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Research Article

NUMBER PLATE DETECTION THROUGH MACHINE LEARNING APPROACH

[1,*]Sundas Naqeeb Khan, [2]Zain Ishtiaq, [3]Samra Urooj Khan, [2]Sonia Arshad, [2]Tooba Noreen, [2]Rafeh ul Hassan and [2]Khadija Rehan

[1]Faculty of Computer Science and Information Technology, Universiti Tun Hussien Onn Malaysia (UTHM), Johor, Malaysia
[2]Department of Computer Science, University of the Punjab, Punjab, Pakistan
[3]Faculty of Electrical and Electronic Engineering, Universiti Tun Hussien Onn Malaysia (UTHM), Johor, Malaysia

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Abstract

An efficient Automatic Number Plate Recognition (ANPR) system is required in the futuristic world. Due to the fact that each county has its own number plate type and style, an unrestricted Number Plate Detection system is still unavailable. Because to the lack of data and the varied plate formations, there hasn't been much work done on Pakistani number plates. To address this problem, a Pakistani vehicle dataset has been collected with diverse plate designs and used it to construct an innovative ANPR system. Using machine learning technique, the suggested framework locates the number plate region. It employs a CNN model, employs strong preprocessing techniques on the recovered plate region, and then uses OCR (Optical Character Recognition) Python-Tesseract to recognize the plate label. The suggested ANPR framework, which uses the CNN and OCR Tesseract for detection and identification, has good accuracy and inference time for a wide range of lighting and style of Pakistani number plates, and may be utilized to construct a real-time system, according to the comparative analysis. Researchers developing ANPR for countries with similar demanding vehicle number plate formats and designs may benefit from the suggested ANPR framework.

Keywords: ANPR, CNN, OCR, ANN, Edge detection, Localization, Sobel mask, Character segmentation, Character recognition, Classification.

INTRODUCTION

The ANPR system is a technology, which captures the number plate of a vehicle for the identification of plundered vehicles [1], and crime detection systems. Though ANPR is a very old research area in image processing, it is still evolving year by year, because detecting the number plate from the image or the video is not an easy task as counting the vehicle from a stream of video [2 - 3]. With the rapid growth and advancement in ANPR, it has become important in terms of security and also for revenue. The researcher can look at this aspect in England as in 2018, after 10.1 billion number plates scans took place, £472 million was generated in fines from 6.96 million penalty tickets. Likewise, the potential for installers to capitalize on ANPR solutions as a new revenue stream is highlighted by recent research published by IHS Markit [4]. The findings indicate that "global market revenues from sales of intelligent ANPR devices are forecast to reach $800m by 2022, growing at a compound annual growth rate of 16.4%". Number late Recognition involves the acquisition of number plate images from the intended scene, using a camera. Either still, images or a photographic video is captured and further processed by a series of image processing-based recognition algorithms to attain an alpha-numeric conversion of the captured images into a text entry. Most of the number plate detection algorithms fall into more than one category based on different techniques. To detect vehicle number plates following factors should be considered:

1. **Plate size:** a plate can be of different sizes in a vehicle image.
2. **Plate location:** a plate can be located anywhere in the vehicle.
3. **Plate background:** A plate can have different background colors based on vehicle type. For example, a government vehicle number plate might have a different background than other public vehicles.
4. **Screw:** A plate may have a screw and that could be considered a character.

After obtaining a good quality image of the scene/vehicle, then the core dependence of any ANPR system is on the robustness of its algorithms. These algorithms need very careful consideration and require thousands of lines of software coding to get desired results and cover all system complexities. As a whole, a series of primary algorithms are necessary for smart vehicle technologies and ANPR to be effective. The image taken from the scene may experience some complexities depending upon the type of camera used, its resolution, lightening/illumination aids, the mounting position, area/lanes coverage capability, complex scenes, shutter speed, and other environmental and system constraints. There is a variety of number plate designs are available in Pakistan, a few of them are shown in Figure 1.

Figure 1. Common designs in Pakistan

Corresponding Author:** ***Sundas Naqeeb Khan,
Faculty of Computer Science and Information Technology, Universiti Tun Hussien Onn Malaysia (UTHM), Johor, Malaysia

LITERATURE REVIEW

Pre-processing is a phrase that describes operations on images at the most fundamental level of abstraction, with intensity images as both the input and output. The intensity image is commonly represented by a matrix of image function values, and these iconic images are similar to the sensor's original data (brightness). The goal of pre-processing is to improve the image data by suppressing unwanted distortions or enhancing some image features important for further processing. Although geometric transformations of images e.g., rotation, scaling, and translation are classified among pre-processing methods. The impact of various picture pre-processing techniques on the performance of Speeded Up Robust Features (SURF is investigated. The effects of proposed approaches such as Histogram Equalization, Multi scale Retinex, and Image Adaptive Contrast Enhancement (IACE) on the SURF in terms of feature point detection are examined and computing time for extracting descriptors. The influence of these image pre-processing approaches on the repeatability of cutting-edge detectors such as Harris-Affine, Hessian-Affine, MSER, Edge Based Regions, Intensity Based Regions, and SURF is next investigated. The repeatability test is carried out on the standard images that have been used as a baseline for evaluating the performance of different systems for feature point detection. Finally, a method for scaling large-resolution photos is presented that may be utilized in conjunction with the IACE approach to improve matching speed while retaining its accuracy and performance level. This study covers how to prepare photographs for analysis, as well as how to extract interesting spots and features. Some of these methods, particularly metrics derived from transforms and basis spaces, can also be used to describe global and local features [5 - 10]. The types of operations that can be applied to digital images to transform an input image a[m,n] into an output image b[m,n] or another representation can be classified into three categories as described in Table 1.

Table 1. Category of Transformation of the Images

Operation	Characterization	Pixel
Point	The output value at a specific coordinate is dependent only on the input value at that same coordinate.	constant
Local	The output value at a specific coordinate is dependent on the input values in the neighborhood of that same coordinate.	P^2
Global	The output value at a specific coordinate is dependent on all the values in the input image.	N^2

As an application of CCTV Traffic surveillance, retrieval of the number plate from the vehicles is an important dimension, which demands intelligent solution. In this research, template matching block of computer vision toolbox has been used to extract the vehicle number plate. It is assumed that images of the vehicle have been captured at a particular resolution and orientation. It is also assumed that alpha-numeric characters on the plate have been written with a particular font style, type and size. This research describes a new SIMULINK model for MATLAB that was created to retrieve the vehicle's number plate. On a plate, each alpha-numeric character is with the help of, extracted and matched along the template picture. Block that matches templates. This block is a perfect fit for the pixel. Compare the original image's pixel value to one of the template pictures and returns the value of the template metric. To further develop this digital signal processing Toolbox, SIMULINK model, and in MATLAB, the computer vision system Toolbox is used. The template matching strategy was employed for this model, Letters and numerals have been recognized using this method. This technique can be used for security purpose e.g., finding stolen cars, and for parking area management etc. A reliable method for extracting car license plates from photos with a complex background and low quality is suggested [11]. The method focuses on dealing with photographs obtained in low-light situations. The procedure is broken down into two parts: 1) using gradient information to find candidate areas in the input image, and 2) identifying the plate area among the candidates and changing the area's boundaries by introducing a plate template [12]. The approach's robustness and accuracy have been demonstrated through a series of studies [13]. The result demonstrates that 90% of the photos taken from a vast underground parking garage are accurately divided [14 - 16].

Edge is one of the most crucial and necessary traits. One of the most well-known research initiatives in the field of computer vision and image processing is edge detection. The initial step in picture analysis and comprehension is edge detection. The goal of edge detection is to retrieve information about shapes, reflectance, and transmittance from a photograph. It's an important step in image processing, image analysis, pattern recognition, computer vision, and human vision. The understanding machine system built for the objective world is directly affected by the accuracy and consistency of its outcomes. The classic Canny operator lacks adaptive capabilities when it comes to Gaussian filtering variance selection [17]. Filtering necessitates human interaction, and the variance of Gaussian filtering has an impact on edge preservation and de-noising [18]. The researchers propose an enhanced edge detection technique [19]. The morphological filtering replaces the Gaussian filtering. Experiments demonstrate that the enhanced Canny operator can successfully filter salt and pepper noise, improve edge detection accuracy, and reach an optimum edge detection effect [20]. The findings of the experiment reveal that the objective evaluation and visual effect are both satisfactory [21 - 24].

Character segmentation has long been a critical area of the OCR process. A good part of recent progress in reading unconstrained printed and written text may be ascribed to more insightful handling of segmentation. The holistic strategies that avoid segmentation by treating complete character strings as units are described. In a LPR system, character segmentation is a critical stage. There are numerous challenges in this process, including the impact of image noise, plate frame, rivet, and space mark, among others. The study provides a new character segmentation algorithm based on the Hough transformation and prior information in both horizontal and vertical segmentation [25]. In addition, for image preparation, a new object enhancement technique is applied [26]. The experiment results suggest that this novel segmentation algorithm performs well [27 - 30].

METHODOLOGY

The LPR programs usually have a set of specific processing steps such as: capturing of image, number plate localization, image pre-processing, and character recognition and identification and at last label management. The detection of number plates is a challenging task due to the variety of plate formats and natural conditions during image acquisition. The accuracy of characterization and identity depends on the performance of the plate acquisition. The system of LPR with all its reviews are illustrated in Figure 2.

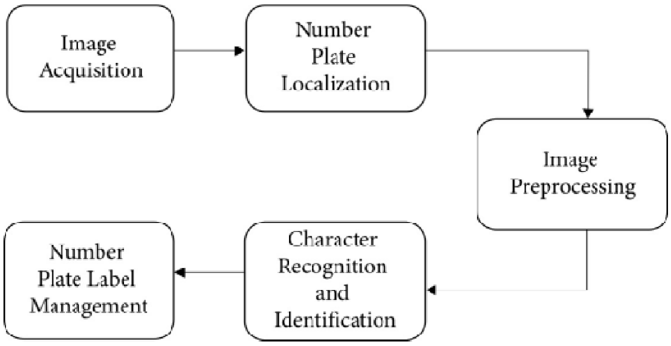

Figure 2. The LPR system

Step-1: Image acquisition is the process of obtaining an image from the camera. This is the first part of the ANPR system. A live or static image is sent to ANPR system from the acquisition device for recognition of number plates. There are basically following two ways of acquiring an image:

1. Using analog or IP (surveillance) camera
2. Using a digital camera or mobile camera

In the proposed system, the images are captured by using a digital camera or a mobile camera. However, the image is not just only the number plate when captured but some background and some unnecessary items.

Step-2: Number Plate Localization is a regression problem where the output is x and y coordinates around the object of interest to draw bounding boxes. Input in this type is also an image but the returned output is “x”, “y”, height, and width numbers around an object of interest.

The localization of the number plate from the entire image can be performed by the Sobel mask. Sobel mask is commonly used for edge detection in image processing. It defines all the edges in the input image. In order to perform localization, pre-processing steps are essential which help to improve the contrast of the uploaded image and also reduce the noise from background, respectively. By doing this, the location of the license plate is more visible for the computer to recognize. To extract only the license plate and remove the other unnecessary items or background, the horizontal localization phase is responsible for identifying the horizontal segmentation of the license plate, same goes for the vertical localization phase.

Step-3: Image preprocessing: An image either captured by digital camera or extracted from frames of video sequences needs pre-processing. Video footage or image may contain variation of brightness or color information known as noise. To cope with such degraded images or video frames, images are enhanced which improves visibility and perceptibility of image. Image pre-processing is a process to work on images at a very low level of output. These functions do not increase the content of the image information but reduce it if the entropy is the information method. The goal of pre-processing includes: removing the noise, enhancing contrast, sharpening or smoothing, elimination or retaining certain features in an image. Development of image data that prevents unwanted distortions or enhances other image features that are appropriate to further the work and analyze the work.

- Gray-scale conversion
- Normalization
- Data augmentation
- Changing brightness
- Standardizing images
- Image binarization

Step-4: Character segmentation: After cropping the license plate, the next step is character segmentation. This is to separate the alpha-numeric character on the license plate individually. Thus, the characters are needed to be transformed into an array of numerical data. It can be achieved by using the Vertical Projection Profile (VPP), said to [31]. The VPP is to determine the brightest color and also the darkest which matches the normal color of a number plate. In this way, the computer can know the gap between each character and separate accordingly. However, there are also some other methods that can be used as well such as Connected Component Labelling (CCA). The CCA label all the connected pixels in the input image. The computer first scan through only the black pixels of the input image, once the black pixel is found, the computer then checks whether its neighbor has been labeled before. If its neighbor has been labeled, then the current pixel will be labeled with the same number as its neighbor. If not, then the current pixel will be assigned with a new label value. The same process will be gone through the cropped license plate and finally separate the characters according to how many labels have been created.

Step-5: Character recognition: It helps in identifying and converting image text into editable text. Most of the number plate recognition algorithms use a single method for character recognition.

Step 5.1: Artificial Neural Networks (ANN): The ANN sometimes known as the neural network which is a mathematical term, that contains interconnected artificial neurons. The ANN model is used for the classification of characters. It contains an input layer for decision making, a hidden layer to compute more complicated associations and an output layer for the resulting decision.

Step 5.2: Template matching: For a computer to recognize each and every character, the first thing is to do appropriate training. The technique, template matching will tell the computer what a character looks like. For example, the character ‘A’ is sharp on top, having two legs at the bottom and one line at the center. When recognizing, the computer will perform the matching on a pixel-by-pixel basis.

Analysis of empirical testing

The presented standardized image data sets for object class recognition which provides a common set of tools for accessing the data sets and annotations. It makes it possible to assess and contrast various approaches. The Pascal Visual Object Classes (VOC) is a benchmark in visual object category recognition and detection, providing the vision and machine learning areas with a standard data set of images and annotations as well as standard assessment techniques. The CNN is a deep learning technique that uses the gradient descent resonant learning algorithm and is a special sort of multi-layer perceptron. It has been demonstrated to be the most effective neural network for recognition and prediction. TensorFlow and Keras is used to train the CNN-based model

"InceptionResNetV2" to compare the performance criteria of the preceding techniques. TensorFlow and Keras are Python packages for training models on huge datasets. 400 images will be trained and 100 validation images in the dataset are used for training. A collection of PakWheels character photos and data that has been cleaned up in various ways, such as bypassing a particularly noisy image is compiled. The recommended object detection network investigates the Number Plate (NP), resizes it to keep it recognizable, and constructs rectangular bounding boxes using PASCAL VOC. InceptionResNetV2, a sequential 4-layer CNN model that is one of the best models at object detection is trained. The model comprises of a convolution layer with 32 filters and a relu activation function with an additional maximum composite layer with group size of 5 and kernel size of 5 (2, 2). To avoid over-fitting, 0.4 loss is employed to delete 40% of neurons, and an information flattening layer is added for node flattening. After that, a dense layer with 128 outputs is added, as well as a ReLU trigger function. Finally, there is a dense layer with 36 outputs and a sigmoid activation function in the last layer (probabilistic final decision). The overall output of 36 neurons is composed of 26 alphabets and 10 digits. A learning rate of $1e^4$ with 200 epochs, the classifier cross entropy reduction function, and Adam's optimization function for training is utilized. The CNN algorithm predicted with 92.89% accuracy, but the accuracy reduced after recreating the license plate tag. The CNN model is overall pipeline which is depicted in the process.

RESULTS AND DISCUSSION

Data set

As it has already been stated, the data they are using for machine learning is "Custom Data.". The largest website for buying and selling cars is Pak Wheels [32]. The exact model that has used is InceptionResNetV2 for training and testing more than 350+ images of car's number plates. The data set based on different kinds of images and these images have some type of properties for presentation such as vertical, horizontal, blurry, good quality and reflection images etc. There are several vehicles with their images available on this site but the focus of dataset is mainly on these vehicles' images such as Mehran, Alto, Cultus, Xli, because these are the most used vehicles in Pakistan specifically.

Analysis of models

Recently, the ANPR has proven to be a key mechanism for safety and traffic management extending from congestion monitoring to parking leading to data retention for reasons monitoring. ANPR provides a simple description of the vehicles and a guide to vehicle tracking and more behavioral analysis. The wide variety of license plates, in different colors, shapes, sizes and designs, is one of the main challenges of LPR. These challenges include adverse weather conditions, poor lighting, and limited camera resolution, as they affect the clarity of real-time images as the camera captures the shot. In the field of ANPR, a detailed review/comparison of the previously available systems, their performance, degree of inferiority and limitations is discussed in Table 2. This table 2 depicts an overview of the comparison, research of the ANPR methodologies previously presented. After examining the proposed methods' performance indicators, researcher concluded that their number plate localization strategies would not produce the best outcomes. The accuracy and mean average precision score of the present approach are defined in the performance rate column. From the comparative analysis in Table 3, it can easily be observed that researcher proposed ANPR system achieved good results. The previous ANPR system used different techniques, namely, edge detection, histogram equalization, and CCA for localization which is not an efficient way to handle every type of vehicle number plate. Their pre-processing techniques did not work well on double-row number plates due to the poor localization approach. The employed CNN-based ANPR framework performs fast and more efficiently in detecting such challenging plates. As a consequence of comparing proposed framework to existing approaches, researcher concluded that employing researcher proposed pipeline on the Pakistani dataset is yield a better outcome.

Table 2. Summary of the comparative study of the existing methods

Plate's type	Proposed method	Performance rate/accuracy	Discussion/remarks
Real-time images	Niblack threshold, blob-coloring, neural network -based OCR	86.1% for recognition	Addressing low-resolution images with an average computation time is 1.5 seconds [33]
Nepali number plates	Grayscale, morphological operation, median filter, phase correlation, cross-correlation in template matching	67.98% for cross-correlation, 63.46% for phase correlation	Due to template matching the average accuracy is low [34]
Indian number plates	Basic preprocessing, PCA for feature extraction, CNN classifier for recognition	Successful execution is done by using Raspberry Pi	Suitable researches are discussed in it [35]
Real-time images	YOLOv2, Warped Planner Object Detection Network (WPOD-NET) for detection, OCR for recognition	For detection is 76.8% and for recognition is 75%	Focus on unconstrained images having single-row number plates [36]
Real-time images	Grayscale, binarization, masking for plate detection, distinguishing definite characters by SVM (deployed using MATLAB 2010a)	92% accuracy for recognition	Cannot recognize motion blurred, overlapped, skewed, and plate with a different language [37]
Indian number plates	Grayscale, binarization, contrast extension, median filter, MATLAB region props function for segmentation, zonal function for feature extraction, template matching for recognition	The recognition rate lies between 75% and 85%	Addressing low resolution, unskew and clear images [38]
Qatar number plates	Rescaling, morphological operation, connected component analysis (CCA), vector crossing, zoning, template matching	Recognition rate is 99.5% with 0.63 ms computation time	High-resolution and single-row images are addressed [5]
Ghanaian number plates	Grayscale, Gaussian kernel, Sobel edge detector, CCA on a binarized image, Tesseract OCR for character recognition	Recognition rate is 60% with 0.2 s computation time	Up to a distance of 5 meters, the detection algorithm performs fairly efficiently [6]
Pakistani number plates	Histogram equalization, distinct feature matching	93% accuracy for recognition	Medium resolution with the single-row number plate [7]
Pakistani number plates	Grayscale, Gaussian filter, canny edge detector, KNN	93% accuracy for recognition	Mainly focus on a car number plate [8]

Table 3. Comparative Analysis of proposed system with [7] [8] [39]

Vehicle types	Resolution	Localization technique	Character/plate recognition	Segmentation	Testing dataset	Overall accuracy/ average score	Can be implemented in real time?
Car, bike, and bus	Medium	Vertical and horizontal histogram	OCR	Yes	50	93%	No
Only car	High (1140 × 641)	Edge detection	KNN	Yes	900	93%	No
Car	Medium	CNN	OCR Tesseract	No	300	70%	Yes

Researcher pipeline tactics are ubiquitous and may be used on any sort of Pakistani vehicle dataset, including automobiles, motorcycles, and buses with double and/or single-row number plates.

Conclusion

Number Plate Recognition involves acquisition of number plate images from the intended scene, using a camera. Either still images or a photographic video is captured and further processed by a series of image processing-based recognition algorithms to attain an alpha-numeric conversion of the captured images into a text entry. After collecting a high-quality image of the scene/vehicle, the robustness of an ANPR system's algorithms becomes critical. These algorithms demand a great deal of thought and thousands of lines of software code to achieve the required results and account for all system complexities. Depending on the camera used, its resolution, lighting/illumination aids, mounting location, area/lanes coverage capabilities, complicated situations, shutter speed, and other environmental and system limits, the image captured from the scene may have certain complications. Collection of images is firstly annotated and then they are trained in a CNN, in researcher case, model is InseptionResNetV2. Trained model detects number plate which is passed to OCR for Character Recognition. Despite the fact that the developed ANPR system has operated brilliantly, there are still some aspects that might be improved with more time. The first would be an increase in the performance of the picture segmentation stage. Instead of downloading photographs from a website, this might be performed by using a more robust picture segmentation technique or an infrared camera. Using an infrared camera, two birds might be killed with one stone, which would also increase the ANPR system's performance in bad weather conditions like rain or mist. The limits revealed during the complementary experiments are the focus of the second group. To make the system more realistic, video instead of static photographs might be utilized as an input, or car brand and model recognition may be included. Aside from the aforementioned concerns, future ANPR system research should focus on developing a standard evaluation approach based on a common testing data set, so that the performance of the numerous ANPR systems developed may be examined equitably.

Conflict of interest: The authors confirm that there is no conflict of interest involve with any parties in this research study.

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