International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.142

Electrical Car Number Plate Detection

Dr.A.Shobana Devi
Asst Professor
Data Science and Business Systems
SRM Institute of Science and Technology
Chennai, India shobanaa3@srmist.edu.in

Kanigicherla Balaji Subrahmanyam
Student
Data Science and Business Systems
SRM Institute of Science and Technology
Chennai, India ks1534@srmist.edu.in

Rasineni Tharun Chowdery
Student
Data Science and Business Systems
SRM Institute of Science and Technology
Chennai, India rc4009@srmist.edu.in

Abstract— Reduced tollgate rates in any other sort of usage, making it more willing for the environment by electrical autos, and even in traffic control and vehicle owner identification, which has become a severe problem in every country, would encourage adoption of electric cars. It could be difficult to spot motorists who drive too quickly and against the rules of the road. Due to the speed of the moving car, it may be difficult for traffic officials to collect the license plate, making it impossible to catch and punish such people. Designing an automatic number plate recognition (ANPR) system is one of the solutions to this issue. There are currently many ANPR systems in operation. Despite the fact that these systems are based on numerous techniques, it is still a challenging task because variables like high vehicle speeds, uneven license plates, different languages used for vehicle numbers, and different lighting conditions can all significantly affect the overall identification rate. With these limitations, the bulk of the systems work. Several ANPR approaches are described in this study, taking picture size, success rate, and processing time into consideration. The study ends with a proposal for an ANPR expansion.

I. INTRODUCTION

Identification are climate, environmental influence, and localization accuracy. Using the color features and probability distribution of the license plate between the two lights is one method for number plate recognition. Template matching is a common technique for algorithms that identify licence plate numbers. The template matching-based License Plate Detection algorithm was created and designed to manage the parking lot system by detecting unregistered vehicles from off-campus. Vertical edges-based car license plate detectionis quite common at the moment. However, some people prefer to locate the location number plate by using image projections in both the horizontal and vertical planes. The license plate area can be located using the Genetic Algorithm and the Hough transform. Concurrently, effective outcomes were achieved by combining block-based algorithms with edge statistics and mathematical morphology. Another technique that takes use of the gaps between the rows counts the edges that are present and, if the number is greater than a set threshold, finds the license plate. The key elements for number plate localization are extracted using a method based on the wavelet transform. The benefit of this method is that it enables you to locate numerous license plates inside the frame. Several of the above-mentioned techniques need a significant amount of compute and are quite sophisticated. It could be a little challenging to use time in real-time applications. Some methods, such as backdrop color and other number plate attributes, might only be employed in certain nations.

II. LITERATURE SURVEY

ITS is crucial in the development of increasingly complex applications for the detection of automobiles and other objects, like multi-object tracking. The authors of [1] made an effort at the structure. The majority of multi-object tracking systems employ one of two methods for object initialization: detection-based tracking (DBT) or detection-free tracking (DFT). In terms of both matching costs and computing performance, the ORB technique performs better than other algorithms.

Vehicle type classification was carried out by the authors of in order to identify applications in a variety of situations, including vehiclemanagement, traffic statistics analysis, and toll collection. The use of computer vision to classify vehicles it has been successfully used in traffic flow modelling and road traffic analysis. The model attained the maximum accuracy of 78.53% when 9000 images from the MIO-TCD dataset were employed.

The authors of created models like SVM and Decision Tree, which are used in a wide range of fields like mathematics, computer graphical user interfaces (GUIs), the web, and many important scientific applications. Python was created with the main goal of making programming simpler so that anyone, wherever in the world, could create their own software. The authors of [4] implemented approach for vehicle detection using transfer learning techniques using base models such as CNN, Inception V3, Inception-ResnetV, MobileNetV2.

Which would be employed in autonomous driving with the use of features like vehicle identification and categorization to support the CPU in real-time situation analysis and decision-making. This was achieved by establishing a system that would detect vehicles used for autonomous driving As a consequence of this study, models with accuracies of 91.8%, 89.1%, 91.4%, 90.8%, 92.3%, and 90.5% were implemented, including Inceptionv3, ResNet, InceptionResnetv2, MobileNetv2, Nasnet, and PNASnet.

The authors of [5] used the RCNN, ZF, and VGG16 networks to identify and recognise the three major groups of autos that are frequently seen in a traffic scene. This process can undoubtedly enhance the sort of automobile.

Without diminishing the effectiveness of the Faster RCNN in detection or failing to fulfil the demands of varied traffic conditions. This is made possible by streamlining the model's algorithm and enhancing the RPN networkdetection of targets in moving vehicles

Purpose of the Research

The goals of this research study are listed in the list below: x To examine further methods that can identify a vehicle's license plate. To offer a solution to the automated

DOI: rp-9788770040723.142

number plate recognition conundrum. To assess and test the suggested method, and to deliver the evaluation's findings.

III. Proposed Strategy

There are three components to the overall issue: Plate area detection, number plate segmentation and character extraction, symbol extraction using optical character recognition, etc.

Plate Area Detection, first The programme will be given an image with a number plate as input, and it will need to recognize the number plate before cropping the image as an output for the following stage. The image must go through the following process in order to extract the number plate from the entire document. x Gray scale image: At this stage, the image must be read and converted to grey scale format. Such conversion won't result in the loss of crucial data, at the very Similarly, working with one channel rather than three will be more convenient. The noise is a major difficulty with our dilemma, x Blur. It is preferable to blur the image in order to lessen them. There are various smoothing techniques. After smoothing, the cumulative error distribution graph that follows compares each of them. indicates that when compared to other smoothing techniques, homogeneous smoothing is the best, according to Figure 1. x Characters are located on the number plate thanks to vertical edge detection. The characters, as we all know, have more vertical than horizontal edges. To solve this problem, one of the best methods is to identify vertical edges that are very close to one another. It is the edge detection.

Vertical edge detection

The characters are found on the license plate. We already know that the characters have more vertical than horizontal edges. Finding vertical edges that are very near to one another is thus one of the greatest strategies [1]. In the subject of computer vision, edge detection is a fundamental and fundamental function. There are numerous types of edge detectors, including Prewitt, Sobel, Canny, and others. Each of them is used to various situations and issues. To solve the given problem, we employ Prewitt, Sobel, and a modified version of Sobel [9]. However, following research and testing, we decided to utilize the modified version of Sobel since it accurately detects vertical edges and significantly reduces the number of horizontal edges that obstruct.

By utilizing techniques like frame difference and contour mapping, we present a novel approach to object detection in Figure 2. First, the image will be converted to RGB, after which the ROI (Region of Interest) will be removed to keep the undesirable portions of the image out of context. Following that, the OpenCV library will process the ROI by figuring out the Threshold, dilation, and contours. Following the discovery of the frame difference, the frame is transformed into a grey image in order to use dilation to detect any potential motion. The bounding box is then mapped using the coordinates of the associated contours. A bespoke CNN model receives the image as an input as a (32 x 32) pixel image from the bounding box, which captures it in its original frame. The algorithm then trains and forecasts the image's class (Truck, Car, Bike).

As we suggested using the CIFAR-10 dataset to train the models on images with a 32 by 32 pixel resolution. The models were trained using the transfer learning technique, which pairs a custom model with a base model that has already been trained using "imagenet" weights. The top layers of the pre-trained model are not included since they limit the size of images that can be trained to about (224 x 224 x 3), while CIFAR-10 only provides images that are (32 x 32 x 3). In order to train the custom model for classifying the photos, we later added custom layers on top of this previously trained model. We divided the dataset into training and testing datasets after pre-processing them.

Processed path

Extraction of number plate location character recognition from vehicle image browsed or captured by camera Vehicle Number Input Image Number

Extraction

Remove Connected Objects on Border from the Plate Location Character Segmentation

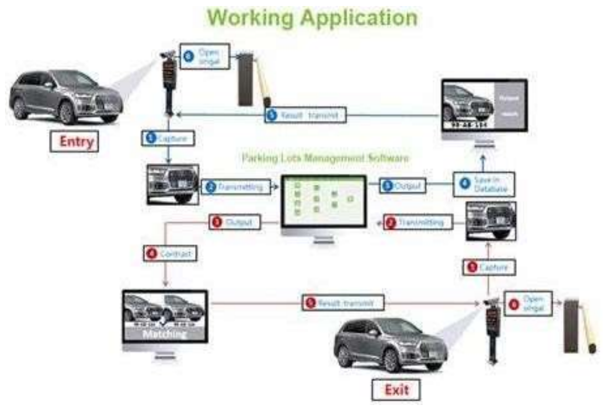


Fig. 1 CIfAr-10 images

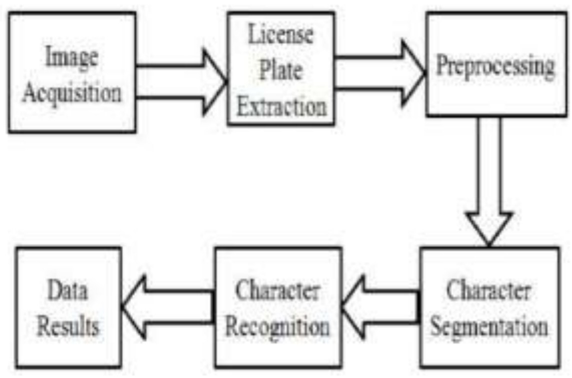


Fig. 2. Proposed Meth

Recently, a number of handcrafted methods have been presented, including the HoG and Haar features [47] and deep learning methods (R-CNN [48], Faster-RCNN [27], and YOLO [49] approaches). While others digest information slowly, some have a low accuracy rate. Among deep learning object detectors that can perform real-time processing.

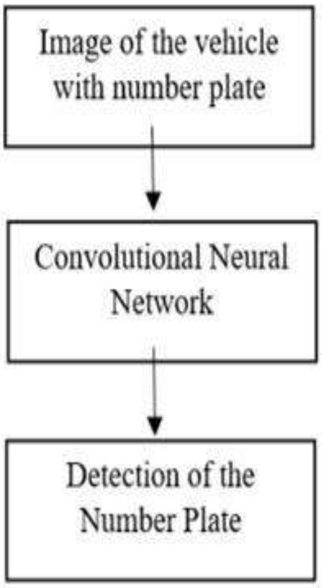
DOI: rp-9788770040723.142

The highest detection rates have been demonstrated using faster-RCNN. Faster-RCNN performance, however, suffers when dealing with small object detection, such as the LP localization in our case. Therefore, this work uses Faster R-CNN for vehicle detection in order to deliver accurate and scaled information in a picture. Additionally, Faster-RCNN performs well for vehicle detection as vehicle size grows. To deal with fluctuating scales, anchors in RPN are created, which employs three scales (128 128, 256 256, and 512 512), three aspect ratios (1: 1, 1: 2, and 2: 1), and nine anchors at each place. The fact that each area proposal's size is different from the others makes it difficult to design effective architecture for a range of sizes.

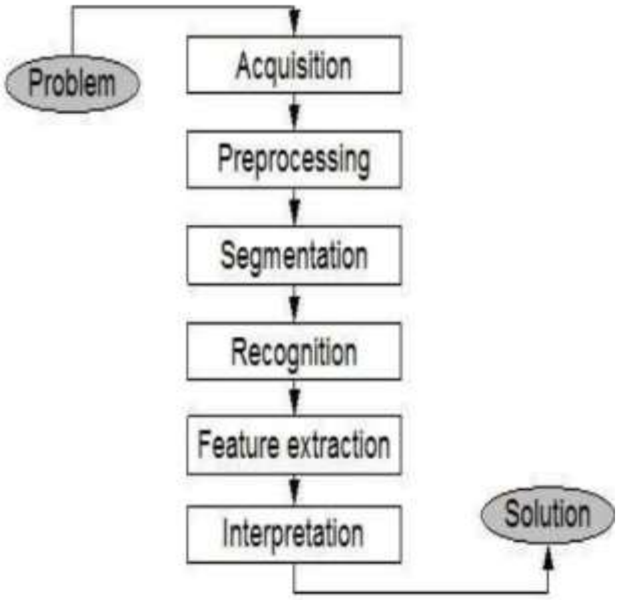
RoI SoftMax probability to categorize vehicles and non-vehicles, and the second of which predicts the coordinates of each region's rectangle.

Variations in the vertical edge detector x Black and white are the only colors present in binary pictures. The Otsu, Niblack, Souvola, Wolf, and Feng procedures are just a few of the threshold-related approaches.

Region of interest (RoI) pooling is used to simplify the problem and derive a fixed-size feature representation. The vectors are enlarged to include the RoI pooling properties. These vectors are finally fed into two fully connected layers, the first of which uses each Using stochastic gradient descent with momentum (SGDM), which changes the weights quickly and lowers inaccuracy, this method trains the faster-RCNN architecture. SGD just needs one sample data set from the training data, in contrast to gradient descent (GD), which uses all training datasets to update the weights and parameters. From each batch, one image was randomly selected for training. The revised sizes were 600 and 1400 for the shorter and longer sides of each image, respectively. shows the results of a quicker RCNN vehicle recognition using images.



A gradient-based histogram will be produced for each candidate. The feature vector will then have a specific length. By providing all of these vectors to the algorithm, we will be able to obtain the appropriate license plate among other things. SVM and setting it up with particular settings. Another strategy built on probabilistic theory was put into practice.



In this scenario, the turns are were initially identified, and any shapes that did not resemble a character were removed. Whether or not the remaining contours are located in a straight line is studied via identification. The likelihood of each character was then determined by removing each character from the license plate. The best candidate was chosen after adding them all up and taking these values into consideration. However, after testing, wewhere Lx and Ly are picture derivatives. Finding only vertical edges is achievable when using the value of. Only vertical edges will be produced if the value of is between 45 and 135. In the Fig. 2 show the outcome and variance of each edge detector.

Each of them took part in specific situations to achieve different objectives. Binary picture manipulation is more useful. After finding vertical edges, we will apply Otsu threshold to our existing image. x Most often, close morphology is used to connect nearby elements. Since our objective is to locate the number plate, we don't need a lot of information about the characters. We employ near morphology, which integrates all letters and numerals, as a result. The results of the morphological process are displayed in Figure 3.

DOI: rp-9788770040723.142

Recognize contours. Using the near morphology, where the area and aspect ratio of the contour must be taken into account, we will discover the contours that resemble licence plates. Additionally, the contours must be positioned horizontally, as seen in Fig. 3.

Identify the best applicant. To find the best candidate among the others, every number plate must be reviewed. The feature vector for each candidate will be computed initially. To do it, we'll use a histogram of directed gradients.

Segmentation The licence plate must be used to extract the characters. There are two fundamental approaches to segmentation; the one projects the image into X axis, while the second looks for outlines that resemble characters.

After completing study and testing, we came to conclusion that second algorithm performs better than first one. In Fig. 4, algorithm's output is shown. Before segmentation, the image must also be transformed to binary format. In this case, the Otsu method is not the best course of action. The Nick, Niblack, and Souvola algorithms outperform the rest, according to our tests of several binary algorithms.

character recognition using optics It is important to recognize the extracted character. To be used for recognition, we revised the 1NN technique. As shown in Fig. 5, the character was divided into 49 distinct components. Each component's white pixel count needs to be recorded. The feature vector, which consists of 49 elements, will be used to identify each character. Figure 6 displays feature vectors for the classes A, B, and C.

After the average element for each class has been established using feature vectors, the distance between an unknown element and all of the average elements in each class must be calculated. Unknown element will be added to the classes in the neighboring hierarchy that are closest to it

IV. Working of Algorithms

Character recognition for license plates frequently uses CNNs. The effectiveness of these systems in detecting odd license plate types or working at night hasn't received much attention, though. We demonstrate an effective ALPR system that recognizes characters using a CNN. The system efficiency was improved by applying a combination of pre-processing and morphological techniques to improve input image quality. The system can recognize license plates with multiple lines, skewed edges, and several fonts, among other qualities.

The best method for putting ALPR systems into practice makes use of deep learning using a convolutional neural network (CNN). Four methods are used by our system to carry out this step: grey scaling, median filter, thresholding, and masking. Multiple layers that independently learn to recognize the distinctive characteristics of an image can make up a CNN network. Every training image is fed into a filter with a different resolution, and the output of each convolved image is fed into the network's next layer.

To recognize the license plate in the pixels in the foreground. the identified number pictures' OCR. A unique set of algorithms is used for each phase. Automatic number plate recognition (ANPR), also known as license plate recognition (LPR), uses video-captured images or datasets to automatically identify a vehicle by its license plate. which are frequently positioned at fixed points along roadways and at parking lot entrances. Reading the image and gaussian blur and convert it to grayscale, Binarize the photo Using the n 8-connected component technique, label the binary image, Regions that are too big, too small, or have an aspect ratio greater than one should be removed. The largest region should be chosen after the regions have been sorted by distance from the Y-axis and collinearity.

V. Results and Discussion

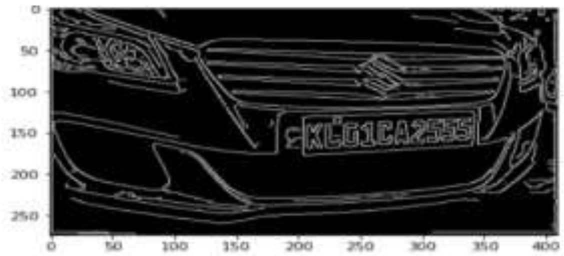
The method was tested with 1469 actual car photographs. The pictures of the vehicles were taken from different perspectives and in varied weather situations. First, Plate Area Detection The exams were divided into five sections. Several subparts determine which side of the subject—front or back—the picture was taken from. The results of the test scenarios used to calculate the plate area Results of Plate Area Detection Subparts 1 Front, 2 Rear, and 3 Rear,

95.3%, 93.15%, 95.5%, and 94.46%, 93.88% If we take the average of the aforementioned data, the average performance of the plate area detection algorithm is (95.3% + 93.15% + 95.5% + 94.46% + 93.88%) / 5 = 94.458%.

After taking into consideration the value for each group, we calculated the overall performance of the segmentation algorithm (56.38% + 77.83% + 64.49%) / 3 = 66.23%. Following segmentation, the extracted lettersare shown in Fig. 7. number plate up:

Optical Character Recognition (C) There are several characters that are similar to one another, such "5 and S" and "O and 0." Examine our OCR solution in light of this information.

DOI: rp-9788770040723.142



Comparing Models

We came to the conclusion that DenseNet-169 fared the best after comparing models against one another based on the provided criteria, with an accuracy of 96% accuracy and an F1 score of 96.3%. The type of car in the video can be accurately predicted by the model. The comparison of the models is shown in Table 1. Figures 11, 12, and 13 display the model's performance metrics graphs, with DenseNet-169 being the best bespoke pre-trained model.

VI. Conclusion

Using the suggested methods, data preparation, and learning the models across more than 100 epochs. DenseNet-169 successfully characterized the dynamically moving items in the frame using a bounding box after precisely anticipating the cars, buses, and trucks in the movie. The creation of a thorough system for traffic routing in crowded areas is the ultimate goal of this thesis. It is important to get dynamic data that shows the traffic flow condition along all feasible routes within a separate road using detectors in order to route traffic inside a city.

VII. Future Work

In the future, we intend to develop and incorporate object detection into the model itself in order to enhance its functionality. By employing coordinate pixel values, we intend to develop an experimental feature that will estimate the speed of moving vehicles and display the results next to the projected label.

References

[1] H. Erdinc Kocer and K. Kursat Cevik, “Artificial neural networks based vehicle license plate recognition. “procedia Computer Scienc, vol. 3, pp. 1033-1037, 201.

[2] Gomathy, V., Janarthanan, K., Al-Turjman, F., Sitharthan, R., Rajesh, M., Vengatesan, K., &Reshma, T. P. (2021). Investigating the spread of coronavirus disease via edge-AI and air pollution correlation. ACM Transactions on Internet Technology, 21(4), 1-10.

[3] Benjapa, R., Kittawee, K., Paruhat P., Thaweesak Y. (2012). License Plate Detection Based on Template Matching Algorithm. Retrieved from International Conference on Computer and Communication Technologies (ICCCT 2012) May 26-27, 2012

[4] Performance enhancement method for multiple license plate recognition in challenging environments ‘https://jivp-eurasipjournals.springeropen.com/articles/10.1186/s13640-021-00572-4’.

[5] Rajesh, M., &Sitharthan, R. (2022). Introduction to the special section on cyber-physical system for autonomous process control in industry 5.0.Computers and Electrical Engineering, 104, 108481.