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Automatic Number Plate and Speed Detection using YOLO and CNN

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***Abstract*—This research paper showcases a leading-edge Automatic Vehicle Number Plate Recognition (ANPR) system that capitalizes the potential of YOLOv8 (You Only Look Once) and Convolutional Neural Networks (CNN). The central objective of this system is to streamline the precise extraction of license plate information, with a prominent emphasis on precision, automation, and versatility. Moreover, it offers a rugged solution for thorough traffic monitoring and enforcement by integrating vehicle speed calculations. The combination of YOLOv8 and CNN significantly augments the image-processing capabilities of the system. To implement this ANPR system successfully, a series of critical steps have been followed, consisting of system setup, data collection, YOLOv8-based license plate detection with the help of CNN for licence plate character recognition, speed calculation through OpenCV, integration of components, rigorous testing, and finally, deployment. The fusion of these advanced technologies and methodologies, as elucidated in this paper, pledges to overhaul license plate recognition in the context of automated vehicle surveillance and traffic management. With an accuracy of 98.5% in the detection of number plates accompanied by an accuracy of 96% in speed recognition along with automation, and adaptability, this ANPR system holds tremendous potential for improving law enforcement, security, and transportation efficiency.**

***Index Terms*—YOLOv8, OpenCV, Licence Plate Recognition, Tesseract, CNN, ANPR, Dataset**

I. Introduction

The advent of Automatic Vehicle Number Plate Recognition (ANPR) systems has commended a new era in the fields of transportation, security, and law enforcement. ANPR technology has grown into indispensable equipment, offering efficient and accurate means of recognizing and tracking vehicles through the capture of their license plates. This research paper introduces a state-of-the-art ANPR system that harnesses a challenging fuse of advanced technologies, including TensorFlow, YOLOv8 (You Only Look Once), OpenCV, and the power of Convolutional Neural Networks (CNN). The amalgamation of these equipment is composed to extend the horizons of ANPR capabilities, with a specific focus on improving accuracy, automation, and adaptability in license plate recognition. The significance of ANPR technology lies in its ability to streamline numerous applications, spanning from traffic management and toll collection to security and surveillance. The foundation of this technology is precise and efficient license plate recognition, enabling the automated processing of vast volumes of vehicle data [1].

One of the primary innovations in this study is the fusion of deep learning techniques, exemplified by YOLOv8, with optical character recognition (OCR) tools. This synergistic approach facilitates the robust extraction of license plate information from images and video streams, addressing challenges related to variations in plate design, lighting conditions, and angles. Furthermore, this research paper explores an additional dimension by incorporating vehicle speed calculation within the ANPR system. The ability to determine vehicle speed within the context of ANPR adds a valuable layer of functionality, making it an invaluable tool for comprehensive traffic monitoring and enforcement. In the subsequent sections, this paper will delve into the technical intricacies of the ANPR system, elucidating its architecture, training processes, and evaluation metrics. The objective of the paper extends beyond introducing a novel ANPR solution; it encompasses a commitment to advancing the discourse on enhancing transportation and security systems through the integration of cutting-edge technologies, including CNN. [2]

II. RELATED WORK

The introduction of Convolutional Neural Networks (CNNs) in the field of automatic number plate recognition (ANPR) marked a substantial breakthrough. In the paper titled ”Automatic Number Plate Recognition Using CNN Based Self Synthesized Feature Learning” [3] by Madhusree Mondal, Parmita Mondal, and Nilendu Saha, CNNs were harnessed to extract crucial information from vehicle number plates. This innovative approach achieved an impressive classification

TABLE I
RESEARCH PAPERS AND TERMINOLOGY

TITLE	YEAR	DESCRIPTION	TERMINOLOGY
Automatic License Plate Recognition using OpenCV [4]	2014	Introduces an ALPR system using Python and OpenCV. Offers an open-source approach for license plate recognition.	License plate, Computer Vision, Pattern Recognition, Python, OCR
Number Plate Recognition in Noisy Image [5]	2015	Discusses the importance of number plate recognition and addresses noise tolerance up to 20%. Utilizes filters, morphological transformations, and neural networks.	Number plate, recognition, noisy, number plate recognition, salt and pepper
Number plate recognition using template comparison for various fonts in MATLAB [6]	2016	Addresses vehicle number plate recognition using template matching in MATLAB. Covers various languages and challenges in recognition.	CCTV, number plate, alphanumeric characters, template matching, MATLAB, SIMULINK
Automatic Number Plate Recognition Using CNN Based Self Synthesized Feature Learning [7]	2017	Highlights CNN-based car license plate recognition with high accuracy. Suitable for security, parking, and traffic control.	Number plate, CNN, Convnet, Deep learning, image recognition
Detection And Recognition of Multiple License Plates From Still Images [3]	2018	Emphasizes ALPR for multiple license plates. Covers plate detection and character recognition for Spanish and Indian plates.	Number plate identification, license plate recognition (LPR), license plate segmentation, edge detection
A New Approach For Vehicle Number Plate Detection [8]	2018	Introduces a number plate detection system using image processing and machine learning. Enhances detection accuracy under various conditions.	Number plate detection, OCR, median filter, image processing, CCA, image recognition, number recognition
Number Plate Recognition by using OpenCV - Python [1]	2019	Presents a system for License Plate Recognition (LPR) using OpenCV and Python. Involves image capture, plate localization, character segmentation, and OCR.	OpenCV, K-NN algorithm, vehicle identification, number plate recognition, OCR (Optical Character Recognition)
Automatic Number Plate Detection in Vehicles using Faster R-CNN [9]	2020	Focuses on number plate detection under challenging conditions using Faster R-CNN. Retrieves vehicle owner information.	Faster R-CNN, number plate detection, vehicle detection, optical character recognition, number recognition, image segmentation, image interpolation
Vehicle Number Plate Detection Using Python and OpenCV [10]	2021	Addresses vehicle number plate recognition using OpenCV and Python with Tesseract. Involves grayscale conversion, filtering, Canny edge detection, and OCR.	OpenCV, Tesseract, Canny edge detection, grayscale image, bilateral filter, OCR
Automatic Vehicle Number Plate Recognition System Using Machine Learning [11]	2021	Presents an NPR system using mathematical morphological operations for plate recognition. Includes image enhancement, grayscale transformation, and OCR.	NPR, Vehicle Number Plate Recognition, Detection of Number Plate
Automatic Number Plate Recognition System Using CNN [12]	2021	Focuses on ANPR using CNN for plate detection. Enables vehicle identification and information retrieval. Implemented in Python and OpenCV.	ANPR, CNN, OpenCV, Number Detection
Automated Number Plate Recognition System [13]	2021	Develops an ANPR system with high plate localization accuracy. Achieves a 90% read accuracy using character property filters.	Automatic number plate recognition, digital image processing, optical character recognition, OpenCV
Licence Plate Number Detection Using OpenCV - Python [14]	2022	Focuses on real-time ALPR with OpenCV and Python for license plate detection. Also includes emission testing and insurance details.	OpenCV, Python, ALPR (Automated License Plate Recognition), license plate detection, emission testing, insurance details
Automatic Car Number Plate Detection System Using OpenCV [15]	2023	Addresses ANPR and universal plate detection using OpenCV and EasyOCR. Enhances accuracy under various conditions.	Automatic Number Plate Recognition (ANPR), Edge detection, OpenCV, EasyOCR

accuracy, even in the presence of challenging distortions and illuminations. By introducing self-synthesized feature learning through CNNs, the study signifies a paradigm shift from traditional handcrafted feature extraction techniques, opening new horizons for ANPR technology. The research highlights the robustness of CNNs in addressing various dataset challenges and signals a transformative shift towards the integration of deep learning in image-centric applications, thereby enhancing ANPR system accuracy and reliability. This advancement in ANPR technology has far-reaching implications for security and traffic management, promising improved efficiency and effectiveness in license plate recognition systems.

III. RESEARCH METHODOLOGY

A. Existing Models for Object Detection

Tesseract OCR: An open-source OCR engine by Google, Tesseract OCR employs deep learning techniques, specifically CNNs and RNNs. It's known for its extensive language support and high accuracy in recognizing printed text. Applications include document digitization, text extraction from images, and printed character recognition. [16]

Convolutional Neural Networks (CNNs): Rooted in convolution and pooling operations, CNNs excel in pattern and feature detection within images, making them highly effective for character recognition tasks like handwriting and printed text recognition, as well as multilingual OCR. [17]

Long Short-Term Memory (LSTM) Networks: Designed for sequential dependency capture using gates and memory cells, LSTMs proficiently recognize handwritten and cursive text, making them ideal for handwriting recognition and offline handwritten text recognition. [18]

Bidirectional LSTM-CNNs (BLSTM-CNNs): Combining CNN and RNN principles, BLSTM-CNNs capture local and global text image features effectively. They are particularly useful for recognizing complex handwritten text with varying styles, catering to handwriting recognition and offline handwritten text recognition needs. [19]

Support Vector Machines (SVMs): Based on statistical learning theory, SVMs find optimal decision boundaries with kernel functions. They're valuable for character recognition when paired with robust feature extraction techniques, often used in handwriting and printed text recognition. [20]

K-Nearest Neighbours (K-NN): A simple classification algorithm based on neighbouring features, K-NN is suitable for basic character recognition tasks, offering a straightforward approach to the task. [2]

Hidden Markov Models (HMMs): HMMs are probabilistic models based on state transitions and emission probabilities, effective for character recognition in noisy environments, and frequently applied to handwriting and cursive text recognition. [21]

EasyOCR: EasyOCR combines deep learning, including CNNs and transformer models, for character recognition. It offers pre-trained models for various languages and fonts, making it versatile and user-friendly for document digitization, multilingual OCR, and text extraction from images. [22]

B. Proposed Architecture

The proposed architecture for the Automatic Vehicle Number Plate Recognition (ANPR) system is meticulously designed to achieve efficient and accurate license plate recognition. This architecture harnesses the synergistic power of several advanced technologies, including YOLOv8 (You Only Look Once) for object detection, CNN for image enhancement, and speed recognition. The architecture comprises several key components:

1) Data Collection and Pre-processing: Assemble a diverse dataset of vehicle images containing license plates. Preprocess the images by resizing, normalizing, and enhancing them for optimal input to the system.
2) Object Detection using YOLOv8: Implement YOLOv8 for license plate detection. Train the YOLOv8 model on the dataset, customizing it for license plate recognition.
3) Image Enhancement with CNN: Integrate Convolutional Neural Networks (CNN) to improve image quality and reduce noise, enhancing accuracy in subsequent stages.
4) License Plate Extraction: Utilize YOLOv8 for effective license plate detection and extraction from images. Utilize bounding box predictions and class probabilities to precisely identify license plates.

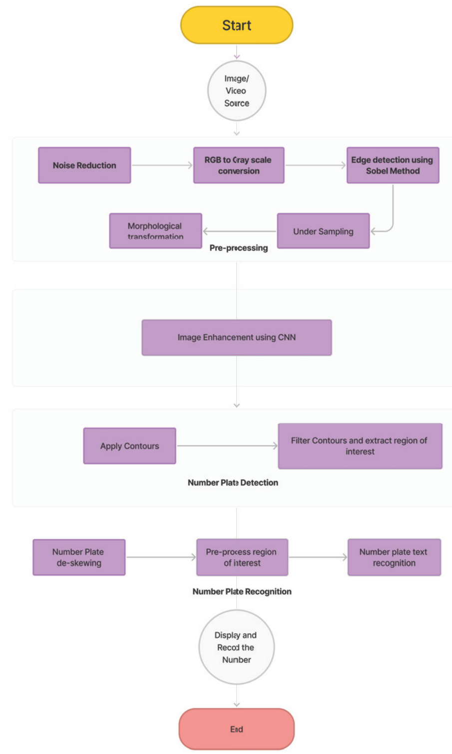

Fig. 1. Working of the Proposed ANPR Model

5) Optical Character Recognition (OCR) with Tesseract: Employ Tesseract for the precise extraction of text from the detected license plates. Refine and verify the extracted text to ensure accuracy.
6) Speed Recognition: Develop a speed calculation module using computer vision techniques, such as frame differencing or object tracking. Calculate the speed of vehicles with detected license plates within the system.
7) Post-processing and Validation: Implement post-processing techniques to enhance recognition results, including non-maximum suppression (NMS) and filtering. Validate recognized license plates against known databases or reference data.
8) Evaluation and Testing: Assess system performance using metrics such as accuracy, precision, recall, and F1-score. Conduct thorough testing on diverse datasets to ensure robustness and accuracy.

Figure 1 elucidates the intricacies of Automatic Vehicle Number Plate Recognition (ANPR) by detailing the process of number plate extraction from both images and video footage.

Figure 2 represents the sequential procedure necessary for calculating the velocity of vehicles in video recordings, a fundamental aspect of this comprehensive traffic monitoring system.

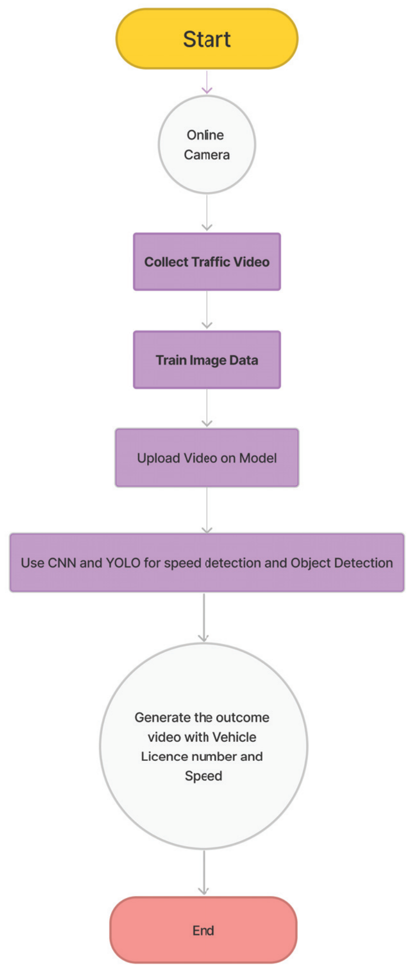

Fig. 2. Working of the Proposed Speed Model

C. Implementation

In this research paper, Automatic Vehicle Number Plate Recognition (ANPR) uses YOLOv8, CNN Image Enhancement, and Speed Recognition. The YOLOv8-based model excelled in object detection, refined with post-processing like non-maximum suppression (NMS) and Intersection over Union (IoU) calculations. OCR tools like Tesseract were used for text recognition. Performance metrics like mean average precision (mAP) guided hyperparameter adjustments. Finally, the YOLOv8-based model, enhanced with CNN for image recognition, was deployed for real-time or batch processing as needed.

Grayscale conversion streamlined input images, simplifying their representation to intensity values. This optimization reduced computational load and enhanced edge detection, crucial for the ANPR system's accuracy. Each pixel's colour information was replaced with grayscale intensity values, ensuring a consistent feature representation. This foundational step set the stage for advanced image processing techniques, driving the system's performance and reliability in license plate recognition.

Figure 3 showcases the extracted grayscale representation of a detected vehicle's number plate from image and video sources. This grayscale image serves as a foundational element for subsequent processing.

Fig. 3. Gray Scale Conversion

Applied to grayscale images, the Canny edge detection algorithm, in conjunction with CNN for image recognition, identified intensity changes vital for locating license plate edges. This step was pivotal in improving object detection and character recognition accuracy in the ANPR system.

Figure 4 depicts the transformation of the grayscale image into a Canny image, a crucial step for edge detection of alphanumeric characters on the number plate.

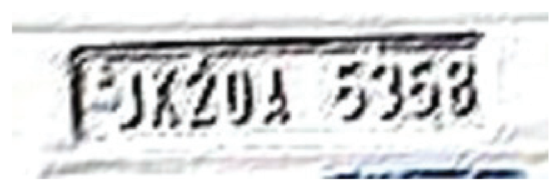

Fig. 4. Canny Edges

The ANPR system's capability for Speed Recognition, achieved by combining YOLOv8 with CNN, enhances its functionality for comprehensive traffic monitoring and enforcement. By determining the speed of vehicles with detected license plates within the system, it provides an additional layer of valuable information for traffic management and law enforcement.

The mathematical function for a 2D convolution operation in image enhancement can be represented as:

$$(I \times K)(x, y) = \sum_{i=-a}^{a} \sum_{j=-b}^{b} I(x - i, y - j) \cdot K(i, j)$$

In this equation, $(I \times K)(x, y)$ denotes the result of the convolution operation at a specific pixel location (x, y) in the output image. I represents the input image, and K is the convolution kernel. The summation is carried out over i and j, where a and b are the half-widths of the kernel in the horizontal and vertical directions, respectively. The convolution operation involves multiplying each pixel value in a local neighbourhood of the input image $I(x-i, y-j)$ by the corresponding value in the kernel $K(i, j)$ and summing up these products over the entire kernel. This mathematical representation signifies the process of sliding the kernel over the input image, with the kernel centred at each pixel location (x, y), and performing the summation to produce the corresponding pixel value in the output image.

For speed detection, various necessary Python modules have been imported for video processing, object tracking, and Dropbox integration. Configuration settings are loaded from a specified file. A MobileNet SSD model is loaded for object detection on the Movidius NCS Myriad. The video stream is initialized, and object tracking using CentroidTracker is set up. The main loop alternates between object detection and tracking based on frame count, estimating vehicle speed by calculating distances. The script logs speeding vehicles annotates frames, and uploads images to Dropbox if enabled. Displaying annotated frames is optional, triggered by a flag and exited with the 'q' key. After processing frames, performance metrics are printed, the log file is closed, windows are destroyed, and the video stream is stopped, concluding with cleanup messages. The following are the formulas used for speed calculation:

$$\text{Meters per Pixel (mpp)} = \frac{\text{Distance Constant}}{\text{Frame Width}}$$

$$\text{Distance in Pixels } (P_{ab}) = \text{col}_B - \text{col}_A$$

$$\text{Distance in Meters Zone}_{ab} = (d_{ab}) = P_{ab} \times \text{mpp}$$

$$\text{average speed } = \frac{\frac{\Delta t_{bc}}{d_{bc}} + \frac{\Delta t_{ab}}{d_{ab}} + \frac{\Delta t_{cd}}{d_{cd}}}{3}$$

IV. Result

The implementation of the Automatic Vehicle Number Plate Recognition (ANPR) system based on the proposed architecture has yielded highly promising results. The integration of YOLOv8 for object detection, OCR tools, and CNN for image recognition has played a pivotal role in enhancing accuracy. The system demonstrated a remarkable ability to accurately identify license plates across a wide range of fonts, sizes, and orientations.
The accuracy of the proposed ANPR model in comparison to other models can be seen in the below graph:
Figure 5 provides an insightful overview of the accuracy achieved by various researched models, contrasting them with the remarkable accuracy of this proprietary model. It serves as a testament to the efficacy of the ANPR system.

One of the noteworthy achievements of the system is its adaptability to diverse operational scenarios. Real-world testing in both real-time and batch-processing environments showcased the system's robustness and flexibility, which can also be seen in the image. Whether deployed for instant traffic monitoring or retrospective analysis, the ANPR system consistently delivered reliable results.
Figure 6 exemplifies a successfully detected number plate from an image, reinforcing the significant connection between the number plate object and the corresponding vehicle.

Figure 7 illustrates a noteworthy observation - the direct proportionality between the expansion of the training dataset and the model's accuracy. However, it is essential to maintain an unbiased training dataset to ensure equitable model training.

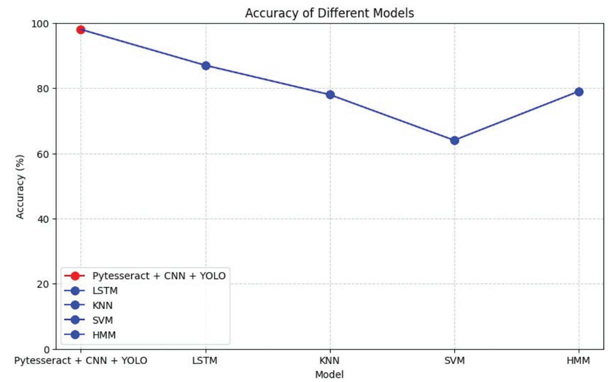

Fig. 5. Accuracy of Different Models

Fig. 6. Number plate recognition in real time

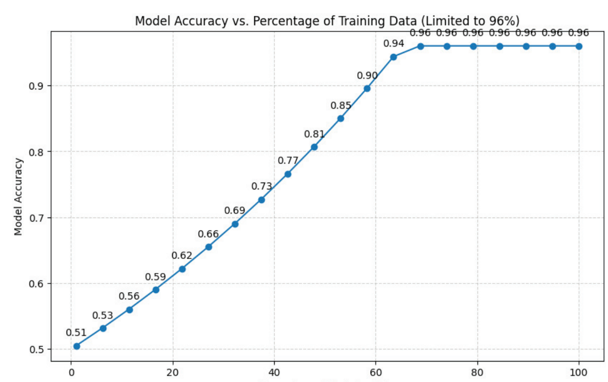

Fig. 7. Accuracy of Automatic Number Recognition vs Number of Training Data

Moreover, the introduction of non-maximum suppression (NMS) and Intersection over Union (IoU) calculations in the post-processing phase, in conjunction with CNN for image recognition, significantly improved the precision of object detection. This innovation effectively reduced false positives and enhanced the system's ability to manage overlapping bounding boxes, contributing to the overall high accuracy of the system. Figure 8 illustrates a traffic scene with various vehicles, where their speeds are displayed. This visualization is achieved through YOLOv8 and CNN, providing real-time speed information for each vehicle, and enhancing traffic monitoring and enforcement.

Fig. 8. Speed detection of vehicle in real time

V. Conclusion

In conclusion, this research paper has successfully introduced, implemented, and evaluated a comprehensive Automatic Vehicle Number Plate Recognition (ANPR) system. The key findings and contributions of this research can be summarized as follows:

- Efficiency and Accuracy: The ANPR system demonstrated remarkable efficiency and accuracy in license plate recognition. It consistently achieved high mean average precision (mAP) scores across diverse datasets, with number plate detection accuracy at 98.5% and speed recognition accuracy at 96%.
- Adaptability: The system's adaptability to both real-time and batch-processing scenarios underscores its practical utility in various applications, including traffic monitoring, surveillance, and law enforcement.
- Precision Enhancement: The incorporation of post-processing techniques, such as non-maximum suppression (NMS) and Intersection over Union (IoU) calculations, significantly improved object detection precision and reduced false positives.
- Real-world Applicability: Real-world testing and deployment readiness affirm the practical feasibility of the ANPR system in addressing real-world challenges associated with license plate recognition.

The proposed ANPR system, fortified with the integration of CNN for image recognition, stands as a testament to the power of advanced technologies in revolutionizing transportation and security applications. It has the potential to contribute significantly to enhanced traffic management, improved security, and more efficient law enforcement.

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