



## A Review of Automatic Number Plate Recognition

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DOI: [10.5281/zenodo.10028637](https://doi.org/10.5281/zenodo.10028637)

Submission Date: 12 Aug. 2023 | Published Date: 21 Oct. 2023

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### Abstract

Automatic Number Plate Recognition (ANPR) is a tool that can be used not only at toll booths on highways, expressways, etc. to speed up the process of toll collection but also by car parking management at malls and movie theaters. With the increase in the number of vehicles, automated systems to store vehicle information are becoming increasingly necessary. Communication is critical for traffic management and crime reduction, and it cannot be overlooked. Automatic vehicle identification using number plate recognition is a reliable method of identifying vehicles. It requires a lengthy time and a lot of practice to develop satisfactory results using present algorithms that are based on the idea of learning. Automatic Number Plate Detection is a unique application in machine learning as it detects images and converts them to text form. The algorithm detects and captures the vehicle image and extracts the vehicle number plate using image segmentation. The extracted image is later sent to optical character recognition technology for character recognition. This system is implemented in areas like traffic surveillance, military zones, and apartments.

**Keywords:** Plate Number Detection, Machine Learning, Crime Reduction, Traffic Management, Recognition, Law Enforcement.

## INTRODUCTION

In the late 1900s, there was a sharp rise in the number of cars on the road. Because there are so many vehicles on the road, it takes a lot of time to identify license plates because the data from license plates is mostly utilized for applications like traffic monitoring, parking management, border monitoring, law enforcement, and other things [1]. Systems for automatic number plate recognition (ANPR) are crucial for managing and monitoring traffic. By removing the number plate and reading the plate identity, which is the special identification number assigned to each car, they are able to recognize certain vehicles. Automatic traffic control, computerized toll collection, vehicle tracking and monitoring, border crossing, security, and many other uses are all possible with ANPR systems. Imaging hardware and computer vision algorithms must be combined to create an ANPR system. Algorithms for computer vision include character segmentation, plate orientation and size, normalization, and number plate localization. In addition to this, it includes optical character recognition pattern recognition techniques. Machine learning techniques are used to learn from input data to improve identification accuracy. The ANPR system may encounter a number of issues, including inadequate resolution, dim lighting, unclear inputs, plate occlusion, various text sizes, and various plate structures. In this study, we propose a machine learning-based method for Nepali license plate recognition that can identify a given plate's identity automatically. For many years, the issue of automatic number plate identification has been the subject of extensive research. In many nations, it has also been successfully used in real-world settings. However, there have only been a very small number of research done thus far on Nepali license plates. For character matching, the majority of them are based on basic distance measurements. Again, not enough study has been done on plate localization and segmentation to handle every circumstance [7]. The author claimed that when taking a license plate, there are a number of aspects to take into

account, including whether to use hardware sensors or software-based change detection triggers to start the capturing mechanism. A license plate image of the proper size, or one whose pixel count is sufficient to allow alphanumeric characters to be seen in the image, must be included in the captured image. This can be established by the camera's distance from the license plate, the size of the CCD sensor that was used to take the photo, the camera's tilt or pan, and the focal length of the lens. Due to the prevalence of retro-reflective materials used in license plate manufacturing, the author also stressed the use of infrared sensors and illumination sources to photograph license plates at night. The three steps below are typically used in literature to describe how to recognize license plates: i) identifying and removing the area containing the license plate; ii) segmenting the characters on the license plate; and iii) identifying each alphanumeric character [2]. Du et al. summarized the justification and the advantages and disadvantages of using boundary, texture, color, character size, or a hybrid of characteristics for extracting license plates from photos in their review work [3]. They discovered that for character identification and segmentation, the majority of researchers favored pixel connectivity, projection profiles, prior knowledge of characters, character outlines, or a combination of these techniques. They found that character recognition techniques varied widely depending on the underlying algorithms, including template matching, horizontal and vertical projections, the Hotelling transform, changes in foreground and background pixels, the Gabor filter, Kirsch edge detection, contour tracking, contour crossing, and topological features. These traditional techniques concentrate on a particular kind of license plate and the circumstances surrounding its collection. Several additional computer vision issues were also solved utilizing traditional learning techniques and handmade features, much like license plate recognition. Deep neural networks (DNNs), a new type of current neural network, altered this method of problem resolution. The invention of Alex Net in 2012 marked the beginning of the deep learning era and showed a notable improvement in the accuracy of object detection tasks in computer vision systems. Alex Net greatly beat traditional techniques with a 10.8% gain in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Due to the disparity in performance, there is a lot of interest in finding and studying various deep-learning architectures for license plate detection and recognition. With training and testing data becoming more complex and difficult, as well as license plate recognition rates increasing and approaching human levels, deep learning algorithms' influence can be seen. Another advantage of DNNs is that a network designed for one data may be used directly on another data without changing the network as the features extracted by the network will be data dependent and hence do not require human intervention. The complete body of literature on license plate recognition methods is large and is mostly based on conventional methods that do not produce the best results [4]. The authors provided a thorough evaluation of these techniques in [2] and [3]. We cover the most cutting-edge techniques for automatic license plate identification in this book. We only discuss neural network-based approaches for recognizing license plates because deep networks have shown a remarkable capacity to surpass conventional machine learning strategies. We highlight the unique network types—convolutional, residual recurrent, or long-short-term memory—used in various earlier publications for the precise tasks of license plate identification, extraction, or recognition. The summarized information also lists some of the most popular data sets for comparison and discusses the findings from the papers under evaluation. We also provide an overview of how fog, motion, and the introduction of fake data affect the ability to recognize license plates. Finally, potential lines of inquiry for this field of study are given [4]. The number plate can be written in non-Roman script and varied typefaces under our suggested method. We employ the OCR (optical character recognition) method to identify characters from a license plate. Character segmentation and character recognition are the two components of OCR. Characters may be extracted from many fonts and non-roman scripts with this OCR technology. OCR accuracy is influenced by the image's quality, contrast, size, and kind of text font. We can employ image processing techniques to improve the image's quality in order to improve OCR [5]. The paper transportation sector uses image recognition technology to extract license plates from complex backgrounds, segment license plate characters, recognize characters, and build a machine learning non-license plate automatic generation algorithm that may increase the effectiveness of non-license plate recognition. The license plate training sample set may successfully accomplish the goal of effectively training strong classifiers due to its diversity and rapid creation rate. The license plate information classification accuracy and anti-interference capability are somewhat enhanced by utilizing a genetic method to optimize the BP neural network [6]. In this study, we outline many use scenarios in the area of automatic number plate identification to investigate the usefulness of synthetic data in industrial contexts. In all situations, synthetic data has the potential to enhance the output of the corresponding deep learning algorithms, greatly reduce the time and work required for data gathering and preprocessing, and completely remove privacy concerns in a sensitive area like automatic number plate recognition [8]. The main goal is to employ and combine various morphological procedures in order to efficiently recognize and translate the license plate of a certain car. This is based on a number of activities, including image enhancement, grayscale conversion, edge detection using bilateral filtering, and extracting the license plate number from the vehicle's photo. Following the completion of the aforementioned procedures, the segmentation method is now being used to locate the text on the license plate using OCR and template matching. This technique can rapidly and reliably identify the license plate number from an image of the car [9]. India has a population of about 1.3 billion people, and every individual there owns at least one vehicle. Given this, it follows that there must be more cars on Indian roadways than there are citizens living there. India is a diverse nation, and this diversity can be seen in the number plates' size, typeface, and other aspects in addition to the language they are written in. States have different definitions of diversity. Although the majority of drivers use English license plates, there is no set legislation regarding how a number plate should look, so some people

tend to obtain license plates that reflect their personal preferences. We developed a technique using Google Tesseract for character recognition and You Only Look Once version 5 (YOLOv5) for number plate detection to combat these issues [10]. A 4-stage ANPR method was proposed by Silva et al. [11]. They chose to perform vehicle detection first, as opposed to other ANPR models where license detection is the first stage. No car with a clearly visible license plate is so overlooked. Instead of building a model from scratch for vehicle detection, they chose to leverage an existing model (YOLOv2) based on specific criteria. A CNN called WPOD-NET, which was created to incorporate features from Yolo, SSD, and STN, is used to detect licenses. They developed their own LP characteristics-based YOLO network for character recognition (OCR), which is capable of accurately detecting LP. An ANPR approach with three sections—license plate extraction, character segmentation, and character recognition—was proposed by Shidore and Narote [12]. Various image preprocessing techniques, such as gray scaling, Sobel edge detection, and thresholding, are applied to a picture after it has been captured with a reliable ANPR camera in order to identify potential LPs. Following that, true LP is retrieved from the image using bounding box analysis. Integrating character region enhancement, linked component analysis, and vertical projection analysis are utilized for character segmentation. In character recognition, two steps are involved. Feature extraction and character normalization. 2) Character recognition with a classifier based on SVM. According to [12], the accuracy level for segmentation is 80%, while for recognition it is 79.84%. In order to collect tolls more quickly, Kulkarni et al. [13] suggested a 4-stage ANPR model [14], which is a blend of various techniques, specifically for Indian LPs. As in [14], a vehicle detection module is present, but license localization is carried out using a "feature-based number plate localization" that was specifically created for Indian LPs. Inductive sensors are used to capture the rear of the car as a result, and various pre-processing techniques are then applied to the acquired image. They have used a technique known as image slicing for segmentation in which the LP is scanned, sliced so that no white pixels are present, and then copied into a matrix. Statistical feature extraction is used for character recognition. Three parts make up the ANPR system that Kashyup et al. [15] suggested. A mixture of image processing methods were used before the number plate was extracted. The region props function is used to segment characters. The process of character recognition involves two steps: feature extraction and template matching for the actual recognition. Finding a small image section known as a template and comparing it to an identical template in the database is the process of "template matching." The technology in question has an accuracy rate of 82.6%. A system comparable to [15] was proposed by Devpriya et al. in [16]. The image is pre-processed by converting the RGB image to a grayscale image, followed by morphological operations, number plate detection, and Closing and Opening morphological analysis. Connected component analysis (CCA) is used in this instance to segment the characters [12]. Then, using template matching, each segmented character is identified, just like [17]. All phases of ANPR employ the YOLOv3 model, which is frequently employed for object detection [18]. Every application makes advantage of TensorFlow. Grayscale conversion is performed on the input photos. An annotated dataset is needed for LP detection. They have utilized LabelImg for this assignment to label the data so that the input image has a bounded box around the license plate, aiding in detection. YOLO models are used for character segmentation and recognition. The YOLO model's character recognition accuracy is 99%, compared to OpenCV's 93%. An artificial neural network (ANN)-based ANPR system based on Indian license plates was proposed by Tiwari and Choudhary [19]. Similar to previous ANPR systems, the acquired image is pre-processed using techniques including Gaussian filtering, wavelet transformation, and image binning. Next, the number plate is recovered, followed by character segmentation and character identification utilizing vector generation. An ANPR system with two stages—license plate detection and character recognition—was proposed by Naren Babu et al. [13]. For both detecting the license plate and identifying the characters on the license plate, they have trained a 37-class CNN single-YOLO model. Additionally, they were able to recognize the characters on the number plate with a 91% accuracy rate and detect the number plate with 100% accuracy. Machine learning is used in the proposed study to identify Arabic license plate numbers. The vehicle's license plate is photographed, and Arabic numeric characters are found on the plate by character segmentation and image processing. The method extracts the license plate area from the vehicle image after recognizing the license plate number area. The background color of the license plate designates the different types of vehicles: private vehicles have a white background, buses and taxis have a red background, governmental vehicles have a blue background, trucks, tractors, and cranes have a yellow background, temporary licenses have a black background, and the army has a green background. Both machine learning-based training and testing of Arabic number characters as K-nearest neighbors (KNN) and Google Tesseract OCR-based identification are used to identify Arabic digits from license plates. 90 photos from the internet and CCTV footage were retrieved and used to test the system. The suggested system successfully recognizes background color, Arabic number characters, and plate numbers, according to empirical results. The overall success rates of background color identification and plate localization have been calculated. Plate localization, background color detection, and Arabic number detection all have success rates of 97.78% overall, 45.56% in OCR, and 92.22% in KNN [20]. The development of an artificial intelligence system for automatic license plate recognition is the topic of the study. Character extraction is used to achieve excellent license plate recognition accuracy on wide camera angles. Studying current license plate recognition methods and developing an artificial intelligence system that operates on wide-angle camera angles with the aid of cutting-edge machine learning and deep learning techniques are the problems at hand. Both hardware-based and software-based solutions were investigated and created as part of the project. Different datasets and competing systems were used for testing. Experiments, literature reviews, and case studies for hardware systems are the key research methodologies. The review of contemporary techniques led to the

selection of the Mask R-CNN algorithm because of its excellent accuracy. The problem was stated, the possible solutions were identified and described, the primary algorithm was selected, and a mathematical foundation was provided. An accurate automatic license plate system was demonstrated and put into use in various hardware environments as part of the development process. The network was contrasted with current adversarial systems. Recall, precision, and F1-score were some of the different objects detecting qualities that were calculated. The obtained results demonstrate that the designed Mask R-CNN algorithm system processes pictures with good accuracy at significant camera shooting angles [21]. The suggested method aims to create a capable automatic authorized vehicle identification system that utilizes the license plate of the vehicle. An infrared (IR) sensor is used to detect number plates, which aids in capturing good images from a camera. The most crucial and challenging task is taking pictures of moving automobiles. Using the R-CNN approach, character segmentation is utilized to extract the area of a vehicle's number plate from an image. Accurate character identification is accomplished using the optical character recognition (OCR) technique. The gathered information is then checked with the databases of the relevant authorities to look into specific information like the owner of the car, the location of the registration, the address, and so forth. Only the gate barricade is opened if the vehicle details match those in the database. This system will take into account road safety measures while minimizing criminal activity. The technology makes an effort to improve number plate detection's effectiveness and accuracy under climatic situations [22].

## CONCLUSION

The work's objective is to use several research publications to investigate the theoretical underpinnings and practical issues of automatic license plate recognition systems.

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#### **CITATION**

M. B. Ahmad, S. H. Ayagi, & U. F. Musa. (2023). A Review of Automatic Number Plate Recognition. In Global Journal of Research in Engineering & Computer Sciences (Vol. 3, Number 5, pp. 26–30). <https://doi.org/10.5281/zenodo.10028637>