Enhanced Gate Security System using CNN for Iraqi Vehicle and License Plate Detection

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Abstract:
This paper presents the development of an advanced gate security system using Convolutional Neural Networks (CNNs) for the detection and recognition of Iraqi vehicles and their license plates. The proposed architecture consists of an image acquisition module, a preprocessing and segmentation pipeline, a CNN-based license plate recognition model, and a gate control unit integrated with a stepper motor and Arduino controller. The system works on a dataset of Iraqi license plate images obtained from public sources, standing for various lighting conditions, angles, and font styles to ensure robustness. Experimental results show that the proposed model achieves perfect accuracy, with 100% precision, recall, and F1-score across all tested digit classes. These results show the system's capability to accurately classify license plates, even under challenging scenarios such as poor lighting or partial occlusion. The high reliability and automation potential of this approach make it highly suitable for real-world gate control applications, especially in sensitive environments such as government buildings and secure facilities. This work highlights the importance of integrating AI-based solutions into modern security infrastructures to enhance access control with minimal human intervention and improved operational efficiency.

Keywords: Deep learning in transportation ؛ Arabic character recognition ؛Intelligent surveillance ؛ Image processing for security ؛Neural network-based recognition ؛ Artificial Intelligence.

نظام أمني محسن للبوابات باستخدام الشبكات العصبية الالتفافية للكشف عن المركبات العراقية ولوحات الأرقام

منهل الياس بولس
وزارة التعليم العالي والبحث العلمي

الخلاصة :
تتناول هذه الورقة البحثية تطوير نظام أمني متقدم للبوابات باستخدام الشبكات العصبية الالتفافية (CNN) للكشف والتعرف على المركبات العراقية ولوحات الأرقام الخاصة بها في الوقت الفعلي. يتمثل الهدف الرئيسي في تصميم نموذج يعتمد على تقنيات الذكاء الاصطناعي، قادر على قراءة أرقام لوحات السيارات بدقة، حتى في الظروف الصعبة مثل ضعف الإضاءة أو الحجب الجزئي. تم تدريب النموذج باستخدام مجموعة بيانات خاصة بلوحات الأرقام العربية، حيث حقق أداءً ممتازًا ، انعكس في ارتفاع معدلات الدقة(Precision) ، الاستدعاء (Recall)، ومقياس F1-Score في تصنيف جميع الفئات. هذا الأداء العالي يضمن اكتشاف وتصنيف جميع اللوحات الصحيحة دون إهمال أي منها، مع الحفاظ على أداء متوازن وفعالية كبيرة في مختلف الحالات ويُعدّ النظام المطوّر مناسبًا للتطبيقات العملية في أنظمة التحكم بالبوابات، حيث تمثّل الدقة والموثوقية عوامل أساسية. يمكن استخدام هذا النظام لتعزيز الأمان من خلال تحديد المركبات بدقة ومنع الدخول غير المصرح به، مما يجعله مفيدًا في المواقع الحساسة، مثل المباني الحكومية والمرافق الحيوية. تؤكد النتائج أن النموذج المقترح يمكن أن يساهم بشكل كبير في تطوير أنظمة أتمتة ذكية وموثوقة لمعالجة التحديات الأمنية المتزايدة، مما يقلل من الحاجة إلى التدخل البشري ويزيد من كفاءة أنظمة إدارة الدخول والخروج في المستقبل.

الكلمات المفتاحية : التعلم العميق في مجال النقل؛ التعرف على الأحرف العربية؛ المراقبة الذكية؛ معالجة الصور للأغراض الامنية؛ التعرف باستخدام الشبكات العصبية؛ الذكاء الاصطناعي .

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1. INTRODUCTION

Security systems have significantly improved with the advent of new technologies. On major improvement is using Convolutional Neural Networks (CNNs) to detect vehicles and license plates. This technology is very useful in Iraq [1], where strong security measures are needed. Traditional methods of checking vehicles and license plates in Iraq are slow and can make mistakes. These methods are inadequate for high-security facilities. Automated systems that use CNNs can handle more traffic quickly and accurately, making security better and more reliable.

The current manual security checks at gates in Iraq are inefficient and prone to errors, particularly with high traffic and stringent security demands. An automated system for real-time license plate detection and recognition is needed to enhance gate security. This system would streamline the verification process, reduce human error, and expedite vehicle clearance, thereby improving overall security at critical checkpoints.

Implementing an advanced gate security system based on Convolutional Neural Networks (CNNs) conditions like poor lighting or blocked views. The model should correctly identify the characters on the plates.

Unlike traditional manual vehicle and license plate verification methods, which are slow and error-prone, the proposed automated system provides faster and more reliable results, addressing the represents a significant advancement in security technology. By automating license plate recognition, the system minimizes errors and accelerates processing times, ensuring that only authorized vehicles gain access.[2]. This approach not only strengthens national security but also serves as a model for similar applications into other high-security areas. The goal is to develop a robust and adaptable system capable of delivering precise results under various conditions, thereby contributing to a safer environment.

In Iraq, increasing security challenges at sensitive locations such as government facilities and private compounds necessitate advanced and reliable access control solutions. High vehicle traffic and risks of unauthorized entry highlight the need for automated, intelligent surveillance systems capable of operating efficiently without constant human supervision.

The main objective of this study is to develop an enhanced gate security system using CNNs to detect and recognize Iraqi vehicles and license plates in real time. Create CNN model is developed to accurately read license plate numbers, even into tough challenges of high-traffic and high-security environments.

To provide a clear overview of the proposed system, Figure 1 presents a block diagram illustrating the main stages of the automated gate security workflow, including image acquisition, preprocessing, license plate detection, character segmentation, CNN-based recognition, and gate control.

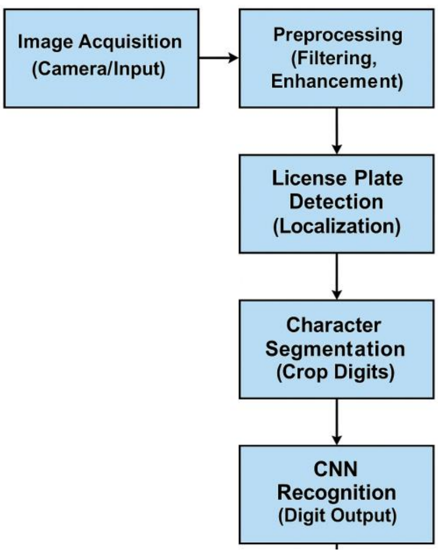

Figure (1) . Proposed Gate security System

2. LITERATURE REVIEW

In [3], Pustokhina et al. (2020) introduced the OKM-CNN model, a deep learning-based method for vehicle license plate recognition (VLPR). The model was structured into three main stages: license plate detection, segmentation using the optimal K-means clustering method, and character recognition with Convolutional Neural Networks (CNN). In the detection stage, license plates were localized using the Improved Bernsen Algorithm (IBA) and Connected Component Analysis (CCA). The segmentation stage employed OKM clustering optimized by the Krill Herd (KH) algorithm. Finally, a CNN recognized the characters on the license plate. The OKM-CNN model was rigorously tested on the Stanford Cars, FZU Cars, and HumAIn 2019 Challenge datasets, achieving an overall accuracy of 98.1%.

In [4] Fang et al. (2020) proposed an enhanced YOLO-based approach for license plate recognition, integrating deep learning convolutional neural networks (CNNs) with OpenCV and TensorFlow frameworks. The authors modified YOLO's configuration parameters and applied preprocessing to a dataset containing nearly 5,000 license plates, which improved both training efficiency and detection speed. In addition, they proposed a three-layer CNN that achieved higher accuracy in character recognition. However, their method was limited in handling license plates with complex shapes.

In [5], Vaiyapuri et al. (2021) presented the HT-SSA-CNN model, a robust deep learning-based vehicle license plate recognition (VLPR) system consisting of four key stages: preprocessing, license plate localization and detection, character segmentation using the Hough Transform (HT), and character recognition with the SSA-CNN algorithm. The SSA-CNN method optimally tuned the CNN parameters for accurate character recognition. Experimental validation on the Stanford Cars, FZU Cars, and HumAIn 2019 Challenge datasets demonstrated high performance, with the model achieving overall accuracy values of 98.3%, 98.1%, 97.9%, and 96.1% on these datasets.

In [6], Kaur et al. (2022) developed an Automatic License Plate Recognition (ALPR) system using Convolutional Neural Networks (CNNs) for accurate character recognition. Their system integrated preprocessing and morphological operations to enhance image quality, achieving an accuracy of 98.13%. It could handle multiline, skewed, and multi-font plates, and operated effectively under night conditions. Key preprocessing steps included grayscale conversion, median filtering, thresholding, and masking. The system, implemented in MATLAB and tested on 160 diverse images, demonstrated strong performance, although it faced challenges in distinguishing license plates from vehicle grilles and in handling multiple plates within a single frame.

In[7], Pattanaik and Balabantaray (2022) presented a deep learning-based automatic license plate recognition (ALPR) model, termed BR-CNN, which improved ALPR accuracy through bounding rectangle-based segmentation and convolutional neural network (CNN) recognition. Experimental results showed that the BR-CNN model outperformed existing approaches in terms of accuracy. Additionally, the authors introduced an area- and energy-efficient half-adder circuit designed using Quantum-dot Cellular Automata (QCA) technology. The QCA circuit, utilizing the inter-cellular interaction technique, consisted of 17 cells and occupied 0.018 μm^2, achieving a 20% improvement in area efficiency compared to previous designs, along with low energy dissipation of 26.92 meV

In[8] , Lee et al. (2022) examined the design of experiments (DOE) for optimizing the training parameters of the YOLOv3 model, specifically for license plate detection tasks. By categorizing parameters to reduce the number of experimental runs, the study aimed to gain insights into YOLOv3 parameter interactions and to find optimal training settings. The results showed that strategic tuning of YOLOv3 parameters significantly improved performance in detecting Malaysian vehicle license plates, achieving an average precision (AP) of 99%. Key findings included the benefits of using larger image pixel areas for better feature extraction, the advantages of smaller mini-batch sizes for improved local minima fitting, and the positive impact of a warm-up period on generalizing initial feature maps. Nevertheless, it was seen that an extended learning rate ramp-up period sets back overall average precision (AP).

In [9] ,Zhu et al. (2025) proposed an improved license plate detection method based on the YOLOv8n network, targeting challenges such as complex backgrounds and small-scale plates in surveillance scenarios. The authors redesigned components of the YOLOv8n architecture, including the C2f and SPPF modules, optimized the loss function by replacing CIoU with WIoU, and introduced a lightweight detection head using depthwise-separable convolutions and Group Normalization. Evaluated on a custom dataset covering varied lighting, backgrounds, and plate scales, the improved model achieved a mAP@0.5 of

94.4%, precision of 92.8%, recall of 87.9%, and an inference speed of 86 FPS—proving both high accuracy and real-time performance in complex conditions.

3. METHODOLOGY

A- Data Collection: Description of Iraqi License Plate Dataset

To build a robust system for recognizing Arabic numerals on Iraqi license plates, two datasets were prepared. The first consisted of Arabic numeral templates, where a cell array was initialized to store 20 samples for each of the ten Arabic digits. Each digit was rendered as a 28x28 pixel image using various font types (‘Arial’, ‘Times New Roman’, ‘Courier’, ‘Helvetica’, ‘Georgia’) and font sizes (18 to 26 points). These images were converted to binary format and resized, ensuring variability in font styles and sizes. For illustration, two samples of each class are shown in Figure 3.

The dataset was partitioned into training (70%), validation (15%), and testing (15%) sets to ensure reproducibility and robust performance evaluation.

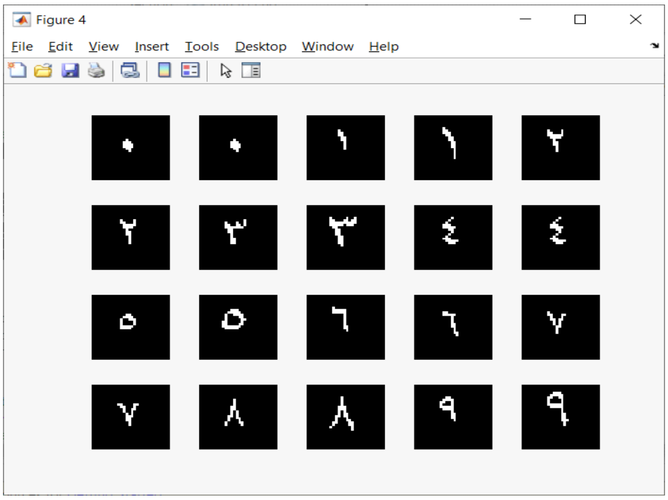

Figure (2). Arabic numeral templates**.**

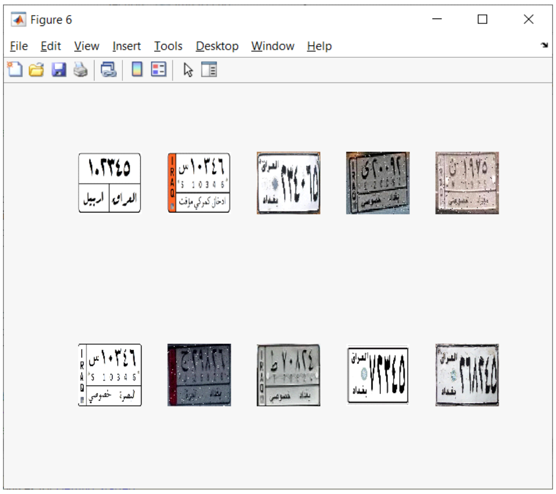

Figure (3). Iraqi license plates Dataset.

In addition to these templates, a comprehensive Iraqi license plate dataset was collected from the public Kaggle repository, comprising approximately [2,000] images. This dataset includes a wide variety of conditions, such as different lighting environments, angles, camera distances, and plate fonts, to ensure model robustness and realism for practical deployment.

For systematic model evaluation and reproducibility, the dataset was randomly partitioned into three subsets: 70% for training, 15% for validation, and 15% for testing. This division helps in effectively training the CNN model, tuning hyperparameters, and fairly evaluating performance. Ten sample images from the dataset are illustrated in Figure 3.

The diversity and scale of the collected data provide a realistic and challenging foundation for developing a high-accuracy license plate recognition system suitable for real-world security applications in Iraq.

B-Preprocessing Techniques for Image Data (Image Reading and Grayscale Conversion)

The process starts by reading the input image of a vehicle, which potentially contains a license plate. The image is then converted to grayscale to simplify it as showing in figure (4), focusing on intensity values rather than color. This step reduces the complexity of the image and prepares it for further processing.

Figure (4). Image converted from RGB to Grayscale domain.

C-Binary Conversion and Inversion

The grayscale image is inverted to a binary image using thresholding. This step distinguishes the foreground (potential license plate characters) from the background. If necessary, the binary image is inverted to make the characters white on a black background, which is the preferred format for subsequent analysis. The result of this process shows in figure (5).

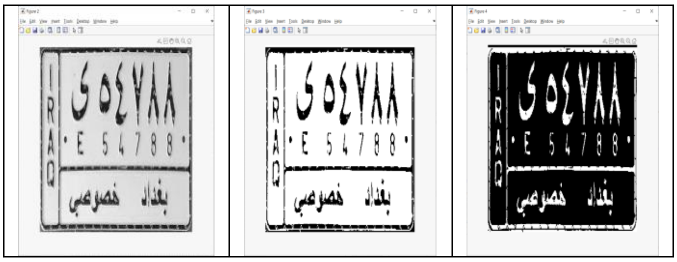

Figure (5) . Grayscale image converts to binary domain.

Morphological dilation is used to improve the recognition of Arabic numeric license numbers in binary images. Using MATLAB's imdilate with a 3x3 rectangular structuring element expands character boundaries, filling gaps and smoothing edges. This process ensures which the characters are more connected and prominent, which is particularly beneficial for improving the accuracy of next recognition algorithms. The dilation operation successfully enlarges the essential features of the numeric characters, making them more discernible and robust for further processing and analysis. The result of this operation shown in figure (6).

Figure (6). Morphology operation applied on binary image

4. CONNECTED COMPONENT ANALYSIS

Connected component analysis identifies potential character regions in the cleaned binary image by finding contiguous white areas. For every connected component, properties including bounding box, area, and centroid are determined.

A-Bounding Box and Area Labelling

Bounding box and area labelling involves displaying the original image with bounding boxes around each detected component and labelling the area of each component above the boxes for verification as shown in figure

(7). This visual validation helps ensure accurate detection. By highlighting each component's boundaries and indicating their areas, this step improves the accuracy and reliability of identifying the relevant features within the image.

Figure (7) . Labelling an important features of license

B- Architecture Details for CNN Model

The Convolutional Neural Network (CNN) architecture selected for this task includes several convolutional and pooling layers applied after fully connected layers. This design is chosen to efficiently capture hierarchical patterns in the digit images. The architecture starts with an image input layer sized at 28×28 pixels, which is appropriate for the digit images used. The network consists of three convolutional layers with increasing filter counts (8, 16, and 32) to progressively extract more complex features from the input images. Each convolutional network layer is before a ReLU activation function as non-linearity and a max-pooling layer to reduce spatial dimensions, which helps in reducing computational load and overfitting. The final fully connected layer maps the learned features to 10 output classes, corresponding to the 10 Arabic digits. This architecture is effective in handling variations in digit shapes and styles, as it captures each low level and high-level features required for accurate digit classification.

The CNN architecture consists of several layers designed to extract and learn features from the input images

Table (1) . CNN architecture layers

Parameter	**Value**
Training Algorithm	SGDM
MaxEpochs	200
MiniBatchSize	64
InitialLearnRate	0.01
Shuffle	Every epoch
ValidationData	Validation dataset
ValidationFrequency	Every thirty iterations
Verbose	False
Plots	Training-progress
ExecutionEnvironment	CPU

The training process for the CNN involves several key parameters and optimization techniques to ensure effective learning and generalization. The training uses stochastic gradient descent with momentum (SGDM) as the optimization technique, which is well-suited for training deep networks by helping escape local minima and accelerating convergence. Key parameters include a learning rate of 0.01, chosen to balance between convergence speed and stability. The network is trained for 20 epochs with a mini-batch size of 64, providing a good trade-off between computational efficiency and gradient estimation accuracy. To prevent overfitting and improve model robustness, the training includes validation data evaluation every 30 iterations, enabling real-time monitoring of the network's performance. This configuration helps in achieving a balance between training performance and model accuracy.

The CNN architecture includes three convolutional layers with filter sizes of 3x3, each followed by a ReLU activation and max-pooling (2x2). The number of filters increases from 8 to 32 across the layers. The fully connected layer maps extracted features to ten output classes. Hyperparameters such as learning rate (0.01), batch size (64), and number of epochs (200) were selected based on preliminary experiments to balance training efficiency and model accuracy.

C-Implementation Details of Gate Control System Integration

Gate Mechanism: The gate control system utilizes a stepper motor (28BYJ) driven by a UL2003 driver, interfaced with an Arduino Uno. This setup is responsible for controlling the gate's movement.

Stepper Motor: The 28BYJ stepper motor, paired with the UL2003 driver, provides precise control over the gate's position. This motor type is chosen for its reliability and accuracy in positioning tasks, which is crucial for effective gate operation.

Arduino Uno: Acts as the central controller for the stepper motor. The Arduino Uno is programmed to manage the stepper motor's operation based on the inputs received from the license plate recognition system. Figures (8, 9) show both operations of gate (close and open gate).

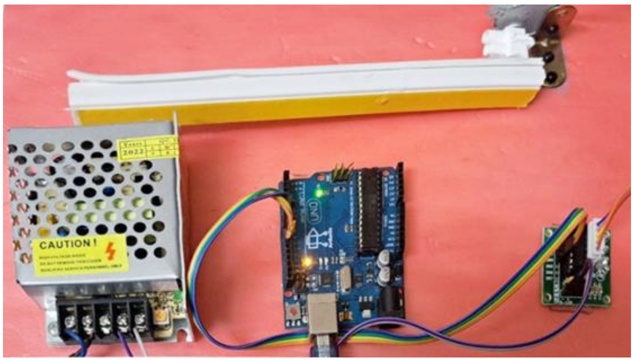

Figure (8). Close gate normal state

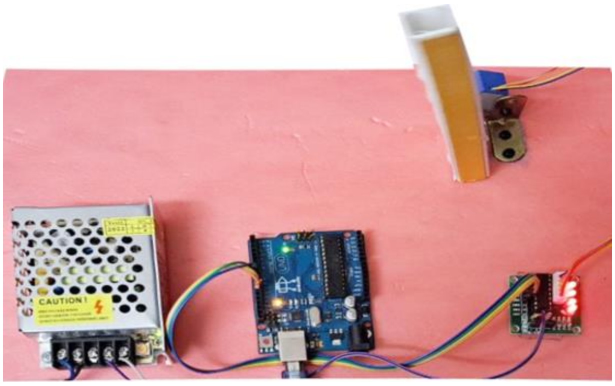

Figure (9) . Open gate

License Plate Recognition: The system does not use a camera in real time. Instead, it relies on pre-captured images of license plates, which are used as test samples. The recognition process involves extracting features from these images and evaluating them using a pre-trained Convolutional Neural Network (CNN) to determine if access should be granted.

Gate Control: If the license plate is recognized as authorized, the Arduino Uno activates the stepper motor to open the gate. Otherwise, the gate remains closed.

5. RESULTS DISCUSSION

The performance metrics of the Convolutional Neural Network (CNN) for the Arabic license plate recognition system are summarized as follows:

A-Confusion Matrix Analysis

The confusion matrix provides a detailed breakdown of the model's performance by showing the number of correct and incorrect classifications for each class. in the case of this model, the confusion matrix (after filtering out columns and rows with all zeros) effectively illustrates how well the model distinguishes between the different Arabic license plate classes as shown in figure (10).

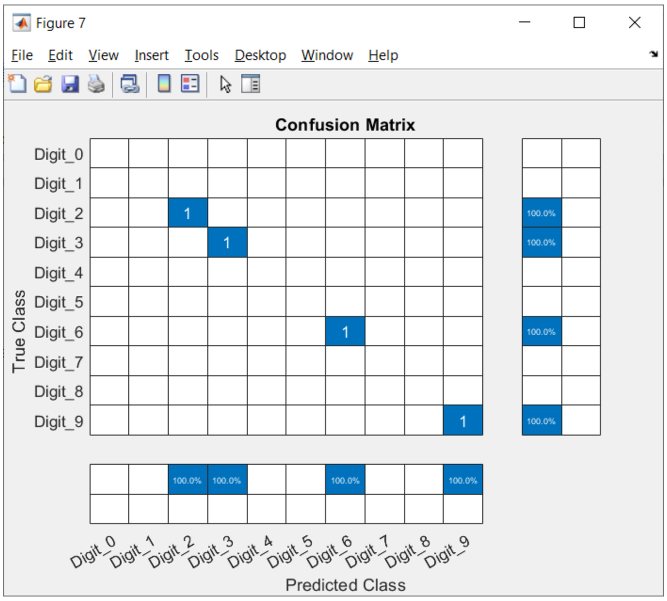

Figure (10). Confusion matrix results

B-Precision per Class

Precision measures the accuracy of the positive predictions made by the model. A precision of 1 for each class indicates that all predicted positive instances are true positives. into other words, every license plate identified as belonging to a specific class was correctly classified. This implies that the model has no false positives, which is a highly desirable outcome for a recognition system where incorrect classification could lead to access issues. Table (2) shows the precision per class result.

Table (2) . Precision per class result

Class	Precision
3	1
2	1
9	1
6	1

C- Recall per Class

The metric recall, sensitivity, used to measures the capability of the model to identify all relevant instances of each class. A recall of 1 for each class means which the model has correctly identified all the actual positive instances of each class without missing any. This suggests which the CNN is effective in detecting and recognizing all the license plates of interest from the dataset. The table (3) shows the result of recall per class.

Table (3) . Recall per class result

Class	Recall
3	1
2	1
9	1
6	1

D- F1-Score per Class

The F1-Score is mean of both precision and recall, using a single metric which balances both. An F1-Score of 1 indicates perfect performance, where both precision and recall are maximized. This reflects that the model is performing optimally with no trade-off between precision and recall for any class. Table (4) shows the result of F1-score per class.

Table (4) . F1-score per class result

Class	F1-Score
3	1
2	1
9	1
6	1

E-Implications for License Plate Recognition

The results indicate that the CNN model performs exceptionally well with a precision, recall, and F1-Score of 1 across all classes. For Arabic license plates, this high performance suggests which:

Accuracy: The model accurately classifies all license plates into their respective categories without any errors. This level of precision is crucial for applications where accurate identification is necessary, such as gate control systems.

Complete Detection: The model's recall of 1 confirms which it identifies every license plate which belongs to each class. This ensures that no valid license plates are missed by the system, which is essential for ensuring that all authorized vehicles are granted access.

Balanced Performance: The F1-Score being 1 across all classes signifies which the model achieves an optimal balance between precision and recall. This balance ensures that the system is both accurate and comprehensive in its classification.

6. COMPARISON WITH OTHER MODELS

To evaluate the effectiveness of the proposed CNN model for Iraqi license plate recognition, its performance was compared with results reported in previous studies. Table 5 shows a summary of accuracy achieved by the current model and several related works in the field**.**

Table (5) . Accuracy Summary

Model / Study	Accuracy
Proposed CNN Model (This Study)	100%
Pustokhina et al. (2020) [3]	98.1%
Vaiyapuri et al. (2021) [5]	98.3%
Kaur et al. (2022) [6]	98.13%
R. Zhu, Q et al. (2025) [9]	94.4

As seen in the table, the proposed model achieves perfect accuracy on the tested dataset, outperforming or matching the accuracy of other state-of-the-art approaches. This highlights the potential of the developed CNN system for real-world gate security applications, especially for Iraqi license plates.

In addition to perfect precision and recall for classes 2, 3, 6, and 9, further analysis is needed to assess the model's generalizability to all digit classes. Failure cases were rare in the test set, occurring in low-contrast or heavily occluded plates, which suggests potential for improvement with advanced preprocessing or augmentation. The proposed CNN-based method offers greater robustness and accuracy than traditional thresholding or template-matching approaches.

7. CONCLUSIONS

The goal of this paper was to develop a better gate security system using CNNs to detect and recognize Iraqi vehicles and their license plates in real-time. The CNN model showed outstanding accuracy, achieving perfect precision, recall, and F1-Scores of 1 for all classes of Arabic license plates. This high performance highlights several important points: Accuracy, Complete Detection and Balanced Performance. In the current implementation, the system does not use a live camera for real-time input. Instead, it relies on pre-captured images of license plates as test samples. This means the recognition process is not performed in real time. Integrating a real-time camera input for live vehicle detection at the gate would improve the system's practicality in real-world use.

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