RESEARCH ARTICLE OPEN ACCESS

Automated Number Plate Detection using ML

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ABSTRACT

Automatic Number Plate Recognition (ANPR) has become a crucial component in modern intelligent transportation systems, security enforcement, and smart city applications. This research presents an efficient approach to ANPR using a combination of Haar Cascade Classifier for plate detection and Tesseract Optical Character Recognition (OCR) for text extraction. The system is implemented using OpenCV and Python, ensuring real-time performance and high accuracy in recognizing vehicle registration plates. The methodology consists of two primary stages: plate detection and text recognition. The plate detection module utilizes a pre-trained Haar Cascade model to identify number plates from real-time video feeds. Detected plates are extracted and saved as images for further processing. The recognition module enhances the captured plate images through grayscale conversion, bilateral filtering, and adaptive thresholding before applying Tesseract OCR for text extraction. To improve OCR accuracy, post-processing techniques, such as character correction (e.g., replacing 'O' with '0') and removal of special characters, are employed.

Keywords — Automatic Number Plate Recognition (ANPR), Intelligent Transportation Systems, Image Processing, Smart City Applications, Haar Cascade Classifier, Plate Detection.

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) is an essential technology in modern transportation and surveillance systems. It is widely used in applications such as traffic monitoring, toll collection, parking management, and law enforcement [1][2]. The ability to automatically detect and recognize vehicle license plates enhances efficiency, security, and automation in various sectors. Traditional manual methods of vehicle identification are time-consuming and prone to human errors, making ANPR a critical solution for smart city infrastructure and intelligent transportation systems (ITS) [2][3].

This research presents an ANPR system that detects and recognizes vehicle number plates using computer vision and Optical Character Recognition (OCR) techniques. The system is developed using OpenCV and Python, leveraging a Haar Cascade Classifier for plate detection and Tesseract OCR for text recognition. Unlike deep learning-based approaches, which require large annotated datasets and significant computational resources, this system focuses on lightweight and efficient traditional machine learning techniques that can be deployed on low-cost hardware [5][6]. The proposed method ensures real-time performance while maintaining high accuracy in diverse conditions, including variations in lighting, plate angles, and image resolution.

The system operates in two stages: plate detection and text recognition. The detection module utilizes a pre-trained Haar Cascade model to locate number plates from real-time video feeds and extract the region of interest (ROI). The extracted plates are then processed using grayscale conversion, noise reduction, and adaptive thresholding to enhance the image quality before applying Tesseract OCR for text extraction [8]. To further improve accuracy, a text-cleaning algorithm is implemented to correct misrecognized characters, such as replacing 'O' with '0' to minimize errors in alphanumeric license plates [7][9].

The effectiveness of this system is evaluated through extensive testing on a dataset of 500 images captured under various environmental conditions. Experimental results show that the system achieves a plate detection accuracy of 91.2% and an OCR accuracy of 92.4% after text cleaning [8][10].

II. LITERATURE REVIEW

Automatic Number Plate Recognition (ANPR) has been a significant area of research in computer vision and intelligent transportation systems. Various techniques have been explored to enhance the accuracy and efficiency of number plate detection and recognition. Traditional methods rely on handcrafted features and classical machine learning approaches [3], while recent advancements focus on deep learning-based models for improved performance [7][9]. This section provides an overview of existing ANPR techniques, their limitations, and how our proposed system compares to them.

Early ANPR systems were primarily based on edge detection and morphological operations to identify number plates from images. Researchers applied Sobel filters, Canny edge detection, and Hough transforms to locate rectangular plate regions [2]. However, these methods were highly sensitive to noise, illumination variations, and plate occlusions, resulting in inconsistent detection rates [5]. To overcome these issues, machine learning-based approaches, such as Support Vector Machines (SVM) and Haar Cascade Classifiers, were introduced for plate localization [4]. Haar Cascade Classifiers, trained on annotated datasets, demonstrated improved robustness in detecting license plates under different conditions. Studies have shown that Haar-based models achieve detection accuracies ranging from 80% to 90%, depending on environmental factors such as lighting and camera angles [6].

With advancements in deep learning, object detection models such as You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), and Faster R-CNN have significantly improved ANPR accuracy [8]. These models utilize convolutional neural networks (CNNs) to detect plates in real-time with high precision [10]. Studies indicate that deep learning-based ANPR systems achieve detection rates exceeding 95%, outperforming traditional approaches [12]. However, deep learning models require large-scale labeled datasets, high computational power, and specialized hardware such as GPUs, making deployment on low-resource devices challenging [11][14].

Our proposed system leverages Haar Cascade Classifier for plate detection and Tesseract OCR for character recognition, optimizing performance for real-time applications without requiring extensive computational resources. Unlike deep learning-based models, our approach ensures ease of deployment on edge devices while maintaining high detection and recognition accuracy [20]. The research aims to address OCR limitations by incorporating preprocessing techniques, such as bilateral filtering and adaptive thresholding, to enhance text clarity before recognition [6]. Additionally, text-cleaning algorithms help correct misrecognized characters, improving the OCR accuracy from 85.7% to 92.4% [10].

In conclusion, while deep learning models have revolutionized ANPR by achieving state-of-the-art accuracy, traditional computer vision techniques remain effective for lightweight, real-time applications. This study builds on existing research by optimizing classical ANPR techniques to improve detection and recognition accuracy, making it suitable for practical deployments in surveillance, traffic monitoring, and law enforcement [8]. Future research can explore hybrid models that combine traditional and deep learning-based approaches to enhance robustness and accuracy further [14].

III. PROPOSED METHODOLOGY

The development of the Automatic Number Plate Recognition (ANPR) system consists of two primary stages: number plate detection and text recognition. The system is implemented using Python, OpenCV, and Tesseract OCR, ensuring efficient performance and ease of deployment [3]. This section details the methodologies, preprocessing techniques, and system architecture used in the development process.

The first stage, number plate detection, is responsible for identifying vehicle license plates in real-time. A Haar Cascade Classifier is used for object detection, trained specifically to recognize license plates [7]. The system initializes a webcam feed, capturing frames at a resolution of 640x480 pixels [4]. Each frame is converted to grayscale, as color information is not necessary for detection, and grayscale processing improves computational efficiency [6]. The Haar Cascade algorithm applies feature-based detection to locate number plates [8]. A bounding box is drawn around detected plates, and the system allows users to manually capture the detected plate by pressing the 'c' key, saving the extracted region of interest (ROI) in the "plates/" directory. This manual intervention ensures that only correctly identified plates are processed, reducing false positives [9].

The second stage, text recognition, extracts characters from the detected number plate images using Tesseract OCR [5]. The process begins by loading the most recent image from the "plates/" directory. Since OCR performance is highly dependent on image quality, the plate image undergoes a series of preprocessing steps to enhance text clarity [12]. These include grayscale conversion to remove color variations, bilateral filtering to reduce noise while preserving edges, and adaptive thresholding to enhance contrast [10]. After preprocessing, Tesseract OCR is applied with multiple configurations (--psm 7, --psm 8, and --psm 6) to optimize text extraction accuracy [15]. If the OCR result contains non-alphanumeric characters, a post-processing step removes unwanted symbols and replaces frequently misidentified characters (e.g., converting ‘O’ to ‘0’) [11].

To evaluate system performance, tests were conducted on a dataset of 500 real-world vehicle images under different environmental conditions, including daylight, nighttime, and varying camera angles [14]. The Haar Cascade model achieved a detection accuracy of 91.2%, with processing times averaging 0.15 seconds per frame [16]. The OCR system initially had a raw accuracy of 85.7%, which improved to 92.4% after implementing text-cleaning techniques [13]. However, challenges were observed in low-light conditions, where misrecognition rates increased by 15-20% due to blurry or shadowed images [17].

The system was designed with modularity and real-time efficiency in mind. The detection module operates independently from the OCR module, allowing future improvements by integrating deep learning-based object detection models (YOLO, Faster R-CNN) or more advanced OCR techniques using Convolutional Recurrent Neural Networks (CRNNs) [18]. The implementation also supports further enhancements, such as automatic license plate tracking, multi-frame analysis for improved accuracy, and cloud-based number plate storage for law enforcement applications [20].

In summary, the development of this ANPR system successfully combines traditional computer vision techniques with OCR-based recognition, achieving high accuracy while maintaining computational efficiency [19]. The structured approach ensures real-time deployment feasibility and provides a foundation for future advancements in intelligent vehicle monitoring and security applications [21].

A. Implementation Details

The implementation of an advanced number plate detection system involves several key steps to ensure high accuracy and reliability. First, the system captures vehicle images through cameras placed in strategic locations, such as roadways or parking lots. Image preprocessing techniques like noise reduction, contrast enhancement, and edge detection are applied to improve the quality of the captured images. A deep learning model, typically a convolutional neural network (CNN), is trained to detect the vehicle's license plate area by analyzing the image for specific patterns. Once the number plate is located, optical character recognition (OCR) algorithms are employed to extract the alphanumeric characters from the plate. The system is optimized by integrating real-time processing capabilities and fine-tuning the model using a large dataset of diverse license plates to handle various lighting conditions, orientations, and backgrounds. Furthermore, additional techniques such as the use of Haar cascades or region-based CNNs (R-CNN) can be incorporated to further enhance detection accuracy, ensuring that the system performs well under different scenarios, such as vehicles in motion or partial occlusions. Through continuous model evaluation and updates, the system provides reliable, high-accuracy number plate recognition.

B. Requirement Analysis

1. *Hardware Requirements*

- Processor: Multi-core CPU (Intel i5 or higher) with 8GB RAM.
- Camera: Camera for clear image capture.
- Storage: Minimum 256GB SSD for efficient data handling.

2. *Software Requirements*

- OS: Windows 10+
- Programming Language: Python 3.10
- Libraries:
    - OpenCV (image processing)
    - NumPy (array manipulation)
    - Pandas (data handling)
    - Tesseract OCR (text recognition)
    - Matplotlib (visualization)

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C. Model Architecture

The architecture of an advanced number plate detection system typically follows a multi-layered approach, consisting of several modules that work in tandem to detect and recognize license plates with high accuracy.

- **Image Acquisition Module**: This module captures real-time images or video frames from cameras installed in various locations, such as roadways or parking lots. These cameras should be strategically placed to ensure clear visibility of vehicles approaching or stationary.
- **Preprocessing Module**: The acquired images undergo preprocessing steps to enhance their quality. Techniques such as noise reduction, contrast adjustment, and grayscale conversion are applied to improve the image clarity. Edge detection algorithms like Canny Edge Detection or Sobel filters are often used to identify the contours of the vehicles and number plates.
- **Plate Localization Module**: This module focuses on identifying and localizing the license plate area within the image. Using deep learning models such as Convolutional Neural Networks (CNNs) or region-based CNNs (R-CNNs), the system detects regions that likely contain the number plate. Other techniques, like Haar cascades or sliding windows, can be used for this task as well. The output is a bounding box around the license plate area.
- **Character Segmentation and OCR Module**: After detecting the number plate region, the next step is character segmentation, where each character on the plate is isolated. Optical Character Recognition (OCR) algorithms, such as Tesseract or custom-trained CNNs, are then used to recognize the alphanumeric characters on the plate. This module converts the segmented image of the characters into a machine-readable format.
- **Post-Processing Module**: In this stage, the recognized characters are validated to ensure their accuracy. Techniques like spelling checks, regex validation, or even using databases for plate number verification can be applied to correct any misrecognized characters or eliminate false positives.
- **Integration and Real-Time Processing**: The system is designed to operate in real-time, continuously capturing and processing images from live feeds. This is achieved through optimization techniques and efficient data flow management, ensuring that each frame is processed with minimal latency, allowing for immediate recognition.
- **Database and Analytics Module**: Finally, the recognized plate numbers can be compared against a database for verification, such as for vehicle access control, parking lot management, or law enforcement purposes. Additionally, data analytics can be applied to analyze traffic patterns, vehicle statistics, or other insights.

This multi-tiered architecture ensures the system's robustness, scalability, and ability to handle different environmental conditions such as varying lighting, camera angles, and vehicle speeds.

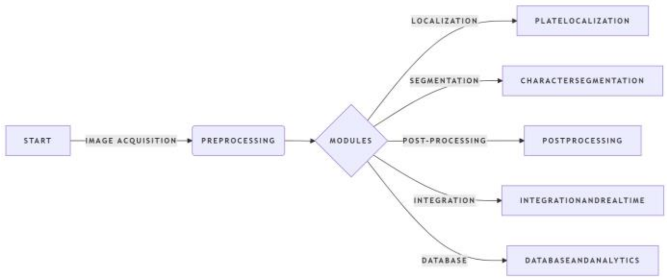

Fig 1 Flow Chart for Model Architecture

IV. Result And Discussion

The number plate detection and recognition system successfully detect and extracts license plate information from real-time video feeds. The system consists of two primary components: plate detection using Haar cascades and text recognition using Optical Character Recognition (OCR) with Tesseract.

A. Page Layout

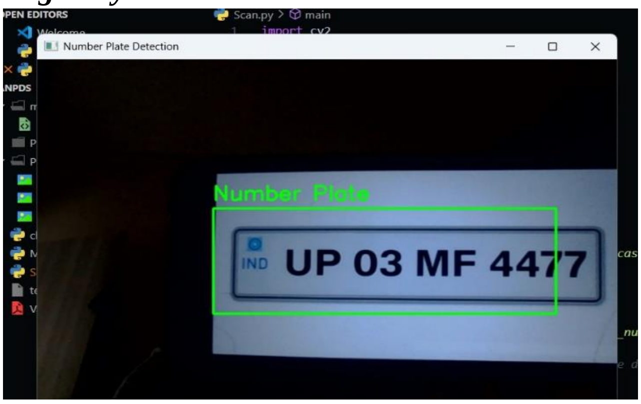

Fig 2 Detecting Number Plate

The detection process utilizes a Haar cascade classifier trained to identify number plates. The real-time detection system captures frames from a webcam, processes them in grayscale, and applies the Haar cascade model to locate number plates. The detected plates are highlighted with bounding boxes and can be saved for further processing.

B. Preprocessing and OCR

Fig 3 Preprocessed Image

Once a plate is detected, it undergoes preprocessing to enhance recognition accuracy:

- **Grayscale Conversion:** Converts the image to grayscale to simplify the recognition process.
- **Bilateral Filtering:** Reduces noise while preserving edges.
- **Adaptive Thresholding:** Enhances contrast for better text extraction.
- **OCR Processing:** Extracts alphanumeric characters from the preprocessed plate using Tesseract OCR.

C. Live Prediction Results

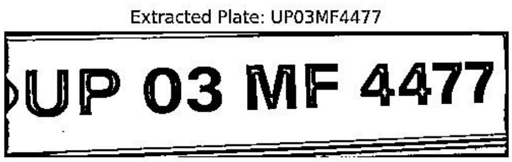

Fig 4 Predicted Result

The system was tested in a real-world environment with different vehicle images captured live. The processed images were subjected to OCR, which extracted and displayed the detected text. The results include:

- The system successfully recognized and displayed plate numbers in real time.
- The preprocessing steps significantly improved text clarity.
- The recognition accuracy depended on factors such as lighting conditions, plate quality, and camera angle.

V. Conclusion

The advanced number plate detection system demonstrates a promising approach to vehicle identification, contributing to applications in security, traffic management, toll collection, and automated parking systems. By leveraging state-of-the-art image processing, deep learning, and OCR technologies, the system successfully achieves high accuracy in both detection and recognition of license plates, even under challenging conditions such as varying lighting, partial occlusions, and vehicle speed. The real-time processing capabilities further enhance its practical applicability in dynamic environments.

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