from ChaRecognition import preprocessing


myx = 0
myy = 0
rect = None


def on_button_press(event):
    global start_x,start_y
    global rect
    # save mouse drag start position
    start_x = event.x
    start_y = event.y
    print(start_x,start_y)
    rect = my_canvas.create_rectangle(start_x, start_y, start_x, start_y, outline="green", tags="box", width = 3)



def on_move_press(event):
    global  start_x, start_y
    global rect
    curX = event.x
    curY = event.y

    # expand rectangle as you drag the mouse
    #rect = my_canvas.create_rectangle(start_x, start_y, 1, 1, outline="green")
    my_canvas.coords(1, start_x, start_y, curX, curY)
    print(start_x, start_y, curX, curY)
```

Figure A1: Python Code of Main UI

```python
    ret, thresh = cv2.threshold(weighted.astype("uint8"), 0, 255, cv2.THRESH_OTSU | cv2.THRESH_BINARY_INV)
    #thresh = cv2.adaptiveThreshold(weighted,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C , cv2.THRESH_BINARY, 50, 0)
    rect_kern = cv2.getStructuringElement(cv2.MORPH_RECT, (3, 3))
    opening = cv2.morphologyEx(thresh, cv2.MORPH_OPEN, rect_kern)
    closing = cv2.morphologyEx(opening, cv2.MORPH_CLOSE, rect_kern)
    detection,ocr_result = chardetection(closing,img, im2arr)
    #ocrcharacterrec(gray)
    return detection ,ocr_result

PATH_TO_NO_REC = 'models\saved_model'#'E:/Tensorflow/workspace/training_chars/exported-models/new_model/saved_model'
PATH_TO_CHAR_LABELS = 'labels\label_map.pbtxt'#'E:/Tensorflow/workspace/training_chars/annotations/label_map.pbtxt'

def chardetection(closing,img, original):
    rec_fn = tf.saved_model.load(PATH_TO_NO_REC)
    # Load label map data
    category_index2 = label_map_util.create_category_index_from_labelmap(PATH_TO_CHAR_LABELS,
                                                                         use_display_name=True)
    img2 = np.zeros_like(img)
    img2[:, :, 0] = closing
    img2[:, :, 1] = closing
    img2[:, :, 2] = closing
    input_tensor2 = tf.convert_to_tensor(img2)
    input_tensor2 = input_tensor2[tf.newaxis, ...]
    input_tensor2 = np.expand_dims(img2, 0)
    detections2 = rec_fn(input_tensor2)
    num_detections2 = int(detections2.pop('num_detections'))
    detections2 = {key: value[0, :num_detections2].numpy()
                   for key, value in detections2.items()}
    detections2['num_detections'] = num_detections2
    classes = detections2['num_detections']
    scores = detections2['detection_scores']
    # detection_classes should be ints.
    detections2['detection_classes'] = detections2['detection_classes'].astype(np.int64)
    image_with_detections2 = img2.copy()
    viz_utils.visualize_boxes_and_labels_on_image_array(
        #image_with_detections2,
        original,
        detections2['detection_boxes'],
        detections2['detection_classes'],
        detections2['detection_scores'],
```

Figure A2: Python Code of Character Recognition

```python
import os
import time

import matplotlib
from PIL import Image
import numpy as np
import tensorflow as tf
import tensorflow_hub as hub
import matplotlib.pyplot as plt
#%matplotlib inline
os.environ["TFHUB_DOWNLOAD_PROGRESS"] = "True"

# Declaring Constants
IMAGE_PATH = "images/rd5.jpg"
SAVED_MODEL_PATH = "models\esrgan-tf2_1"

def preprocess_image(image):

    hr_image = image#tf.image.decode_image(tf.io.read_file(image_path))
    # If PNG, remove the alpha channel. The model only supports
    # images with 3 color channels.
    if hr_image.shape[-1] == 4:
      hr_image = hr_image[...,:-1]
    hr_size = (tf.convert_to_tensor(hr_image.shape[:-1]) // 4) * 4
    hr_image = tf.image.crop_to_bounding_box(hr_image, 0, 0, hr_size[0], hr_size[1])
    hr_image = tf.cast(hr_image, tf.float32)
    return tf.expand_dims(hr_image, 0)

def save_image(image, filename):
    """
      Saves unscaled Tensor Images.
      Args:
        image: 3D image tensor. [height, width, channels]
        filename: Name of the file to save to.
    """
    if not isinstance(image, Image.Image):
      image = tf.clip_by_value(image, 0, 255)
      image = Image.fromarray(tf.cast(image, tf.uint8).numpy())
    image.save("%s.jpg" % filename)
    print("Saved as %s.jpg" % filename)
```

Figure A3: Python Code of Super Resolution

# APPENDIX B: PREDICTIVE ANALYSIS

```
#Import data
data <-read.csv("rec_results",TRUE,",")
class(data)
head(data)


data

#install required packages to plot data
install.packages("tidyverse")
install.packages("ggplot2")
install.packages("colorspace")

library(tidyverse)
library(ggplot2)

plot <- ggplot(data=data, aes(x=resolution, y=sharpness, col=is_recognized))

plot <- plot + geom_point(aes(size = 5))
plot


data$is_recognized.yes <- factor(data$is_recognized)
contrasts(data$is_recognized.yes)

#Creating Training and test set
install.packages('readr')
install.packages('caret')
library(readr)
library(caret)
inTrain <- createDataPartition(y = data$is_recognized.yes, p = .70, list = FALSE)
training <- data[inTrain,]
testing <- data[-inTrain,]

dim(training)
dim(testing)

data.fit = glm(is_recognized.yes ~ resolution + sharpness, data=training, family=binomial)
summary(data.fit)
probabilities <- data.fit %>% predict(testing, type = "response")
predicted.classes <- ifelse(probabilities > 0.5, "yes", "no")
mean(data.pred == training$is_recognized.yes)
contrasts(testing$is_recognized.yes)
```

Figure B1: R Studio Code

```r
data.prob = predict(data.fit, testing, type="response")
data.pred = rep("yes", dim(training)[1])
data.pred[data.prob > .5] = "no"
table(data.pred, training$is_recognized.yes)
mean(data.pred == training$is_recognized.yes)
#calculate precision and recall
install.packages("ROCR")
library(ROCR)
demo(ROCR)
help(package=ROCR)
pred <- prediction(data.prob,testing$is_recognized)
eval<- performance(pred,"acc")
abline(h=0.76, v=0.45)
roc <- performance(pred,"tpr", "fpr")
plot(roc, colorize=T,main = "ROC Curve", ylab = "True Positive Rate", xlab = "False Positive Rate")
abline(a=0, b=1)
par("mar")

par(mar=c(1,1,1,1))
plot(eval)
```

Figure B2: R Studio Code to plot ROC graph

```r
predict(data.fit, newdata=data.frame(resolution=c(2077, 594), sharpness=c(1261,746)), type="response")
predict(data.fit, newdata=data.frame(resolution=c(576, 378), sharpness=c(722,1314)), type="response")
predict(data.fit, newdata=data.frame(resolution=c(472, 540), sharpness=c(1481,1135)), type="response")
predict(data.fit, newdata=data.frame(resolution=c(884, 1350), sharpness=c(1378,251)), type="response")
predict(data.fit, newdata=data.frame(resolution=c(336, 450), sharpness=c(4623,4457)), type="response")
```

Figure B3: R studio code to Predict test images

# APPENDIX C: DATA COLLECTION FOR PREDICTIVE ANALYSIS

```
resolution,sharpness,is_recognized
3212,711.623865910939,yes
3060,929.0946036306076,yes
2664,11451.67884086226,yes
1176,1678.9213162211217,yes
3168,4115.355270567895,yes
2350,5950.595258286807,no
238,20848.265141350657,no
864,15312.902339582382,yes
270,18081.222193263224,no
492,13755.712571881817,yes
154,9261.796635182998,no
135,4831.464996189606,no
160,7369.2220659722225,no
155,8063.348382471962,no
1035,3239.1644608327433,no
272,3614.7060130118225,no
2091,9736.772818784724,yes
140,1309.2208333333333,no
2679,11752.759748326487,no
600,8987.034073765433,no
1750,10015.60107903855,no
170,16666.1723183391,no
840,9919.671111111109,no
2091,9842.74236069355,yes
437,12126.781412457287,no
800,10008.2471484375,no
1296,12801.080448480818,no
480,25871.53422839506,no
1558,16667.586699765216,no
1326,15214.826346312462,no
6583,3226.9895777198026,yes
1325,10624.23858511926,yes
5236,2989.4062955720287,yes
10549,1480.7503736765502,yes
3484,514.8565856577749,yes
7830,1128.800676474197,yes
6880,5441.914784058857,yes
960,12937.717127700616,yes
9118,6954.056922508941,yes
13230,449.36327488146514,yes
10856,544.0235249825304,yes
8316,2374.0768678071167,yes
3420,5454.080271270553,yes
448,1118.506040404443,no
4725,2067.5015649505895,yes
4368,9460.35987100845,yes
3250,5789.680168573308,yes
3990,3198.4939457038586,yes
2668,8904.305936783609,yes
4238,11036.33588817862,yes
3600,9451.608809019204,yes
2240,14863.509493494012,yes
1710,6771.717783667529,yes
10277,3802.323951584097,yes
3348,10873.647518263328,yes
```

Figure C1: Part of the CSV Data File

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