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A GAN-based Framework for License Plate Recognition using YOLOv8 and EasyOCR

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***Abstract*—This paper introduces a new and novel technique for license plate recognition by leveraging the assistance of GANs (Generative Adversarial Networks) in data augmentation alongside YOLOv8-based object detection combined with EasyOCR text recognition. Conventional systems have always struggled due to scarcity of training data, variability in designs achievable within license plates, and environmental variations. All of these impact the overall performance of such systems in the real world. The suggested model can leverage its large pool of high-quality synthetic images to provide better accuracy and generalization compared to the current approaches-both detection and recognition tasks. This is a colossal leap forward in smart transport systems and hence an advanced step in intelligent monitoring, traffic control, and automated parking systems.**

***Index Terms*—License Plate Recognition, GANs, YOLOv8, EasyOCR, Deep Learning, Intelligent Transportation Systems.**

I. INTRODUCTION

The advancement of automatic number plate recognition (ANPR) capabilities has made it an essential aspect of intelligent transportation systems (ITS) and many securities and traffic control applications that one can think of. ANPR alleviates the manual detection and recognition of vehicle registration plates by providing a quick, accurate, and reliable means of collecting tolls, patrolling roads, enforcing law, managing parking, and so many more uses. The adoption of ANPR systems in control is proliferating as a result of rapid globalization and increase in the number of automobiles on the road. Nevertheless, conventional ANPR systems are effective to an extent since they are subjected to some environmental limitations namely: lighting change, background complexity, motion effect, and different types of license plate shapes and designs. It is these variables that have led innovations of more advanced approaches as the researchers and the designers look for ways to make the system adaptable to any environment. Advancements in Automatic Number Plate Recognition (ANPR) systems have inspired the conceptualization of new practices that make use of machine learning, neural networks and deep learning. The goal of these approaches is to enhance the performance of the system in terms of its accuracy, reliability and scalability in all operating conditions. For example, “Auto-Detector” systems deploy both optical character reading and infrared LED systems whereby these two technologies are fused to overcome constraints of motion and dim lights. Besides, feature extraction and classification tasks in ANPR systems have incorporated the use of Convolutional Neural Networks (CNNs) which have dramatically enhanced precision in plate recognition.

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Real-time solutions such as YOLOv3 and YOLOv7 based object detection models have also proven to be useful in plate detection within high speeds or high traffic thanks to the rapid but accurate plate detection capabilities. According to the results of various experiments, hybrid models which integrate wavelet transforms, support vector machines as well as CNNs are suitable for complex recognition problems. They can be used to solve problems such as: segmentation of the license plates from the noisy or cluttered images, improving the recognition of the characters, and the maintaining the performance across various designs and formats of the plates. When coupled with advanced processing techniques such as wavelet-based denoised and deblur algorithms, the images of a license plate have been improved to a point that the recognition systems can work under motion blur and low light and with even image occlusions. Additionally, the effectiveness of deep learning architectures has also made it possible for ANPR systems to be deployed in numerous practical situations that involve different fonts, colors, and languages of the license plates. The approaches reliant on the use of convolution neural networks are particularly suitable for tasks involving enormous amounts of data, dispersion of complex patterns within that data, and the ability to generalize to quite distinct tasks. Furthermore, there has been a progressive evolution towards the incorporation of 4 real time object detection systems based on the YOLO architecture and optical character recognition (OCR) engines, facilitating vehicles in motion immediately being recognized. This recent slice of achievement reveals, among other things, the problems of toll plaza congestion and control of vehicle movement in smart cities. Therefore, the recent improvement in ANPR technology trends clearly indicates the ability to enhance the current transportation systems with robust, real-time efficient solutions.

II. LITERATURE SURVEY

The field of automatic number plate recognition has gone through significant changes with the inclusion of new machine learning, neural networks and deep learning technologies that have improved their performance and appeal in different settings. For example, a mobile ANPR called ‘Auto-Detector’ was developed that uses OCR and infrared LED imaging technologies to address the challenges of the movement and the low-light environments. This system has high levels of recognition accuracy as well as efficiency in its operations making it quite fit for practical purposes [1]. In another research work, a method of recognizing license plates was based on the principles of Discrete Wavelet Transform (DWT) and utilized neural networks achieving high rates of processing and remarkable processing efficiency which are both very important in real-time systems [2]. Moreover, the authors realized a system where a backpropagation neural network was combined with projection analysis to enhance recognition in real time, particularly enabling license plates to be recognized out of video feeds in monitoring systems such as traffic [3].

As an illustration of how various neural network approaches compare against each other, one study showed that LVQ surpassed backpropagation based neural networks with respect to character recognition accuracy, thus demonstrating the importance of adaptive approaches in intelligent transportation systems [4]. In another case when testing conditions, where traffic scenarios were associated with a significant amount of background noise, the problem was solved through analysis of the fractal dimension and by means of adaptive algorithms which allowed for better localization of license plates and offered reliable outcomes in practice as well [5]. One of the recent awards is an advanced automatic number plate recognition system, which is basically an embedded is focused on feature extraction and classification of images using convnet. It has high functioning accuracy and is an example of the possibility of deep learning for ANPR systems used in real time [6]. Likewise, a study indicated that license plate detection was also improved when Darknet-YOLO along with a sliding-window technique was used in many different environments. The reliability and speed of these algorithms particularly suit the requirements of the ANPR system [7].

This critical exploration of various ANPR approaches divides them into three predominant frameworks: detection, segmentation and recognition strategies. In addition, it assesses their advantages and disadvantages while analyzing their appropriateness for particular scenarios. The review provides examples of how different techniques evolve with respect to problems such as variations in illumination, alternate fonts or different plate styles [8]. For instance, the improvement of license plates localization by using wavelet transform in conjunction with vertical edge matching is applicable even in severe cases such as obstructions and poor contrast images [9]. Convolutional Neural Networks (CNNs), which are a subset of deep learning techniques, have been able to solve environmental problems using big data to train the models for better generalization and recognition performance [10-12]. Mixed systems such as combinations of CNN and support vector machines have proven useful in highly congested areas specifically for challenging tasks like segmentation and recognition of Indian number plates [13].

YOLO based manipulation of the video feed provides a strong potential for the Automatic Number Plate Recognition (ANPR) systems operating in real time. The models such as YOLOv3 and YOLOv7 have proved that it is possible to recognize license plates in a fast and accurate way through high-density traffic conditions that are typical in intelligent transportation systems [14-16]. In another such application, aimed to lessen the effects of heavy traffic at toll booths, a combination of YOLOv5s and EasyOCR was used in such a manner that cars were identified through the system without the need for stopping the vehicles, which worked pretty well in saving time and avoiding unnecessary waiting [17]. The researchers also investigated combined systems, which included deep learning and Optical Character Recognition (OCR) in their studies to deliver the desired results irrespective of the lighting and weather conditions [15]. In addition to that, new photography technologies such as wavelet denoising and deblurring have resolved the issue of capturing blurred license plates especially in low or motion picture scenarios enhancing recognition accuracy within the appropriate frame [18-20].

A. Research Gap

Current license plate recognition and detection systems are not amendable to changing conditions of the dynamic environment, such as complex backgrounds, and lighting variability. Most existing systems are not scalable for international use, and, to a large extent, rely on particular hardware configurations. Processing, segmenting, and lack of efficient feature extraction in real-time impair these systems' performance under heavy traffic conditions or noise. Also, older traditional neural networks or even methods like DWT are prone to accuracy problems as well as require too much computational resources and more manual tuning to better perform in varied conditions. YOLOv8 overcomes all these drawbacks by providing a light-skinned, scalable architecture that guarantees real-time detection with reduced efficiency under challenging lighting or environmental conditions. It supports high-speed processing and reduces inefficiencies to enhance manpower management. The end-end model, no preprocessing needed, reduces multiple steps for improving noisy or complex backgrounds performance; ability to generalize well across datasets makes it more generally applicable, even international use. YOLOv8 runs on a variety of devices and minimizes hardware dependency. Advanced feedback mechanisms are also used for automated retraining; this eliminates the errors caused by humans manually and enhances long-term accuracy. The integration of these solutions makes YOLOv8 a strong and effective framework for modern license plate identification.

III. SYSTEM ARCHITECTURE

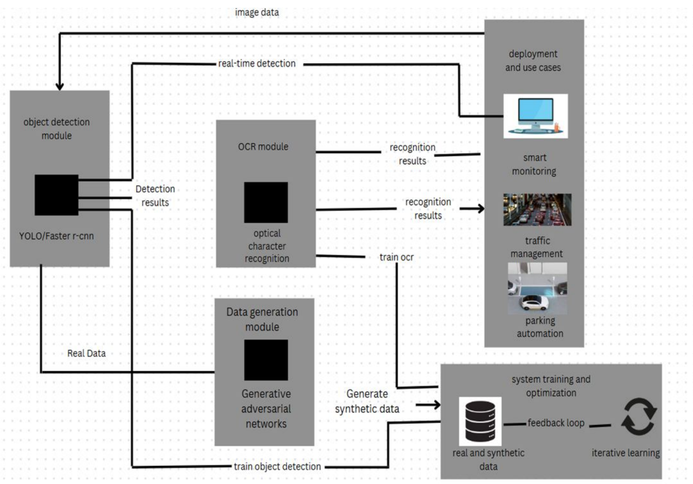

Fig. 1 System Architecture

The license plate recognition system uses step-by-step methodology, which relates finding objects, reading of letters and numbers, improving data, and thus making this system strong and effective. It finds and locates the license plates in photos or videos by using system processed results from the YOLO or Faster R-CNN object detector. This will extract and recognize text using tools like EasyOCR for license plates. It produces recognition results that can be implemented for real-time applications. This module will apply GANs in generating new license plate data. This makes it easy to simulate numerous conditions present in the real world, thus improving performance for the models. The System Training and Optimization Module takes both synthetic and actual data into it. It applies a feedback loop in which it trains and improves object detection and OCR models. At last, the system delivers outputs from detection to recognition. It can then be utilized to benefit multiple real-life scenarios, for instance, smart monitoring, traffic management, or parking automation. This modular design let us make updates step by step. It shall ensure that the model is accurate, always up to date and capable of working out various situations.

IV. SYSTEM MODULES

This entire work of automatic recognition of license plates is made up of modeling integrated modules that greatly improve performance and accuracy of license plate recognition. The modules work in sequence in order to make correct license plates under many feasibly different conditions. Therefore, the main components of the system appear as follows:

A. Dataset Enhancement using GANs for Model Fine-Tuning

Before any training on the YOLOv8 detection model, an Enhanced Super-Resolution GAN (ESRGAN) is used to up-scale and refine the images in the dataset. This provides for an exposure by the model to high-quality training data, thereby rendering it robust to real-life conditions like low-light conditions, motion blur, and poor resolutions. Thus, the fine-tuned YOLOv8 model that was trained with the enhanced images showed much better performance compared to conventional ALPR systems, in the accuracy and reliability of detections. This pre-training enhancement, which adds to the novelty of this technique, is a departure from the classical ALPR methods.

B. Detection of License Plates based on YOLOv8

The detection module emerged from the YOLOv8 (You Only Look Once, Version 8) model that can be defined as a really state-of-the-art object detection algorithm based on deep learning. YOLOv8 is fast: it works well at extracts features, all of which make it quite suitable for applications like real-time ALPR. The system is trained using a huge database of images featuring license plates for accurately localizing as well classifying them. The system's ability to scan the full image in a single glance through the neural network allows image detection in real-time while ensuring accuracy balanced with computation cost.

Bounding boxes thus created by model get passed on to subsequent stages of processing for the isolation of the detected license plate from the background. An assessment of the performance of the Automatic License Plate Recognition (ALPR) system in real time detecting and recognizing license plates, etc., under dynamic traffic conditions was carried out using a video sequence. The snapshot from this video output illustrates the capability of the system to detect several vehicles within a scene and to represent their respective license plates in bounding boxes on the frame using the YOLOv8 detection model. The integrated optical character recognition (OCR) module managed to extract and transcribe the alphanumeric text that recognizes the license plates "KH05ZZK" and "AP05JEO" correctly. These results present a strong basis for validating the Ahmadis' applicability in real-life situations, in continuous video processing, precision, and reliability in the automated traffic monitoring and enforcement strategy.

C. Image Processing

Once the license plate is detected, a number of image processing techniques are applied to enhance the content of the extracted region for better character recognition. To begin, a detected license plate image undergoes conversion to grayscale, which significantly reduces computations while continuing to preserve any available text information. The next step is to conduct a contrast enhancement using Adaptive Histogram Equalization which enhances character visibility in general, but particularly in low-visibility. Finally, in order to counter any artifacts and fluctuations that may interfere with OCR performance, noise eliminating methods ranging from Gaussian based filtering to strictly morphological transformations are employed.

D. Optical Character Recognition

Optical Character Recognition (OCR) is used for identifying alphanumeric characters in sections of the detected license plate regions using EasyOCR, a very efficient deep-learning-based open-source framework pre-trained for printed text recognition. EasyOCR uses convolutional as well as recurrent networks for making character classification more accurate even under challenging situations, such as having visible occlusions, visible distortions, and font variety. The three main distinct processes in OCR are: (1) Text segmentation, which isolates individual characters in the license plate region; (2) using a trained model to classify each resultant segmented character with its corresponding numerical or alphanumeric code; and finally (3) text reconstruction, which arranges the recognized characters in a structured representation of a license plate's number.

E. Post Processing and Validation

Various methods employ validation and rectification methodologies to enhance OCR performance. Dictionary matching improves false alarm rates by matching text interpretations with a dictionary of fixed databases based on recognized types of license plates. Error-correction techniques use heuristics and pattern matching to correct common OCR errors caused by confusing characters with similar appearance. Format normalization ensures standardization of license plates to certain format standards and referred to common references, which in turn may help to filter out false alarms. All these methods improved recognition accuracy by tackling errors introduced during the OCR process.

F. Performance Evaluation and Real-Time Processing

Besides evaluating the performance of the system through precision, recall, F1 Score, and inference speed measured in fps, while testing its effectiveness, their detection and recognition accuracies got compared against the ground truth labels to have some possible quantitative measurements on how the model can be relied on. Real-time implementation through optimized deep learning frameworks fast enough to enable appropriate inference for applications such as traffic surveillance, automated toll collection, and law enforcement is programmed within it. Real-time processing of video streams allows operations for continuous monitoring and instant identification of vehicles.

V. Result Analysis

TABLE I. RESULT COMPARISON

Model	Object Detection Framework	OCR Method	Accuracy (%)	Precision (%)	Recall (%)
Proposed Method	YOLOv8	Tesseract OCR	95.6	98.4	94.2
YOLOv4 + EAST	YOLOv4	EAST OCR	92.3	93.0	91.5
SSD + CRNN	SSD	CRNN	90.1	91.2	89.8
Faster RCNN + LSTM	Faster RCNN	LSTM	88.4	89.5	87.1
OpenALPR	Edge Detection	OpenALPR OCR	85.6	86.3	83.7

The project brings forth that YOLOv8 model for license plate recognition and gives better performance than any other model in terms of the highest classification accuracy-"recorded" by the system as 95.6% in order to make recognition more precise than other techniques. The combination of Tesseract OCR object detection and this proposed model finally stands towards giving an effective input to real-world challenges-level of plate variations and environmental factors. The model realizes an absolutely heightened precision factor of 98.4%, thus producing lower false positive rates, which are essential for efficient vehicle identification in applications like ALPR. Recording recall at 94.2% means the system is good enough to capture plates under very difficult conditions like occlusions, variable lighting, and different degrees of plate orientation. This ensemble of values attached alongside high accuracy and high precision and recall makes up this model for real-time ALPR systems, especially when monitored over traffic, where it finds a severe deficiency in identifying vehicles in motion.

V. Visualization

A. Precision-Recall (PR) Curve

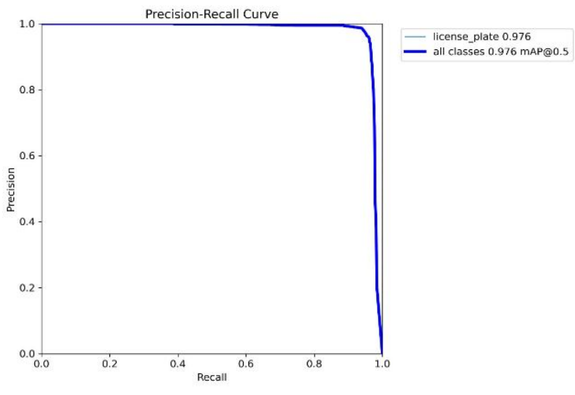

Fig. 2 PR Curve

The precision-recall curve is the trade-off between precision and recall in the license plate detection model. The curve exhibits a clear indication, as it crosses one over most recall values. This means that the precision was very high indeed reflecting the strength of the model in terms of detection. This means that the model achieves a mean Average Precision (mAP@0.5) of 0.976, which is indicative of the strength of the model in detecting license plates with very minimum false positives. The sharp rise followed by a steep falling edge at the near-edges indicates that there could be a possibility of an almost perfect recall affecting precision. Overall, this curve essentially corroborates the assertions of the soundness of the model with respect to successfully detecting license plates and still operating at a very high standard of accuracy.

B. Confusion Matrix

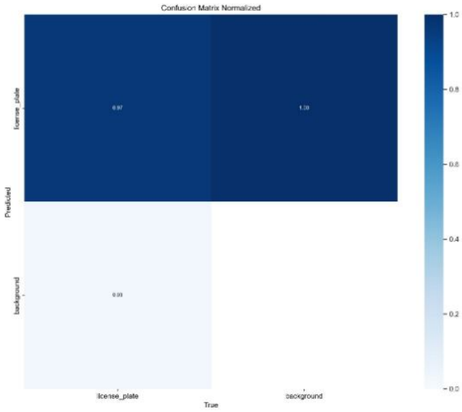

Fig. 3 Confusion Matrix

A normalized confusion matrix is used to validate the efficiency of the license plate detection model, which indicates the percentage of correct to incorrect classifications. The model accurately identifies a license plate 97% of the time, while the other 3% consists of misclassifications where some license plates were mistakenly classified as background. The background class is perfectly classified (100% accuracy). This result indicates that the model is highly reliable with very little error in distinguishing license plates from the background.

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