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Real-Time Vehicle License Plate Recognition (VLPR) Using Deep CNN

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Abstract
This research introduces a dual-component Vehicle License Plate Recognition (VLPR) system designed to improve the accuracy and efficiency of automated traffic monitoring systems. The first component employs YOLOv8 for real-time detection of vehicle license plates, capitalizing on its advanced capabilities to effectively manage variations in environmental conditions and plate obfuscation. The second component, a custom Convolutional Neural Network (CNN), is optimized for high-precision character recognition from the detected plates. Trained on a dataset of over 33,000 images, the system achieves a detection accuracy of 97.30% and a character recognition accuracy of 98.10%, demonstrating its robustness and effectiveness. This integrated approach not only enhances the reliability of automated traffic monitoring but also holds significant promise for applications requiring high accuracy and real-time data processing across various operational settings.

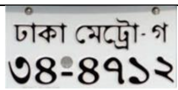
Keywords: YOLOv8, Convolutional Neural Network (CNN), Vehicle License Plate Recognition (VLPR), Real-time Processing, Accuracy

1. Introduction
The Convolutional Neural Network (CNN)-based Real-Time Vehicle License Plate Recognition (VLPR) process developed here autonomously identifies Bangla license plates from images and accurately sequences the license plate numbers as they appear on the actual plates. Globally, VLPR technologies have been deployed for various applications for some time; however, their successful implementation in Bangladesh has remained elusive. CNNs are categorized as a special type of feed-forward, multi-layer neural network architecture with deep learning capabilities. Like many other soft computing techniques, CNNs were primarily inspired by the findings from a series of rigorous biological tests aimed at understanding the mechanisms of the mammalian visual cortex.
VLPR systems are pivotal not only for parking management but are also increasingly used in toll collection, security enhancements, traffic management, and even at gas stations, presenting a wide array of potential applications. However, the unique linguistic and design characteristics of Bangla license plates mean that international VLPR solutions fall short, as they are not tailored to handle the specific attributes of Bangla text.
Typically, the three phases of Automatic Number Plate Recognition (ANPR) are character recognition, character segmentation, and number plate detection. In the character segmentation and identification

process, only the number plate is recognized and further processed from the entire input image. Identifying the number plate is challenging, largely due to variations in the types and designs of number plates, which are influenced by environmental factors. If this step fails, the accuracy of character segmentation and identification is subsequently compromised. The technological challenges associated with plate identification, character segmentation, and character recognition have garnered significant attention in studies [1, 2, 3, 4], yet numerous issues remain unresolved.

The complexity of the Bangla language, with its intricate lexical structure, complicates traditional image processing techniques for effectively handling license plate recognition on a large scale. Studies, such as those by Gonçalves et al. [5], have highlighted the limitations of existing methods when confronted with the demands of extensive datasets.

Table 1: Different Classes Of License Plates [7]

Vehicle Category	Plate Color	Character Color	Example
Private	White	Black	
Commercial	Green	Black	

In Bangladesh, the Bangladesh Road Transport Authority (BRTA) issues vehicle license plates (VLPs) in the conventional format of "city, vehicle class letter, and vehicle number" [6]. The first row of a VLP displays Bangla words and characters that denote the region’s name and the type of vehicle. Six Bangla digits in the second row assign a unique number to each vehicle. This number is crucial for distinct vehicle identification. According to the regulations of the Government of Bangladesh, the license plates feature the following Bangla letters: অ, ই, উ, এ, ক, খ, গ, ঘ, ঙ, চ, ছ, জ, ঝ, ত, দ, ধ, ন, ট, ঠ, ড, ঢ, প, ফ, ব, ভ, ম, য, র, ল, হ, শ, স, and the numbers ০, ১, ২, ৩, ৪, ৫, ৬, ৭, ৮, ৯, equivalent to 0 through 9. Business vehicles display black text on a green background, whereas private automobiles feature black text on a white background. Various VLP sections are illustrated in figure 1.

Figure 1: Annotations of Bangladeshi VLP

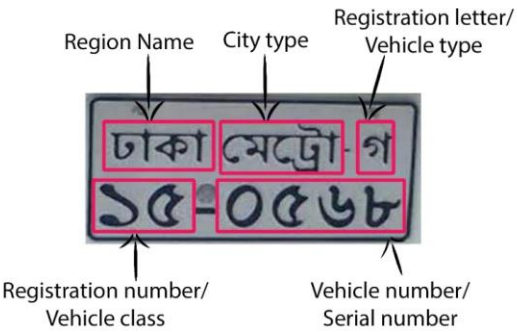


Figure 2: LP Detection Dataset Example

In this study, the identification of a license plate is accomplished in three stages: first, the license plate is identified from the live video stream; second, the characters on the detected license plate are recognized using a CNN model and segmentation techniques. Object detection methods from live video enable real-time license plate detection from the video stream. A deep convolutional neural network, YOLOv8, processes video frames consecutively to recognize a license plate, marked by a bounding box in each image. Once the license plate is detected, the observed license plate, now the region of interest (ROI), is enhanced based on the pixel values of the grayscale image. Subsequently, the ROI is converted into a binary image using Otsu's threshold, and then the image of the ROI is inverted, turning all white pixels to black and all black pixels to white. Character localization on this new ROI image is performed using Creative Commons (CC) analysis, which evaluates several geometric characteristics of text, such as region area, aspect ratio, and the lengths of major and minor axes. This filtering step eliminates almost every false positive. Applying a threshold—the proportion of white pixels—helps to remove a few additional false positives. Finally, a model CNN identifies the extracted LP characters as editable characters after they have been resized to 64x64 pixels. Extensive use of imagery is made here, with more than 33,000 character images and 104 output classes, where each object—the characters and digits on the license plate—is identified by a unique predefined class label.
The remainder of this paper is organized as follows: Section 2 provides a brief review of related works, Section 3 presents our framework based on CNN for license plate recognition and character recognition, and Section 4 outlines the results and comparisons. In the final section, we draw our conclusions and discuss future approaches.

2. Literature review

Edge detection, feed-forward neural network-based OCR algorithms, plate localization, and other classifications have already been presented as techniques that were implemented using various ways. We have covered several articles and pertinent works connected to our work in this part. In [8, 9, 10], and [11], they accomplished recognition, segmentation, and detection using neural networks. For the license plate recognition, some of them used CNN and YOLO as detectors. The author outlines a reliable and efficient ALPR technique in [8] to identify the license plate. Their object detector is built on Yolo. More precisely, they have presented two-stage approaches for the segmentation and recognition of metro names, serial numbers, and registration numbers using data-augmented methodologies. In [11], they recognized registration and serial numbers and finished the number plate location using the YOLOv3 algorithm. They have trained deep CNN based on ResNet-20 to recognize the character.
Goodfellow et al. [3] introduced a novel deep CNN approach for recognizing multi-digit numbers from Google Street View imagery. Their method integrates the localization, segmentation, and recognition tasks into a single model that operates directly on image pixels, simplifying the processing pipeline significantly compared to traditional methods. This unified approach allowed the model to be trained effectively on real-world images, achieving a character recognition accuracy of 97.84% on the publicly available Street View House Numbers (SVHN) dataset. Additionally, on a more challenging internal dataset, the model achieved over 90% accuracy in recognizing street numbers, demonstrating its robustness and efficiency in handling complex and diverse data sets.
Haque et al. [7] created an ALPR method, especially for Bangla license plates. For character segmentation and recognition from noisy and varyingly oriented license plate photos, their system used a novel Line Segmentation and Orientation (LSO) technique. Preprocessing the system involved edge identification,

morphological processes, and adaptive cropping and resizing to efficiently highlight the license plate area. Template matching and the LSO algorithm were combined for recognition, and the result was an 84.87% accuracy. On a dataset of 119 car photos divided into standard, incorrect font, and old license plate categories, the system was evaluated and shown to be quite effective in all three cases.

Chowdhury et al. [12] introduced a comprehensive deep-learning system for the identification of Bangla number plates from noisy video footage, crucial for traffic monitoring and law enforcement in Bangladesh. They implemented a robust preprocessing routine using several filters, notably the Conservative filter and Wavelet denoising, to enhance the image quality from videos. For number plate detection, techniques like Haar-Cascade and contour-based edge detection were used, coupled with ANN back-propagation for character recognition. Their methodology demonstrated promising results, achieving a character recognition accuracy of approximately 95.74% across a dataset comprising numerous images of varying quality and noise levels. This approach significantly contributes to the reliability of vehicle tracking systems under challenging visual conditions.

Atikuzzaman et al. [13]. presented a CNN-based vehicle number plate detection and categorization system designed to function in real-time on camera-captured video data. Three primary phases are included in this system: recognition, class letter segmentation, and plate detection. They detected license plates accurately using a HAAR feature-based classifier and recognized class letters from segmented plates using a CNN. On a dataset of 5500 license plates, including a combination of still and video-derived photos, their system obtained a class letter segmentation accuracy of 94.61% and a license plate detection accuracy of 96.92%. The system's effectiveness and promise for practical applications in traffic and vehicle management systems are evidenced by the 91.38% successful recognition rate it achieved overall across the dataset.

Rabbani et al. [14] implemented a method for detecting and recognizing Bangladeshi vehicle license plates using morphological operations and CNN. They introduced a comprehensive system that handles various aspects of image processing, including resizing, binarisation, connected component analysis, image enhancement, and noise filtering. BRTA has established standards for the uniform size and aspect ratio of license plates in Bangladesh. Their method demonstrated high accuracy in license plate detection at 92.78%, character segmentation at 96.45%, and character recognition at 99.03%. This robust approach ensures effective application in toll collection, car parking management, and stolen vehicle identification.

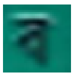
3. Dataset

The dataset for this project was meticulously constructed through a multi-step process to ensure a comprehensive and robust collection of data for training our machine learning model. Initially, a video was captured and then dissected into individual frames to isolate moments that prominently displayed vehicle license plates. Using YOLOv8, a powerful object detection system, the plates were precisely located within these frames. This detection process utilized a dataset named "Plates" retrieved from Roboflow [19], which contains over 6,000 annotated images. Each image in this dataset was labeled with bounding boxes that accurately delineate the license plate regions, ensuring the YOLO model was finely tuned for this task.

Following the detection of license plates, the next phase involved segmenting each plate into character blocks and processing the images in a left-to-right (LTR) reading format to emulate the natural reading pattern. This meticulous segmentation produced a new dataset specifically tailored for character recognition. The dataset was further enriched by incorporating additional character block samples from

other datasets, namely BLPDB [20, 21], Poribohon-BD [22], and LPDB-A [23]. This strategic amalgamation not only diversified the dataset but also significantly expanded the training data.
The resulting dataset comprises an impressive array of 104 classes, each corresponding to a unique character or numeral relevant to Bangladeshi license plates, as detailed in the attached class list. This expansive dataset includes 33,000 images, organized into 104 distinct folders, with each folder representing a specific class. These classes feature a variety of characters from the Bengali script, ensuring that the dataset adequately captures the linguistic diversity observed on Bangladeshi roads.

Figure 3: Template Example With Extracted Characters Of LP

Character	English	Bengali	Character	English	Bengali
	Ta	ত		DA	ড
	Sha	শ		Chatto	চট্টো
	Ba	ব		Raj	রাজ
	Cha	চ		Dhaka	ঢাকা
	Ma	ম		Chandpur	চাঁদপুর

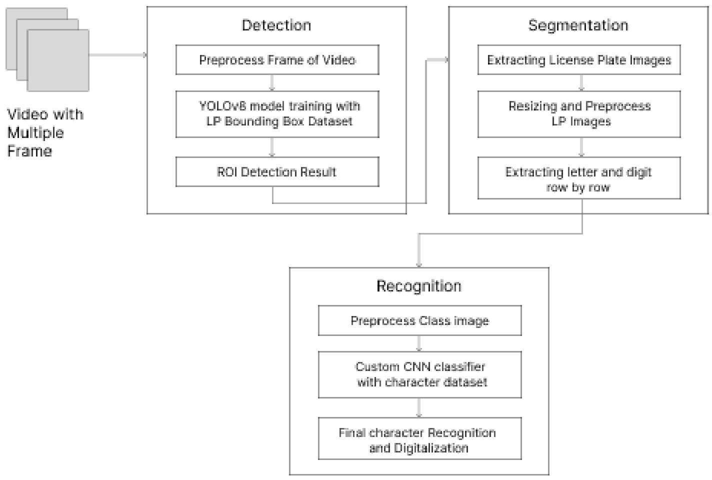
4. Proposed methodology

The proposed method comprises three components: identification, segmentation, and recognition of the class letters of license plates from video frames. Under various conditions, plates might be detected and distinguished with excellent accuracy by combining complex features and temporal data. However, more properties increase the computing load significantly. It is essential to develop a system that can identify class letters from video frames with the highest precision and minimal computation time.
The three-step system proposed for identifying the classes and detecting Bengali license plates is illustrated in Figure 4. This system includes license plate detection, character segmentation, and recognition.

4.1 Image Preprocessing

License plate (LP) images are collected from various types of vehicles, including buses, trucks, cars, motorbikes, and trains. Once captured, the images undergo preprocessing to enhance their quality for character recognition. Factors such as image quality, brightness, presentation clarity, camera motion, and other influences affecting image processing are carefully addressed. The preprocessing steps applied include converting RGB images to grayscale, using median filters to reduce noise, enhancing contrast with kernel-based filtering, and converting images to a binary format.

Figure 4: Proposed Number Plate Detection And Recognition System Architecture



4.2 Detection of ROI

Identification of the license plate from the input image represents the first challenge in this study. To address this, YOLOv8 was selected as the convolutional neural network model. The method benefits from many advantages of YOLO over other CNN models discussed in the literature. License plate images can be found and identified with sufficient accuracy by the real-time object detection model YOLO. Addressing this problem with several image processing techniques, the approach has shown comparable accuracy to YOLO for this specific assignment, although it was not scaled for the entire dataset. The remarkable generalization capability of YOLO allows it to perform admirably on data on which it has not been trained. YOLO is also particularly effective at eliminating background noise from the actual data, which is why it was chosen for this work.

Several significant technological advancements underpin YOLOv8's enhanced performance. The addition of the CSPNet backbone and a new C2f module, based on the ELAN structure from YOLOv7, improves feature fusion and enhances gradient flow efficiency. This structure ensures the model remains lightweight while boosting its ability to process gradient information effectively. Furthermore, YOLOv8's transition to an anchor-free detection approach, utilizing a task-aligned assigner, enables more dynamic and precise object detection, adapting more accurately to the physical dimensions of detected objects. These innovations not only enhance the model's accuracy but also contribute to its robustness, making it highly effective across diverse and challenging environments [15].

The implementation of the YOLOv8 model for license plate (LP) detection commenced with meticulous configuration of the network architecture, specifically tailored to LP identification needs. The model was structured to process input images using a convolutional neural network with layers adept at recognizing the nuanced features of license plates. Training parameters were carefully calibrated, with a learning rate set to initially adapt quickly and then gradually decrease to fine-tune the weights of the neural network. The batch size was chosen to balance the computational load and the model's convergence rate effectively. Input preprocessing was added to the model pipeline to ensure the images were not only normalized in size but also enhanced for better feature extraction, which is crucial for precisely finding LPs in various images. The YOLOv8 model was then trained on the "Plates" dataset with a split of 87:4:8 for training, testing, and validation, providing a rich learning environment and robust validation steps.

Figure 5: Result Analysis

The efficacy of the YOLOv8 model was rigorously tested, achieving an impressive 97% accuracy rate in license plate (LP) detection—a testament to the model's robust training and the quality of the "Plates" dataset. Precision and recall metrics were also evaluated, with the model exhibiting high precision and indicating a low rate of false positives. This is crucial in applications where misidentification can lead to significant repercussions

4.3 Localization and segmentation of character components

After detecting and extracting the plate area, specific operations are performed to isolate the expected elements from the number plate. It is observed that there are nine separate elements on each number plate. These nine specific elements are isolated, and all other detected elements are removed to enhance processing efficiency.

4.3.1 Image Binarisation: Image binarisation involves converting a grayscale image into black and white. The images are binarised by selecting a threshold between 128 and 255 intensity, and using the parameter returned from the threshold image. The inverse value is then calculated by subtracting the binarised image from 255.

4.3.2 Finding Expected Contours: Initially, all contours from the previous output image are identified and stored. The specific nine elements of the contour list are then calculated from left to right and row by row, which facilitates the detection of the minimum region where the number lies sequentially. Each localized character or candidate text region is assessed using various geometric properties of text to determine if they are actual text characters. These are subsequently stored as text characters. An algorithm filters out any candidate text region that does not meet the following conditions:

- Area between 400 and 4000
- Both MajorAxisLength and MinorAxisLength are less than or equal to 100
- ROIArea/IImageArea ratio is between 0.02 and 0.25

Each character from the Bangladeshi License Plate that meets the above criteria is extracted, resized to a fixed size of 30×30 pixels, and stored as an array in a series of no more than nine content pieces for testing in the CNN.

4.4 Recognition of the Extracted Characters

In this thesis, a custom CNN model, as presented in Figure 6, comprises three 2-dimensional convolutional layers (Conv2D) and three dense fully connected (FC) layers. This structure enables the model to derive the output from the total result. Initially, the model was defined as a sequential model because the sequential model API facilitates the development of deep learning models in most situations. A pair of Conv2D layers with 32 nodes each, 3x3 kernel size, Rectified Linear Unit (ReLU) as the activation function, padding value "Same," and glorot_uniform initialization with a 0 seed was configured. The input shape corresponds to the dimensions of the training image, specifically a 64x64x3 (width x height x depth) resized image used for both training and testing.
In subsequent layers, another Conv2D layer with 64 nodes, followed by a third Conv2D layer with 128 nodes, both maintaining the same kernel size, activation function, padding, and initialization settings, were added. Each Conv2D layer is accompanied by a MaxPooling2D and a batch normalization layer. The three-dimensional RGB image processing through batch normalization adjusts activations within the batch using an axis parameter of 3. The MaxPooling2D layer, with a pool size of 2x2, maximizes the most significant feature in each patch of the feature map, aiding in feature prominence.
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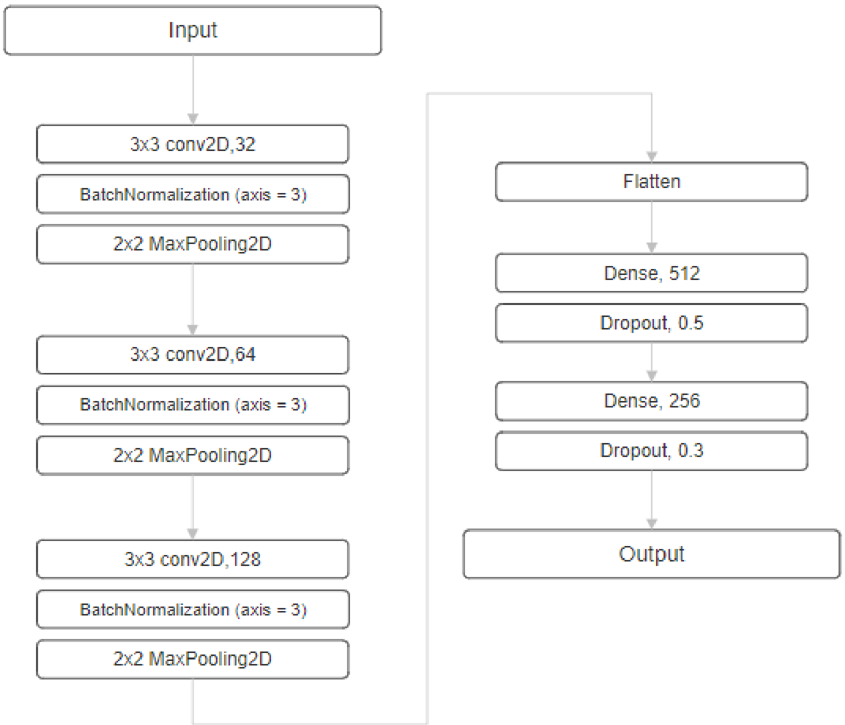
Figure 6: Proposed CNN Model

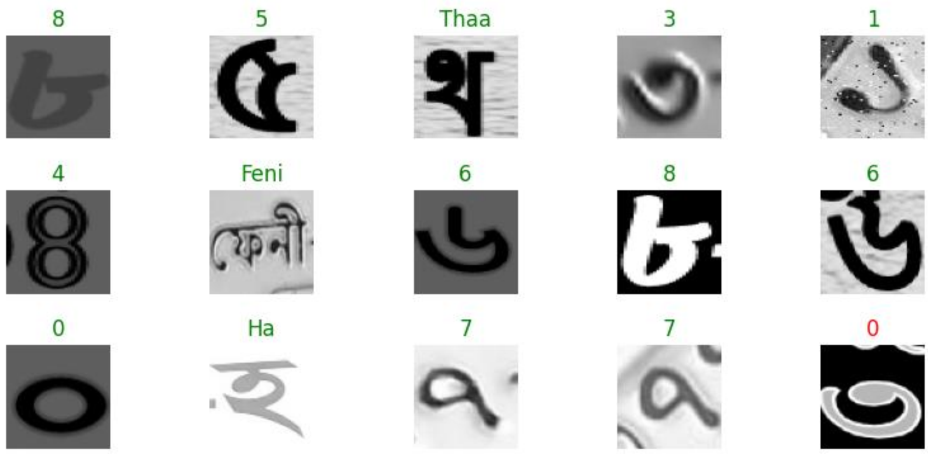


To prevent overfitting, 20% of input nodes are randomly dropped at a rate of 0.2. The input layer data is then flattened from three dimensions to a one-dimensional array for processing in subsequent layers. The network incorporates three dense FC layers; the first with 512 nodes and the second with 256 nodes, both employing ReLU activation and dropout rates of 0.5 and 0.3, respectively. The final layer comprises 104 nodes, reflecting the number of predicted output classes ranging from 0 to 9, alongside various characters from the Bengali script, using SOFTMAX as the activation function.

The model is compiled with categorical cross-entropy as the loss function and the Adam optimizer to optimize performance metrics. The categorical cross-entropy calculates the deviation of the predicted value ($\hat{y}$) from the actual label, where a deviation indicates a loss, influencing the overall model accuracy The learning rate for the model was initially set to 0.001 and the batch size was set to 64 for optimal training. Our model was saved to preserve better results from the previous epoch. The learning rate was reduced by a factor of 0.5, and the minimum learning rate was set at 0.00001 values. The training data was split by 80% for the training set, with the rest used for the validation set.

20–30 epochs were run in total after pre-processing and training every picture to compare the outcomes according to the dataset. An accuracy of 97% in character recognition and license plate detection was achieved, using the expected and real numbers. F1-Score 0.98, Accuracy 0.98, Precision 0.98, Recall 0.98

Figure 7: Resultant Output



After training and testing, the final output (an editable form of the LP characters) will be displayed sequentially, corresponding to the class map.

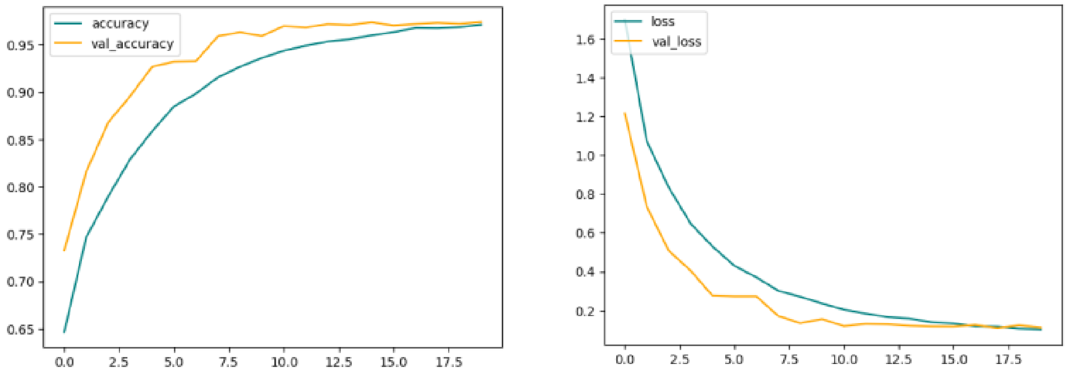
5. Experimental result and analysis

This study aims to conduct a comprehensive evaluation of various methodologies applied in the field of license plate recognition. The spectrum of approaches examined ranges from advanced deep-learning algorithms to conventional image-processing methods. The effectiveness of each technique is meticulously analyzed based on key performance indicators such as detection accuracy, character segmentation effectiveness, and overall identification rate.

The analysis extends to a detailed examination of the strengths and limitations of each method, providing crucial insights into their applicability in practical scenarios. This assessment not only illuminates the comparative advantages of sophisticated machine learning models over traditional techniques but also pinpoints their operational challenges.

By exploring these diverse methodologies, the study endeavors to establish optimal practices that enhance accuracy and operational efficiency. The findings are expected to guide subsequent research and development efforts, paving the way for the development of more robust and efficient license plate recognition systems. These systems aim to offer increased reliability in varied real-world environments, addressing both current and emerging needs in automated vehicle identification.

Figure 8: Accuracy And Loss Function Matrix



Since each dataset presents a different set of difficulties, the results are obtained from a broad variety of datasets, guaranteeing a comprehensive validation of tested procedures in various settings. These results will be discussed at length in the discussion that follows, with a focus on the implications of each method's performance and possible directions for future study and improvement.

Table 2: Result Comparison

Method/Model	Accuracy
DistBelief (Dean et al., 2012) implementation of deep neural networks [3]	Detection: 96%, Recognition: 90%
YOLO using ImageAI library[12]	Detection: 98%, Recognition: 90%
Sobel Edge Detection with Morphological Operations [7]	Detection: 84%, Recognition: 80%
Line Segmentation and Orientation Algorithm [16]	Detection: 95.8%, Recognition: 84.87%
Fuzzy Neural Network [17]	Detection: 80%, Recognition: 87.22%
Haar-Feature Proposed CNN [13]	Detection: 96.92%, Recognition: 91.38%
Feedforward Neural Network [7]	Detection: 84%, Recognition: 80%
Morphological [14]	Detection: 93.78 %, Recognition: 97.03%
Proposed Methodology: YOLOv8 and Custom Deep CNN	Detection: 97 .3%, Recognition: 98.10%

6. Conclusion

The primary objective of this work is to utilize Convolutional Neural Networks (CNNs) for effective license plate identification and recognition. Demonstrating superior accuracy over traditional image processing methods, even with relatively small training datasets, CNNs have proven indispensable in interpreting complex visual inputs with high precision. This capability is critical for enhancing functionalities in automated systems that require accurate recognition of textual and numerical information. This study highlights the significant performance improvements facilitated by CNNs and underscores their essential role in advancing the automation and management of vehicle registrations.

Looking forward, future research will aim to enhance the current vehicle license plate recognition system through several avenues. Integrating more diverse datasets, which include license plates from different countries and are subjected to various lighting and weather conditions, is expected to improve system robustness and accuracy. Furthermore, exploring more advanced neural network architectures, such as Transformer models, may yield improvements in processing speed and recognition accuracy. Implementing real-time adaptive learning, wherein the system dynamically updates its model based on new data encountered in operational environments, could significantly boost performance across diverse real-world scenarios. Expanding the application scope to include pedestrian and other vehicle identification could lay the groundwork for a comprehensive traffic monitoring system. These initiatives will focus on refining the accuracy, speed, and applicability of the license plate recognition technology, driving it toward broader practical implementation and integration into smart city infrastructures.

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