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ML Based Number Plate Recognition Model using Computer Vision

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***Abstract*— In this research paper the Number Plate Recognition System (NPRS) is used which is one of the smartest and most high-tech detection systems. This is a system of different technologies where an interface enables the system to automatically detect and read the unique ID of a number plate of vehicles from the real-time captured images. It is basically the process of extracting the pixel data from the digital images and converting it into ASCII values or the plain text of the number plate. The system first detects the vehicle and then takes a real-time image of that vehicle. To get the solution to this problem, a deep learning model known as YOU ONLY LOOK ONCE (YOLO) and its latest version YOLOv8 is used for detecting the license plates. This model's main aim is to make use of different types of morphological operations so that the specifically required number plate can be detected and translated efficiently. Once we get the desired number plate, we can perform various important operations or tasks such as checking it with the databases to check for stolen vehicles, for tracking the vehicle's movement, etc. It can help to improve public safety and enhance the efficiency of the transportation system.**

Keywords*— *NPRS, YOLOv8, high-tech detection system, real-time capturing, image processing, deep learning, morphological operations.

I. Introduction

The increasing number of vehicles on roads around the world has made it necessary to improve traffic management and security systems. One such system is the number plate recognition model, which can identify a vehicle's registration number and other essential details using computer vision technology. Implementation This technology can be used for various applications, such as toll collection, traffic law enforcement, and parking management. Traditional methods for number plate recognition have been less efficient and often require manual intervention, making it time-consuming and prone to errors. In recent years, there have been significant developments in computer vision-based number plate recognition models, which have demonstrated better accuracy and efficiency.

The primary objective of this research paper is to build the number plate recognition model using YOLOv8 and evaluate its accuracy for number plate recognition. The efficiency of the model will be gauged based on evaluation parameters, and the dataset will be used to train the model based on real scenarios to achieve maximum accuracy during testing.

The project will focus on three primary objectives: detecting the number plate with more accuracy, detection from various distances, and clarity in extracting numbers using YOLOv8 modes and then achieving the highest accuracy of the model by training it on the dataset. To achieve these objectives, the model will be trained with more datasets to improve its prediction accuracy. The model's real-time performance in practical scenarios will also be considered to ensure its reliability and effectiveness.

Hardware specifications play a crucial role in the performance of an ML-based number plate recognition model employing computer vision. It is recommended to use a multi-core CPU with a minimum clock speed of 2.4 GHz, a dedicated graphics card, at least 16GB of RAM, and an SSD with at least 256GB of space. Windows 10 or Linux is advised as the operating system.

The software specification for an ML-based number plate recognition model includes several elements such as data preprocessing, feature extraction, machine learning model, post-processing, integration, testing and validation, maintenance, and support. These elements are critical in ensuring that the model performs accurately, reliably, and efficiently.

In conclusion, this research paper will render a computer vision model using YOLOv8 for the detection of number plate in either moving or static vehicles with real-time detection and evaluate the accuracy, precision and efficiency of the model. By training the model with more datasets and considering real-time performance, this research aims to improve the reliability and effectiveness of number plate recognition systems. The results of this research will have

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significant implications for traffic management and security systems worldwide.

II. Literature Review

In this research paper, we address the problem of image detection in multi-normal and multilingual (LP) natural scenes [1]. The architecture of this system uses a pipeline and two stages of deep learning. The system was first trained to detect digital symbols in complete raw images using a deep learning-based detector called YOLOv2. The system's second step is to use the cropped image to identify the image from the received number. In this model, two recognition machines are compared here: a segmentation approach and joint detection. We have proposed a new semi-automatic annotation and detection procedure. The proposed system is evaluated using two databases collected from real traffic monitoring and parking access monitoring. It showed that a system using two YOLO steps performs better in the context of multi-regular and multi-lingual coding. Some more tests are performed on a publicly available Kaggle database and show that the proposed system is better than other state-of-the-art methods.

Jordan seeks to create a precise ALPR for LP [2]. The suggested method makes use of a YOLO3-based, two-stage convolutional neural network (CNN). The YOLO3 grid architecture is modified to a sparse grid to identify small objects because the dimensions of the LP letters are extremely small in comparison to the frame size. The suggested method reduces false positives by using temporal data from various frames. In order to track LP cars and weed out anomalies, sequential data structures are required. Since there isn't a Jordanian number database to my knowledge, this study suggests a brand-new one named JALPR database. The dataset, which is accessible online, contains actual videos of moving automobiles throughout Jordan. For comparison, two well-known commercial software programs were chosen. The suggested approach obtains a recognition accuracy of 87% in experiments on real YouTube films, compared to commercial systems' recognition accuracy of less than 81% for Jordanian characters [2].

This demonstrated a reliable and effective ALPR system based on cutting-edge YOLO object detection [3]. For each phase of ALPR, Convolutional Neural Networks (CNN) are trained and modified to become more resilient under various circumstances (such as shifting camera, illumination, and background). Using straightforward data augmentation methods like reverse license plates (LP) and changed characters, we segment and recognize distinctive characters in two steps. On both datasets, the ALPR technique that was used produced intriguing results. First, our system performed better than the commercial Sighthound and OpenALPR systems (89.80% and 93.03%) in the SSIG database of 2000 frames from 101 vehicle films, obtaining a recognition rate of 93.53% and 47 frames per second (FPS), respectively, and much better than the prior findings (81.80%) [3]. Second, we propose the UFPR-ALPR dataset, a larger public dataset for ALPR that is aimed at a more realistic setting. This dataset includes 150 movies and 4500 still images that were taken while cameras and moving vehicles (including buses, trucks, cars, and motorcycles) were in motion. On our suggested database, the test version of the commercial system produced a recognition rate that was under 70%. However, our system outperformed it with a recognition rate of 78.33% and 35 FPS [3].

A survey was done regarding various ANPR implementation strategies. Nearly 78 reference books' accuracy findings were analyzed by the writers [4]. The basic ANPR processes include capturing images of the vehicle, identifying number plates, segmenting characters, and recognizing characters. The size, location, background, and screw of the number plate are all factors to be considered. The survey found that the most accurate method for detecting plates was Canny's edge detection. To get better results, apply techniques like image binarization, CCA (Connected Component Analysis), vertical and horizontal projection, and character segmentation. The subsequent phase involves character recognition, which frequently involves the use of Artificial Neural Networks, template matching, or optical character recognition (OCR) techniques.

It suggested a technique for character recognition (CR) and driver's license validation (LPD) as a combined application with good accuracy and performance [5]. The system is made for Iranian licenses with varying resolutions, settings, uncommon numbers and characters, multiple background colors, and diverse fonts. In this instance, the system removes Persian characters from the input photographs in two steps and uses a fine-tuned You Only Look Alone (YOLO) version 3 platform for each defined level. In contrast to the real system, a significant number of vehicle photos were gathered under testing and training situations that were both challenging and straightforward. Test findings reveal that of 5719 images, end-to-end accuracy is 95.05% [5].

An end-to-end process for automatic license plate identification without pre-selection is provided by LPRNet [6]. Our method, which draws inspiration from recent developments in deep neural networks, achieves up to 95% accuracy on Chinese benchmarks: NVIDIA R GeForce TMGTX 1080 at 3ms; Intel R CoreTMi7-6700K at 1.3 md and CPU plate [6]. LPRNet can be taught to a finite extent because it is a lightweight convolutional neural network. LPRNet, to our knowledge, is the first actual RNN-free license plate recognition system. The LPRNet technique can be utilized to develop an internal solution for LPR as a result, displaying good accuracy even when tested against Chinese characters.

F. Liu et al. suggested a deep neural network-based license plate detection model in 2020 that includes a state-of-the-art attention mechanism [8]. The attention mechanism helps focus attention on just the most important components of the license plate image. The suggested model has a 99.47% accuracy rate when applied to a dataset of Chinese license plates [8].

It proposed a data-time-based detection number approach (detection/recognition) instead of a single frame selection to automatically detect and recognize vehicles on the road [9]. Two processes that have been proposed here, can be used to improve system accuracy by querying license plate databases (for example, the Department of Motor Vehicles database containing a list of licenses issued and vehicle models). The test results show that using the time-advanced approach of our proposal can improve the key results by 15.5 percentage points (p.p.) (an increase of 23.38%). In addition, an additional 7.8 p.p. was achieved by two processing methods, reaching a final recognition rate of **89.6%** in a database with 5,200 image frames of 300 vehicles registered at the Federal University of Minas Gerais (UFMG) [9].

It offers a numbering scheme that takes location and recognition into account [10]. Artificial intelligence can be used to address the issue of losing your mouse. The text recognition accuracy will increase once the location has been determined. The use of artificial intelligence will be used to train the location and recognition systems. The Tesseract-OCR system will be used to perform the recognition after the localization system has been trained using the YOLOv5 network. Number tracking is the first application of YOLOv5 [10].

In this, we propose an analysis effect on the reinnervation of the recognition pattern of the plaque and the deep nervous system using the Brazilian synthetic tile image database for object detection numbers [11]. Variations in rotation, size, and volume are used in the suggested data set to evaluate hardness. As a result, the effect of using artificial tile shapes on the accuracy of the system responsible for locating and classifying real tile symbols and their recognition was evaluated in experiments carried out at three stages: character segmentation, letter recognition, and number recognition (2.54%, 1.09%, and 2.49%, respectively). It is only possible to achieve the digit recognition step with 62.47% accuracy using a trained neural network that has been tested on real plates and with synthetic data [11].

The paper provides a thorough analysis of the most recent advancements and strategies in Automatic Number Plate Recognition (ANPR) [13]. Computer vision (CV) systems are among the several algorithms that have been thoroughly compared and evaluated in real-time. ANPR technology employs recognition techniques to detect and identify traffic signs. Even with the greatest algorithm, using an ANPR system may need additional hardware to produce more accurate results.

In 2019, S. J. Kim et al. introduced the dual attention network, a deep neural network with a unique design for recognizing license plates (DAN) [15]. To increase recognition accuracy, the DAN model employs two different kinds of attention processes. An accuracy of 98.37% was attained by the suggested model using a dataset of Korean license plates [15].

The OCR approaches, which are prone to misalignment and a variety of sizes, were first recognized by Muhammad Tahir Qadri [16]. His modification can be utilized to improve real-time OCR identification from varied sizes and angles. A pre-programmed mechanism for detecting and identifying vehicles using their license plates is displayed. a synthesis of the model's image processing methods for locating and identifying the vehicle in the system's databases. S.Kranthi and K.Pranathin have proposed Automated License/Number Plate Detection/Recognition (ANPR) as a method for identifying a vehicle's image and verifying its number plate number. ANPR is used to display vehicles that may be stolen or involved in criminal activity. Using ANPR is a simple method to spot a stolen car on the road, in a parking lot, or at a traffic light. The project "Automatic Vehicle Number Plate Recognition System Using Machine Learning" is the focus of this entire section.

Many applications, including toll-collecting systems, parking management, and law enforcement, have made extensive use of number plate recognition (NPR) models [17]. Some recent research on NPR models will be covered in this literature review. Deep neural networks (DNNs) and a region proposal network were used in the approach for identifying car license plates described by K. Nishimura et al. (2020). (RPN). Using a dataset of Japanese license plates, the suggested approach had a 98.3% accuracy rate [17]. A complete deep learning system for recognizing license plates that uses a thin network architecture for efficient inference on mobile devices was presented by Y. Cai et al. in 2021, the suggested model had a 97.53% accuracy rate when applied to the dataset of Chinese license plates [17].

Convolutional neural networks (CNNs) and optical character recognition (OCR) methods were proposed by A. K. Awasthi et al. in 2020 for a license plate recognition system, the system's accuracy on a dataset of Indian license plates was 96.2% [18]. A unique method for license plate identification and recognition based on a two-stage deep learning model was proposed by M. Shareman et al. in 2020. The license plate region is in the first stage, and the characters are in the second stage. When applied to a dataset of Iranian license plates, the suggested model had an accuracy of 97.34% [18].

III. PROPOSED SYSTEM

The proposed model uses YOLOv8, trained on a customized dataset, to detect number plates on vehicles. It is designed to handle increasing vehicle counts and improve traffic management. The model is trained to recognize number plates in diverse conditions and is deployed in a real-time system. Additional techniques like data augmentation and transfer learning enhance accuracy. The model's effectiveness is evaluated using precision, recall, and mAP. It enables tasks such as automated toll collection, parking management, law enforcement support, and traffic analysis. Continuous monitoring and occasional retraining ensure optimal performance in changing conditions.

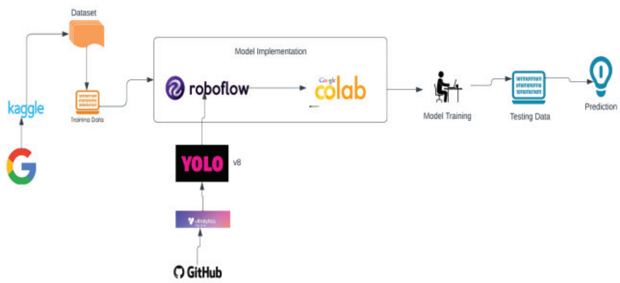

Fig. 1. Flowchart for the Proposed System

A. Image Acquisition

A vital first step in creating a computer vision-based ML model for number plate identification is image capture. This involves collecting pictures of license plates through scanners and cameras, among other sources. The correctness of the model is significantly influenced by the clarity and resolution of the recorded photos. To increase the quality of the captured photos, pre-processing techniques including noise reduction, contrast enhancement, and image segmentation can be used. The algorithm may also be accurately trained to recognize number plates using a sizable dataset of labeled photos. The model can work in real-world circumstances and achieve high identification rates thanks to the application of computer vision algorithms during picture gathering.

B. Vehicle Detection

An ML-based number plate recognition model employing computer vision must include vehicle detection. It includes applying object identification techniques i.e., YOLO to recognize and locate automobiles in an image or video stream. The model may then concentrate on the areas of interest (ROIs) corresponding to the number plates for additional processing after the cars have been identified. This method shortens the processing time while simultaneously increasing the model's accuracy. The number plate recognition model can successfully identify license plates in various detection situations, including parking lots, freeways, and toll booths, by including vehicle detection.

Fig. 2. Training Graphs of the Trained Model

C. Dataset Preparation

The creation of the dataset is a crucial stage in the development of a computer vision-based ML model for number plate recognition. It entails gathering a sizable and varied collection of number plate-labeled photos. The dataset should include a range of situations, lighting settings, and font, color, and size variants. To prevent false positives, the collection should contain pictures of cars with and without license plates. To expand the dataset's size and variety, data augmentation techniques including flipping, rotating, and scaling might be used. When the dataset is ready, it may be divided into training, validation, and testing sets for the creation and assessment of the model. For the purpose of creating a reliable and accurate number plate recognition model, a well-prepared dataset is essential.

D. Training the Model

The most important stage in creating a computer vision-based ML model for number plate identification is training the model. The loss function can be minimized by, feeding the labeled dataset into the model, and back-propagating the model weights. For the training process, the Roboflow model and Google Colab is used. Number of epochs, batch size, and learning rate should be changed, which can lead to an improvement in performance. The performance of the model may be assessed after training using the validation and test sets. To further enhance the model's performance, fine-tuning strategies like transfer learning can be used.

E. Number Plate Localization

The development of a computer vision-based ML-based number plate recognition model requires number plate localization as a key step. It entails locating the area of interest (ROI) in the picture or video frame that has the license plate. The ROI may be located using a variety of methods, including edge detection, thresholding, and morphological procedures. Once the ROI has been located, it may be cropped and treated to enhance the image's quality. Since improper localization can lead to false positives or missing detections, it has a significant influence on the model's performance. The model can successfully identify and recognize number plates in a variety of situations, such as poor light or high-speed settings, by applying computer vision algorithms for number plate localization.

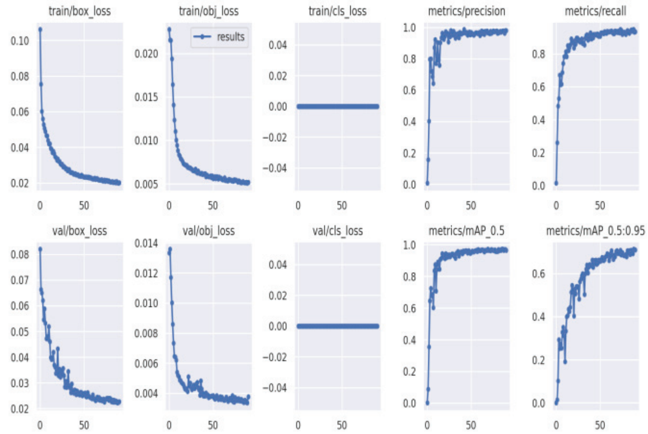

Fig. 3. Training Graphs of the Trained Model

IV. Result

The accuracy of the YOLOv8 is 97.2%, which is a good score and the highest of all the other YOLO models. Therefore, we have proven to be the best model for the detection of number plates and vehicle detection as compared to the other YOLO models. At first, the camera will be used to capture images. Then the model will perform the preprocessing, training, detection, validation, inference, and evaluation of the dataset. Based upon all these processes the model is trained. After training the model, it is tested on the test dataset. Finally, the number plates are detected for real-time image capturing through the camera. The last recorded information will be displayed on the screen.

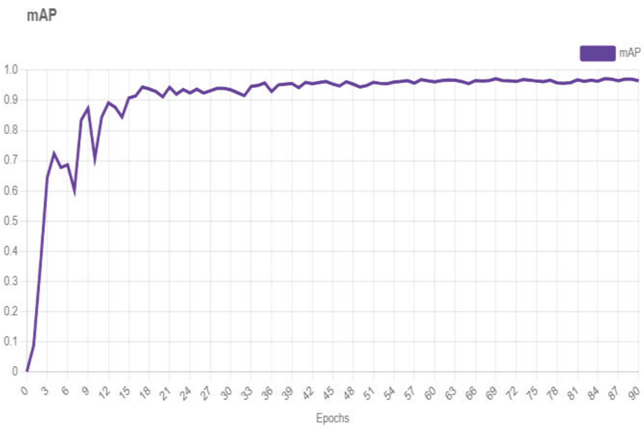

Fig. 4. mean Accuracy Graph (mAP) of the Trained model

The above-given graph can be used to evaluate the mean accuracy of the trained model. Also, is given in Figure 4, how the accuracy is increasing so rapidly.

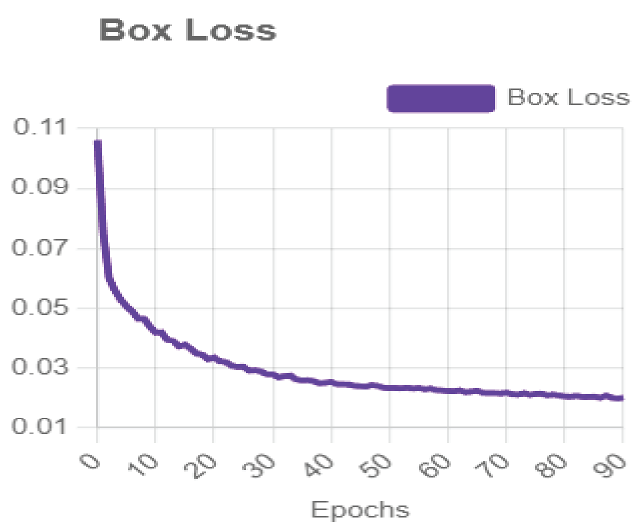

Fig. 5. Box Loss Graph for the Trained Model

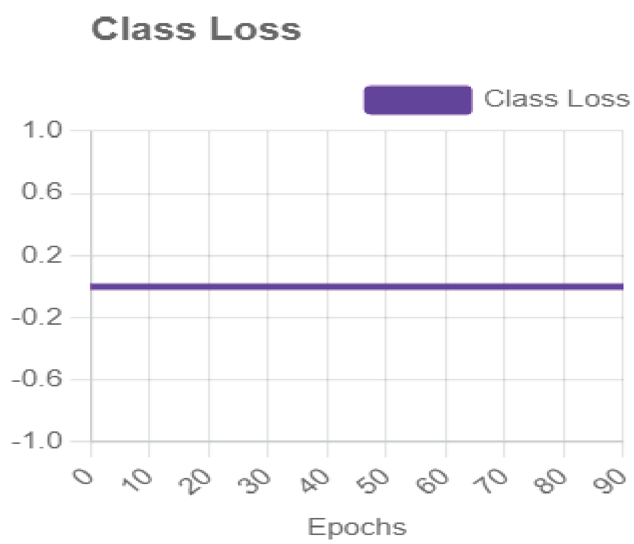

Fig. 6. Class Loss Graph for the Trained Model

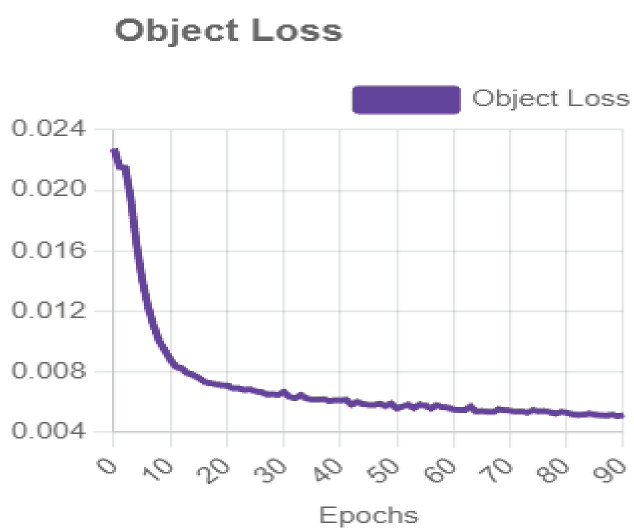

Fig. 7. Object Loss Graph of the Trained Model

TABLE I. TABULAR REPRESENTATION OF THE ACCURACY, PRECISION AND RECALL ACHIEVED AFTER TRAINING AND TESTING OF THE YOLOV8 MODEL ON THE CUSTOM DATASET

YOLO Models	Parameters		
	Accuracy	*Precision*	*Recall*
YOLOv8	97.2%	97.6%	94.5%

Fig. 8. Outputs of the Trained and Tested Model

Fig. 9. Real-time detection using a webcam

V. Conclusion

We propose a number plate recognition model using the YOLOv8 model for vehicle number plate recognition and using our custom dataset of number plates. We have trained our dataset using the YOLOv8 model, this model can detect multiple cars and number plates in a single frame. The results shown in this paper are achieved with higher accuracy as compared to other ANPR, KNN, and CNN models.

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