DETECTION AND RECOGNITION OF IRAQI LICENSE PLATES USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT:

Due to the large population of motorway users in the country of Iraq, various approaches have been adopted to manage queues such as implementation of traffic lights, avoidance of illegal parking, amongst others. However, defaulters are recorded daily, hence the need to develop a mean of identifying these defaulters and bring them to book. This article discusses the development of an approach of recognizing Iraqi licence plates such that defaulters of queue management systems are identified. Multiple agencies worldwide have quickly and widely adopted the recognition of a vehicle license plate technology to expand their ability in investigative and security matters. License plate helps detect the vehicle's information automatically rather than a long time consuming manually gathering for the information. In this article, transfer learning is employed to train two distinct YOLOv8 models for enhanced automatic number plate recognition (ANPR). This approach leverages the strengths of YOLOv8 in handling complex patterns and variations in license plate designs, showcasing significant promise for real-world applications in vehicle identification and law enforcement.

KEYWORDS: Automatic number plate recognition, machine learning, transfer learning, queue management, YOLOv8.

1. INTRODUCTION

Due to the rising number of cars, the management of intelligent traffic has become essential to identify and monitor vehicles that violates the law guiding queue management systems. Intelligent traffic gathers information about the vehicle so that it can be used in monitoring systems and security. For the identification of the license plate, there are two approaches: manual recognition by humans and automatic recognition by computer programs. As mentioned by Abod (2015), manual plate identification is useful, however automatic recognition are more advantageous because under different situations, it would be easier to recognize a license plate.

Automatic number plate recognition (ANPR) has been the subject of interest for decades, especially those who work in managing queue systems using image processing and artificial intelligence. Previous studies about license plate recognition and tracking can be broadly considered in two parts: license plate localization and license plate classification (Abbass & Marhoon, 2021; Hussein, & Tawfeeq, 2023). Studies that have conducted research on the former have focused on identifying numerous attempts to solve the problem of possible license plate area detection from an image or video (Abbas, & Mohamad, 2023). Different modern methods have applied various approaches, techniques, and algorithms for image processing to design their license plate detection systems. Kaur and Kaur (2014) proposed a method for localization of Indian license plates. They used bilateral filtering for noise removal, adaptive histogram equalization for contrast enhancement, and morphological operations and Sobel edge detection were used for plate area detection. In related studies, Chowdhury, Khan, and Uddin (2017) proposed a method for plate localization, where they used a sliding concentric window as a segmentation technique to separate the region of interest, which is the plate, and then further utilized morphological image processing to localize the plate inside the image. However, these approaches do not ensure region of interest segmentation for vehicles with a dark background license plate, and white colour of characters.

To develop an approach that would be usable regardless of the colour or size differences, Asif *et al.* (2017) used the YUV colour space to identify the car's backlight region. In addition to the use of distinctive histogram method to determine a map of heuristic energy in the relevant area, including the dense edge section. Other studies on license plate localization are Rabbani *et al.* (2018), Omran and Jarallah (2018), and Farag, El Din, and El Shenbary (2019). In the separate works of these authors, improved visuals were achieved by using a haze removal approach with application of the Wiener filter to remove the noise, combination of morphological techniques and vertical Sobel edge detection, and discrete wavelet transform. However, the limitations of the studies in this paragraph include some methods being limited to viewing the vehicle from behind and inconsistency in results when other regions have the same license plate aspect ratio as the detected zone.

On the other hand, studies on the second broad part of license plate recognition and tracking, which is the license plate classification, have been made to the identification scheme for license plates. Akhlis, and Sugiharti (2017) determined the significance of each letter and number in the plate by first utilizing Otsus' Method to extract plate image and then converted it to binary. Whereas, Bacic, and Yan (2018) developed a template matching method for determining plate characters by employing secondary positioning method, while the phase correlation and cross-correlation structured methods were reported to be effective by Sharma (2018). Although, there were success recorded in these studies, some of the shortcomings were that some studies considered all of their dataset images being captured from the rear, they didn't address how plate rotation plays a role in the recognition process, and their approach could only distinguish a limited number of characters.

ANPR systems are critical for various applications, including traffic monitoring, law enforcement, and access control. Although, it is worth noting that in each country, vehicles have unique plate number properties written on their license plates from the front or rear side with different types, colour, scale, font styles, aspect ratios (which is a ratio of length to width or width to height), and areas. Specifically, in Iraq, the

effectiveness of standard ANPR systems is significantly hindered by the wide variation in license plate designs. The plates vary in font styles, scales, and even the same plate for the same vehicle can have multiple aspect ratios (the front plate aspect's ratio differs from the back plate), which are not standardized across the region. This diversity makes it difficult for conventional ANPR technologies, which typically rely on predefined templates or simpler image processing techniques, to accurately detect and interpret the plates.

To overcome the limitations of existing ANPR systems in Iraq, this article develops a robust solution using advanced artificial intelligence techniques. The process consists of three steps: detection, segmentation, and recognition. In detection, it detects the license plate location. In segmentation, it depends on what is segmented from the car plate from the original image and segmenting the plate into characters. After that is the cropped image recognition where systems that recognize the license plate have various applications like monitoring traffic systems, tool ticketing, and parking fees.

The rest of the article is organised thus: the next section discusses the theoretical background and development of the vehicle tracking system consisting of the localization and classification. Thereafter, the results of the system and tests random vehicle images are discussed and conclusions and suggestions for future work are given.

Theoretical Background:

Distinctive features of Iraqi license plates, such as their numbering system, background noise, plate size, camera's field of view, scene complexity, unwelcome features, plate color, plate position, and plate tilt, varies. Classification presents a number of difficulties, including plates of varying sizes, short datasets that cause overfitting, and the time required to analyze the model of a convolutional neural network (CNN) during training. This section will introduce CNNs, transfer learning, object detection and its uses.

A description of a CNN is that it is a regularized type of feed-forward neural network with the independent ability to learn feature engineering on its own using filters or kernel optimization. CNNs are also known as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN) and this is founded on the shared-weight architecture of the convolution filters or kernels. These filters are known to slide along input features, while providing feature maps, which are basically translation-equivariant responses (Zhang *et al.*, 1990).

The layers of a CNN include an input layer, hidden layers (which include one or more layers that perform convolutions) and an output layer. Using the layer's input matrix, the hidden layer specifically includes a layer that computes a dot product of the convolution kernel. This product is usually the Frobenius inner product, and its activation function is commonly the rectified linear activation function. Notably, a feature map is generated by the convolution operation as the convolution kernel slides along the input matrix for the layer, which in turn contributes to the input of the next layer. Thereafter, other layers such as the pooling layers, fully connected layers, and normalization layers, follow suit. A typical CNN architecture is shown in Figure 1 below.
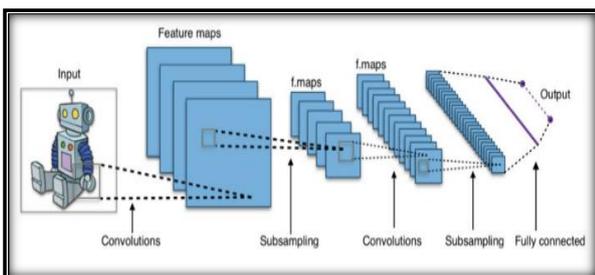

Figure 1: ypical CNN Architecture

Another important theoretical concept in machine learning is the transfer learning concept. In transfer learning, there is a reuse of knowledge learned from a task for boosting performance on a related task (West *et al.*, 2007). An example of transfer learning follows from an image classification scenario, where knowledge gained in the learning process of car recognition could be similarly adapted in the recognition of trucks. The reuse and transfer of information from tasks that have been previously learned to new tasks has the prospective to provide significant improvement in learning efficiency. This process is related to multi-objective optimization cost-sensitive machine learning as a result of transfer learning's use of training with various objective functions. An illustration is given in Figure 2 below.
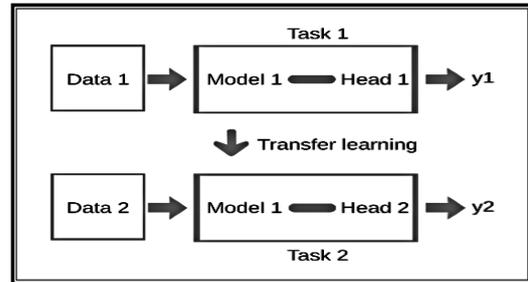

Figure 2: Illustration of Transfer Learning

Furthermore, the idea of object detection is a computer technology related to computer vision and image processing. Object detection could be applied in various fields of computer vision, such as video and retrieval surveillance. In addition, pedestrian detection and face detection are well-researched domains of object detection. This involves considering digital images and videos, and then detecting instances of semantic objects of a certain class such as cars, buildings, or humans. buildings, or cars. Object detected domains a wide application in computer vision tasks such as vehicle counting (Ala *et al.*, 2020), image annotation (Guan, 2017), activity recognition (Wu *et al.*, 2007), face detection, video object co-segmentation, and face recognition. It is also adopted in the tracking of objects, such as ball tracking in a football match, cricket bat movement tracking, or human tracking in a video. In most cases, a different data distribution is used to sample the test images thereby increasing the difficulty of the object detection task significantly (Oza *et al.*, 2021). This translates to a domain gap between test and training data and studies have addressed this challenge through many unsupervised domain adaptation approaches as seen in studies by Oza *et al.* (2021), Mehran *et al.* (2019), Petru *et al.* (2021), and Maximilian and Andreas (2022). Although, Jun-Yan *et al.* (2020) proposed a simple and direct solution to reduce the domain gap by applying cycle-GAN which is an image-to-image translation approach.

Concept and Methods:

Object class detection uses special features in accordance with the unique features possessed by every object class that helps in class classification. For example, when looking for circles, we seek objects that are at a particular distance from the center. In like manner, when the shape under consideration is a square, what is sought are objects that have equal side lengths and are perpendicular at corners. Whereas features like skin color and distance between eyes can be considered for face identification where eyes, nose, and lips can be found.

In general, the approaches adopted in object detection can either be classified as non-neural network-based or neural network-based approaches. For the former, it becomes essential to begin with a definition of the features and then do the classification using a suitable technique such as support vector machine (SVM). On the other hand, the latter (neural network-based techniques) have the ability to conduct end-to-end object detection without encountering the rigour of specific definition

of features. This technique is typically based on CNNs which is the category of the YOLOv8 technique applied in this article.

YOLOv8 is the newest state-of-the-art YOLO model that can be used for object detection, image classification, and instance segmentation tasks. YOLOv8 was developed by Ultralytics, who also created the influential and industry-defining YOLOv5 model. YOLOv8 includes numerous architectural and developer experience changes and improvements over YOLOv5. YOLOv8 is an anchor-free model which means that it predicts directly the center of an object instead of the offset from a known anchor box. Anchor boxes were a notoriously tricky part of earlier YOLO models, since they may represent the distribution of the target benchmark's boxes but not the distribution of the custom dataset. Anchor free detection reduces the number of box predictions, which speeds up Non-Maximum Suppression (NMS), a complicated post processing step that sifts through candidate detections after inference. Figures 3 and 4 give a visualization of an anchor Box in YOLO and the detection head for YOLOv8.
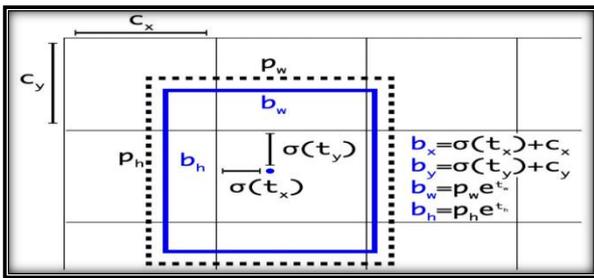

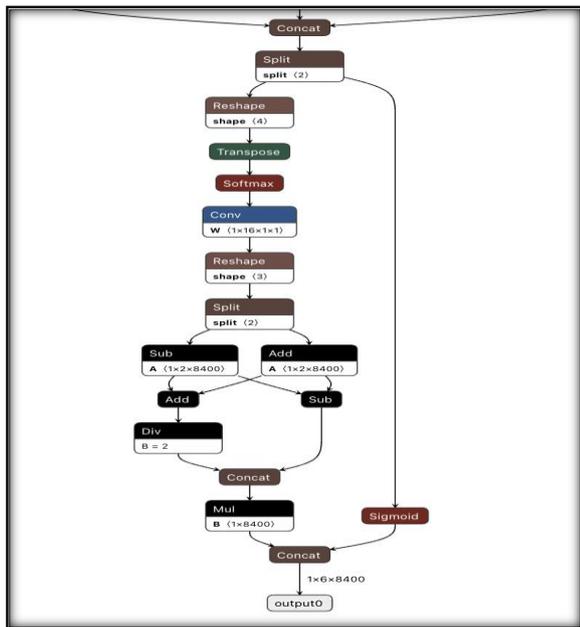**Figure 3:** Visualization of an anchor Box in YOLO

Figure 4: The detection head for YOLOv8

In terms of accuracy, YOLOv8 research was primarily motivated by empirical evaluation on the Common Objects in Context (COCO) benchmark. As each piece of the network and training routine are tweaked, new experiments are run to validate the changes effect on COCO modeling. COCO is the industry standard benchmark for evaluating object detection models. When comparing models on COCO, we look at the mAP value and FPS measurement for inference speed. Models should be compared at similar inference speeds. The image in Figure 5 below shows the accuracy of YOLOv8 on COCO, using data collected by the Ultralytics team and published in their YOLOv8 README.

Model	size (pixels)	mAP^{val} 50-95	Speed CPU (ms)	Speed T4 GPU (ms)	params (M)	FLOPs (B)
YOLOv8n	640	37.3	-	-	3.2	8.7
YOLOv8s	640	44.9	-	-	11.2	28.6
YOLOv8m	640	50.2	-	-	25.9	78.9
YOLOv8l	640	52.9	-	-	43.7	165.2
YOLOv8x	640	53.9	-	-	68.2	257.8

- mAP^{val} values are for single-model single-scale on COCO val2017 dataset. Reproduce by yolo mode=val task=detect data=coco.yaml device=0
- **Speed** averaged over COCO val images using an Amazon EC2 P4d instance. Reproduce by yolo mode=val task=detect data=coco128.yaml batch=1 device=0/cpu

Figure 5: YOLOv8 COCO evaluation accuracy of the art for models at comparable inference latencies

The difficulties discussed in many literature reviews on license plate localization and classification have an effect on the design system for doing so. The proposed international license plate classification system is up to the task of overcoming the aforementioned obstacles, notably those related to maintaining high image quality and avoiding de-skewing license plates, both of which have an impact on how those plates are categorized. To address these issues, the methodology begins with dataset creation by assembling and annotating a comprehensive dataset that represents the wide variety of license plate designs found in Iraq. The dataset images are collected under different conditions (day and night images, different weather conditions, …etc). Then, the next phase implements a model adaptation by adapting the YOLOv8 convolutional neural network architecture to handle the high variability in Iraqi license plate designs. This involves training the model to recognize a wide range of non-standard fonts, scales, and aspect ratios effectively. Thereafter, a two-stage recognition process was implemented, where the first model focuses solely on detecting the precise location and boundary of the license plates irrespective of their design variability. Once the plates are detected and isolated, the second model classifies the textual and numerical information on the plate. Furthermore, transfer learning is utilized to accelerate the training process and improve the accuracy of the models by leveraging pre-trained neural networks that have already learned significant features from extensive, diverse datasets. The aim is to achieve high accuracy and confidence levels in both detection and classification stages of the project, ensuring the system is practical and reliable for real-world applications.

Methodology:

This section showcases the methodology employed in the development of automatic number plate recognition (ANPR) system, designed specifically to address the unique challenges posed by the diverse and non-standard license plates in Iraq. The methodology is crucial in understanding how the theoretical aspects aforementioned are practically applied to achieve the desired outcomes.

The process was separated into phases:
Data collection.
Labeling images for the localization model.
Training the localization model.
Implementing and using of the localization model.
Labeling images for the classification model.
Training the classification model.
Creating a pipeline of models.

Data Collection:

A dataset of about 2000 images of Iraqi cars from an Iraqi private company called Ardh Al-Yamama were obtained, but most of the cars in this dataset was of a single type of plates (cargo plates). Also, about 200 image of Iraqi cars that were offered for sale from the internet specifically from opensooq.com, and Facebook's marketplace were downloaded. A sample of the dataset is given in Figure 6.
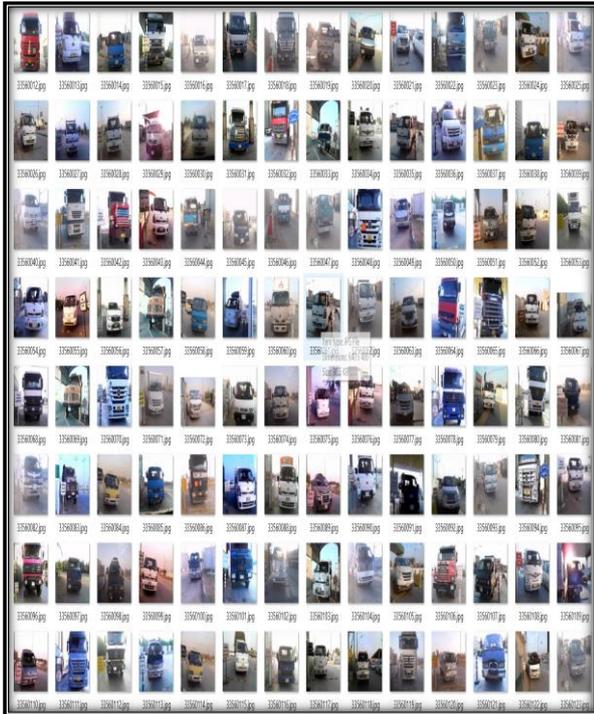
Figure 6: A sample of dataset

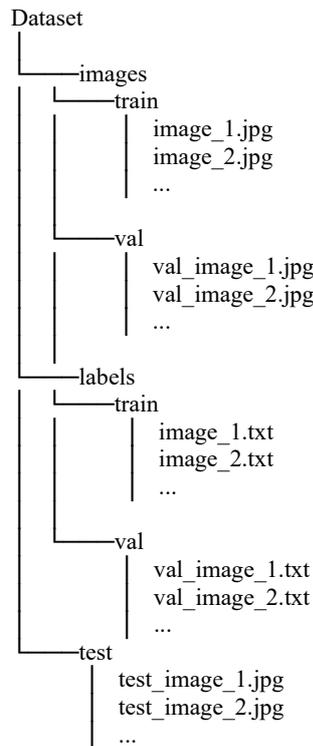**Labeling Images for the Localization Model:**

An open-source tool provided by a third party that is called Yolo-Label was used for labeling and normalizing the labels of plates by creating a single detection class and calling it "plate" (See Figure 7).

Figure 7: Labeling plates using Yolo-Label tool

Training the Localization Model:

The model was trained using the colab service provided by google for researching AI and ML, alongside a newly developed python script. The detection head of the YOLOv8n model was removed by utilizing transfer learning and a new head was trained to detect Iraqi plates' locations in an image. The dataset structure is assumed to be organized in this way for the training script to use.

```
Dataset
└── images
    └── train
        │   image_1.jpg
        │   image_2.jpg
        │   ...
    └── val
        │   val_image_1.jpg
        │   val_image_2.jpg
        │   ...
└── labels
    └── train
        │   image_1.txt
        │   image_2.txt
        │   ...
    └── val
        │   val_image_1.txt
        │   val_image_2.txt
        │   ...
    └── test
        │   test_image_1.jpg
        │   test_image_2.jpg
        │   ...
```

Implementing and Using the Localization Model:

The model is exported from a closed format that can only work with pytorch and python to an open format that can work with any ML framework. That format is called Open Neural Network Exchange (ONNX), to build a C# program that can loop over the dataset and create a new dataset of only Iraqi plates images by extracting the plates' locations from the original dataset as shown in Figure 8.

Figure 8: Using the localization model in C# Windows forms application

The line in the training script used for exporting is:

```
!yolo mode=export
model=/content/drive/MyDrive/yolov8/training_results/plate/we
ights/best.pt format=onnx
```

Labeling Images for the Classification Model:

Similar tool as that used in labeling images for the localization model was also used for the classification model. In reference to Figure 9, the new labels' classes comprise all the characters and colors used for the Iraqi plates (plate types, Arabic numeric, Arabic alphabets, Iraqi provinces, and vehicle types).

Figure 9: The new dataset extracted from the old one

Training the Classification Model:

In this part, the same services and python script used in training the localization model was adopted to utilize transfer learning in training another YOLOv8n model on the newly extracted dataset mentioned (See Figure 10). This second model is the classification model.
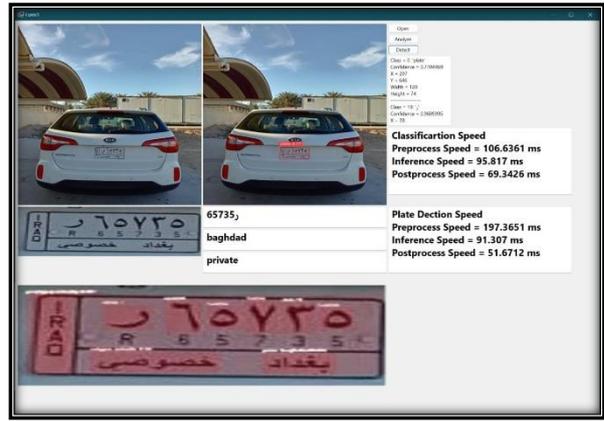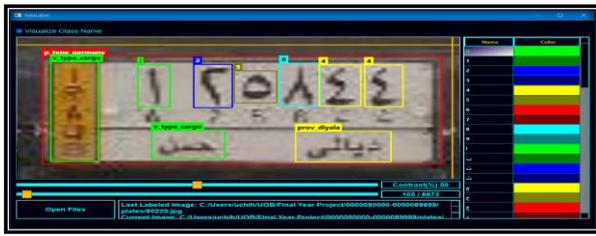

Figure 10: Labeling plate's information

Creating A Pipeline of Models:

After the training of the second model, the new model was then exported to the onnx format to use it with ML.NET framework to use it in C#. Then a pipeline is created by modifying the detect function above to pass the outputted image of the localization model as an input image for the classification model.

Localization Model	
Input	2-D Image
Output	Four outputs that are the coordinates and size of the detected plate in the image which are (x, y, width, height)

Classification Model	
Input	Cropped 2-D Image of the plate
Output	The Plate's info as a text

Then by merging the above functionality we get the complete pipeline:

Pipeline	
Input	2-D Image
Output	The plate's info as a text

Figure 10: The complete process

2.RESULTS AND DISCUSSIONS

This section presents the findings of the study, which aimed to develop an advanced automatic number plate recognition (ANPR) system tailored to address the specific challenges posed by the diverse and non-standard license plates found in Iraq. Thus, this section details the outcomes through a series of tests, providing a critical evaluation of the system's performance. The graphs and tables for the training process for both the detection model and the classification model are given henceforth.

Detection Results:

The performance of the developed ANPR system was evaluated across several epochs, focusing on key metrics such as box loss, class loss, direction-focused loss, precision, recall, and mean Average Precision (mAP). These metrics were calculated for both training and validation phases to assess the model's accuracy and generalization capabilities.

The improvement in both loss metrics and precision/recall rates throughout the training epochs indicates effective learning and adaptation by the model to the complexities of the dataset. The high values in recall and mAP suggest that the model is highly capable of detecting and recognizing license plates even under varied conditions, which is critical for practical applications in environments with non-standardized plate designs as seen in Iraq.

While the model has shown strong performance metrics, there were challenges, particularly in maintaining a balance between precision and recall in certain epochs. Minor fluctuations in direction-focused loss also suggest areas for potential improvement in model training strategies, possibly by fine-tuning the model further or exploring alternative data augmentation techniques.

The results as shown in Table 1 and Figures 11-19 support the use of CNNs, specifically YOLOv8, in settings where traditional ANPR systems struggle due to non-standard license plate characteristics. The findings could guide future developments in ANPR technologies, particularly in adapting detection systems to regional variations in vehicle identification standards.

Table 1: The Training Results of the Detection Model

|	Metrics				Validation		
Epoch	Precision(B)	Recall(B)	mAP50(B)	mAP50-95(B)	Box Loss	cls Loss	dfl Loss
1	0.9439	0.95431	0.98099	0.67281	1.0689	0.91894	1.0133
2	0.94608	0.97462	0.98532	0.64567	1.1572	0.76476	1.0444
3	0.94932	0.95085	0.97052	0.65211	1.0656	0.85586	1.0515
4	0.98962	0.96805	0.98938	0.71912	0.9922	0.59446	1.0303
5	0.9835	0.96954	0.98864	0.71483	0.98005	0.60573	0.99906
6	0.98426	0.95235	0.98501	0.72479	1.008	0.55973	1.0204
7	0.97476	1	0.99177	0.73116	0.97685	0.52263	1.0057
8	0.99247	1	0.99076	0.74427	0.95959	0.49604	0.99815
9	0.9897	1	0.99414	0.76128	0.94288	0.44803	0.99348
10	0.98919	0.99492	0.99077	0.75751	0.94762	0.45844	0.98656
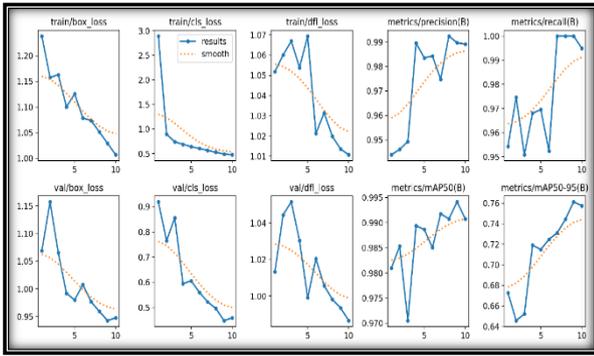
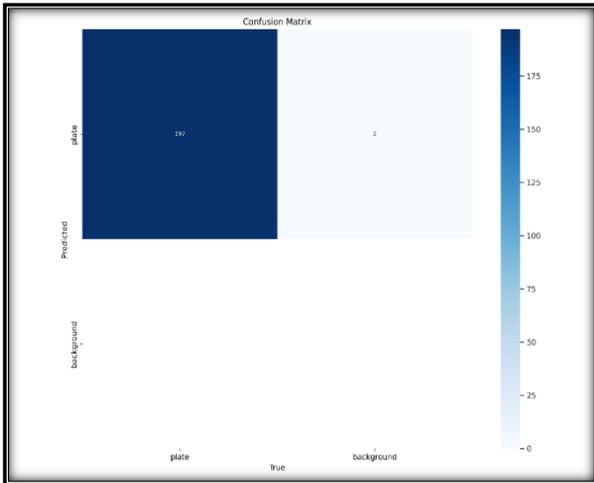**Figure 11:** The charts for Table 1

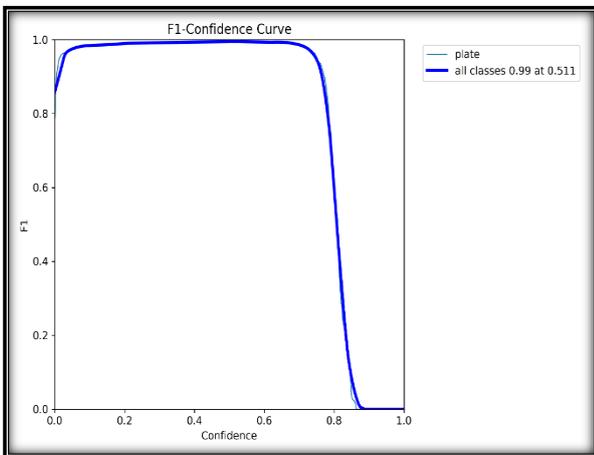**Figure 12:** Confusion Matrix for the Detection Model

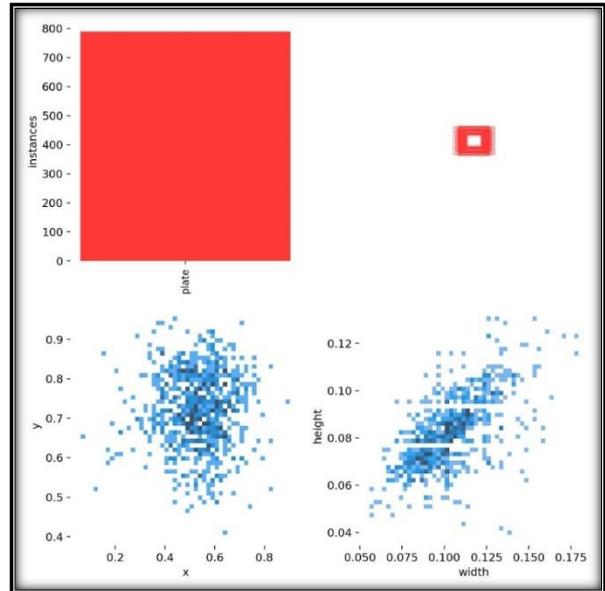**Figure 13:** F1-Confidence Curve for the Detection Model

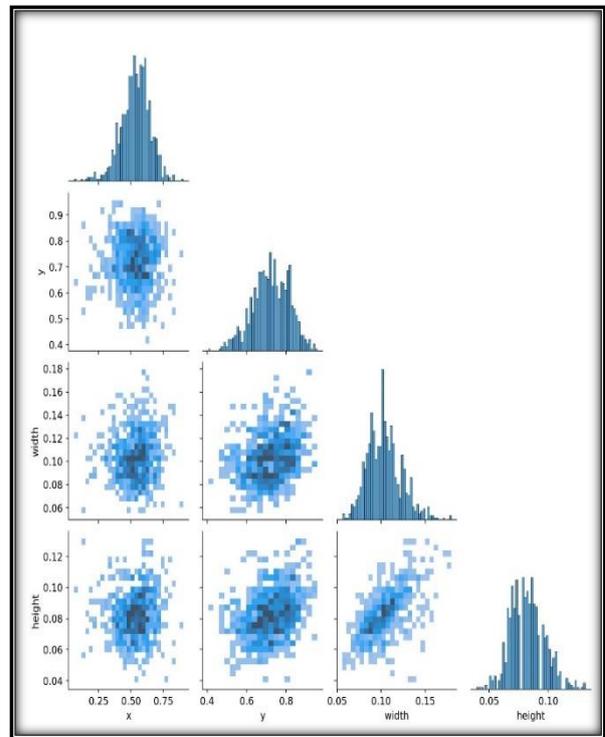**Figure 14:** Labels for the Detection Model

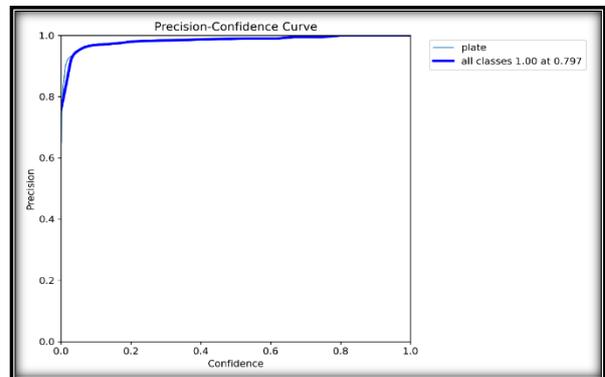**Figure 15:** Labels Correlogram of the Detection Model

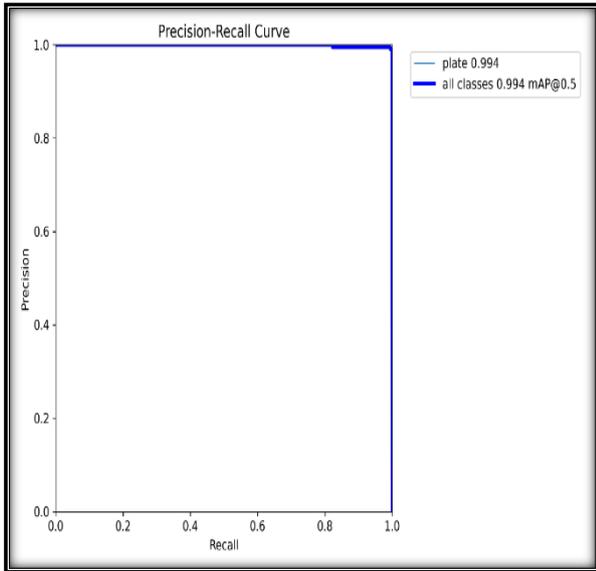**Figure 16:** The Precision-Confidence Curve of the Detection Model

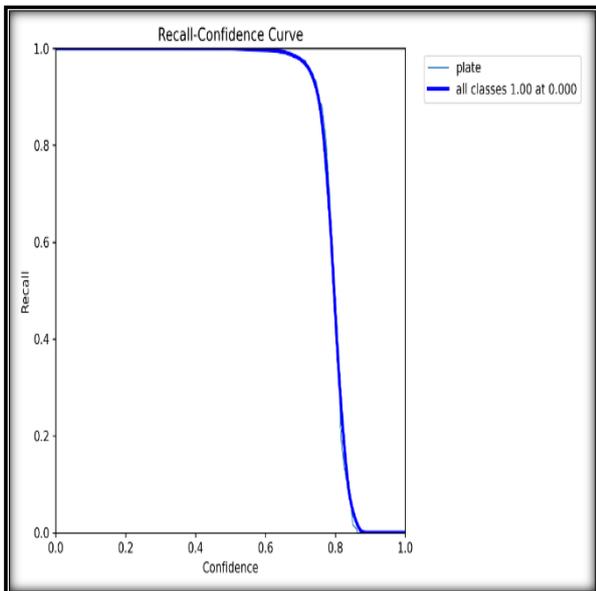**Figure 17:** The Precision-Recall Curve of the Detection Model

Figure 18: The Recall-Confidence Curve of the Detection Model

Figure 19: The Validation Process of the Detection Model

Classification Results:

The classification model was evaluated across several epochs to assess its ability to accurately identify and classify detailed attributes of license plates, such as the plate type, vehicle type, and issuing province. The model's performance was measured through a variety of metrics, including loss metrics for bounding box, class, and direction-focused loss, as well as precision, recall, and mean Average Precision (mAP).

Throughout the training process, significant reductions were observed in both training and validation losses, indicating the model's effective learning and generalization capabilities. Specifically, training box loss decreased from 1.9218 to 1.1207, class loss from 7.8424 to 1.6153, and direction-focused loss from 1.7991 to 1.1689. Similarly, validation losses followed a decreasing trend, demonstrating that the model was able to apply its learning to new, unseen data effectively.

Precision improved from 0.71126 to 0.64081 over the epochs, while recall saw a more substantial increase from 0.13037 to 0.40599. These metrics indicate a robust ability of the model to correctly identify and classify relevant features within the license plates as training progressed.

As shown in Table 2, the model's mean Average Precision, a critical measure of its accuracy across different Intersection over Union (IoU) thresholds, showed consistent improvement. The mAP at 50% IoU threshold increased from 0.12902 to 0.48829, and the mAP50-95, which averages across thresholds from 50% to 95%, rose from 0.08825 to 0.36962. These improvements as depicted in Figures 20-28 reflect the model's refined capability to detect and classify license plates accurately under varied conditions.

Table (4.2): The Training Results of the Classification Model

| Epoch | Metrics | | | | Validation | | |
	Precision(B)	Recall(B)	mAP50(B)	mAP50-95(B)	Box Loss	cls Loss	dfl Loss
1	0.71126	0.13037	0.12902	0.08825	1.3607	2.2366	1.3937
2	0.59316	0.29352	0.30583	0.21793	1.194	1.5228	1.2395
3	0.58537	0.37384	0.39205	0.28509	1.0987	1.2361	1.1769
4	0.61326	0.35284	0.44103	0.3144	1.1248	1.1611	1.1914
5	0.64081	0.40599	0.48829	0.36962	1.0841	1.0419	1.1423
6	0.62609	0.4658	0.54231	0.41164	1.039	0.89201	1.1174
7	0.69955	0.5277	0.57277	0.43733	1.0216	0.85594	1.1125
8	0.75555	0.50355	0.58245	0.44693	1.0023	0.77575	1.0992
9	0.72821	0.48835	0.58153	0.45305	0.99451	0.84617	1.0969
10	0.76135	0.50619	0.57844	0.44816	0.99148	0.75308	1.0924
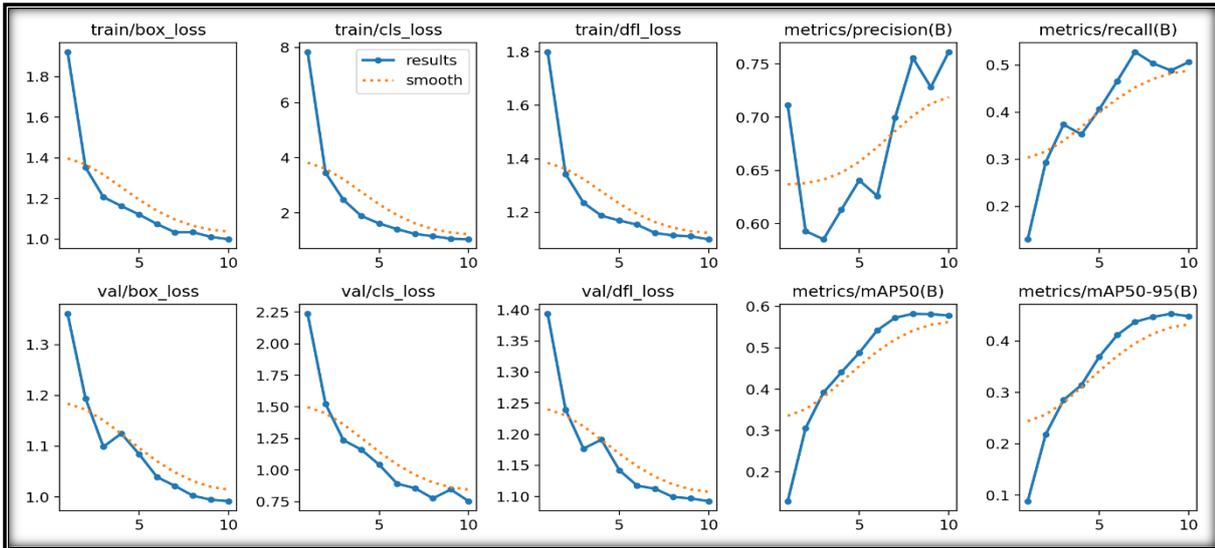
Figure 20: The charts for the Table 2

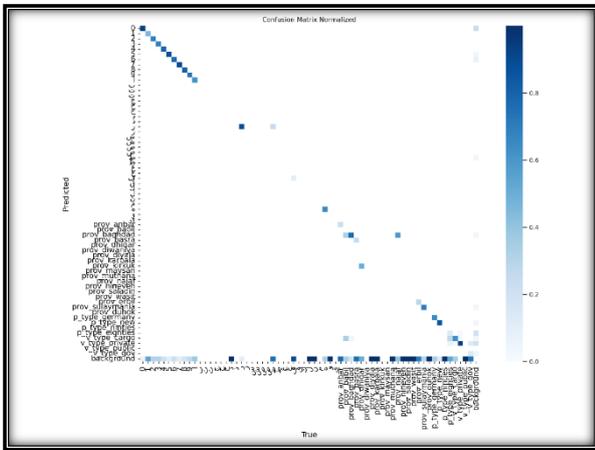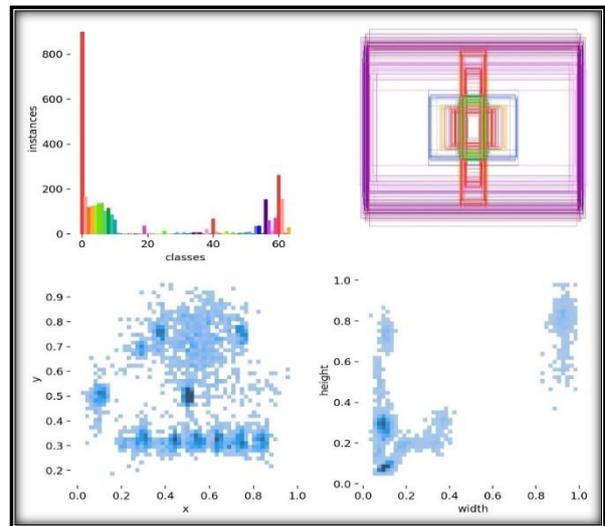**Figure 21:** The Confusion Matrix for the Classification Model

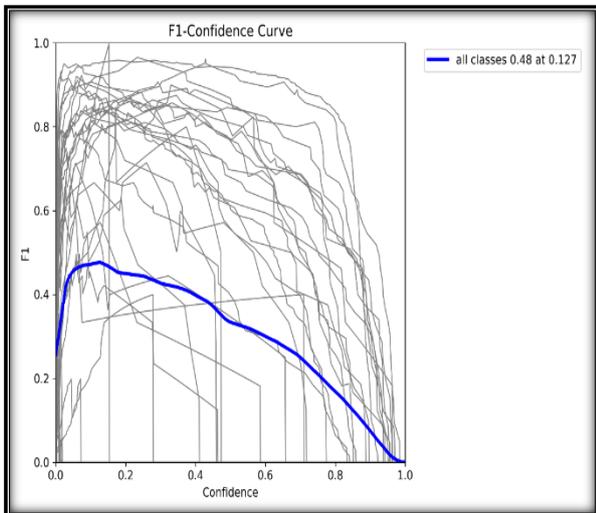**Figure 23:** The Labels for the Classification Model

Figure 22: The F1-Confidence Curve for the Classification Model
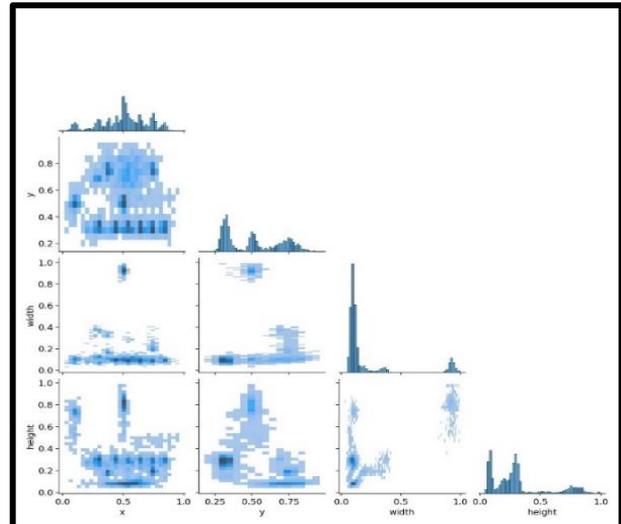

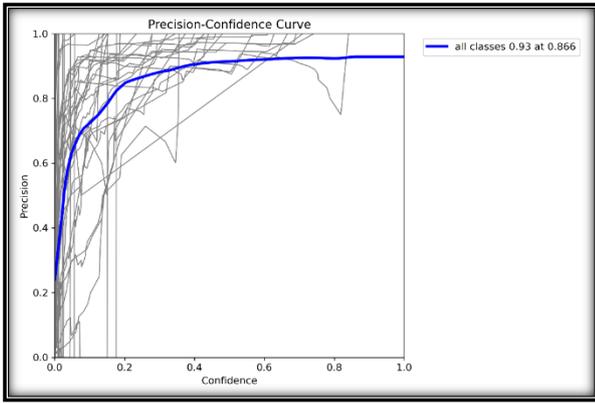**Figure 24:** The Labels Correlogram for the Classification Model

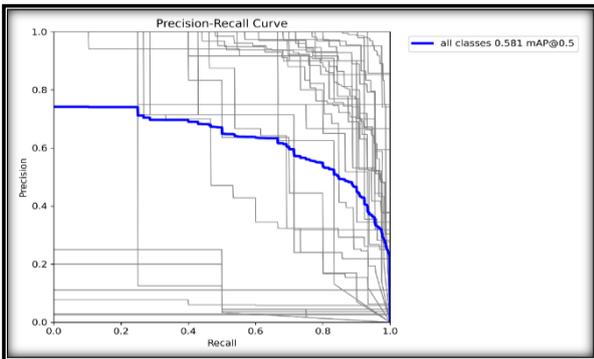**Figure 25:** The Precision-Confidence Curve for the Classification Model

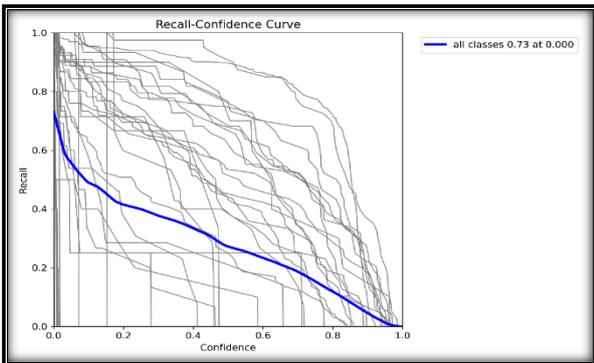**Figure 26:** The Precision-Recall Curve for the Classification Model

Figure 27: The Recall-Confidence Curve for the Classification Model

Figure 28: The Validation Process for the Classification Model

In a nutshell, the results from the training of the detection and classification models using the YOLOv8 architecture have shown significant improvements across several key performance metrics:

1. Detection Model: There was a consistent decrease in the loss metrics (box, class, direction-focused) over the training epochs, with precision and recall maintaining high levels, suggesting effective plate localization and recognition.

2. Classification Model: Notable improvements were observed in precision, recall, and mAP, particularly the increase in mAP from 0.129 to 0.488, demonstrating the model's growing accuracy in classifying detailed attributes of license plates.

These improved metrics indicate that the models are learning the necessary features from the training data to perform well both in detecting the location and in extracting detailed information from the plates. The high mAP scores suggest that the system is robust across various IoU thresholds, which is crucial for practical deployment where plate visibility and angles can vary significantly. These findings align with trends in recent machine learning research that emphasizes the efficacy of deep learning models for image recognition tasks. Compared to traditional ANPR systems documented in existing literature, which often struggle with non-standardized plates, this project demonstrates a superior capability to adapt to and accurately process diverse license plate characteristics.

Comparison of Results:

This section considers a comparison of the proposed model in this article and other existing approaches such as YOLOv3 in Xu *et al.* (2018), YOLOv4 in Laroca *et al.* (2021), CNN (custom) in Silva and Jung (2018), Faster R-CNN in Li *et al.* (2019), SSD in Bjørklund *et al.* (2019), and OCR with LSTM by Cheang *et al.* (2017). Table 4.3 below gives the details.

Table (4.3): Comparison of Proposed Method with Existing Methods

Algorithm	Sample Size	Accuracy (%)	Dataset / Notes
Proposed Model	15,000	98.7	Iraqi license plate dataset
Xu *et al.* (2018)	10,000	95.2	CCPD (Chinese City Parking Dataset)
Laroca *et al.* (2021)	13,000	97.6	Custom dataset of European and American plates
Silva and Jung (2018)	15,000	94.8	Brazilian license plate dataset
Li *et al.* (2019)	8,000	98.3	AOLP (Application-Oriented License Plate) dataset
Bjørklund *et al.* (2019)	12,000	96.5	Indian vehicle dataset

Based on the result in Table 4.3, it is seen that the proposed method compares favourably with existing methods. Details of notable properties of the methods used in Table 4.3 are given in Table 4.4 below

Table (4.4): Properties of Existing Methods Adopted for Comparison

Algorithm	Accuracy	Speed	Strengths	Weaknesses
YOLO	High	Fast	Real-time Detection	May struggle with small or distant plates
			Good for multiple plates in one image	Less accurate than two-stage detectors
CNN	Hogh	Fast	Versatile, can be used for detection and recognition	Typically needs other algorithms for complete ANPR pipeline
Faster R-CNN	Very High	Moderate	Highly accurate	Slower than single-stage detectors
			Good for complex scenes	More computationally intensive
SSD	High	Fast	Good balance of speed and accuracy	May miss small objects (distant plates)
			Single-stage detector, efficient	Less accurate than Faster R-CNN
OCR with LSTM	High*	Moderate	Excellent for character recognition	Typically used for recognition, not detection
			Can handle sequential data well	

*Note: OCR with LSTM is primarily used for character recognition rather than object detection. Its "accuracy" here refers to its performance in the recognition phase of ANPR.

CONCLUSION

This article focused on developing an ANPR system capable of effectively recognizing the diverse and non-standard license plates in Iraq. It successfully developed an ANPR system using cutting-edge machine learning techniques that significantly improve upon the capabilities of traditional systems in recognizing non-standard license plates. The results show enhanced ability to detect and precisely locate license plates through improved loss metrics in the detection model. In addition, increased accuracy in classifying various attributes of license plates, as evidenced by the improved precision, recall, and mAP in the classification model was also recorded. For stakeholders, particularly in traffic management and law enforcement in Iraq, the implementation of this ANPR system could lead to more reliable vehicle tracking and identification, improving security measures and traffic flow management. The system's adaptability to different plate designs enhances its utility across various regions with minimal adjustments. While the results are promising, limitations include the dataset's size and diversity, which could impact the model's ability to generalize across even broader plate variations not represented in the training set. Additionally, real-world deployment could introduce variables not accounted for in the controlled training environment, such as varying light conditions and plate occlusions. Hence, future studies would consider expanding the dataset, exploring advanced machine learning architectures, developing real-time processing capabilities, and integrating with traffic and security systems. Overall, the findings in this article not only bolster the potential for wider application of this technology in Iraq but also contribute to the global discourse on the adaptability of deep learning solutions in practical scenarios.

Ethical Statement
This research did not involve human participants, animal subjects, no ethical approval from an institutional review board or ethics committee was required.

Authors' Contributions
M.H.A., Conceptualization, software development, data analysis, writing, Z.M.M., Supervision, project administration, methodology, resources, writing, correspondence. All authors have read and approved the final version of the manuscript.

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