**Mathematics and Computer Science**
2021; 6(6): 92-104
http://www.sciencepublishinggroup.com/j/mcs
doi: 10.11648/j.mcs.20210606.13
ISSN: 2575-6036 (Print); ISSN: 2575-6028 (Online)

# A Character Segmentation Method to Increase Character Recognition Accuracy for Turkish License Plates

**Gulsum Cigdem Cavdaroglu[1, *], Mehmet Gokmen[2]**

[1]Department of Information Technologies, Faculty of Economics, Administrative and Social Sciences, Isik University, Istanbul, Turkey
[2]Altamira Digital Ventures, Istanbul, Turkey

## Email address:
cigdem.cavdaroglu@isikun.edu.tr (G. C. Cavdaroglu), mehmet@altamira.com.tr (M. Gokmen)

[*]Corresponding author

## To cite this article:
Gulsum Cigdem Cavdaroglu, Mehmet Gokmen. A Character Segmentation Method to Increase Character Recognition Accuracy for Turkish License Plates. *Mathematics and Computer Science*. Vol. 6, No. 6, 2021, pp. 92-104. doi: 10.11648/j.mcs.20210606.13

**Received**: September 19, 2021; **Accepted**: October 16, 2021; **Published**: December 31, 2021

**Abstract:** Automatic License Plate Recognition is a computer vision technology that provides a way to recognize the vehicle's license plates without direct human intervention. Developing Automatic License Plate Recognition methodologies is a widely studied topic among the computer vision community to increase the accuracy rates. Automatic License Plate Recognition systems include image acquisition and character segmentation phases. Although there are many studies, the research in character segmentation and improving recognition accuracy remains limited. The lack of an international standard for license plates and the misinterpretation of ambiguous characters are challenging problems for Automatic License Plate Recognition systems. Several academic works have shown that the ambiguous character problem can be overcome by using a second model that contains only these characters. In this study, we propose a new methodology to reduce the character recognition errors of Automatic License Plate Recognition systems. One of the reasons for the low accuracy rates is the problem of ambiguous characters. In most studies using OCR, it was observed that a single model was used for alphanumeric characters during the recognition phase. Instead of using a single model, using separate models for letters and digits will improve the recognition process and increase accuracy. Therefore, we determined whether the characters are letters or numbers, and we expressed the license plates in the form of letters - digits. The method suggested for segmenting blobs worked with an accuracy of 96.12% on the test dataset. The method recommended for generating letter-digit expressions for the license plates worked with an accuracy of 99.28% on the test dataset. The proposed methodology can work only on Turkish license plates. In future studies, we will expand our method by using the license plate dataset of a different country.

**Keywords:** License Plate Recognition, Character Segmentation, Optical Character Recognition, Letter-digit Expression, Image Processing

## 1. Introduction

Automatic License Plate Recognition (ALPR) is a computer vision technology that provides a way to recognize the vehicle's license plates without direct human intervention [1]. The advancement of technology has triggered many researchers' interest in studying the computer vision techniques used in ALPR systems. The grow up of smart city applications also supported this increase [2]. This market's growth is driven by the rise in demand from traffic surveillance applications and infrastructure growth in emerging economies [3]. The ALPR system is now a mature field with many well-understood methods and algorithms and is now being spun out into commercial applications. ALPR systems can generally include image acquisition and character extraction phases. In the image acquisition phase, the images of the vehicles are captured. In the character extraction phase, the license plates' characters are extracted using several image processing techniques.

In the ALPR system, usually, surveillance cameras are used. Since these cameras are placed in the area for general purposes, usually larger scene images are retrieved. Therefore, first, it is necessary to locate and extract the license plate region from this image. Then, the alphanumeric characters in the license plate need to be extracted correctly from the background. Finally, an Optical Character Recognition (OCR) system is used to recognize the characters.

As a result, an ALPR system consists of four steps as shown in Figure 1: (1) image acquisition, (2) license plate recognition and extraction, (3) character segmentation, (4) character recognition [4].

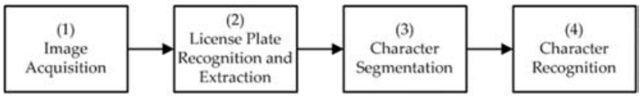



***Figure 1.*** *Four steps in a traditional ALPR system.*

The first two steps detect the vehicle and capture the image. Then the potential regions within the image that may contain the license plate are detected. In the third step, characters are isolated from the background within the detected region. In the last step, the characters are recognized. This work is focused on the character isolation phase. Hence, the discussions of the vehicle detection algorithms and character recognition methods are beyond the scope of this paper.

The objective of the paper is to increase character recognition accuracy. Therefore, we determined whether the characters are letters or numbers, and we expressed the license plates in the form of letters - digits. The rest of the paper proceeds as follows: Section 2 presents a brief background of the ALPR systems and the methodologies used in these systems. Section 3 explains the problem and the challenges about the problem. Section 4 describes the proposed methodology. Section 5 presents the experiments and performance measurements. Section 6 explains the limitations of the work. Finally, Section 7 concludes the paper with a summary of the main points and outcomes.

## 2. Related Work

ALPR systems have received much attention recently from the research community. This research's characteristics can be summarized as follows: (1) First, this research is restricted locally since the license plates tend to be different for different countries. Furthermore, in most countries, there is no standardization of license plates. (2) Second, these systems consist of several steps, as mentioned before. Each segment is critical in order to perform the other steps with a good amount of accuracy. However, in some literature on these systems, some of these steps are not discussed in detail. As a result, each work is focused on a specific part of the whole process. Since this paper focuses on the character segmentation phase, the literature review covers only character segmentation methodologies.

Galindo et al. proposed a system that implements horizontal and vertical projection to extract the license plate characters. They transformed the obtained numbers into vectors. The total success rate of the system is 76.00% [5].

Dalarmelina et al. presented a system that implements Tesseract 4.0, which is used as OCR. This version of Tesseract is based on a Long Short-Term Memory-based recognition engine. Their main goal is to improve the performance in real-time. They used the confusion matrix to measure the performance of the proposed algorithm. They indicated that the accuracy of the proposed algorithm is 83.00% [2].

Peixoto et al. presented a system that implements Deep Learning techniques to improve the digits and feature representations. They developed a dataset that contains 2000 images. They indicated that data augmentation techniques and the increase in locally connected layers had increased accuracy. They used a publicly available dataset with Brazilian plates to measure the accuracy of the system. The presented approach can correctly detect and recognize the license plates in 63.18%. Considering the segmentation and recognition of each character individually, the accuracy is 99.00% for the segmentation and 93.00% for the recognition [6].

Silva et al. presented another methodology that uses supervised classification techniques to recognize the characters. First, they modeled the pixel sequence behavior in texts to describe the character classes. Then, they determined the pixel behaviors in each class. The main goal of the authors is to achieve good performance in real-time. So, they measured the performance of the methodology in terms of time complexity. Their algorithm can recognize 92.336 characters per minute. Although this work's goal is far from this study, its methodology is interesting since it is based on pixel behaviors [7].

Panchal et al. used an integrated segmentation approach to segment the characters. This approach consists of a Harris corner detection method and a connected component-based method. They consolidated the connected components' analysis with several features, such as pixel counts, aspect ratio, and height of characters. They used a dataset that consisted of 35 good images and 30 challenged images. The accuracy of the characters' segmentation is 97.14% in good images and 90.00% in challenged images. Thus, the overall accuracy of the proposed method is 93.84% [8].

Liu and Lin presented a hierarchical architecture combining supervised K-Means and Support Vector Machines (SVM). They first classify characters into subgroups and then implement the support vector machine technique to classify them. As a result, they reduced the number of SVMs and their complexity by the proposed approach. The overall accuracy of the system is indicated as 98.99% [9].

Akhtar and Ali implemented a vertical projection-based technique to segment characters. The image is first projected on the horizontal axis. They used summing black pixels of each column. Since there are gaps between each character, there are no black pixels in between. The value of the histogram is zero in these gaps. The nonzero values in the histogram represent characters. These individual peaks are cropped out to get the characters out of the license plate. Then they used four different methodologies to recognize the characters. The accuracy indicated in this work is as follows: (1) k-NN method: 83.40% problems: making mistakes between visually ambiguous characters, such as '8' and 'B,' 'I' and '1,' 'O' and 'D,' 'G' and '6'. (2) Neural Network method: 89.47% problems: making mistakes between 'O' and 'G' and very rarely between '2' and 'Z.' (3) SVM method: 87.50% problems: making mistakes between '8' and 'B,' 'I' and '1,' 'G' and '6,' although it gave correct output for 'O' and 'D' most of the time. (4) Random Forest Classifier: 90.90% problems: completely removed ambiguity between 'G' and '6' and reduced the error in detecting characters '8' and 'B,' 'I,' and '1' to a greater extent than SVM [1].

Mahalakshmi and Tejaswini used various methods to recognize the characters, and then the accuracy of the methods was compared. They implemented four methods: (1) Template Matching, (2) SVM, (3) OCR, and (4) Artificial Neural Network. They indicated that the recognition stage is the final stage of the ALPR system and the accuracy of the segmentation of the characters has a significant effect in this stage. The segmentation stage's main problems are indicated as the malformed characters, the noisy characters, the broken characters, and the incomplete characters. Furthermore, the extracted characters do not have uniform size and thickness. All of these affect the segmentation phase. To overcome these difficulties, they used a predefined ambiguity set containing similar characters, such as 0, 8, B, and D. The final recognition rate is indicated as 95.60%. The accuracies of the other methods used in this work are indicated as (1) Template Matching: 97.50%, (2) SVM: 97.00%, (3) Artificial Neural Network: 94.12% [10].

Patel et al. indicated that several methods could be used to extract the characters. These methods include image binarization, Connected Component Analysis, vertical and horizontal projection. The accuracy of the presented methods is: (1) two-layer Probabilistic Neural Network: 89.10% (only letters), (2) statistical feature extraction: 85.00%, (3) Feature Salient: 95.70%, (4) SVM integration with feature extraction: 93.70% (English characters, Chinese, numeral, kana), (5) Multi-layered Perceptron ANN: 98.17% (letters and digits), (6) OCR Tesseract: 98.70% (letters and digits), (7) Character Categorization, Topological Sorting, and Self-organizing Recognition: 95.60% (letters and digits), (8) Hierarchical Neural Network: 95.20% (letters and digits), (9) Probabilistic Neural Network: 96.50% (letters and digits), (10) Back Propagation Neural Network: 93.50% (letters and digits) [4].

Anagnostopoulos et al. cropped the candidate license plate region using Bicubic Interpolation and then subjected it to Sliding Concentric Windows for segmentation. To optimize the results, they used a threshold value of 0.7. They segmented the characters, and each character was resized to specific pixel size. The overall accuracy of the presented approach is indicated as 89.10%. The accuracy of the segmentation phase is indicated as 86.00% [11].

Ozturk and Ozen used vertical and horizontal histogram methods to segment the characters. Column sum vectors are used to determine the boundaries of characters. As a result, adjacent characters are separated in two. The overall accuracy of the presented approach is indicated as 96.50% [12].

The character segmentation process developed by Zheng et al. consists of character height estimation, character width estimation, and blob extraction. To estimate the character height, color reverse, vertical edge detection, and horizontal projection histogram are used. The edges of the license plate characters are analyzed using the Sobel mask and image binarization algorithms. The color of the characters is made black. The method uses a horizontal projection histogram to find the boundaries of a character. It uses image binarization and vertical projection histogram to estimate the character width. By implementing vertical projection, the gaps between characters are found. The method uses blob checking to remove the non-blob characters from the segmented characters. They used a total of 169 visible license plates in 160 testing images for the experiments. The detection rate is indicated as 96.40%. They used 587 license plate images with 3502 characters located by the license plate detection step to test the segmentation algorithm. The correct segmentation rate is indicated as 98.82% [13].

Ying Wen et al. performed pre-processing steps such as horizontal and vertical correction, image enhancement to segment the characters correctly. Then the image is transformed into black characters and white background. The overall accuracy of the presented approach is indicated as 93.54% [14].

Pan et al. implemented a three-step procedure for character segmentation. In the first step, horizontal, vertical, and compound tilts are corrected. Then, to detect the connected boundaries, auxiliary lines are drawn between the first and last characters. In the final step, the noise is removed, and the characters are segmented. They used a database including 200 images to test the approach. The accuracy of the segmentation approach is indicated as 100.00% [15].

Lakshmi et al. used vertical projection and thresholding methods to segment the characters [16].

Kocer and Cevik used various methods, such as Contrast Extension, Median Filtering, and Blob Colouring, to segment the characters. By implementing contrast extension, the image is made sharp. Noisy regions are removed by implementing median filtering. Closed and contact fewer regions are detected by implementing the blob coloring method to a binary image. The overall recognition percentage of the system is 95.36%. The accuracy of the segmentation approach is indicated as 98.82% [17].

Shapiro and Dimov used the character clipper to segment the characters. They implemented feature extractor, classifier, post-processor, and training phases. They used two datasets to test the approach. The first dataset contains 1000 images, and the accuracy for this dataset is 85.20%. The second dataset contains 400 relatively good images, and the accuracy for this dataset is 92.30% [18].

Puranic et al. presented an ALPR system for Indian license plates. They used different procedures during the training phase to handle the problematic characters. They used an additional training set for the ambiguous characters such as I/1, B/8, and O/D. The presented approach's overall accuracy is indicated as 80.80% for Indian license plates [19].

Chang et al. performed a comparison of distinguishing parts of ambiguous characters. The overall accuracy of the presented approach is indicated as 93.70% [20].

Xie et al. presented a character segmentation method that uses the number of alternating white and black pixels. This algorithm is based on calculating the numbers of white and black transformations per column. The overall recognition accuracy is indicated as 97.70% [21].

Zheng et al. implemented a three-step procedure to segment the characters. The first step is to estimate the character height. In this step, the upper and lower boundaries of the character are located. In the second step, they estimate the character width. In the final step, they used a block extraction algorithm to verify the character segments. The overall recognition accuracy of the method is indicated as 94.03%. The accuracy of character segmentation is indicated as 98.82% [13].

Deba et al. eliminated border regions and noisy regions to segment the characters correctly. Then the heights of the characters are compared with other license plate characters' heights. The overall accuracy of the presented approach is indicated as 99.00% [22].

Badr et al. implemented several steps to segment the characters. First, the image is converted to a binary image using an Adaptive Threshold Filter. Then noise is removed by getting the Connected Components using Flood Fill. To decide if it is a noise or not, they used the component ratio and the number of pixels in that component. Then, to ensure that no two components are merged, they implement a maximum filter for thinning the characters. In the next step, a horizontal projection is implemented to detect the boundaries between the characters. The peaks in the horizontal projection are indicated as the gaps between the characters [23].

Zhu et al. presented another methodology to segment the characters. First, they used vertical projection since it performs quickly and efficiently. During this process, the standard width of the character can be adjusted dynamically. This adjustment makes the projection more flexible. The overall accuracy of the presented approach is indicated as 93.50% [24].

The segmentation process that is presented by Ahmed et al. is based on pixel count. They used vertical projection and the number of pixels in each column. A histogram is plotted based on the vertical projection values. The characters are segmented depending on the transition from a crest to its corresponding trough. Then some threshold is taken to avoid unnecessary segmentation [25].

Li and Chen presented a function to segment the characters. They treat the binary image as a matrix. They use a sum function to calculate the row vector of the sums of each column. Then they research the matrix along the horizontal direction by a loop. When the sum of some column is less than one and the next column's sum is greater than 1, this region is segmented from this column. The overall accuracy of the presented approach is indicated as 80.00%. The accuracy of the segmentation algorithm is indicated as 95.00% [26].

Zou et al. proposed a robust license plate recognition model to improve the accuracy of license plate recognition under unrestricted conditions. This model includes license plate feature extraction, license plate character localization, and feature extraction of characters. To extract the features of license plates, they used deep separable convolutions and spatial attention mechanisms. The proposed method combines the contextual location information of the license plate feature characters to locate the relative position of each character. They implemented the model on different datasets. The average recognition rate is 96.45% [27].

Pustokhina et al. presented a deep learning-based license plate recognition model that operates on three main stages: (1) license plate detection, (2) segmentation using optimal K-means clustering, (3) license plate number recognition system. In the second stage, they implemented optimal K-means clustering with Krill Herd algorithm. The overall accuracy of the model is 0.981 [28].

Rahman et al. proposed a computationally light graph-based greedy algorithm for the character segmentation phase. This algorithm does not require any detection as pre-process. The accuracy of the algorithm is 99.75%. However, they filtered out non-digit and non-character blobs manually [29].

Selmi et al. proposed an automatic framework for license plate detection and recognition from complex scenes. This framework is based on a mask region convolutional neural network. The accuracy rate of this algorithm is 99.3% on one test dataset and 98.9% on another test dataset. The segmentation phase of the proposed system is divided into two parts: (1) detecting each character in the license plate using a mask-region-based convolutional neural networks method, (2) improving character detection in each license plate. The average accuracy of the character segmentation of the proposed system is 97.925%. On the other hand, the speed of the proposed framework is limited [30].

Henry et al. presented a deep automatic license plate recognition system designed to be applicable to multinational license plates. The method is mainly based on you only look once (YOLO) networks. The authors unified the character segmentation and recognition steps into one by treating characters as objects. The overall accuracy of the proposed system is 99.34% [31].

Silva and Jung presented an end-to-end automatic license plate recognition method. This method is based on a hierarchical convolutional neural network. The accuracy of the whole system is 89.15% for the SSIG dataset and 85.19% for the European dataset [32].

Although there are many studies, the research in character segmentation and improving the accuracy rates remains limited.

# 3. Problem Definition

### *3.1. Challenges*

ALPR systems and the OCR phase of this system are among the most widely studied problems in pattern recognition and computer vision [33]. Despite being widely studied, these topics remain challenging problems when used in unconstrained environments [2]. The challenging problems which arise in this domain are listed and explained below:

1. There is no standardization of license plates. License plates tend to be different for different countries and regions in the same country [1]. The diversity of license plate formats is caused by several features, such as plate sizes, plate backgrounds, character sizes, plate textures, etc. [2]. For better recognition of license plates, intelligent algorithms are required [10]. Several techniques were proposed to improve the system by many research groups. Therefore, this research is a challenging task and is restricted locally [1, 2].
2. The misinterpretation of ambiguous characters: The characters like (O - 0), (I - 1), (B - 8), (C - G), (A - 4), (D - 0), (D - O), (K - X), (G - 6), (2 - Z) are similar and may confuse character recognizer. Character recognition methods should deal with all these defects [1, 10, 19]. Ambiguous characters on license plates are critical challenges in the industry and limit the ALPR system market [3, 34]. Although the character recognition stage has attracted more attention in ALPR systems, the ambiguous character problem remains an open problem in the area. Additionally, the ambiguous character problem has rarely been studied directly.

### *3.2. Turkish License Plate Types*

All countries use license plates to identify the vehicles and register them officially. The registration identifier can be a numeric or alphanumeric ID that identifies the vehicles uniquely. Different countries use different digit and letter combinations to create the registration identifier. Some countries assume that the letters and numbers must appear in particular locations, allowing for repeating letters and numbers. This causes lots of different combinations in real life. Early 20th-century license plates also varied in size and shape. In 1957, standardization of plates came, then the automobile manufacturers agreed with governments and international standards organizations. On the other hand, peculiar local variants still exist.

The license plates may be 110mm x 526mm or 210mm x 320mm in Turkey. The height of the characters can be 77mm, the distance between the characters may be 10mm, and the difference between the regions may be 77mm. The characters can be ordered in a single line or two lines. Although license plates have an official standard, many vehicles in traffic have license plates that do not meet the standards. This makes the ALPR process harder. The common forms of Turkish license plates are given in Figure 2.

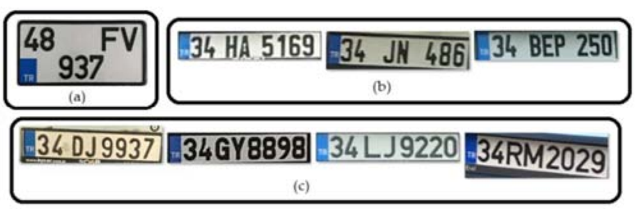



***Figure 2.*** *The common forms of Turkish license plates.*

Two distinct regions are evident: (1) a blue region with the "TR" letters, (2) the main region that consists of letters and digits. The order of the letters and digits on Turkish license plates is one of the following:

1. NNLXXXX, NNLXXXXX,
2. NNLLXXX, NNLLXXXX,
3. NNLLLXX, NNLLLXXX.

NN is a 2-digit number that indicates the city that the license plate is authorized. NN is followed by a letter (L) or several letters (LL or LLL). The letters are followed by a 2-digit (XX), a 3-digit (XXX), or a 4-digit (XXXX) number. The number of the digits depends on the letters' size before, not exceeding six letters and digits together.

### *3.3. Problem Definition*

This section points out some of the problems encountered in the extant research. This paper aims to improve character segmentation accuracy and label the characters as digits or letters. According to the literature, character segmentation seems to be a common problem in ALPR systems. One of the most challenging steps in the ALPR process is the third step in segmenting the characters. Several works have shown that we can overcome the ambiguous character problem by using a second model that contains only these characters. In the literature, there are different methodologies to segment the characters in different license plates. Therefore, we can use separate OCR systems to overcome the challenge caused by the ambiguous characters: (1) an OCR system for letters, (2) an OCR system for digits. Using separate OCR systems will increase the character recognition phase's accuracy rate since it will solve the ambiguous character problem.

When it comes to the Turkish license plates, this process can sometimes be more challenging since the number of characters and the distance between the characters can vary. Although the standards indicated that the distance between the characters might be 10mm, and the difference between the regions may be 77mm, many vehicles in traffic have license plates that do not meet the standards. Figure 2, (a) and (b) represent license plates with acceptable gaps between the characters. It is easy to segment the characters since there is a clear distance between the regions in these images. However, (c) represents license plates that do not have any gaps between the characters. Therefore, the distance between the regions in these images is not eligible to separate the characters correctly.

In this paper, a methodology is presented to overcome this challenge to identify the segments correctly. If we separate the regions accurately, we can use different models explicitly created for the letters and digits in the character recognition step. To do this, we should first know if a character is a letter or a digit. In particular, to our knowledge, no study has considered labeling the characters as letters or digits.

### *3.4. Dataset*

The dataset [35] used in this work consists of 876 license plate images. Ninety-five of them are challenging images. The license plates in the challenging images considered difficult are non-standard license plates. When trying to process these license plates with traditional license plate recognition methods, some characters that are letters are predicted as numbers, and some characters that are numbers are predicted as letters. In this study, before the recognition stage, the recognition accuracy was increased by separating the characters that are letters and numbers from each other. Some sample images from the dataset used are shown in Figure 3.

***Figure 3.*** *Sample images from the dataset used.*

# 4. The Proposed Methodology

Since ALPR systems have received much attention recently from the research community, the recognition process's accuracy rates are generally above 80.00%. The presented methodology in this paper is focused on the main challenges that decrease the accuracy rates. This can be achieved by improving the recognition process of ambiguous characters, uch as (O - 0), (I - 1), (B - 8), (A - 4), (D - 0), (G - 6), and (2 - Z). One of the most critical steps in the license plate recognition process is the character segmentation process. This step has an essential effect on the character recognition step. The ambiguous characters decrease the accuracy rates of those steps. Some of the ambiguous characters are letter-digit pairs. In most studies using OCR, it was observed that a single model was used for alphanumeric characters during the recognition phase. Instead of using a single model, using separate models for letters and digits will improve the recognition process and increase accuracy. However, after the segmentation of the characters, each character must be examined and labeled as letters or digits. As a result of this process, a plate letter-digit expression representing the plate can be obtained. The plate letter-digit expression presents the license plates in a regular expression format. For example, NNCCNN that the first two characters are digits, the following two characters are letters, and the last two characters are digits. Using this format will be possible to use separate models for letters and digits in the character recognition stage. The proposed methodology changes the 3rd and fourth stages of ALPR systems, as shown in Figure 4.

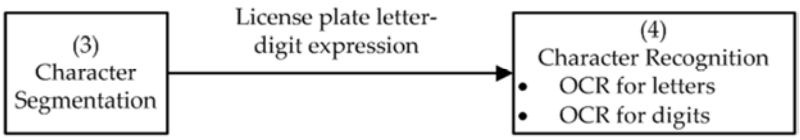



***Figure 4.*** *The updated stages by the proposed methodology.*

Figure 5 shows the new flow.

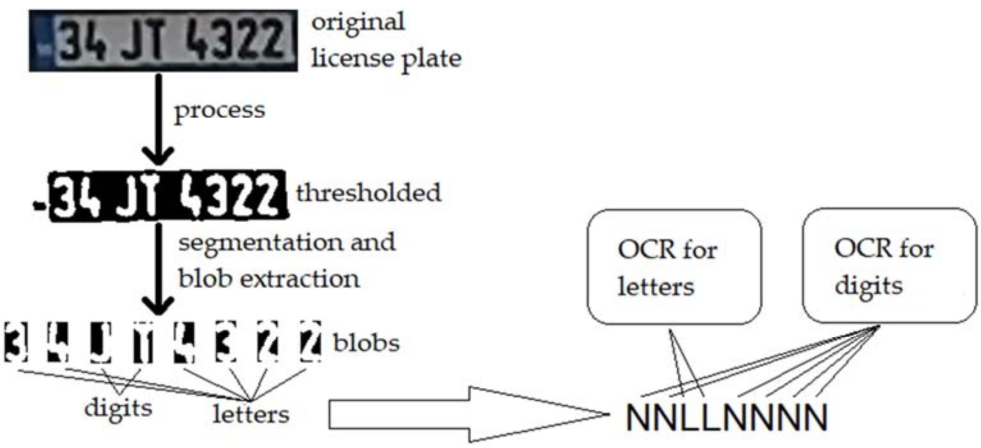



***Figure 5.*** *An example flow diagram for the proposed methodology.*

Before proceeding with this process, the license plate region must first be extracted from the whole picture. A common technique for plate extraction is to implement several image processing filters consecutively. After these filters are implemented on the original plate image, the plate region is detected as binary. These methods are not particularly new and have been used for many years in ALPR systems. The methods performed are given in Figure 6.

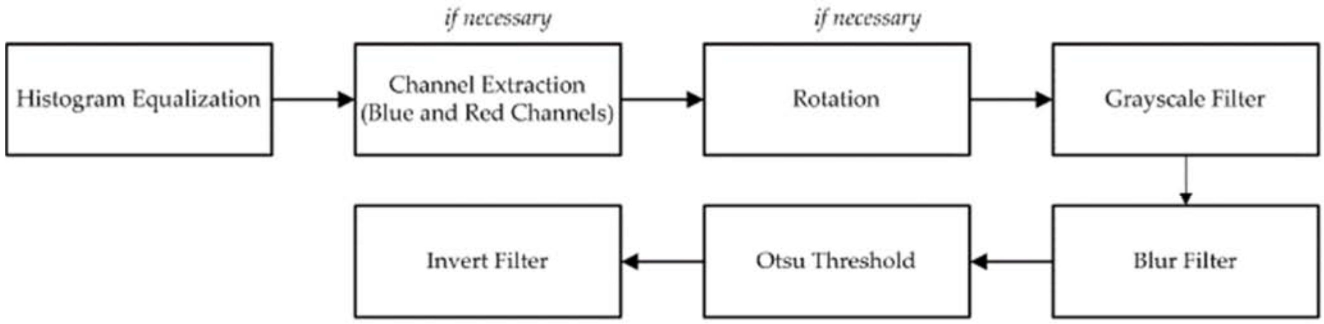



***Figure 6.*** *The flow of the plate region detection.*

A histogram equalization filter was applied to the original image first. Afterward, a two-option path was followed: (1) direct grey value filtering, (2) the blue part with the TR symbol on some plates caused the image's problem as a separate block. We applied blue channel extraction and red channel extraction filters respectively to overcome this problem. Then the obtained images are merged to get a single binary image. Some images have an angular problem due to the image angle, and the plate needs to be aligned to the horizontal axis. For this purpose, a horizontal alignment process is applied to these images. Gaussian blur filter is applied to the final image, and then the Otsu threshold filter is applied. The image obtained as a result of thresholding was inverted, and an inverted image was obtained. This image is the image to be used for character segmentation.

Figure 7 shows two examples of this flow.

After this stage, there are two new steps in the methodology:

1. Obtaining blocks with higher accuracy on the binary image,
2. Labeling each block obtained as letters or numbers and constructing a regular expression for the license plate.

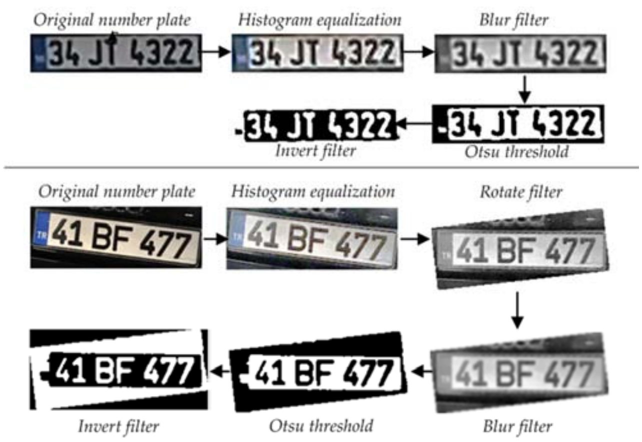



***Figure 7.*** *Examples of the process.*

### *4.1. Obtaining the Blocks*

Before the character segmentation phase, some images were distorted due to the filters applied to the image. Therefore, the pixels in the upper and lower parts of the characters are deleted. Unfortunately, this makes it impossible to obtain blocks. An example of this case is given in Figure 8 that highlights the problem:


***Figure 8.*** *Distorted parts of the characters.*

In the fields shown in 1-2-3-4-5-6-7 and 8 in Figure 8, white pixels prevent the characters from being obtained as a separate block from the other part of the plate. These areas must be removed in order for the character to be removed as a block. For this, vertical and horizontal histograms of the image were used. To fix the bottom and the top parts of the image, a vertical histogram was used. To fix the left and the right parts of the image, a horizontal histogram was used.

#### *4.1.1. Fixing the Image Using Vertical Histogram*

In the vertical histogram information, the horizontal column gives the pixel sequence numbers along with the image height. The vertical column gives the number of white pixels along that pixel. Vertical histogram information of the image given in Figure 9:

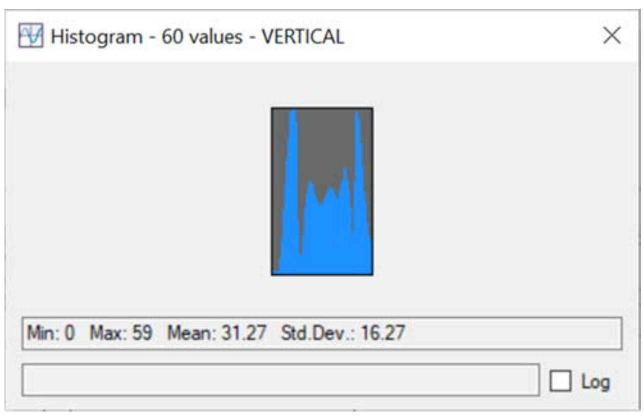



***Figure 9.*** *Vertical histogram of the image.*

After this step, the middle-numbered index information is obtained along the horizontal column. For the image given in Figure 9, which is 60 pixels high, the median index value will be 30. This middle index valued column corresponds to the middle of the characters. Moving up and down from the middle index, the number of white pixels increases across the characters' regions. The width of the image reaches a peak at a certain point relative to the pixel value. After the peak value, the number of white pixels increases for a certain period. It then decreases as the white regions obtained due to the processes on the plate begin and due to some character deterioration. The test image's peak values were obtained as 14 on the left and 50 on the right. These values are shown in Figure 10.

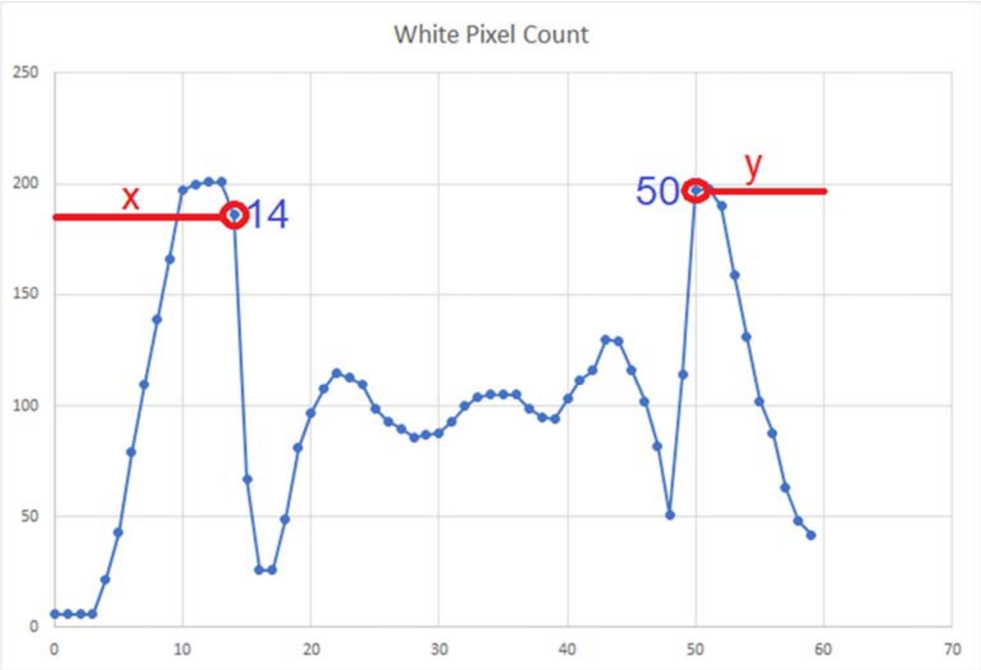



***Figure 10.*** *Peak points in the vertical histogram.*

The regions indicated by x in Figure 10 before the 14-row pixel and the regions indicated by the y in Figure 9 after the 50-row pixel are painted black, and the blocks are separated from these regions. In Figure 11, these regions and the blocks finally obtained are shown.

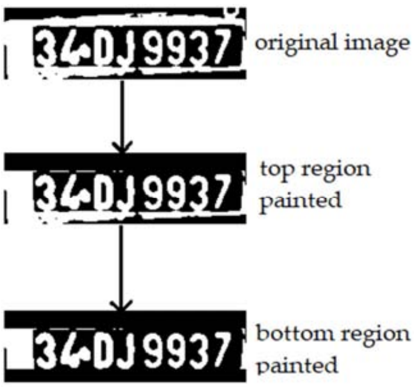



***Figure 11.*** *The top and bottom parts of the pixels are painted.*

### *4.1.2. Fixing the Image Using Horizontal Histogram*

In the horizontal histogram information, the horizontal column gives the pixel sequence numbers along the image width, and the vertical column gives the number of white pixels along that pixel. Horizontal histogram information of the image given in Figure 12:

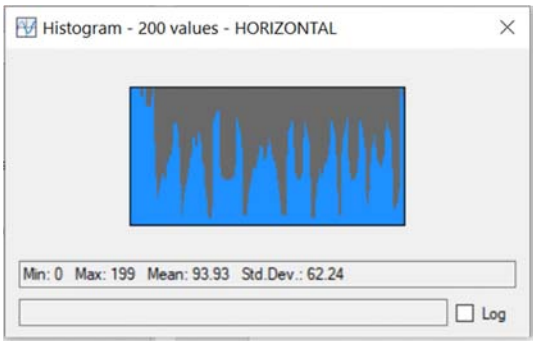



***Figure 12.*** *Horizontal histogram of the image.*

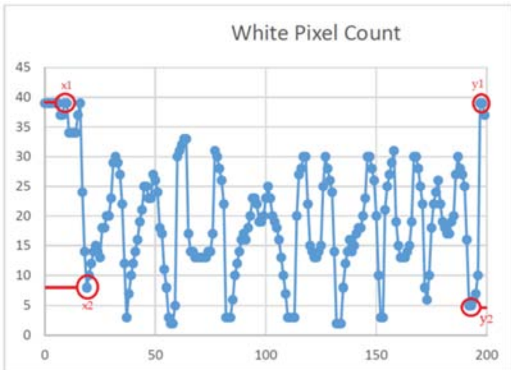



***Figure 13.*** *Peak points in the horizontal histogram.*

The white pixel values in the far left and rightmost regions should be checked in the horizontal histogram. We checked the pixel values starting from the far left to fix the left region. It was observed that there are no characters in the parts where the number of white pixels is above 90% of the image height. To prevent the pieces in these regions from being treated as blocks, we painted these parts black. When the number of white pixels is below 24% of the image height, it was observed that the blocks adjoin the white zone. We painted these pixels black to remove this problem. We checked the pixels starting from the far right to fix the right region. We performed the correction in the same way. As a result, four different peak points were determined considering the horizontal histogram, and the relevant regions were replaced with black pixels. The peak values in the horizontal histogram are shown in Figure 13.

The regions indicated by x1, x2, y1, and y2 in Figure 12 are the peak values. These regions are painted black, and the blocks are separated from these regions. In Figure 14, these regions and the blocks finally obtained are shown.

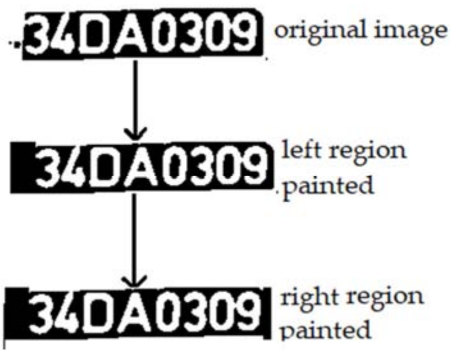



***Figure 14.*** *The left and right parts of the pixels are painted.*

This process allows the blocks to be separated from the other regions with higher accuracy. In this way, thanks to the increase in the accuracy of the input images given to the next step, the character step, the accuracy in the recognition phase also increases.

### *4.2. Labelling the Blocks and Constructing the Letter-Digit Expression*

The next step aims to distinguish the characters on the plate as letters and digits and use separate models for letters and digits in the character recognition stage. In this way, (O - 0), (I - 1), (B - 8), (A - 4), (D - 0), (G - 6), (2 - Z) which are frequently mixed letter-digit pairs, the recognition accuracy will be increased. Standards of the information on the plate have been used for this process. The first two characters in Turkish plates are digits. After these two characters, there are 1-2 or 3 letters. Then there are 2-3-4 or five digits. There should be 10mm space between characters and 77mm space between letter and digit blocks. Using this information, it is easy to label characters as letters and digits. However, some of the plates in use do not comply with these standards, although stated in the standards. Figure 15 shows these plates as an example:


***Figure 15.*** *Standard and non-standard Turkish license plates.*

In Figure 15, the gaps between the different character regions in the left image are pretty evident, whereas the image on the right is not observed. This creates a problem in the labeling of characters as letters or digits. The algorithm developed for this problem's solution works as follows: The first two characters are absolutely letters. After the second character, the horizontal distances between the blobs are calculated. Horizontal distances are expected to reach the peak in two points since there are three regions on the plate. These peak values are found after all horizontal distances have been calculated. After the first two characters are marked as letters, digit information is added to the letter-digit expression until the first peak is reached. The letter information is added to the letter-digit expression when the first peak is reached. Afterward, letter information is added to the letter-digit expression until the second peak value is reached, and digit information is added to the letter-digit expression when the second peak value is reached. After this stage, there is no other peak value, and the remaining characters on the plate are digits. As a result of this process, letter-digit expression information about the plate is obtained. These processes are shown in Figure 16.


***Figure 16.*** *Gaps between the characters.*

## 5. Experiments and Results

In this section, we will illustrate some experimental results. Experiments and observations were carried out on the test data set given in [35]. Some of the license plates in this dataset are license plates that comply with the standards. In such license plates, the separation of characters from each other and the formation of the letter-digit expression can be achieved with high accuracy. However, some license plates in the dataset do not comply with the standards. Such license plates do not have the required distance between the digit and letter regions. This makes it difficult to distinguish the blobs from each other. As a result, it makes it difficult to distinguish letters and digits from each other, and a particular method must be applied to form the letter-digit expression.

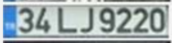
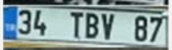
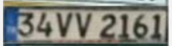
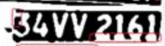
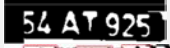
The proposed method was tested by performing the following steps:

1. All license plate images have been processed with the traditional license plate recognition method. Correctly segmented license plates and incorrectly segmented license plates were observed. Errors were observed for each image, and corrections to be applied were explained.

2. Suggested corrections have been applied to the images. It is ensured that the regions are correctly distinguished from each other. The accuracy value for the correct separation of the blobs has been calculated.
3. Letter-digit expressions were created based on the blobs obtained. A separate accuracy value has been calculated for this process.

In the following section, 10 sample images are taken into consideration, and these steps are explained. Table 1 summarizes the details of the separation of the blobs.

***Table 1.*** *Ten sample results obtained during the evaluation process.*

| Original Image | Side | Invert Image | Diff. | Processed Image | Result |
|---|---|---|---|---|---|
|  | - |  | L |  | T |
|  | - |  | L |  | T |
|  | T, L, B |  | H |  | T |
|  | T |  | H |  | T |
|  | T |  | H |  | T |
|  | - |  | L |  | T |
|  | L, R |  | H |  | T |
|  | L, B |  | H |  | T |
|  | T, L |  | H |  | T |
|  | T, B |  | H |  | T |

In the first column, the image of the original license plate is given. In the second column, the side that makes it difficult to separate the blobs is specified. L means left, R means right, T means top, and B means bottom in this column. In some images, problems were observed on more than one side. These situations are expressed by specifying more than one letter, such as L-R and B-T-L. The third column shows the inverted image obtained in the last step of the image processing process. The regions marked in red on this image are the regions that cause the blobs to be incorrectly segmented. In some images, these regions, such as left, right, top and bottom, are observed only on one side, and in some images, they can be observed on more than one side, such as left-right, left-top, left-right-top. Several different situations may cause these regions: (1) non-standard pictures, etc., in the license plate, may cause the problem, (2) the angle at which the image was taken may cause the problem, (3) non-standard license plates may cause the problem. The fourth column indicates the degree of difficulty of the problem. L denotes low difficulty; H denotes serious difficulty. The fifth column shows the image after the suggested corrections have been applied. The last column indicates whether the result is true (T) or false (F).

The next step is to determine whether the successfully segmented characters are letters or digits. At this point, it is vital whether the license plates comply with the standards. This distinction can be made quickly since there will be a certain amount of space between the letter regions and the digit regions on the license plates that comply with the standards. However, since the spaces between the letter regions and the digit regions are not sufficient in license plates that do not comply with the standards, the method suggested at the point of discrimination will be used. The proposed method's main idea is to calculate the distances of the blobs from each other using the computed point information in the image plane for each character blob. Then, using the two highest values from the distance values obtained, two-letter regions and one-digit regions are separated. Then, the letter-digit expression of the license plate is generated. Table 2, created for the 10 sample license plates considered, shows the difficulty level and the results obtained in the letter-digit expression generation.

***Table 2.*** *Letter-digit expressions for ten sample license plates.*

| Processed Image | Diff. | Expression | Result |
|---|---|---|---|
|  | H | NNLLNNNN | T |
|  | L | NNLLNNNN | T |
|  | L | NNLLNNNN | T |
|  | H | NNCNNNNN | F |
|  | L | NNLLNNNN | T |
|  | L | NNLLLNN | T |
|  | L | NNLLLNN | T |
|  | H | NNLLNNN | T |
|  | L | NNLLNNN | T |
|  | L | NNLLNNN | T |

Accuracy measurement was carried out for two different phases. The first measurement was carried out to determine the accuracy of the proposed method for accurately segmenting blobs. In 34 out of 876 images in the used dataset, the segmentation was performed incorrectly. The reasons for these errors can be summarized: the image is obtained at a wrong angle, blurry, light problems in the image, and ghosting problems in the image. Nevertheless, the method suggested for segmenting blobs correctly worked with an accuracy of 96.12% on this dataset. The second measurement was carried out to determine the accuracy of the proposed method for generating the license plates' letter-digit expressions. If the blobs are not obtained correctly, the letter-digit expression also cannot be generated correctly.

For this reason, 34 images where blobs could not be segmented correctly were excluded in the second phase. In 6 of the remaining 842 images, the letter-digit expression was generated incorrectly. The reasons for these errors can be summarized as non-standard plates, not enough distance between letter and digit regions, and the use of letters with a large width in the letter region. The method suggested for generating letter-digit expressions for the license plates correctly worked with an accuracy of 99.287% on this dataset. Table 3 presents examples of images that have been processed incorrectly. In the first column, examples of incorrectly segmented blobs and incorrectly generated letter-digit expressions are presented in the second column.

***Table 3.*** *Incorrectly processed images.*

| Phase 1: Segmentation | Phase 2: Letter-Digit Expression |
|---|---|
|  |  |

## 6. Limitations

There are several limitations to the proposed methodology. An apparent limitation is the ability to work only on Turkish license plates. Due to the use of license plates subject to different standards in different countries, ALPR systems can be developed specifically for countries. Each country's application of different standards on license plates makes it compulsory to use different methods. The proposed solution has also been developed in a way that it can only work on Turkish plates.

Another limitation is that the images in the dataset used were obtained during daylight hours. For this reason, the proposed method used in character segmentation cannot be applied to images taken at night.

Another limitation is that the proposed image segmentation method does not give correct results in blurry images. In the proposed method, it is assumed that the image contains clear license plate characters.

When the proposed character segmentation method does not work correctly, it is impossible to generate the letter-digit expression correctly. Unfortunately, this problem has no solution, as characters must be segmented clearly to generate a letter-digit expression.

## 7. Conclusion and Future Work

In this study, a solution is proposed to increase character recognition accuracy on Turkish license plates. ALPR methodologies are a widely studied topic in the literature. There are many studies on this subject, both commercially and academically. Since it has been a subject that has been studied for many years, the accuracy values in ALPR systems are 80% and above. Therefore, the proposed solution does not aim to provide a solution with higher accuracy.

Conversely, it aims to reduce error rates in existing systems. Most of the errors in ALPR systems stem from the character recognition stage. Using a single OCR for letter and digit characters in the character recognition phase also cause erroneous recognition of often confused letter-digit pairs. The proposed solution ensures that all characters are labeled as letters and digits before they reach the recognition stage, thus making it possible to use different OCR models for letters and digits. The accuracy rate for the creation of letter-digit expressions for Turkish license plates is 99.287%.

The proposed solution can only work on Turkish license plates. This is because Turkish license plate standards were used in the proposed method to generate letter-digit expressions. Therefore, this method cannot be used for license plates of different countries. However, it is possible to expand the solution by placing different countries' standards in the method. The authors plan to expand the method using the license plate dataset of a different country in future studies. In this way, these results' applicability will be tested on new datasets containing license plates of both Turkish and other countries.

The character segmentation part of the proposed solution is suitable for processing images taken during daylight hours only. However, in future studies, the authors plan to develop the character segmentation method using datasets containing Turkish plates shot at night.

The character segmentation part of the proposed solution does not give accurate results in blurry images. The authors plan to expand the character segmentation method to work with blurry images in future studies.

The accuracy rates in the methods used in ALPR systems are 80% and above. Considering the commercial applications, these rates go up to 90% -95%. However, there is always an error rate in any system. Therefore, even better results are achieved when using the proposed methodology. Overall, the proposed method was the one that aimed at improving the recognition accuracy before the OCR phase.

## References


[1] Akhtar, Z., Rashid, A. (2020). Automatic number plate recognition using random forest classifier. SN Computer Science, 1.3, 1-9.

[2] Dalarmelina, N. D. V., Teixeira, M. A., Meneguette, R. I. (2020). A real-time automatic plate recognition system based on optical character recognition and wireless sensor networks for ITS. Sensors, 20 (1), 55.

[3] Businesswire: Deployment of ANPR systems in security and surveillance, and traffic enforcement applications - Research and Markets. Available online: https://www.businesswire.com/news/home/20170822005793/en/Global-Automatic-Number-Plate-Recognition-ANPR-System (accessed on 09 04 2021).

[4] Patel, C., Shah, D., Patel, A. (2013). Automatic number plate recognition system (ANPR): A survey. International Journal of Computer Applications, 69 (9), 21-33.

[5] Galindo J., Castro, C., Braga, A. (2016). Sistema automatico para reconhecimento de placas de automoveis baseado em processamento digital de imagens eredes perceptron de multiplas camadas [Automatic system for recognizing license plates based on digital image processing and network perceptron multiple layers]. In Proceedings of the XIX Encontro Nacional de Modelagem Computacional, 19-21.

[6] Peixoto, S. P., Cámara-Chávez, G., Menotti, D., Gonçalves, G., Schwartz, W. R. (2015). Brazilian license plate character recognition using deep learning. In Proceedings of the XI Workshop de Visão Computacional.

[7] da Silva, F. A., Artero, A. O., de Paiva, M. S. V., Barbosa, R. L. (2012). ALPRs-A new approach for license plate recognition using the SIFT algorithm. VIII Computer Vision Workshop.

[8] Panchal, T., Patel, H., Panchal, A. (2016). License plate detection using Harris corner and character segmentation by integrated approach from an image. Procedia Computer Science, 79, 419-425.

[9] Liu, W. C., Lin, C. H. (2017). A hierarchical license plate recognition system using supervised k-means and support vector machine. International Conference on Applied System Innovation, 1622-1625.

[10] Mahalakshmi, S., Tejaswini, S. (2017). Study of character recognition methods in automatic license plate recognition (ALPR) system. International Research Journal of Engineering and Technology, 4, 1420-1426.

[11] Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V., Kayafas, E. (2006). A license plate recognition algorithm for intelligent transportation system applications. IEEE Transactions on Intelligent transportation Systems, 7 (3), 377-392.

[12] Ozturk, F., Ozen, F. (2012). A new license plate recognition system based on probabilistic neural networks. Procedia Technology, 1, 124. 128.

[13] Zheng, L., He, X., Samali, B., Yang, L. T. (2013). An algorithm for accuracy enhancement of license plate recognition. Journal of Computer and System Sciences, 79 (2), 245-255.

[14] Wen, Y., Lu, Y., Yan, J., Zhou, Z., von Deneen, K. M., Shi, P. (2011). An algorithm for license plate recognition applied to intelligent transportation system. IEEE Transactions on Intelligent Transportation Systems, 12 (3), 830-845.

[15] Pan, M. S., Yan, J. B., Xiao, Z. H. (2008). Vehicle license plate character segmentation. International Journal of Automation and Computing, 5 (4), 425-432.

[16] Lakshmi, C. J., Rani, A. J., Ramakrishna, K. S., Lantikiran, M., Siddhartha, V. (2011). A novel approach for Indian license plate recognition system. International Journal of Advanced Engineering Sciences and Technologies, 6 (1), 010-014.

[17] Kocer, H. E., Cevik, K. K. (2011). Artificial neural networks-based vehicle license plate recognition. Procedia Computer Science, 3, 1033-1037.

[18] Shapiro, V., Gluhchev, G., Dimov, D. (2006). Towards a multinational car license plate recognition system. Machine Vision and Applications, 17 (3), 173-183.

[19] Puranic, A, Deepak, K., Umadevi, V. (2016). Vehicle number plate recognition system: a literature review and implementation using template matching. International Journal of Computer Applications, 134 (1), 12-16.

[20] Chang, S. L., Chen, L. S., Chung, Y. C., Chen, S. W. (2004). Automatic license plate recognition. IEEE Transactions on Intelligent Transportation Systems, 5 (1), 42-53.

[21] Xie, F., Zhang, M., Zhao, J., Yang, J., Liu, Y., Yuan, X. (2018). A robust license plate detection and character recognition algorithm based on a combined feature extraction model and BPNN. Journal of Advanced Transportation.

[22] Deb, K., Khan, I., Saha, A., Jo, K. H. (2012). An efficient method of vehicle license plate recognition based on sliding concentric windows and artificial neural network. Procedia Technology, 4, 812-819.

[23] Badr, A., Abdelwahab, M. M., Thabet, A. M., Abdelsadek, A. M. (2011). Automatic number plate recognition system. Annals of the University of Craiova Mathematics and Computer Science Series, 38 (1), 62-71.

[24] Zhu, Y., Huang, H., Xu, Z., He, Y., Liu, S. (2011). Chinese style plate recognition based on artificial neural network and statistics. Procedia Engineering, 15, 3556-3561.

[25] Sarfraz, M., Ahmed, M. J., Ghazi, S. A. (2003). Saudi Arabian license plate recognition system. International Conference on Geometric Modeling and Graphics, 36-41.

[26] Songke, L., Yixian, C. (2011). License plate recognition.

[27] Zou, Y., Zhang, Y., Yan, J., Jiang, X., Huang, T., Fan, H., & Cui, Z. (2020). A robust license plate recognition model based on bi-LSTM. IEEE Access, 8, 211630-211641.

[28] Pustokhina, I. V., Pustokhin, D. A., Rodrigues, J. J., Gupta, D., Khanna, A., Shankar, K., Joshi, G. P. (2020). Automatic vehicle license plate recognition using optimal K-means with convolutional neural network for intelligent transportation systems. Ieee Access, 8, 92907-92917.

[29] Rahman, R., Pias, T. S., Helaly, T. (2020). GGCS: A Greedy Graph-Based Character Segmentation System for Bangladeshi License Plate. In 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-7). IEEE.

[30] Selmi, Z., Halima, M. B., Pal, U., Alimi, M. A. (2020). DELP-DAR system for license plate detection and recognition. Pattern Recognition Letters, 129, 213-223.

[31] Henry, C., Ahn, S. Y., Lee, S. W. (2020). Multinational license plate recognition using generalized character sequence detection. IEEE Access, 8, 35185-35199.

[32] Silva, S. M., Jung, C. R. (2020). Real-time license plate detection and recognition using deep convolutional neural networks. Journal of Visual Communication and Image Representation, 71, 102773.

[33] Namysl, M., Konya, I. (2019). Efficient, lexicon-free OCR using deep learning. International Conference on Document Analysis and Recognition, 295-301.

[34] Automated number plate recognition (ANPR) and detection sensor market report explored in latest research. Available online: https://www.pharmiweb.com/press-release/2020-01-03/automated-number-plate-recognition-anpr-and-detection-sensor-market-report-explored-in-latest-rese (accessed on 09 04 2021).

[35] Turkish license plate dataset. Available online: https://github.com/muratlutfigoncu/turkish-license-plate-detector (accessed on 09 04 2021).