EMITTER International Journal of Engineering Technology
Vol. 14, No. 1, June 2026, pp. 24~41
DOI : 10.24003/emitter.v14i1.999

Accurate Automatic Recognition of Iraqi License Plates Using YOLOv11n and Enhanced OCR Techniques

Aymen Saad[1,2], Usman Ullah Sheikh[1], Zaid Abdi Alkareem Alyasseri[3,4]

[1]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor, Malaysia
[2]Department of Information Technology, Technical College of Management, Al-Furat Al-Awsat Technical, University, Kufa, Iraq
[3]Information Technology Research and Development Center (ITRDC) University of Kufa Najaf, Iraq
[4]College of Engineering, University of Warith Al-Anbiyaa, Karbala, Iraq
Corresponding Author: aymen.abdalameer@atu.edu.iq

Received February 13, 2026; Revised March 14, 2026; Accepted May 25, 2026

Abstract

Automatic License Plate Recognition (ALPR) systems are widely utilized for traffic monitoring, law enforcement, and security applications. While previous ALPR techniques have demonstrated high accuracy on uniform license plate formats, recognizing license plates in many countries particularly in Arabic-speaking regions remains a significant challenge due to the complex structure and diverse designs of the plates. Moreover, visual similarities between certain English letters and Arabic numerals often lead to misinterpretations by Optical Character Recognition (OCR) systems. This study proposes an efficient ALPR framework tailored for the new Iraqi license plates, employing image processing and deep learning (DL) techniques. The system integrates the YOLOv11n object detection model for accurate license plate localization, and OCR for character recognition. To address the OCR misclassification issue, particularly those caused by Arabic-English character similarities, the OCR component is enhanced using Character Index Checking (CCI) and Regular Expression Patterns (REP), resulting in more stable and accurate recognition outputs. The proposed method was evaluated on a real dataset of Iraqi license plates under varying illumination, viewpoints, and background complexity. Experimental results demonstrate strong end-to-end ALPR performance, achieving 100% plate detection accuracy, 99.8% recognition recall, and 99.5% mAP@0.5, confirming the robustness and practical effectiveness of the proposed system.

Keywords: Iraqi License Plate Recognition (ILP), Deep Learning (DL), Optical Character Recognition (OCR), Character Index Checking (CCI), Regular Expression Patterns (REP).

1. INTRODUCTION

The occurrence of a great many more cars on the road in recent years has also prompted concern for road safety, accident prevention, and security [1]. Rising most acutely to the fore are accidents and hit-and-run crimes. Therefore, the development in computer vision and deep learning has thrown some creative ideas, including ALPR systems [2-3]. Traffic surveillance, policing, and even the frequency of accidents depends greatly on these systems. However, the ALPR systems currently available are very difficult to apply in practice, especially in places like Iraq, where there is a great variety in form, size, and typography, not to mention language [4]. In addition, adverse lighting and too many cars in one picture bring all new obstacles to get clear detection and identification [5].

Conventional ALPR systems may be driven by conventional image processing methods, which can lack durability and flexibility when dynamic environmental circumstances are considered [6]. YOLO (You Only Look Once)-enabled deep learning models greatly increased the accuracy and efficiency of object detection, hence qualifying them for license plate identification [7]. The most advanced version, YOLOv11n , is best in real-time object identification due to its ability to realize a lot of items at the same time with high accuracy and speed. Despite these strides, more fine-tuning must be done to deliver consistent performance in different and challenging settings.

This research implements a view camera for car systems with an automated license plate identification system using the YOLOv11n detector and EasyOCR character recognition. License plates allow the system to track incoming cars from all sides and at the same time record possible accident events, hence enhancing traffic safety. The extraction of alphanumeric characters has been improved by Checking Character Index (CCI) and Regular Expression Pattern (REP) which in turn further improves the accuracy of alpha-numeric character extraction. The primary research questions guiding this study include:

1. How effectively can YOLOv11n detect and recognize license plates under varying lighting conditions and diverse plate formats?

2. To what extent do the Checking Character Index (CCI) and Regular Expression Pattern (REP) technologies improve classification accuracy for license plate recognition?

By addressing these questions, this research contributes to the field of automatic number plate recognition by improving detection accuracy, robustness, and computational efficiency. The findings of this study have significant implications for traffic monitoring, accident prevention, and law enforcement applications.

The rest of this paper is organized as follows: Related studies in license plate detection and identification are reviewed in Section 2. The originality and main contributions of this research are detailed in Section 3. The suggested approach is outlined in Section 4, along with the system architecture, deep learning models, and software integration. Experimental findings and performance assessments are presented in Section 5. Conclusions and future work are covered in Section 6.

2. RELATED WORKS

The evolution of YOLO object detection models has greatly heightened the accuracy and speed of automatic license plate recognition (ALPR) systems. Major issues concerned with real-time spotting and recognition of plates have been gradually mitigated with the evolution from YOLOv5 to the later versions like YOLOv10 and YOLOv11n [7]. This is because the greater integration of YOLO models has allowed for real-time processing, improved detection precision, and the capacity to address challenging scenarios especially with varying plate layouts and environmental conditions. These in return have largely been made possible owing to the inherent speed and single-pass object detection able nature of YOLO models.

Sapkota et al., [8] discussed the development of YOLO-v1 up to YOLO-v10, giving significant steps forward over the past decade in public safety, automotive technology, healthcare, and industrial manufacturing and retail operations. It focuses on enhancement in detection speed, accuracy, and computational efficiency as well as the shortcomings of prior versions. The review presents the current shortfalls and suggests the directions of future research, particularly the integration of multimodal data processing and improvements in language models for enhancing object detection. This detailed analysis does not only give a history of the evolution of YOLO models but also reveals the prospect of its application in AI research.

A novel method for enhancing automated toll collection is introduced through the integration of the YOLOv11n computer vision architecture with an ensemble OCR technique, utilizing only a single camera per toll plaza. The system under consideration achieved high performance. It had an average precision of 0.895. Key to this, also with a 98.5% license plate recognition accuracy, 94.2% axle detection accuracy, and a 99.7% OCR confidence rate, is intelligent tracking of vehicles using Intersection over Union regions, axle counting that is automatic based on spatial wheel detection, and real-time system monitoring via an extended dashboard interface. The system was trained on a dataset of 2,500 images captured under varied environmental conditions; it proved to be highly robust and efficient and greatly minimized the requirements on the hardware. In short, this is a scalable, precise-oriented evolution in intelligent transportation systems for enhanced operation performance and user experience in modern tolling infrastructure [9]. Rather, this paper presented a weather-adaptive convolutional neural network framework for improved performance in license plate detection under adverse weather conditions, implemented with the YOLOv10 architecture. This combines the weather-specific data augmentation techniques for strength of the robust automatic license plate recognition system under all environmental scenarios. Performance of the framework was evaluated with the main evaluating metrics like precision, recall, F1-score, mAP@50, and mAP@50-95 across different model configurations and strategies of augmentation. Results of experiments provided evidence of a significant enhancement of the detection accuracy under tough weather conditions, therefore offering the prospect for robust ALPR deployment in environmentally arduous regions [10].

A new study, YOLO-based multi-task model approach has been suggested for integrating vehicle color recognition with the detection of license plates and their optical character recognition. The proposed model achieved impressive results with average mean accuracy (mAP) scores of 0.778, 0.963, and 0.881 for OCR, LP, and VCR detection, respectively. Having been benchmarked against the traditional two-stage systems, the model is 3.07 times faster, hence speaking to the efficiency gains which come about with deploying YOLO in the processing of simultaneous tasks [11].

Recently, in a study, a modified lightweight YOLOv5s model was suggested for enhanced accuracy and speed in license plate detection on mobile devices. The original Focus layer was replaced by a better Stemblock network which keeps good feature extraction power while considerably reducing the parameter count and overall computational complexity. Furthermore, the backbone of YOLOv5s is replaced with ShuffleNetv2 that is more efficient, providing a lighter model without the loss of detection performance. To compensate for information loss resulting from channel recombination in the backbone, a function enrichment unit was added to facilitate better interactions between functions upon fusion. Additionally, multi-level features (low, medium, high) extracted from the layers of ShuffleNetv2 were merged to produce a strong result. When tested on the CCPD dataset, this improved version model reached an average precision of 96.6%, working at a speed of 43.86 frames per second, and having a reduced parameter size of only 5.07M, surpassing all others. A modern ALPR system unites YOLO with normalization streams for improved LP localization and recognition under complex backgrounds, therefore, forming a two-phase network solution under multi-image scale change to handle the hassle of cropped LP discovery and increase stalwartness to actual situations. The apparatus is put to the test on a fresh dataset bearing life-like conditions to exhibit performance when only a few samples can be learned from [12].

A comparative study of different YOLO versions (5, 7, 8, and 9) in cloud-based LPR systems reveals that YOLOv8 offers the best performance for real-world deployment, achieving an accuracy of 78% in cloud testing. This study highlights the evolution of YOLO models and their impact on enhancing LPR accuracy and processing efficiency, providing insights into selecting the most appropriate model for specific applications [13].

Layout-independent YOLO-based ALPR systems have been designed to process license plates with a variety of formats found in different regions. These systems incorporate post-processing rules to enhance recognition accuracy and have been demonstrated to outperform previous work and commercial systems on several public datasets. The real-time computing efficiency and robustness of the systems are also proved with evidence of multiple vehicles presence. The method obtained an average recognition rate of 96.9% on eight public datasets (of five different local) in experiments, which significantly outperformed previous work and commercial systems in terms of Chinese LP, OpenALPR-EU, SSIGSegPlate, and UFPR-ALPR datasets [14]. In same hand, Saad et al. [15] delivered an ALPR system using YOLOv8 for detecting and an enhanced OCR using Easy-OCR with CCI. It achieves engaging performance in discerning various license plates including ones from Iraq, Turkish and USA plates and achieves mean average precision (mAP) of 99.5% in character recognition. But such misrecognition of character exisits in this model.

This study shows the development of an ALPR system using Yolo-v11 and EasyOCR. Vehicle license plate detection and license plate character recognition are the two main components of this system.

3. ORIGINALITY

The originality of this research lies in the development of a highly accurate and robust automatic license plate recognition (ALPR) system specifically tailored for the newly standardized Iraqi license plates. While previous works have applied various YOLO versions and conventional OCR approaches to ALPR tasks across different regions[9, 14-15], significant challenges persist in recognizing plates with complex, bilingual (Arabic-English) formats and region-specific design variations, such as those recently adopted in Iraq.

First, this study introduces the application of the advanced YOLOv11n model for the detection of Iraqi license plates, exploiting its state-of-the-art accuracy and real-time processing capability. To our knowledge, this is among the first works to adapt YOLOv11n for Iraqi plates, which feature unique structural elements and bilingual codes, further complicating detection and recognition beyond what has been previously addressed for Western or East Asian license plate datasets [15][21].

Second, a key innovation is the enhancement of the optical character recognition (OCR) component. Instead of relying solely on conventional OCR pipelines, which are prone to misclassifications due to visual similarity between certain Arabic numerals and Latin letters, this study proposes a two-stage error correction mechanism:

1. Character Index Checking (CCI): This mechanism proactively detects and corrects common OCR misclassifications between visually similar characters (e.g., "0" vs. "O", "2" vs. "Z", "8" vs. "B") that are prevalent on Iraqi plates due to their mixed alphanumeric nature. Such systematic post-processing of OCR results is a novel addition compared to prior ALPR systems, which rarely address this challenge explicitly [15].

2. Regular Expression Patterns (REP): The adoption of regex-based parsing tailored to the official Iraqi plate format ensures structural and

semantic validity of recognized plate numbers. This not only reduces recognition errors but also enforces strict compliance with governmental plate conventions a critical but previously underexplored aspect for practical deployment [22].

Third, the system is comprehensively evaluated on an expanded and augmented dataset of actual Iraqi plates, addressing real-world variations in illumination, angle, and image quality. The proposed method achieves near-perfect performance metrics (100% detection accuracy, 99.8% recall, mAP 99.5%), which, according to a comparative analysis, outperform previous state-of-the-art ALPR approaches in this domain [9, 14-15].

The novelty of this work does not lie in modifying the internal YOLOv11 architecture [23], but in designing an end-to-end ALPR framework optimized for Iraqi plates and in introducing a position-aware OCR correction pipeline (CCI) combined with format validation (REP) to mitigate Arabic–Latin character ambiguity.

4. SYSTEM DESIGN

Utilizing the YOLOv11n n model and EasyOCR offers an avenue for significant improvements in ALPR systems, particularly for multi-type license plate recognition, aiming to enhance and address the limitations. This study provides a description of the system pipeline followed, the YOLO-v11 model training and evaluation process, the text recognition improvement process, and a final regular expression-based template extraction.

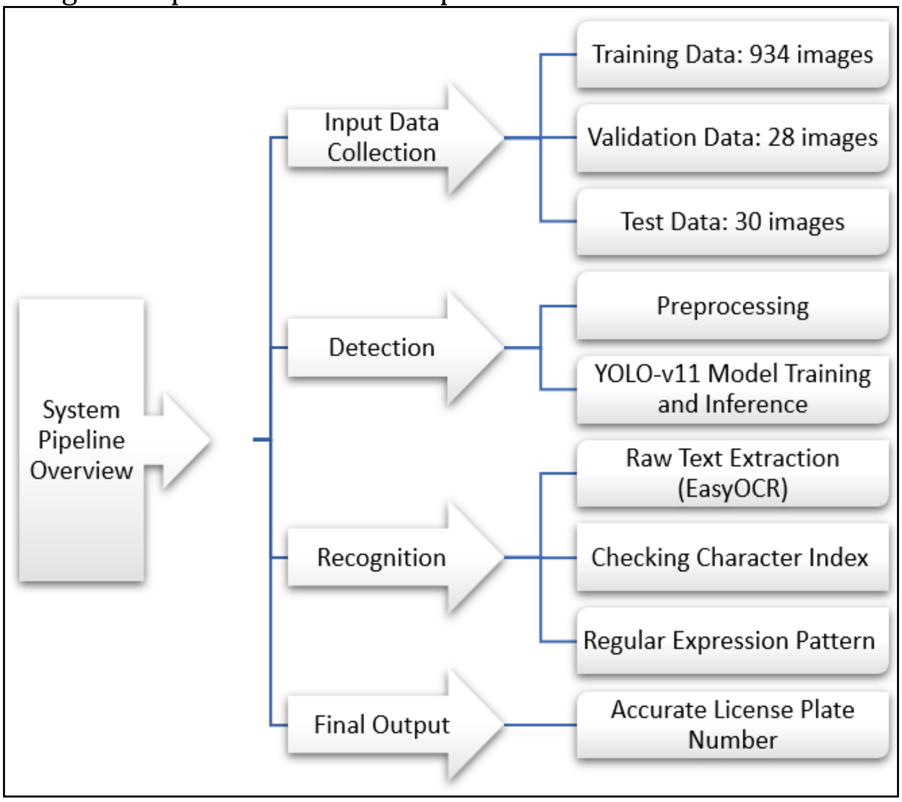

Figure 1. Proposed standard approach to pipeline.

The process starts with an "Input frame", which is then passed through an "annotation" step. The next step is to detect LP only from the whole frame using YOLO-v11. After that, a prediction of the text's subsequent symbols and a "Check Character Index" step are performed to verify the validity or quality of the detected license plate. Finally, an "OCR to Recognition LP" step is carried out to optically recognize the alphanumeric characters on the license plate. The whole course of this work is shown in Figure 1.

4.1 Dataset

Publicly accessible data sets include Caltech Cars, EnglishLP, UCSD-Stills, AOLP, OpenALPR-EU, and SSIG are often used to assess ALPR systems. These datasets include many LP layouts and were gathered under various settings and situations; see Table 1, for more information. The methodology outlined in the present study can be applied broadly to the various datasets under investigation.

Table 1. Various publicly available LP datasets.

Rrf.	Dataset	Year	Images	Resolution
[16]	Caltech Cars	1999	126	896×592
[17]	EnglishLP	2003	509	640×480
[18]	UCSD	2005	291	
[19]	AOLP	2013	2049	Various
[20]	OpenALPR	2016	108	
[21]	SSIG	2016	800	
[15]	Iraqi	2024	292	640×640

Iraqi license plates

The current design of Iraqi license plates was officially introduced in 2022, adopting standardized European dimensions and format, as illustrated in Figure 2.

Figure 2. Example of Iraqi LP.

The left section of the plate includes a vertical band displaying the country code "IRQ" for Iraq, alongside the regional code "KR," which denotes the Kurdistan Region. On the right side, a horizontal segment indicates the city code using a two-letter representation "DD". This city codes corresponds to administrative regions as follows: Baghdad = 11, Nineveh = 12, Maysan = 13, Basra = 14, Anbar = 15, Al-Qadisiyyah = 16, Al-Muthanna = 17, Babylon = 18, Karbala = 19, Diyala = 20, Sulaymaniyah = 21, Erbil = 22, Halabja = 23, and Dohuk = 24. The numerical structure of the plate is governed by specific rules. Vehicles with numbers ranging from 1 to 99,999 are accompanied by the letter "A" numbers at regular intervals, such as 100,000; 200,000; ... up to 900,000 are appended with the letter "M". For plates exceeding 100,001, the second digit from the left is omitted and replaced with a corresponding letter (B, C, D, E, F, G, H, J, K, L) based on the omitted digit [24-27].

In this study, we will use the same type of data as in our previous research [15], with an increase in the number of images using augmentation techniques such as grayscale, contrast, saturation and exposure to ensure the robustness of the model.

4.2 Preparation License Plate

4.2.1 Annotation image step

The annotation process for this study was conducted using Roboflow [28-30], a robust platform designed for labeling and managing image datasets. Images from the input datasets, comprising 934 training images, 28 validation images, and 30 test images, were uploaded to Roboflow for annotation. The platform facilitated the creation of bounding boxes around license plate regions, ensuring precise localization for the YOLO-v11 model. Annotations included class labels and coordinate data, which were meticulously reviewed and adjusted to enhance accuracy. Roboflow's intuitive interface allowed for collaborative annotation and version control, enabling iterative refinements. The annotated dataset was then exported in a format compatible with the training pipeline, ensuring seamless integration into the ALPR system's development workflow, as shown in Figure 3.

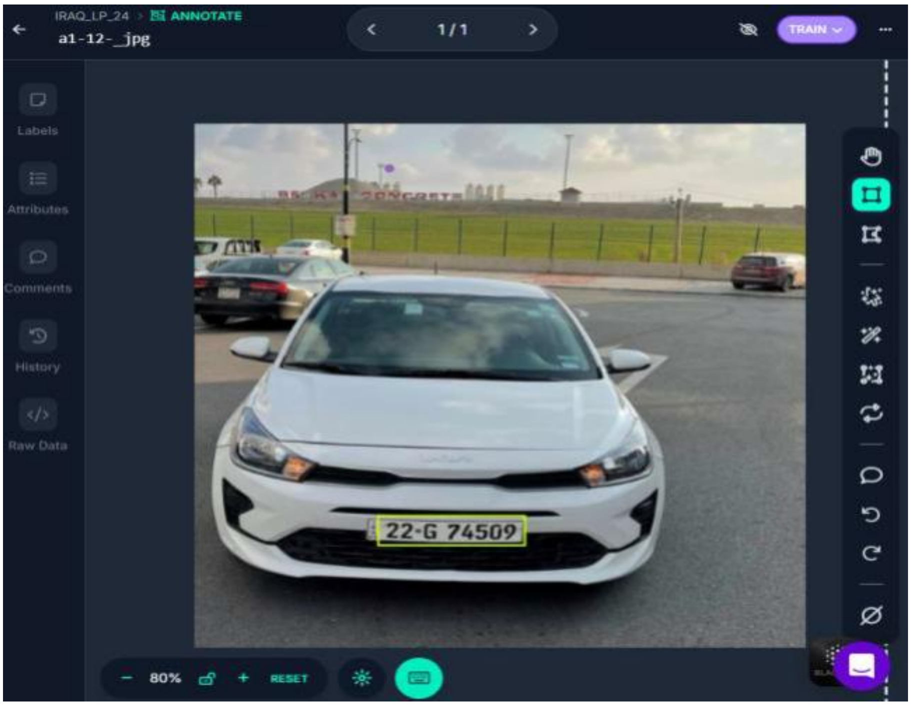

Figure 3. Example of Annotation labels.

4.2.2 Preprocessing image

The pretreatment dataset follows a standard format; for instance, every picture is the same size. This step ensures that your dataset is consistent before training a model. Preprocessing is applicable to all of the images in your train, valid, and test datasets. We utilized the preprocessing functionalities provided by the Roboflow system to enhance the quality and consistency of our dataset. The applied preprocessing steps included:

- Auto-Orientation: Automatically aligned images to the correct orientation.
- Resize: All images were resized to a uniform dimension of 640×640 pixels to ensure consistent input for the neural network.
- Grayscale Conversion: Applied to 25% of the images to increase robustness against color variations.
- Contrast Adjustment: Performed using contrast stretching to improve the visibility of key features.
- Saturation Augmentation: Randomly varied within a range of -25% to +25% to simulate different lighting and color conditions.
- Exposure Augmentation: Adjusted within a range of -5% to +5% to account for variations in image brightness.

Comprising 992 license plate photos after the augmentation process, the dataset is split into training (80%), validation (10%), and testing (10%). Photos are captured and annotated with "Label Img" using the method used in vehicle detection.

4.3 YOLO-v11 Architecture to Detect LP

Table 2. Training Hyperparameters Used for YOLOv11n Model

Category	Setting
Model variant	YOLOv11n
Input size	640×640
Dataset split	80% train, 10% val and 10% test (992 images after augmentation)
Epochs	200
Batch size	64
Optimizer	Adam
Initial learning rate	0.001
Confidence threshold (inference)	0.50
mAP metric	mAP@0.5

The YOLO-v11 model is used to detect the license plates after annotation, because of its exceptional efficiency and accuracy in object detection tasks. As indicated in Table 2, the details of the hyperparameters were used to train the model.

YOLOv11n improves upon the shortcomings of its predecessors by utilizing cutting-edge backbone and neck architectures to enhance performance in both feature extraction and object detection. Number plate detection is the technique of binding the plate from the surrounding region. The outcome will be a sub-image with just the license plate because the plate placement has been set. Training completes the testing; then the model is loaded from storage. YOLOv11 follows a one-stage detector design comprising a backbone for feature extraction, a neck for multi-scale feature fusion, and a detection head for bounding box regression and class prediction. In this work, we adopt the YOLOv11n variant to balance speed and accuracy for real-time ALPR deployment.

4.4 Optical Character Recognition

Using the EasyOCR framework, the textual content of license plates was extracted and converted into machine-editable text. Upon detecting a license plate within an image, EasyOCR utilizes object recognition to localise the plate and returns its bounding box coordinates: Xmin, Ymin, Xmax, and Ymax. The image is then transformed into a numerical array, and the Region of Interest (ROI) corresponding to the license plate is cropped based on these coordinates.

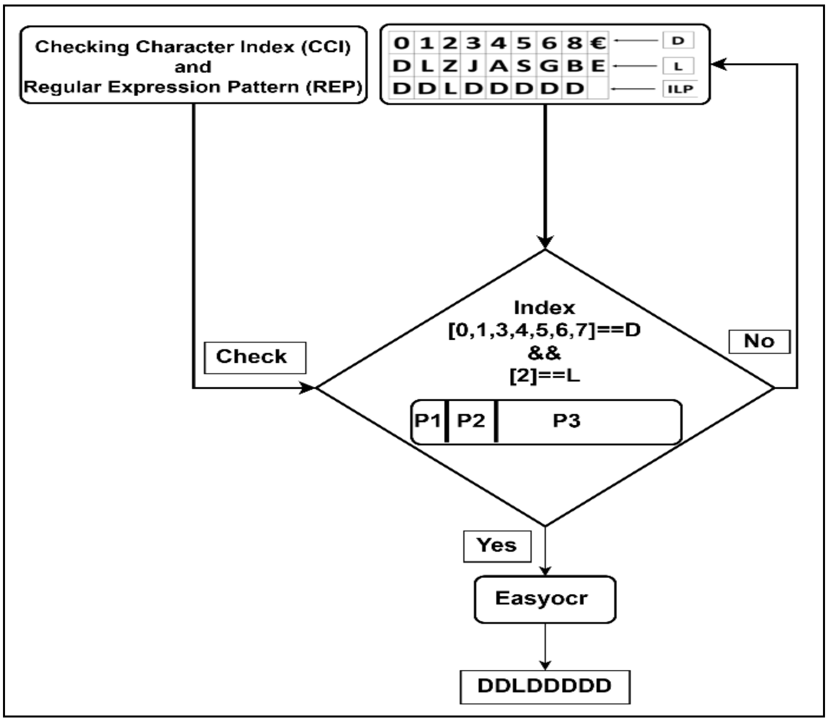

Figure 4. Illustrates Checking Character Index and Regular Expression Pattern Stage.

The ROI is then cropped from the image using these coordinates, isolating the license plate for text extraction. The cropped ROI is processed using EasyOCR, a robust optical character recognition (OCR) tool, to extract the text from the license plate, converting the visual content into editable text (e.g., "ABC123"). Algorithms for segmenting and formatting text might affect OCR accuracy. Sometimes, depending on the picture backdrop, word extraction from depending on the background of the image, it can be challenging to extract words from it. Therefore, we used two methods, which are Checking Character Index (CCI) and Regular Expression Pattern (REP), to enhance EasyOCR by providing a more consistent license plate identification system.

The extracted text is then post-processed to enhance the result and format it as required, as illustrated in Figure 4. This strategic integration of the CCI and REP stages within the overall analytical pipeline serves to enhance the reliability and accuracy of the license plate recognition process by proactively identifying and rectifying common OCR-related character misclassification errors. By addressing these issues at an earlier juncture, the subsequent stages of the methodology can operate on more robust and reliable textual data, thereby improving the overall performance and applicability of the proposed approach across the diverse range of datasets under investigation.

4.4.1 Checking Character Index (CCI)

After detecting the license plates, our method introduces a novel stage checking the character index. The current methodological approach includes a specific stage designed to address and rectify common character misclassification errors that frequently occur within the context of OCR processes. Such classification errors, where characters are misidentified as alternative alphanumeric symbols ("0" is misidentified as "D", "1" as "L", "2" as "Z", "3" as "J", "4" as "A", "5" as "S", "6" as "G", and "8" as "B") that we uncovered in our previous work [16]. Additionally, we identified a recurring misinterpretation of the letter "E," which is frequently read by OCR systems as the Euro symbol "€". These types of recognition errors pose a significant challenge and can substantially degrade the accuracy and reliability of subsequent license plate recognition processes.

The algorithm underlying this CCI stage requires three primary arguments as input: the source image file path, a dictionary mapping characters to integers ("dict_char_to_int"), and a complementary dictionary mapping integers to their corresponding characters ("dict_int_to_char"). The algorithm first extracts the textual information from the OCR-generated output and then formats this extracted text based on specific criteria. Specifically, the algorithm verifies that the first 8 characters of the extracted text comprise a combination of numbers and letters in the expected DDLDDDD format, where 'D' represents digits and 'L' represents letters.

These maps help turn the letters that look like their matching digits (such as 'O' for '0') into actual numbers and vice versa.

Character to Integer Mapping:
dict_char_to_int = {O→0, L→1, Z→2, J→3, A→4, S→5, G→6, B→8, E→€}
Integer to Character Mapping:
dict_int_to_char = {0→O,1→L, 2→Z, 3→J, 4→A, 5→S, 6→G, 8→B, €→E}

While the task of applying the mappings for character conversion belongs to the "format_text" function. Conditions refer to the logical checks that determine the flow of execution and validity of the extracted text. In this case, they should handle only valid number plates and apply the mappings correctly; thus, acting as filters to prevent from wrong processing and to ensure the output meaningful.

4.4.2 Regular Expression Pattern (REP)

Iraqi license plates, our work comes up with a way of handling their structure through a specialized pattern matching technique recognizing the enormous issue that Iraqi license plates present, our work proposes a method for dealing with their structure using a particular pattern-matching algorithm. The provided Regular Expression Pattern Pattern (REP) is designed to extract structured data that includes a province code, an optional mid character, and a sequence of digits in the format commonly used for geographic or administrative identifiers. For example, through a regular expression pattern as below, i.e.,

pattern=b
(11|12|13|14|15|16|17|18|19|20|21|22|23|24|25|26|27|28|29) →P1
\.? \s*([A-Z0-9€]?) →P2
\.? \s*(\d{ 5,6})\b", →P3

The method will enable precise processing and parsing of the components of such plates. Breaking down the pattern, the first segment (P1) captures specific province codes ranging from 11 to 29, ensuring that the match begins at a word boundary. Following this, (P2) allows for an optional mid character, which can be an uppercase letter, digit, accommodating variations in the format. The final component (P3) matches a sequence of 5 to 6 digits, also starting and ending at word boundaries, ensuring that the extraction focuses on well-defined groups of numeric data.

5. EXPERIMENT AND ANALYSIS

For ALPR system, we used two main models: YOLOv11n for object detection and improved EasyOCR for optical character recognition. The dataset contains 292 original Iraqi license plate images, expanded to 992 images after augmentation. A visual representation of the model performances is depicted in Figure 5 for a clearer understanding.

The YOLOv11n Nano model was trained using the following hyperparameters: a learning rate of 0.001, a minimum confidence threshold of 0.50, a batch size of 64, and a total of 200 epochs. The Adam optimizer was employed to facilitate efficient and adaptive gradient updates during training. A maximum of 100 images per batch were processed in each iteration. The model achieved outstanding performance, precision, recall and mean Average Precision at IoU (mAP50) 99.8%, 100%, 99.5% respectively. Evaluation metrics confirm the high accuracy, robustness, and reliability of the YOLOv11n Nano model in both license plate detection and text localisation tasks within the ALPR system.

Figure 5. LP detection using Yolo-v11.

This study introduces the integration of two enhancement stages Character Index Checking (CCI) and Regular Expression Pattern (REP) to improve the reliability of license plate recognition. The CCI stage is specifically designed to detect and correct common OCR misclassification errors, such as recognizing the digit '0' as the letter 'D', '1' as 'L', '2' as 'Z', '3' as 'J', '4' as 'A', '5' as 'S', '6' as 'G', and '8' as 'B'. Complementing CCI, the REP module is employed to extract structured license plate information, typically comprising a province code, an optional mid-character, and a numeric sequence in a format that reflects standardised geographic or administrative identifiers in Iraqi license plates. The suggested approach incorporates both CCI and REP into the post-processing pipeline and is based on YOLOv11n for license plate identification and EasyOCR for character recognition. The work aims to proactively correct recognition errors and ensure structural consistency prior to final OCR interpretation, significantly improving the overall accuracy of the license plate identification procedure.

To quantify the effectiveness of the proposed OCR enhancement stages, we conducted an ablation study using the same 200 test images. Three configurations were evaluated: (i) baseline EasyOCR without post-processing, (ii) EasyOCR with Character Index Checking (CCI) [15], and (iii) EasyOCR with CCI and Regular Expression Patterns (REP). The baseline OCR frequently produced visually plausible but structurally invalid outputs due to Arabic–Latin character similarity and inconsistent spacing/symbol insertion. Adding CCI reduced symbol-level confusion by enforcing position-aware character correction, while adding REP further improved reliability by enforcing compliance with the official Iraqi plate format.

We evaluated 200 images under various settings, including camera angles and illumination intensity. Every outcome for the region of interest (LP) identification task was accurate. Nevertheless, as illustrated in Table 3, the system failed to read 15 plates in the recognition character challenge.

Table 3. Comparison between the results.

No	Image	Output
1		**2 J76500)**
2		**6 Z2 € 67346**
3		**[2Z H78224**
4		**Q2 5 78812]**
5		**Z2 H75443**
6		**22 0 49227**
7		**Z13 27804**
8		**U Z4H 16424**
9		**22 6 _ 74155**
10		**22 70028**
11		**D F" 75531**
12		**21 0 26174**
13		**Z1 0 3892**
14		**€ Z2 0 7874**
15		**H2ZF7028**

6. CONCLUSION

This study presents a highly accurate automatic recognition system for Iraqi license plates by powerful YOLOv11n algorithm and an enhanced OCR pipeline. YOLOv11n ensures robust and precise plate detection, while

EasyOCR is optimized to improve character recognition through refined processing at the Character Index Checking (CCI) and Regular Expression Pattern (REP) stages. Advanced object detection capabilities are provided by YOLOv11n . The test results carried out in the development of an automatic vehicle license plate detection system with the YOLOv11n algorithm were precision, recall and mean Average Precision at IoU (mAP50) 99.8%, 100%, 99.5% respectively. These results further elaborate that it successfully detected and identified all the symbols on the vehicle license plate. For recognition tasks, 200 images were tested in a range of conditions, such as camera angles and lighting levels. For the task of detecting regions of interest LP, every result was accurate. However, the system was unable to read 15-LP. We assume that is because of the complex visual effects of light and shadow or low resolution, which cause the characters to look like other characters. In the future, we will expand our system to other environments, such as nighttime and low-light conditions and low-resolution images.

REFERENCES

[1] A. Dutta, L. M. Samaniego Campoverde, M. Tropea, and F. De Rango, **A comprehensive review of recent developments in VANET for traffic, safety & remote monitoring applications**, *Journal of Network and Systems Management*, vol. 32, no. 4, p. 73, 2024. https://doi.org/10.1007/s10922-024-09853-5

[2] M. N. Khan and S. Das, **Advancing traffic safety through the safe system approach: A systematic review**, *Accident Analysis & Prevention*, vol. 199, p. 107518, 2024. https://doi.org/10.1016/j.aap.2024.107518

[3] A. Nair, V. Patil, R. Nair, A. Shetty, and M. Cherian, **A review on recent driver safety systems and its emerging solutions**, *International Journal of Computers and Applications*, vol. 46, no. 3, pp. 137–151, 2024. https://doi.org/10.1080/1206212X.2023.2293348

[4] A. H. Abdulkhaleq, A. W. Altaher, A. Saad, and H. M. Al-Jawahry, **Automatic vehicle license plate recognition using lightweight deep learning approach**, *2023 6th International Conference on Engineering Technology and its Applications (IICETA)*, pp. 143–148, 2023. https://doi.org/10.1109/IICETA57613.2023.10351297

[5] X. Yu and M. Marinov, **A study on recent developments and issues with obstacle detection systems for automated vehicles**, *Sustainability*, vol. 12, no. 8, p. 3281, 2020. https://doi.org/10.3390/su12083281

[6] K. Mohan and S. K. Pandey, **A deep-learning based real-time license plate recognition system for resource-constrained scenarios**, *Pattern Recognition*, pp. 226–242, 2024. https://doi.org/10.1007/978-3-031-78498-9_16

[7] M. L. Ali and Z. Zhang, **The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object**

detection, *Computers*, vol. 13, no. 12, p. 336, 2024. https://doi.org/10.3390/computers13120336

[8] R. Sapkota, R. Qureshi, M. Flores-Calero, C. Badgujar, U. Nepal, A. Poulose, *et al.*, **YOLOv10 to its genesis: A decadal and comprehensive review of the You Only Look Once series**, *Preprints*, 2024. https://doi.org/10.20944/preprints202406.1366.v2

[9] K. Sivakoti, **Vehicle detection and classification for toll collection using YOLOv11n and ensemble OCR**, *arXiv preprint arXiv:2412.12191*, 2024. https://doi.org/10.48550/arXiv.2412.12191

[10] U. Saha, B. Saha, and M. A. Imran, **A weather-adaptive convolutional neural network framework for better license plate detection**, *Sensors*, vol. 24, no. 23, p. 7841, 2024. https://doi.org/10.3390/s24237841

[11] Y.-L. Khor, Y. J. Wong, M. Tham, Y. C. Chang, B.-H. Kwan, and K.-C. Khor, **Multi-task YOLO for vehicle colour recognition and automatic license plate recognition**, *2024 IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS)*, pp. 1–7, 2024. https://doi.org/10.1109/EAIS58494.2024.10570013

[12] S. Zhu, Y. Wang, and Z. Wang, **A lightweight license plate detection algorithm based on deep learning**, *IET Image Processing*, vol. 18, no. 2, pp. 403–411, 2024. https://doi.org/10.1049/ipr2.12956

[13] K. Oublal and X. Dai, **An advanced combination of semi-supervised normalizing flow & YOLO (YoloNF) to detect and recognize vehicle license plates**, *arXiv preprint arXiv:2207.10777*, 2022. https://doi.org/10.48550/arXiv.2207.10777

[14] R. Laroca and D. Menotti, **Automatic license plate recognition: An efficient and layout-independent system based on the YOLO detector**, *Conference on Graphics, Patterns and Images (SIBGRAPI)*, 2020. https://doi.org/10.5753/SIBGRAPI.EST.2020.12978

[15] A. Saad, U. U. Sheikh, and Z. A. A. Alyasseri, **An efficient layout index characters for automatic license plate recognition system based on the YOLO-v8 detector**, *2024 IEEE 8th International Conference on Signal and Image Processing Applications (ICSIPA)*, pp. 1–5, 2024. https://doi.org/10.1109/ICSIPA62061.2024.10701017

[16] California Institute of Technology, **Caltech Computational Vision: Archive**, 1999. Available Online: http://www.vision.caltech.edu/html-files/archive.html.

[17] V. Srebrić, **EnglishLP database**, 2003. Available Online: http://www.zemris.fer.hr/projects/LicensePlates/english/baza_slika.zip.

[18] L. Dlagnekov, **Video-based car surveillance: License plate, make, and model recognition**, M.S. Thesis, *University of California, San Diego*, 2005.

[19] G.-S. Hsu, J.-C. Chen, and Y.-Z. Chung, **Application-oriented license plate recognition**, *IEEE Transactions on Vehicular Technology*, vol. 62, no. 2, pp. 552–561, 2013. https://doi.org/10.1109/TVT.2012.2226218

[20] OpenALPR, **OpenALPR Cloud API**, 2019. Available Online: http://www.openalpr.com/; https://github.com/openalpr/cloudapi.

[21] G. R. Gonçalves, S. P. G. da Silva, D. Menotti, and W. R. Schwartz, **Benchmark for license plate character segmentation**, *Journal of Electronic Imaging*, vol. 25, no. 5, p. 053034, 2016. https://doi.org/10.1117/1.JEI.25.5.053034

[22] P. Wang, G. R. Bai, and K. T. Stolee, **Exploring regular expression evolution**, *2019 IEEE 26th International Conference on Software Analysis, Evolution and Reengineering (SANER)*, pp. 502–513, 2019. https://doi.org/10.1109/SANER.2019.8667972

[23] T. Spoorthi and S. P. Anandaraj, **A hybrid AI model combining YOLOv11 and Easy-OCR for real-time detection of vehicles and high-security registration plates in intelligent traffic systems**, *International Journal of Intelligent Transportation Systems Research*, 2026. https://doi.org/10.1007/s13177-026-00637-6

[24] M. H. Abbas and Z. M. Mohammed, **Detection and recognition of Iraqi license plates using convolutional neural networks**, *Science Journal of University of Zakho*, vol. 13, no. 1, pp. 7–17, 2025. https://doi.org/10.25271/sjuoz.2025.13.1.1344

[25] S. Sh. Altyar, S. S. Hussein, and L. A. Tawfeeq, **Accurate license plate recognition system for different styles of Iraqi license plates**, *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 2, pp. 1092–1102, 2023. https://doi.org/10.11591/eei.v12i2.4186

[26] Y. Dawood, H. S. Alhadawi, A. S. Mahdi, and F. T. Al-Dhief, **Improved automatic license plate recognition system in Iraq for surveillance system using OCR**, *Proceedings of the 2nd International Conference on Emerging Technologies and Intelligent Systems*, pp. 270–277, 2022. https://doi.org/10.1007/978-3-031-20429-6_26

[27] R. H. Finjan and A. S. Rasheed, **Iraqi multi-style license plate recognition system using Efficient Dets model**, *International Journal of Latest Engineering Research and Applications*, vol. 7, no. 5, pp. 79–84, 2022.

[28] N. J. O. Suganob, R. Concepcion II, R. K. Billones, and E. P. Dadios, **Dehusked coconut vision-based counting on a manufacturing plant utilizing the YOLOv8, ByteTrack, and Roboflow algorithms**, *Intelligent Computing and Optimization*, pp. 101–111, 2024. https://doi.org/10.1007/978-3-031-73321-5_11

[29] L. Öztürk and B. Şin, **Deep learning-based detection of Grapevine fanleaf virus in Türkiye: A comparative study of ROBOFLOW 3.0, YOLO-NAS, YOLOV11, and YOLOV12**, *Ciência e Técnica Vitivinícola*, vol. 41, no. 1, pp. 1–13, 2026. https://doi.org/10.1051/ctv/20264101001

[30] J. M. Villarroel, L. C. De Jesus, J. B. Ancheta, H. Villaruel, and L. Samaniego, **Comparative analysis of YOLOv12 and RF-DETR models for coffee leaf disease detection using Roboflow**, *2025 IEEE 14th Global Conference on Consumer Electronics (GCCE)*, pp. 1493–1494, 2025. https://doi.org/10.1109/GCCE65946.2025.11274815