**Indian Vehicle License Plate Extraction and Recognition Using Morphological Operations and Deep Learning**

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***Abstract:***

***License Plate Extraction and Recognition (LPER) play a vital role in various applications within intelligent transport systems (ITS), including surveillance, traffic flow monitoring, stolen vehicle tracking, and parking lot management. This paper presents a comprehensive system design for implementing LPER specifically tailored to Indian License Plates. The LPER process encompasses three essential stages: License Plate Extraction, segmentation, and classification. Each stage necessitates specialized techniques adapted to real-world scenarios, each characterized by distinct attributes.***

***The license plate extraction techniques are utilized to accurately locate the license plate region, which is succeeded by segmentation algorithms that effectively isolate individual characters. Subsequently, a classification step is employed to recognize these segmented characters. The overall efficacy of the process hinges upon the precision achieved at each sequential step. To significantly enhance the classification step's performance, we propose an innovative amalgamated approach that integrates segmentation and classification into a cohesive single-stage process. This integration harnesses the power of deep learning methodologies, incorporating Morphological and*** ***Enhanced sliding contract window (ESCW)-based number plate detection alongside the employment of the AlexNet neural network.***

***Our experimental findings underscore the efficacy of this proposed approach, showcasing an outstanding accuracy of 97.2% in accurately recognizing characters on vehicle license plates. This achievement notably surpasses the accomplishments of prior endeavors in this field, signifying a significant advancement in LPER technology.***

***Keywords:***

***deep learning, artificial neural network, License plate extraction and recognition(LPER)***

1. **INTRODUCTION**

Recognizing the license plates of vehicles has evolved into a complex task due to the distinctive characteristics inherent in these identifiers. This shift in focus towards License Plate Recognition (LPR) has become a pivotal aspect of Intelligent Transportation System (ITS) research [1]. The applications of LPR span diverse areas, from traffic law enforcement to the implementation of smart toll collection and speed control stations [2,3]. However, the process of extracting text from license plate images encounters numerous challenges, including issues like noisy and dirty images, occlusion, variations in license plate types and sizes, fluctuations in camera quality, and the dynamic nature of climatic and lighting conditions.

The accuracy of text recognition is directly influenced by the quality of input images, underscoring the critical role of preprocessing techniques in enhancing efficiency. Common preprocessing methods involve image binarization [4] and the removal of unnecessary elements to address concerns such as shadows and noise. Each method adopts a unique approach tailored to the level of noise present in the original image.

In the realm of text recognition, effective feature extraction plays a pivotal role in enabling classifiers to accurately distinguish between different classes. The size of feature vectors utilized for recognizing license plate characters requires careful consideration, encompassing statistical, size and shape, area, and color features, as well as techniques like Scale Invariant Feature Transform (SIFT) [3].

Learning-based approaches [5,6] in character recognition prominently feature Artificial Neural Network (ANN), employed for detection after extracting features from characters. The training of ANN for character recognition involves specific layers and neurons, utilizing methods such as feedforward backpropagation, feedback, and feedback self-learning. Support Vector Machine (SVM) [7], a classification learning technique [5], is frequently combined with other methods, such as ESCW, to mitigate errors in license plate candidate detection, segmentation, and execution time.

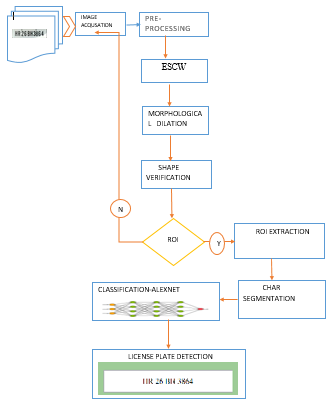
In the current landscape, deep learning techniques, particularly those leveraging Convolutional Neural Networks (CNN), are widely adopted in computer vision tasks to achieve state-of-the-art performance. Diverging from previous methods, this paper employs AlexNet CNN methods [8,9] to pinpoint individual regions of each license plate character, enabling subsequent recognition. The proposed system, combined with ESCW [10,11,12] and deep learning techniques based on AlexNet, can achieve automatic feature extraction and classification. The following sections of this paper are organized as follows: Section 2 provides background information and related works, while Section 3 presents the proposed approach. The paper concludes with a summary of findings.

1. **BACKGROUND AND RELATD WORKS**

This paper presents a computer vision and character recognition algorithm focused on the integration of a novel segmentation technique implemented in a license plate recognition system capable of handling outdoor conditions when parameterized properly. The LPs of Indian vehicles may exhibit different styles, and the first challenge addressed is the standardization of these plates. While Indian LPs adhere to standards set by the authority, they can vary in colors and the compound mode of characters. The character count is flexible, incorporating characters from 0 to 9 along with Persian Alphabets A-Z, or it may have specific symbols. However, there is consistency in standard font and font size.

To extract the plate region, various techniques such as edge extraction, Hough transform, vector quantization, and template matching have been applied. Additionally, neural network approaches have been introduced to achieve high accuracy. The novel contributions of this algorithm include morphology, colors and gray-scale processing, shape recognition techniques based on image algebra, and spatial frequency-based techniques. These innovations exploit the significant variations present in the license plate region, making the system robust in recognizing license plates under diverse conditions.

**PROPOSED** **WORK:**



**Fig.1.** Details of experimental setup.

The subsequent section discusses the proposed scheme, which shows promise in addressing the mentioned limitation. Once the extracted license plates are received, we proceed with pre-processing, license plate extraction, and recognition operations. Our proposed method employs enhanced sliding contract window for image segmentation. As mentioned earlier, the extracted license plates often suffer from issues such as varying sizes, non-normalization, tilting, non-uniform brightness, and noise. To overcome these challenges, we incorporate a pre-processing stage before applying segmentation algorithms. Additionally, post-segmentation annotation is necessary, but it can be a time-consuming task. Hence, we strive to utilize an algorithm that combines segmentation and annotation. It is important to note that the image quality of all license plates is not uniform, and the camera's viewing experimentation does not account for node-mobility, as shown in Fig. 1. For character extraction, recognition, and classification, we utilize 1000 images from the Kaggle database, as existing literature suggests trust-based Trouting methodologies to be the most promising.

The dataset used in this study comprises 1000 actual samples extracted from surveillance cameras. However, deep learning techniques often require a large amount of training data, presenting a challenge. To address this, augmentation methods are employed to introduce changes in angles, sizes, resolutions, and other features. The learning algorithm used in recognition is designed to identify each of the four components of the Indian license plate with specific labels, employing multiple scale feature maps to enhance target detection accuracy. This approach eliminates the challenges of image segmentation and reduces the time required for annotation. Furthermore, the use of AlexNet for text recognition improves the License Plate Recognition (LPR) system. In our classification process, we categorize characters based on their state, district, and number. In military applications, where efficient data collection is crucial, obstacles may hinder direct communication between entities like traffic control, vehicle monitoring, and toll information-collection centers. In such scenarios, our system achieves a performance improvement of up to 99.2%. The implementation of this project was carried out using the MATLAB programming language [13].

|  |  |
| --- | --- |
| **Specifications** | **Details** |
| Software | Matlab R2023b |
| Processor | Intel® core ™ i3-5005U CPU@ processor 2.90 GHz 2.00GHz |
| RAM | 8 GB |
| System | Windows-10 Pro, 64-bit Operating System |

1. **SIMULATION RESULTS AND DISCUSSION**

In this section, we provide a comprehensive explanation of the simulation setup used for experimentation, an overview of the License Plate Recognition (LPR) model depicted in Fig. 1, and the evaluation metrics employed for performance measurement. Subsequently, we present the experimental results and conduct a detailed performance analysis.

* 1. **SIMULATION SETUP**

Character recognition encompasses several essential technologies, including image data reading, image gray value manipulation, binarization, image adjustment, discrete noise point removal, character segmentation, character refinement, and feature extraction in the preprocessing stage. In our study, we specifically concentrate on the segmentation and character recognition techniques based on a single image, allowing us to achieve the desired outcomes. The research on digital image processing technology primarily centers around image digitization, image enhancement, image restoration, and image segmentation. The following steps outline our approach:

1. **Image preprocessing**:

Image pre-processing plays a crucial role in image analysis, especially in tasks like Vehicle License Plate Recognition (LPR). Proper pre-processing is essential to ensure effective and accurate recognition results. The main objective of pre-processing is to enhance the quality and legibility of license plate (LP) characters before they undergo segmentation and recognition algorithms. Several commonly used techniques are employed in pre-processing, including converting RGB images to grayscale, reducing noise, and performing image binarization. These techniques contribute to improving character clarity and ensuring optimal outcomes in subsequent stages of the LPR system.

Binarization is a key step in image pre-processing, involving the conversion of an image into a binary representation with only two-pixel values, typically white and black. Binarization simplifies the image and facilitates the detection and extraction of the license plate number, as the edges in the binary image become clearer. The binarization process involves selecting a threshold value. Pixel values in the image are analyzed against the threshold value, and if a pixel's value exceeds the threshold, it is set to white or black. Global thresholding is a straightforward approach that may or may not yield accurate results, depending on the image's characteristics. To address this, adaptive thresholding, such as the Otsu Thresholding method, is employed. Adaptive thresholding calculates the threshold for smaller regions within the image, resulting in improved accuracy. These techniques effectively reduce the complexity of the image input.

After comparing the two thresholding methods, we found that the Adaptive Threshold method yielded more robust results compared to the Otsu Threshold method.

1. **Morphological and sliding window-based Number Plate Segmentation and extraction:**

We apply a morphological operator for images that have been dilated once horizontally and once vertically. On the same bright pixel, another horizontal dilation is used. It performs operations like intersect, union, inclusion, and complement are included in this group. That character shape based on the image is encoded in the structuring element. The size of the 3×3 structuring element has its origin at the center pixel. It is moved across the image, and its elements are matched with the set of underlying pixels at every pixel. If both sets of elements fit the set condition of operator The Enhanced Sliding Contract Window (ESCW) method [4] has gained significant attention in recent years, particularly in the context of neural network recognition technology based on deep learning. This method has been effectively utilized for image segmentation. Here, we describe the process of segmentation using the ESCW method:

Morphological Operations: The process begins with the application of morphological operators on the input image. Two dilations are applied: one horizontally and one vertically. This can be achieved using the imdilate function in MATLAB. Another horizontal dilation is performed on the same bright pixel.

Structuring Element Encoding: The character shape based on the image is encoded in a structuring element. A 3×3 structuring element is commonly used, with its origin located at the centre pixel. The structuring element is designed to represent the desired shape or pattern that needs to be matched in the image.

Sliding Window Iteration: The enhanced sliding window, defined by the morphological operations and structuring element, is employed. This window is systematically moved across the image, pixel by pixel, based on the specified step size.

Element Matching: At each position of the sliding window, the elements of the structuring element are compared with the underlying pixels in the image. If the elements of both sets meet certain conditions (e.g., matching or satisfying the set condition of an operator), further processing is performed.

Operator Operations: Operations such as intersect, union, inclusion, and complement are applied based on the matching conditions. These operations help define the relationship between the structuring element and the underlying pixels in the image.

Segmentation Criteria: The segmentation process involves defining criteria based on the results of the operator operations. Segmentation decisions are made depending on whether the conditions for the desired shape or pattern are satisfied.

Output Segmented Image: The segmentation process results in an output segmented image where regions of interest that match the desired pattern have been identified.

The algorithm consists of the following steps:

1.Creation of two concentric windows, labelled as A and B, with dimensions X1xY1 pixels and X2xY2 pixels, respectively, starting from the upper left corner of the image.

1. Calculation of statistical measurements within windows A and B
2. Definition of a segmentation rule: If the ratio of the statistical measurements between the two windows exceeds a threshold specified by the user, the central pixel of the windows is considered to belong to a Region of Interest (RoI).

To illustrate, let x and y represent the coordinates of the pixel being examined in the inspected image I. The pixel value at the corresponding coordinates x and y in the resulting image IAND is set either to 0 (indicating no RoI) or to 1 (indicating RoI), based on the following equations:

If (measurement\_A / measurement\_B) > threshold:

IAND (x, y) = 1 (RoI)

Else:

IAND (x, y) = 0 (no RoI)

This segmentation process effectively distinguishes RoI pixels from non-RoI pixels within the image, enabling subsequent steps in character recognition and analysis.

1. **Classification Hybrid deep learning model based on** **Alex Net CNN:**

Based on its high-level rich features, the proposed Alex Net CNN model [6,8] is used to classify the number plate into several types. Alex Net, a base model for number plate classification by tuning, is utilized for classification. Alex Net has five convolutional layers, three completely connected layers, and five fully connected layers. Dropout can help with the over fitting issue. One of the transfer learning frameworks used to differentiate observed number plates is the convolutional neural network. For classification, an image must have a label applied to it. The proposed method shows how a pre-trained convolutional neural network Alex Net can be retrained using transfer learning to classify a set of number plate images. Alex Net contains a total of 25 layers.

The fixed size is illustrating to image in the network the size is227× 227× 3. The pre-trained last three layers of the Alex Net network are changed with a few layers that are fine-tuned for classification, such as a fully connected layer, SoftMax layer, and classification output layer, to retrain the network. After the network structure has been constructed, training choices are defined. A stochastic momentum gradient descent (SGDM) optimization model, a 0.0003 initial learning rate, and epochs (min 5 to max 500) denote total training time on the complete training dataset are all available as training options. The network was trained based on defined layer architecture, training datasets, and training options. The testing image is then passed to the classification module, which contains the trained network that is used to predict or classify the provided image into various types. has shown the retrain Alex Net CNN model.

AlexNet, the first convolutional network to leverage GPU for enhanced performance, incorporates a crucial feature of ReLU (Rectified Linear Unit) nonlinearity. This architecture facilitates multi-GPU training by distributing half of the model's neurons on one GPU and the remaining half on another, allowing for the training of larger models while simultaneously reducing training time. Additionally, AlexNet introduces the concept of overlapping pooling, contributing to its overall efficiency.

Let's see why it trains faster with the ReLU. The ReLU function is given by f(x) = max(0,x)

1. AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer.

2. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU.

3. The pooling layers are used to perform max pooling.

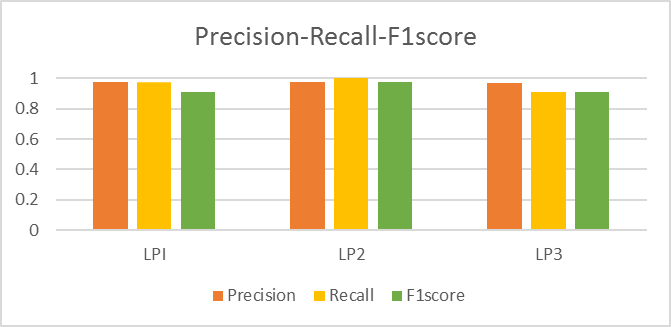
4. Input size is fixed due to the presence of fully connected layers.

5. The input size is mentioned at most of the places as 224x224x3 but due to some padding which happens it works out to be 227x227x3

6. AlexNet overall has 60 million parameters.

1. **RESULT AND DISCUSSION:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Input image Dataset | Pre-processing-segmentation-ESCW | Alex Net | | |
| precision | recall | F1 score |
|  |  | 0.97917 | 0.87757 | 0.8938 |
|  |  | 0.97815 | 0.90127 | 0.90632 |
|  |  | 0.976 | 0.86422 | 0.9772 |
|  |  | 0.97036 | 0.90934 | 0.9093 |
|  |  | 0.97655 | 0.86706 | 0.86277 |
|  |  | 0.97823 | 0.93172 | 0.90031 |
|  |  | 0.97699 | 0.90959 | 0.88139 |
|  |  | 0.97841 | 0.87814 | 0.87929 |



**Fig.2** Plotof Precision, Recall, and F1score.

1. **CONCLUSION:**

In this study, we focused on the recognition of vehicle number plates using License Plate Extraction and Recognition (LPER) techniques. The process involved two main steps: segmentation and classification of the LP images using kaggal dataset. <https://www.kaggle.com/datasets/saisirishan/indian-vehicle-dataset>.

we successfully detected the license plate and employed Morphological and ESCW to segment the image from the original dataset. Our proposed approach utilized a hybrid technique utilized Alex Net CNN model for classification. Following classification, the images were evaluated based on threshold values. During the simulation, we calculated precision, recall,and F1 score, which yielded a remarkable result of 97.2%.

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