Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 09 Issue 01
2025
Research Article
https://doi.org/10.56979/901/2025

Deep Learning-Based Vehicle Number Plate Recognition in Smoggy Environments with Image Enhancement

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Received: April 13, 2025 **Accepted:** May 26, 2025

Abstract: The vehicles on road is increasing quickly due to the ongoing industrial revolution and the quick development of technology. Along with the rise in motor vehicles, there has also been a rise in traffic infractions, which can sometimes be a contributing factor to criminal activity. Existing surveillance systems are seriously threatened by these issues. This study's objective is improve existing surveillance by implementing reliable method for automatic license plate recognition. In order to standardize input data and enhance model generalization, the research presents a strong method for automatic car license plate recognition and identification. Preprocessing and data augmentation are highlighted. Picture scaling to provide consistent dimensions, pixel value normalization for efficient model convergence, and other preprocessing methods like contour detection and adapted thresholding for precise plate localization and character segmentation are important steps. Based on empirical results, the model is able to obtain an 86.30% validation accuracy with batch size 128 and demonstrates that model has excellent learning capabilities and performs well when applied to new data. The recommended system, which uses deep learning architecture with advanced preprocessing techniques, provides an effective complete solution for detecting and recognizing automobile license plates. The remarkable degree of precision attained throughout prolonged testing proves its practical viability, opening the path for future advances in autonomous vehicle tracking and traffic control systems.

Keywords: K-Nearest Neighbor; Neural Network; Deep Learning; Data Analysis; GST; CL

1. Introduction

Rapid development and population expansion in recent decades have resulted in a large increase in automobile ownership, which has led to an increase in road-related criminal activity. The increase in vehicle traffic has produced an urgent demand for License Plate Recognition (LPR) systems, which employ image processing techniques to extract alphanumeric letters from license plates. These systems are crucial for applications including transportation networks, traffic control, and security [1]. Despite technical developments, detecting license plates remains difficult owing to factors such as poor picture quality, changing lighting conditions, weather impacts, and varied typefaces and camera capabilities. Manual traffic control has proven problematic in metropolitan places as the number of cars has increased. Automatic License Plate Recognition (ALR) systems have grown more important, with applications ranging from ticketing and speed prediction to surveillance and self-driving automobiles. ALR systems use massive surveillance networks to follow cars and collect information such as license plate numbers. However, the efficiency of LPR systems is strongly reliant on image quality, which is influenced by environmental conditions such as light, weather, and camera angle [2].

Edge-based methods, color-based techniques, texture analysis, and hybrid deep learning models are all now used for detecting car plates. However, more sophisticated image processing and machine learning approaches are required to increase the accuracy of these systems. AVNPRS (Automatic Vehicle Number Plate Recognition System) uses Optical Character Recognition (OCR) to analyze license plate data and is commonly used in traffic control, parking management, and law enforcement. The system's performance is impacted by a variety of elements, including picture capturing circumstances, illumination, and plate deformations, particularly in outdoor settings. Despite continued study, obstacles in reliable plate identification persist [3].

Despite technological advancements, license plate recognition remains a complex task due to various challenges, like low image resolution, inconsistent lighting conditions, reflections, adverse weather, and variations in font styles. These factors significantly influence the overall accuracy and processing speed of the recognition systems. To address these issues, researchers explored multiple approaches for enhance the performance, reliability of license plate detection technologies [4].

2. Literature Review

The integration of CNNs and YOLO V3 model significantly enhances identification of the Regions of Interest ROI, leading to improved Optical Character Recognition (OCR) accuracy [4]. The proposed method involves several key stages: image segmentation for data augmentation, the use of CNNs for character recognition, YOLO V3 for precise region detection, and Wiener filtering to reduce image blur. A curated dataset of 6,439 images featuring alphanumeric characters in Indian Number Plate Font utilized optimize CNN model's performance and compatibility.

Similarly, conducted an extensive study employing various image processing techniques across different phases of license plate recognition—such as image acquisition, region detection, character segmentation, and database comparison. Their research explores multiple strategies for building efficient and reliable license plate recognition systems, particularly suited for dynamic environments like moving vehicles and automated surveillance, eliminating the need for human intervention [5].

The introduced a smart digital toll management system designed to streamline toll collection and systematically manage both driver and vehicle data. Complementing this, Mir, Md Nazmul Hossain (2021) evaluated Automatic Number Plate Recognition (ANPR) systems to enhance the development of intelligent toll infrastructures. Meanwhile, Laroca et al. (2019) identified common challenges in ANPR systems, including poor camera quality, complex environmental conditions, and damaged license plates. They advocate integrating ANPR with advanced technologies like the IoT and Radio-Frequency Identification (RFID) to enhance accuracy plus efficiency [6].

Further, a report that Indian government has endorsed use YOLOv3 model to automatic vehicle identification at toll booths and in urban areas, contributing significantly to the advancement of intelligent transportation systems [7].

The emphasized the use of digital cameras combined with advanced algorithms—particularly CNNs—for character recognition and image enhancement in license plate reader technologies. Additionally, focused on a machine learning-based approach to automatic towing management. Their method includes defining bounding boxes for alphanumeric characters, converting these regions to grayscale images using the K-Nearest Neighbors (KNN) algorithm for the accurately detect license number plates [8].

3. Proposed Methodology

The purposed methodology describe in Fig 1.

3.1. Data collection

"Foggy License Plates Worldwide" collection seeks to improve vehicle number plate identification in low visibility environments such as fog and smog. The dataset, obtained from, https://data.mendeley.com/datasets/rgpddwxrx5/1 is an invaluable resource for creating deep learning models and picture enhancement techniques. The Monodepth2 Network simulates fog using monocular depth estimation, allowing models to be trained and evaluated under unfavorable circumstances that mimic real-world settings. The collection contains 433 photos of automobiles in different real-world scenarios. Each picture has PASCAL VOC bounding box annotations for vehicle number plates.

A portion of the collection concentrates on English license plates, and photos are titled sequentially with the prefix "Cars" followed by a numerical identification. The dataset's diversity and annotation richness make it perfect for developing algorithms that can handle the complexity of real-world license plate identification.

3.2. CNN model for training

The CNN built in Keras is proposed to perform classification tasks such as identifying characters and objects in pictures. The sequential model structure allows for easy layer-by-layer construction, maintaining flexibility throughout the model's growth. Model Foundation: Model initialization entails removing prior sessions, especially in iterative settings like Jupyter Notebooks, to assure a fresh start. Convolutional layers are crucial to the CNN and allow the model to learn spatial hierarchies of information. The model starts by recognizing broad traits with bigger kernels, then refines them with smaller kernels. Equation (1) defines the convolution process, which retains the original input size with a stride of 1 and "same" padding.

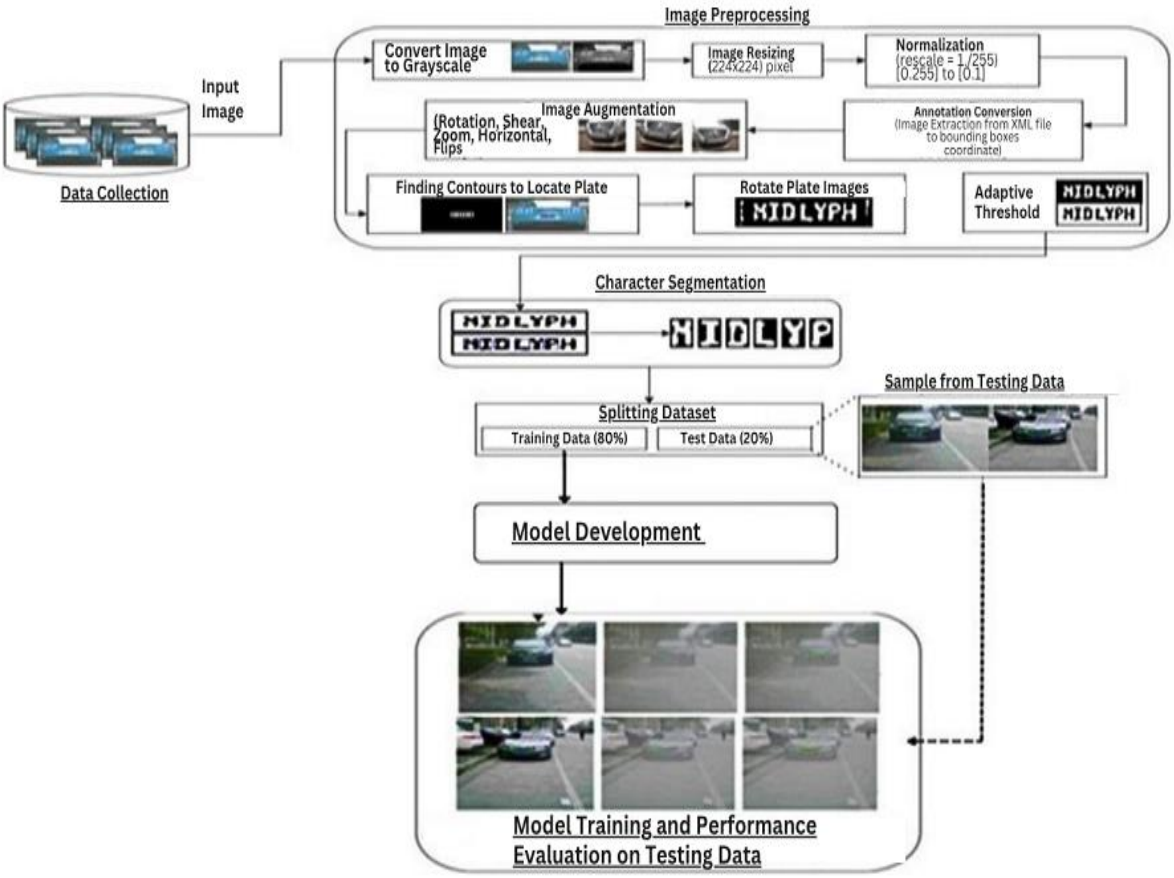

Figure 1. Purposed Research Methodology Framework

(i,j)=(I∗K)(i,j)=m∑n∑I(m,n)K(i−m,j−n) (1)

Dimensionality Reduction: A MaxPooling layer decreases the spatial dimensionality of feature maps, reducing computational load and preventing overfitting. The operation is mathematically described.

yi=Rmax{yr∗r}(r,r) (2)

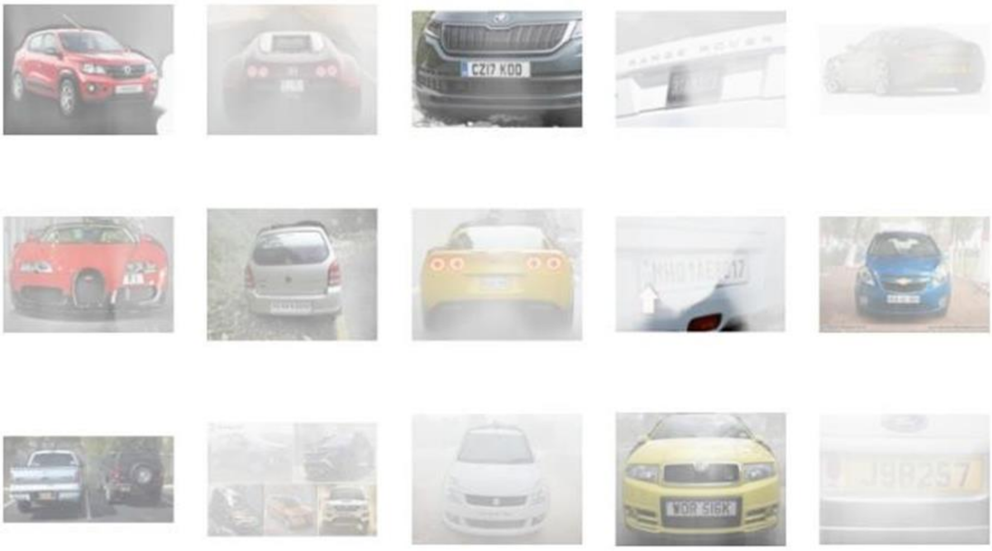

Figure 2. Different Climate Variables

Data Flattening and Interpretation: After pooling, feature maps on flattened 1D vector, which may then be processed by fully linked layers for interpretation. Dense layers use nonlinearities to extract complicated patterns from data.

Regularization: Dropout layers are used to deactivate random neurons during training, enhancing model generalization by reducing dependency on individual neurons.

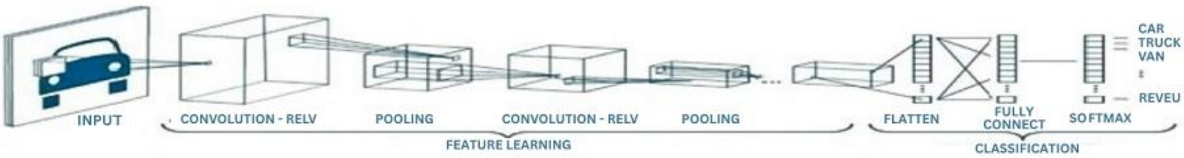

Figure 3. CNN Architecture

Fine-Tuning VGG16: VGG16 is noted for depth and simplicity, modified by leaving last layer alone to suit a new job with a bespoke output size. By unfreezing the final few layers, they become trainable on the new dataset and may be updated while training. This method uses the previous levels to extract generic features such as edges and textures, while the subsequent layers focus on task-specific aspects. If necessary, further layers might be added to the structure to complete the task at hand.

Adapting ResNet50: ResNet50, a deep residual learning architecture, has been altered to meet the new purpose. The model is loaded without the top classification layers, then custom layers are created to tailor it to the unique requirements.

A Global Average Pooling layer is used to minimize feature dimensions, followed by fully linked (dense) layers that capture task-relevant patterns. The final output layer is customized for the individual aim, such as predicting bounding box coordinates. To improve learning, the network's last 50 layers are unfrozen, allowing them to fine-tune on fresh input, while the first 50 levels are frozen to preserve broad characteristics gained during pertaining.

$$y = (x, {}^{*}\overline{W}_{i}) + W_s x \quad (3)$$

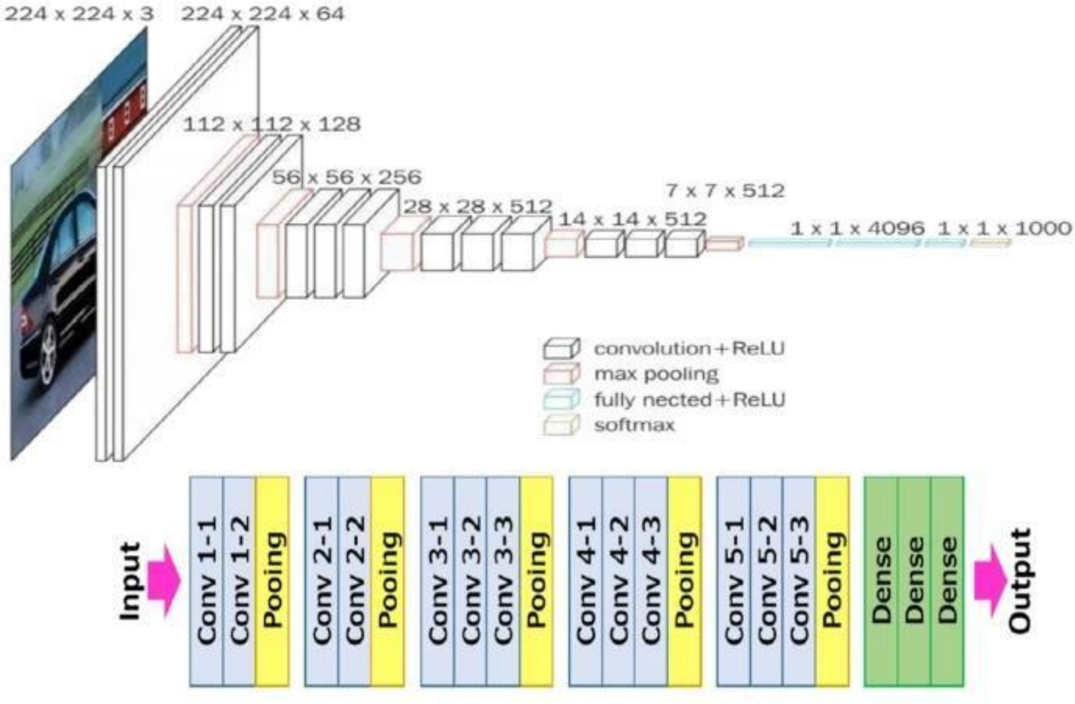

Figure 4. VGG16 Architecture

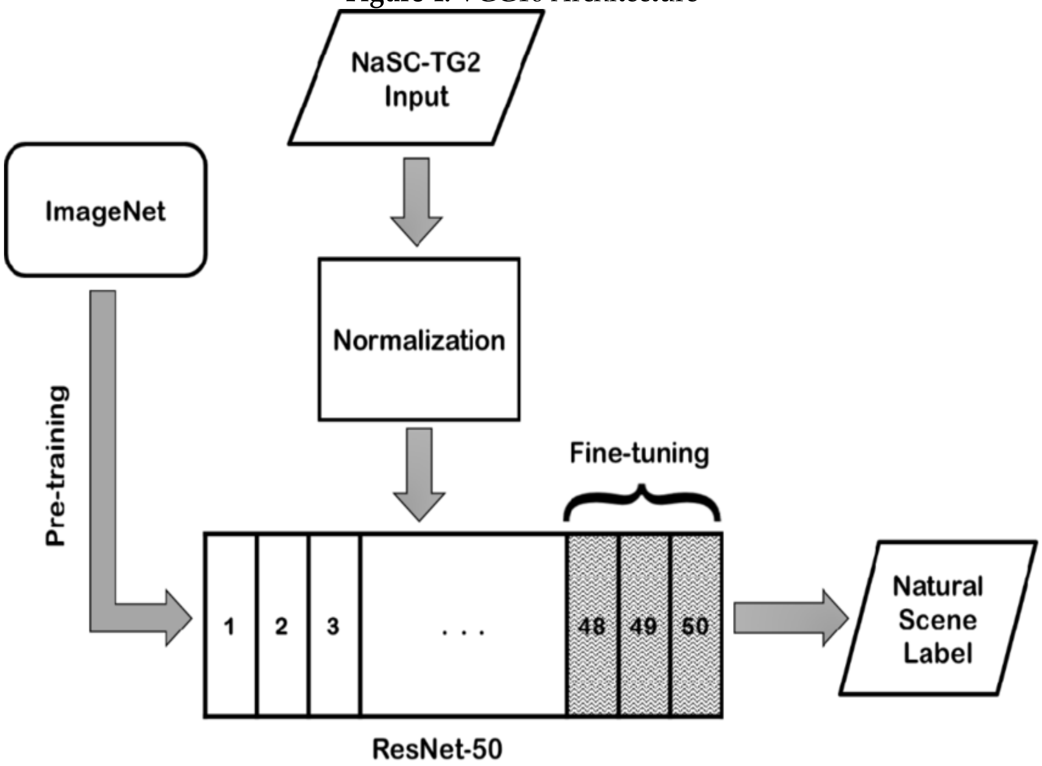

Figure 5. ResNet 50

4. Experimental Results

In this research study, used two models, MobileNetV2 and ResNet50, to recognize vehicle number plates. Both models were built with and without picture enhancing techniques. The findings were assessed for accuracy and loss, and the models were trained for 1 to 10 epochs. The findings for the ResNet50 model are as follows. Figures 5, 6 show accuracy of the ResNet50 model, without picture augmentation then the resulting accuracy loss, respectively.

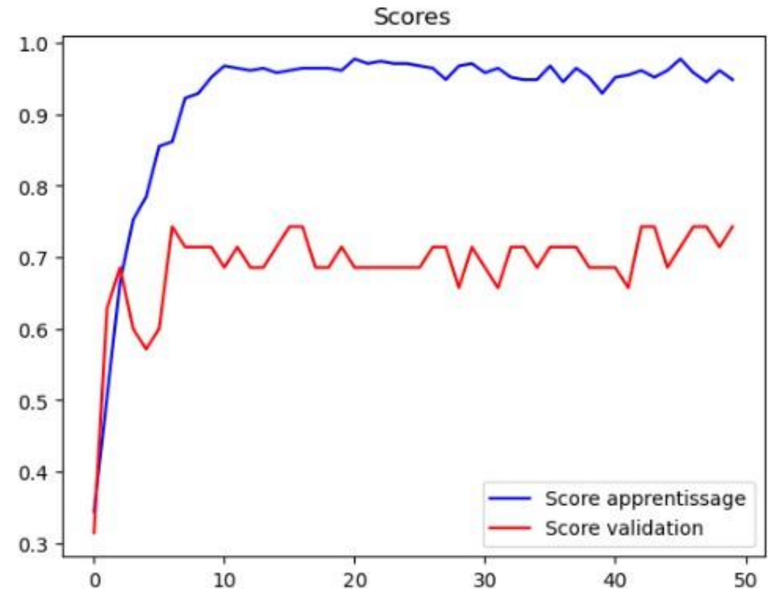

Figure 6. Epochs with training and validation accuracy

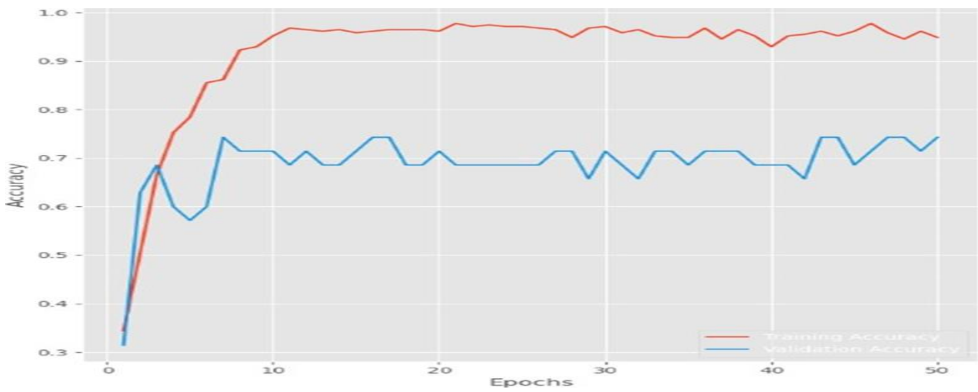

Figure 7. Accuracy and Epochs

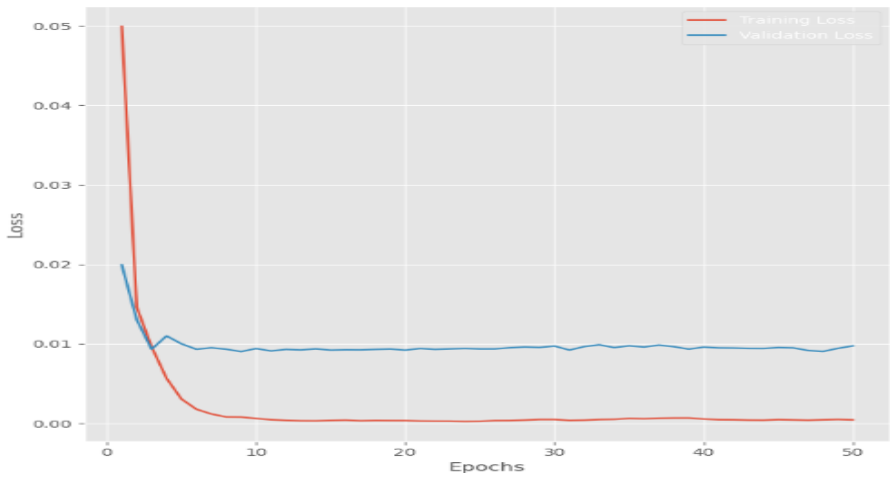

Figure 8. Epochs vs. Loss (Accuracy, Validation)

Table 1. Training and Validation accuracy with different batch size

Batch size	Training Accuracy	Validation Accuracy
16	96.74	74.29
32	96.30	70.11
64	92.76	79.31
128	89.20	86.30

Table 2. Training and Validation loss with different batch size

Batch size	Training Loss	Validation Loss
16	5.1369e-04	0.0127
32	5.1208e-04	0.0108
64	0.0014	0.0155
128	0.0034	0.0145

4.1. Performance Comparison across Different Models

The proposed approach outperforms previous methods, as reflected in impressive performance metrics. The batch size of 128, the model achieves accuracy of training 89.20% and validation accuracy of 86.30%, indicating robust learning capability and strong generalization to unnoticed data.

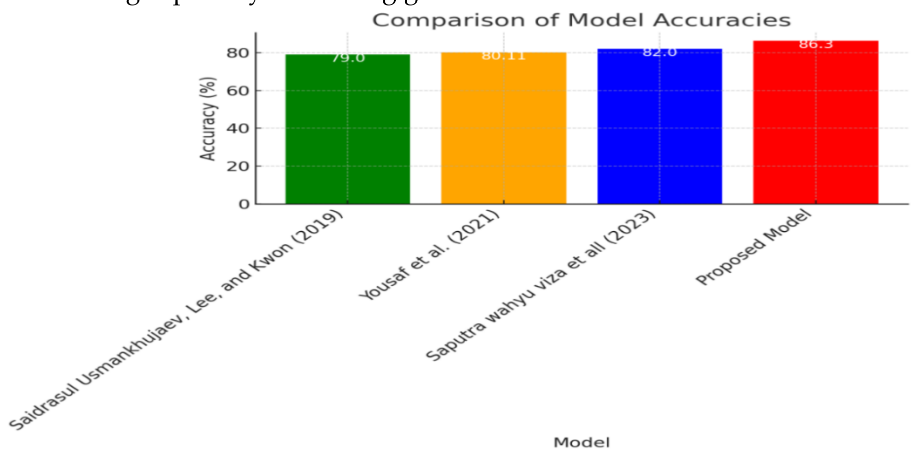

Figure 9. Performance Comparison

The performance especially notable for compared earlier investigations. Saidrasul Usmankhujaev, Lee, and Kwon (2019) found 79% accuracy, which is much lower than the suggested model. This apparent contrast demonstrates the improvements and efficacy of the methodology used in the suggested solution, which might be attributed to more complex neural network topologies, deeper layers, or enhanced data preparation techniques. Yousaf et al. (2021) attained an accuracy of 80.11%, showing significant improvement over earlier studies. However, the suggested model outperforms this by a significant margin. This might be ascribed to the suggested model's capacity to grasp and learn from the dataset's subtleties, which could be the result of more efficient feature extraction methods or a better network setup. Saputra Wahyu Viza et al. (2023) reported an accuracy of 82%, which is comparable to that of the suggested model. Nonetheless, the suggested model outperforms this current work with an accuracy of 86.3%, indicating that the methods used proposed solution—whether through data augmentation, model design, or training strategies—provides a more advanced approach to tackling the problem at hand.

Table 3. Comparison of proposed model with existing model

Model	Accuracy
Saidrasul Usmankhujaev, Lee, and Kwon (2019)	79%
Yousaf et al. (2021)	82%
Saputra wahyu viza et all(2023	80.11
Proposed Model	86.3%

5. Conclusion & Future Work

The suggested methodology's strength stems from its comprehensive preprocessing and data augmentation procedures, which are critical for standardizing input photos and boosting the model's capacity to generalize across varied, previously unknown samples. The preparation cycle starts with transforming photos to gray scale, which reduces complexity while keeping crucial visual cues needed for effective recognition. Following that, resizing guarantees that all input photos have uniform dimensions, which align with the neural network's input needs.

Normalization is used to scale pixel values within a predefined range, resulting in faster and more consistent convergence during training. Additional approaches, such as adaptive thresholding and contour detection, aid in the exact identification and isolation of license plates in pictures, therefore efficiently preparing them for character segmentation. These preprocessing processes improve the model's overall performance by providing high-quality, consistent input data.

The design of the model is based on sophisticated deep learning frameworks, especially ResNet50, which uses deep convolutional layers to uncover detailed patterns from processed photos. The model achieves high performance in both license plate localization and character recognition by fine-tuning certain layers and adapting the architecture to the job at hand.

Performance assessments confirm the model's usefulness, with a validation accuracy of 86.30% at a batch size of 128. This illustrates the model's excellent learning capability and stability in handling new, previously unknown data, making it appropriate for real-world deployment.

To summarize, the suggested system provides a comprehensive and high-performance solution for automatic license plate detection and identification. Its success stems from a mix of strong preprocessing techniques and a properly customized deep learning strategy. The positive findings open up new avenues for future advances in intelligent vehicle monitoring and management systems.

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