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ORIGINAL CONTRIBUTION

Intelligent Vehicle Number Plate Recognition System Using Yolo For Enhanced Security In Smart Buildings

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***Abstract*— The demand for advanced security solutions has increased with the continuous growth of urban infrastructure; hence, automated surveillance systems are vital across universities, hospitals, and commercial spaces. This project proposes an end-to-end Automatic Number Plate Recognition (ANPR) system to identify vehicle license plates by capturing high-speed images under optimal lighting conditions, isolating and analyzing plate characters, and translating the visual data into machine-readable text. By deploying these models on embedded systems, the system uses Convolutional Neural Networks (CNNs) and YOLO (You Only Look Once) for real-time object detection and recognition. The solution leverages the power of edge computing to achieve high performance and low latency for effective vehicle monitoring, data logging, and enhancing overall security infrastructure in buildings.**

***Index Terms*— Automatic Number Plate Recognition (ANPR), Deep Learning, YOLO, Vehicle identification, Smart security systems**

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I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) technology is becoming a significant part of intelligent transport systems and the urban security framework to manage vehicle identification autonomously and increase the operations' precision, efficiency, and scalability [1]. These systems find wider applications such as enforcement of traffic laws, toll collection, parking associations, access control, and surveillance [2, 3, 4]. Usually, the ANPR process has three major components: license plate detection, character segmentation, and character recognition. The first step, positioning or localizing the license plate within a digital image, is exceptionally vital for all the proceeding operations. The area that contains the license plate needs to be obtained from the entire image background using techniques such as structural analysis, edge detection, and color-based masking [5, 6]. In the next step, characters or digits are separated from the plate image, and this process is known as segmentation. Plate detection has several environmental issues, including changes in lighting, rotation of the plate, and font of the letters used. Segmentation of images done in advanced arrangements and component-based analysis greatly improves the precision of the segmentation process [7].

The last step comprises interpreting the characters into words using Optical Character Recognition (OCR) using methods like vision scissoring and character boundary refinement [8, 9]. The characters are then recognized and transformed into standard formats (e.g., ASCII) to store or analyze [10, 11]. Implementing artificial intelligence, especially machine learning and deep learning technologies, is steadily increasing in modern ANPR systems to enhance system performance. CNNs, LSTM models, YOLO, and faster R-CNN have been proven under differing environments [12]. Also, cloud and edge computing technologies allow for real-time processing and scaling for large projects beyond increasing efficiency, which is crucial for public safety, crime control, and emergency management. ANPR helps law enforcement agencies monitor stolen vehicles and track suspicious activities for better traffic surveillance and unattended vehicle monitoring [13]. The passage's event logging becomes automated through ANPR at airports, governmental facilities, and military zones. The data remains valuable for forensic analysis and optimizing transport infrastructure, like markings of date and time, vehicle movements, and entrance or exit records.

From an ANPR system's perspective, many issues exist, such as environmental sounds, license plate format differences per jurisdiction, motion blur, imagery resolution, and even occlusion. The solution to these problems is to achieve more sophisticated algorithms and adjustable models. This paper presents an economically efficient ANPR framework comprising sophisticated image processing and machine learning to optimize ANPR accuracy while minimizing processing time. The system is engineered to operate dependably in uncontrolled settings and produces or-

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ganized data outputs that seamlessly merge with larger surveillance and monitoring systems. This approach can positively impact automated vehicle identification systems and supports the overarching purpose of constructing a smart, safe, and responsive transport network.

II. RELATED WORK

There is considerable research on license plate detection; Badr et al. [14] divide license plate recognition into three channels: red, green, and blue. Every network's picture is input into CNN, which trains the hierarchical characteristics, and the outcomes are fed into SVM, creating the objective probabilities label values. Bhardwaj and Kaur [15] employ the multi-directional design you only look at once (MD-YOLO) to tackle multi-directional issues with the highest accuracy rate. MD-YOLO estimates the center coordinates of any object based on its width and height. Radzi and Khalil-Hani [16] discuss a specific feed-forward multi-layer that can automatically extract characteristics for licensing identification. Abdullah et al. [17] proposed a practical identification approach for Malaysian license plates to distinguish license plates in single and double lines using smearing. Hamey and Priest [18] used genesis to address the challenge of recognizing license plates in low-intensity, poor images. Plate recognition difficulties include blob separation, segmentation, and character recognition.

Bhardwaj and Gujral [19] developed an ML model for Turkish license plates of a custom dataset of 3,458 images and applied smearing to enhance model robustness. The system uses TensorFlow and Keras library for CNN to extract visual features and process using an LSTM network for sequence decoding. Kumari and Prakash [20] proposed an ANPR system using ML to capture images in infrared and perform background subtraction, noise reduction, and license plate localization by identifying RoI to extract key features. Sytem has defined the character boundaries using canny edge detection and segmented and classified using ANN based on pattern matching. Sung et al. [21] offer a comprehensive review of various ANPR methodologies and analyze their accuracy and performance, providing valuable insights into the strengths and limitations of existing techniques.

Wang et al. [22] proposed a system in Australian contexts associated with the variety of appearance, patterns, and colors from different states. The plates used in the covers, in addition to the use of non-standard substances, complicate matters. Scale-invariant feature transformation (SIFT) features are employed to construct a license plate identification scheme [23]. Chang et al. [24] built a real-world automatic number plate recognition software. Ullah et al. [25] outline a two-stage license plate recognition approach that uses fuzzy domains for plate localization and neural networks for detection. Menon and Omman [26] offer a sensor platform for regulating a vehicular obstacle using image-based license plate recognition. The approach proposed recognizes license plates in challenging circumstances like those characterized by fluctuating license plate backgrounds, fonts, and deflections to identify characters; a standard optical character detection process is employed. Zhang et al. [27] used an adaptive image segmentation technique and linked components analysis to create a unique system for detecting automotive license plate neural networks.

A. System Design

The design plan for the system starts with the data collection module, which gives the system's image database constraints and collects images for the license plates from renowned and trusted websites for an extensive collection of license plate images from various countries [28]. After acquiring the data, it moves to the next step, the data processing module. In this step, the raw input data goes through a series of pre-processing steps to ensure it is ready for model training. As a first step, the images undergo cleansing processes, including removing noise and correcting distortions and inconsistencies. The system processes and arranges the images in the same file order based on pixel resolution to ensure dataset uniformity, allowing for further normalization. Then, it splits the dataset into training and testing subsets to enable model validation. The system constructs input sequences from the prepared images and generates output targets: the characters on the license plates. It then arranges the processed information into structured .xlsx files, enabling integration into systems using machine learning algorithms.

The model training and recognition module uses a CNN for further training on the processed data [12, 29]. The model can learn the details of the license plate images and character identification through this deep learning approach. The pre-processed images form the input to the CNN model, while the output includes the symbols deciphered from the license plates. In the system design, the last step is output and result presentation, where the identified numbers on the license plates are displayed. The system functions are then assessed for effectiveness using indicators such as detection, character recognition, and overall OCR accuracy to evaluate trust and verification metrics from real-case scenario usage. Figure 1 synthesizes the overall flow chart of the system.

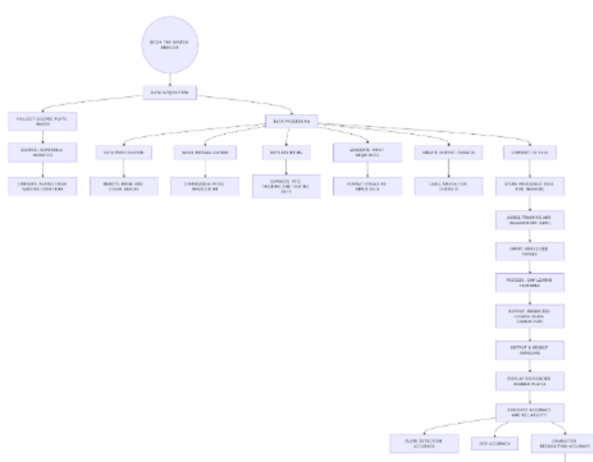

Fig. 1. System flow chart

The proposed system includes a modular camera, sensors, a controller, GSM, and integrated servers. It attempts to prevent illegal automobiles by matching the stored automotive information. The camera photos are turned to grayscale and improved by altering the histogram. The system employs the Sobel technique of edge detection to extract edges. The system then performs morphology on the segmented image and segments the image with edges. Finally, it identifies the characters using CNN. Many systems have developed a plate identification system utilizing deep learning and created an OCR system using a bespoke dataset [30]. The database was created artificially by combining photographs from the internet with sounds and backdrops. SUN and Sandford's databases are utilized as backdrops. YOLO real-time license plate detection systems operate using an object detection framework. The CNN used for character recognition implements an input layer with 7.63 neurons for seven letters.

Photos are normalized by transforming the RGB image to grayscale, removing distortion, and binarizing. The system uses a related components approach for license plate retrieval based on background image dimensions, height, and other parameters like size and minor axis length. The retrieved license plate letters are segmented using horizontal and vertical screening. Eventually, CNNs are used to recognize the symbols. The CNN model learned from a diverse set of 1,100 images for each of the 37 alphanumeric characters, reinforcing the model's learning capabilities with diverse representations. Such thorough dataset tuning improves the model's functionality in character recognition under different lighting conditions, fonts, and styles.

Out of the complete dataset comprising 37,000 images, 29,600 were allocated for training the model and 7,400 for testing to attain a more even assessment of the model's performance. The research applied a learning rate decay policy, which set the starting learning rate to 0.6 to lessen the cross-entropy loss in the reduction and convergence phases during the training session. This approach helped the model generalize better and accurately recognize license plate characters. The average precision attained was 96%. Create an automated recognizer. The researchers divided the technique into three categories: license plate identification, feature extraction, and character recognition. Figure 2 shows the architecture used for plate detection.

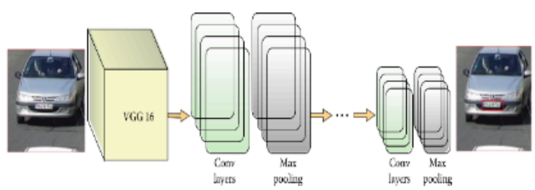

Fig. 2. The deep architecture used in the proposed method for plate detection [31]

B. Number Plate Localization

Candidate regions typically take the form of rectangular-shaped boxes with general geometric features to frame the license plate. Most automobiles have a license plate as a rectangular image, which results in a standard geometric feature in the image [24]. Thus, geometric features can be a means to separate the license plate region in isolation from the rest of the vehicle, as shown in Figure 3. When images are captured, the system structures them in an overlay of square bounding boxes to simplify image extraction. Using mathematical morphology, the system determines regions of interest and sharp edges and then analyzes intensity and edge variance gradients. Edges surrounding objects in the gradient image can be regarded as incomplete because of gaps in the original image. As a solution, the edges formed by Sobel edge detection on the grayscale image were further enhanced by square structuring elements, resulting in rounded morphologic dilation. Rounded rectangular window dilation fills gaps in Indeed and improves the continuous representation of object borders. The expanded gradient mask greatly increases the described value of the plate shape and thus makes localization worse, but spatial plate discontinuities are much easier despite the minor discontinuities of shape [32, 33].

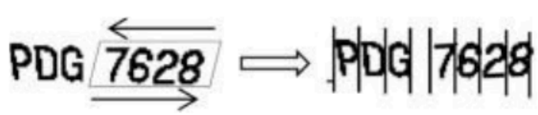

Fig. 3. Example of Plate Segmentation [30]

C. Plate Detection

Usually, plate images are noisy due to environmental influences. An input image is a standard solution to this issue. As a primitive phase in imaging analysis, Gaussian filtering, a natural filtration that smooths and removes distortions, is used. The initial stage in this step is to apply a Gaussian filter to the collected photos to improve their quality. Convolutional neural network solutions are then created to identify the plates' placement. The recommended plate recognition structure is shown in Figure 4. Source frequency for deep networks includes other copies of 312. As a response, our proposed method reflows the incoming vehicle image to 1: 2 squares.

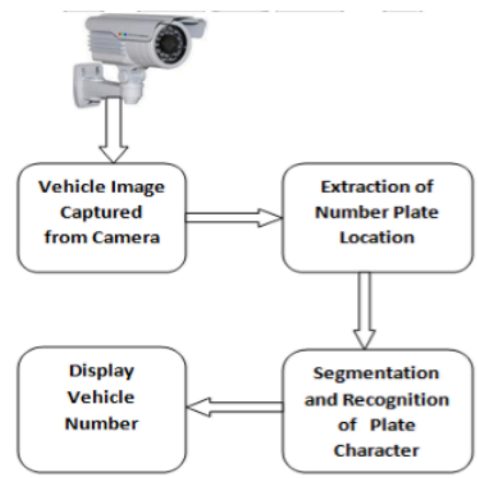

Fig. 4. Capturing images by digital camera [34]

III. METHODOLOGY

Starting with object tracking is recommended if real-time applications require improved detection accuracy. All current algorithms look for number plates in every frame, which is inefficient since they only take up a tiny portion of the image. To limit the image areas not associated with cars, the proposed method first attempts to determine the presence of vehicles within the image to alleviate a large amount of processing and accelerate the operation. Neural networks, consisting of multiple layers of convolutional networks, perform car detection [25, 35]. Vehicle detection relies on enhanced features obtained through CNNs. The proposed approach combines high and low-level features from the initial and later layers of the convolutional neural networks alongside advanced attributes extracted through the convolutional neural networks. In addition, we have added several layers to capture diverse features from the related images. The different kernels at each layer also vary in size; thus, the system can obtain pertinent and distinctive information from images with differing detail levels.

A. ER Diagram

An Entity Relationship (ER) diagram depicts a database's logic structure, including its components, such as data and relations. As integrated in Figure 5, the ER diagram captures important information alongside their interactions with neatly structured visuals for the proposed system.

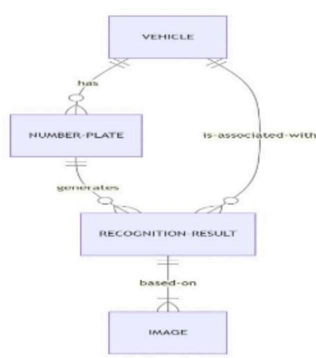

Fig. 5. ER diagram

B. System And Software Requirements

TABLE I
SYSTEM AND SOFTWARE REQUIREMENTS

System Requirements	Software Requirements
Processor: i5	Python 3
Min. 8 GB RAM	Tensor Flow
Camera	Open CV
GPU	YOLO

C. System Implementations

The control structure of the system is centralized. In this model, the administrator takes care of registering all users, which includes applicants and members. Two-factor authentication consists of a user ID and an access key to access any module within the system. Applicants are bound to possess a user ID and a gate pass, which is the first step toward security. Access for registered members is granted via their user ID and registration number, ensuring higher level identification and authorization. The system runs on an Android server-based architecture, enabling real-time interactions and user engagement through modules. All sensitive information, including user data, system credentials, and permissions for access, is kept safe within a GraphQL-based database system. This architectural design permits easy and controlled data retrieval, scalable user account information administration, and relevant access privileges throughout numerous application modules.

D. YOLO Algorithm

YOLO (You Only Look Once) utilizes CNNs for object recognition. CNNs attempt to optimize performance by figuring out how input and output shapes correlate considerably through an increase in the number of hidden layers. Although YOLO is exceptional for real-time video monitoring, it suffers from slow image processing speed. Neural network design requires extensive coding and parallel execution on GPUs. However, when trained on deeper architectures, neural networks perform well. Fundamental AI techniques for image processing are applied to ease the code complexity and improve access speed.

In the scenario of number plate recognition, Python implements multiple programming paradigms, including structured programming (for data cleansing and image splitting), object-oriented programming (to construct models of vehicles, plates, and recognition systems), and functional scripting (for rapid data changes and building pipelines.) Moreover, image processing with OpenCV, OCR performed with Tesseract, and several mathematical operations conducted in parallel with NumPy, making Python's arsenal complete for constructing reliable real-time number plate detection and recognition systems. An optimal framework for developing deep learning-based systems for number plate recognition is TensorFlow. It's an open-source software, and its core is written in C++ for speed, which is then softened by Python bindings, allowing ease of use. CNNs and other forms of neural networks can use TensorFlow, which allows for accurate detection and recognition of license plates [10]. Characterized by plate recognition image procurement, segmentation, and detection, OpenCV is an image processing toolkit used alongside Tensorflow to make a fully functioning recognition system. Written in C and C++, the software toolkit is open-source and cost-free, making its utilization extremely convenient.

E. OPTICAL Character Recognition

Despite this, ANPR technology can assist in public safety, security, and automatic interactions with transportation and road vehicle systems. The software part of the system can operate on any personal computer or laptop and is integrated with other software or databases. Enhancement of image transforms begins with the detection and normalization processes followed by plate image enhancement, after which OCR character recognition binds numeric character extraction from the plate. ANPR system designs and implementations are categorized into two main approaches. One approach performs the entire operation in real-time at the lane; in the other approach, images from several lanes are collected and sent to a remote computer, where the OCR step will be executed later. The system recognizes and extracts vehicle license plates from static images and live video footage. OCR is performed for text extraction on selected areas of interest using a basic OCR model built with PyTorch. GPU resources had to be split between the two frameworks to optimize the performance of both TensorFlow and PyTorch. ROI filtering segments: The license plate area from the complete vehicle image. The system further processes the cropped region to enhance the image, allowing precise character recognition. If the recovered numbers plate picture contains more letters or languages than numbers and constants, we implement OCR filtration to clip for the vehicle number or variables, removing the remaining undesired characters in the last product.

IV. RESULT AND DISCUSSION

The performance metrics indicate that the proposed CNN-based number plate recognition system is effective. Also, the plate detection accuracy of 97.5% proves that the system can successfully and reliably recognize vehicle license plates in the image displays containing a great deal of pictorially heterogeneous background. Such a high detection level indicates that the image pre-processing methods and object detection strategies have been performed adequately and optimally.

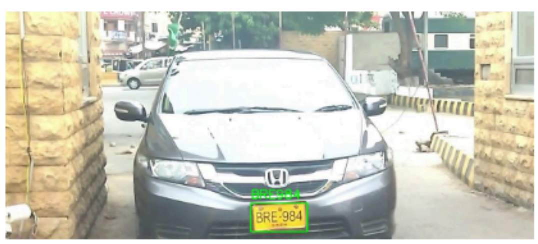

Fig. 6. Captured image by digital camera

The character recognition accuracy of 96.8% signifies that the system can read and construct individual alphanumeric characters appearing on the plates, which is essential to ensure that the recognized plates are accurately positioned concerning spatial references and deciphered with maximum precision. The overall OCR system accuracy of 95% attests to the combined dependability or reliability of the two significant steps, the detection and recognition steps. Although this figure is somewhat lower than the separate elements, it indicates a strong and functional system intended for traffic monitoring, vehicle security surveillance, and vehicle registration enforcement. These findings indicate that plateaued performance commensurate with the described borders suggests the CNN-based approach is a sound design choice for systems while revealing some additional potential areas of improvement for more challenging scenarios, including when images are out of focus, poorly lit, or logos and other components obstruct numbers and letters.

TABLE II
SYSTEM ACCURACY

Parameter	Accuracy
Plate Detection	97.5%
Character Recognition	96.8%
OCR	95%

V. CONCLUSION

This technology will successfully use and detect the plate reorganization of the numbers from the images, which consists of the vehicle number and then character segmentation. This project can provide information about the arrival date and time of the vehicle regarding in and out time and the captured image of the license number plate with complete data backup saving in the database of computer as in the excel sheet format so that we can provide or view any information that will be required urgently. To successfully recognize numbers from vehicle license plates on several pictures, the system automates the number plate identification system for smart security. To retrieve missing vehicles, capturing records can help identify reckless drivers and may automate other processes currently done by hand. Darkness detections, vehicle classification, license plate recognition, and trying to log on are great examples of how these methodologies deliver satisfactory results while remaining cost-effective. Incorporating such methods and techniques could help it perform better. The main application of license plate recognition is vehicular monitoring.

A. Future Recommendation

We aim to enhance the proposed system by focusing on overnight surveillance, occlusion handling, 3D modeling, and vehicle tracking. Automated vehicle identification systems affect threat detection and defense significantly. Brighter and higher-resolution cameras should be employed to strengthen the system's performance, and governments will likely adopt the system due to its cost-effectiveness and environmentally friendly nature, especially when implemented across various regions. Registration details can be entered manually at a low cost, making the system accessible for deployment in different countries. Many existing ANPR systems simultaneously process a single vehicle's plate. However, multiple license plates may appear in the frame simultaneously in real-world scenarios. Innovative ANPR systems are capable of handling multiple number plates for enhanced security. In contrast, some systems rely on offline vehicle images as input for processing, which may lead to discrepancies in results. Therefore, achieving accurate outcomes may require different real-time and offline processing strategies. A fine-to-coarse strategy could effectively segment multiple vehicle license plates within a single image.

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