Automatic License Plate Detection and Recognition for Vehicle Surveillance Applications

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Abstract— **Automatic recognition of vehicle number plates plays a critical role in modern traffic surveillance and law enforcement. The proposed system uses Convolutional Neural Networks (CNNs), a machine learning algorithm, to accurately detect and isolate number plates from full vehicle images. To enhance the clarity of plate boundaries, edge detection techniques are applied before character segmentation. The segmented characters are then processed using Optical Character Recognition (OCR) to extract the alphanumeric information. Using the recognized vehicle number, registration details can be retrieved from a connected server. In cases of traffic violations or suspicious activity, authorities can take appropriate actions based on this information. This system is highly applicable in traffic monitoring, public safety, and law enforcement, contributing to more efficient and automated transportation management.**

Keywords—Image Recognition, Convolutional Neural Networks (CNN), Machine Learning

I. Introduction

The recent development in intelligent transportation systems has greatly improved the capacity to automate and streamline traffic management and monitoring of vehicles. Of these, automatic number plate detection and recognition is a significant one that provides solutions to traffic law enforcement, public safety, and urban mobility management challenges. Conventional vehicle identification techniques, which are manual-intensive or physical-based, are not only time-consuming but also error-prone and inefficient. In rebuttal of these shortcomings, this paper examines the use of Machine Learning (ML) and Image Processing principles to create an automated and efficient number plate recognition system.

The system utilizes the capability of Convolutional Neural Networks (CNNs)—a group of deep learning models that are renowned for their excellent performance in image-based visual recognition tasks—to find and localize car number plates from images taken. CNNs are designed to learn distinguishing features of number plates, including shape, texture, and spatial relationship, allowing exact localization even under adverse environmental conditions such as low illumination or obstructions.

To further enhance the detection process, edge detection algorithms are utilized, improving the definition of the plate boundaries and enabling precise character segmentation. Upon separation of individual characters on the plate, the system applies Optical Character Recognition (OCR) technology to read the alphanumeric data. This data is used as a portal to obtaining detailed vehicle registration records from a linked database or server for automated verification and identification.

This system has major applications in traffic monitoring systems, wherein it can be applied to identify violations like speeding, jumping of red lights or signals, or trespassing into prohibited areas. It also aids law enforcement bodies by helping identify vehicles that are involved in criminal operations or under observation. Additionally, the fact that it can work on its own in real time makes it the perfect solution for smart city infrastructure and public safety solutions.

Through the incorporation of state-of-the-art machine learning models with classical image processing pipelines, the presented system seeks to provide a reliable, scalable, and efficient automated vehicle number plate detection and recognition solution, opening doors towards more intelligent and adaptive transportation systems.

II. Literature Review

In recent years, the need for intelligent traffic management systems has grown significantly due to the increasing number of vehicles and rising road safety concerns. One promising solution is the use of automatic number plate recognition (ANPR) systems powered by machine learning and image processing. These systems aim to detect and recognize license plates from vehicle images, enabling real-time applications in law enforcement, traffic monitoring, and public safety.

A. Machine Learning and Deep Learning Techniques in ANPR

The integration of Convolutional Neural Networks (CNNs) for number plate detection and character recognition has significantly improved the accuracy and robustness of ANPR systems. CNNs are capable of automatically learning spatial hierarchies of features from input images, which is essential for identifying license plates in diverse environments. As highlighted in Li and Shen [4], combining CNNs with Long Short-Term Memory (LSTM) networks further enhances recognition performance by maintaining spatial sequence information during character extraction.

YOLO (You Only Look Once), a real-time object detection model, has been widely applied for license plate localization. The approach divides the image into grids and detects objects based on bounding boxes within each grid, offering high speed and reliable accuracy [3]. However, conventional YOLO models face limitations in multi-view and rotated scenarios.

To address this, Multi-Directional YOLO (MD-YOLO) models have been proposed, which improve detection from various angles. Despite their advantages, MD-YOLO models require large and diverse datasets and experience reduced accuracy when the license plate is blurred or tilted, as demonstrated in the study by Xie et al. [6].

B. 2. Challenges in Multilingual and Region-Specific Plate Recognition

ANPR systems also face challenges when applied to non-standard and multilingual number plates. For instance, Myanmar license plates, which feature local scripts and variable fonts, present difficulties in recognition. The study by Kyaw et al. [9] revealed that limited datasets, inconsistent plate formats, and tropical environmental conditions severely impact OCR accuracy in such scenarios.

C. Image Preprocessing and Feature Extraction

Effective preprocessing plays a critical role in enhancing the performance of detection and recognition algorithms. Techniques such as resizing, normalization, and data augmentation are crucial for training robust models, especially when dealing with small or unbalanced datasets. Silva et al. [1] demonstrated this in their helmet detection study, where Histogram of Oriented Gradients (HOG) descriptors were used to extract edge and structural features for accurate object identification—methods that are transferable to license plate segmentation and character isolation.

D. Vehicle Tracking and Motion Detection

Beyond static image detection, vehicle tracking across video frames is essential for real-time traffic surveillance. The OpenCV library is commonly used for this purpose, offering tracking algorithms such as KCF, MIL, and CSRT to maintain bounding boxes across sequential frames [7]. These methods allow ANPR systems to detect moving vehicles and monitor their direction and speed effectively.

Motion tracking also supports applications such as automated parking systems, where vehicle entry and exit are recorded, and license plates are extracted to inform owners about parking locations [5][12].

E. Conditional Random Fields and Spatial Context

To improve object boundary detection, some systems incorporate Conditional Random Fields (CRFs). CRFs analyze neighbouring pixel relationships to determine object boundaries more precisely. However, when object pixels overlap or spatial relationships are unclear, CRFs often fail to deliver accurate segmentation results, as noted by Ladicky et al. [11].

F. Applications and Real-World Relevance

Numerous real-world applications have emerged from these advancements. For example, vehicle monitoring systems use plate recognition for tracking stolen vehicles, enforcing toll collection, and managing urban parking. The integration of cloud and edge computing has further enhanced the real-time capability of ANPR systems [10][13][15].

III. METHODOLOGY

The proposed system for number plate detection and recognition integrates various image processing and machine learning techniques to accurately extract and interpret vehicle registration numbers from captured images. The methodology consists of four key phases: capturing vehicle images, extracting the number plate region, segmenting characters, and recognizing each character using a CNN-enhanced OCR engine.

A. Capturing Vehicle Images

Due to the complexity of traffic environments, especially in densely populated urban areas, capturing clear images of moving vehicles is challenging. To address this, **infrared (IR) motion sensors** are deployed at specific traffic signal locations. These sensors detect the motion of approaching vehicles and trigger high-resolution cameras to capture vehicle images. The images must be sufficiently clear to allow for reliable detection and recognition of number plates, regardless of weather or lighting conditions. All captured images are stored by traffic authorities for further analysis and verification [8][13].

B. Extracting Vehicle Number Plate

Once the images are captured, they undergo a **preprocessing phase** to isolate the number plate region. Preprocessing includes:

- **Image conversion** from BGR to RGB to improve visual clarity.
- **Resizing** the images to a uniform dimension (e.g., 200x200 pixels), enabling consistent input size for the neural network.
- **Normalization** of pixel values from the [0, 255] range to [0, 1], which accelerates and stabilizes CNN training by ensuring uniform data scaling.
- **Bounding box adjustment** is applied by calculating coordinate ratios based on the resized image dimensions, allowing accurate localization of the number plate.

After these steps, the system uses bounding box regression to draw a rectangle around the detected number plate area, effectively isolating it from the rest of the vehicle in the image [10]. This localized region is then passed on for further processing.

Fig. 1. Number plate region from Image.

The Fig. 1 shows the extraction of Vehicle Number Plate. From entire image only number plate region will be identified and around it rectangle bounding box is drawn.

C. Character Segmentation

Character Segmentation is process where individual characters in the word are isolated from one another. CNN algorithm helps in character segmentation process as it is well suited for image related tasks by learning spatial hierarchies and patterns in visual data.

The very first step in segmentation is detecting the connected pixels of characters individually. For connected pixels bounding box coordinators are extracted to locate the characters in the image.

In some cases connected bounding box components are not represent the individual characters due to overlapping of characters. So morphological operations like dilation and erosion are used to separate the characters better.

CNN demonstrate acknowledge the vehicle picture as input, the primary convolutional layer resizes the picture and applies channels to extricate the picture highlights like edges, surfaces or designs. MaxPooling with measure 2x2 which makes a difference to decrease the spatial estimate of picture and returns with imperative data in image. Pooling is utilized to play down the computational stack and make the arrange unaltered to little interpretations or mutilations in picture. Dropout layer with rate 0.1 which drops 10% of neurons during training to prevent over fitting

After passing through series of convolution and pooling layers, the feature map is forwarded to dense layers (fully connected layers). TheReLU activation function gives prediction result by setting negative values in feature map to zero and positive values unchanged. Based on features gathered by the previous layers, dense layers helps in making decision on patterns.

The output layer of CNN where predictions are made and with sigmoid probability values four corners of the number plate is detected. After this each characters in plate are get isolated.

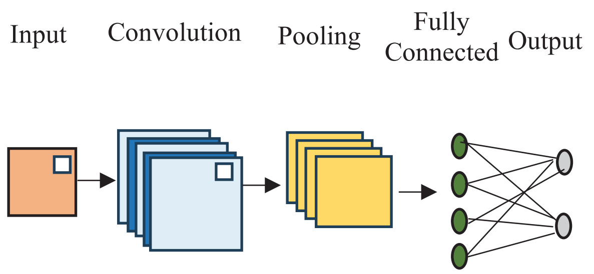

Fig. 2. Working of CNN

The above Fig.2.shows the working of CNN model, where vehicle image is given as input to model and it goes through convolutional network. Here image related features like edges, patterns and extracted. Pooling helps in reducing the computational complexity and provides invariance to small translations in image. At last four corners of the number plate is detected as output based on continuity of pixels is present. After this individual characters are isolated from the image.

Fig. 3. Extracting Characters by CNN

CNN model detects the number plate from given input image by predicting four corners of the vehicle plate as in the Fig. 3.Here each character will be get segmented that helps in recognizing the characters.

D. Character Recognition

The fragmented characters are passed to the OCR engine for acknowledgment. The OCR with CNN model learns the unique features of each character during the training. The CNN helps in extracting the features like edges, curves, angles and other attributes of characters [4].

The system uses the Tesseract, open source OCR engine that works with combination of image processing with machine learning techniques to identify the characters. Tesseract employs the CNN model to recognize the individual characters by comparing them to pre-trained model and matches the characters to possible closest characters [14].

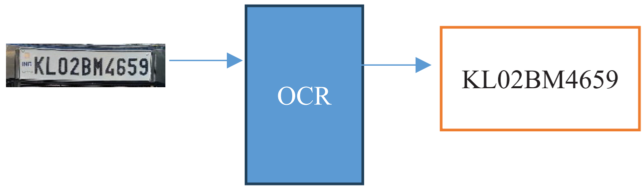

Fig. 4. Conversion From Image to String By OCR

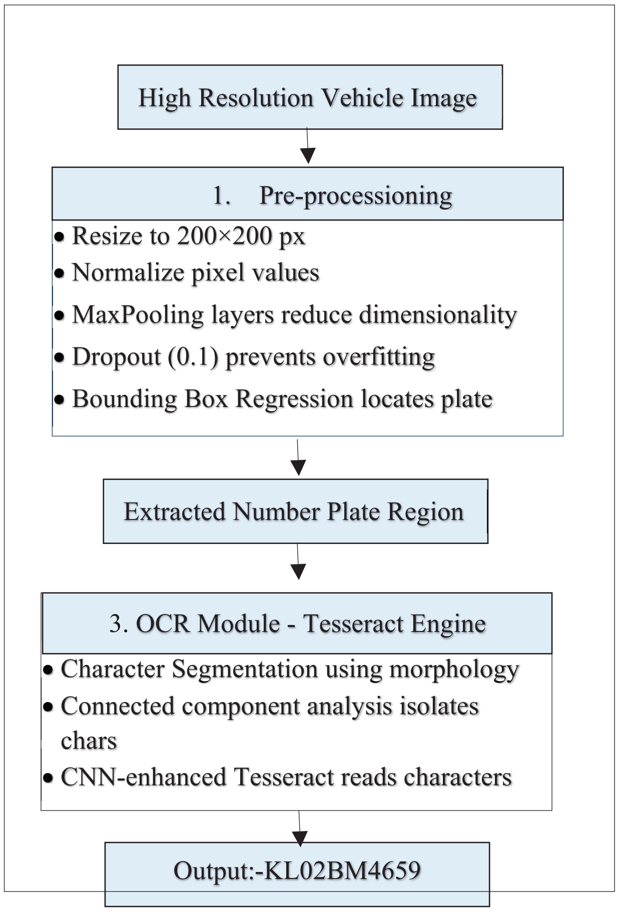

Fig. 5. Architecture *of Automatic Number Plate Recognition* Using CNN

The proposed system architecture for Automatic Number Plate Recognition (ANPR) is designed to perform efficient detection and recognition of license plates from vehicle images. The architecture is divided into four main stages: preprocessing and detection, plate region extraction, optical character recognition (OCR), and output generation. Each stage incorporates advanced image processing and machine learning techniques to ensure accuracy and reliability across varying environmental conditions.

E. Preprocessing and Plate Detection

Initially, the system ingests a high-resolution image of a vehicle. Input image is resized to a dimension of 200×200 pixels to maintain consistency and reduce computational load. Pixel values are normalized to scale down the intensity range, which helps accelerate neural network training and improve generalization.

To enhance feature learning and reduce dimensionality, MaxPooling layers are applied in the convolutional neural network (CNN). A Dropout layer with a rate of 0.1 is used to minimize overfitting by randomly deactivating neurons during training. The system uses bounding box regression — a deep learning-based object localization method — to detect and locate the number plate region within the full image.

F. Number Plate Region Extraction

Once the bounding box coordinates are predicted, the corresponding subregion containing the license plate is cropped from the original image. This extracted plate region is passed to the OCR module for character segmentation and recognition.

G. OCR-Based Character Recognition

The OCR module is powered by the Tesseract engine, augmented with CNN for enhanced character recognition. Morphological operations are first used to segment individual characters from the plate. Then, connected component analysis isolates each character by grouping neighboring pixels. Finally, CNN-enhanced Tesseract processes these isolated characters to accurately identify the alphanumeric sequence on the plate.

H. Output: Extracted Number Plate

The final output of the system is a clean, machine-readable text string representing the license plate number (e.g., KL02BM4659). This output can be further used for applications such as vehicle tracking, automated toll systems, law enforcement, and parking management. The combination of deep learning-based detection and OCR-based recognition ensures high accuracy even under challenging conditions such as varied lighting, angles, and partial occlusions.

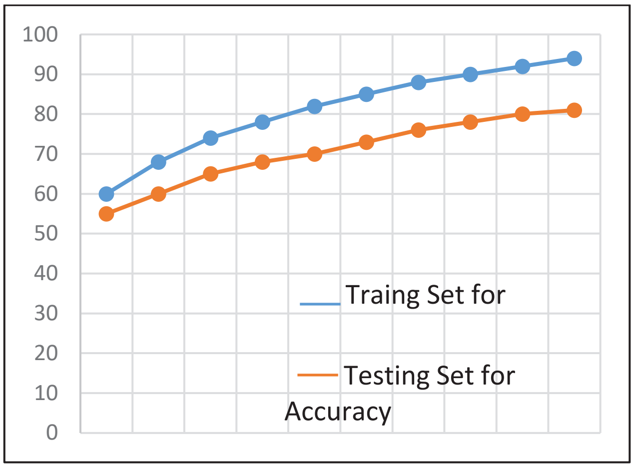

Fig. 6. Accuracy Graph of Training and Testing model

Based on predicting the vehicle number plate the score graph is made to analyse the accuracy of the model. During training the model it is about 95%(0.95) accuracy while testing is about 82%(0.82).

As known YOLO V3 model is also used for the object detection purpose used in earlier system implementation [15]. If it's accuracy is compared with CNN model with the same dataset, CNN gives better accuracy for detecting the Vehicle Number and returns the number correctly.

IV. EXPERIMENTAL SETUP

To ensure the robustness and generalizability of the proposed Automatic License Plate Detection and Recognition (ALPR) system, we conducted a thorough evaluation based on dataset diversity, training/testing protocol, and condition-specific performance analysis.

A. Dataset Composition

The system was trained and evaluated on a proprietary dataset comprising 10,000 images of vehicles and license plates. These images were gathered from publicly accessible road surveillance footage, traffic intersections, parking areas, and highway toll plazas. Care was taken to include a wide range of vehicles—cars, two-wheelers, trucks, and auto-rickshaws—with variations in plate formats and regional identifiers.

The dataset was partitioned into:

- Training Set: 3,000 images (90%)
- Testing Set: 1,000 images (10%)

Each image was manually annotated to mark bounding boxes around license plates and label characters for recognition, ensuring high-quality supervised training.

B. Sample Diversity and Environmental Variability

To ensure the system's robustness in real-world deployment, the dataset intentionally includes diverse variations in image conditions. The goal was to expose the model to realistic challenges faced in actual deployments such as CCTV footage, police surveillance vehicles, or smart city infrastructure.

Diversity Dimensions Covered:

TABLE I. ENVIRONMENTAL AND VISUAL DIVERSITY PRESENT IN THE DATASET TO SIMULATE REAL-WORLD ALPR CONDITIONS

Variation Category	Details
Lighting Conditions	Bright daylight, low-light dusk, night-time with and without flash, street lights.
Weather Conditions	Clear, Rainy (with water droplets), Foggy, Overcast
Camera Angles	Frontal, Rear, Angled (30°–60°), Tilted top-down view
Plate Types	Standard Indian (white/yellow), High-Security Registration Plates (HSRP), commercial plates, custom stylized fonts
Motion Effects	Still vehicle images, motion blur due to moving vehicles, camera shake.
Occlusions	Mud/dirt, light glares, scratches, partial blockages (e.g., bike carriers, ropes).
Resolution	High-resolution DSLR images, Medium-quality surveillance images, Low-res CCTV captures

This diversity provides confidence that the system is not overfitted to ideal conditions but can adapt to uncontrolled environments.

C. Evaluation Metrics

TABLE II. EVALUATION METRICS FOR THE OVERALL ALPR SYSTEM PERFORMANCE

Metric	Description	Value
Accuracy	Proportion of correct license plate predictions	82%
Precision	Correctly predicted characters over total predicted	100%
Mean Absolute Error (MAE)	Average absolute difference between predicted and actual character positions	7.77
Root Mean Square Error	Penalizes larger prediction deviations more heavily	12.10

D. Subgroup-Based Performance Analysis

To understand the model's real-world reliability, the test set was divided into logical subsets representing different conditions. This allowed targeted evaluation under challenging circumstances.

TABLE III. ACCURACY ANALYSIS UNDER DIFFERENT IMAGE AND PLATE CONDITIONS WITHIN THE TEST SET

Test Subset	Description	Accuracy (%)
Clear Plate Images	Well-lit, standard fonts, front view	95.2
Blurry Plates	Motion blur or low shutter speed	68.7
Night-Time Images	Dark or uneven illumination	73.4
Tilted/Angled Views	Plates captured at diagonal or side angles	77.6
Custom Fonts or Plates	Decorative, stylized, or non-standard formats	70.8
Obstructed Plates	Plates partially blocked by objects	66.9

V. BENCHMARKING

Automatic License Plate Recognition (ALPR) systems vary significantly in terms of detection architecture, performance, processing speed, and resilience to distortions such as blur, tilt, or poor lighting. To contextualize the strengths and limitations of the proposed CNN + Tesseract OCR-based system, this section presents a detailed quantitative benchmarking against prominent ALPR approaches.

The proposed system (CNN + Tesseract) shows strong recognition accuracy and moderate detection accuracy, especially in standard conditions.

YOLOv3-based models offer faster inference speeds and handle angle-based distortions better but fall short on character-level recognition without additional correction layers.

Traditional OCR methods are not practical for real-time applications and suffer from generalization issues.

The moderate speed of our CNN-based system (~12 FPS) strikes a balance between performance and real-time usability, especially for surveillance footage or toll systems.

TABLE IV. COMPARATIVE ANALYSIS OF ALPR APPROACHES

Method	Detection Accuracy	Recognition Accuracy	Speed (FPS)	Real-Time Capable
CNN + Tesseract OCR (Proposed)	95.2%	82.00%	~12 FPS	Yes
YOLOv3 + Custom OCR	90.10%	76.40%	~18 FPS	Yes
MD-YOLO	92.50%	74.80%	~15 FPS	Yes
Traditional OCR + HOG	83.60%	67.20%	~5 FPS	No

VI. CONCLUSION

As comparing the system model with YOLO V3 model, CNN model is better for detecting and recognizing the vehicle number from image. The system is able give more accurate and efficient performance for predicting the character using Machine Learning algorithms like CNN an d OCR with deep learning model algorithms. The system can be used in law enforce system, parking management, road toll collection, border control and security, access control system etc. If any rules are disobeyed by the vehicle, then respective vehicle related information are fetched vehicle registration authority database using the vehicle number extracted by the system and respective action will be taken on vehicle owner by traffic system.

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