Sri Lankan Vehicle Plate Recognition System

Final Project Report

Group D

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Section I: Abstract

This literature illustrates the challenges faced in recovering highly distorted images obtained from CCTV video frames. The images used in the dataset are of low resolution and distorted by motion blur, perspective distortion, reflections, low illumination, and other lighting conditions. This work employs several image processing techniques such as Otsu thresholding, morphological transformation, contouring to extract the number plate region, increase resolution using the ESRGAN model, noise recognition, spatial and frequency domain filtering, and degradation modeling to remove distortion and enhance the image quality, and finally Optical Character Recognition to identify the characters present in a restored license plate. The project has its drawbacks and limitations as higher machine learning and deep learning techniques were not utilized, and the degradations could not be modeled accurately. However, this work demonstrates the general process that must be implemented to restore highly distorted images along with the limitations of the traditional image processing theoretical techniques.

The literature is organized as follows: Section II provides an overview of the overall system. Section III discusses the methods adapted from the related work. The technical approach utilized is explained in Section IV. Section V gives the experimental results. The report concludes with Section VI.

Keywords: License plate recognition, Image enhancement, Image processing, Super-resolution

Section II: Introduction

Vehicle number plate recognition is a potential research area in smart cities and the Internet of Things. The employment of automated systems to preserve vehicle information for multiple reasons is necessitated by an exponential growth in the number of vehicles. Vehicle license plate detection is important in detecting problematic vehicles, such as those involved in road accidents, or in capturing any vehicle that violates the rules. Rapid motions of the vehicles may make it harder for a surveillance camera to recognize the license plate. The camera's image becomes blurred as a result of the vehicle's rapid speed. As a result, the image becomes unrecognizable, undetectable, and degrades, resulting in the loss of some visual information. In such instances, image deblurring and enhancement techniques can be used to retrieve any helpful indication from the images for identifying the vehicle's license plate.

An effective process for identifying Sri Lankan vehicle license plates has been discussed in the following system. The system proposed the concept of developing several methods for identifying a number plate that has been extensively degraded by motion, extensive lighting conditions, shadows, reflections, and rotations. The goal of this project is to obtain a latent image that reduces the strain on human eyes while identifying a blurry license plate.

To get the intended outcomes, the algorithm checks all the possible enhancement techniques considering all system complexities. As a whole, a series of primary algorithms are utilized to enhance the images effectively. The license plates are localized using thresholding, and morphological filters and the extracted region is resized using the super-resolution technique. In the image enhancement stage, several image processing techniques such as Laplacian filter, band-reject filtering, histogram equalization, and image restoration using inverse degradation functions were used. After enhancing the images, the Optical Character Recognition algorithm is used to identify the numerals on the license plate. The project may contain flaws and limitations since the application of the algorithm is dependent on the types of noises in a given image and the restoration process which will be followed in this project is blind restoration as we don't have prior knowledge of the degradation present in the images.

Section III: Related Work

There is a large amount of research carried out in the field of automatic license plate extraction and character recognition with the rising interest in smart cities, self-driving cars, IoT, etc. Some of the literature referred to for this work is as follows: the detailed survey of algorithms used in Automatic Number Plate Recognition(ANPR) by Lubna et.al [1], where the current approaches, techniques, and algorithms used in ANPR systems were discussed, recognition of vehicle license plates based on image processing by Tae-Gu Kim et.al [2], which proposes a mechanism to recognize license plate details of vehicle images acquired using CCTV, and image processing based validation of unrecognizable numbers in severely distorted license plate images by Sangsik Jang, et.al [3]. Apart from these papers, image preprocessing and restoration techniques discussed in the Digital Image Processing book written by Rafael C. Gonzalez and Richard E. Woods [4] were implemented and tested for the dataset used.

The technical approach utilized throughout this project was greatly influenced by the general process of a number plate recognition system discussed in the literature survey written by Lubna, et.al [1]. Since the dataset utilized throughout the project replicated a low-resolution image set obtained from CCTV captures, the accuracy of preprocessing techniques implemented in the paper written by Tae-Gu Kim, et.al [2], such as super-resolution using Super-Resolution Generative Adversarial Network (SRGAN) algorithm to increase the resolution of the images, binarization using an optimal threshold value calculated using the Otsu binarization technique, and morphological filters to enhance the boundary lines of the license plate area to easily localize and extract a license plate were tested to the dataset.

However, most of the preprocessing techniques used in the majority of papers fail to recover the highly distorted images of the dataset up to a satisfactory level to recognize the characters present using the Optical Character Recognition method, and therefore, the future works of this project will be inspired by the novel approach of using an intentionally degraded set of reference numbers that can replicate the highly distorted characters and comparing the cross-correlation between the degraded references and unrecognizable characters in test images to identify the characters present in the license plate introduced in the paper written by Sangsik Jang, et.al [3].

Section IV: Approach

The main objective of the number plate detection system is to restore a low resolution, degraded image of a number plate and then detect the characters present in the image. Since the degradations applied to a specific image will be unknown in most scenarios, the blind restoration approach is taken to retrieve the original image.

Figure 1 shows the workflow which is followed to recognize the characters and digits of a given number plate image using Python and supported packages.

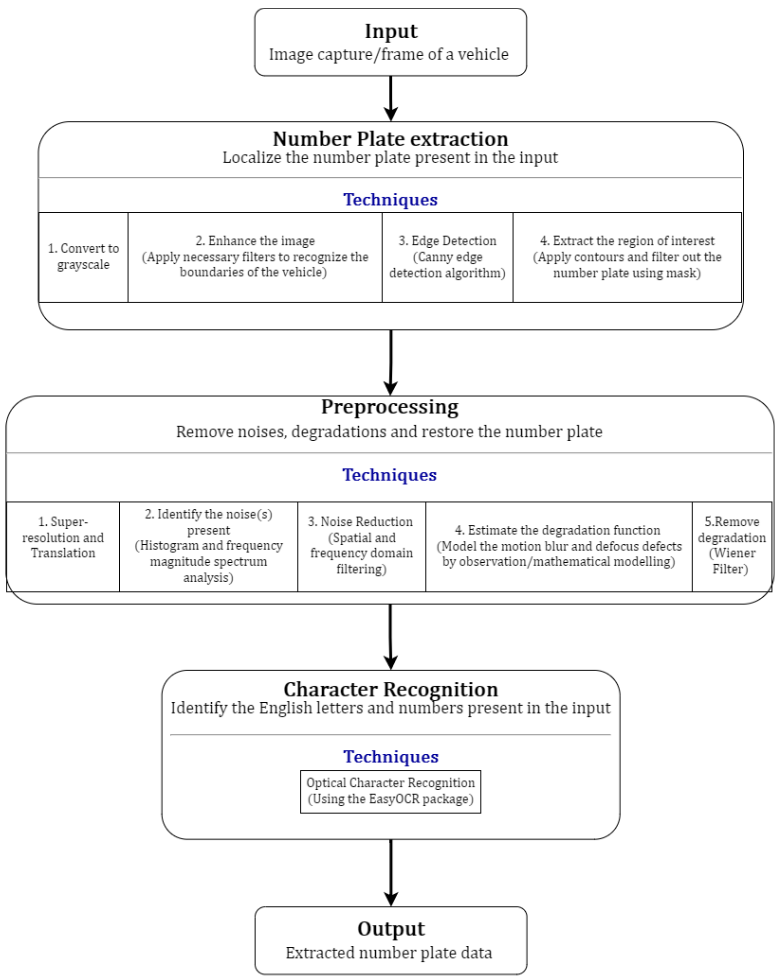


Figure 1: Process of the Number Plate Recognition System

1. **Input**

   The input to the system can be either a full image of a vehicle containing the number plate or a frame containing only the number plate, distorted by multiple noises and degradations.

2. Number Plate Extraction

This step is necessary only when the complete frame of the vehicle is given instead of the number plate itself. Since our region of interest is only the number plate region, it is segmented and extracted in this step. The number plate extraction is done under the following 4 steps.

2.1 Convert to Grayscale

The RGB input images are converted to grayscale so that the computational complexity of future procedures is reduced by storing the information in the image in 8 bits per sampled pixel. This conversion simplifies the noise and degradation recognition and edge detection processes.

2.2 Enhance the Image

To identify the region of the number plate, simple enhancement techniques such as equalizing and resizing are applied to increase the contrast of the image and clearly detect the boundaries of the image.

2.3 Extract the Region of Interest

Given an image of a vehicle that contains the license plate, the region containing the license plate is extracted in four steps as follows.

1. **Binarization**: The image is binarized to enhance the image to separate the background from the foreground of the objects present in the image. The Otsu's thresholding method is utilized here to identify the optimal thresholding value and apply it to the image without manually identifying the best threshold value that works for a specific image.

   The main algorithm in this method involves iterating through the possible threshold values and calculating the weighted within-class variance given by the relation:

$$\sigma_{\omega}^{2}(t) = q_0(t)\,\sigma_1^{2}(t) + q_2(t)\,\sigma_2^{2}(t)$$

where

Class probabilities $q_1(t)$ and $q_2(t)$:

$$q_1(t) = \sum_{i=1}^{t} P(i) \quad \text{and} \quad q_2(t) = \sum_{i=t+1}^{I} P(i)$$

Class means $\mu_1(t)$ and $\mu_2(t)$:

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \quad \text{and} \quad \mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)}$$

Class within-class variances $\sigma_1^{2}(t)$ and $\sigma_2^{2}(t)$:

$$\sigma_1^{2}(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \quad \text{and} \quad \sigma_2^{2}(t) = \sum_{i=t+1}^{t} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)}$$

The algorithm outputs the image binarized using the threshold which minimizes the weighted within-class variance.

2. **Morphological closing:**

   A close morphological operator is used to fill in image region boundary pixels so that the boundary of the license plate will be enhanced.

   The morphological closing operation is defined as a dilation followed by an erosion that ultimately removes the dark spots present in the image and connects the bright cracks which will close up the gaps between bright features.

   The morphological closing operation can be represented mathematically considering set A and the erosion of the dilation of that set B (for images these are objects in the images) as follows.

   $$A \cdot B = (A \oplus B) \ominus B$$

   where $\oplus$ and $\ominus$ denotes dilation and erosion respectively.

3. **Plate region detection:**

   Contours are drawn in the morphological closed image to determine the objects present in the image. Since the number plate is generally rectangular, a closed rectangular contour (a polygon with 4 points) is filtered out from the objects detected.

   Afterward, the rest of the image except the license plate region is set to black (0) to clearly detect the license plate.

4. **Plate extraction and translation:**

   The rest of the image apart from the license plate is cropped out so that the rest of the procedures can be applied mainly focusing on the region of interest, which is the license plate itself.

   Warp transformation is used here to retranslate the rotated or angled number plates to get them into the right position. The perspective transformation is applied to map the 4 points of the corners of the number plate to the corners of the image.

3. **Preprocessing**

Since the inputs are expected to be highly distorted and noisy, they have to be eliminated to clearly recognize the characters present. This task is achieved in 5 steps as follows.

3.1 Super-resolution using ESRGAN

Most of the images taken from the surveillance cameras are in very low resolution because the cameras are set to capture wide areas. Extracting a high-resolution number plate is a problem because of the image resolutions of the cameras. In order to obtain a better resolution number plate, we can use either interpolation methods or super-resolution techniques. The image interpolation cannot preserve sharp edges. Therefore, the number extraction or recognition of the interpolated images is difficult. However, the super-resolution algorithm treats the low-resolution image as a distorted version of a higher-resolution image

Super-Resolution Generative Adversarial Network (SRGAN) is a deep learning model consisting of a generator and discriminant network. The model is capable of generating realistic textures during single image super-resolution by upscaling photo-realistic images up to x4 times. ESRGAN is an enhanced version of SRGAN. ESRGAN achieves better visual quality with more realistic and natural textures. ESRGAN uses a perceptual loss function composed of an adversarial loss and a content loss. The adversarial loss directs to the natural picture manifold, which is represented by a discriminator network trained to distinguish between super-resolved images and original photo-realistic images. Therefore, the deep residual network can recover photorealistic textures from highly low-resolution photos.

Therefore, ESRGAN is chosen as the best model to increase the resolution of the extracted images.

3.2 Identify the noise present

Multiple noises introduced to the images during image acquisition due to lighting conditions and transmission errors must be detected so that they can be reduced in the next stage. The types of spatial noise (Gaussian, Rayleigh, Gamma, Impulse, etc) present are identified by observing the histograms, while the high-frequency noise present is observed from the magnitude spectrums.

3.3 Noise reduction

After recognizing the noises present, they are eliminated or reduced using appropriate spatial filters such as mean and median filters and frequency domain filters such as band-reject, high pass, or low pass filters.

3.4 Estimate the degradation function

Since the degradations we are focusing on mainly are motion blur and low light conditions, an estimate for the degradation function is created by image observation. An appropriate estimation will be modeled that can be used in the next step to remove the degradation.

3.5 Remove degradation and restoration

Since the input images are affected by noise and the inverse filtering technique is not capable of handling noises, the image is restored by applying the Wiener filtering technique using the degradation function modeled in step 3.5.

4. **Character Recognition**

   The information present in the enhanced image is segmented using the Optical Character Recognition technique. For this, the freely available package EasyOCR contains the model implementing the OCR algorithm.

5. **Output**

   The English letters and characters detected in step 4 are displayed as the output

Section V: Experiment

The implementation of the approach and the results are given in [this](#) folder.

The input image can be either a full frame of a vehicle containing the number plate or just the region containing the number plate, the dataset can be of two types of RGB images as shown in figures 2 and 3.

Figure 2: Dataset containing the full frame of a vehicle

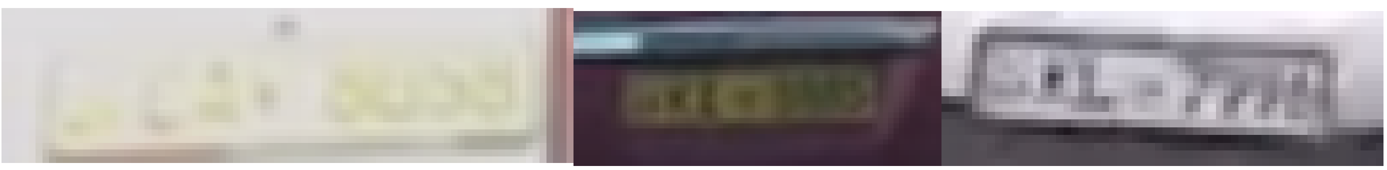


Figure 3: Data set containing only the number plate region

For the images containing the full frame of the vehicle, the number plate was extracted separately after enhancing the images containing various noises and degradations. Once the images are enhanced and the region of interest is extracted, the English characters and the digits present on the number plate are recognized and displayed as shown in figure 4.

Figure 4: Expected results of the system

Result evaluation:

There are mainly four factors that influence the evaluation of our model.

1. Pixel accuracy

Every pixel of the initial picture has to be processed, and our final enhanced image should show the vehicle plate numbers. Here we can evaluate manually whether the numbers seem clear or not.

2. Noise and blur detection

Our model has to predict which filter to use for each image, and detect which noise affects the particular image accurately.

3. Number Plate Extraction

Here our model has to extract the exact location of the number plate in the image, which can be evaluated by manually identifying whether the model indicates the correct position of the number plate.

4. Character Recognition

Character recognition is the part that needs to be read precisely. To evaluate this we will collect many labeled number plates dataset and calculate the accuracy of our model.

Evaluation Steps

1. Initially collect a huge amount of vehicle plate samples
2. label them according to their plate numbers.
3. Apply some filters to damage them manually.
4. By using our image processing model predict the exact vehicle numbers of damaged images.
5. Compare our results with the label and can check the accuracy of our model.

Results:

1. License Plate Localization

To extract the number plate out of an image of a vehicle, the following steps were taken.

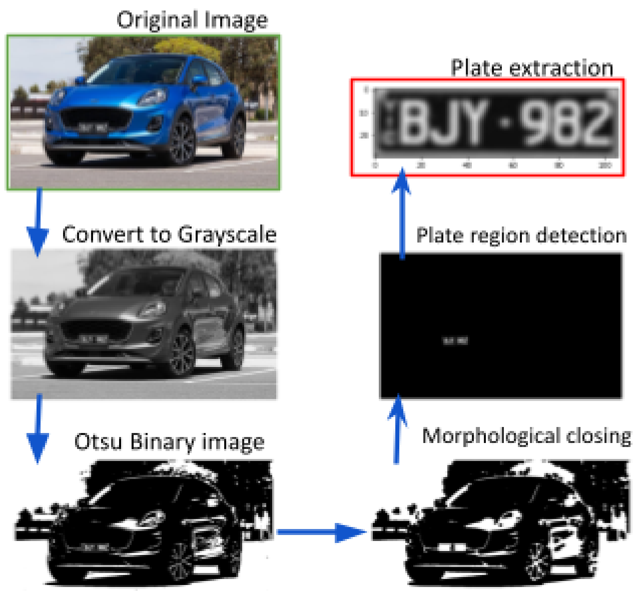


Figure 5: Number plate localization and extraction procedure

As discussed in the approach section, the image was converted to grayscale, and the binarized image using the threshold calculated by the otsu algorithm was obtained. Afterward, the morphological closing technique was applied to identify the boundary of the license plate. Figure 5 clearly shows how the morphological filter enhances the image and segments the license plate region. Then, contours were drawn and the rectangular license plate location was identified by detecting the boundary with 4 points. A mask was then applied to detect and extract the region with the license plate.

- Note: Canny edge detection method was also explored to detect the edges. However, it was observed that Otsu-thresholding along with the morphological closing filter gives better accuracy in detecting the boundary of the plate.

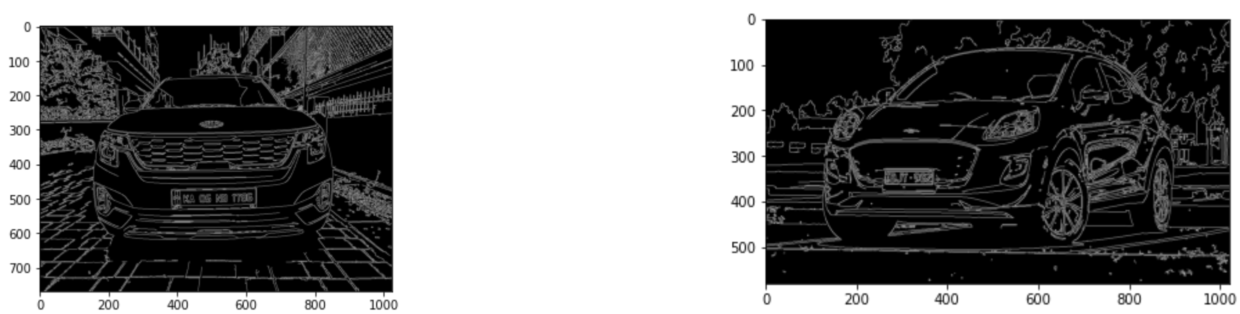


Figure 6: results after canny edge detection

2. Super-resolution using ESRGAN

As figure 3 shows, the dataset used for this study is of very low resolution with sizes 23x84,20x58,29x69 respectively. However, for the enhancing techniques and character recognition techniques to have better accuracy, the image resolution must be increased. As discussed in the approach section, the ESRGAN model was used to increase the image resolution, and the resulting resized images had the sizes of 80x336, 80x224, 112x272. The sizes of the images were increased by approximately 4 times than the original image.

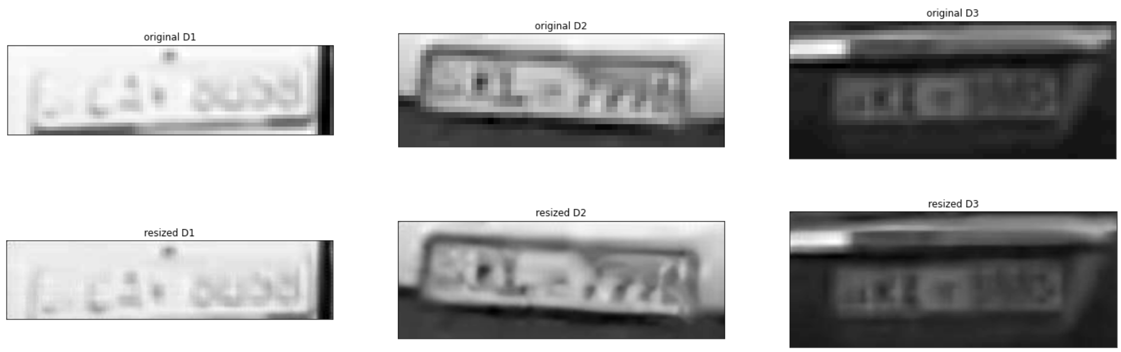


Figure 7 : Original images and the resized images

3. Image enhancement

The resized images contained all the fine details that were in the original image. However, since the original number plates were severely degraded, the numbers on the license plate could not be easily identified. To recognize the numbers using OCR methods, the images were enhanced using different spatial and frequency domain filtering techniques.

a. Spatial Domain Filtering

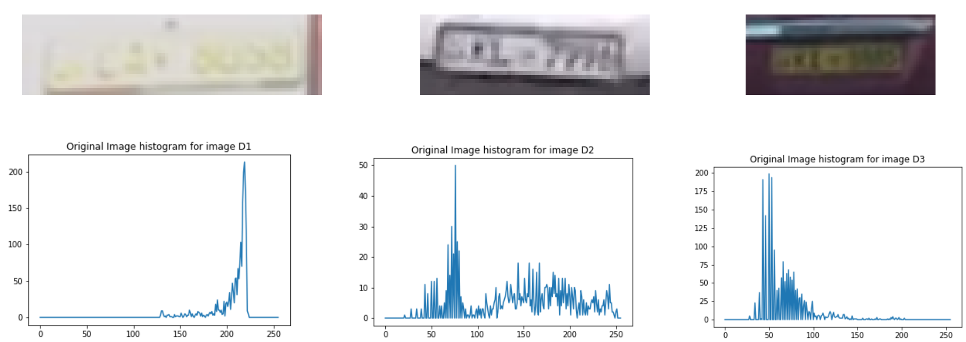
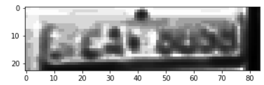
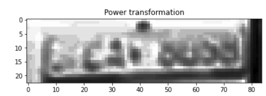
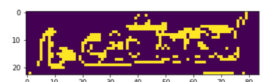
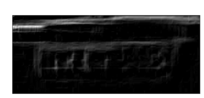


Figure 8: histograms of the images

To identify the spatial domain noise present, the histograms of the images were analyzed. By observing the first histogram it was assumed that the number plate is taken under high lighting conditions. The third histogram contains darker intensities.

According to the histogram of the image, enhancement techniques were applied in the spatial domain. The following table shows the techniques and the relevant output.

Spatial domain Technique	Output
Image equalization	
log transformation	
Power transformation	
Contrast stretching	
Gray level slicing	
Otsu thresholding	
Laplacian filter	  
Prewitt filter	  
Sobel filter	  
Max hat filter	  

The edge detection methods were applied to detect the edges of the numbers in the license plates. However, the results obtained from these techniques were not satisfactory.

b. Frequency Domain Filtering

To reduce the noise present in the frequency domain, frequency-domain noise reduction methods were tried out.

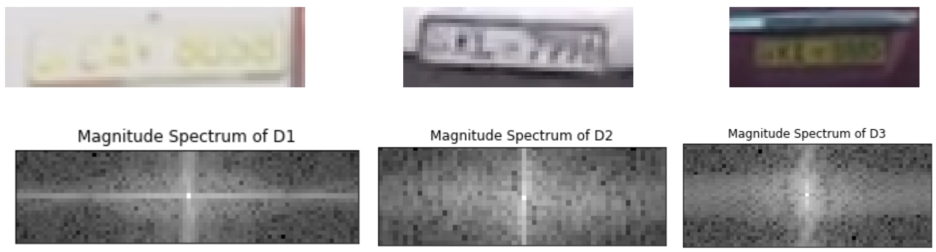
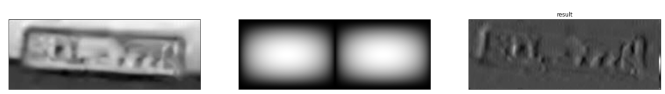
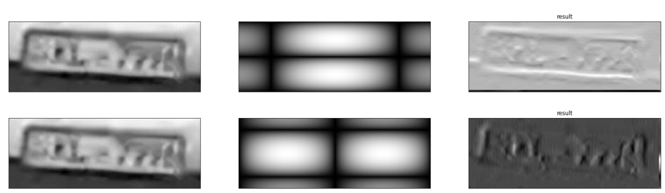
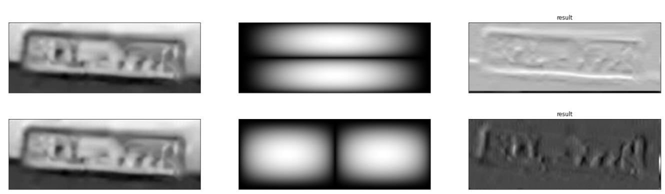
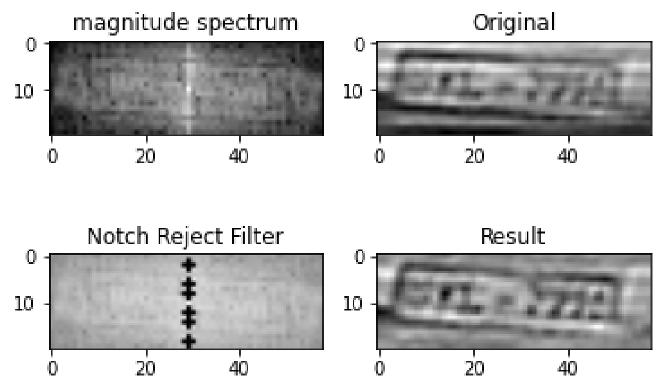


Figure 9: magnitude spectrum of the images

Observing the magnitude spectrums of the images in figure 9, the high-frequency noises were identified in the images. To remove the high frequencies, basic low-pass filters were applied in the frequency domain as shown in figure 9.

Frequency domain Technique	Output
Laplacian filter	
Prewitt filter	
Sobel filter	

Notch filter	

4. Image Restoration

As in image enhancement, the principal goal of restoration techniques was to improve the image so that the character recognition algorithm can output better results.

Restoration techniques were implemented by modeling a gaussian degradation and applying the inverse process to recover the original image as shown in figure 10.

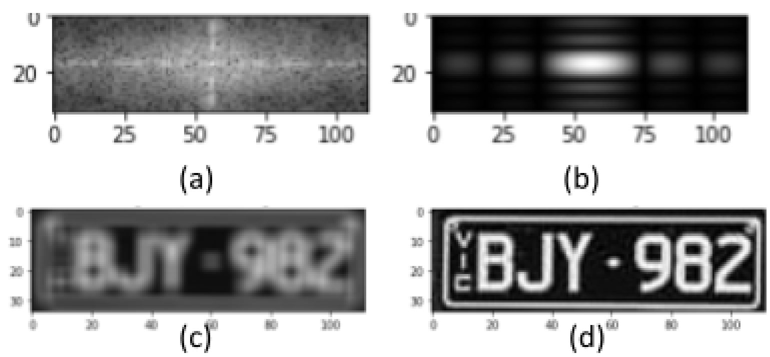


Figure 10 : (a) Magnitude spectrum of the Gaussian blurred image (b) Magnitude spectrum of the modeled gaussian blur (c) Image distorted by Gaussian blur (d) Image restored by applying the inverse process

As the figure 10 shows, the degradation was modeled correctly and applied the inverse of the degradation function to the distorted image in the frequency domain, and the image was recovered.

However, this technique failed to recover the test images as the degradation function could not be modeled accurately. (See figure 11)

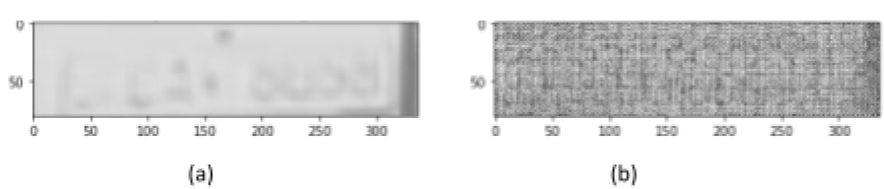


Figure 11: (a) Degraded image (b) Restored image

Observing the restored image given in figure 11 it was identified that additional noise was present in the image. Therefore, the Wiener filter was applied to restore the image with the noise present.

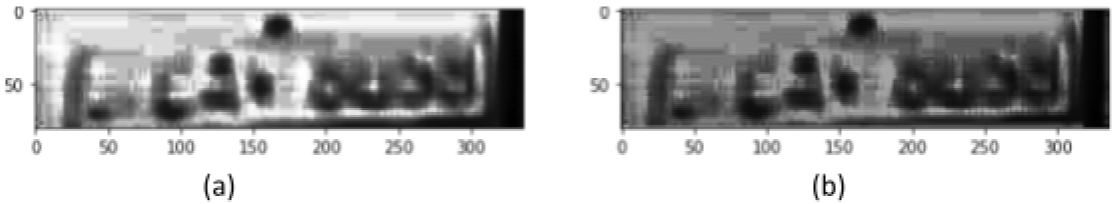
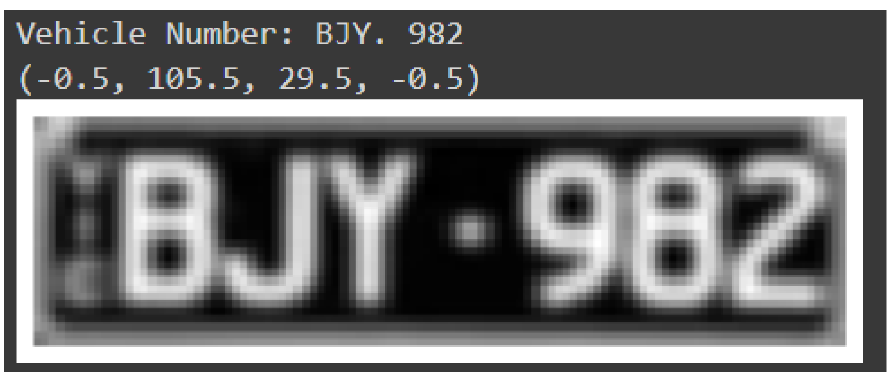


Figure 12 : (a) Degraded image in dataset (b) Restored image using Wiener filter

As it can be seen, this technique didn't give any satisfactory results.

5. Character Recognition

Optical Character Recognition technique was used to identify the characters present in a restored image as shown below. The easyocr package available in python was used to implement this.



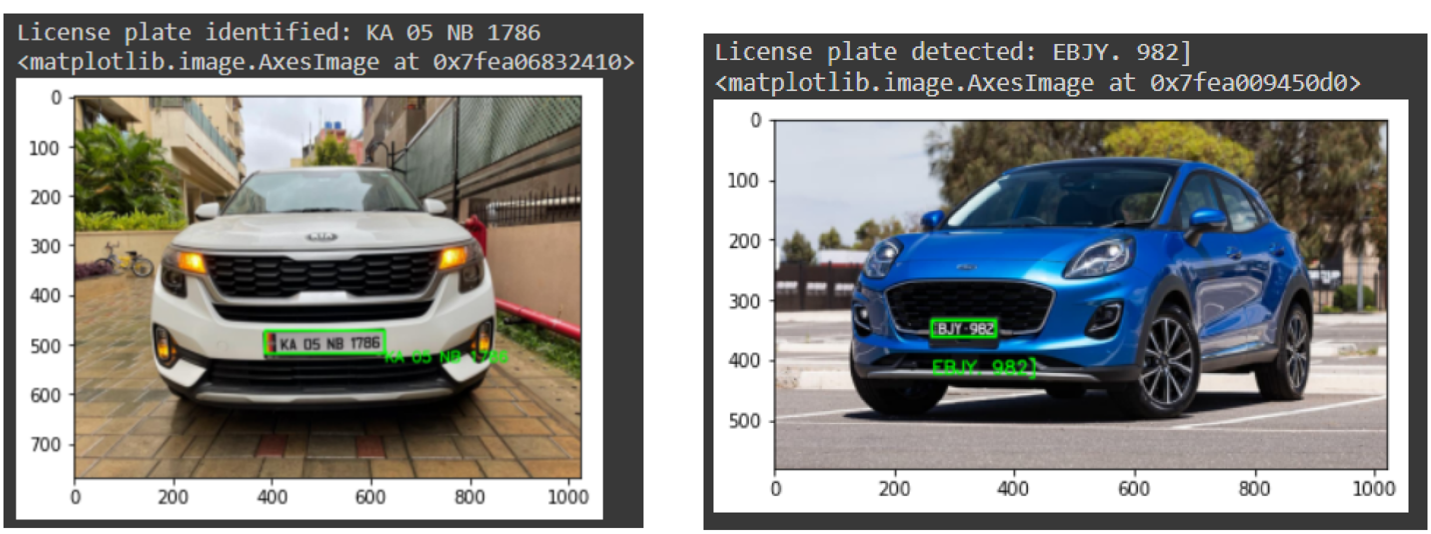


Figure 13: Characters Recognized in the license plate

Section VI: Conclusion

In this study, we proposed a system to recognize and identify the number plate from an image. The provided method can be used to successfully extract a number plate the image and the extracted images are translated and then resized using the ESRGAN model. The resized images may contain several noises due to low resolution, high or low lighting, and motion blur. Therefore, before recognizing the numbers in the license plate, these images undergo spatial filtering, and frequency filtering to remove the noises. The noise removal and image restoration process is an important part of the process. The proposed system shows how several techniques have to be applied according to the noise present in the images. The optical character recognition method is performed on the enhanced images to find the numbers from the image. The project has its own drawbacks and limitations as we are not using higher machine learning or deep learning algorithms but it works efficiently for an average use case.

Therefore, in future works, the next step is to use a set of reference character images that are intentionally degraded using the same factors estimated from the input image, so that the characters in the reference character images can be compared to the characters in the input using cross-correlation between them[3].

Section VII: References

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Section VIII: Contribution of Team Members

1. Liyanage S.N - E/17/190: Localization and extraction of number plate
2. Varnaraj N - E/17/358: Spatial Domain Filtering
3. Amarasinghe R.A.A.U - E/17/012: Frequency Domain Filtering
4. Devindi G.A.I - E/17/058: Image resolution enhancement, Image restoration