Automatic License Plate Recognition of Bangladeshi Vehicles using Template Matching Technique

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Bachelor of Science in Computer Science and Engineering

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CANDIDATES' DECLARATION

We, hereby, declare that the thesis presented in this report is the outcome of the investigation performed by us under the supervision of Mr. Emam Hossain, Department of Computer Science and Engineering, Ahsanullah University of Science and Technology, Dhaka, Bangladesh. The work was spread over two final year courses, CSE4100: Project and Thesis I and CSE4250: Project and Thesis II, in accordance with the course curriculum of the Department for the Bachelor of Science in Computer Science and Engineering program.

It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma or other qualifications.

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CERTIFICATION

This thesis titled, **"Automatic License Plate Recognition of Bangladeshi Vehicles using Template Matching Technique"**, submitted by the group as mentioned below has been accepted as satisfactory in partial fulfillment of the requirements for the degree B.Sc. in Computer Science and Engineering in June 2019.

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ABSTRACT

Identification of vehicles is a much needed function for traffic surveillance and control systems. Vehicles can be recognized through license plates which consist of alphabets and numbers. Nowadays, the importance of automatic traffic monitoring has enthralled the attention to the intelligent transport systems. It is a labor intensive job to identify all passing or parked vehicles' license plates which can be palliated by Automatic Number Plate Recognition (ANPR) technique. ANPR is systematized to locate and recognize the number plate of a moving vehicle automatically. There are no fixed rules for number plates for Bangladeshi vehicles corresponding to other countries. The recognition procedure of number plates for Bangladeshi vehicles is very tenacious due to the diversity of conditions and patterns. Automatic license plate recognition of Bangladeshi vehicles using template matching technique is represented in this paper. This system is divided into three prime portions such as number plate localization, segmentation and recognition of Bangla characters. Detection or localization of number plate accurately is the main challenge as various problems such as blurriness due to motion of vehicles, complicated backgrounds, divergence of distance, aged and angled license plates etc., can emerge.

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Chapter 1

Introduction

It is suspected that there are more than half a billion cars on the roads over the universe at present. All of the vehicles have their Vehicle Identification Number (VIN) as their identifier which is primary. Actually, VIN is a license number that enunciates a judicial license to partake in the public traffic policy.

All vehicles world-wide should have its license number written on a license plate - mounted onto its body (at least at the back side) and any vehicle without properly mounted, well-readable and well visible license plate should not run on the streets. Various suspicious activities can occur if there is no legal license plate and with the help of illegal license plate or unregistered license plates, any criminal activity can happen and thus innocent people suffer a lot. So, in order to avoid all of the illegal acts, the process which has become a crying need now-a-days, is nothing but Automatic Number Plate Recognition.

Automatic Number Plate Recognition is a particular form of Optical Character Recognition (OCR). ANPR is a type of technology that enables computer systems to study automatically the registration number (license number) of vehicles from digital pictures. Studying automatically the registration number means transforming the pixels of the digital image into the ASCII text of the number plate.

Considering the ANPR point of view, the quality of image is always a major fact. Special technique is needed in order to avoid blurry portions of images in case of capturing images of fast-moving vehicles. It can decrease the accuracy of recognition of license plates drastically. Short shutter time needs to be applied with the combination of high-power illumination in order to ensure the well-balanced image quality. Infrared Radiation (IR) is the best illumination as the retro-reflective plates reflect this type of light perfectly which is not perceptible for the human eye. A constant decent image quality is provided as this combination works really fine during day and night. ANPR cameras are specialized types of CCTV cameras which has software built into it in order to help identifying and capturing license plates on both still and moving vehicles. ANPR technology inclines to be region-specific, owing to the variation of plate from place to place. Basically, it is based on the image processing system.

Automatic Number Plate Recognition System is being implemented all over the universe for surveillance applications. ANPR system can also be implemented in automated enforcement of traffic rules and obligations. Automated enforcement of speed restrictions and associated traffic codes, such as inhibition on specific classes of vehicles (such as those containing explosives or chemicals) implementing particular routes can be applied by ANPR technique. Speed limitation can be mechanistic with the License Plate Recognition (LPR) system obstructing the vehicle at two or more locations and conditioning whether transit among those stoppages and times violated speed limits. An alert to traffic police can be issued automatically by a billing database that a violation is in force. Road security and safety traffic rules are ensured by the LPR technique. It eradicates the redundancy of the time-consuming acts and other violations.

1.1 Motivations and Objectives

In the context of Bangladesh, Automatic Number Plate Recognition plays an important role. Bangladesh Police are taking measures to widely generate automated surveillance systems such as ANPR to lessen the hustles or errors and to increase the efficiency. It is also expected to help combat the traffic gridlock in Dhaka. As assumed, Dhaka's two main problems are crime and traffic jam. In this case, ANPR will be efficient. According to Figure 1.1,

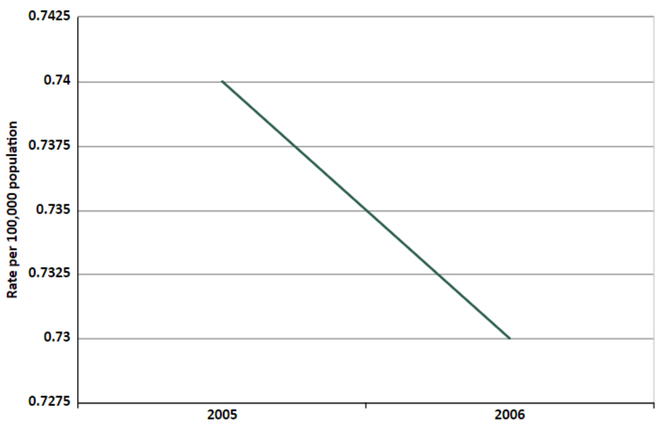

Figure 1.1: Motor Vehicle Theft Rate in Bangladesh (2005-2006)

Bangladesh motor vehicle theft rate was 0.7 cases per 100,000 population in 2006, which was unchanged from the rate of preceding year. Gradual advancements and a huge successive progress can be achieved easily by applying ANPR system. Violation of traffic rules being the biggest concern nowadays for Bangladesh, the implementation of ANPR can make the process easier compared to manual traffic surveillance in Bangladesh. If a vehicle runs away after an accident, it can be traced through its number plate. When any vehicle goes through a road within Dhaka city, its number plate will be identified by ANPR technique.

Chapter 2

Literature Review

Several former researches work for recognition of number plate which paved the way to possibilities for the proposed pathway are highly notable.

Considering [1] it is clearly visible that character recognition is performed through various well-known procedures like Fuzzy Logic, Artificial Neural Networks, Support Vector Machine (SVM) based character recognizers. On license plate, stability to noises and modifications of position of characters are allowed using neural network. For image pre-processing, vertical edge density is used to determine candidate for plate region. For gray scale conversion, after the separation of the R, G and B elements from the 24-bit color value of every pixel, the calculation of 8-bit gray value takes place. For density of edge, Sobel Operator is used to calculate gradient image. By the use of Multilayer Perceptron (MLP) Neural Network, the characters which are segmented, are recognized. Failure to the detection of number plate can occur due to the presence of other sign-boards, banners, name-plate of organizations besides the roads and moreover, smashed license plates hamper the recognition process. In a vehicle, existence of so many characters and words may create confusion to the detection process.

Studying [2] it appears that line detection is performed by using Hough Transform which is very sensitive to deformation of a plate boundary needs many memories. Difference of gray value for the boundary detection can show better performance than using line information, though it still has difficulties recognizing a car image which has many similar parts of gray values to a plate region. The HLS method is used for this recognition. Though RGB model is good for color representation on a color monitor, it isn't the best model to represent tint, shade and tone. But HLS model is able to represent all of them. The H.L.S combines Hue, Lightness and Saturation which is the representation of a three-dimensional color space. The vertical axis represents the variation of lightness which differs from white to black.

Analyzing [3] it seems that morphological operations are used to detect the high contrast area as effective features to detect license plates. A proper solution to remove the problem of noise and various conditions, License Plate Recovery is used. This method is robust to various types of skewing, scaling and rotations of the extracted plate. First of all, in the character analysis algorithm distance calculation between each pair and finding an index of maximized character with minimum distance is necessary. The total widths and heights of each character close to that cluster is required. Then the averages of widths and heights are counted. For each element are close to the averages, the character can be said as a correct character. This is presented to solve the total license plate from its fragments and co-ordinates in the directions are denoted. In CA algorithm, the average weight, the average height and the number of correct characters is observed. Then it is verified that if the pixel touches to the top or the bottom of the region. After operating the binary to the new region and labelling, a new set of possible characters is gained from the desired region. Then CA algorithm is applied to obtain the correct character set and new number of characters. After denoting the boundaries, that region is recognized as a license plate with the denoted boundaries.

In [4], Choudhury A. Rahman et al. divided the procedural system architecture into three major portions such as outdoor part, indoor part and communication link. In outdoor part, images are being captured in different intersection and for analyzing images from camera, those captured images are sent to the central control station which is the indoor part of this system. Then Communication link connects all these cameras to the central control station. The proposed algorithm for this system is based on pattern matching for recognition of license plate characters. In this algorithm, there are fifteen different histograms for each of the letters from A-Z in the 'alphabet' library and fifteen different histograms for each of the digits from 0-9 in the 'number' library. There is flow chart for character recognition that indicates which one of the histograms in the library should be used for the comparison. The histogram extracting from a segment is first normalized before comparing. The process of normalization is done by comparing the width of the segment to the library. After normalization, pattern matching process is being continued. The algorithm only takes characters of which matches are equal or more than 70%.

Considering paper [5] it is notable that OCR algorithm is applied in this system to manage more deformable images. There are two modules in this license plate recognition system. Firstly, plate detection. Finally, character segmentation and recognition. This propounded system can detect the license plates in different locations to identify the rotation free characters in the plates. Magnitude is used to detect vertical gradients. Morphological analysis and erosion operation are applied to minimize the unwanted noise. In this system, three geometrical features are evaluated area, orientation and density. The main axis and reverse rotation transformation are applied to normalize the character image. In the character segmentation part connected-component based methods are applied and there are two properties -the digits on the license plate are fixed and the characters are in horizontal orientation. Feature extraction must be implemented before character recognition. To implement OCR algorithm there are two features such as extraction of crossing count and in this part, it extracted the sub images from the number of hatch and in extraction of peripheral background, area is applied to calculate the character boundary to the image boundary.

In [6], Takashi Naito et al. have merged the idea that main problems in License Plate Recognition can be solved for small scale facilities such as to understand a sensing system capability for capturing clear image, to understand another sensing system eligible to capture clear image for running vehicles and to develop recognition algorithms efficient for sensor placement adequate for inclined plates. The sensing system method is applied by pairing the image captured with 2 CCDs at a fixed time and under various exposure conditions. A wide dynamic image in range and clear would be gained. The formula of synthesizing algorithm tells that the gray levels at a pixel co-ordinate (x, y) in each image framed by CCD1 is greater than 0 but less than that of CCD2. Again, the gray levels at a pixel co-ordinate (x, y) in each image framed by CCD2 is greater than CCD1 but less than saturation level, which is 255. The equation of dynamic range of the sensing system tells that the signal-to-noise ratio is powered by the inverse of gamma is multiplied by the co-efficient determined by exposure condition. The algorithm to recognize license plate, binarization of the total image is performed. Character region extraction says that the binarized image must be labeled as well as segmented. The total region of hypothesis should align each candidate region has to be proportional to those of real license plate and it is the geometrical property.

Paper [7] presents that for the solution of the low-contrast and dynamic range problems, the histogram equalization is applied. The histogram equalization says that the ratio of i and m is multiplied by 255, where i is the difference between input pixel value and minimum pixel value and m is the difference between maximum pixel value and minimum pixel value. Median filtering can perform to decrease the noise. This filtering says that the corresponding processed result in the x, y axis is equal to the median of the original image in the x-k, y-l axis, where k and l are the members of predefined region which is the covered region by a median filter. The searching range reduction says that the particular object is kept at the center of an image at the time of making a shot. The particular region is exact at the center 4/9 area. Localization method says that, in the three-map retrieving, the saturation, edge and intensity map are applied for character segmentation. The saturation is equal to the difference between 1 and the resultant. For hybrid binarization technique, the average value of license plate is defined by the division of the multiplication of the peaks and its function by the multiplication of image length and image width for removing the dirt from local regions. The threshold is the half of the sum of the average height and width.

According to [8], there are four segments such as image enhancement, vertical edge extraction, background curve and noise reduction, plate search and segmentation. Firstly, the license plate which is rectangular has intense edge and texture information. So, the captured vehicle image is enhanced to clarify the plate area. By using Sobel operator, vertical edge image becomes extracted. The method has proposed a simple algorithm to remove background curves and noise from the edge images. If there is a very long (background curve) or very short (noise edge) actual edge length, then the edge point will be deducted from the edge image. After removing the background curves and noise in the edge image, sliding of a rectangular window is performed to search the plate in the residual image and segment it out from the real vehicle image.

In [9], Md. Ruhul Amin et al. implemented Sobel Edge Detection Operator for detecting edge of a captured image and Otsu method is implemented for detecting intensity of the pixels. Again, Hough transformation is applied for the number plate localization technique. After executing localization and extraction of number plate that portion is sent to a Bangla OCR named Shabdayon which is developed in C++ language to recognize the character of the number plate for next process. In addition, the text output is then stored to a database so that it can check whether it is valid or invalid number plate from server.

Studying [10] it appears that the input image is first segmented by Hue-Lightness-Saturation (HLS) color space from RGB color space. Basically, the HLS model has three-dimensional color space which are Hue, Lightness and Saturation. In graphical formation, the vertical axis represents lightness from white to black. The horizontal line from the center of the double cone represents saturation. Hue is represented with an angle centering on the lightness axis. For doing segmentation of input image, the distributed genetic algorithm is implemented. It can take an image as input and return a label image as output. This method completely follows three main steps such as Evaluation, Selection and Mating. For each step, the system stability is given by the percentage of pixels on the segmented image matching with previous time step for measuring accuracy.

Analyzing [11] it seems that detection and capturing a vehicle image are considered as the first steps. Detection and extraction of number plate are the second steps. Finally, image segmentation technique is implemented to extract vehicles' number plate and Optical Character Recognition (OCR) is used for individual character recognition and using database it can give actual information.

In [12], the authors implemented Hough transform to detect lines and in morphological based approach it works with brightness, symmetry, angles and in textures-based approach it is usually applied to identify text in images. This system consists of four particles and it works like a photo is taken and then sent to pre-processing step. After that VLP detection receives that image. In this procedure photos are converted to gray color and normalization, histogram equalization are applied. After that Hough transform algorithm is applied to detect boundary lines. Detecting those images, it sends them to the segmentation unit and after that OCR recognizes the character using HMM model and finally it shows it result in ASCII characters.

Scrutinizing [13] it is notable that in the license number identification period, the experimental work of the license plate candidates is conducted. The identification period comprises of two principal tasks – separation of character which is dealt with a hybrid of blob coloring techniques followed by connected components and recognition of character with iterative pathways. While seeking for license plate in an input image, the quad colors (black, white, red and green) should be focused. Extra data for discriminating genres of license plates can be provided by the compositional semantics of license numbers. In the license plate locating module, an input RGB image is intersected into two categories as color edge detection and color model transform. The color edge detector rejects irrelevant edges by sensing only three types of edges as red-white, green-white and black-white and discarding additional edges in an image. Transformation of the RGB (Red, Green, Blue) space into the HSI (Hue, Saturation, Intensity) space is performed for the fuzzification of edge, hue, saturation and intensity of the image. A fuzzy map is integrated by a two-stage fuzzy aggregator. On the basis of the aggregated fuzzy map, the large interesting domains are destined to be license plate candidates. In the license number identification module, input license plate candidates are preprocessed conducting binarization, labelling of connected component and noise dismissal. Binarization takes place in order to highlight characters and subdue background. A connected component algorithm banishes unwanted image domains. Categorization of character, Topological Sorting, Template Test, Self-organizing (SO) recognition take place to recognize characters.

Perusing [14] it appears that for wavelet transform, Haar scaling function is implemented. Every gray-level image bands' pixel value is binarized by a threshold which is predefined. The four sub-images LL, LH, HL and HH determine the original lowpass-filtered image, horizontal directional characteristics, vertical directional characteristics and cater-corner characteristics respectively. After completing wavelet transform, license plate is located roughly. In LH sub-image, the region along with high horizontal difference as well as a reference line with maximum horizontal difference is observed. Considering the reference line, the area of searching of license plate can be diminished. As the size of license plate may vary depending on the distance between car and camera, the size of the searching mask must be decided before tracing the region which is candidate. The horizontal projection curve is examined cautiously to obtain the peaks. Various maximal sets of all peaks define the probabilistic width of the license plate. The possible license plate region will be the analogous mask with maxima value. After extracting all license plate regions and ascertaining the features of candidate regions according to the geometrical properties, a column search is carried out. Calculation of the value of total pixels are conducted in the checking unit. The column for which the value gets smaller than the threshold, is refused from being a part of license plate region. The left and right limit of license plate can be traced by implementing the column search method. The row search method can trace the top and bottom limit.

Analyzing [15] it seems that obtaining an image, the Pre-processing part performs the adjustment of the input image and after that Harris Corner algorithm is implemented for the extraction of the feature or all the corner points from the image. The Sliding Window (SW) method takes part with a view to tracing the most probable license plate region. In order to adjust the majority of images, Soft Thresholding (ST) is implemented as a portion of Sliding Window (SW). Aspect ratio (AR) boundary is established to eliminate multiple possible candidate region of license plate. In the segmentation part, Super Resolution method is applied to maximize the license plate which paves the way to implement the Adaptive Thresholding method skillfully. Then morphological function is applied to eradicate the redundancy of license plate region. Later, CCA is implemented to trace the connected component from the license plate. In order to neglect false-detected non-character region, AR, PC and Height are consolidated as the soft threshold.

In [16], Bai Hongliang and Liu Changping have divided the system into four sections and these are vertical edge detection, edge statistical analysis, hierarchical-based method and morphology-based license plate extraction method. Kirsh, Rober, Susan operators are notable ways for edge detection. Linear filter is applied to smooth the image before vertical edge detection. The process of fixing the regions are divided into three such as attaching the lines, attaching the line to rectangles and detecting the rectangles. Fake license plates are also detected in hierarchical based method part. Edge statistics method faces a little dilemma to detect the license plate and then hierarchical based method is applied. In this method forth scale layer is used to recognize an image clearly. Component analysis, feature extraction, abbreviation of candidate regions is applied in morphology-based license plate extraction methods.

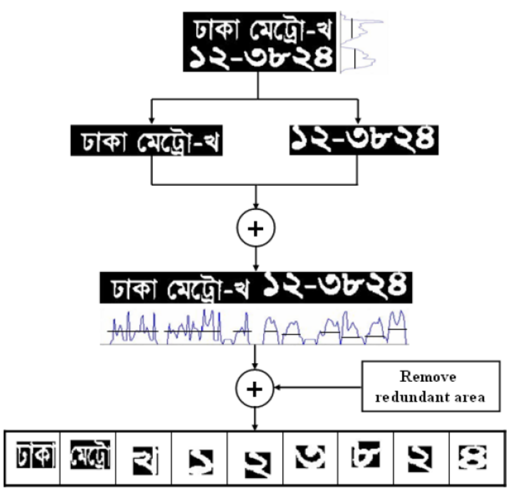

Figure 2.1: Bangla Character Segmentation System (adopted from [1])

Figure 2.1 deals with the sytem involved in Bangla character segmentation where characters are segmented in three phases according to [1].

(a) (b) (c) (d)

Figure 2.2: Examples of successful number plate detection and recognition (a) Gray scale image, (b) after enhancement plate region detected, (c) successful number plate extraction and (d) successful character recognition (adopted from [1])

Grayscale image of vehicles shown in Figure 2.2 are blurry as well as noisy to detect the number plates. After performing preprocessing operations the image has been enhanced. So, the number plate can be clearly detected and extracted successfully. Further, characters from the plate are recognized successfully.

The literatures are summarized and reviewed in a table including its methods, datasets and accuracy like below:

Table 2.1: Summarization of Literatures

Papers	Datasets	Methods	Accuracy
[1]	Used their own dataset	Edge Analysis Method combined with mathematical morphology, Vector Quantization (VQ), Diverse Neural Network Architectures like Pulse Coupled Neural Networks (PCNNs), Time Delay Neural Networks (TDNNs).	92.1% in Number Plate Detection and Extraction, 97.53% in Segmentation, 84.16% in Number Plate Character Recognition.
[2]	Used their own dataset	Hough Transformation, HLS (Hue, Lightness and Saturation).	81.25% in recognition using Edge Detection. 85% using Gray Value, 91.25% using HLS Color Model.
[3]	Used their own dataset	CA (Character Analysis) algorithm.	The average accuracy of the license plate detection is 98%.
[4]	Used their own dataset	Pattern Matching procedure, Histogram Extraction, Normalization process.	The average accuracy rate is equal or more than 70%.
[5]	Used their own dataset	Morphological Analysis, Erosion Operation, Reverse Rotation Transformation, Connected Component based methods.	98.6% accuracy rate in case of the rotation free character recognition.
[6]	Used their own dataset	Binarization, Synthesizing Algorithm, Sensing System Capability, CCD (Charge Coupled Device) Comparison.	99.3% of accuracy in case of extracting images of original licenses and the plate is successfully recognized.
[7]	Used their own dataset	Histogram Equalization, Median Filtering, Binarization.	The total rates of location and segmentation are 97.1% and 96.4% respectively.

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Table 2.1 – continued from previous page

Papers	Datasets	Methods	Accuracy
[8]	Used their own dataset	Vertical Edge Extraction using Sobel Operator, Sliding Procedure.	Location rate 91.3% using Line Sensitive Filters, 99.7% using the proposed method.
[9]	Used their own dataset	Sobel Edge Detection Method, Otsu Method, Hough Transformation.	The accuracy rate of the localization of plate region is 88%, the extraction of the plate is 77% and the recognition unit is 62% .
[10]	Used their own dataset	Hue-Lightness-Saturation (HLS), Distributed Genetic Algorithm.	The accuracy of extraction rate is 92.8%.
[11]	Used their own dataset	Image Segmentation Technique, Optical Character Recognition (OCR).	Failure to the accuracy rate can occur and the average accuracy rate of license plate recognition is quite decent.
[12]	Used their own dataset	Hough Transformation (HT) Method, Normalization, Histogram Equalization, Optical Character Recognition (OCR), HMM (Hidden Markov Model).	97.61% is the accuracy rate in case of character segmentation module. 97.52% is the accuracy rate in case of OCR module. In case of the whole system the rate is 92.85%.
[13]	Used their own dataset	Blob Coloring Technique with Connected Components, Color Edge Detection, Fuzzification, Binarization, Topological Sorting, Self-Organizing (SO) Recognition.	The overall accuracy rate with first group of images is 98.8% and with second group of images is 96.7%.

Continued on next page

Table 2.1 – continued from previous page

Papers	Datasets	Methods	Accuracy
[14]	Used their own dataset	Haar Scaling Function, Binarization, Horizontal Projection, Column Search Method, Row Search Method.	The Overall accuracy rate is 92.4%.
[15]	Used their own dataset	Harris Corner Algorithm, Sliding Window (SW), Soft Thresholding (ST), Super Resolution Method, Adaptive Thresholding, Connected Component Analysis (CCA).	The accuracy rate of this proposed method is 93.84%.
[16]	Used their own dataset	Vertical Edge Detection, Hierarchical-based Method, Morphology-based Method, Edge Statistics Method.	Overall 99.6% accuracy rate in detection of license plates.
[17]	Used their own dataset	Edge Extraction using Sobel Operator, Template Matching.	98% for the standard numerals and 82% for the unknown numerals.
[18]	Used their own dataset	Binarization, Edge Detection, Histogram Analysis, Dilation, Erosion, Labeling, Filtering, Adaptive Thresholding, Support Vector Machine (SVM)	Total accuracy score is 93.21%.
[19]	Used their own dataset	Hough Transform, Contour Algorithm, Optical Character Recognition (OCR)	Overall accuracy score is 98.94%.
[20]	Used their own dataset	Hough Transform, Contour Algorithm, Optical Character Recognition (OCR)	Overall accuracy score is 80%.
[21]	Used dataset from BRTA	Plate Extraction, Segmentation, Template Matching	Total accuracy score is 90%.

Chapter 3

Methodology

Basically, ANPR system works in a successive way such as at first an image is captured and then it begins the image processing steps. One of the crucial steps is pre-processing the captured image as the captured image has a high possibility of being blurry, color-inaccurate and unprepared for the recognition phase. In recognition phase, OCR is generally implemented to recognize characters.

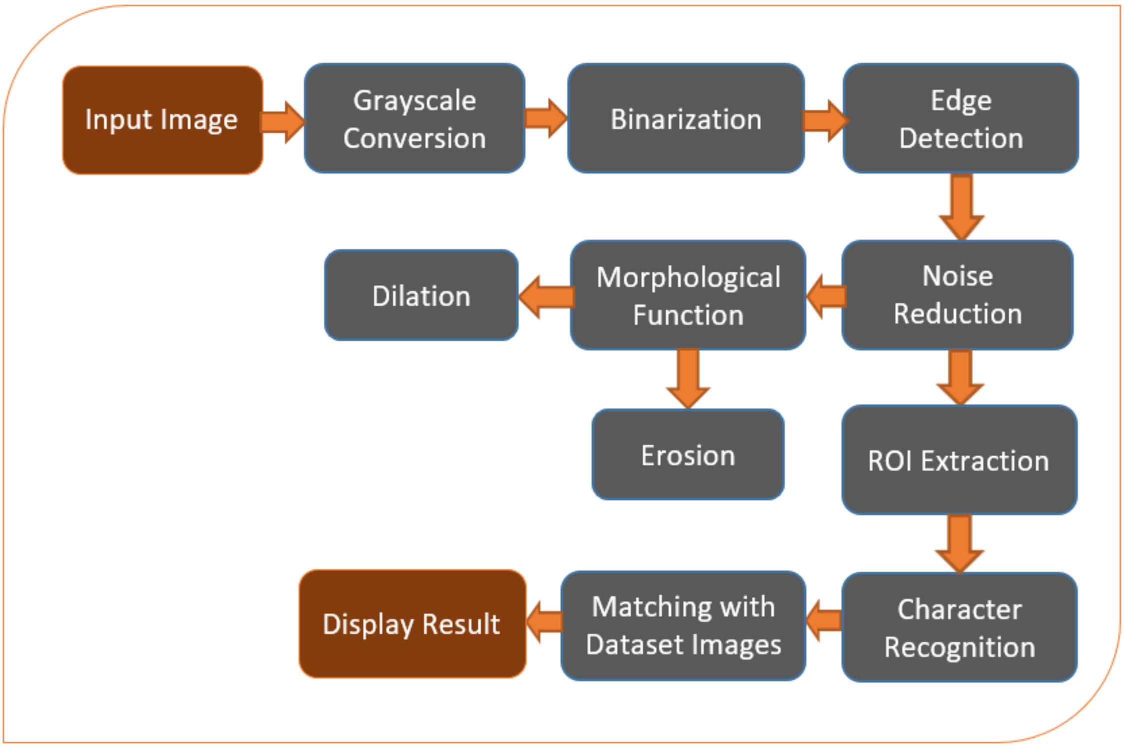

Figure 3.1: Block Diagram of Our Implemented Methodology of Automatic Number Plate Recognition

Our implemented method deals with three basic phases for fully recognizing the license plate and these are locating the license plate, segmentation of the plate and recognizing the characters of the license plate. The detection phase is performed by completing several branch steps which are very important for the later steps. Firstly, a true color or RGB image is taken as input. Then it is converted into grayscale or intensity image. Grayscale image is binarized using Otsu's method. Sobel Operator is implemented for detecting edges. Noise is reduced using Morphological approach. Image dilation and erosion are performed in order to improve the input image which combine Morphological function. After these pre-processing procedures, ROI (Region of Interest) extraction is performed. Thus the localization process of number plate is accomplished. Finally, segmentation and recognition of characters of license plate are performed.

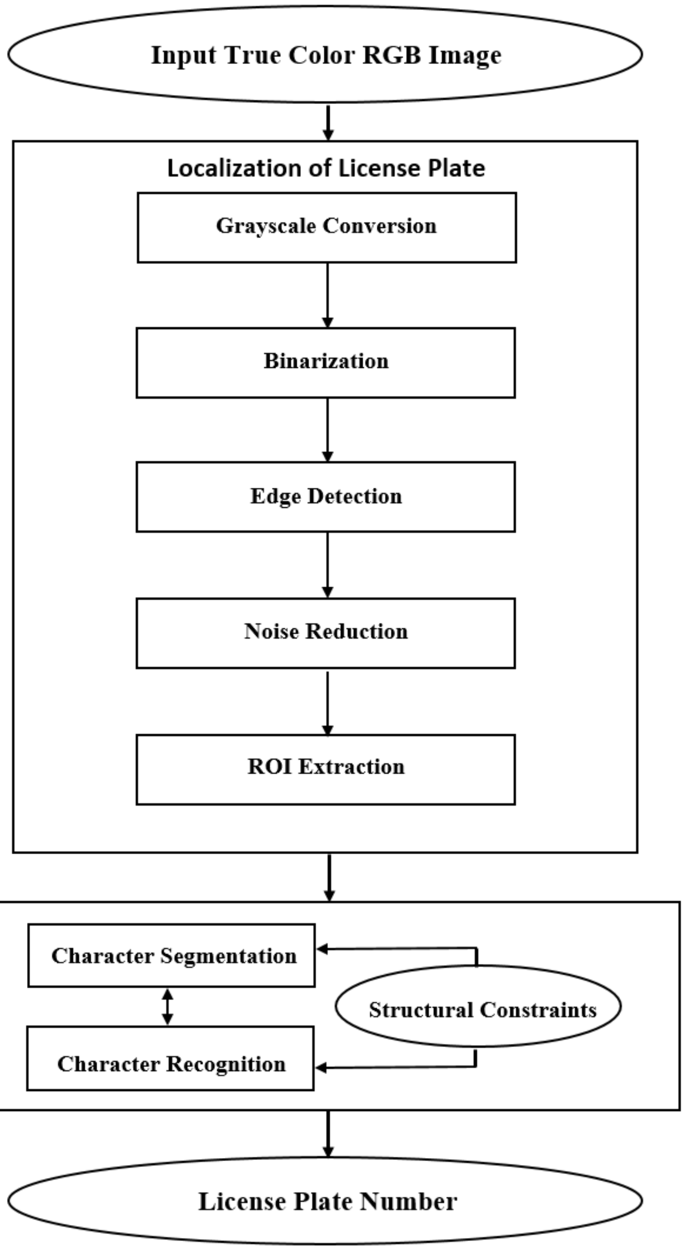

Figure 3.2: Algorithm for Our Implemented Methodology of Automatic Number Plate Recognition

Algorithm of our implemented method works according to Figure 3.2 and the block diagram of Figure 3.1 refers to the methodology of our implementation.

3.1 Localization of Number Plate

With a view to locating number plate, some pre-processing steps are essential. The input image is not always guaranteed with being fully perfect. It can carry so many difficulties or challenging atmosphere with it. As a result, some pre-procedural steps need to be taken. These are illustrated as below:

3.1.1 Grayscale Conversion

Our proposed algorithm is independent of the type of colors in image and depends mainly on the gray level of an image for processing and extracting the required credentials. MATLAB function "rgb2gray" simply converts the RGB image into gray image. It converts the RGB values to grayscale values by forming a weighted sum of the RGB components. The formula and a sample of input image and converted gray image is shown below:

$$0.2989 * R + 0.5870 * G + 0.1140 * B$$

(a)

(b)

Figure 3.3: Sample of grayscale conversion from (a) original input image to (b) gray image

A color image is taken as input and is converted to an equivalent gray image by performing grayscale conversion which is simply appeared in Figure 3.3.

3.1.2 Binarization

It is the procedure which helps creating a binary image from two dimensional or three-dimensional grayscale image by replacing all values above a globally determined threshold with 1s and setting all other values to 0s. There are some local and global binarization methods.

For global binarization, the following methods are used:

- Fixed Thresholding Method
- Otsu Method
- Kittler-Illingworth Method

For local binarization, the following methods are used:

- Niblack Method
- Adaptive Method
- Sauvola Method
- Bernsen Method

Among the above methods, we have implemented Otsu Method which is a global binarization method.

3.1.2.1 Otsu's Binarization Method

(a) (b)

Figure 3.4: Sample of Binarization using Otsu's method from (a) grayscale image to (b) binary image

For automatic binarization level decision in image processing, Otsu's thresholding method is used based on the shape of the histogram. Iterating through all the possible threshold values and calculating a measure of spread for the pixel levels of each side of the threshold are indulged in Otsu's thresholding method, i.e. the pixels that either falls in foreground or background. The target is to determine the threshold value where the sum of background and foreground spreads is at its minimum.

After acquiring the grayscale image and implementing Otsu's method in order to binarize the grayscale image, Figure 3.4 is achieved.

3.1.3 Edge Detection

Edge detection is a process which detects the presence and location of edges conformed by sharp changes in an image's intensity. The boundaries between regions are defined by edges in an image, which helps with segmentation and recognition of object. Edge detection of an image significantly reduces the amount of data and filters out unnecessary or useless or redundant information, while preserving the essential structural properties in an image. The general method of edge detection is to study the changes of a single image pixel in an area and to use the variation of the edge neighboring first order or second-order to detect the edge efficiently.

Various techniques or methods are used for detecting edges one of which is Differential Operator Method. It consists of the following methods:

- Sobel Edge Detection Operator
- Robert's Cross Operator
- Laplacian of Gaussian
- Prewitt Operator
- Canny Operator

Another technique or idea is to implement mathematical morphology for edge detection. It is a better technique than Differential method.

We have implemented Sobel Edge Detection Operator for extracting the edges from the gray image as it suits maximum environments and works just fine.

3.1.3.1 Sobel Edge Detection Operator

The Sobel edge detection operator extracts all of the edges in an image, regardless of direction. Sobel operation has the advantage of providing both a differencing and smoothing effect. It is implemented as the sum of two directional edge enhancement operations. The resulting image appears as a unidirectional outline of the objects in the original image. Constant bright regions become black, while changing bright regions become highlighted. Derivative may be implemented in digital form in several ways. However, the Sobel operators have the advantage of providing both a differencing and a smoothing effect. Because derivatives enhance noise, the smoothing effect is particularly attractive feature of the Sobel operators.

Table 3.1: Sobel masks of 3x3 dimension

(a) Horizontal edge extractor [G_y]

-1	-2	-1
0	0	0
+1	+2	+1

(b) Vertical edge extractor [G_x]

-1	0	+1
-2	0	+2
-1	0	+1

The operator consists of a pair of 3×3 convolution kernels as shown in the above table. One kernel is simply the other rotated by 90°. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (G_x and G_y).

(a) (b)

Figure 3.5: Sample of edge detection using Sobel operator from (a) binary image to (b) edged image

The gradient magnitude is given by:

$$|G| = \sqrt{G_x^2 + G_y^2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |G_x| + |G_y|$$

It is much faster to compute. Figure 3.4 represents the application of Sobel operator to a binary image and achievement of an edged image from that binary input image which seems pretty much sharper to locate the license plate quite lucidly.

3.1.4 Noise Reduction

The ultimate goal of image noise measurement is always to accurately remove the noise which is called de-noising. There are some approaches which are used in reduction of noise. Following are of the same:

- Spatial Approaches
- Transform-domain Approaches
- Non-local Approaches
- Other Approaches

To remove the noise, we used box or mean or average filtering which is very effective for the noise removal. Because mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e. reducing the amount of intensity variation between one pixel and the next. It is also known as Box filter or Average filter. It is often used to reduce noise in images.

The idea of mean filtering is simply to replace each pixel value in an image with the mean or average value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, as shown in Figure 1, although larger kernels (e.g. 5×5 squares) can be used for more severe smoothing. (Note that a small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.)

We have also implemented other approaches of noise reduction which include morphological function. It provides an efficient way for reduction of noise and thus enhances the binary edged image.

Table 3.2: 3x3 averaging kernel

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

There are some properties of mean filtering. They are given below:

- It must be odd numbered
- The sum of all the elements should be 1
- All the elements should be same

Since it is a 3x3 mask that means it has 9 cells. The condition that all the elements sum should be equal to 1 can be achieved by dividing each value by 9. So,

$$1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 + 1/9 = 9/9 = 1$$

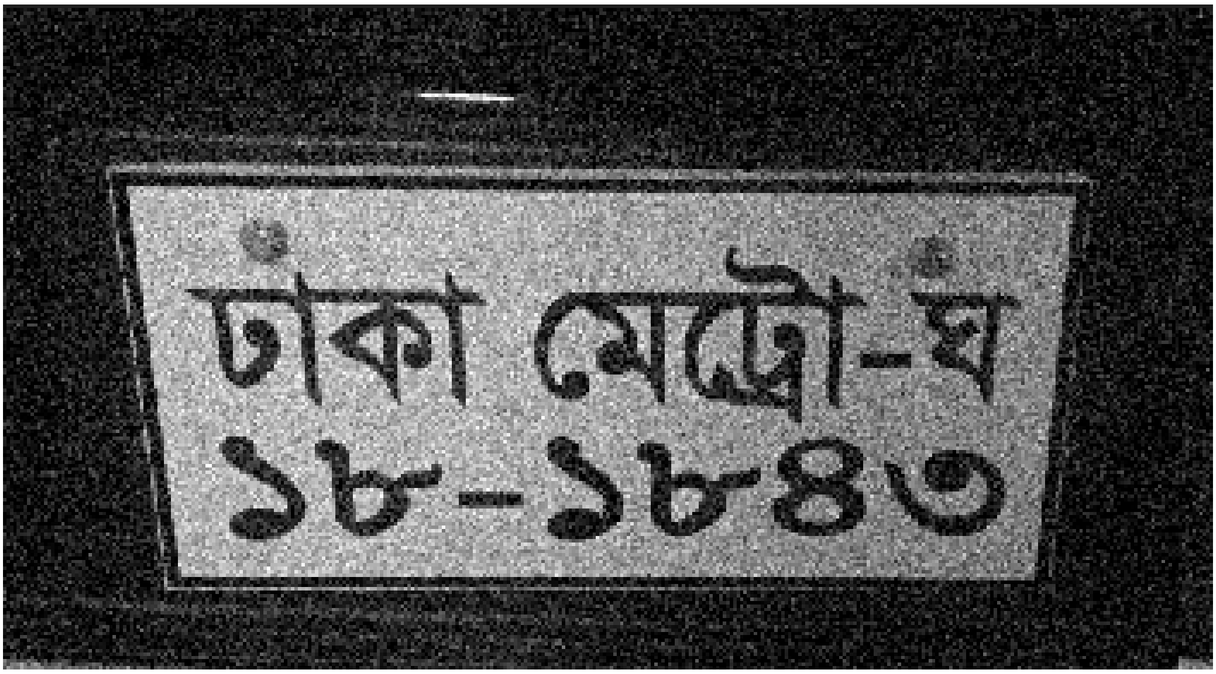

Figure 3.6: Original image

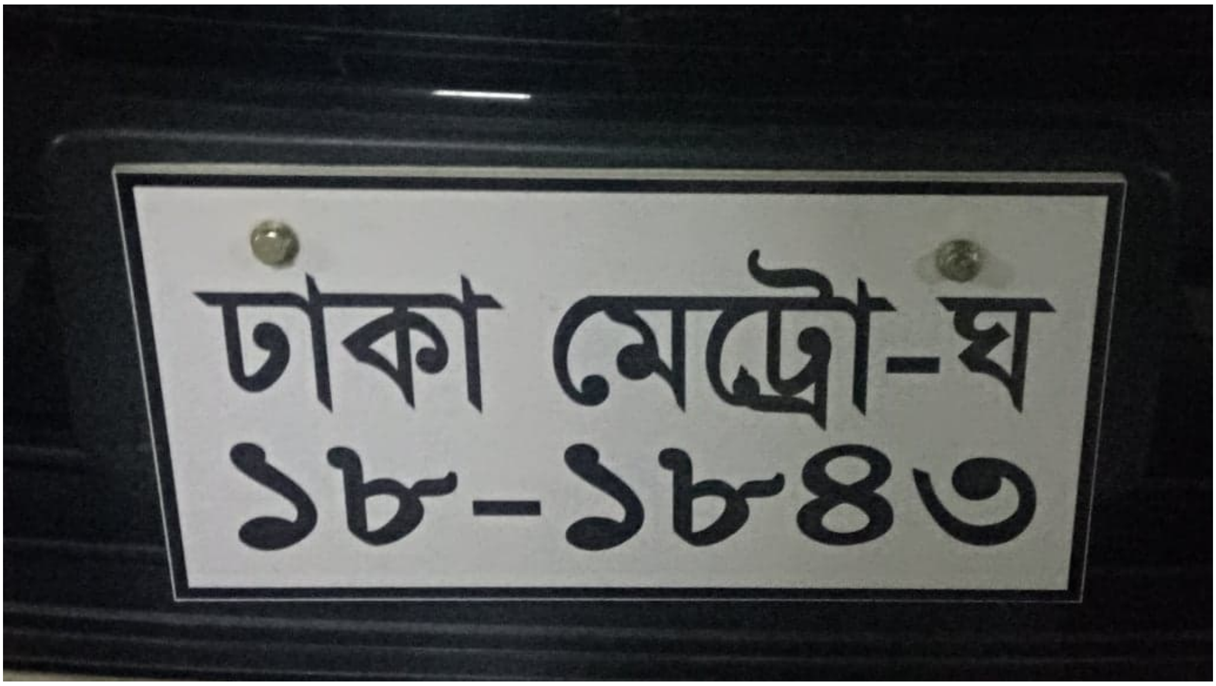

Figure 3.7: Filtered image (Average filtering)

3.1.4.1 Morphological Function

It is a collection of non-linear operations related to the shape or morphology of features in an image. The other approaches of Noise Reduction include Morphological function which easily dispel the noise and improve the image quality. Two morphological functions are implemented into our proposed methodology which are – Dilation and Erosion.

3.1.4.1.1 Dilation

It adds pixels to the boundaries of objects in an image. It grows or thickens objects in a binary image. Thickening is controlled by a shape referred to as Structuring Element. Structuring element is a matrix of 1's and 0's.

3.1.4.1.2 Erosion

It removes pixels on object boundaries. It uses Hit or Miss Transformation. In this transformation, an object represented by a set X is examined through a structural element represented by a set B. The structuring element is a shaped matrix. It shrinks objects in a binary image.

In our proposed algorithm, we implemented Dilation and Erosion of image to make it noiseless or to reduce noise.

3.1.5 ROI Extraction

A region of interest (ROI) is a portion of an image that is filtered or performed some other operation on. A common use of an ROI is to create a binary mask image. In the mask image, pixels that belong to the ROI are set to 1 and pixels outside the ROI are set to 0. The ROI classes and functions support some masking methods. The output of segmentation process is all the regions that have maximum probability of containing a license plate.

We have implemented Connected Component Labeling algorithm for ROI extraction to finally locate the license plate. MATLAB function "regionprops" does the extraction. It efficiently extracts the region of the license plate.

3.1.5.1 Connected Component Labeling

Contiguous regions are also called objects, connected components, or blobs. Mathematically, A region $R \subset S$ is defined as connected under $c(s)$ if for all s or $\forall_s$, $r \in R$, there exists a sequence of M pixels, $s_1, .., s_M$ such that $s_1 \in c(s), s_2 \in c(s_1), .., s_M \in c(s_{M-1}), r \in c(s_M)$. This means that there must be a connected path from s to r. As grayscale image has values between 0 and 255 in each pixel, it can be started from any pixel which has value 0 (black pixel treated as background) and can be started to grow each connected set. Additionally, the neighborhood system is chosen to select the nearest pixels for region growing purpose. Usually, there are two neighborhood systems, i.e., 4-point neighborhood and 8-point neighborhood method denoted as N_4 and N_8 respectively.

Table 3.3: Neighborhoods of a Pixel

(a) 4-point Neighborhood

	N	
W	S_0	E
	S	

(b) 8-point Neighborhood

NW	N	NE
W	S_1	E
SW	S	SE

Considering the above figure, it seems that S_0 is at the center when 4-point neighborhood is considered. s_1 is the central pixel surrounded by eight neighboring pixels. N (North), E (East), W (West), S (South) and other four derived values denote the sides of the center pixel.

3.2 Character Segmentation of Number Plate

Characters are segmented in order to shape the template of the number plate. Characters can be segmented in the following ways:

- Explicit Segmentation
- Implicit Segmentation
- Holistic Approach

We have implemented Explicit Method as it dissects each character also. In the explicit segmentation, the input word image of a sequence of characters is portioned into sub images of individual characters, which are then classified. This process is termed as a dissection. Vertical segmentation approach lies in the category of explicit segmentation. In this approach, after the preprocessing of the input image, the word image is scanned from top to bottom. The positions of all these columns are saved for which the sum of foreground black pixels is either 0 or 1.

In thesis-II we have implemented line segmentation, word segmentation and character segmentation successfully for Bangladeshi vehicles' license plates.

3.2.1 Line Segmentation

The features of the license plates of Bangladeshi vehicles are divided two lines. City name, metro, a hyphen and letter are situated in the first line of the license plates of Bangladeshi vehicles. Again, six digits and a hyphen are situated in the second line of the license plates of Bangladeshi vehicles. It is not a great approach to segment all of the eleven features first. So, we need to perform a line segmentation to divide all the features into two segments.

We need to scan the input image horizontally to execute the license plate. Then, we can count the frequency of black pixels in each row to construct the row histogram. The position between two consecutive lines where a number of pixels in a row zero indicates a boundary between two lines.

For the license plate segmentation of the Bangladeshi vehicles, we need to convert the original image into a binary image first. After converting the original image into a binary image, we need to perform the line segmentation approach.

Figure 3.8: Original image of Bangladeshi license plate

Figure 3.9: Original image indicating 2 lines

The mechanism of line segmentation in the images of license plates of Bangladeshi vehicles is described below. We used LSO algorithm to segment the images of license plates of Bangladeshi vehicles. It first divide the binary image of the license plate into two separate lines, which contains separate features.

Figure 3.10: The binary image after applying line segmentation

Firstly, we calculated the average of top and bottom row of a random connected component from the binary image and save the connected component in an array.

Secondly, we checked and saved rest connected components one by one in the array along with the chosen random connected component if their number of top row is less and number of bottom row is greater than the value of average row of the chosen random connected component.

Thirdly, we reorganized the connected components of both arrays according to the ascending order of their top row number in the binary image.

Then, according to the number of top row in the binary image of first connected component of both arrays first and second line has been chosen.

3.2.2 Word Segmentation

After performing the line segmentation, we need to divide each line into different segments. This is Word Segmentation. In order to perform the word segmentation, we need to scan each line vertically.

The number of black pixels in each column is calculated to construct the column histogram. We used region based segmentation algorithm to perform word segmentation. The portion of each line, which remains with continuous black pixels is considered to be a word in each line. If there is no black pixel in a vertical scanning, it will be considered as the spacing between two words. And, different words in different lines are separated. So, the binary image can be considered as a collection of words.

Again, we have performed word segmentation directly in case of the segmentation of an image of the license plate of the army cars. Only word segmentation is applied on it.

Figure 3.11: Word segments

Now, an example of applying word segmentation in a binary image is given below:

Figure 3.12: Upper Word segments

Figure 3.13: Lower Word segments

Figure 3.14: Combined image of Word Segmentation in both lines

3.2.3 Character Segmentation

We have segmented the license plates of Bangladeshi vehicles by performing line segmentation and word segmentation that divides the license plate into different segments according to their features. Now, we need to perform character segmentation to divide the words into different characters.

We can perform the character segmentation only in city name and metro as they are associated with different characters. We have to perform some operations to divide the words into different characters. The operations are described below.

Firstly, we have detected the zones. The texts of Bengali alphabets are partitioned into three zones. The upper zone denotes the partition above the headline. The middle zone denotes the portion of basic characters below the headline. And the lower zone denotes the portion where some of the modifiers can reside. The imaginary line which separates the middle and lower zone is called the base line.

Now, we need to find out the headline of the word which is called 'Matra' in order to segment the character separately from the segmented word.

A row histogram is constructed by counting the frequency of each row in the word. The headline is determined by the row with the highest frequency value.

Now, after removing the headline, the characters in a word are isolated and it can easily be separated by detection of character between baseline and headline. Then, we need to eliminate the 'Matra' in order to find a differentiation line between characters successfully.

We need to detect the connected components below the base line which contains the lowest point called 'Base Point'. The depth first search algorithm helps to detect the characters below the baseline successfully.

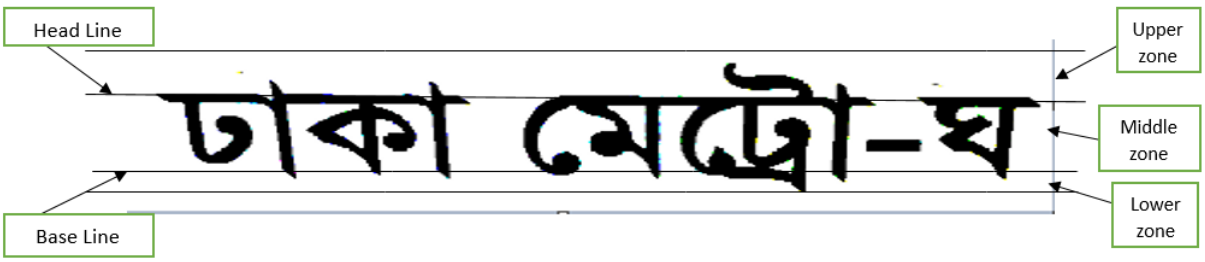

Figure 3.15: Different zones of the texts of Bengali alphabets

But we cannot perform the character segmentation perfectly because Matra Elimination is a very problematic task for Bengali alphabets. Though Matra Elimination is not an easy process, it is a very tough work to perform character segmentation without Matra Elimination. So we'll try to improve it in future.

After all, we have performed the line segmentation and word segmentation in the images of the license plates of Bangladeshi vechicles. And in the images of the license plates of the army cars, we have performed only the word segmentation. No line segmentation is performed here.

3.3 Character Recognition of Number Plate

Character recognition is the process to classify the input character according to the predefined character class. With the increasing interest of computer applications, modern society needs that the computer should read the text. The character recognition system helps in making the communication between a human and a computer easy.

Primarily, characters can be recognized using two types of methods one of which is Online Method. It consists of the following sub methods:

- k-NN Classifier
- Direction Based

Another is the Offline Method. It consists of the underlying methods:

- Clustering

- Feature Extraction
- Template Matching
- ANN

Clustering has the following sub methods:

- k-Means
- Hierarchical
- SOM
- EM

Feature Extraction has the following sub methods:

- Projection
- Zoning
- Border Transition
- Graph Matching

Template Matching consists of the following types:

- Pixel Level Template Matching
- High Level Template Matching

ANN has the following recognition techniques:

- BPNN
- RBFNN
- Parallel BPNN

We have implemented Template Matching technique with a view to recognizing the characters of a number plate. It is a very simple and effective method which efficiently recognizes characters based on correlation.

3.3.1 Template Matching

Template matching is a technique in computer vision used for finding a sub-image of a target image which matches a template image. This technique is widely used in object detection fields. The crucial point is to adopt an eligible "measure" to quantify similarity or matching. We have implemented high level template matching as it operates on an image that has typically been segmented into regions of interest (ROI).

There are different techniques for matching the template. These are as follows:

- Optimal Path Searching
- Euclidean Distance
- The Edit Distance
- Correlation Coefficient

We have implemented template matching technique based on correlation coefficient. MATLAB function "corr2" computes the correlation coefficient between two matrices of the same size.

At first, the reference template pattern moves to all possible positions within the block of data. For each position, it computes the "similarity" between the reference template pattern and the respective part of the block of data.

Secondly, it computes the best matching value using the following formula:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}}$$

Here,

$\bar{A}$ = Mean (A)
$\bar{B}$ = Mean (B)
A = First input array
B = Second input array
r = Correlated coefficient

The value of correlated coefficient is achieved by the above formula and it correlates the input image with every image in the template for best matching. The value of correlated coefficient is between -1 and +1.

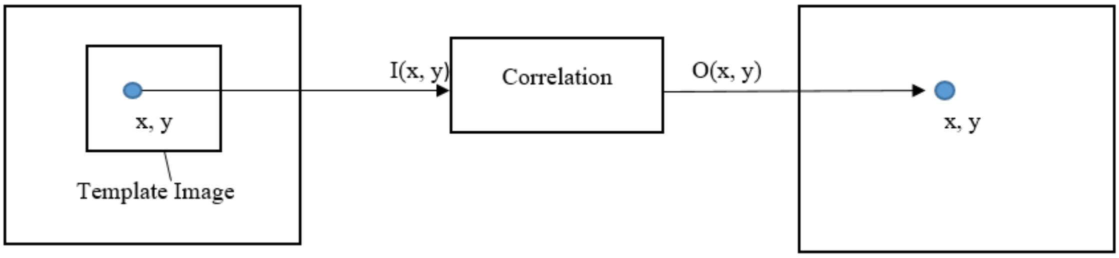

Figure 3.16: Template Matching Technique using Correlation Coefficient

We have collected templates for every English letters and numbers in the form of bitmap (.bmp) images from the internet. A snapshot of some of these are as follows:

Figure 3.17: Snapshot of the Binary Bitmap Images of Character Templates

In our algorithm, the letters corresponding to the binary input image are read. Hence, they are matched with the templates starting from the first pixel of the region of interest to the last pixel. Characters are recognized if any match is found. Then every subsequent letter in the number plate are appended in the number plate string. A sample of the procedure can be shown as follows:

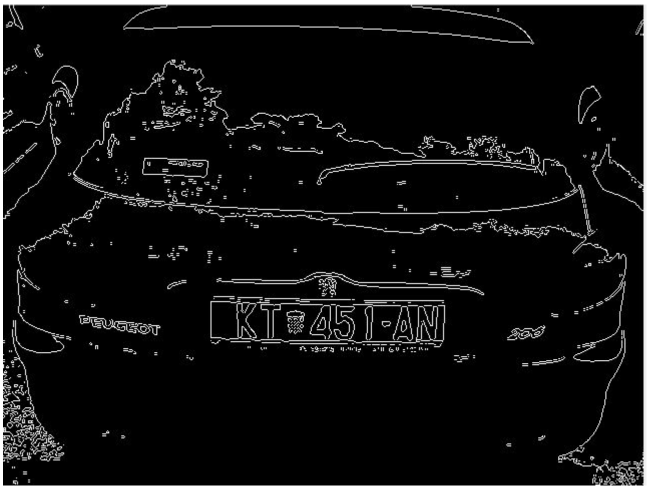

Figure 3.18: Sample of Edged Input Image

When the above pre-processed image is taken as input and the area or region of interest is extracted, the correlation coefficient works on that extracted boundary and searches for matches by each pixel. When a match is found, it extracts each character sequentially and the final license plate number is displayed.

Figure 3.19: Extracted region of interest (License plate)

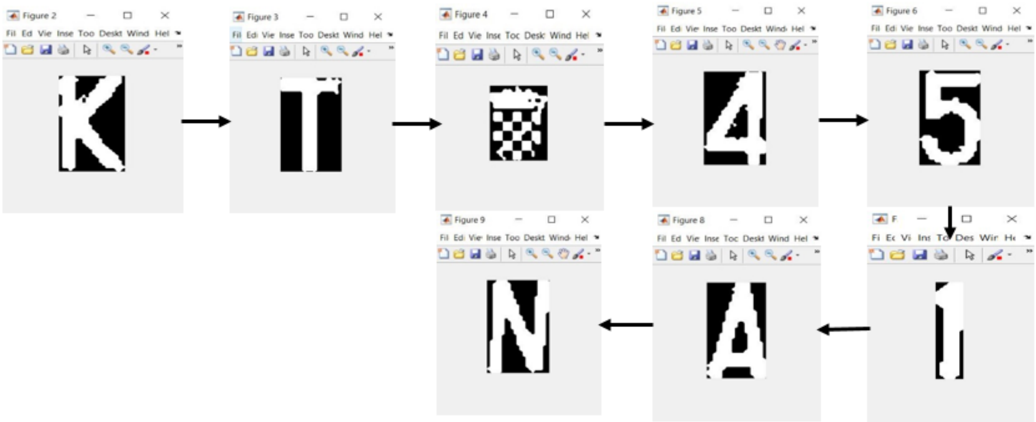

Figure 3.20: Recognition of sequential characters of the input image

Considering Figure 3.20, it clearly seems that these characters are identical to the given input image characters while Figure 3.19 displays the extracted ROI (Regions of Interest) from the input image. So, it can be said that the extraction of license plate has become successful.

In thesis-II, we have worked with Bangla datasets.After performing the detection and segmentation of the license plates of Bangladeshi vehicles successfully, we need to recognize the license plates of Bangladeshi vehicles by Template Matching technique.

Template matching is a technique in digital image processing for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot, or as a way to detect edges in images.

As the templates of the license plates of Bangladeshi vehicles are not available in the internet, so we made the template images of the license plates of Bangladeshi vehicles by slicing the images. Moreover, some template images of the license plates are rare such as the license plate of army car. Since there are some images of army car in our dataset, so we used the template images which is made by slicing the images of the license plates remaining in our dataset.

Before matching the templates with an original image, we need to normalize or standardize all the images in our dataset in order to keep all of the images under same brightness. It is too problematic to match the template image with the images of different brightness. It is a process that changes the range of pixel intensity values and change the brightness or darkness of an image.

If we want to match a darker template image with a brighter image, it can never be matched. Again, if we want to match a brighter template image with a darker image, it can never be matched. The darker template image will match with a darker image and the brighter template image will match with a brighter image. That's why we need to normalize or standardize all the images to convert them in the same pixel intensity value and same brightness by changing the range of pixel intensity values and brightness.

Moreover, before applying the template matching technique, we need to convert the original image to a binary image. And we also convert the template images into binary images. As both original images and template images are converted into binary images, so now we can perform template matching technique. We used cosine similarity algorithm in applying the template matching technique because this algorithm shows the perfect way to match the template image with the original image successfully.

The mechanism of template matching technique with cosine similarity algorithm is described below. Cosine similarity is the cosine of the angle between two n-dimensional vectors in an n-dimensional space. It is the dot product of the two vectors divided by the product of the two vectors' lengths or magnitudes.

The angle between two images is inversely proportional to the similarity of that two images. If the cosine of the angle between two images decreases, the similarity of that two images will be increased. If the cosine of the angle between two images decreases, the similarity of that two images will be increased.

Again, the cosine of the angle between two images is proportional to the similarity of that two images. If the cosine of the angle between two images increases, the similarity of that two images will be increased. If the cosine of the angle between two images decreases, the similarity of that two images will be decreased.

At the time of license plate recognition with template matching technique, we matched the template image with the features of the license plates of Bangladeshi vehicles. We know that there are eleven features in a license plates of Bangladeshi vehicles. They are city name, metro, letter, six digits and two hyphens. We need to match all the features with the template images individually which shows a similarity or correlation result in percentage (%).

Again, at the time of license plate recognition with template matching technique we found a single template matched multiple times with an original image. In this case, the template matched multiple times with the original image shows the multiple times template matching with rectangles. But it shows the similarity or correlation result in the average of the similarity of multiple times template matching in percentage (%). And it shows this average similarity multiple times according to the number of same features.

Now, an example of applying template matching technique in a binary image is given below.

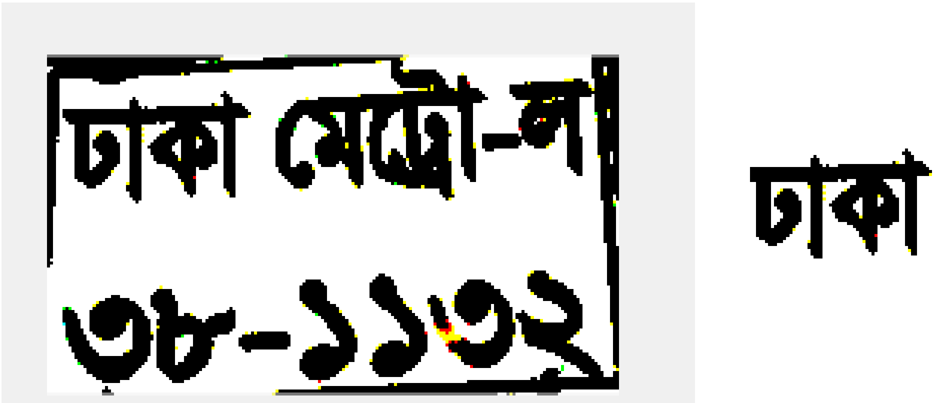

Figure 3.21: Original image with template image

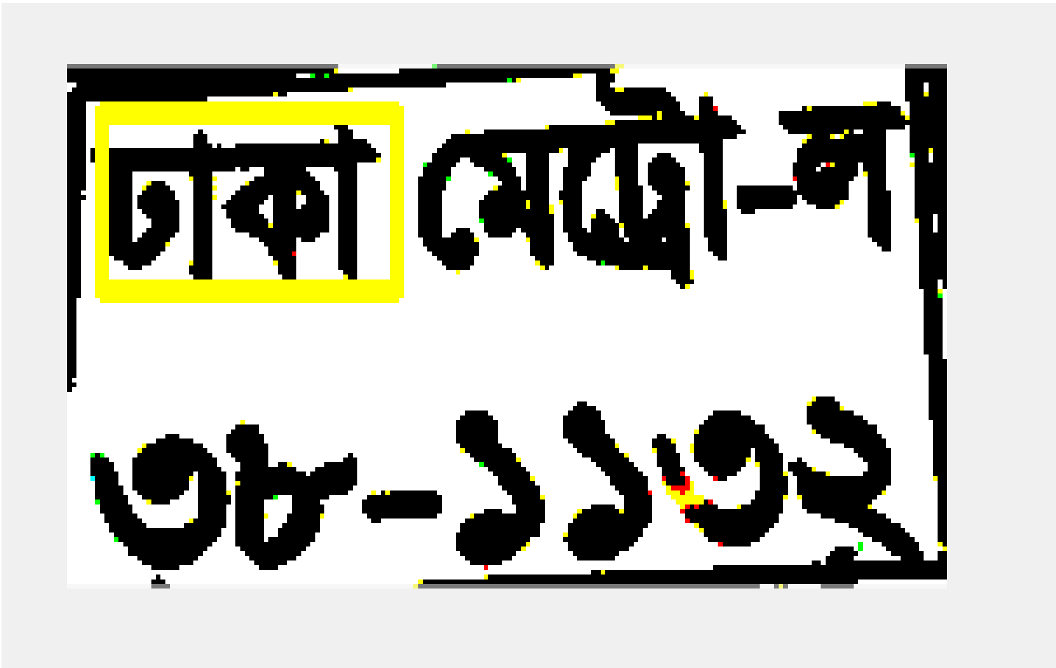

Figure 3.22: Original image after template matching (single time matched)

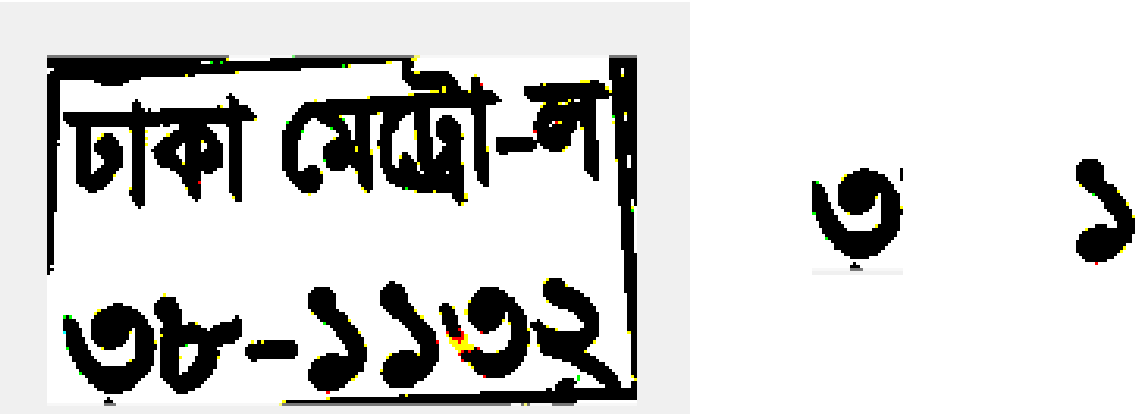

Figure 3.23: Original image with numeric template image

Figure 3.24: Original Image after template matching (multiple times matched)

Chapter 4

Results & Discussion

While demonstrating an ANPR system, the topic that rises above all is nothing but the accuracy of the recognition of the characters of the plate. Although ANPR systems have been around for over several years, one misconception which is often falsely claimed is that ANPR system reads 100 percent license plates 100 percent of the time. It is ideal but is simply not possible. Accuracy plays a crucial role in the selection of appropriate license plate reader. The factors that are hindrance to the path of accuracy of license plate readers are as follows:

- License plate missing from the vehicle
- License plate outside of the camera's field of view
- Plates mounted in a manner which is inconsistent with the law of the state entered, i.e. plate is displayed in the rear window of the vehicle
- Damaged license plates
  - Plate is bent or distorted in a manner that alters the shape of characters that construct origin
  - Portions or fragments of the plate are missing
- Obstructed plates
  - An object, such as the ball of a trailer hitch, prevents clear view of the registration number
  - Any object that obscures the outline of registration number

Simple accuracy measurement can be done using the following formula:

$$\text{Accuracy rate} = \frac{\text{Number of recognized license plate images}}{\text{Number of original input images}} * 100$$

4.1 Finding the Accuracy

We haven't worked on any recognized dataset for English license plates at the time of our defense-I. Rather we have collected some random images from various websites and implemented these in our algorithms. A rough calculation can be performed to calculate the accuracy of our implemented method, i.e., we have 20 images of vehicles in our database for English license plates. Our program gives correct output for 15 images. That means, it can fully recognize the license plate numbers except blurry, noisy, dark situations. So, in this scenario, the accuracy rate of our proposed system has appeared to be 75%.

After defense-I, that means in defense-II we have worked with license plates of Bangladeshi vehicles and this time, we have created our own dataset by capturing images of the cars and other vehicles like motor cycles, trucks etc. Additionally, there are some images of army cars in our own dataset. The images of our dataset are captured by a SAMSUNG DUOS mobile phone containing one 5 megapixel camera lens. We have tried to capture most of the images from different angles of the different types of vehicles available in the Dhaka city for achieving variations in accuracy results of Bangla character recognition. Some of the images are captured at the parking lot of our residential area.

We have captured 162 images in total for the dataset of Bangladeshi vehicles' license plates. At first, we have captured the images of the vehicles having Bangladeshi license plates. After capturing the images, a CSV (Comma-Separated Values) file is generated using Microsoft Excel 2016 which consists of the important criteria of the images individually. After the completion of generating the CSV file, it is imported into a python file. Then we have trained our dataset and successfully tested it within a fixed ratio which gave us an accuracy score of 79.67% as 129 images of Bangladeshi license plates have been successfully recognized among our 162 captured images.

After recognizing the license plates of Bangladeshi vehicles successfully, the accuracy score has been determined by training and testing our dataset. We have attempted to train and test our dataset by implementing various algorithms. But only one algorithm is implemented with a view to obtaining the perfect accuracy score for our model. The steps of finding the accuracy rate are elaborated in later sections.

4.1.1 Training & Testing the Dataset

After matching the templates of the license plates with the modules of the license plate images, we have generated an Excel (.xlsx) file which has been converted into a CSV file later. The CSV file consists of several columns which represent the information of city name, metro, letter, two hyphens and six types of digits which may be same or different. The visibility of the images are boolean values which is true or false indicating whether the license plate is successfully recognized or not. And the other information are in numerical values. The CSV file contains 13 columns consisting of the unique image number, city name, metro, letter, two hyphens and six types of same or different numbers and the visibility of the images.

A machine learning model can be trained with a specific dataset in order to transform into a specific prediction model by training. It is essential to retain the model frequently. We have trained 70% data of the dataset and the rest 30% data habe been reserved for the testing issue. With a view to determining the proper accuracy of our dataset, we need to train and test the dataset.

Firstly, we have imported the dataset in the python file with **pandas** module. Spyder IDE (Integrated Development Environment) has been used for data splitting. We have implemented some machine learning algorithms such as Random Forest Classifier and Logistic Regression using the python scikit learn module which are perfect for supervised learning. Function **train_test_split** provided by scikit learn module is imported with a view to training the dataset. Then a fixed test size is defined which is 0.3. Furthermore, We have used Binary Classification method for training the dataset in order to find the proper accuracy. We have set the first seven columns of the dataset as the featured columns and the last column (visible) as a predicted column which defines either the image of the vehicle's license plate is successfully recognized or not. Lastly, We have examined that 70% data are successfully trained and 30% data are tested.

4.1.1.1 Reasons Behind Training Only 70% Data

We haven't trained more or less than 70% data, trained only 70% data because 0.7 is the ideal ratio for training the dataset. The testing data can verify whether our model is predictive or not. We have some data which is not provided in the training. If the model predicts some values around the training score, it is enough to prove that we have trained the data successfully.

4.2 Accuracy Evaluations on Various Algorithms

After training and testing data in the 70%-30% ratio, we have fitted the instance using the Logistic Regression algorithm. The instance was fitted with the featured columns and a predicted column (visible). After fitting the instance, the result has provided an accuracy score which is less than 1. Next, the score is multiplied by 100 in order to convert the accuracy into percentage.

The result shows 61.34% accuracy after 70% training and 30% testing of the data by applying the Logistic Regression algorithm.

It is clear that 61.34% accuracy is not a good result as well as not enough for us to complete the task successfully. So, we need to increase the accuracy of this dataset. To improve the accuracy, we have required to implement some machine learning algorithms. This process is called **Improving Performance with Ensembles**.

In order to improve the performance of the model, we have implemented **Bagged Decision Trees** algorithm, **Random Forest** algorithm, **Extra Trees** algorithm, **AdaBoost** algorithm, **Stochastic Gradient Boosting** algorithm and **Voting Ensemble** algorithm. All of these machine learning algorithms can classify the model in different ways and can show different results to improve the accuracy score.

It is obvious to implement the **Random Forest** algorithm with extra importance in order the find the accuracy. The result displays 73.34% accuracy after 70% training and 30% testing of the data by applying the Random Forest algorithm. Hence, it delivers the best accuracy of all results found by applying all the other machine learning approaches.

The comparisons of the Random Forest model with the other machine learning models are listed below:

- Random forests are among the most popular machine learning methods thanks to their relatively good accuracy, robustness and ease of use. It provides two straightforward methods for feature selection: mean decrease impurity and mean decrease accuracy.
- The Random Forest model is better than Decision Trees model. Because this model combines hundreds or thousands of decision trees, trains each one on a slightly different set of the observations, splitting nodes in each tree considering a limited number of the features. The final predictions of the random forest are made by averaging the predictions of each individual tree. When we don't bother much about interpreting the model but want better accuracy. Random forest will reduce variance part of error rather than bias part, so on a given training data set decision tree may be more accurate than a random forest.
- When our independent features are categorical, random forest tends to perform better than logistic regression. With continuous features, logistic regression is usually better. It all depends on the specifics off the problem being solved.
- Random forest models overfit a sample of the training data and then reduces the overfitting by simple averaging the predictors, which is totally useless for new data. Again, gradient boosting uses regression trees for prediction purpose where a random forest use decision tree. The random forest is easy to parallelize but boosted trees

are hard to do. In this case, we can apply Gradient Boosting model, which performs better than Random Forest model.

- When all the variables are relevant, both Random Forest and Extra Trees methods seem to achieve the same performance. Since Extra Trees model seem to keep a higher performance in presence of noisy features, Extra Trees are better than Random Forest model.

- Voting Ensemble model performed better than our individual k-NN, random forest and logistic regression models in order to improve the accuracy score.

So, we can improve the accuracy score by using different models according to their advantages of classification method.

4.3 Discussion on Accuracy Results

After finding the accuracy score, we have to discuss the result whether it can be improved or not. That's why, we applied some of the techniques which analyzes the result well. We tried to get the best feature selection of our dataset as well as we tried to reduce the features of our model to improve the accuracy score.

We applied the sequential feature selection such as forward selection and backward elimination as well as Principle Component Analysis in order to improve the accuracy score. The analysis of the result is described below in detail.

4.3.1 Sequential Feature Selection

First of all, we applied forward selection and backward elimination technique which shows the feature combinations sequentially according to the best accuracy score of the combinations of the features. In order to get the best case of the feature combination, we need to apply the forward selection and backward elimination technique.

Feature Selection is a very critical component in our model. Because our model presents data with high dimensionality. And when it presents data with very high dimensionality, models usually choke. The reasons of choking are given below:

- Training time increases exponentially with number of features.

- Models have increasing risk of overfitting with increasing number of features.

In order to apply forward selection and backward elimination technique, we have to implement sequential feature selection algorithm which makes a proper way to use forward selection and backward elimination technique. It helps with these problems by reducing the dimensions without much loss of the total information. It also helps to make sense of the features and its importance.

Sequential feature selection algorithms are a family of greedy search algorithms that are used to reduce an initial d-dimensional feature space to a k-dimensional feature subspace where $k < d$. The motivation behind sequential feature selection algorithms is to automatically select a subset of features that is most relevant to the problem. The goal of feature selection is two-fold which are as below:

- Improving the computational efficiency.
- Reducing the generalization error of the model by removing irrelevant features or additional noises.

Above all, Sequential Feature Selection algorithms remove or add one feature at the time based on the classifier performance until a feature subset of the desired size k is reached.

There are four types of Sequential Feature Selection Algorithms. They are given below:

- Forward Selection
- Backward Elimination
- Forward Floating Selection
- Backward Floating Elimination

But we need only forward selection and backward elimination for our model. Because, our main target is to get the best feature combination according to the accuracy.

In the sequential selection algorithm, Random Forest Algorithm is also applied in order to identify the accuracy score. Because, identifying the accuracy score is also necessary to get the best feature combination.

4.3.1.1 Forward Selection

Forward selection is a type of stepwise regression which begins with an empty model and adds in features one by one. In each forward step, we can add the one feature that gives the single best improvement of accuracy to our model.

In other words, no independent feature is entered into the equation first and each one is added one at a time if they contribute to the accuracy improvement.

After applying forward selection to our model, we got the combinations of features according to the accuracy improvement which is represented in the following graph.

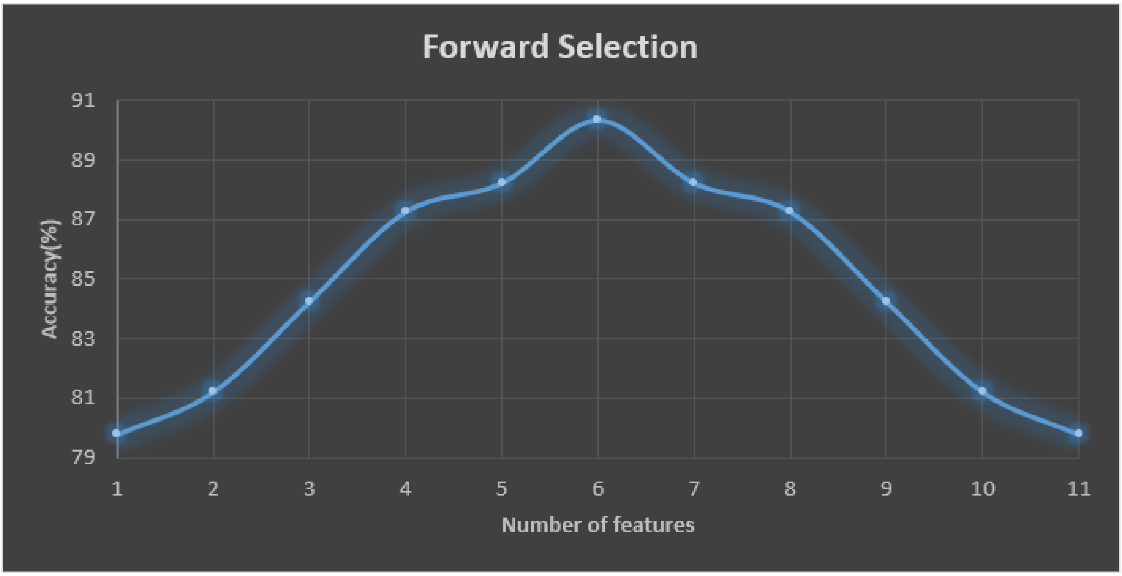

Figure 4.1: Forward selection technique

4.3.1.2 Backward Elimination

Backward elimination is the reverse process of forward selection technique. It begins with a full set of features and deletes in features one by one. In each backward step, we can delete the one feature that gives the single best improvement of accuracy to our model.

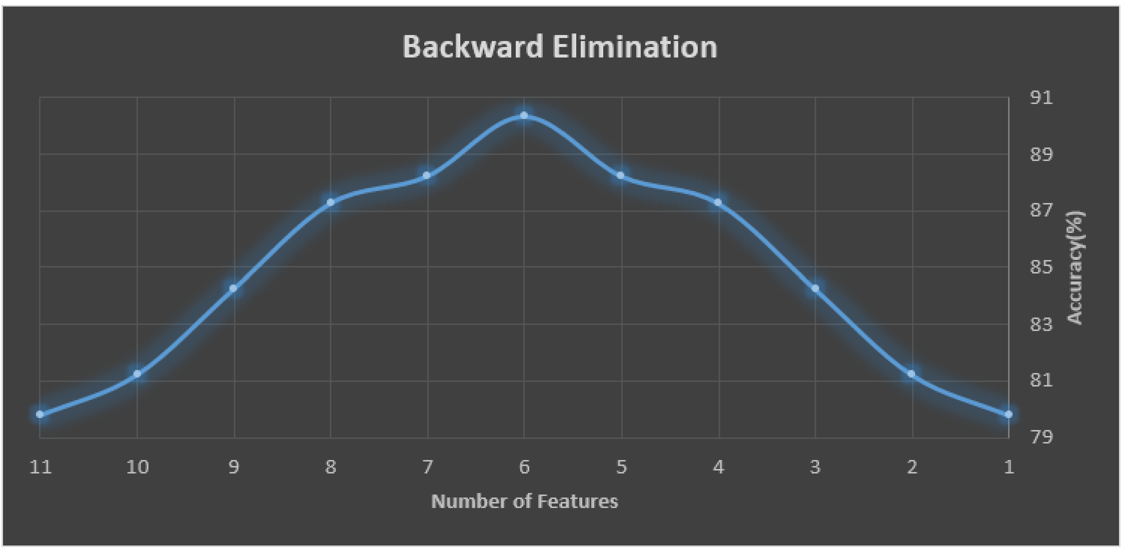

Figure 4.2: Backward elimination technique

In other words, all the independent features are entered into the equation first and each one is deleted one at a time if they do not contribute to the accuracy improvement.

After applying backward elimination to our model, we got the combinations of features according to the accuracy improvement which is represented in Figure 4.2.

4.3.1.3 Analysis of Forward Selection and Backward Elimination

There are some criteria found in forward selection and backward elimination techniques. They are given below:

- In both forward selection and backward elimination techniques, it shows that when the number of features is 6, it provides highest accuracy score, that's why the best feature combination is 6 for both forward selection and backward elimination techniques.
- The accuracy is same when the number of feature is one (first feature) for the forward selection and when the number of features is nine (last feature) for the backward elimination.
- The accuracy is same when the number of feature is nine (last feature) for the forward selection and when the number of features is one (first feature) for the backward elimination,
- The forward selection technique is the reverse work of the backward elimination technique.

4.3.2 Feature Extraction or Reduction

Feature extraction can be viewed as a preprocessing step which removes distracting variance from a dataset, so that downstream classifiers or regression estimators perform better. The area where feature extraction ends and classification, or regression, begins is necessarily murky. An ideal feature extractor would simply map the data to its class labels, for the classification task.

4.3.2.1 Principal Component Analysis (PCA)

PCA is a dimension-reduction tool that can be used to reduce a large set of features to a small set that still contains most of the information in the large set. In other words, it is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of features into a smaller one that still contains most of the information in the large set.

It is a statistical procedure and linear dimensionality reduction algorithm to find a more meaningful basis or coordinate system for our data and works based on covariance matrix to find the strongest features. It is used when we need to handle the curse of dimensionality among data with linear relationships, i.e. where having too many dimensions or features in your data causes noise and difficulties as well as increases features space. So, this approach is used to reduce the dimensionality of the model in order to avoid the curse of dimensionality.

We also applied principle component analysis to reduce the dimensionality of the model in order to avoid the curse of dimensionality. Because there are eleven features in our model. The increased number of features increases feature space, which causes the curse of dimensionality. That's why, we need to reduce the number of features by eliminating the less important features. And so, we used it for dimensionality reduction.

The eigenvectors and eigenvalues of a covariance or correlation matrix represent the "core" of a Principle Component Analysis. The eigenvectors which are known as principal components, determine the directions of the new feature space, and the eigenvalues determine their magnitude.

In case of Principal Component Analysis, variance means summative variance or multivariate variability or overall variability or total variability. Below is the covariance matrix of some three variables. Their variances are on the diagonal and the sum of the three values is the overall variability.

It is necessary to normalize data before performing Principle Component Analysis. The Principal Component Analysis calculates a new projection of our model. If we normalize our data, all the features have the same standard deviation, thus all features have the same weight and our Principal Component Analysis calculates relevant axis. Since the sample per class is less in our model, Principle Component Analysis performs well in order to reduce the dimensionality

PCA finds a vector that "best represents" our data set in a much lower dimension. To get better accuracy, we need to find a vector that "best discriminates" between your classes. In this case, Linear Discriminant Analysis (LDA) works better than Principle Component Analysis.

After applying Principle Component Analysis to our model, we got the important features according to their "Explained Variance Ratio" which is represented in Figure 4.3.

Here, we have eleven features in which hyphen1 and hyphen2 are less important according to their explained variance ratio. Without these two features, the explained variance ratio

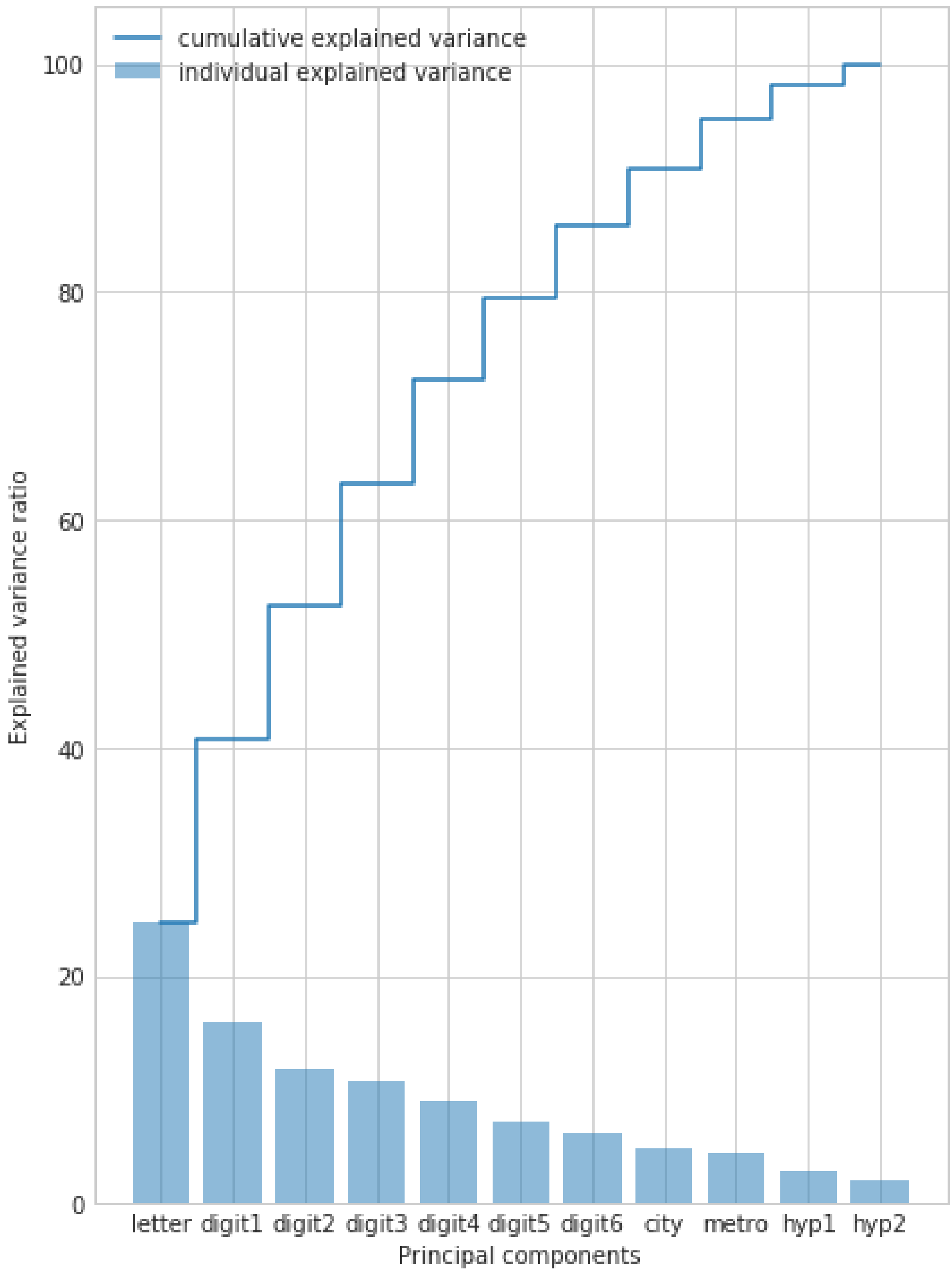

Figure 4.3: Principal Component Analysis

is appeared to be above 95%. So, we can eliminate these two hyphens in order to reduce dimensionality.

4.4 Comparison of Accuracy Results

Our accuracy rate can be compared with the accuracy rate found in the literatures [1], [4], [9], [12] and [17]. By doing so, a vast idea carrying the pattern of correctly matching or recognition or execution of the implemented algorithm can be gathered easily.

In [1], Edge Analysis method combined with mathematical morphology, Vector Quantization (VQ), Diverse Neural Network architectures are used and 84.16% accuracy is gained in recognition of character.

Studying [4], it seems that Choudhury A. Rahman et al. used Pattern Matching, Histogram Extraction, Normalization process and achieved 70% accuracy.

In paper [9], after localizing the license plate perfectly, OCR is used for character recognition and 62% accuracy is achieved.

Considering [12], it appears that Tran Duc Duan et al. implemented Hough Transformation (HT) Method, Normalization, Histogram Equalization, Optical Character Recognition (OCR), HMM (Hidden Markov Model) and achieved 97.52% accuracy.

Paper [17] shows that, Sobel Operator is used for detection of edges and template matching procedure is used with a view to recognizing the characters and 98% accuracy is gained.

A table can be drawn which holds the accuracy rates for respective methods that are implemented using the specific algorithms. Such table can be shown as below:

Table 4.1: Comparison of the accuracy rate of implemented method with other methods

Units of ANPR System	**Method**	**Accuracy Rate (Percentage)**
Recognition of Character	Our Implemented Method	75
	Methods used in [1]	84.16
	Methods used in [4]	70
	Methods used in [9]	62
	Methods used in [12]	97.52
	Methods used in [17]	98

So, it can be seen from table 4.2 that our implemented method offers a decent percentage of accuracy comparing the other five methods which are considered as enriched and effective. In certain conditions, it offers a good result. Our implemented method works just fine in case of clarity of the image and the lightness, normal distances, non-curvature, non-blurriness of the license plate set on the rear or front side of a vehicle.

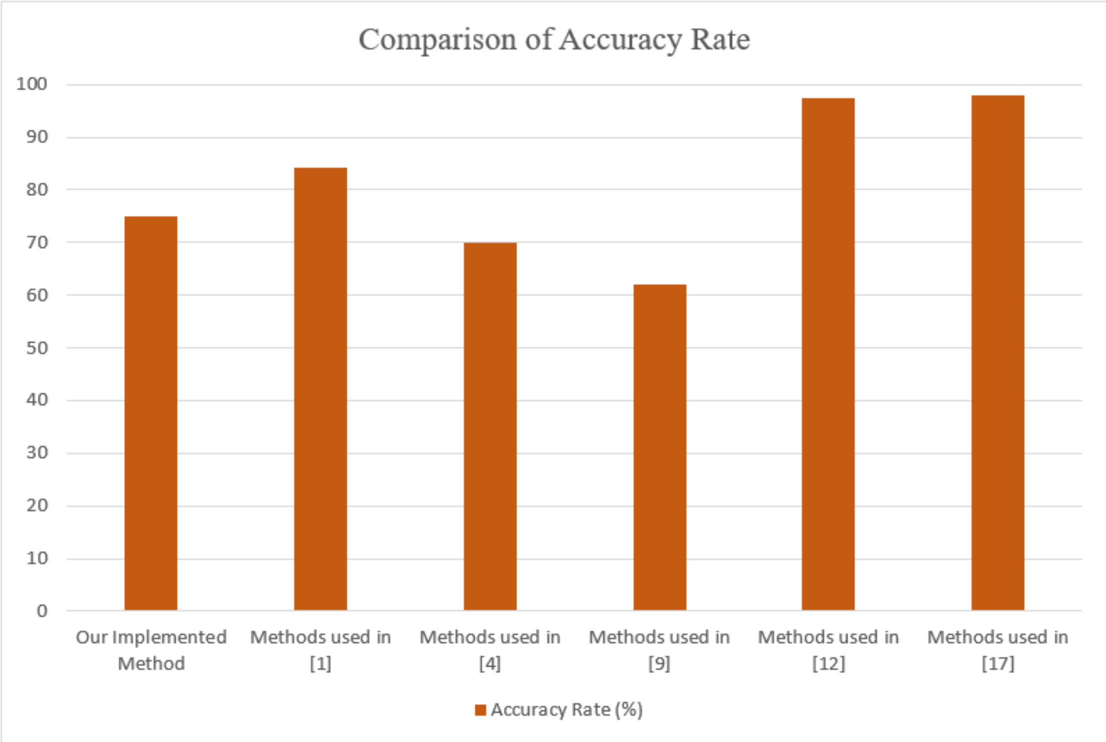

Figure 4.4: A column graph of comparison of accuracy rate in character recognition

The above comparison of accuracy rate among our implemented method and other five methods are drawn through a column graph as shown in Figure 4.4.

In order to increase the obtained accuracy rate of our implemented method in defense-I, we have focused on our lackings those were hindrance to the better accuracy rate. Some of the limitations have been successfully overcome by us in defense-II. We have studied more papers regarding ANPR to find out various approaches for the betterment of the accuracy rate of our implemented method and also we have implemented the Template Matching technique with extra preprocessing techniques such as Skewness Correction and sequential feature selection algorithms like Forward Selection and Backward Elimination.

After defense-I, we can compare again our improved implemented method with some other previous methods studied in the literatures [1], [18], [20] and [21].

Considering paper [18], it seems that the license plate is detected by grayscale to binary conversion, edge detection, histogram analysis, and dilation, erosion, labeling and filtering. They performed word segmentation by region based technique with adaptive thresholding. They used Support Vector Machine (SVM) for character recognition. Their total accuracy score is 93.21%.

Paper [20] shows that Hough transform and contour algorithm are used in order to localize the number plate. Optical Character Recognition is applied to recognize the characters. Total accuracy is 98.94%.

In paper [21], the license plate is detected by filtering, sobel edge detection, thresholding and morphological operations. Then it is segmented by line, word and character segmentation. Overall accuracy is 80%.

Table 4.2: Comparison of the accuracy rate of improved implemented method with other previous methods

Units of ANPR System	Method	Accuracy Rate (Percentage)
Recognition of Bangla Character	Our Improved Implemented Method	79.67
	Methods used in [1]	84.16
	Methods used in [9]	62
	Methods used in [18]	93.21
	Methods used in [20]	80
	Methods used in [21]	90

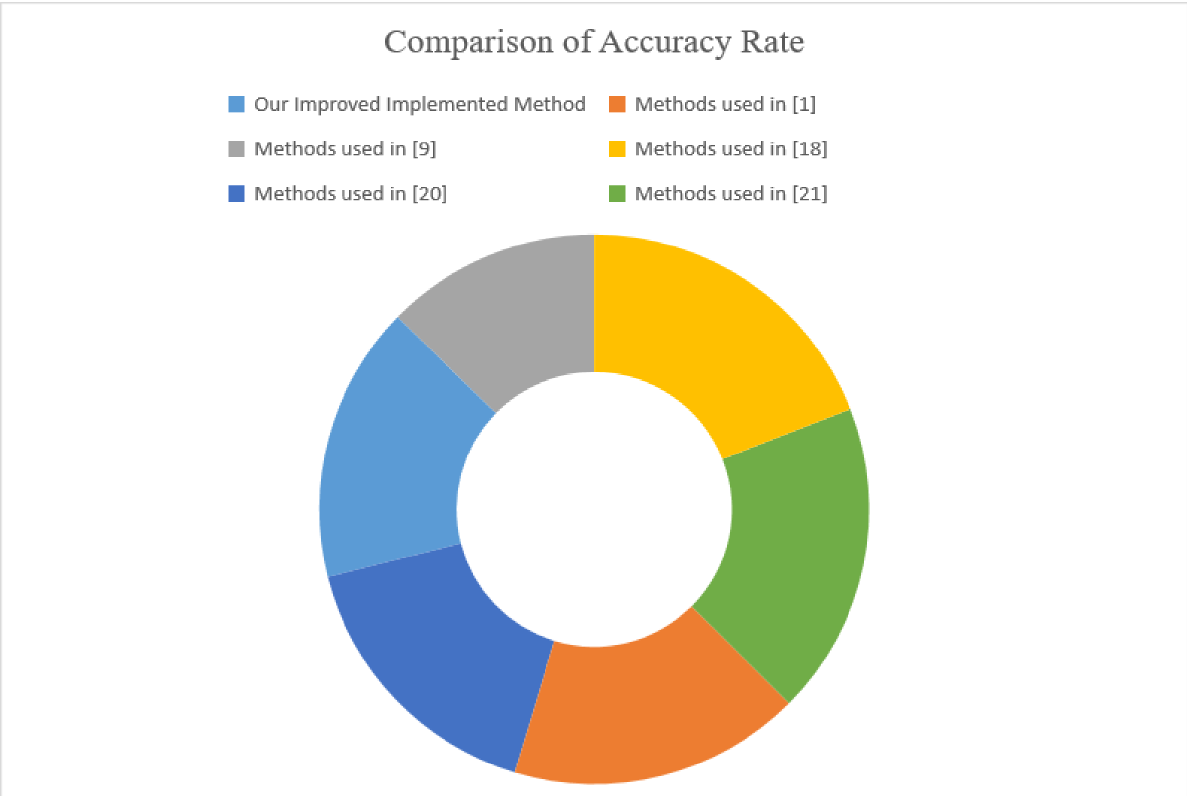

Figure 4.5: A sunburst graph of comparison of accuracy rate in bangla character recognition

Everything has its limitations. Our proposed method also has some limitations. As we have not trained the image datasets that we have used for our implementation, it might have some limitations at different conditions. The following limitations are hindrance to the path of our implemented methodology:

- It struggles in very dark environments
- It suffers when the vehicle is at a huge distance from the camera
- Skewness of license plate can make it difficult to locate
- Too much blurry image can make it unable to perform its functions

After defense-I we have tried to overcome some limitations and in defense-II some limitations still remain there which we will try to overcome in the near future. The limitations left after defense-II can be stated as below:

- Character Segmentation cannot be performed perfectly because of "Matra Elimination" process.
- Though we have performed Principal Component Analysis (PCA) to reduce the dimensionality to the features, we perform least discriminant analysis to reduce the dimensionality of the features.
- Some vehicles are too old and the license plates of these vehicles are blurry. So, it is too tough to recognize the license plates of these vehicles from the captured images.
- The images are captured in the different modes of daylight. So, some images cannot be recognized which are dark.

Chapter 5

Future Plan

Although we had so many things to implement or to do a lot of more different stuffs, we are stuck into some limitations now. But we are confident enough that we believe not to remain idle getting stuck into this position of our work. We wish to implement our proposed method for recognizing Bangla character too in the near future and will also try to create our own dataset and train the dataset for more accuracy. Besides, we believe that we will make this proposed algorithm more efficient and more accurate.

Chapter 6

Conclusion

After all, we can ensure that Automatic License Plate Recognition will help to control the traffic in our country. This type of technology will be very much helpful for the crime detection and some other violence eradication in our country. So, we will select the proper technique to activate this system in order to assist the traffic surveillances as soon as possible for the betterment of our beloved country.

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