# NUMBER PLATE AND LOGO IDENTIFICATION USING MACHINE LEARNING APPROCHES 

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#### Abstract

The ability to recognize license plates is affected by a number of issues, such as the presence of extraneous information, variations in the size and type of the text, blur, skew, and other environmental factors. It is not always easy to recognize the numbers on license plates because there are so many different types of licence plates and so many different situations in which they can be displayed. As a result of the relatively poor segmentation results produced by region-based approaches, better segmentation algorithms are required for the process of separating out individual license plates. The license plate can be placed in any part of the image that you like. Because the license plate can be identified based on its attributes, the algorithm processes only the pixels that share analogous qualities. The amount of time required to process the image will increase if each and every pixel in it is processed. In this study, two additional methods that are proven to be effective in segmenting the license plate of a vehicle are investigated.


The first technique divides the license plate by utilizing edge information. This segmentation technique demonstrates a high level of effectiveness, providing an average segmentation outcome of $85 \%$. The second approach utilizes information about number plate shape and color. Visualization techniques are applied to segment number plates using the information of the hybrid feature. The approach achieves an average segmentation rate of $93 \%$. Although segmentation using the edge-based and hybrid approaches is executed at a similar speed to segmentation using the region-based approach, the latter provides better segmentation outcomes.

The fundamental objective of this paper is to devise a method that is capable of producing an automatic licence plate recognition system that is durable, accurate, and reliable.

Keywords: Automatic Number Plate Recognition (ANPR), Convolution Neural Network (CNN), Character Segmentation Image Segmentation, Optical Character Recognition, Edge \& Pixel Detection.

## 1. INTRODUCTION

Image processing and recognition of various patterns in an image and are the most significant areas in which researchers are focusing their attention. Over the past decades, academicians from all over the world have focused a significant portion of their attention and energy on the automation of various activities. There has been increase in the number of motor vehicles over the course of the past few years. Given the growing number of vehicles on the road, it is more important than ever to pay particular attention to the effective management of traffic. This is especially true given the current state of the economy. Control of vehicles is essential for a number of reasons, the most important of which are safety issues; hence,
the development of intelligent vehicle management solutions is required. A registration code serves as a completely unique identifier of the car and is present in every vehicle. Recording motors manually is a time-consuming and labor-intensive process that is both expensive and inefficient. Therefore, the automation of the process of determining the reputation of a car registration code is typically advantageous.

### 1.1 Automatic Number Plate Recognition

ANPR, or Automatic Number Plate Recognition, is the process of determining an automobile's registration number from a photograph of a motor vehicle or a collection of photographs of motor vehicles. ANPR is an abbreviation for "Automatic Number Plate Recognition," which describes the process of recognizing a car

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registration number by utilizing the equipment. The full term is "Automatic Number Plate Recognition." The term "Automatic Vehicle Identification" (AVI), "Automatic Number Plate Recognition" (ANPR), "Car Plate Recognition" (CPR), "Automatic License Plate Recognition" (ALPR), and "License Plate Recognition" are some of the names that have been used to refer to it in the industry. Other names include "Car Plate Recognition" (CPR) and "Automatic License Plate Recognition."
The monitoring of stationary, non-moving targets by stationary ANPR systems is accomplished by the utilization of high-resolution, infrared cameras. Readers can be placed on a variety of stationary items that are encountered on the road, such as sign boards, street lights, telephone poles, entry-exit gateways, and other gateways.


Figure 1 Block Diagram of ANPR System.

## 2. LITERATURE REVIEW

The scope of this work encompasses both the field of image processing and that of artificial neural networks (ANN). The optical character recognition system receives as input an image of a document that contains multiple scripts of text. In order to process the image of the document, a few preprocessing steps are required. The basics of digital image processing are broken down into easily digestible chunks. The identification of specific graphical representations of characters can be accomplished through the application of a wide variety of categorization strategies. Template matching, statistical analysis, structural analysis, artificial neural networks (ANN), support vector machines (SVM), and a few other methods are examples of the approaches that fall under this category. In addition, a clear and straightforward explanation of the principles of ANNs, as well as approaches to neural network training and script identification that are pertinent to the job, are included.

### 2.1 Introduction to Image Processing

A visual representation of something is referred to as an image, whereas the binary representation of visual data is referred to as a digital image. Photographs, graphics, and individual still frames from videos are all valid formats for these images. For the purposes of this discussion, an image is a photograph that was either produced or copied before being saved in digital format.

There are two types of graphics that can be used to describe an image: vector graphics and raster graphics. A raster image that is saved in bitmap format is sometimes referred to as a bitmap. In order to make it possible to store and send digital images, they are given an encoding that takes the form of binary files. A system or regulated manner of organizing and storing digital images is referred to as a file format. There is a possibility that the image data will be compressed differently depending on the file type used.

An image is a function that depicts the properties of an object in a space that is only two dimensions deep. These properties can include the color of the object or the intensity of its level of brightness. $x$ and $y$ are the spatial coordinates of a point in the image, and the value or amplitude of " $f^{\prime \prime}$ is referred to as the grey level or the intensity of the image at that point. An image can be defined as a two-dimensional function called $f(\mathrm{x}, \mathrm{y})$, where x and $y$ are the spatial coordinates of a point in the image ( $x, y$ ). It is possible to acquire images from a broad variety of resources, such as scanners, cameras, networks, and many others. Images can be gathered from these and many more sources. It is possible to process these photos, and the image that is produced as a consequence can either be displayed immediately or stored to a disc in the form of a file in order to be retrieved at a later time.

Images may be analogue or digital. Analog images are mathematically represented as a continuous range of values, with the position and intensity being the only two parameters that need to be specified. The intensity of an analogue photograph shifts continuously across its field of view. An example of an analogue image would be something displayed on the screen of a television or a computer monitor. A collection of picture elements that have the smallest sampling units possible is what makes up a digital image. These components are referred to as pixels, and they are responsible for determining the level of brightness. The operation of processing in fact takes place on digital images.

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The process of converting an analogue image into a digital image involves a number of steps, two of which are sampling and quantization. The process by which an analogue image is converted into a digital image is depicted in figure 2.


Figure 2: Analog to Digital conversion. The data that make up an image are conceptually represented as a three-dimensional array of pixels, as shown in Figure 3. The term "band" or "channel" is used to refer to each of the arrays. The number of rows will specify the height of the image, while the number of columns will specify the width of the image.


Figure 3 Representation of a digital image.
Images can either be black and white or coloured. Only one band is present in monochrome images, while at least three bands are present in colour photographs. There are many different colour models, the most common of which are RGB, CMY, and CMYK. The Red, Green, and Blue values of each pixel are what are used to represent the colour in the RGB colour model. For instance, the pixels with intensities of $(255,0,0),(0,255,0)$, $(0,0,255),(0,0,0)$, and $(255,255,255)$ respectively represent red, green, blue, black, and white pixels. The cyan, magenta, and yellow components of a pixel are what make up its representation in the CMY colour model. According to the CMYK colour model, each pixel is represented by components that are cyan, magenta, yellow, and black. As a result, each pixel that makes up a colour image is not made up of a single sample but rather a collection of samples.

A detailed survey of the traditional and state-of-theart ANPR approaches is presented to gain an indepth sight into the present scenario of licence plate recognition. From the literature survey carried out in the chapter, a lot of significant work has been
done in the field of automatic vehicle plate recognition. Researchers have contributed new theories in this field. A number of commercial ANPR systems are available nowadays and yet there are many challenges in registration number recognition.

In view to recent literature work, ANPR needs attention for different languages, size, dirt and poor lighting. State-of-the-art ANPR approaches have still had difficulty recognizing licence plates from complex environments. There is a need to develop a more accurate and reliable system for ANPR. The current level of accuracy is almost $89 \%$ subject to the database and the environment under the consideration [49]. The claimed accuracy cannot be compared as experiments are performed on different data sets of vehicles and there is no universally accepted data set for this purpose. A robust system is needed to extract plate area and further its recognition that can work better subject to the selected environment. ANPR needs to overcome challenges in the extraction of the text area and its segmentation with more accuracy to implement in real life situation under different environment.

A new automated vehicle plate recognition system is required to improve the results for Indian vehicles. The system should be able to correctly recognize the licence plate number from the image of the vehicle. There is no standard database of Indian images of vehicles available in the literature. Therefore, there is a dire need to develop benchmarked data-set containing images of vehicles having Indian licence plates. A data-set of 561 images of vehicles carrying Indian licence plates is developed from various parking lots of Hyderabad, Telangana, India. Development of a benchmark database of Indian vehicle images will provide a new direction in the area of licence plate detection and recognition.

These research gaps have motivated us to build an automatic vehicle plate recognition system using a new method based on features of characters. All these gaps have been key catalysts towards doing more and contributing towards taking the field of license plate detection and recognition forward.

## 3. SEGMENTATION APPROACHES

The licence plate identification algorithm that is now being executed on the processing unit is, in most cases, the most crucial component of the system. The procedure of recognition can be broken
down into three primary tasks: 1) Identification of the location of the licence plate based on the image
2) licence plate character segmentation 3) The recognition of the characters on registration plates. This chapter will begin by analyzing the primary methods of completing these activities that have been described in the previous research.

### 3.1 Localization of Number Plate

An image acquisition system will, almost always, produce a picture of the vehicle along with its licence plate in the majority of cases. It is possible that the licence plate is visible in any part of the image. In order for character recognition to take place, it is necessary to locate the vehicle's licence plate in the background image of the vehicle. During the localization phase, the licence plate is extracted from the background image by identifying the features that set it apart from the rest of the image. These features are the ones that make the licence plate distinctive. After the area of interest has been located through the use of these features, it is extracted and examined more thoroughly to determine whether or not it is a licence plate. The proportion of the plate's width to its height, the number of edges, and the color of the plate are all potential factors that could be used during the verification process. If the candidate turns out to be an authentic licence plate, then it will proceed to the next stage of the process. In the event that this does not occur, the search procedure is repeated in various other areas of the image. If there is no portion of the photograph that satisfies the verification criteria, the image is categorized as one that does not contain a licence plate.

It has been claimed that there are a few various ways to locate the licence plate from the image of the car, and each of these approaches is distinct in terms of the amount of time it takes to compute, how challenging it is, and the percentage of the time that it is successful. In this part of the article, we are going to discuss and contrast a few of the most typical ways that a licence plate can be located. The procedures are categorized according to the many types of photos that are searched for in order to locate the licence plate.

### 3.2 Review of Character Segmentation for License Plates

After recovering the licence plate region from the input image, the character string was divided. This revealed the characters. Any licence plate identification system relies on accurate character segmentation because even a capable character
recognition module cannot identify incorrectly segmented characters. Character segmentation requires several priorities. The licence plate characters may touch if the image is fuzzy due to vehicle speed or low image resolution. The licence plate may appear faded if the image has too much or too little light, making character pixel isolation difficult.

### 3.2.1 License Plate Character Segmentation Based on Binary Images

Given the amount of studies that use vertical and horizontal pixel projections for character segmentation [10], [13], [14], this method is the most common and easiest. After applying a threshold to convert a greyscale image to binary, image columns or rows are linked to form a projection vector. The projection's local minimums are the characters' segmented spaces. Even though this method is simple, the binarization threshold value determines its success rate. Setting the binarization threshold incorrectly can make segmentation harder. This may break or collide the characters in the image, making the work harder.
An active contour model for character segmentation was proposed by Capar and Gokmen [6], and their work was based on a variational fast marching algorithm. In the first step of the process, coarse character locations are figured out by using a regular fast marching technique [9] in conjunction with a speed function that is gradient and curvature dependent [14]. After that, the precise limits of characters are figured out using the assistance of a one-of-a-kind rapid marching strategy, which is dependent on information about gradient, curvature, and shape similarity.

### 3.2.2 Grey-Level Character Segmentation Based on Images

Adaptive local binarization methods were implemented in many different systems [5], [6], and [7] as a solution to the problem that was caused by the use of a single global binarization threshold. In these local binarization approaches, a picture is first cut up into blocks measuring m by n , and then a threshold is selected for each individual block. The binarization presented in [3] is consistent with the block division methodology described above, which Otsu [8] uses to build his dynamic binarization method. The size of the characters that were anticipated to appear in the photos was estimated in advance by the utilisation of the settings of the camera as well as the distance that exists between the camera and the cars.

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License plate character segmentation in video sequences was the impetus for the invention of the method described in [1], which simultaneously utilises spatial and temporal information. This method was developed so that licence plate characters could be extracted from the video. The modelling of a Markov Random Field, also known as an MRF, is the first step in the character extraction process. In this step, the element of randomness is used to explain the degree of uncertainty involved in the process of assigning pixel labels. It is possible to employ MRF models to quantitatively take into account previous contextual knowledge or limits. It is feasible to make use of local spatial and contextual dependencies when doing binarization. [7].

### 3.3 Review of Recognizing Letters and Numbers on License Plates

The difficulty of optical character recognition was addressed in both [13] and [86] by the development of two distinct PNNs: one for the recognition of letters, and the other for the recognition of numbers. PNNs were trained and tested on patterns that were noisy, tilted, and degraded, and the results were quite positive, with identification rates of above $90 \%$ in most cases. In addition, the authors of [12] discovered an astonishing identification rate that was greater than $99.5 \%$. PNN can be generated in a fraction of the time it takes to train standard feed-forward networks [16] due to the fact that the hidden-layer neurons in PNN only need to be taught once and are specified by the number of training patterns [15]. [18] PNNs can be used to create more complex.

## 4. DESIGN OF PROPOSED METHOD

Automatic Number Plate Recognition (ANPR) is a computer-based technology that captures a full image of a number plate using a high-resolution optical camera. This image is then methodically processed to obtain a string of characters from the number plate in any environment. In the method that has been suggested, a Deep Artificial Neural Network is combined with adaptive learning techniques. Additionally, many algorithms are suggested for various modules in order to achieve one hundred percent success in recognition by using a trained CNN network.

### 4.1 Objectives of the Proposed work

The suggested framework has the potential to play a significant role in the smart city mission, block diagram of the proposed method is shown in fig:4.


Figure 4. Block Diagram of Proposed ANPR.
I. To discuss current state-of-the-art techniques for "Automatic Vehicle Plate Recognition", as well as the benefits and drawbacks of existing techniques. Furthermore, the proposed research will examine the suitability of plate area extraction algorithms in various circumstances (including day/night, rain, significant traffic versus few vehicles, and varying illumination).
II. To design a system that will locate Vehicle plate areas and recognise vehicle plate numbers. Preprocessing options include the median filter, Gaussian filter, and Mexican filter. Artificial Neural Networks, Connected Component Analysis, Edge detection, and hybrid algorithms can all be used to detect licence plates.
III. The hybrid algorithm will concentrate on geometric qualities of the actual plate region, as well as structural behaviour-based features. Techniques such as horizontal and vertical projection, bounding box, and blob analysis can be utilised for character segmentation.
IV. The suggested technology will recognise the vehicle licence plate number without the need for human involvement. As a result, by decreasing the requirement for humans, the suggested method will save time and money.

Automatic recognition of vehicle licence plates could be useful in traffic monitoring systems. A system like this might be used in parking lots, motorways, bridges, and tunnels. The proposed system can assist a human operator while also improving service quality. The proposed technology has the potential to be employed in security. Toll collecting, radar-based speed control, parking management, access control, crime investigation systems, and border patrolling could all benefit from this technology. For photographs of poor quality or that are unclean, the created approach produces superior results.

### 4.2 Number Plate Localisation

The process of "localization" is an essential step that lays the groundwork for successful licence plate recognition in any jurisdiction. Recognition

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will not be successful in reaching its goal if the localization of NP is not performed with precision. At this stage, our goal is to localise the region containing the number plate (NP) from the original image by making use of image processing algorithms that are morphologically based. Fig. 5


Figure 5 Process Flow of Localization.
There are two different kinds of elements that are used for structuring: flat and non-flat. A binary valued neighborhood that is either two-dimensional or multidimensional and in which only the correct pixels are included in the morphological calculation and the false pixels are not included is referred to as a flat structuring element. The pixel in the image that is now being processed can be located by locating the origin, which is the pixel in the center of the structuring element[15]. To produce a flat structural element, you can make use of the strel function. Both binary and grayscale images can make advantage of the flat structural elements that are available


Figure 6 Accurate structure element approach.

### 4.3 Number Plate Patterns

The Indian number plate is mandated by law vehicle equipment in India, being the main part of vehicle registration. They are available in a range of colours and combinations. The RTO is a crucial department that oversees all vehicle-related services in each state. The RTO is in charge of your driver's licence, number plate, car insurance, and the paperwork required in purchasing a vehicle. Every vehicle in India is given a unique licence or registration number by the RTO agencies in each state. These number plates are an important component of India's transportation culture. This section will explain what number plates are and how they differ in India.

### 4.3.1 Introduction to Number Plates

Number plates are unquestionably one of the most crucial components of any vehicle. All motorised road autos in India are given a unique registration number. These Vehicle registration plate numbers are issued by each state's district RTO (also known as the number plates). When your car runs a red light or is involved in a traffic collision, this identifying number is displayed. The police will simply check your information based on your

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licence plate. Number plates are similar to vehicle names. Every vehicle must have them linked to the back and front of their vehicle.
In India, there are now eight different types of licence plates. They are:

TABLE 4. 1 VARIOUS COLOURS USED IN INDIAN NUMBER PLATE DESIGN.

| $\begin{aligned} & \hline \text { Sl. } \\ & \text { No } \\ & \hline \end{aligned}$ | Number Plate Type | Description |
| :---: | :---: | :---: |
| 1 | White-colored Number Plate | This is a typical licence plate. They are only to be used for personal purposes. |
| 2 | Yellow-colored <br> Number Plate | These can only be used for business objectives and cannot be used for personal gain. To operate the vehicle, the driver must also hold a commercial driver's licence. |
| 3 | Green-colored <br> Number Plate | Electric vehicles, such as autos and buses, can only use them. |
| 4 | Red-colored <br> Number Plate | For brand-new vehicles, these are temporary licence plates. They are only valid for one month and the owner must purchase a permanent licence plate after that. Only a few states, however, do not provide temporary licence plates. |
| 5 | Blue-colored Number Plate | These are only supplied to the cars of foreign officials. <br> These plates must have letters like CC (Consular Corps) and UN (United Nations) (United Nations). On the licence plate, the diplomat's country code must be displayed. |
| 6 | Black-colored <br> Number Plate | The vehicles with 'A' class are used for luxury resort transportation. |
| 7 | Upward Arrow <br> Number Plate | These are only for military vehicles. |
| 8 | Red-colored Number Plate with Indian Emblem | Previously, these were reserved for government leaders such as the President and Governors. They are not currently in use. |

Indian licence plate design: A registration number is assigned to every vehicle in India. Each state's regional transportation office issues this number. The licence plates are usually positioned on the vehicle's front and back [80]. For licence plates, different countries employ different coding styles and colours. There are three different types of licence plates in India. The following are the
standard patterns for the newest Indian licence plates.

Eight characters Licence Plate
AANN NNNN

Nine Character Licence plate

## AANN A NNNN

Ten characters Licence plate

## AANN AA NNNN

Where " $A$ " represents the English letter and " $N$ " represents a number. In India, the first, second, and third standard patterns of licence plates have eight, nine and ten characters, respectively. The first two letters of the English alphabet represent the state code for which the car is registered. The district code is represented by the next two numeric digits. The series code is presented in the next two alphabets, which are optional. Each plate's last four numbers are unique.

The Table 4.2 explains the coding style of Indian license number plate: TS 09 ER 3034.
Table 4. 2 Coding style of Indian license plate

| Characters/ <br> Numbers | Code |
| :---: | :---: |
| TS | State code for Telangana |
| 09 | District code for Hyderabad |
| ER | Series Code |
| 3034 | Number Unique for every vehicle |

To match the characters from the trained dataset, the correlation approach for each extracted character is employed. The retrieved character is compared to a set of similar template images during classification. The recognised character is the most comparable template after all the templates have been compared to the extracted character.


Figure 7 Input Image

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Figure 8 Segmented Number Plate.


Figure 9: Binarized Number Plate Image

## 5. SCOPE

As a result of the research, it is now possible to propose a method for wide range of applications for an automatic licence plate recognition system, including monitoring the flow of traffic, determining the make and model of specific vehicles, automating the process of enforcing parking regulations, and many more. The implementation of ANPR systems is becoming increasingly widespread as a result of rapid developments in technology, such as the introduction of machine learning and deep learning, a decrease in the cost of computational operations, and an increase in the precision of various image processing methods[26][27][29]. As part of the research, this method will be conceptualised and developed.

## 6. PROPOSED ALGORITHM

This section introduces a new algorithm for automatic car plate recognition. Character characteristics were employed in this technique to extract character regions from the vehicle image. The correlation approach is used to recognise the characters.

## Algorithm (Number Plate Recognition Algorithm)

## Input: Image of Vehicle

Output: The vehicle's registration number is written on the license plate.

## Procedure:

To find a perfect match, the character's geometric qualities are used. The suggested features-based recognition system avoids the issues and introduces a new modified method for character extraction,
which improves the character recognition process that do not fulfil the approximate location.

## Begin

1 Take the Input image as " X ".
$2 \mathrm{X} \leftarrow$ pre-process (X); // Apply Pre-processing to smoothen image.
3 Extract region of X as RoI where RoI is a set of sub regions.
4 RoI := $\left\{r_{1}, r_{2}, r_{3} \ldots r_{\mathrm{n}}\right\}, 1 \leq i \leq n$
for each region $r_{i}$ $g r \mathrm{p}_{\mathrm{I}} \leftarrow$ make_group $\left(\mathrm{r}_{\mathrm{i}}\right)$
end for
5 G is a group as $\left\{\operatorname{grp}_{1}, \operatorname{grp}_{2} \ldots g \mathrm{rpm}_{\mathrm{m}}\right\}, m \leq=n$
6 If $m>t h_{1}$
RoI $\leftarrow$ filter regions $(\mathrm{RoI})$
Go to step 4;
End if
7 If $m<t h_{2}$
$\mathrm{R} \leftarrow$ regroup region( R )
Go to step 4;
End if
8 RoI is the final set of extracted regions as RoI $:=\left\{r_{1}, r_{2}, r_{3} \ldots r_{\mathrm{n}}\right\}, 1 \leq k \leq n$
9 Label each $\mathrm{r}_{\mathrm{i}}$ of RoI $(1 \leq i \leq n)$ based on the classification.
10 Based on the recognition technique, each extracted character region is recognized.
11 Output Registration number End of procedure.
To compare the similarities between the extracted character and the stored templates, the geometrical features of the characters are utilised. The identified character will be the most comparable template. The process is repeated for all of the licence plate's

extracted characters, and the result is the recognised licence plate registration number

Figure 10: Data Tuning

## 7. IMPLEMENTATION

The data set is partitioned into two complimentary subsets termed training data set and test data set in cross-validation. The suggested application is built on a training data set and tested on a test data set. Multiple rounds of crossvalidation utilizing different partitions are used to

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reduce variability. The collected dataset is discussed in detail in section 7.1. There have been some initiatives in the literature to create standard vehicle picture databases. These data sets have served as the foundation for the researcher's ANPR systems.

### 7.1 Vehicle Image Dataset

Images are recorded in real time using digital cameras and in-built mobile cameras. The photographs in the database are mostly of fourwheelers. This benchmarked database will meet the future needs for training and text data sets. The research community can potentially utilize this data collection to do study on Indian licence plates.

Table 7. 1 Images Used In The Proposed Work

| Different Types of Datasets | Number of <br> Images |
| :---: | :---: |
| Set 1 (Pictures taken during the daytime in |  |
| full color (large)) |  | $70^{\text {Set 2 (Larger View with close angles) }} ⿵ ⺆ 80$

The aforementioned method takes an image as an argument and then applies a "Haar Cascade" that has been pre-trained to recognise Indian licence plates. The scaleFactor parameter specifies a value that can be used to scale the input picture for improved licence plate detection. min Neighbors is only a parameter that can be used to reduce the number of false positives;
The process of segmentation can be achieved by carefully modifying the image's threshold, erosion, dilation, and blurring settings in order to make it almost noise-free and simple to manipulate. This will make the image more suitable for the task at hand. After using contour detection to extract the characters, we make some adjustments to the
parameters in order to achieve a more satisfactory end result locating each individual character.

Table 7.2 Sample Outputs Of Proposed Localization


Table 7.3 Output From Segmentation \& Recognition Module

| $\begin{gathered} \text { Case } \\ \text { No } \\ \hline \end{gathered}$ | Obtained Number Plate | Region for Segmentation |
| :---: | :---: | :---: |
| I | $\begin{aligned} & \text { Number Plate LOCALISED Image } \\ & \qquad \sqrt{M \mid B .4695} \end{aligned}$ | ALPHA-NUMERIC for Segmentation |
| II |  | ALPHA-NUMERIC for Segmentation |
| III | Number Plate LOCALISED Image 12783030 | ALPHA-NUMERIC for Segmentation |
| IV | Number Plate LOCALISED Image (ANIO.O32 2 | ALPHA-NUMERIC for Segmentation |
| V | Number Plate LOCALISED Image | ALPHA-NUMERIC for Segmentation |
| VI | Number Plate LOCALISED Image | ALPHA-NUMERIC for Segmentation |

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Table 7. 4 Segmentation \& Recognition Of Characters

| Segmented | Original | Neural Network Database of Alpha Numeric Set |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\cdots$ | M | $\underset{\text { cosm }}{ }$ | $\underset{\operatorname{cosem}}{\mathbf{M}}$ | M | M |
| 3 | H | $\underset{\text { casm }}{\text { H }}$ |  | $\underset{\text { cast }}{\text { C }}$ | $\underset{\text { casth }}{\text { H }}$ |
| 0 | 0 | O | ${ }_{\text {case }}$ | Cobes | Cabes |
| 2 | 2 | $\underline{2}$ | $\underbrace{}_{\text {casa } 23}$ | $\underset{\operatorname{cose} 2 .}{ } \mathrm{L}^{4}$ | $\underset{\text { casa } 25}{\text { 2 }}$ |
| E | E | $\underset{\text { cese }{ }_{\text {E }} \text { E }}{ }$ |  | $\underset{\operatorname{cosex} 4}{\text { E }}$ | $\underset{\text { cast }{ }_{\text {E }} \text { S }}{ }$ |
| P | P | $\underset{\text { case }{ }^{\text {P }} \text { 2 }}{ }$ | $\underset{\sim}{\text { casem }}$ | $\underset{\text { cosp }}{\text { P }}$ | $\underset{\text { coses }{ }^{\text {P }} \text { S }}{ }$ |
| $\pm$ | 1 | $]_{\cos 12}$ | [1] | $]_{\text {cose } 14}$ | $\underset{\text { cise } 15}{\text { IT }}$ |
| $5$ | 5 | $5$ | $5$ | $\underset{\operatorname{coses} 54}{5}$ | $5$ |
| 4 | 4 | $4$ | 4 <br> class 4 | $4$ | $4$ |
|  | 3 | $\underset{\operatorname{coss} 3.2}{3}$ | $3$ | $3$ | $3$ |

concatenating the results, and displaying the licence plate number as a string. Because we have all of the characters, we must feed them one by one into our trained model, which should recognise them and chevalier! For our Convolutional Neural Network model, we'll use Keras[25].

In order to perform estimation, which is also referred to as "learning" in the terminology of the neural network literature, it is necessary to locate the set of weights for each input or prior layer node values that minimise the model's objective function. Finding this set of weights is accomplished by finding the values that minimise the model's objective function. In the case of a continuous numeric field, this means minimising the sum of the squared errors of the final model's prediction in comparison to the actual values, whereas classification networks aim to minimise an entropy measure for both binary and multinomial classification issues[21].


Figure 11 Performance Validation at Layer 1 module




Figure 12 Gradient performance at 3000 epochs at Layer 1


Figure 13 Regression output performance at Layer 1

In a similar manner, the training time in seconds for each of the three activation functions and the various numbers of layers is presented in Table 7.5. It should come as no surprise that the length of training takes longer as the number of hidden layers grows, as this is directly proportional to the amount of information being processed. The Tan-Sigmoid model provides the best results for training time, whereas the Purelin model provides the worst.

Table 7. 5 Analysis Of Activation Functions

| Lay <br> ers | Purelin <br> (Training <br> Time) /sec | Log-Sigmoid <br> (Training <br> Time)/sec | Tan-Sigmoid <br> (Training Time <br> )/sec |
| :---: | :---: | :---: | :---: |
| 1 | 3.26 | 00.31 | 00.29 |
| 2 | 3.41 | 00.46 | 00.44 |
| 3 | 3.45 | 00.54 | 00.53 |
| 4 | 3.50 | 00.55 | 00.45 |
| 5 | 3.58 | 00.48 | 00.40 |

Table 7.6 A Comparison Of The Localisation Of Existing \& Proposed Methods

| Reference | Image Size | Localization <br> Rate (\%) | Localization <br> Time (ms) |
| :---: | :---: | :---: | :---: |
| Anagnostopoulos <br> et al.[4] | $640 \times 480$ | 89.10 | 117 |
| X. Zhai et al.[5] | $640 \times 480$ | 97.80 | 43 |
| Le et al.[6] | $640 \times 480$ | 97.37 | --- |
| Zhu et al.[24] | $640 \times 480$ | 89.45 | 35.01 |
| Juan Yepez [25]] | $640 \times 480$ | 98.45 | 20 |
| Proposed System | $640 \times 480$ | 99.50 | 15.36 |



Performance Analysis od Recognition

## 8. ANALYSIS OF PREVIOUS WORK.

The time complexity of the proposed neural network is expressed, where ' $t$ ' is the training time and ' $n$ ' is the number of epochs. The network consists of five layers with $i, j, k, l$, and $m$ nodes respectively.
$\mathrm{O}(\mathrm{n} * \mathrm{t} *(\mathrm{ij}+\mathrm{jk}+\mathrm{kl}+\mathrm{lm})) \quad \ldots$. Eqn (8.1)
In this equation, $i$ stands for the total number of nodes in the input layer, ' j ' stands for the total number of nodes in the second layer, ' $k$ ' stands for the total number of nodes in the third layer, ' l ' stands for the total number of nodes in the fourth layer, and ' $m$ ' stands for the total number of nodes in the fifth layer.

$$
\text { or } \mathrm{O}(\mathrm{n} * \mathrm{t} * \mathrm{w}) \ldots \quad \operatorname{Eqn}(8.2)
$$

Where " $w$ " represents the weight that needs to be updated or adjusted so that the data set can be balanced.
$\mathrm{w}=\mathrm{ij}+\mathrm{jk}+\mathrm{kl}+\mathrm{lm}$ that is sum of $\mathrm{n}^{*} \mathrm{n}_{-} \mathrm{i}$ between layers.
If we make the assumption that there are $n$ layers, then each of those layers has gradient iterations and n neurons. The entire amount of time required for back propagation is found to be $\mathrm{O}(\mathrm{n} 4)$.
Before we begin the computation for the total amount of time it took to effectively train the data set using the neural network with varying degrees of hidden layers, let's see how many "weights" (interlinks between the neuronal nodes) need to be updated and balanced for any given dataset. [17]. Before commencing the training time calculation for the actual amount of time it took for the neural network to train the data set with a variety of rising hidden layers.

## For First Hidden Layer:

Number of Weights $=150$ (I/p layer) x $105(\mathrm{H} / 1$
$70 \%$ of $\mathrm{I} / \mathrm{p})+105 * 36$
$(\mathrm{O} / \mathrm{P}$ Layer $)=15,750+3780$
$=19,530$ in iterations weights are to be balanced.
For 2 Hidden Layers:
Number of Weights $=150$ (I/p layer) x $105(\mathrm{H} / \mathrm{l}$ $70 \%$ of I/p) $+105 * 36$ (O/P Layer)
$=15,750+7,770+2,664$
$=26,184$ in iterations weights are to be balanced.
For Proposed 5 Hidden Layers:
Number of Weights $=150$ (I/p layer) x 105(H/l
$70 \%$ of $\mathrm{I} / \mathrm{p})+105 * 36(\mathrm{O} / \mathrm{P}$ Layer $)+105 * 74(2$
$\mathrm{H} / 1)+74 * 52(3 \mathrm{H} / 1)+52 * 36(4 \mathrm{H} / 1)+36 * 25(5$
$\mathrm{H} / \mathrm{l})+25$ * 36 (O/P Layer)

$$
=15,750+7,770+3,848+1,872+900+900
$$

$=31,040$ in iterations weights are to be balanced.

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Before we begin the computation for the total amount of time it took to effectively train the data set using the neural network with varying degrees of hidden layers, let's see how many "weights" (interlinks between the neuronal nodes) need to be updated and balanced for any given dataset. [17]. Before commencing the training time calculation for the actual amount of time it took for the neural network to train the data set with a variety of rising hidden layers.
For $2 \mathrm{H} / \mathrm{L}$ training 1533 Numerals: 44 seconds
Number of weights adjusted: 26,184.
Average Time to adjust one neuron weight: 0.00168 or 1.68 milli sec
For Five Hidden Layer training with 1533 Numerals: 40 Seconds
Number of weights adjusted: 31,040.
Average Time to adjust one neuron weight: 0.00128 Sec or 1.28 milli sec
From the calculations above, it can be seen that by raising the No. of $\mathrm{H} / \mathrm{L}$ to 5 , we significantly enhanced the architecture of the network as a whole. Table 7.6 and Table 7.7 where it is revealed that their processing time but not the temporal complexity of their method, which was used in their computation, allow for a comparison with prior approaches As a result, the complexity calculation for each hidden layer shows that we have increased accuracy and decreased overall computation time.

Table 7.7 Time Complexity In Order To Balance The Weight Of The Neuron.

| No of <br> Hidden <br> Layer | Weights need to be <br> balanced | Average Time to <br> adjust neuron weight <br> (mili sec) |
| :---: | :---: | :---: |
| 1 | 19,530 | 1.48 |
| 2 | 26,184 | 1.68 |
| 3 | 29,240 | 1.81 |
| 4 | 30,536 | 1.47 |
| 5 | 31,040 | 1.28 |



Figure 15: Performance Analysis of Recognition

## 9. CONCLUSION

The main aim of this paper is to determine algorithms for pre-processing, localizing, segmenting, and recognizing number plates, as well as developing a system with the ability to recognize vehicle plates. This objective was successfully achieved as the developed system effectively identifies Indian license plates. This paper presents a very effective and dependable system for extracting and recognizing characters from Indian number license plates. This approach utilizes the attributes of alphanumeric characters (A-Z, 0-9), including area, height, breadth, perimeter, and aspect ratio, to extract the characters representing the car number from the vehicle image.
Character recognition is dependent on a procedure known as template matching. The proposed approach is evaluated using a dataset including 561 photos of mobile vehicles that were gathered in a live environment. To evaluate the efficacy of the suggested framework, several experiments are conducted. The experimental results indicate that the proposed approach achieves a high level of accuracy, with $96.69 \%$ for character region extraction and $95.34 \%$ for character identification. These results are equivalent to those reported in existing literature. This framework can be employed for the creation of several real-world applications, including toll management systems, automatic parking systems, intruder detection systems, and more.
A benchmarked dataset of 561 vehicle photos is constructed. This data collection is used to test the application that has been developed. The research community can potentially utilize this data collection to do study on Indian licence plates. In 96.69 percent of cases, the developed algorithm successfully extracted the character regions, and in 95.34 percent of cases, it correctly detected the licence plate number. The proposed technique is simple and resilient, according to the findings of the experiments.

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