ANALYTICAL STUDIES ON TECHNIQUES AND ALGORITHMS OF AUTOMATIC NUMBER PLATE RECOGNITION

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Abstract - The city's efforts to improve traffic make a big step forward when licence plates can be read. It explains how an intelligent transportation system should work and what steps should be taken for it to be successful. Because the number of cars is growing so quickly, ANPR is a must-have for managing traffic control. Automatic number plate recognition (ANPR) is mostly used to keep an eye on traffic and keep people safe. Number plate recognition uses image processing and the most recent advances in technology to automatically read the characters on a vehicle's licence plate. In the last few years, there have been a number of technological advances in the field of studying how to read licence plates. Image processing techniques like OCR make it possible for traffic surveillance to solve a wide range of problems that come up during criminal investigations, the collection of tolls, the monitoring of traffic, the regulation of speed, and the management of parking, among other things. If you want to control traffic and keep an eye on a large number of people in a transportation system, you need an ANPR system. Image processing techniques and the collection of photos of vehicles for use in the dataset have made it possible to keep an eye on traffic on a large scale. Automatic License Plate Reader (ANPR) is a way to take the steps needed to run a good intelligent transportation network. Traffic control has become an absolute must because the number of cars has grown so quickly. The main goal of ANPR is to keep an eye on and record traffic for defence purposes. To read the text on licence plates, number plate recognition uses image processing, optical character recognition (OCR), and edge detection technology. The model is made up of three different parts called, respectively, the module for car detection, the module for licence plate segmentation, and the module for recognition. Image processing made us more determined to stop a wide range of illegal activities, such as armed robberies of cars, breaking traffic rules, and the way law enforcement is handled. This review study looked at all of the different designs for reading licence plates that have been put into use so far.
Keywords- ANPR Deep Learning, Segmentation, Machine Learning, Classification, Artificial Intelligence

I INTRODUCTION

License plate recognition is a powerful way to find records and get information. But the usual way to read a license plate is a lot of work. When done by hand, finding licence plates to find

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hidden gems of information is not as useful. ANPR architecture has been made in many different ways, and the automatic recognition of licence plates is an important part of the intelligent traffic network. ANPR architecture is hard to get right because the visibility of the licence plate in the picture depends on how far away the camera is. In this huge open area, moving cars are too small to record and still get the licence plate number. It is hard to tell what a licence plate is from a blurry picture. One of these solutions is a CCD camera with the ability to pan, tilt, and zoom (PTZ). For each stage, different scholars have come up with their own methods, each of which has its own pros and cons. There are three main steps in the process of reading a licence plate. There, people are identified by their interests, licence plates, and personalities. Here is a quick look at the parts that make up the licence plate system. Auto-Number-Plate (ANPR) software on a device can read your licence plate and figure out what kind of car you drive. The images that come out of a camera show the licence plates of passing cars. The main job of an ANPR is to read and understand licence plates.[1]

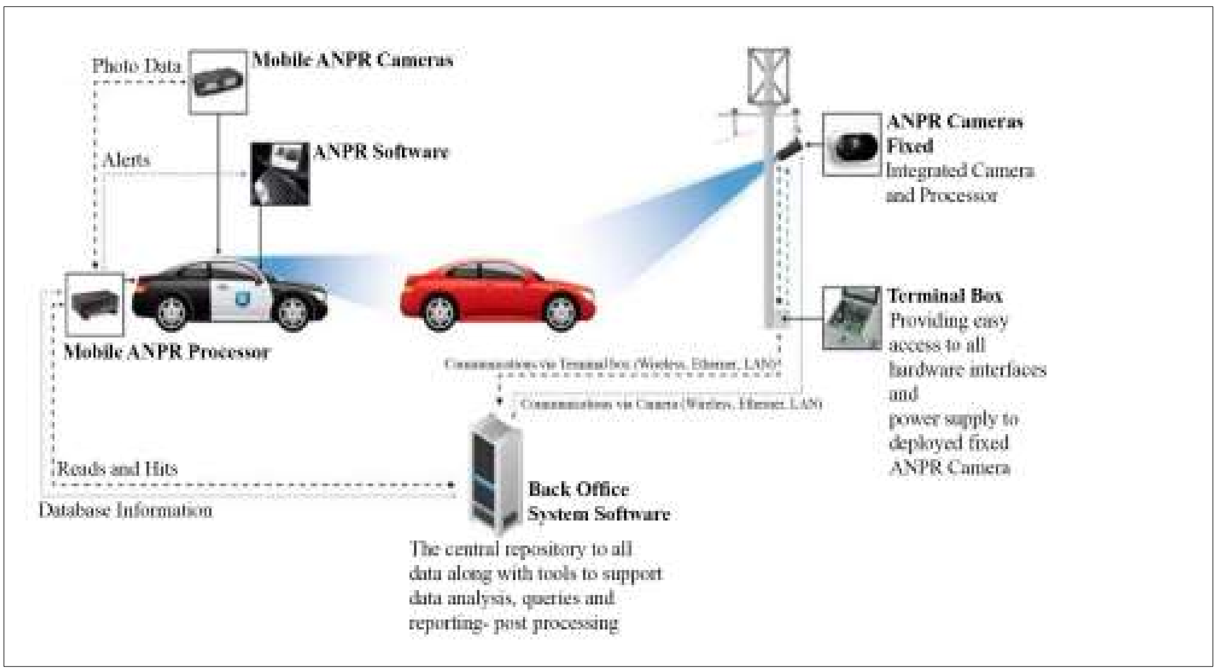

Figure 1. Typical ANPR System Diagram of a Fixed ANPR System (right) and a Mobile ANPR System (left)

License plate recognition -License plate recognition is a powerful way to find records and get information. But the usual way to read a licence plate is a lot of work. When done by hand, finding licence plates to find hidden gems of information is not as useful. ANPR architecture has been made in many different ways, and the automatic recognition of licence plates is an important part of the intelligent traffic network. ANPR architecture is hard to get right because the visibility of the licence plate in the picture depends on how far away the camera is. In this huge open area, moving cars are too small to record and still get the licence plate number. It is hard to tell what a licence plate is from a blurry picture. One of these solutions is a CCD camera with the ability to pan, tilt, and zoom (PTZ). For each stage, different scholars have come up with their own methods, each of which has its own pros and cons. There are three main steps in the process of reading a licence plate. There, people are identified by their interests, licence plates, and personalities. Here is a quick look at the parts that make up the licence plate system. Auto-Number-Plate (ANPR) software on a device can read your licence plate and figure out what kind of car you drive. The images that come out of a camera show the licence plates of passing cars. The main job of an ANPR is to read and understand licence plates.[2]

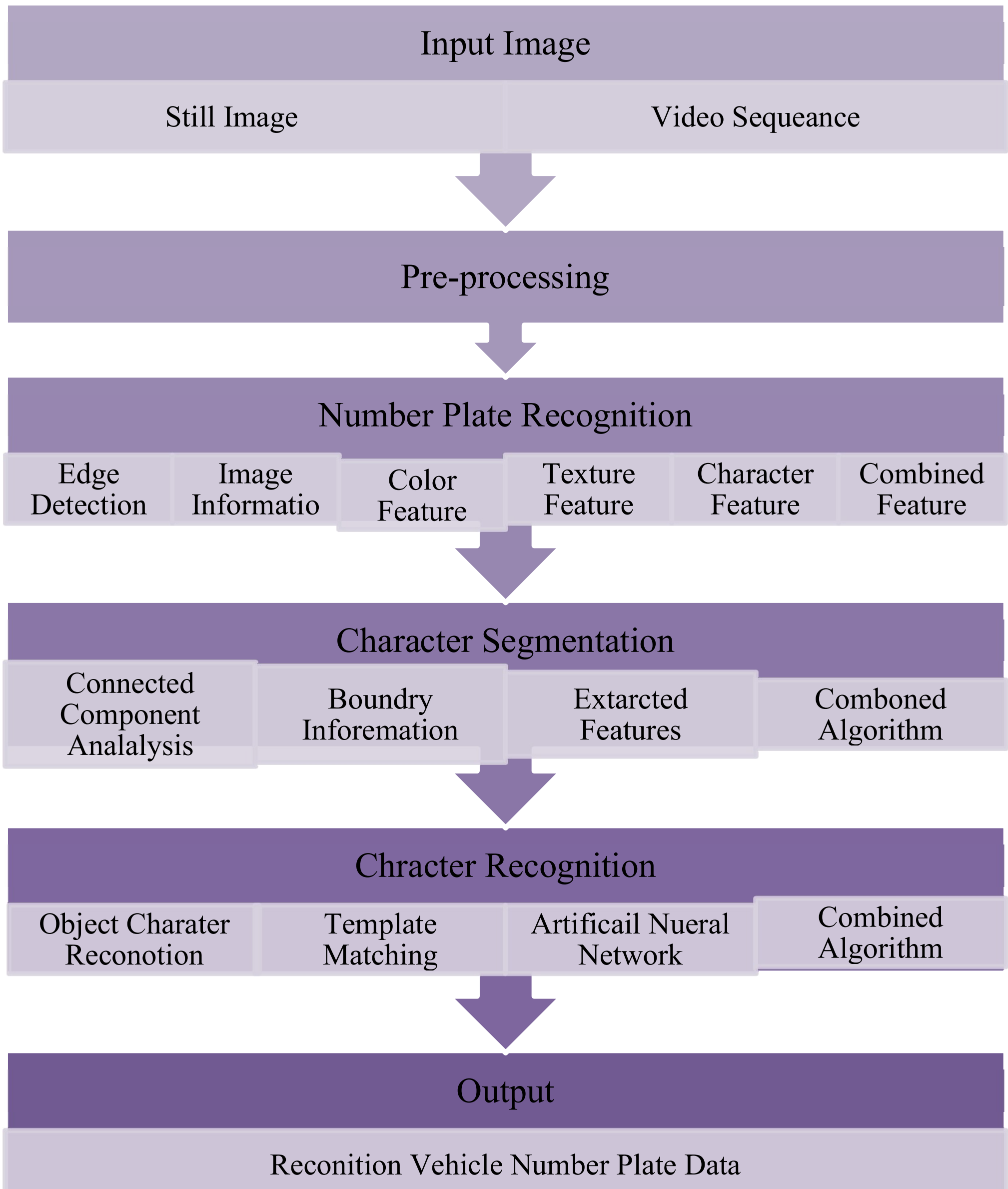

Figure 2. General processes of number plate recognition system

License Plate Detection-In this section, we'll talk about different ways to figure out where licence plates are in photos. A typical industrial ANPR system has a colour camera, a black-and-white camera, and an infrared (IR) projector that works in sync with the cameras. When there isn't a lot of light, the monochrome camera with an IR projector finds the plates. It's important to remember that for the IR projector to work, the licence plates of the cars should have been covered with things that reflect IR. When the exposure time of the camera is set correctly, infrared projectors can find dirty plates even during the day. The exposure time of the camera, which is the opposite of how strong the infrared projector is, has a lot to do with how clear the licence plates are. Since moving vehicles blur photos with long exposure times, and low exposure times make photos look dark. This means that the IR projector's output power needs to be changed based on how long the monochrome camera is open for. Also needed is an adaptive process that changes the exposure time in real time based on how much light is around. In an adaptive process that changes the exposure time, the thickness of the characters on the plate is used as feedback. Thin characters mean that there is a lot of light in the room. Because of this, exposure times have to be shorter. But if you want thick letters, that means there isn't much light around, so you'll need a longer exposure time to get a good picture. Steps for making changes depend on the situation and how they will be used, so they have to be found by doing. For example, at sunrise, the sun's rays will be reflected back at cars going from west to east. In this case, the exposure time should be cut down to a point where the reflections go away. For alleged traffic violations to be punished with fines there needs to be a colour camera at the scene. As was said in the introduction, there are many algorithms that can find the exact location of plates in an image. We have tried out most of the algorithms that have been suggested. None of the algorithms work if the plate is dirty or if there isn't enough difference between the characters and the background. Figure 1 and Figure 2 show what happens when the Hough transform and the vertical Sobel edge operator are used on a dirty plate and a clean plate, respectively.

Number In order to do Plate Recognition, pictures of licence plates in the target area are taken with a camera. A series of recognition algorithms based on image processing are used on the photos that have been acquired to turn them into text. This can be done with still photos or a video made up of photos. After getting a high-quality image of a scene or vehicle, an ANPR system relies heavily on how well its algorithms work. To get the results that are needed and take into account all system problems, these algorithms need a lot of analysis and millions of lines of software code. A core set of algorithms is needed for ANPR and other smart car technologies to work.

II RELATED WORK

Figure 2 shows the main steps that ANPR systems take. Input to an ANPR system is the collection of images, and outputs are NPE (number plate extraction), CS (character segmentation), and CR (character recognition) [9]. Once the vehicle has been correctly identified, the data can be retrieved and used for further processing as needed. Information from the cars is sent to the back office system software so that it can be used for data analysis, questions, and reports. Since ANPR systems not only take pictures of the vehicles but also store information about them in a central database, this information can be used for many other intelligent transportation applications. In addition to making a complete database of how traffic moves, this could also identify vehicles by marking them with the date, time, and exact location. The next step would be to use this information in models and analyses of different transportation networks.

Number Plate Recognition (NPR), Automatic License Plate Reading (ALPR), License Plate Reading (LPR), Automatic Vehicle Identification (AVI), and Car Plate Recognition are all names for the same thing (CPR) This report gives an in-depth look at how ANPR works right now. The article gives a summary of how ANPR systems work and looks at their pros and cons. This study aims to improve the state of the art in smart car technology for future academics by doing the following: • Giving a full understanding of ANPR algorithms from the past and the present Automatic number plate recognition (ANPR) has three main steps: number plate extraction, segmentation, and recognition. This section will analyse and present a survey of ANPR image processing-based techniques for each of these steps, along with a short explanation of how they work and a summary of their performance when it's relevant. The goal of this review is to: combine the results of different vehicle recognition algorithms that researchers have used and tested; combine the results of previous ANPR reviews and surveys; The goal of this part is to do a full evaluation of all the relevant literature up to this point. In this section, we put together information from studies and new developments in related fields of technology. What comes next is a talk about the latest changes and advances in the relevant technology. Christos-Nikolaos E. Anagnostopoulos [1] said in 2014 that despite a lot of research, the LPR problem has not been solved. (licence plate recognition). So, this paper will mostly be about image processing techniques that can help the young researcher learn more about this area and find good answers.

In 2013, Shan Du,Mahmoud [2] Automatic licence plate recognition (ALPR) is the process of reading licence plates and getting important information from a photo or series of photos. With or without a database, the extracted information can be used for many things, like electronic payment systems (for paying tolls or parking fees) and highway and arterial monitoring systems for keeping an eye on traffic. The ALPR uses different kinds of imaging technologies, such as colour, black-and-white, and infrared. The quality of the photos an ALPR takes is one of the most important parts of how well it works. In the real world, ALPR needs to be able to read licence plates quickly and accurately in a variety of settings, such as indoors, outdoors, during the day, and at night.

Sahil Shaikh [3] talks about how this new way of reading licence plates is presented. It uses a series of image processing steps to read licence plates. Four to six algorithms are used to get the same results. Plate localisation uses a variety of well-known ways to process images. As part of the extraction process, images are made better, unsharp masking is used to find edges, filters are applied, and component analysis is done. To get individual characters from a licence plate, you have to separate parts that are connected. Template Matching is in charge of the OCR process.

Norizam Sulaiman [4] an automatic licence plate recognition system has been made, which shows how image processing is used. The name for this system in general is Automatic Number Plate Recognition (ANPR). Automatic systems that read licence plates are used a lot in safety and security systems, especially in garages and parking lots. The main job of this technology is to keep the roads safe, but it is also used to keep track of things like vehicle speeds and licence plate numbers. The goal of this method is to help police solve cases where a car or motorcycle has been stolen. In this system, the main way to look at images of licence plates was with Optical Character Recognition (OCR). A big problem with this method was that the converted text or data was often wrong. Also, car plates in different countries have different numbers of characters, colours, and sizes. So, this research uses a combination of image processing and optical character recognition (OCR) to correctly recognise car plates on vehicles in Malaysia. The end result of the study is a system that can read licence plates reliably, even though they have different (and often different) colour schemes. As part of this research project, we are also making a graphical user interface (GUI) to read licence plates.

Reza Azad and Hamid Reza Shayegh [5] License Auto identification has a big effect on how parking is managed and how traffic is watched. In this study, we come up with a fast, real-time way to find plates that are tilted or not up to par. The proposed method starts with an adaptive threshold that changes the image to binary. Then, edge detection and morphological processes were used to figure out where the plate numbers were. The last step is to fix any tilt in the plate. When measured against another paper data set with images of the background from different distances and points of view, the correct plate extraction rate was 98.66%.

In the year 2013 Ronak P Patel [6] because automatic licence plate recognition (LPR) is so popular, many different ways to do it have been made. Most of them, though, were limited by things like constant lighting, slow-moving vehicles, set routes, and static scenery. As much as possible, we tried to simulate real-world conditions in our research.

Najeem Owamoyo [7] first made Automatic Number Plate Extraction, Character Segmentation, and Recognition for cars in Nigeria. Nigeria does not follow the rules for licence plates as it should. Each plate has characters that stand for a different state in Nigeria and a different level of government in that state. Due to the different ways that number plates can be shown, it is important to be able to extract, segment, and recognise them.

Sourav Roy and Joydeep Mukherjee [8] Presents a method for recognizing vehicle number plates based on a simple and effective morphological operation and the sobel edge detection method. This is the most interesting and difficult area of research in the last few years. We also show a simple way to separate the different letters and numbers on a licence plate. After reducing the amount of noise in the source image, our goal is to use histogram equalization to make the binary image have more contrast. We focus on two important steps: first, finding the licence plate, and then breaking the characters apart so that they can be read one by one.

Divya gilly and Dr. Kumudha Raimond [9] LPR technology, which was just introduced and is mostly used in parking lots, toll booths, and the signal system, makes it easy to find cars that cross the line before the green light turns on. This study shows how LPR can be used in the real world. This strategy uses a "template-matching" approach to reach its goals.

. Isack Bulugu [10] This article shows how to make plate numbers easier to read by getting rid of noise, making the image flat, and bringing out important details. Automatic Number Plate Recognition (ANPR) was first proposed by Rupali Kate [11] as a real-time embedded system that reads characters from a picture of a licence plate. This is a busy place for academic research. Researchers in many countries have spent a lot of time and energy on automatic vehicle identification and tracking (VNPR).

P.Kumaresan and Dr.S.A.K.Jil [12] has shown a way that licence plates can be used to identify cars in real time. This system would use image processing to separate the letters on a photo of a plate so that they could be read. Image processing and pattern recognition could help improve this RTVLPIS that has been streamlined.

Sharifi Kolou [13] Compare the accuracy, performance, complexity, and usefulness of a number of well-known LPD algorithms under different conditions. The results of this analysis can help designers and end users choose which method is best for their projects. Based on our research and analysis, we've found that the dynamic programming algorithm is the fastest and the Gabor transform is the most accurate.

Kumar Parasuraman and P.Vasantha Kumar [14], it has been shown that ITSs need to know where the licence plate is in order to be able to read it. The goal of this project is to come up with and use a practical way to recognise Indian licence plates. This is an effective way to find licence plates, break them up, and read the characters on them.

S. Hamidreza Kasaei, S. Mohammadreza Kasaei and S. AlirezaKasaei, [15] The Persian License Plate Detection and Recognition System is an image processing method that can be used to find a car's licence plate. This system is important because it could be used for things like automatic toll collection, enforcing traffic laws, and keeping restricted areas safe. In fact, it is a type of automatic inspection system for transportation, traffic, and security systems. For automated transportation systems to be able to read licence plates, licence plate location data must be very accurate. This work shows how morphology and template matching can be used in real time to make a licence plate identification system that is fast, accurate, and fully automated. In this method, the first step is to separate the licence plate from the digital image of the car that the camera took under different lighting, tilt, distance, and angle conditions.

[16] The results of research on a smart but simple algorithm for reading car licence plates are given. This method, which is based on matching patterns, can be used to recognise licence plates in real time, which can help with censuses and other projects that need to collect data. For the proposed system, C++ prototypes have been made, and test results for reading Alberta licence plates have been shown.

[17] People have said that the technology used to read licence plates on cars needs to be updated because traffic engineering and automation have gotten better. In this paper, we use a case study involving the identification of a photo of a car licence to show how automatic licence plate recognition works. We also describe in detail the steps needed to do this, such as pre-processing, edge extraction, licence plate location, character segmentation, and character recognition [17]. Suhan Lee's proposal from April 2013 says that recognising car models from photos is one of the hardest things to do to help intelligent transportation systems. The solutions we have now only work for vehicles that are stopped in the line of sight. Still, videos have rotation, which makes it harder to recognise things. To fix this, we need a way to fix the way the skewed point of view makes things look wrong.

[18]. As was already said, automatic identification and recognition of vehicle licence plates is a key part of many traffic-related applications and a hot topic of research in the field of image processing. There are many ways, strategies, and algorithms that can be used to find and read licence plates today.

[19]. advocated for a full system that could identify and track moving vehicles and read their licence plates. It has a part that can read characters, a part that can read licence plates, and a detector that can find vehicles that are moving. Here, we use a Gaussian mixture model to estimate the background, and we propose a block variance-based method for reliably extracting licence plates in real time. Autonomous vehicle licence plate identification depends a lot on the next step, which is getting the plate from the vehicle's licence data. Using a method based on the region, the characters that make up the licence plates are taken apart. Changes in lighting don't affect this method, and it can handle differences in character size, thickness, skew, and even small character breaks with little to no loss in readability. One of the best things about our system is that it can work in real time and doesn't need any other sensors (like infrared sensors) to work.

[20] argued that most interpolation methods used in the past to turn a low-resolution video into a high-resolution one make the video look blurry. Blurring an intra frame of a video makes it lose some of its fine details and important information about the edges. Because of this, we offer a hybrid interpolation method that works well and doesn't depend on data from outside sources. The suggested method combines an anticipatory, spatial domain, region-adaptive unsharp masking operation with a discrete cosine transform-based interpolation method. This helps keep some of the finer details and important edge information in the reconstructed video frame. presents a new method for removing the background that is based on sigma-delta and is designed for use in traffic scenes in cities with lots of people. The original sigma-delta method is an interesting alternative because it is very good at computing. But in complicated urban settings, the backdrop model quickly breaks down because cars that move slowly or stop for a short time can "pollute" the scene. The foreground detection mask then needs to be improved through more foreground validation steps. The suggested method aims to create a more stable background model by giving each pixel a confidence score. This way, no extra processing steps or algorithms with higher computational costs are needed. This measure of certainty can be used to update a chosen background model one pixel at a time. The proposed algorithm's benefits are shown by comparison tests and a quantitative evaluation of how well it works in typical urban traffic situations.

III NUMBER PLATE EXTRACTION METHODS

The first and most important step of ANPR systems is getting the number plates out of the image or video. The extraction rate is a way to measure how well licence plates can be extracted from a set of photos or cars in a given scenario. Every lane has its own camera, but high-definition models may be able to watch many lanes at once. Installing more than one lane means that more expensive readers are needed to read the licence plates of passing cars. In real-life situations, there are many things that could go wrong. For example, a stationary camera might take pictures of a car with the letters on the licence plate tilted or skewed. The number plate could be dirty, broken, or hard to reach (since different types of vehicles have their number plates affixed at different positions of the vehicle body). Light, blurry motion, reflections, fog, and other things make it hard for the system to read the licence plate. Number plate extraction algorithms that rely on geometric features may have trouble if several identical shapes have been painted or stuck onto the body of the vehicle. Other algorithms are needed in addition to rectangular features to get rid of clutter. The algorithms have to be reliable enough to separate the licence plate from the background. Researchers have used a wide range of attributes to find licence plates. In the next section, we'll take a quick look at a few different ways to pull out features.

A-NP Extraction Using Edge Information

The standard shape of a number plate is a rectangle with a clear aspect ratio. Before any more work was done, all of the photos in [21] were resized so that they all had the same aspect ratio. The authors used several techniques from previous research proposals [22] and compared how well they worked on their own dataset. In one of the tested ways to get licence plates, the information about the vertical edge was used. The Sobel operator is used to find the edges that go up and down. By comparing the extracted edges to a minimum and maximum length that has already been set, we can find exactly where the licence plate is. [23] said that the extraction rate was 99.99 percent, but the real rate for 141 images is only 65.25 percent. In [24], information from both the vertical and horizontal edge histograms is used to pull out licence plates. When tested on 50 photos with a range of fonts and lighting, the accuracy of extraction was 90%. Edge detection algorithms are usually used to find and analyses all the rectangles in the collected data when licence plates are being extracted. Most of the time, there is a clear change in colour between the car's body and the area where the licence plate is. Filters or algorithms for edge detection are used to tell the difference between the two. Using a simple method called the Sobel filter, as shown in [25], edge extraction can be done with little trouble. When detecting edges, you can use vertical edge detection to get the vertical lines and horizontal edge detection to get the horizontal lines, or you can use both at the same time to get a complete rectangular shape. Rectangle lines on the licence plate can be used to figure out its location by figuring out its shape. Different filters to find the edges In [26], comparisons are made between the Sobel, Canny, Gabor, and Log-Gabor filters used in ANPR systems.

B-NP Extraction Using Global Image Information

As part of binary image processing, pixels are looked at to see how they connect, and then based on how they connect, they are labelled as parts .In [27], they use spatial metrics like aspect ratio and area to get the number plates. In particular, [28] showed how to get licence plates in two steps. In the first phase, the changing light conditions are handled by Otsu's Threshold Method, which is a powerful yet simple adaptive thresholding method. The CCA method is used to find square or rectangular shapes in an image after it has been turned into two colours. In the second step, edge detection and the closed curve approach are used on the data that was collected to make sure that the image that was made is a number plate. When tested with more than 2500 images in the Moroccan format, this method worked 96 percent of the time for video sequences. With a success rate of 96.6 percent, the linked component analysis method described in [29] was able to pull out a nearly four-hour-long low-quality movie. With contour detection methods, binary images can be used to find the things that go together [30]. The geometric parts of a licence plate are chosen for processing based on how much they look like the plate as a whole. But if the image that is taken isn't very good, this method could cause problems with distortion. Cross correlation in [31] is used for the same reason. The 2D cross correlation is done while using a number plate template that has already been saved to find the number plate region. But because it takes so long, it's not a popular choice.

C-NP Extraction Using Color Features

In some countries or regions, licence plates may have to be a certain colour. In addition to looking at work that had already been published, we put ANPR systems to the test by using colour to pull number plates out of images. In short, the idea of combining the colours of the plates is the key to the general method of getting information from licence plates. Also, these colour differences only happen in the plate region, which makes the features stand out. came up with a method based on the unique designs on Chinese licence plates. All of the pixels from the images they collected were used in their method. The pixels were then sorted by things like hue, brightness, and saturation (HLS). In the HLS colour model, there are 13 different colour groups instead of the six in the RGB model. Grayscale was left out in favour of a system based on colour. Standards for licence plates on the Chinese mainland were used to choose the colour scheme. They found that 90% of photos could be correctly identified in any kind of light. Black, green, white, and red are the only colours used to read licence plates in [32], and colour edge detectors can only pick up on those three colours. Seven of the 35 sensors are green-white, seven are red-white, and seven are black-white. As part of the experiment, about 1088 photos from different situations were looked at. The accuracy of number and colour plate location is 97.9%. After converting the original colour image to a hue, saturation, and lightness (HLS) colour model, the colours of each pixel in [33] are put into groups using a neural network. The neural network thinks that the colours of Korean licence plates are white, green, and red. The number colour plate shows the area with the most colours by making horizontal and vertical projections of the same colour combination.

D-NP Extraction Using Texture Features

The way this method works depends on the information on the licence plate. As shown by the grey scale, there is a big difference in tone between the colours of the characters and the colours of the plate's background. Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG) are used by [34 to read licence plates. Keeping in mind that the number plate is rectangular, we can use the LBP method to classify the texture and the HOG method to get a histogram. With 89.7 percent accuracy, find 110 photos. But this method doesn't work for photos that are blurry, dark, or turned in an odd way. Sensors for 2021, the 21st century, and the 3028th century 8 of 35 Using a line weight density map to find plates is another reliable method that has been used in many studies. This can be used in tandem with other methods for even better outcomes. Using a scan line technique, the peaks are made by the change in colour of the grey scale level, which is related to the number of letters on the licence plate (for more information, see [35] The authors of came up with the idea of using horizontal line scanning with different thresholds to find plates in real time or complex images. The traditional model based on Hough transforms was compared to the experimental results. The traditional model had a detection accuracy of 69.8% and took 8–10s to process (see [58] for details). When we look at [36]we can see that when the line scan method is used, the extraction rate is 99.2%. Now, it only takes 0.3–0.5s to find the plate, which is a huge improvement.

E-NP Extraction Using Character Features

Character feature extraction has been used in a lot of studies to come up with ways to figure out what characters are on a plate. This is how the picture is looked at to see if there are any characters on the licence plate. When the necessary characters have been found, the number plate region is taken out. The method in [37] finds all the character areas in the image before applying the number plate attributes. This process is done with the region-dependent technique, which looks like characters. There is a list of all the character-based regions, and a neural network is used to put them into groups. About 30 of the picture's pixels are labeled, and the ratio of the binary image objects to the characters in 38] is the same. With the help of Hough's transformation, it is possible to find straight lines. The same change is made to both the top and bottom parts of these objects with binary labels. The number plate area is the space between two parallel lines that fits within a certain range and has the same number of objects as the characters. Scale-space analysis is used in [39] to figure out what the information on licence plates means. This method is used to get out big shapes that look like blobs and smaller shapes that look like lines. [40] starts by separating the areas that have characters by character width and contrast between the character area and its background. Then, the process for removing licence plates is done in the plate area, and the distance between characters is measured. This method can be used to get an extraction accuracy of about 99.5%. For the first step in classifying characters, the first-stage classifier in [41] makes a list of all possible regions that look like characters. After that, the set of data is sent to a second-stage classifier. In the second step of the classifier, blank spaces are taken out of the original data set. In this method, the first stage classifiers are a set of 36 AdaBoost classifiers. In the second stage, the Scale-Invariant Feature Transform (SIFT) algorithm is used to train a classifier called Support Vector Machine (SVM) to recognise and describe local parts of number plate images. It takes a long time to figure out where a number plate is by extracting features from binary images. That's because it's hard to keep track of so many different things in such small binary pictures. If the image also has other words on it, these steps will fail even more often.

F-NP Extraction Using Feature Learning

Few extraction methods look at more than one property of the licence plate, which is what is needed for effective detection. These methods of extraction are examples of hybrid methods of extraction.This paper uses You Only Look Once (YOLO), an object detector based on a Convolutional Neural Network (CNN) that was made in [42]. It's a two-step process that uses simple data augmentation methods like reading characters backwards and licence plate numbers. At every step, the CNNs are trained and fine-tuned. The final model works well on two different sets of data that have nothing to do with each other. The first database from the Smart Surveillance Interest Group (SSIG) is called SSIG-SegPlate Database. The system does a much better job than the commercial systems OpenALPR and Sighthound, which have recognition rates of 93.3% and 89.80%, respectively. It also does a much better job than the older techniques [43] which are only accurate to 81.80%. Just like in the real world, the other dataset includes images from a wide range of situations. This open-access library is called UFPR-ALPR, which is an acronym. Researchers from the Federal University of Paraná in Brazil put together the UFPR-ALPR data set, which is now kept in the VRI Laboratory. About 4500 still pictures and 150 short video clips were all taken by the camera as the cars drove by. The data set has information about buses, motorcycles, cars, and trucks. This system works well with 35 FPS and an identification rate of 78.33%, while test versions of commercial systems had recognition rates of less than 70%.[44] were able to improve the accuracy of NP recognition by combining character recognition and segmentation with Hidden Markov Models (HMMs). In this case, the Viterbi method was used to find the most likely NP.

G-Number Plate Segmentation Methods

The next step, "character segmentation," depends on being able to pull licence plates out of a scene or image. There might be a problem with the contrast, lighting, or angle at which the single licence plate is shown. Depending on how the licence plate was taken, more processing steps like de-skewing, de-blurring, or other methods may be needed before the characters can be separated. Depending on the strategy chosen, this can happen either during the extraction process or after a possible region has been separated. use a preprocessing technique called bilinear transformation to deal with crooked images of licence plates. In this case, the isolated number plate is turned into a more typical, upright rectangle.

In [45], both the vertical and horizontal tilts of licence plates are fixed using the least squares method. The Karhunen-Loeve (K-L) transformation is used to change the character coordinates in [46] into a 2D variance matrix. Next, we use the rotation angle and Eigenvectors to make up for both vertical and horizontal image tilt. Some ways to figure out the vertical tilt angle are the K-means cluster based line fitting, the least squares based line fitting, and the K-L transform. Even though the "threshold application" part of the process of converting a binary image may seem simple, it is actually a very difficult step. If the threshold value is wrong, it can be hard to separate characters that are connected, either within characters or with the number plate frame.Because there are so many different camera settings and lighting conditions, a single threshold value might not work for all of the photos. Before binarization, the picture needs to be improved. Image enhancement could mean anything from getting rid of noise to making the contrast stronger to using histogram equalization techniques. In [47], a way was shown to find the licence plate. Then, the plate was improved by changing it from grayscale to colour, all with the goal of using gradient analysis across the whole image. The Niblack binarization method in [49] changes the picture threshold based on the standard deviation and the local mean. In [48], each individual pixel uses the local threshold method. The threshold is found by taking the average grey levels in a window centred on the pixel and subtracting the given constant value. In [50], a new way to cut down on background noise and make the text stand out was given. In this case, it was thought that each character would take up about 20% of the space that the number plate used. First of all, the levels of the greyscale are between 0 and 100. Then, the pixels are made 20 percent bigger by scaling them up by a factor of 2.55. Characters stand out more, and background noise is toned down.

H-NP Segmentation Using Vertical/Horizontal Projection

The letters and background on a licence plate stand out from each other. In the final binary representation of the licence plate, the character and the background each have their own value. can separate text into its parts by projecting pixels in both the vertical and horizontal planes. are some examples of works that use projection techniques. On the binary number plate, vertical projection is used to figure out where letters start and end, and then horizontal projection is used to separate them. In [51], both noise-reduction analysis of the character sequence and vertical projection are used to pull out the characters. This method can process more than 30,000 photos in 10–20 milliseconds with a 99.2% accuracy rate. The 560 photos in the database are used to test the method described in [53] for profile projection. We were able to get a 95.4 percent segmentation rate by using how well they could find multiple number plates in a single image. After giving it a lot of thought, we've decided that the easiest and most common way to do it is to use both horizontal and vertical pixel projections. Since projection techniques don't depend on where the characters are, they could be useful for segmenting characters. Still, you'll need to know ahead of time how many characters there are. The projected values may be affected by the quality of the image and the noise in the background.

Table 1. Performance Summary of ANPR system techniques.

	Procedure		Database	Image Condition	Extraction Rate	Segmentation Rate	Overall Recognition Rate	
	Extraction	Segmentation	Recognition					Problem Areas
[54]	Otsu Adaptive thresholding, CCA, Edge Detection-Canny	Closed curves	Template Matching	Set 1: 533 Set 2: 651 Set 3: 757 Set 4: 611 (Video Sequences)	Various situations with different Light Conditions	Set 1: 96.37% Set 2–4: 96.06%	Set 1: 98.1% Set 2: 96.37 % Set 3: 93.07 % Set 4: 92.52 %	—

	Procedure		Database	Image Condition	Extraction Rate	Segmentation Rate	Overall Recognition Rate	
	Extraction	Segmentation	Recognition					Problem Areas
[55]	Edge statistics and morphology techniques	Bounding box	Template Matching	9745 images	—	98%	82.6%	Not suitable for different orientations.
[56]	Used provided Images	—	HOG feature and Extreme Learning Machine	69 images, 45 images used as trainers, 5 classes	Low resolution portion of the image, 15–18 px height	—	90%	Day time only, no license localization process is applied.
[57]	Morphology Techniques	Region props bounding box using Matlab	Template Matching	30 images	Low brightness, contrast	92%	98%	—
[58]	Histogram Analysis using HOG	Vertical Histogram	OCR – Template Matching	110 images	Various Conditions	89.7%	—	Cannot detect beyond 30-degrees horizontal/ vertical angle, if

	Procedure		Database	Image Condition	Extraction Rate	Segmentation Rate	Overall Recognition Rate	
	Extraction	Segmentation	Recognition					Problem Areas
								the car is moving (image blur) or there is low light
[59]	Object detection, CNNs—(YOLO Detector)	Character Segmentation CNNs, Bounding box	Data augmentation, Distant CNNs for letter and Digits	SSIG Dataset: 2000 Frames, UFPR-ALPR: 4500 Frames	1920 × 1080 pixels	SSIG: 100.00 % UFPR-ALPR: 98.33%	SSIG: 97.83 % UFPR-ALPR: 90.37 %	Adjustments have to be made for other than Brazilian formats. Dependent on license plate layout.
[60]	Cascade classifier with LBP features (Local Binary Pattern)	—	Tesseract's OCR	1300 images	640 × 480 pixels with 50 × 11pixels aspect ratio of license plate, variou	98.35%	92.12 %	Dependent on standardization for detection too, overall accuracy is for front side license plate only at fixed 90d angle, High

	Procedure		Database	Image Condition	Extraction Rate	Segmentation Rate	Overall Recognition Rate	
	Extraction	Segmentation	Recognition					Problem Areas
					s conditions			processing time.
[61]	LBP, Character and edge information	Vertical Histogram	Tesseract OCR with preprocessing techniques	1200+ images	250 pixels wide, Various conditions and colors	100%	90%	High processing time.
[62]	Vertical and horizontal edge histograms	Connected component labeling and morphological method	Statistical features matched with stored ones	50 Images	Variable size and style, Latin script only	90%	93%	Very Limited dataset tested
[63]	Image resizing using nearest neighbor interpolation, Preproc	CCA labelling and morphological operations	OCR algorithms	958 images	HD images, various conditions	98.10%	99.50 %	Computationally intensive cost, HD camera used—memory and time constraints

	Procedure		Database	Image Condition	Extraction Rate	Segmentation Rate	Overall Recognition Rate	
	Extraction	Segmentation	Recognition					Problem Areas
	essing and geometrical conditions							
[64]	—	Preprocessing techniques, Otsu's Thresholding	Bounding box feature and template matching OCR	14 images	8 mp camera, different timings and distances	—	—	Limited set of images, cannot recognize low quality images, works for standardized format only

IV METHODOLOGY

Automatic Number Plate Recognition (ANPR) can only work with the help of image processing technology. It is one of the things that the vehicle needs to be able to see the range plate. In today's world, there are so many different kinds of cars that it would be hard to keep track of them all by hand. Because of this method, it is now easy to keep a record and use it when needed. The main goal of this project is to use licence plate readers to make an automatic vehicle identification system that is both cheap and effective. When the car first gets to the checkpoint, the system will take a picture of how the car looks at that moment. After that, a method called "victimization segmentation" is used to get the photos that were taken. Optical character recognition is used to figure out what each character is. Then, the information that was gathered is compared to what was already in their info.

The goal of this thorough review is to give an overview of the unique machine-learning and deep neural network method that is used to identify Automatic License Plate Recognition based on photos. Information-gathering

Searched databases

We used the five databases Science Direct, Scopus, Springer, the Association for Computing Machinery (ACM), and the Institute of Electrical and Electronic Engineers (IEEE) to do this review of the relevant literature (IEEE Explore Digital Library). For the purposes of this poll, the range of time was set at 2015 to 2020.

Searched Terms:

For survey of papers, following search expression was defined: ("Convolutional Neural Network" OR "Machine Learning" OR "Artificial Neural Network" OR "Deep Learning") AND ("Automatic range Plate Recognition " OR "Plate Recognition" OR "machine learning based techniques Classification"" Title;Authors;Affiliation;Address;Email;Abstract;Keywords; and Publication Note")

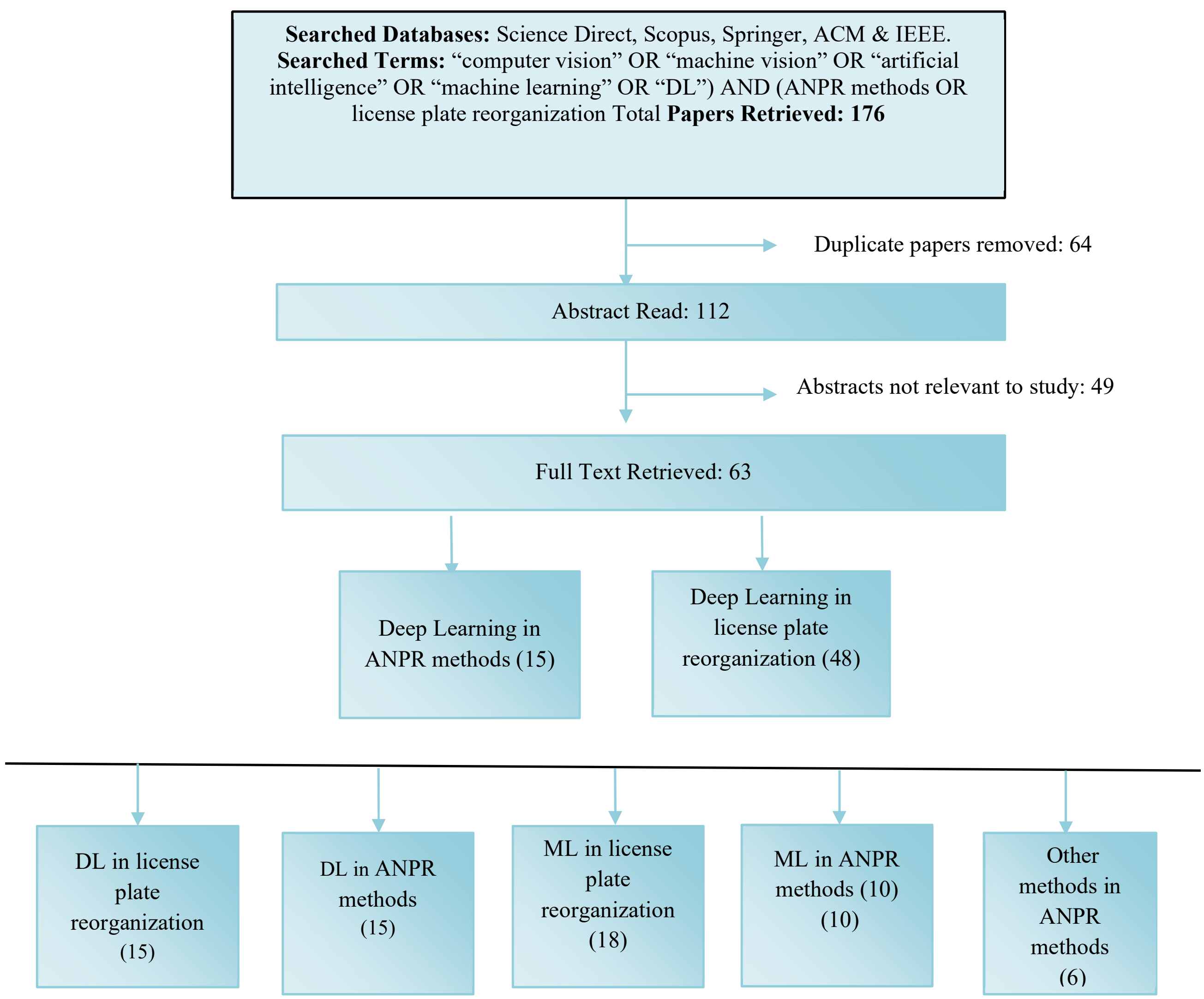

Figure 3 : Research Methodology Flow

Inclusion criteria:
In order to find the paper that meets the criteria given, the first part of the selection process was to look at the titles and abstracts of the papers. The second part was to get rid of any papers that were already there.

Exclusion criteria
Papers that are not specifically dealing with Automatic range Plate Recognition techniques using deep learning/CNN were excluded from the study.

Data Analysis
After selecting more than 50 papers found to be suitable for the review data analysis has been done by keeping following points into consideration:

Year of Publication
In the last few decades, researchers have paid more attention to how CNN/Deep Learning can be used for Automatic License Plate Recognition. If you know when the book came out, you can figure out why people are interested in it again.

Purpose of the study In the study, different kinds of work were done for different keywords, such as Title, Authors, Affiliation, Address, Email, Abstract, Keywords, and Publication Note. Some of the reasons why these tasks were done were to classify, divide, and do other similar things. How deep learning is put together

Deep learning architectures A plan for a system that can automatically read licence plates is shown. Several types of Automatic License Plate Recognition have used different neural networks, such as Deep Neural Networks, Convolution Neural Networks, and Recurrent Neural Networks. The current ANPR methods do a great job with photos that have a lot of contrast and a lot of light, but they have trouble with low-contrast, blurry, noisy images.

V PUBLICS DATASET

Table 2 shows some of the image data sets that can be used to test ANPR algorithms on both public and commercial vehicles. Scholars find a lot of value in these databases, and many people use them, as long as they give credit. Researchers can use these photos to figure out how well their algorithms work. These databases are made up of a lot of photos taken in real time in different places. Backgrounds, lighting, environmental factors, plate location, physical factors, size, style format, and possible latency all affect how different these photos and movies are. Some of them have both commercial and open-source versions. The open-source ones often use different OCR algorithms based on larger datasets to improve accuracy.
Table 2 ANPR Datasets available to the research community.

Datasets	Size (1 k = 1000)	Version and Availability 2
Sighthound	Over 3 million images	Open source Commercial Publicly available to the research community
ImageNet	Over 14 million images	Publicly Available
UFPR-ALPR	4.5 k images	Non-commercial use only Available on request for academic purposes
CompCars, CCPD: Chinese	136.7 k images	Open source under MIT license
City Parking Dataset, City Parking Dataset	250 k unique images	Open source under MIT license
Make and Model Recognition	291.7 k images	Latest versions of dataset can be provided upon request
Make and Model Recognition	291.7 k images	publicly available to the research community Latest versions of dataset can be provided upon request
Cars Dataset by Stanford	16.1 k Images	Publicly available for research purpose only
Oriented License Plate Recognition	2 k images	Non-commercial Research purposes only images Available with attributions
GTI: Grupo de Tratamiento de Imágenes	3.4 k with vehicles while 3.9 k without vehicles in scene, 4000 from other sources	Publicly Available

VI CONCLUSIONS AND FUTURE RESEARCH

This paper gives a full review of the ANPR algorithms that have been suggested and tested in recent studies that are relevant. We put these algorithms into groups based on the characteristics that are needed at different stages of the recognition process. Each step is broken down into its individual parts and given a full performance review, along with any concerns or problems that need to be addressed. But if the datasets being compared aren't the same, it's impossible to evaluate and compare them in the same way, as we'll see below. Because ANPR systems depend on complex optical, processing, and digital capabilities, it may take a long time for licence plates to be recognised. The ANPR solutions on the market right now don't offer a standard set for all countries. Instead, each company needs to be given a system that works well in different parts of the world. This is because the system that has already been made isn't good enough. Instead, it needs to be designed for the area where it will be used, taking into account all of the things that will affect it. OCR engines are often made to fit the needs of a certain country. The camera's library or engine, which comes with it, needs to be checked to see if it can recognize the necessary countries. Every ANPR solutions system that a vendor sells has its own unique set of pros and cons. The best of these is the one that meets the needs of the area with a system that has been shown to have an effect on the way things are in that area. In the years to come, researchers in the field of ANPR will face a number of problems. One of these problems is the need to work on making algorithms that work better for formats that are not standardised, no matter where they are used. Also, all suggested and built algorithms need to be tested to see how well they work in real-time situations, not just on pictures that have already been taken. Also, the system needs to have high-resolution cameras so that strong algorithms can be used to cut down on processing times and improve the ability to recognise things.

Together, the similarities and the problems make it easy for the optical character recognition system to be fooled. This can happen if the picture is taken from more than one angle or if there is a tiny tilt, broken letters, different typefaces, snow or dirt on the characters, or if the letters are broken. In the end, it is strongly suggested that the proposed algorithms be tested in a variety of real-world situations, such as moving vehicles, fast speeds, low contrast, poor or too much lighting, and real-time situations. Recent advances in deep learning have made it possible for computer vision systems to be used in a wide range of new ways. These uses include autonomous driving that is safe, accurate object recognition, and the automatic reading of images in a number of different settings [174]. Other real-time object detectors, like YOLO, can be trained and tested to work with this system [175]. A lot of people in the tech world are interested in the Android platform, and a lot of apps are being made just for it. Many researchers have come up with ideas for ANPR systems that are based on android platforms. But their performance is very limited, and they can only do a few things. These are things that could be made better in the future so that a phone-based system for identifying cars could be a little more accurate.

Some of the challenges for the future are memory resources, using Global Positioning System coordinates for geo-tagging, and using online databases for specific applications. In addition to ANPR systems that use image processing, RFID-based vehicle verification systems are becoming more common and are being used in many countries for different transportation-related purposes. Radio frequency identification, which is based on vehicle recognition, is another way to keep track of cars and find out where they are. Even though it does something on the road that is similar to what an image processing-based ANPR identification system does, it is called something else. RFID technology has been shown to be a good way to solve a number of tracking and localization problems, especially those that are more common in systems that use image processing. The most difficult and time-consuming part of CS/ML-based ANPR systems is getting the licence plate number from the environment. However, this is also the most important part of the recognition process. During the process of using RFID for extraction and identification, this technology could be used to find cars that were missed, which would help the ANPR. RFID technology also makes it possible to check the speed of a vehicle. With RFID technology, the car can be tracked no matter where it is or whether it is in or out of the camera's line of sight. This is true no matter where the camera is. Depending on the type of RFID technology that is used, the car can be easily tracked wherever it goes on the road for the whole trip. RFID also makes it possible to pay tolls with the card. In a nutshell, it is needed for radio frequency identification (RFID), but cameras are needed for automatic number plate recognition (ANPR) systems that use image processing. RFID doesn't need a camera and can talk to a tag on a moving vehicle. This gets rid of a lot of the problems that come with technologies that rely on cameras. Combining image-processing-based Automatic Number Plate Recognition (ANPR) technology with RFID technology may be useful in a number of road-related situations and may make the system work better,

REFERENCE

1. Intelligent Transportation Systems Magazine IEEE, Vol.6, Issue.1, pp.59 – 67, 2014.
2. Shan Du,Mahmoud Ibrahim,Mohamed Shehata and Wael Badawy, "Automatic License Plate Recognition (ALPR):A State-of-the-Art Review", IEEE Transactions on Circuits & Systems for Video Technology, Vol. 23, Issue.2, pp.311-325, IEEE 2013.
3. Sahil Shaikh, Bornika Lahiri, Gopi Bhatt and Nirav Raja,"A novel approach for Automatic Number Plate Recognition", International Conference on Intelligent Systems and Signal Processing (ISSP), pp.275 – 380, IEEE 2013.
4. Norizam Sulaiman, "Development of Automatic Vehicle Plate Detection System", 3rd International Conference on System Engineering and Technology, pp.130-135, IEEE 2013.
5. Reza Azad and Hamid Reza Shayegh," New Method for Optimization of License Plate Recognition system with Use of Edge Detection and Connected Component",3rd International Conference on Computer and Knowledge Engineering (ICCKE 2013), pp. 21 – 25, IEEE 2013.
6. Ronak P Patel, Narendra M Patel and Keyur Brahmbhatt,"Automatic Licenses Plate Recognition", International Journal of Computer Science and Mobile Computing (IJCSMC) , Vol. 2, Issue. 4, pp.285 – 294, 2013.
7. Najeem Owamoyo, A.Alaba Fadele and Abimbola Abudu, "Number Plate Recognition for Nigerian Vehicles", Academic Research International Journal (ARIJ), Vol.4, Issue.3, pp.48- 55, 2013.
8. Sourav Roy, Amitava Choudhury and Joydeep Mukherjee, "An Approach towards Detection of Indian Number Plate from Vehicle", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol.2, Issue.4, pp.241 – 244, 2013.
9. Mukt Shabd Journal Volume IX, Issue V, MAY/2020 ISSN NO : 2347-3150 Page No : 1509
10. Luo, X.; Ma, D.; Jin, S.; Gong, Y.; Wang, D. Queue length estimation for signalized intersections using license plate recognition data. IEEE Intell. Transp. Syst. Mag. 2019, 11, 209–220. [CrossRef]
11. Lin, H.Y.; Dai, J.M.; Wu, L.T.; Chen, L.Q. A vision-based driver assistance system with forward collision and overtaking detection. Sensors 2020, 20, 5139. [CrossRef] [PubMed]

12. Thangallapally, S.K.; Maripeddi, R.; Banoth, V.K.; Naveen, C.; Satpute, V.R. E-Security System for Vehicle Number Tracking at Parking Lot (Application for VNIT Gate Security). In Proceedings of the 2018 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 24–25 February 2018; pp. 1–4.
13. Negassi, I.T.; Araya, G.G.; Awawdeh, M.; Faisal, T. Smart Car plate Recognition System. In Proceedings of the 2018 1st International Conference on Advanced Research in Engineering Sciences (ARES), Dubai, United Arab Emirates, 15 June 2018; pp. 1–5.
14. Kanteti, D.; Srikar, D.; Ramesh, T. Intelligent smart parking algorithm. In Proceedings of the 2017 International Conference on Smart Technologies For Smart Nation (SmartTechCon), Bengaluru, India, 17–19 August 2017 ; pp. 1018–1022.
15. Shreyas, R.; Kumar, B.P.; Adithya, H.; Padmaja, B.; Sunil, M. Dynamic traffic rule violation monitoring system using automatic number plate recognition with SMS feedback. In Proceedings of the 2017 2nd International Conference on Telecommunication and Networks (TEL-NET), Noida, India, 10–11 August 2017; pp. 1–5.
16. Chaithra, B.; Karthik, K.; Ramkishore, D.; Sandeep, R. Monitoring Traffic Signal Violations using ANPR and GSM. In Proceedings of the 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), Mysore, India, 8–9 September 2017; pp. 341–346.
17. Felix, A.Y.; Jesudoss, A.; Mayan, J.A. Entry and exit monitoring using license plate recognition. In Proceedings of the 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), Chennai, India, 2–4 August 2017; pp. 227–231.
18. . Du, S.; Ibrahim, M.; Shehata, M.; Badawy, W. Automatic license plate recognition (ALPR): A state-of-the-art review. IEEE Trans. Circuits Syst. Video Technol. 2012, 23, 311–325. [CrossRef]
19. Birgillito, G.; Rindone, C.; Vitetta, A. Passenger mobility in a discontinuous space: Modelling access/egress to maritime barrier in a case study. J. Adv. Transp. 2018, 2018, 6518329. [CrossRef]
20. . Alonso, B.; Pòrtilla, Á.I.; Musolino, G.; Rindone, C.; Vitetta, A. Network Fundamental Diagram (NFD) and traffic signal control: First empirical evidences from the city of Santander. Transp. Res. Procedia 2017, 27, 27–34. [CrossRef]
21. Croce, A.I.; Musolino, G.; Rindone, C.; Vitetta, A. Route and Path Choices of Freight Vehicles: A Case Study with Floating Car Data. Sustainability 2020, 12, 8557. [CrossRef] 13. Nuzzolo, A.; Comi, A.; Papa, E.; Polimeni, A. Understanding taxi travel demand patterns through Floating Car Data. In Proceedings of the 4th Conference on Sustainable Urban Mobility; Springer: Skiathos Island, Greece, 24–25 May 2018; pp. 445–452.
22. PlateRecognizer. Plate Recognizer ALPR. Available online: https://platerecognizer.com/ (accessed on 25 November 2020).
23. ParkPow. a division of ParkPow. Available online: https://parkpow.com/ (accessed on 25 November 2020). Sensors 2021, 21, 3028 29 of 35

24. . Kyaw, N.N.; Sinha, G.; Mon, K.L. License plate recognition of Myanmar vehicle number plates a critical review. In Proceedings of the 2018 IEEE 7th Global Conference on Consumer Electronics (GCCE), Nara, Japan, 9–12 October 2018; pp. 771–774.
25. Chou, J.S.; Liu, C.H. Automated Sensing System for Real-Time Recognition of Trucks in River Dredging Areas Using Computer Vision and Convolutional Deep Learning. Sensors 2021, 21, 555. [CrossRef] 18. Bakhtan, M.A.H.; Abdullah, M.; Abd Rahman, A. A review on license plate recognition system algorithms. In Proceedings of the 2016 International Conference on Information and Communication Technology (ICICTM), Kuala Lumpur, Malaysia, 16–17 May 2016; pp. 84–89.
26. Ahmad, I.S.; Boufama, B.; Habashi, P.; Anderson, W.; Elamsy, T. Automatic license plate recognition: A comparative study. In Proceedings of the 2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), Abu Dhabi, United Arab Emirates, 7–10 December 2015; pp. 635–640. [CrossRef]
27. Zheng, D.; Zhao, Y.; Wang, J. An efficient method of license plate location. Pattern Recognit. Lett. 2005, 26, 2431–2438. [CrossRef]
28. Ashourian, M.; DaneshmandPour, N.; SHARIFI, T.O.; Moallemb, P. Real time implementation of a license plate location recognition system based on adaptive morphology. Int. J. Eng. 2013, 26, 1347–1356. [CrossRef]
29. Hongliang, B.; Changping, L. A hybrid license plate extraction method based on edge statistics and morphology. In Proceedings of the 17th International Conference on Pattern Recognition, Cambridge, UK, 26 August 2004; Volume 2, pp. 831–834.
30. Haider, S.A.; Khurshid, K. An implementable system for detection and recognition of license plates in Pakistan. In Proceedings of the 2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT), Karachi, Pakistan, 5–7 April 2017; pp. 1–5.
31. Farhat, A.A.; Al-Zawqari, A.; Hommos, O.; Al-Qahtani, A.; Bensaali, F.; Amira, A.; Zhai, X. OCR-based hardware implementation for qatari number plate on the Zynq SoC. In Proceedings of the 2017 9th IEEE-GCC Conference and Exhibition (GCCCE), Manama, Bahrain, 8–11 May 2017; pp. 1–9
32. Yepez, J.; Ko, S.B. Improved license plate localisation algorithm based on morphological operations. IET Intell. Transp. Syst. 2018, 12, 542–549. [CrossRef]
33. Hommos, O.; Al-Qahtani, A.; Farhat, A.; Al-Zawqari, A.; Bensaali, F.; Amira, A.; Zhai, X. HD Qatari ANPR system. In Proceedings of the 2016 International Conference on Industrial Informatics and Computer Systems (CIICS), Sharjah, United Arab Emirates, 13–15 March 2016; pp. 1–5.
34. . Kanayama, K.; Fujikawa, Y.; Fujimoto, K.; Horino, M. Development of vehicle-license number recognition system using realtime image processing and its application to travel-time measurement. In Proceedings of the 41st IEEE Vehicular Technology Conference, St. Louis, MO, USA, 19–22 May 1991; pp. 798–804.
35. . Busch, C.; Domer, R.; Freytag, C.; Ziegler, H. Feature based recognition of traffic video streams for online route tracing. In Proceedings of the 48th IEEE Vehicular Technology

Conference. Pathway to Global Wireless Revolution (Cat. No. 98CH36151), Ottawa, ON, Canada, 21 May 1998; Volume 3, pp. 1790–1794.
36. . Khan, M.; Mufti, N.; others. Comparison of various edge detection filters for ANPR. In Proceedings of the 2016 Sixth International Conference on Innovative Computing Technology (INTECH), Dublin, Ireland, 24–26 August 2016; pp. 306–309.
37. Pechiammal, B.; Renjith, J.A. An efficient approach for automatic license plate recognition system. 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM). IEEE, Chennai, India, 23–24 March 2017, pp. 121–129.
38. Sarfraz, M.; Ahmed, M.J.; Ghazi, S.A. Saudi Arabian license plate recognition system. In Proceedings of the 2003 International Conference on Geometric Modeling and Graphics, London, UK, 16–18 July 2003; pp. 36–41.
39. Dev, A. A novel approach for car license plate detection based on vertical edges. In Proceedings of the 2015 Fifth International Conference on Advances in Computing and Communications (ICACC), Kochi, India, 2–4 September 2015; pp. 391–394.
40. Wang, S.Z.; Lee, H.J. Detection and recognition of license plate characters with different appearances. In Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems, Shanghai, China, 12–15 October 2003; Volume 2, pp. 979–984.
41. . Lee, H.J.; Chen, S.Y.; Wang, S.Z. Extraction and recognition of license plates of motorcycles and vehicles on highways. In Proceedings of the 17th International Conference on Pattern Recognition, Cambridge, UK, 26 August 2004; Volume 4, pp. 356–359.
42. Huang, Y.P.; Chen, C.H.; Chang, Y.T.; Sandnes, F.E. An intelligent strategy for checking the annual inspection status of motorcycles based on license plate recognition. Expert Syst. Appl. 2009, 36, 9260–9267. [CrossRef]
43. Sferle, R.M.; Moisi, E.V. Automatic Number Plate Recognition for a Smart Service Auto. In Proceedings of the 2019 15th International Conference on Engineering of Modern Electric Systems (EMES), Oradea, Romania, 13–14 June 2019; pp. 57–60.
44. Kim, D.S.; Chien, S.I. Automatic car license plate extraction using modified generalized symmetry transform and image warping. In Proceedings of the 2001 IEEE International Symposium on Industrial Electronics Proceedings (Cat. No. 01TH8570), Pusan, Korea (South), 12–16 June 2001; Volume 3, pp. 2022–2027.
45. . Kashyap, A.; Suresh, B.; Patil, A.; Sharma, S.; Jaiswal, A. Automatic number plate recognition. In Proceedings of the Communication Control and Networking (ICACCCN), Greater Noida, India, 12–13 October 2018; pp. 838–843.
46. . Slimani, I.; Zaarane, A.; Hamdoun, A.; Atouf, I. Vehicle License Plate Localization and Recognition System for Intelligent Transportation Applications. In Proceedings of the 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT), Paris, France, 23–26 April 2019; pp. 1592–1597
47. Anagnostopoulos, C.N.E.; Anagnostopoulos, I.E.; Psoroulas, I.D.; Loumos, V.; Kayafas, E. License plate recognition from still images and video sequences: A survey. IEEE Trans. Intell. Transp. Syst. 2008, 9, 377–391. [CrossRef]

48. Wu, B.F.; Lin, S.P.; Chiu, C.C. Extracting characters from real vehicle licence plates out-of-doors. IET Comput. Vis. 2007, 1, 2–10. [CrossRef]
49. Li, M.; Sun, T.; Liu, H. Image Recognition of Steel Plate Based on an improved Support Vector Machine. In Proceedings of the 2018 IEEE International Conference on Information and Automation (ICIA), Wuyishan, China, 11–13 August 2018; pp. 1411–1415.
50. Al-Shemarry, M.S.; Li, Y. Developing Learning-Based Preprocessing Methods for Detecting Complicated Vehicle Licence Plates. IEEE Access 2020, 8, 170951–170966. [CrossRef] 129. Dia, Y.; Zheng, N.; Zhang, X.; Xuan, G. Automatic recognition of province name on the license plate of moving vehicle. In Proceedings of the 9th International Conference on Pattern Recognition, Rome, Italy, 14–17 May 1988; pp. 927–929.
51. Ko, M.A.; Kim, Y.M. A simple OCR method from strong perspective view. In Proceedings of the 33rd Applied Imagery Pattern Recognition Workshop (AIPR'04), Washington, DC, USA, 13–15 October 2004; pp. 235–240.
52. . Kim, M.K.; Kwon, Y.B. Multi-font and multi-size character recognition based on the sampling and quantization of an unwrapped contour. In Proceedings of the 13th International Conference on Pattern Recognition, Vienna, Austria, 25–29 August 1996; Volume 3, pp. 170–174.
53. . Hu, P.; Zhao, Y.; Yang, Z.; Wang, J. Recognition of gray character using gabor filters. In Proceedings of the Fifth International Conference on Information Fusion. FUSION 2002.(IEEE Cat. No. 02EX5997), Annapolis, MD, USA, 8–11 July 2002; Volume 1, pp. 419–424.
54. mani, I.; Zaarane, A.; Hamdoun, A.; Atouf, I. Vehicle License Plate Localization and Recognition System for Intelligent Transportation Applications. In Proceedings of the 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT), Paris, France, 23–26 April 2019; pp. 1592–1597
55. Kashyap, A.; Suresh, B.; Patil, A.; Sharma, S.; Jaiswal, A. Automatic number plate recognition. In Proceedings of the Communication Control and Networking (ICACCCN), Greater Noida, India, 12–13 October 2018; pp. 838–843.
56. Kraisin, S.; Kaothanthong, N. Accuracy Improvement of A Province Name Recognition on Thai License Plate. In Proceedings of the 2018 International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP), Pattaya, Thailand, 15–17 November 2018; pp. 1–6.
57. 141. Vaishnav, A.; Mandot, M. An integrated automatic number plate recognition for recognizing multi language fonts. In Proceedings of the 2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), Noida, India, 29–31 August 2018; pp. 551–556
58. Sferle, R.M.; Moisi, E.V. Automatic Number Plate Recognition for a Smart Service Auto. In Proceedings of the 2019 15th International Conference on Engineering of Modern Electric Systems (EMES), Oradea, Romania, 13–14 June 2019; pp. 57–60.
59. Laroca, R.; Severo, E.; Zanlorensi, L.A.; Oliveira, L.S.; Gonçalves, G.R.; Schwartz, W.R.; Menotti, D. A robust real-time automatic license plate recognition based on the YOLO

detector. In Proceedings of the 2018 International Joint Conference on Neural Networks (IJCNN), Rio de Janeiro, Brazil, 8–13 July 2018; pp. 1–10.
60. Desai, G.G.; Bartakke, P.P. Real-Time Implementation Of Indian License Plate Recognition System. In Proceedings of the 2018 IEEE Punecon, Pune, India, 30 November 2018; pp. 1–5.
61. Henry, C.; Ahn, S.Y.; Lee, S.W. Multinational license plate recognition using generalized character sequence detection. IEEE Access 2020, 8, 35185–35199. [CrossRe
62. Haider, S.A.; Khurshid, K. An implementable system for detection and recognition of license plates in Pakistan. In Proceedings of the 2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT), Karachi, Pakistan, 5–7 April 2017; pp. 1–5.
63. Hommos, O.; Al-Qahtani, A.; Farhat, A.; Al-Zawqari, A.; Bensaali, F.; Amira, A.; Zhai, X. HD Qatari ANPR system. In Proceedings of the 2016 International Conference on Industrial Informatics and Computer Systems (CIICS), Sharjah, United Arab Emirates, 13–15 March 2016; pp. 1–5
64. Yogheedha, K.; Nasir, A.; Jaafar, H.; Mamduh, S. Automatic vehicle license plate recognition system based on image processing and template matching approach. In Proceedings of the 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA), Kuching, Malaysia, 15–17 August 2018; pp. 1–8