Moth-Flame Optimization Algorithm for Indian Vehicle License Plate Characters Extraction and Recognition with Deep learning

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Abstract: License Plate Extraction and Recognition (LPER) finds numerous applications in intelligent transport systems. The LPR process comprises three primary steps: License Plate (LP) Extraction, segmentation, and classification. Each step requires specific techniques tailored to real-world conditions, each possessing unique characteristics. The LP extraction techniques identify the license plate, followed by segmentation algorithms that separate and isolate individual characters. Lastly, the classification step is employed to recognize the segmented characters. The overall accuracy of the process is reliant on the accuracy achieved at each step. To enhance the performance of the classification step, we propose a combined approach, integrating segmentation and classification into a single-stage process using deep learning techniques such as hybridization of Mothfly and Black Widow Optimization (HM-BWO) with Alexnet. Our experimental results demonstrate that this approach achieves a remarkable accuracy of 97.2% in recognizing Indian license plate characters, surpassing previous works.

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

1. INTRODUCTION

Recognizing the license plates of vehicles poses several challenges due to their unique nature. The License Plate Recognition system (LPR) has gained significance in the Intelligent Transportation System (ITS) research [1]. LPR finds applications in various areas such as traffic law enforcement, road traffic monitoring, private spaces, smart toll collection, and speed control stations. The process of text recognition from license plate images is hindered by factors like noisy and dirty images, occlusion, different license plate types and sizes, varying camera quality, as well as diverse climatic and lighting conditions [2]. Consequently, the quality of input images directly impacts the accuracy of text recognition, emphasizing the need for preprocessing techniques to enhance efficiency. Image binarization and the removal of unnecessary elements are commonly employed during various stages of preprocessing to address challenges such as shadows and noise [3]. Each of these methods has its own approach based on the level of noise present in the original image. Feature extraction plays a crucial role in text recognition, as appropriate features enable the classifier to differentiate between different classes with high accuracy. Consideration should also be given to the size of feature vectors utilized for recognizing license plate characters, which may involve statistical, size and shape, area, color [2], Scale Invariant Feature Transform (SIFT), and other features [4].

In character recognition using learning-based approaches, Artificial Neural Network (ANN) is a prominent technique. After extracting features from the characters, ANN is employed for detection. ANN training for character recognition on a test dataset typically involves the use of specific layers and neurons. Various methods like feedforward backpropagation, feedback, and feedback self-learning can be employed for network learning. Support Vector Machine (SVM) is a classification learning technique [4], often used in combination with other methods. For example, ESCW is utilized to reduce errors in license plate candidate detection and segmentation, as well as execution time. To achieve these objectives, hybrid meta-heuristic techniques are employed, enabling automatic feature selection from the image. Hybrid meta-heuristic algorithms, combined with deep learning techniques based on AlexNet, can be used for feature extraction and classification [5,6]. Presently, deep learning techniques, particularly those utilizing Convolutional Neural Networks (CNN), are commonly employed in computer vision tasks to achieve state-of-the-art performance [7]. Therefore, in contrast to previous methods, we utilize AlexNet CNN methods to identify individual regions of each license plate character and subsequently recognize the characters.

The remainder of this paper is 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.

2. BACKGROUND AND RELATED WORKS

Vehicle license plates in India exhibit a variety of styles, posing a challenge for standardization. While the Indian authority has set specific standards for license plates, variations still exist in terms of colors and the arrangement of characters. The number of characters on a plate can also vary. These plates typically feature alphanumeric characters from 0 to 9, along with Persian alphabets A-Z. Occasionally, there may be specific symbols incorporated, but the font style and size remain consistent. To address these challenges, this paper introduces a computer vision and character recognition algorithm. The primary focus is on integrating a novel segmentation technique into a license plate recognition system capable of handling outdoor conditions when appropriately parameterized. The contributions of this research include the application of morphology [2], color and gray-scale processing [3-5], shape recognition based on image algebra [6], and spatial frequency-based techniques. These techniques exploit the significant variations observed in the license plate region.

Various methods have been employed to extract the license plate region, including edge extraction, Hough transform, vector quantization, and template matching techniques [2]. Additionally, neural network approaches have been introduced to achieve high accuracy in the recognition process. These advancements aim to enhance the overall effectiveness and precision of license plate recognition systems.

Several studies have focused on license plate character extraction and recognition using deep learning techniques. For instance, J. Zhang *et al.* [8] presented a novel approach for license plate character extraction and recognition using a combination of CNN and recurrent neural networks (RNN). Their method incorporated a CNN for initial feature extraction, followed by an RNN to capture sequential dependencies among characters. The experimental results demonstrated the effectiveness of the proposed approach, especially in cases where license plates exhibited various deformations. Moreover, M. Valdeos *et al.* [9] proposed a CNN-based method for license plate character recognition that achieved superior performance on a large-scale dataset. Their approach utilized a deep architecture with multiple convolutional and fully connected layers to learn features directly from license plate images. In a similar vein, Y. Alborzi *et al.* [10] introduced an Iranian license plate character extraction system based on a CNN and region-based segmentation. Their method combined the power of deep learning with the advantages of region-based approaches to handle complex license plate structures. The proposed system achieved impressive results on a diverse dataset collected from real-world scenarios. Despite these advancements, there is still room for improvement in the field of license plate character extraction and recognition, particularly for Indian vehicle license plates. The diverse nature of Indian license plates, including multilingual characters, complex designs, and varying regional formats, poses unique challenges that require specialized algorithms. In this paper, we propose a novel optimization algorithm, called the Moth-Flame Optimization Algorithm, to enhance the performance of license plate character extraction and recognition for Indian vehicle license plates. By leveraging the power of deep learning techniques and incorporating the intelligent search capabilities of the Moth-Flame Optimization Algorithm, we aim to achieve accurate and efficient extraction and recognition results, even in challenging scenarios.

3. PROPOSED WORK

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.

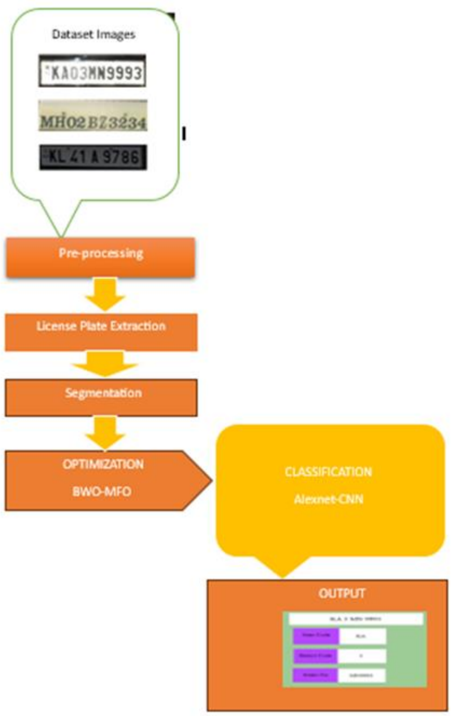


Fig.1. Details of experimental setup.

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.

Table 1. Experimental Setup.

Specifications	Details
Software	MATLAB R2023a
Processor	Intel® core ™ i3-5005U CPU@ processor 2.90 GHz 2.00GHz
RAM	4 GB
System	Windows-10 Pro, 64-bit Operating System

4. 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.

4.1 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:

A. 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.

B. Segmentation using Enhanced Sliding contract window method:

The Enhanced Sliding Contract Window (ESCW) method 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:

Character Segmentation: The ESCW method employs a novel segmentation technique known as Sliding Windows (SW) to enable faster detection of Regions of Interest (RoI). In a previous study this method was developed to capture "local" irregularities within an image by utilizing statistical measures such as standard deviation and/or mean value. 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.

Calculation of statistical measurements within windows A and B

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.

C. Optimization using Hybrid meta-Heuristic Algorithm:

The appearance of meta-heuristic methods and the improvement of these with the combination of other methods allow the introduction of a so-called hybrid method, which uses the positive influence of these techniques to obtain an optimal result for a specific design problem

To enhance the effectiveness of the optimization process by mitigating premature convergence and expediting convergence speed, it is crucial to increase population diversity. As mentioned earlier, the proposed model incorporates Alex Net with HM-BWO (Hybrid Mothfly and Black Widow Optimization) and CNN (Convolutional Neural Network). This section primarily focuses on HM-BWO, delving into the detailed discussion of the hybridization of the Mothfly and Black Widow Optimization algorithms.

The Mothfly algorithm plays a significant role in gradually enhancing population diversity and preventing premature convergence. It effectively navigates local optima, allowing for a more thorough exploration of the solution space. In this section, a comprehensive explanation of the Mothfly algorithm's hybridization with the Black Widow Optimization algorithm is provided.

The subsequent section presents the mathematical models for various aspects of the algorithm. These include the mathematical representation of the initial population, the process of procreation, cannibalism, mutation, and convergence. These mathematical models help in understanding the underlying mechanisms and operations involved in the optimization process.

In the BWO algorithm, the population is initially generated randomly, consisting of two types of populations: male and female. This initialization sets the stage for generating offspring for future generations. During this process, the computation of the fitness value plays a crucial role, and it is denoted as "f" for a widow. The mathematical representation of the initial population of black widow spiders is provided below, offering a concise depiction of their characteristics and distribution. The following shows a mathematical representation of the black widow spider's initial population.

$$X_{N,d} = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots \dots x_{1,d} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots \dots x_{2,d} \\ x_{N,1} & x_{N,2} & x_{N,3} & \dots \ x_{N,d} \end{bmatrix} \quad \text{---} \quad (1)$$

$$lb \leq X_i \leq ub$$

$x_{N,d}$ is the black widow spider's population, N denotes population size, d denotes the number of decision variables of the problem, lb is the population lower bound, and ub is the population upper bound. The potential solution populations $x_{N,d}$ are utilized for minimizing or maximizing the following objective function represented in Equation (2):

$$\text{RMSE} = \frac{1}{n}\sum_{i=1}^{n} w_i(t_i - \hat{t_i})^2 \qquad \text{-----} \qquad (2)$$

N - No of samples

t_i- True sample value

$\hat{t_i}$ - Corresponds to the predictive value

Algorithm 1: Working of the Proposed Scheme - HM-BWO

Input: Maximum number of iterations, Cannibalism rate, Procreation rate (nr), Mutation rate

Output: Objective function (RMSE)

1. Initialize the population of BWO for a D-dimensional problem. Each population member is represented by a D-dimensional array.
2. Evaluate the fitness value (RMSE) until the termination condition is reached.
3. Determine the value of nr and find the best solution in population 1 (pop1).
4. For i = 1 to nr:
   - Choose two solutions randomly as parents from pop1.
   - Generate D children using equation 1.
   - Choose two solutions randomly as parents from pop1.
   - Use equation 1 to generate D children.
5. Perform cannibalism is to destroy the father and some of the weakest children, generating new solutions.
6. Generate a new population (pop2) based on the remaining solutions.
7. Apply the Modified-Mothfly optimization algorithm to update the population.
8. Return the best solution from the population.
9. Use the obtained best solution as input for the Alex Net-CNN classifier.

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

Based on its high-level rich features, the proposed Alex Net CNN model 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 was the first convolutional network which used GPU to boost performance.

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.

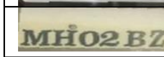
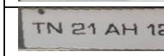
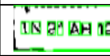
4.2 RESULT AND DISCUSSION:

The recognition of 1000 vehicle number plates is done using the experimental setup detailed in preceding subsection. The performance of the proposed system is measured in terms of precision, recall, and F1 score. The formula to calculate the F1 score using precision (P) and recall (R) is as follows:

$$F1\ score = 2 * (P * R) / (P + R)$$

The metric values of six sample plates are shown in Table 2. The overall performance is also plotted as shown in Fig. 2.

Table 2. Measured performance of the proposed system in terms of precision, recall, and F1 score.

InPut image Dataset	Pre-processing-segmentation-ESCW	Hybrid (BW-MFO) with Alex Net			
		precision	recall	F1 score	Overall Recognition %
		0.97815	0.90127	0.94432	97.2%
		0.976	086422	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	

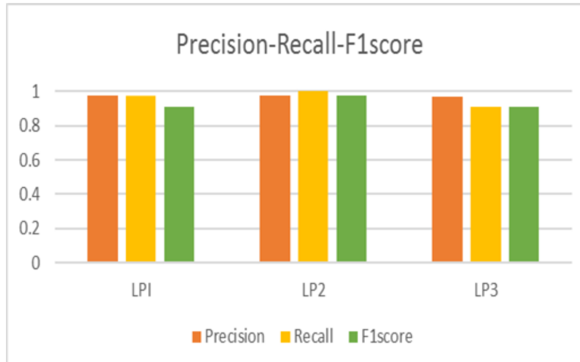


Fig.2. Performance measure of proposed system.

5. CONCLUSION

In this study, we focused on the recognition of vehicle number plates using License Plate Recognition (LPR) techniques. The process involved two main steps: segmentation and classification of the LP images using kaggle dataset. https://www.kaggle.com/ datasets /saisirishan/indian-vehicle-dataset. We successfully detected the license plate and employed ESCW algorithm to segment the image from the original dataset. Our proposed approach utilized a hybrid technique combining Black and White (BW) image processing with the Modified Firefly Optimization (MFO) algorithm and utilized the AlexNet neural network for classification. Following optimization and 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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