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Optimizing Car License Plate Recognition Through Gray Wolf Optimization Algorithm

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Abstract
License plate recognition is an essential part of contemporary surveillance systems since it is helpful in many applications, including parking management, vehicle access control, traffic control, and law enforcement. This project aims to provide a robust and dependable method for detecting license plates that will outperform existing approaches in accuracy and dependability. This observation method uses contemporary technology to address challenging troubles related to license plate recognition. Our methodology is primarily based on the Faster R-CNN structure, an established model for picture item detection. The novel thing, even though, is how Gray Wolf Optimization—which draws notion from the searching conduct of gray wolves—is mixed with the Faster R-CNN network. The accuracy is greatly improved by this synergistic combination, which also improves detection abilities. Moreover, an improved ResNet-50 model is blanketed to improve the classification system similarly, ensuring accurate license plate detection in several situations. The extensively utilized "car license plate detection" dataset is used to assess the recommended technology very well, confirming its efficacy in practical settings. The empirical outcomes show exceptional performance, with a median precision of 98.21%, demonstrating how nicely the hybrid method works to attain the very best stage of license plate detecting accuracy. This painting establishes a new benchmark in license plate identity using cutting-edge technology and innovative techniques, starting the door for enhanced safety and surveillance.

Keywords
License Plate, Faster-RCNN, Gray Wolf Optimization Algorithm, Resnet-50, Object Detection.

I. Introduction

The fundamental issue in numerous towns worldwide is traffic blockage, resulting in numerous drawbacks, lost time, extra fuel consumption, and air pollutants [1]. Traffic blockage has worsened in the past few years because more and more people now own automobiles, and towns keep growing. Therefore, powerful traffic control technology enhances traffic management and reduces blockage [2].

This research project's primary intention was to create a sophisticated technique for spotting license plates on motors that might handle difficulties including converting lights, occlusions, and plate deformities. One prospective solution to the problem of traffic blockage is innovative traffic monitoring structures, which might be Internet of Things (IoT) enabled. An IoT sensor network and embedded device are hired to accumulate real-time traffic statistics using such structures [3]. The system's layout flow leads to a new IoT-enabled intelligent site monitoring system on smart gates. Cameras hooked up at smart gates seize pictures of passing vehicles. Automated facial detection technology in [4] and license plate recognition (LPR) are essential to these sophisticated traffic surveillance structures. License Plate Recognition (LPR) with Grey Wolf Optimization (GWO) [5], non-most suppression (NMS) [6], and the Faster R-CNN deep gaining knowledge of the model [7] are then used to locate and extract registration from License Plate for the vehicle photographs captured on intelligent gates. Grey wolves inspired GWO, a swarm intelligence-primarily based optimization method that can be used to improve the LPR models' parameters. NMS is carried out on the observed plates to get rid of repeated license plates. The system monitors vehicle movement and evaluates traffic density to regulate gate access.

Our traffic monitoring system uses data to optimize traffic flows in urban areas. Traffic congestion is lessened in smart cities thanks to automatic gating and real-time visibility. The main research contribution of this paper in the field of car license plates is: This research presents an innovative methodology for the automatic recognition of car license plates by combining the latest deep-learning techniques and optimization algorithms. The main contribution is integrating the Faster R-CNN object detection network with the Gray Wolf Optimization algorithm to improve performance. A ResNet-50 layer has also been added to classify paintings. Experimental results on a standard dataset showed an average accuracy of 98.21%, which places the proposed methodology among the world's leading methods.

The remainder of this paper is structured as follows: Section II. discusses earlier research on car license plate recognition, CNN topologies, model optimization, and hardware acceleration methods pertinent to this study. The suggested approach, which combines Grey Wolf Optimization with Faster R-CNN and ResNet-50 models, is covered in section III. . Sections IV. and V. show the simulation findings and conclusions, respectively.

II. Literature Review

This section overviews research on automatic license plate recognition (ALPR) systems. ALPR systems, essential for transportation security, employ CNN technology, achieving 98.57% accuracy in Bangladeshi plate recognition. These systems use preprocessing and segmentation techniques for effective surveillance and traffic monitoring, aiding in stolen vehicle tracking presented in [8]. A YOLO and OCR-net deep learning approach accurately detected and recognized distorted plates for autonomous vehicle applications in [9]. An Arabic/Latin plate recognition method achieved 85-89% average accuracy rates in Iraq and Malaysia, outperforming state-of-the-art baselines. However, privacy concerns limited the datasets discussed in [10]. In [11] presented An Indian ALPR technique combining deep learning and random forests attained 98.5% accuracy for Intelligent Transport Systems, surpassing existing methods for applications like toll collection and traffic monitoring. In [12] presented, Hybrid approaches identified plates in complex scenarios, but segmentation and recognition remained critical. A four-step License Plate Recognition (LPR) system (acquisition, extraction, segmentation, recognition) developed in MATLAB emphasized parking and access control systems in [13]. For Jordanian plates, a plate detection method leveraged rectangularity, achieving 95% accuracy to address issues in the current system in [14]. An end-to-end model using YOLOv4 obtained 99.37% localization and 96.31% text recognition rates on Bangladeshi plates in [15]. A 98.06% accurate Indian system utilized the VGG16 architecture, prompting the exploration of more complex deep models in [16]. An Iraq-focused ALPR approach achieved 97% plate recognition success in [17], while a combined classical and deep learning technique optimized Egyptian LPR, with deep methods excelling at plate detection and traditional approaches at character recognition in [18]. Deep learning methods showed promise for automatic license plate recognition (ALPR) systems but faced challenges in complex urban environments, necessitating further research to improve robustness in [19]. A two-deep network approach eliminates explicit segmentation, mitigating errors and achieving state-of-the-art accuracy on license plate datasets in [20], positioning it for traffic-related applications. In [21], A system based on K-Nearest Neighbors (KNN) and Python enabled plate recognition for applications like toll collection. Critical for weighbridge automation, a new truck license plate database, and method attained 95.82% recognition, given the diversity in [22]. An integrated algorithm leveraging morphology, neural networks, and optical character recognition (OCR) enabled complex traffic surveillance in [23]. In contrast, a convolutional neural network system demonstrated superior accuracy over traditional methods for vehicle tracking in [24]. In [25], An integrated traffic monitoring toolkit performed vehicle counting, motion tracking, and license plate recognition under real-world conditions. Fast-LPRNet achieved state-of-the-art plate recognition through an optimized deep neural network, showing robustness across challenging datasets in [26]. In [27], Pruned AI models enabled real-time facial and license plate recognition for surveillance. Modern machine learning methods enabled high-accuracy plate recognition at wide angles, demonstrating the potential for advanced transportation safety systems in [28]. In [29], An SDC model sharply improved recognition, presenting strong potential for automated intelligent transportation. The YOLOv5 architecture achieved 98.5% stationary license plate detection, requiring country-specific training data in [30]. Protocol analysis found that AODV outperforms DSR for vehicle networks on metrics like throughput and delay, which is vital for IoT transportation in [31]. In [32], A hierarchical convolutional neural network demonstrated accurate vehicle and plate recognition by dividing the problem into specialized sub-task RCNNs. An image-processed pipeline reached 94.17% plate recognition accuracy, meriting future AI advances to address defects and ambiguities in [33]. In [34], an Automatic License Plate Recognition (ALPR) system (using SVMs, K-NN, and RBF Neural Network) was developed for the Kurdistan Region of Iraq. Its accuracy is 96.72% under various lighting situations. The recognition is enhanced through Gabor feature vectors, wrapper subset evaluation optimization, and dimensionality reduction. The study highlights how successful these techniques are for ALPR in that area. A MATLAB-based ANPR system for Iraqi license plates is presented in [35], using BPNN. It performs accurate recognition in low-quality photographs, improves identification speed and accuracy in complex scenarios, and permits decisions on access restriction based on database comparison. A license plate recognition system for Iraqi plates was presented in [36] using character recognition and image processing methods. The technology reliably recognizes plates and makes stylistic distinctions based on size by utilizing a BPNN with RP method, which is implemented in MATLAB R2014a.

III. Architecture of the Proposed Approach

Recent advancements in computer vision and deep learning have shown immense promise for automating license plate detection. Accurate and real-time license plate recognition is crucial for various security and monitoring systems. This paper explores the synergistic integration of ResNet-50 for license plate detection and Faster R-CNN for object detection and optimization using the Grey Wolf Optimizer (GWO). Integrating these networks and an optimization technique like the Grey Wolf Optimizer can address the challenges of accuracy, speed, and resource utilization. The steps of the proposed approach are demonstrated in the Fig. 1.

A. *The preprocessing step*

Data preparation is a crucial stage in both machine learning and data analysis. It entails preparing raw data for analysis or model training by cleaning and arranging it. The main preprocessing processes in this study are:

- Adjusting the Bounding Box.
- RGB conversion.
- Data shuffling.
- Data partitioning.

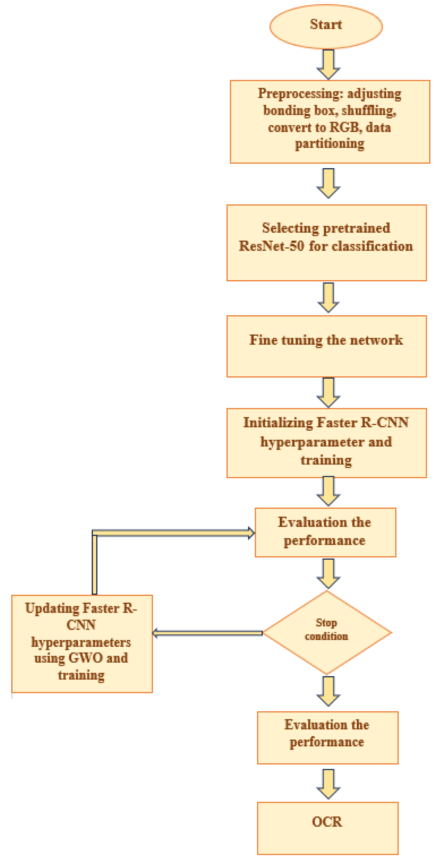


Fig. 1. Steps of the proposed method.

In Adjusting the Bounding Box processes, the Bounding box is resizing for machine vision tasks to match scaled images, and to do must establish the initial bounding boxes (x_min, y_min) and (x_max, y_max), Maintain the aspect ratio when resizing the image, Determine the Resizing Scale, and finally Scale Bounding Boxes to your liking this. Grayscale or single-band images are converted into pseudo-color RGB images by using RGB conversion to improve viewing. The steps for these processes are to Begin with image data in grayscale and then Replicate the intensity levels for all three RGB channels to produce pseudo-color images. For every channel, the same intensity level is used. Applying a color scheme, usually one that resembles a gradient. Rearranging data instances (rows or samples) in a dataset randomly or in a pseudo-random manner is known as a data shuffling process. The information partitioning technique is essential inside the fields of the device, getting to know and information evaluation. A dataset is divided into two separate subsets of the test and schooling sets. A schooling set is used to explore patterns and relationships in the statistics and optimize parameters; at the same time, the take-a-look-at set is used to evaluate a model's performance and generalizability. Data shuffling or randomization strategies, which entail the random reordering of statistics instances, are generally used to enhance the effectiveness of the getting-to-know process. In addition to ensuring a fair subgroup department, this method reduces bias. Furthermore, RGB reconstruction enhances viewing by replicating intensity levels using the red, green, and blue channels. This technique can transform Grayscale or single-channel images into pseudo-colored RGB images. Because of the division's well-planned architecture, representation and distribution are guaranteed, ensuring the data is consistently available during the learning process. Standard procedures for a robust model evaluation include time-based splitting, random sampling, and more complex techniques like cross-validation. Proper data division prevents overfitting and improves the model's dependability. This paper uses 70% training and 30% test sets.

B. The Proposed Combination of ResNet50 and Faster R_CNN

The seminal ResNet-50 architecture for image categorization leverage's identity shortcut connections to address the vanishing gradient quandary, enabling the training of expansive networks, as expounded in "Deep Residual Learning for Image Recognition" [37]. By leaping layers via shortcuts, extremely deep architectures encompassing 50, 101, or 152 tiers manifest feasibility. Recent endeavors around ResNeXt [38], SENet [39], and Non-local Neural Networks [40] further galvanize the outsized impact of ResNet on computer vision feats. The residual learning blueprint eschews gradients fading in myriad applications. Progressive works validate the versatility, extensibility, and influence of the ResNet innovation. The identity shortcuts manifest the crux for instituting and propagating gradients across myriads of tiers without attenuation. ResNet streamlines hitherto colossal models while propelling state-of-the-art image categorization. Faster R-CNN [41] builds on previous work like R-CNN and Fast R-CNN to provide an efficient and accurate object detection algorithm. The essential contribution is introducing a Region Proposal Network (RPN) that shares convolutional features with the detection network, enabling nearly cost-free region proposals. This improves on previous slow methods like Selective Search. Recent improvements to Faster R-CNN include context reasoning modules [42], Light-Head R-CNN [43] to reduce computations, and Relation Networks [44] to predict relations between objects. These demonstrate Faster R-CNN remains an influential foundation for object detection research.

C. Improving the Most Advanced Picture Classifications and Accurate Object Recognition of ResNet50 Using Faster R-CNN by our Proposed

ResNet50's identity shortcuts could enable training a Feature Pyramid Network built on top of the RPN to improve multi-scale detections without vanishing gradients. The shared convolutional features between the ResNet50 classifier and Region Proposal Network could provide computational and modeling efficiencies. ResNet-50, with its core innovation of residual blocks, addresses the vanishing gradient problem by learning residual mappings. It is designed for image classification and consists of 50 layers organized into three stages with varying residual blocks. Each block includes 1×1 and 3×3 convolutions along with skip connections. Using residual blocks enables the training of deep networks by facilitating gradient flow, making it a key innovation. ResNet-50's success has influenced subsequent network designs in computer vision. To modify ResNet-50 for facial recognition, follow these steps: Add Specialized Layers, fine-tune, Transfer Learning, and Remove the Final Layers. The Remove Final Layers function removes the final three layers (totally linked, softmax, and classification) intended for general picture categorization. Transfer Learning uses pre-trained weights from big datasets to build the ResNet-50 model. This provides good initial parameter values that speed up learning to discriminate facial features. In Fine-Tuning, specific classification layers are used in place of the current feature extraction capabilities to collect crucial facial characteristics for identification. Retraining replaces fully connected layers with convolutional feature extraction, retraining the network to identify license plates instead of generic objects. A Faster R-CNN detection network uses bounding box regression and a classifier to handle the discovered regions. All components of the Faster R-CNN model with RPN and detection network are trained end-to-end using labeled data. In conclusion, practical tuning of hyperparameters and training procedures is essential for Faster R-CNN to identify different objects accurately. Among the tactics include adjusting detection thresholds, preventing overfitting by regularization, and boosting variability to manage different object appearances. In conclusion, careful coordination of backbone pre-training, region proposal generation, detection network design, and end-to-end optimization is needed to train an accurate Faster R-CNN detector.

D. Grey Wolf Optimizer (GWO)

The Gray Wolf Optimizer (GWO), as elucidated in [45], constitutes a fledgling bio-inspired metaheuristic algorithm replicating gray wolves' social hierarchy and predation strategies to realize optimization. Specifically, GWO stratifies the population into alpha, beta, delta, and omega wolves, with the alpha wolf steering the overall bearing. Additionally, GWO recapitulates the enveloping technique deployed by wolves while hunting quarry to refine solutions iteratively. Compared to algorithms like particle swarm optimization, GWO has exhibited swift convergence and enhanced escapability from inferior local optima [46]. Contemporary GWO research spotlights augmentations for intricate optimization challenges [47]. GWO mimics lupine social conduct and hunting tactics, demonstrating faster convergence, better optima avoidance, and applicability to complex multi-variable optimization predicaments across domains. Modifying machine learning hyperparameters, such as object detector detection thresholds, to increase accuracy is a crucial use case for Grey Wolf Optimizer (GWO). GWO uses its bio-imitated wolf pack behaviors to hone those parameters further. To be more precise, GWO seeded a population of potential solutions and then iteratively assessed how fit they were to find alpha, beta, and delta wolves, to be more precise, GWO seeded a population of potential solutions and then iteratively assessed how fit they were to find alpha, beta, and delta wolves, to find the best solution. The system adjusts placements based on leader cues and random exploration to prevent becoming trapped in local optima. Initializing the random wolf population, assessing bounding box quality using an IOU cost function, updating the hierarchy to highlight the best solutions, adjusting positions by leader direction, and stopping the process when predefined criteria are met are the main steps of the process. Through this repeated search method, Grey Wolf Optimizer (GWO), an optimization tool, is well-suited for fine-tuning critical object detection hyperparameters because it strikes a balance between exploring new areas and exploiting effective solutions. ResNet50 and Faster R-CNN are integrated with GWO in this work to improve detection accuracy by refining parameters. This fusion of cutting-edge bio-inspired optimization and state-of-the-art networks improves practical applications wanting precise, quick car license detection. The following equations are presented in an attempt to model encircling behavior mathematically:

$$\vec{D} = \left|\vec{C}.\vec{X}_P(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t) = \vec{X}_P(t) - \vec{A}.\vec{D} \tag{2}$$

where $\vec{X}_P$ is the prey's position vector, $\vec{X}$ represents the position vector of a grey wolf, $\vec{A}$ and $\vec{C}$ are coefficient vectors, and t is the current iteration. Here are how the vectors $\vec{A}$ and $\vec{C}$ are computed:

$$\vec{A} = 2\vec{a}.\vec{r1} - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r2} \tag{4}$$

where components of $\vec{A}$ are linearly decreased from 2 to 0 throughout iterations, and $r1$ and $r2$ are random vectors in [0, 1]. The GWO algorithm's pseudo code is shown in Fig. 2.

```
Initialize the grey wolf population X_i (i = 1, 2, ..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
X_α=the best search agent
X_β=the second best search agent
X_δ=the third best search agent
while (t < Max number of iterations)
  for each search agent
      Update the position of the current search agent by equation (3.7)
  end for
  Update a, A, and C
  Calculate the fitness of all search agents
  Update X_α, X_β, and X_δ
  t=t+1
end while
return X_α
```

Fig. 2. Pseudo code of the GWO algorithm.

To mathematically simulate the hunting behavior of grey wolves, the following equations are used:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_{\beta=} \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{5}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \tag{6}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{7}$$

IV. Simulation Results

This section describes the experimental design and the outcomes attained with the suggested technique. License plate recognition is integral across applications. The "car license plate detection" dataset herein encompasses 433 images with bounding box markings denoting plates. Explicitly, this dataset contains images and labels compiled to train and assess license plate detection algorithms and models, advancing computer vision, notably for automatic license plate recognition (ALPR) systems, vehicle tracking, and surveillance. The "car license plate detection" dataset facilitates the creation and development benchmarking of license plate detection models. By providing labeled license plate data, this dataset facilitates research into optimizing the accuracy, robustness, and efficiency of ALPR systems. As license plate detection is an essential upstream task for recognition, this dataset helps lay the algorithmic foundation to unlock additional vehicle analytics applications. In a field requiring stringent real-world performance, standardized datasets accelerate progress.

The parameters used for simulation purposes are shown in Table I.

TABLE I.
SYSTEM PARAMETERS

Parameter	Value
Number of epochs	10
Learning rate	0.0001
Momentum	0.9
Batch size	16
Image dimension	(227) *(227)

This research utilizes Faster R-CNN for car license detection, integrating Gray Wolf Optimization (GWO) to optimize the detection threshold. Crucial preprocessing involves resizing images to 227x227 pixels, RGB conversion, and a 70%/30% train/test split.

The Faster R-CNN model is then trained using a ResNet-50 pre-trained network. Stochastic Gradient Descent is employed, with 10 epochs, a 0.0001 learning rate, and 0.9 momentum. GWO adjusts the detection threshold to balance precision and recall, optimizing a cost function considering region and classification performance. GWO hyperparameters include 4 iterations, a population size of 5, and threshold bounds of 0.001 to 0.99. GWO maximizes Faster R-CNN's car license detection capabilities on the preprocessed dataset by tuning the detection threshold. The integrated GWO-Faster R-CNN approach balances accuracy and generalization.

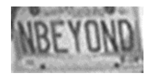
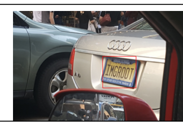
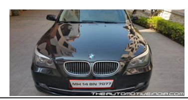
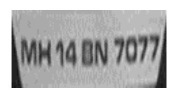
After accurate object detection, character recognition is performed using optical character recognition (OCR). OCR automatically converts printed or handwritten text in images into machine-readable text. OCR systems analyze character patterns and shapes, translating them into digital text for computer processing and understanding.

OCR is crucial for digitizing physical documents. The process begins by cropping and resizing detected objects to enlarge them. To optimize OCR, resized objects are converted to grayscale, establishing black characters on white backgrounds. OCR is then applied, extracting present characters. The obtained optimal threshold is presented in Table II. Table III demonstrates the network's performance on sample images, including erroneous detections. Overall, integrating optimized OCR with the object detection model enables the complete pipeline - from detecting regions of interest to recognizing the textual content within. Applying OCR post-detection extracts actionable information from images in an automated manner.

TABLE II.
THE OPTIMAL THRESHOLD OBTAINED FROM THE GRAY WOLF OPTIMIZATION ALGORITHM

Parameter	Value
Threshold	0.7911

TABLE III.
THE NETWORK'S PERFORMANCE IN WHICH THE PROPOSED APPROACH MADE A MISTAKE

# Sample	The object detection results	The processed section for OCR	Final result	Descriptions
1			N8EYOND	False recognition of B as 8
2			AD00008	Object detection couldn't capture license plates completely
3			IMGROOT	–
4			MH14BN7	–

1) *Intersection Over Union Plot*

The IoU plot visualizes alignment between predicted and ground truth bounding boxes in object detection tasks like license plate detection. It assesses model prediction accuracy by considering IoU scores for each prediction. In this IoU plot, each sample corresponds to a region of interest the model tried to detect. The IoU value measures overlap between the predicted and ground truth bounding boxes for that sample. Key Components:

1. Samples: Each point represents a specific detection made by the model for a given sample. The x-axis lists all evaluated samples.

2. IoU Values: The IoU value indicates alignment between predicted and ground truth bounding boxes, ranging from 0 (no overlap) to 1 (perfect alignment).

High IoU values indicate accurate detection and localization. IoU evaluates bounding box accuracy, as shown in Fig. 3. Our proposed method's average IoU of 0.8823 demonstrates strong alignment between predicted and ground truth bounding boxes across instances. The IoU plot shows most detections clustered around the mean, indicating precise license plate localization. The range of IoU values also shows system adaptability to different plate shapes, orientations, and obstacles. The maximum IoU score of 0.9841 represents nearly perfect prediction matching cases, highlighting effective detection under ideal conditions. The minimum IoU score of 0.7312 corresponds to challenging situations where localization was more difficult. Analysis of high and low IoU values reveals model strengths and areas needing improvement. The overall IoU distribution and the average score of 0.8823 demonstrate reliable localization across varied scenarios. This is shown in Fig. 4.

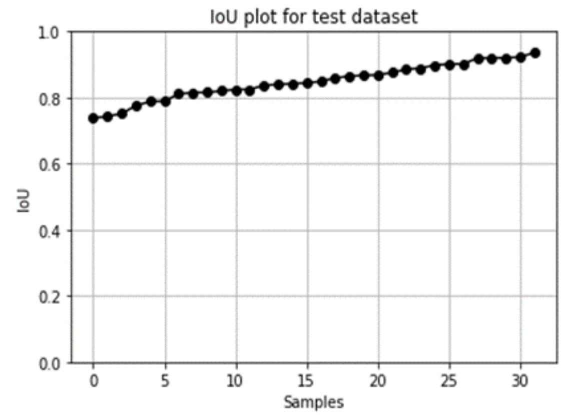


Fig. 4. The IoU graph depicting the outcomes of the suggested technique.

2) *Average Precision Plot*

This section assesses the effectiveness of our suggested car license-detecting technology using the Average Precision (AP) metric. The AP plot delineates the give-and-take between precision, the proportion of correct positive identifications out of all positive calls, and recall, the proportion of correct positive identifications out of all positive labels in the data. High precision symbolizes low false positives, while high recall symbolizes detecting a substantial ratio of existing positives. Our technique has realized a stellar AP score of 0.9821, bespeaking its reliability and accuracy in pinpointing car licenses in diverse situations. Across recall levels, the AP plot in Fig. 5 shows consistent performance. High precision, even at high recall, allows for reliable detection and effective identification of many positive samples. Total quality is combined into a single statistic, the AP-AUC, demonstrating holistic efficacy. The optimal performance of our suggested license plate recognition technique is based on the 0.9821 AP, which broadens the range of possible practical uses in autonomous cars, safety systems, and surveillance that require accurate and quick detection in challenging environments. This demonstrates suitability for a wide range of applications with stringent accuracy requirements. When faced with unknown data, the approach's generalization capacity is validated by its high accuracy, even with tiny dataset sizes and complex backdrops.

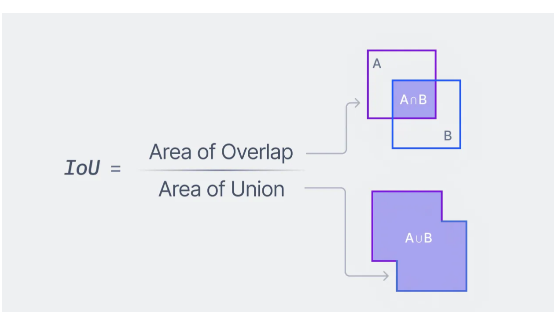


Fig. 3. The evaluation way of intersection over the union.

3) *Statistical Evaluation of the Proposed Method Using the Introduced Metrics*

This section conducts a thorough statistical evaluation of our suggested license plate detection method using four essential performance metrics: average detection time, which measures computational speed; intersection over union, which assesses license plate localization accuracy; accuracy, which measures effective object recognition and localization; and average precision, which measures precision-recall balance. Our method exhibits an impressive 94.0% accuracy (Fig. 6). Its impressive 0.9821 Average Precision highlights its dependability and resilience. Exact license plate localization in various contexts is demonstrated by an average Intersection over Union of 0.8823, which is supported by high values independent of size, direction, or occlusion. With an average detection time of just 7.44 milliseconds, real-time video applications can operate at a noticeable lag-free rate of 134.41 frames per second. The statistical analyses support our approach's efficiency, accuracy, and precision—all essential for practical use.

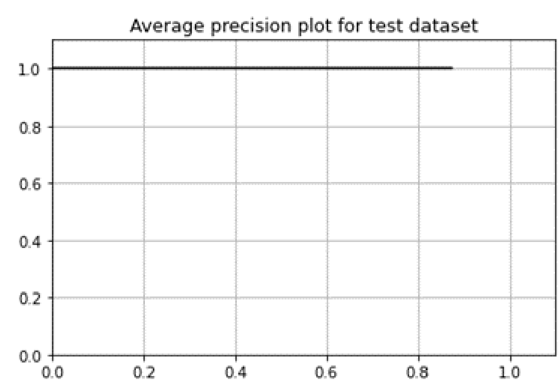


Fig. 5. The proposed method's AP plot.

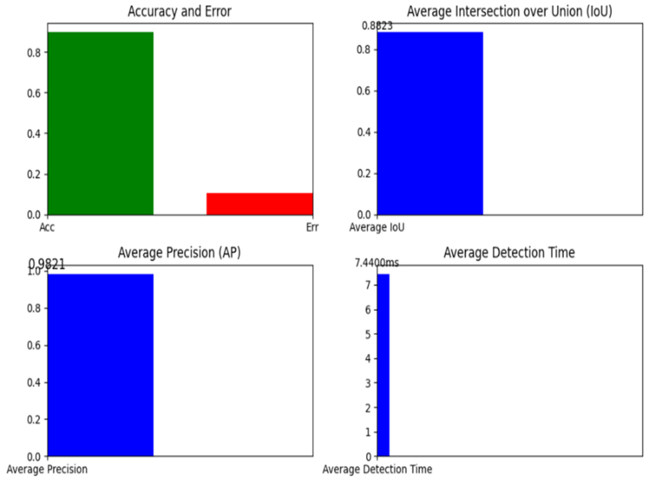


Fig. 6. Comprehensive assessment of the introduced approach.

4) *Comparison*

The outcomes of our paper on automobile license plate detection in conjunction with current techniques and cutting-edge methods in the industry. A comparative analysis of performance indicators and results between our suggested method and other established methodologies aims to highlight our approach's unique benefits, innovative contributions, and possible drawbacks.

This thorough analysis provides insights into our methodology's applicability in a variety of real-world circumstances in addition to illuminating its effectiveness. This extensive study aims to shed light on how the novel methodology advances the discipline of automobile license detection and the rapidly developing field of computer vision. To achieve end-to-end ALPR, the study [48] employed a hierarchical Convolutional Neural Network (CNN), first recognizing vehicles and plate regions and then using a second CNN for character recognition. Limited training data is mitigated by using synthetic and augmented data. The OpenALPR and SSIG datasets yield an average precision of 90.94% and 96.09%, respectively. Additionally, On the FZU cars dataset, a different model that combines CNN and K-means-based segmentation for license plate identification achieved an average precision of 97% [49].

This project uses a Faster R-CNN network with Gray Wolf optimization for license plate detection, while ResNet-50 is excellently tuned for class. It outperforms previous strategies, with an average precision of 98.21%, when tested on the "car license plate detection" dataset. Table IV summarizes the contrast between these two papers and our proposed approach.

TABLE IV.
A COMPARISON BETWEEN THE SUGGESTED APPROACH AND OTHER ONES

Reference	Method	Dataset	AP Score
[48]	Hierarchical Convolutional Neural Network (CNN)	The OpenALPR (European) and the SSIG (Brazilian) datasets	90.94% for the Brazilian dataset and 96.09% for the European dataset
[49]	Utilizing a convolutional neural network (CNN) and segmentation based on K-means clustering	The FZU vehicles dataset	97%
Proposed method	Faster RCNN and ResNet-50 with GWO	The car license plate detection	98.21%

This work advances the constantly evolving discipline of license plate detection by utilizing deep knowledge of computational optimization and establishing new avenues for intelligent transportation programs.

V. CONCLUSION

The license plate detection on the CNN "vehicle license plate detection" benchmark dataset turned into completed with a notable expected precision of 98.21% with the recommended method, which mixes Faster R-CNN, Gray Wolf Optimization, and ResNet-50. A novel innovation that resulted in a massive development in detection overall performance was the integration of the bio-inspired Gray Wolf Optimization approach to alter the detection threshold of the Faster R-CNN community. A sophisticated ResNet-50 version was brought for license plate class to enhance the average accuracy further. With an average intersection over union (IoU) of 0.8823 across test samples, evaluation of the IoU revealed robust bounding box alignment and correct license plate localization.

With an AP-AUC value of 0.9821, the average precision (AP) plot constantly showed top-notch precision even at high take-into-account ranges, highlighting the method's dependability in effectively figuring out positive samples. The statistical assessment metrics validated the suggested method's excellent performance, accuracy, and localization capability. These metrics blanketed 94.0% accuracy, 0.9821 average precision, 0.8823 imply IoU, and 7.44 ms average detection time. By surpassing today's strategies on benchmark datasets, the comparative analysis showed that the developed approach pushed the limits of accuracy for license plate detection. This looks at confirmed a way to effectively resolve arduous computer vision duties by merging cutting-edge deep learning architectures, including Faster R-CNN and ResNet, with bio-stimulated optimization techniques.

Finally, the combination of superior item detection, category fashions, and optimization algorithms produced terrific license plate detection overall performance, indicating the wide variety of applications to which this technique can be used in real-world smart transportation.

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CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

AUTHOR CONTRIBUTION STATEMENT

Both Authors have proposed the research problem, performed the computations, and supervised the findings of this work. Also, both discussed the results and contributed to the final manuscript.

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