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Multi-layer skip Connection Enabled CNN for License Plate Detection and Recognition

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Abstract

License plate detection and recognition are critical components in a variety of applications, including intelligent vehicle systems, smart trafficking and law enforcement. Existing models which are used for this purpose have poor performance and are not cost-effective. So in order to achieve a stable and accurate license plate detector and recogniser, an integrated approach to license plate identification and recognition that takes advantage of cutting-edge techniques in object detection and character recognition is enabled. It utilises the multi layer skip connection CNN model for recognition along with YOLO model for detection. These are validated using public standard datasets like ALOP, ALPR, ANPR and ChineseLP. Along with these, UFPR-ALPR is used to validate CNN skip connection. Finally, the best performing versions for both YOLO part as well as CNN part are pipe-lined to provide a final working model which will be the most efficient and accurate. The model after analysis indicates that YOLOv8 is best performing among all versions with F1 score of 98 %, recall of 96.84 % and precision of 99.19 %. The CNN skip connection has99.68 % training accuracy, 0.0123 % training loss, 97.46 % validation accuracy, and 0.2444 % validation loss, and is best performing model for recognition.

Keywords: *Object Detection, YOLO, Character Recognition, Deep Learning, CNN, Sequential connection, Skip connection*

1. Introduction

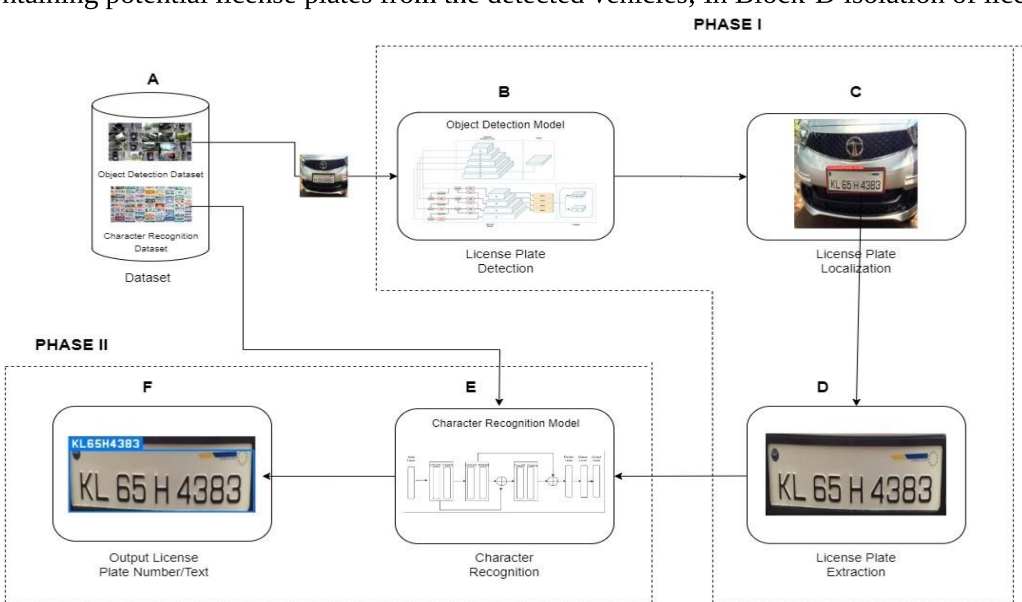
Traffic rules are violated on the roads and it's hard to identify who is violating the traffic rules by traffic police. Also, manual handling of traffic management, parking management, law enforcement, and vehicle tracking has became difficult due to rise in number of cars. All of these problems can be solved if we can find way to effectively and accurately track the license plate number of the vehicles. Traditional methods for detecting and recognizing license plates depended mainly on handmade characteristics and heuristic-based algorithms, which frequently struggled to generalize across varied environments and light conditions [3-5]. Our research seeks to overcome critical issues in license plate detection and recognition, such as adaptability to changing lighting conditions, occlusions, and complicated backdrops.

Proposed model takes an image as an input and gives us the number plate characters as output through internal functioning of model. We focus on license plate detection and recognition utilizing cutting-edge deep learning algorithms. We intend to investigate the most recent advances in object detection algorithms. Furthermore, we look into the use of optical character recognition algorithms to extract alphanumeric characters from detected license plates. Our research seeks to overcome critical issues in license plate detection and recognition, such as adaptability to changing lighting conditions, occlusions, and complicated backdrops. Since OCR is pretrained, we cannot analyse it quantitatively so in order to analyse the character recognition in more efficient way, we developed a two different CNN model for license plate character recognition.

The system is divided into two parts- detection and recognition. The system is meant to smoothly process user inputs, which can take the form of images. After receiving an input, the system enters in detection phase, where it uses powerful machine learning techniques [22-24] to identify vehicles within the frame. The detection phase uses cutting-edge object detection algorithms, with a focus on the YOLO architecture. it provides real-time performance and great accuracy, making it an excellent choice for license plate detection tasks. Once a vehicle is successfully spotted within the frame, the algorithm proceeds to locate the license plates on it. This localization procedure is critical for identifying the area of interest holding the license plate, which is frequently hidden by factors such as vehicle orientation, lighting conditions, and occlusions. YOLO excels at accurately locating objects within complicated scenes, allowing the system to properly identify and extract license plates from observed vehicles.

After extracting the license plates, the system moves on to the recognition step, where it uses Optical Character Recognition (OCR) to decipher the alphanumeric sequences imprinted on the plates. OCR is crucial in turning the visual information present on license plates into machine-readable text, allowing for further analysis and processing. The recognition procedure begins with preprocessing processes designed to improve the quality of the retrieved license plate photos. Preprocessing techniques may include image scaling, normalization, noise reduction, and contrast enhancement. By performing these procedures, the system ensures that the input images are optimized for OCR processing. The recognition process concludes with the production of machine-readable text reflecting the alphanumeric sequence found on the license plate. This text can then be used for a variety of purposes, including vehicle identification, access control, toll collecting, and law enforcement.

Figure 1: Process Flow of Proposed Approach; Block-A is dataset collection for both detection and recognition; Block-B is Object detection model, In Block-C license plate are localized within regions of interest containing potential license plates from the detected vehicles; In Block-D isolation of license plate



from rest of the image occurs, which is crucial for extracting license plate information like characters; In Block-E character recognition model is present; In Block-F Segmentation of individual characters from the localized license plates occurs so that it can be machine-readable.

Machine learning techniques and its other varient is getting popularity due to its feature extraction capability and have been applied in various applications including autonomous vehicle systems [18,22,24,27], traditional image processing based tasks [19-21],[23],[25-29] and vision based satellite image processing [30-31].

Overall, the two-phase system described in this research paper provides a complete solution for license plate detection and recognition. By merging YOLO with powerful Skip-connection based CNN algorithm, the system has the potential to speed up operations involving vehicle recognition and information retrieval. The proposed workflow can be visualized in Figure 1. The structure of the rest of the article is as follows: Section 2 concisely examines the studies in license plate detection and recognition; in Section 3, phases of the proposed approach are discussed; Section 4 reveals the experimental outcomes. Concluding remarks and future directions of the approach are presented in Section 5.

2. Related Works

An overview of all relevant research on licence plate identification and detection is provided in this section. part 1 discusses the classic approaches to licence plate detection while part 2 focuses on several deep learning-based algorithms that have been utilised for licence plate detection. This portion concludes with a tabular summary that compares several detection and recognition models, each of which is compared separately with our suggested model. Subsection 3 provides a detailed explanation of the originality and contributions.

2.1 Traditional Approaches

Conventional techniques for identifying licence plates depended on manually designed feature extraction and traditional machine learning algorithms. These methods frequently included a number of pre-processing stages, area of interest (ROI) identification, and character recognition in order of precedence.

The major components of the suggested method by Kurchaniya et al.[3] proposed connected component algorithm for character segmentation, the wiener filter for noise reduction, morphological operations for number plate localization, and template-based matching for character identification. X. Ascar et al. [4] suggested using the binary technique for pre-processing in conjunction with a technique known as the kernel density function. The position of the licence plate can be determined using the filtered binary value of the image by multiplying the binary value by the image's original value. Similarly, In the pre-processing phase, Ganta et al.[5] uses a number of image processing methods, including morphological transformation, Gaussian smoothing, and Gaussian thresholding. Subsequently, border-following contours are applied and filtered according to character dimensions and spatial localization for number plate segmentation. Character recognition is then accomplished using the K-nearest neighbours algorithm following the region of interest filtering and de-skewing processes. The four main components of the suggested model are segmentation, character recognition, licence plate region extraction, and pre-processing of the acquired image. When the acquired image has a high light intensity, using the Sobel edge detection technique directly or using a threshold will not effectively detect the licence plate region. During segmentation, the characters get deformed due to the use of morphological processes. suggested an innovative approach using a special edge detection method to address the aforementioned problems[9].

In this study, a robust technique for character localization, segmentation, and recognition inside the localised plate is presented. Grayscale images are created by converting images. Since the Hough transform is used to determine Hough lines, the segmentation of a greyscale image produced by identifying edges for smoothing the image is used to reduce the amount of connected part, after which the connected part is computed[10]. The many techniques for identifying the number plate number are covered in this approach given by Laroca et al.[11] which locates the licence plate, character segmentation, which divides the extracted characters into individual parts and character recognition, which turns a pixel into meaningful information. Grayscale converts a colourful image to grayscale. Binarization further converts a grayscale image into a black and white version[11].Traditional approaches[19-21] used manually developed feature extraction algorithms to characterise the isolated candidate regions and differentiate licence plates from other objects or artefacts. For licence plate classification, features like shape, texture, colour, and gradient orientation were frequently collected and input into classifiers like Support Vector Machines (SVM), k-Nearest Neighbours (k-NN)[5], or decision trees. The unique features of licence plates were taught to these classifiers through hand annotation of datasets.

2.2 Deep Learning Based Approaches

A paper on automatic system for LP detection and recognition based on deep learning proposed by Z.Selmi et al.[1] divided into three parts: detection, segmentation, and character recognition. To detect an License Plate, pre-processing is done to segment the License Plate and finally to recognize all the characters. The suggested approach seeks to use sensors to summarize and analyze different approaches and advancements in licence plate recognition in the deep learning era. Four steps License Plate Extraction, Image Pre-processing, Character Segmentation, and Character Recognition are included in the proposed ALPR system. Four distinct approaches to character recognition have been tested: MobileNet, Inception V3, ResNet 50, and Convolution Neural Network (CNN)[2]. This work has presented a unique approach for both character identification and licence plate detection that is based on a backpropagation neural network (BPNN) and feature extraction model that works well in dim lighting and complex backdrops[6]. The method to extract the input image's vertical edges is based on the two-dimensional wavelet transform. In order to identify prospective licence plate areas, the high density of vertical edges is computed first. After this, a plate/non-plate CNN classifier is used to confirm these possible regions. Following the identification of the licence plate, the characters are separated using a straightforward technique based on the empty space between the characters. Lastly, a different CNN classifier is trained to classify these character candidates [7].

The suggested approach by Shivakumara et al.[12] combines recurrent and convolutional neural networks, namely BLSTM (Bi-Directional Long Short Term Memory), to recognise objects. Because of its strong discriminative capacity, CNN has been employed for feature extraction; concurrently, BLSTM may extract context information by using historical data.

Key Contributions of proposed Method

1. We have analyzed various versions of state-of-the art model YOLO, which are yolov5, yolov7, yolov8 and yolov9 for license plate detection task. we concluded Yolov8 is best performing model after testing on 4 different datasets i.e ALPR, ALOP, ANPR and Chinese LPR. Our model outperforms existing state-of-the art models for licese plate detection.
2. We have come up with a novel Multi-layer skip connection enabled CNN for license plate recognition task which This allows for more efficient learning of discriminative features for

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character recognition. our proposed model outperforms the existing approaches for character recognition from license plate.

3. Created a comprehensive end-to-end model for character recognition and licence plate detection. YOLO and skip-connection CNN both elements work together to provide the full pipeline for character detection and licence plate recognition.

3. Material and Methods

To learn more intrinsic features of license plate detection and character recognition, we will describe each phase of system along with its working and features.

3.1 Phase I: Object Detection

The phase I of our system is object detection. Object detection is important in license plate recognition systems because it allows license plates to be identified and localized inside pictures or video frames. In this project, cutting-edge object detection algorithms were used, with a focus on the YOLO (You Only Look Once) model architecture. The YOLO model family is well-known for its ability to detect objects in real time with great accuracy and efficiency.Throughout the experiment, we thoroughly examined and compared four distinct versions of the YOLO model: v5, v7, v8, and v9. Each version has its own unique features and improvements, making it appropriate for a variety of applications, including license plate detection. We can roughly compare all these versions on different features as shown in the table below.

3.1.1 YOLOv5

YOLOv5 is a modern object identification model introduced by Ultralytics. It is an extension of the YOLO architecture, which is intended to achieve high accuracy and real-time performance. It presents unique architecture designs and optimization methodologies, which improve detection performance while reducing computational complexity. YOLOv5 is especially well-suited for real-time applications, making it a popular choice for license plate detection tasks where efficiency is critical. It is especially well-suited for real-time applications, making it an appealing option for license plate identification tasks where efficiency is critical.

The architecture is a lightweight and efficient object detection model known for its speed and accuracy. This architecture has various benefits for license plate detection, including real-time performance, high accuracy, and adaptability to a variety of settings. However, issues such as dataset diversity, occlusion, and multilingual character recognition require further investigation and development. Furthermore, integrating YOLOv5 with other technologies, such as CNN for license plate recognition, provides chances to expand system capabilities.

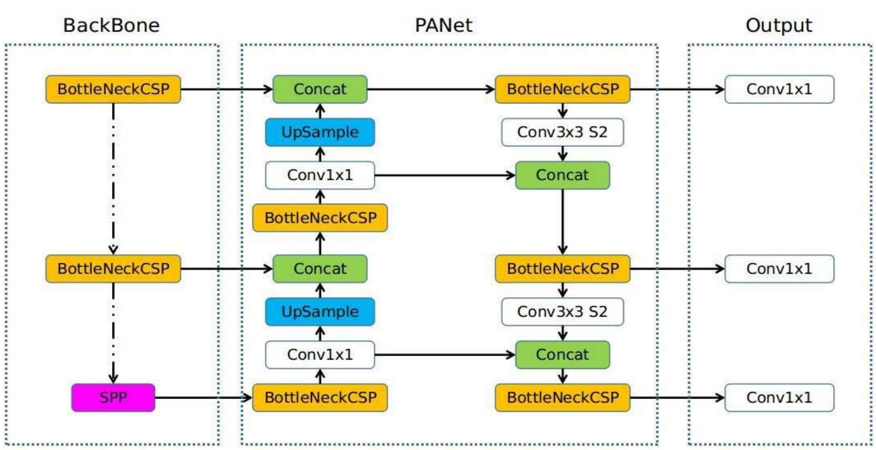

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Figure 2 : Architecture of YOLOv5

3.1.2 YOLOv7

YOLOv7 incorporates innovations in model design and training approaches to improve detection accuracy and efficiency. It could involve enhancements to backbone networks, feature extraction layers, or attention methods to capture more complicated spatial connections and semantic information. This version builds on the basis provided by its predecessors, including improvements to architecture design and training tactics. It seeks to solve constraints identified in previous versions while striking a balance between detection accuracy and processing efficiency. YOLOv7 improves performance in tough settings and can handle a wide range of object identification tasks, including license plate localization.

It efficiently extracts features from input photos using a powerful backbone architecture, which is often built on convolutional neural networks (CNNs) such as ResNet or CSPDarknet. These backbone networks capture hierarchical representations of picture characteristics, which are required for accurate object detection. The YOLOv7 architecture would explicitly target license plate detection by quickly localizing and classifying license plates in pictures or video frames. It would have to deal with a variety of obstacles, including changing lighting conditions, occlusions, and license plate designs.

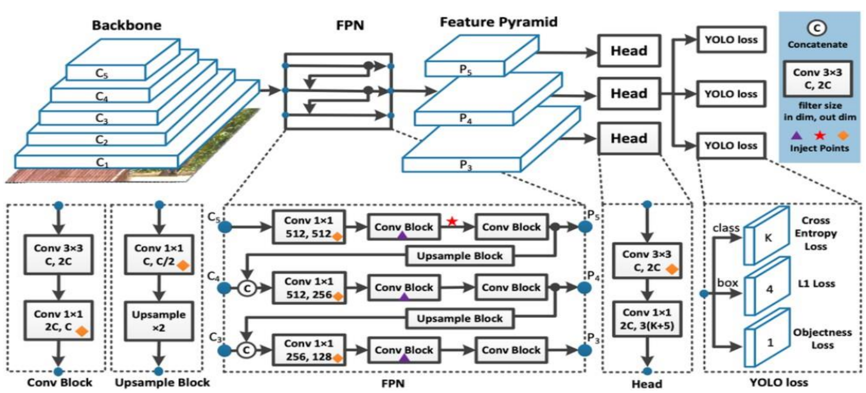

Figure 3 : Architecture of YOLOv7

3.1.3 YOLOv8

YOLOv8 makes further advances in object detection by employing novel techniques including attention mechanisms and feature fusion. This version focuses on increasing model economy and inference speed while maintaining accuracy. It may use techniques like model distillation, quantization, or network pruning to reduce model size and computational complexity while retaining performance. It stresses accuracy and resilience, making it ideal for applications requiring exact localization and identification of objects, such as license plates. It outperforms in scenarios with complicated backdrops, occlusions, and variable illumination conditions.

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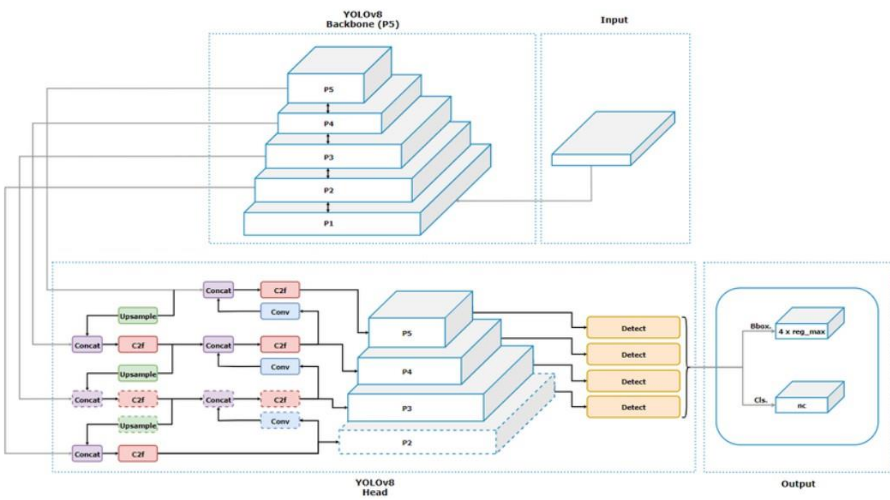
YOLOv8 typically uses a more powerful backbone architecture than previous versions. This backbone network, which is commonly built on ResNet or Darknet variations, extracts features from input photos. The deeper and wider design enables this model to record more intricate spatial characteristics, hence improving its detection skills. The YOLOv8 design would need to overcome a number of critical difficulties associated with license plate detection. These difficulties include differences in license plate size, position, and perspective, as well as lighting conditions, occlusions, and background clutter. To adequately address these fluctuations, the design would need to be both durable and flexible.

Figure 4 : Architecture of YOLOv8



3.1.4 YOLOv9

YOLOv9 is the latest edition of the YOLO model family, including cutting-edge advances in deep learning and computer vision. It focuses on improving both speed and accuracy, resulting in real-time object detection with unsurpassed performance. It pushes the limits of object identification performance by investigating novel architectures, loss functions, and training methodologies. It may experiment with advanced concepts such as self-attention processes, multi-scale feature fusion, or domain-specific optimizations to produce better detection outcomes. It has sophisticated features including dynamic anchor assignment and multiscale prediction, which enhances its adaptability and effectiveness in a variety of contexts.

In the context of license plate detection, YOLOv9 would likely build upon the advancements and principles established by its predecessors in the YOLO series. This version may include more developments in backbone architectures to boost feature extraction capabilities. YOLOv9 would include a complex backbone architecture capable of extracting hierarchical features from input photos. This backbone mightbe built on the most recent advances in convolutional neural network (CNN) designs, such as ResNet, EfficientNet, and Darknet. These designs are well-known for their capacity to properly record complicated visual patterns, which is critical for accurately detecting objects such as license plates.

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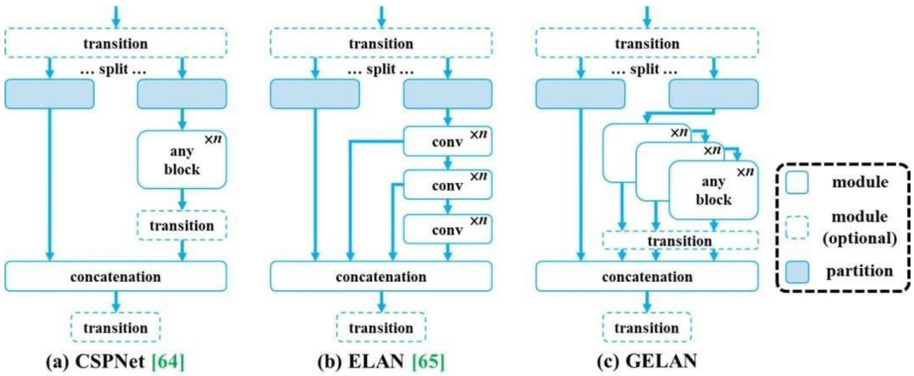

Figure 5 : Architecture of YOLOv9

3.2 Phase II: Character Recognition

The phase II of our system is character recognition. After object detection, next step is character recognition where the extracted license plate number is found using various machine learning algorithms. In this paper, we've used Optical Character Recognition(OCR) for character recognition of license plate. Character recognition with OCR (Optical Character Recognition) is the technique of identifying and interpreting characters in photographs or scanned documents. This technology converts printed or handwritten text into digital format, allowing for automated data entry, text search, and document analysis. Three different types of OCRs are used i.e. easy-
OCR, paddleOCR and tessaractOCR. EasyOCR is praised for its user-friendly API and broad language coverage, whereas PaddleOCR excels in performance and scalability thanks to its base in the PaddlePaddle deep learning architecture. TesseractOCR, developed by Google, provides open-source accessibility and significant customization capabilities. Each framework has its advantages, with EasyOCR excelling in simplicity, PaddleOCR in performance, and TesseractOCR in customisation. The choice is made based on variables such as ease of use, performance requirements, language support, and project customization demands. While OCR is an effective tool for character identification, it is often based on pre-trained models that cannot be further trained or fine-tuned for specific needs. To overcome this constraint and obtain more accurate and specialized character recognition, custom Convolutional Neural Network (CNN) models can be created from scratch. These CNN models are trained particularly to recognize characters on license plates. In this context, two kinds of CNN architectures are frequently used: sequential models and models with skip connections. Both sequential CNN models and networks with skip connections can be trained on labeled datasets of character images, such as the UFPR-ALPR dataset mentioned above. During training, the models learn to map input images of characters to their respective classes or labels via an optimization method, with the goal of minimizing a loss function that measures the difference between predicted and ground truth labels.

3.2.1 Sequential CNN Model

Sequential convolutional neural network (CNN) models are critical components of license plate character recognition systems. These models are intended to process input photos and extract essential features that assist in detecting alphanumeric characters on license plates. A typical sequential CNN model has numerous layers, each of which performs a specific function in the recognition process.

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Sequential CNN models are built by layering convolutional layers, activation functions, pooling layers, and fully connected layers successively. These models process input images sequentially, extracting hierarchical features at varying degrees of abstraction. The last layers of the network are typically fully connected layers followed by softmax activation, which produces the probabilities for each character class. Sequential CNN models are easy to create and train, making them ideal for character recognition tasks.

The batch number formula for training a sequential CNN model is determined by various parameters, including the amount of your dataset, the computational resources available, and the desired balance between training speed and model correctness.A common formula for computing the batch number (N) is:

$$\boldsymbol{N} = \frac{\boldsymbol{T}}{\boldsymbol{B}}$$

Where, N is the total number of batches, T is the total number of samples in the dataset and B is the desired batch size.

The configuration of our sequential CNN model that we've used is described below:

Total number of images = 37234

Number of classes = 36

Number of training images = 29788 (80 percent)

Number of validation images = 7446 (20 percent)

Table 1: Configuration of sequential CNN model

Layer(type)	Output Shape	Param
rescaling(Rescaling)	(None,40,40,3)	0
conv2d(Conv2D)	(None,40,40,16)	448
max pooling2d(MaxPooling2D)	(None,20,20,16)	0
conv2d1(Conv2D)	(None,20,20,32)	4640
maxpooling2d1(MaxPooling2D)	(None,10,10,32)	0
conv2d2(Conv2D)	(None,10,10,64)	18496
maxpooling2d2(MaxPooling2D)	(None,5,5,64)	0
dropout(Dropout)	(None,5,5,64)	0
flatten(Flatten)	(None,1600)	0
dense(Dense)	(None,128)	204928
dense 1(Dense)	(None,36)	4644

3.2.2 CNN Model with Skip Connection

In license plate character recognition systems, convolutional neural network (CNN) models with skip connections have emerged as an effective method for recognizing alphanumeric characters on license plates. These models use skip connections, also known as residual connections, to allow for the smooth flow of information through the network while reducing the vanishing gradient problem.

CNN models with skip connections, also known as residual networks or ResNets, use skip connections to bypass one or more layers of the network. These skip connections improve gradient flow during training, addressing the vanishing gradient problem and allowing for deeper network training. Skip connections allow the network to acquire more sophisticated and abstract representations of characters, resulting in increased recognition performance. Furthermore, skip connections encourage feature reuse and

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help to reduce overfitting, making CNN models with skip connections ideal for character recognition tasks with little training data.

Table 2 : Configuration of CNN model with skipconnection

Layer(type)	Output Shape	Param	Connected to
input1 (Input Layer)	[(None,40,40,3)]	0	[]
rescaling(Rescaling)	(None,40,40,3)	0	['input1[0][0]']
conv2d(Conv2D)	(None,40,40,16)	448	['rescaling[0][0]']
max pooling2d(MaxPooling2D)	(None,20,20,16)	0	['conv2d[0][0]']
conv2d1(Conv2D)	(None,20,20,32)	4640	['maxpooling2d[0][0]']
conv2d2(Conv2D)	(None,20,20,32)	9248	['conv2d1[0][0]']
add(Add)	(None,20,20,32)	0	['conv2d2[0][0]','conv2d1[0][0]']
maxpooling2d1(MaxPooling2D)	(None,10,10,32)	0	['add[0][0]']
conv2d3(Conv2D)	(None,10,10,64)	18946	['maxpooling2d1[0][0]']
conv2d4(Conv2D)	(None,10,10,64)	36928	['conv2d3[0][0]']
add1(Add)	(None,10,10,64)	0	['conv2d4[0][0]','conv2d3[0][0]']
maxpooling2d2(MaxPooling2D)	(None,5,5,64)	0	['add1[0][0]']
flatten(Flatten)	(None,1600)	0	['maxpooling2d2[0][0]']
dropout(Dropout)	(None,1600)	0	['flatten[0][0]']
dense(Dense)	(None,128)	204928	['dropout[0][0]']
dense 1(Dense)	(None,36)	4644	['dense[0][0]']

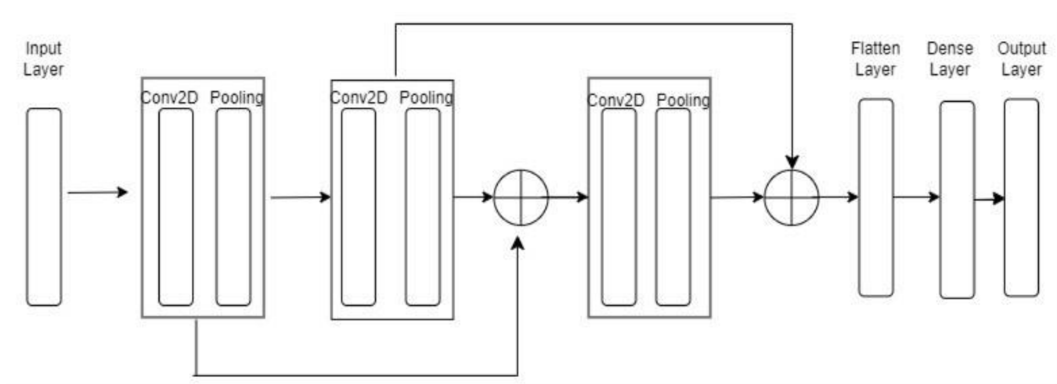

Figure 6 : Basic diagram of CNN model with skipconnection

4. Experimental setup and assessment

The experiment involves python programming language and various libraries which runs on NVIDIA-SMI having with 6GB memory having GPU capability. For the training, 100 iterations were found suitable to assess the proposed approach. To validate the performance, standard evaluation measures are also utilized.

4.1 Dataset

The dataset is critical for training and evaluating the performance of license plate detection and recognition algorithms. For detection part, we've used four different standard and public dataset- ALOP (Automatic License Plate Object), ANPR (Automatic Number Plate Recognition), ALPR (Automatic License Plate

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Recognition) and ChineseLP. The ALOP dataset contains 2000 images, ALPR contains 4500 images, ANPR contains 2000 images and the ChineseLP dataset contains 1500 images. All of these dataset is divided into three categories- Training(70 percent), Validation(20 percent) and testing(10 percent) and each has its own significance. These datasets were chosen for their license plate image diversity, which covers a wide range of real-world circumstances and issues.

For recognition part, we've used UFPR-ALPR dataset, a widely recognized benchmark dataset designed exclusively for license plate recognition applications. The UFPR-ALPR dataset is a comprehensive collection of images of license plates taken under a variety of environmental conditions. Each image in the dataset is carefully annotated with the alphanumeric characters seen on the license plate, resulting in ground truth labels for training and evaluation.

Table 3: Dataset table used for license plate detection

Dataset	Description	Annotations	Challenges
ALOP	Diverse collection of vehicle images	Bounding boxes around license plates	Weather, Distance
ANPR	Annotated images for no. plate recognition	License plate and character annotations	Multi-country plates, Font variations
ALPR	Real-world scenarios with varying conditions	Annotations for plate regions and characters	Occlusions, Image distortions
ChineseLP	Focus on Chinese license plate detection	Annotations tailored to Chinese plates	Character format, Environmental diversity

4.2 Qualitative Analysis

To measure the quantitative behavior, standard evaluation metrics have been referred and utilized in the proposed study. We first perform qualitative analysis of Phase I i.e. detection part in which analysis of different YOLO versions is performed on a standardised and public dataset (ALOP). Next, we perform qualitative analysis of Phase II i.e. recognition part in which analysis of different CNN models is performed on a standardised and public dataset (UFPR-ALPR).

Here we begin by performing qualitative analysis of Phase I with the help of different graphs of various versions. The detailed explanation is provided for better analysis.

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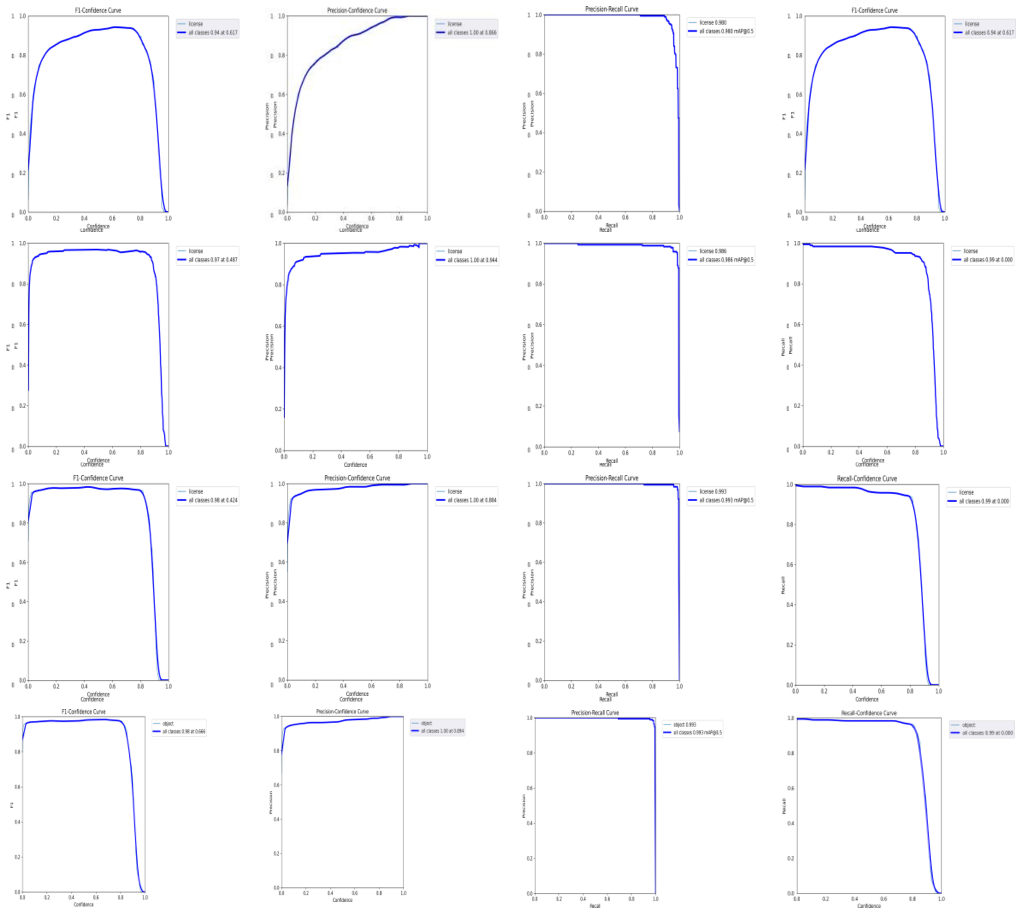
Table 4 : Qualitative analysis of different YOLO versions used for detection



The first column shown in above set of graphs shows F1 score of different YOLO versions that we've used i.e. V5, v7, v8 and v9 respectively. The F1 score provides a balance between precision (the ability of the model to correctly identify positive samples) and recall (the ability of the model to find all positive samples). By simple analysis, we can easily say that v8 and v9 have better F1 scores than other two versions.

The second column shown in above set of graphs shows P curve of different YOLO versions that we've used i.e. V5, v7, v8 and v9 respectively. Precision is defined as the ratio of true positive predictions to total positive predictions (true positive plus false positive). A better precision means fewer false positives among positive predictions. Here v8 has best P score among all the versions.

The third column shown in above set of graphs shows PR curve of different YOLO versions that we've used i.e. V5, v7, v8 and v9 respectively. Recall is the ratio of true positive predictions to total positive cases (true positive + false negative). The PR curve gives information on the models capacity to recover relevant instances (recall) while maintaining high precision. The YOLOv8 model has best PR score and is therefore best performing in that sense.

The fourth column shown in above set of graphs shows R curve of different YOLO versions that we've used i.e. V5, v7, v8 and v9 respectively. Recall, also known as sensitivity or true positive rate,

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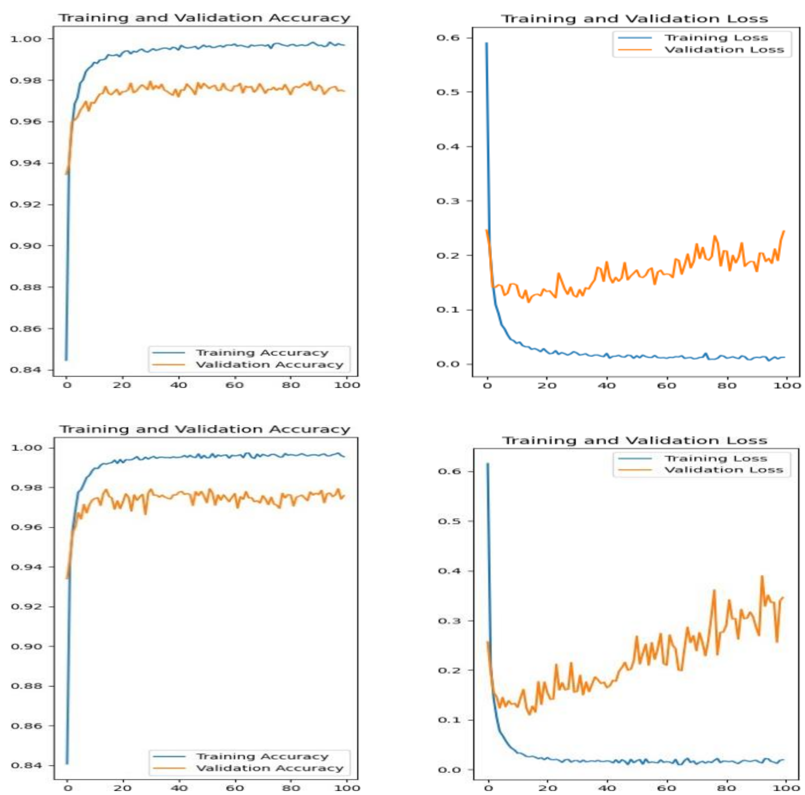
is the proportion of actual positives recognized properly by the model. A higher recall means that the model can accurately capture the majority of positive cases. The V9 is the best performing as it has highest R score.

Next we perform qualitative analysis of Phase II with the help of different graphs of various model. The detailed explanation is provided for better analysis.

Table 5: Qualitative analysis of different CNN models used for recognition



The first column of above set of graphs shows the training and validation accuracy of both sequential CNN model and CNN model with skip connection respectively. Training accuracy indicates the percentage of successfully categorized samples in the training set. A high training accuracy implies that the model is effectively learning from the training data and producing correct predictions. Whereas validation accuracy is identical to training accuracy, except it is calculated on a distinct dataset called the validation dataset. It gives an estimate of how well the model will perform on unseen data. A high validation accuracy indicates that the model has generalized effectively and can make accurate predictions on previously unseen data. By comparing the

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The second column of above set of graphs shows the training and validation loss of both sequential CNN model and CNN model with skip connection. The training loss is calculated as the difference between the expected output of the model and the actual ground truth labels for the training data. It measures how well the model performs during training, with lower numbers representing higher performance. Whereas validation loss, like training loss, computes the difference between predicted and actual values. It acts as a proxy for how well the model will perform on new data. Lower validation loss suggests improved generalization performance. By comparing the training and validation losses of the sequential CNN model and the CNN model with skip connection, we can assess their respective training effectiveness and generalization ability.

4.3 Quantitative Analysis

Quantitative analysis for license plate detection and recognition involves a comprehensive evaluation of various performance metrics to assess the effectiveness and accuracy of detection and recognition systems. This analytical process typically entails the systematic review and measurement of key indicators such as precision, recall, F1 score, and other relevant variables. By quantitatively assessing these metrics, we can gain valuable insights into the performance of the detection and recognition algorithms under different conditions and scenarios.

The quantitative analysis for license plate detection on different YOLO versions is presented in the table.

The table presented above displays the performance metrics, including F1 score, Precision, and Recall, for each YOLO version applied to different datasets. These metrics serve as indicators of the effectiveness of each YOLO version in accurately recognizing license plates across diverse datasets. By examining these performance metrics, we can evaluate the performance of each YOLO version in terms of its ability to detect and localize license plates with precision and recall. This analysis aids in the selection of the most suitable YOLO model for license plate detection tasks based on its performance across various datasets.

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Table 6: Quantitative analysis of different YOLO versions on various datasets

		ALOP				**ALPR**				**ANPR**				**ChineseLP**	
Model	**F1**	**P**	**R**		**F1**	**P**	**R**		**F1**	**P**	**R**		**F1**	**P**	**R**
YOLOv5	0.929	0.999	0.869		0.984	0.972	0.927		0.928	0.968	0.893		0.984	0.972	0.926
YOLOv7	0.968	0.953	0.984		0.915	0.899	0.933		0.970	0.963	0.978		0.917	0.982	0.861
YOLOv8	0.979	0.991	0.968		0.932	0.968	0.900		0.922	0.949	0.897		0.907	0.904	0.911
YOLOv9	0.986	0.984	0.989		0.980	0.977	0.984		0.974	0.972	0.978		0.836	0.835	0.839

Table 7: Quantitative analysis of different CNN models for character recognition

Model	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**
Sequential CNN Model	99.54	0.0198	97.58	0.3664
CNN Model with skipconnection	99.68	0.0123	97.46	0.2444

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This table compares the performance metrics for each of the CNN models utilizedin the study. The Training Accuracy and Validation Accuracy metrics measure the model's ability to accurately identify samples throughout the training and validation phases, respectively. Incontrast, the Training Loss and Validation Loss show the errors made by the model during training and validation, with smaller values indi- cating better performance. This analysis aids in determining the best effective CNN model for license plate recognition based on its performance across various criteria.

Figure 6: Above images are the results obtained when Phase I i.e. detection phase is performed on car images with different conditions. In first image sideways view of license plate of car is present, in second image normal front view of license plate is present and in third image low resolution vehicle picture is present. Although these conditions are different from each other and can be caused in real-time, our detection model accurately detects license plate with high confidence.

Figure 8: Above images are the results obtained when Phase II i.e. recognition phase is performed on car images with different conditions. In first image sideways view of license plate of car is present, in second image normal front view of license plate is present and in third image low resolution vehicle picture is present. After successful detection of these license plates, our recognition model accurately recognises license plate characters.

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Table 8: Performance comparison of proposed YOLOv8 with the existing state-of-the-art methods using precision, recall and F1 score

Method	Precision(P)	Recall(R)	F1Score
L-norm[33]	96.10	95.40	95.30
MSER&SIFT[34]	90.47	83.73	86.96
IP&CV[35]	93.80	91.30	92.53
Edge-based[36]	95.00	81.00	87.44
CNN[37]	92.60	96.80	94.65
Edge-clustering[38]	91.00	96.00	93.43
YOLOv8(Proposed)	99.19	96.84	98.00

Table 9: Performance comparison of proposed Skip-connection CNN with the existing methods for character recognition

Method	Training Accuracy	Testing Accuracy
SVM with RBF Kernal[38]	96.40	93.35
Standard ELM[38]	91.07	87.77
RBF kernal-based ELM[38]	99.40	96.38
LeNettype-1[39]	74.63	73.78
LeNettype-2[39]	89.00	85.86
AlexNet[39]	98.97	97.06
CNN with Skip-Connection(proposed)	99.54	97.58

4. Conclusion

The proposed work of license plate detection and character recognition has been carried out to detect license plate of different vehicles in different orientations, surroundings, quality etc. The system works in two stages: initial detection with YOLO models, followed by license plate identification. Multiple YOLO variants were tested and compared to establish the most successful detection model. The four public standard datasets used in the experimental evaluation were ALOP, ALPR, ANPR, and ChineseLP. YOLOv8 outperformed the other YOLO versions evaluated, with a precision of 99.19%, recall of 96.84%, and F1 score of 98.00%. These findings demon- strate YOLOv8's ability to reliably detect license plates in a variety of settings. For license plate recognition, OCR models were first evaluated, but due to their pre-trained nature, they were substituted with CNN models for analysis. Training and validation tests on the UFPR-ALPR dataset yielded good results: 99.68% training accuracy, 0.0123% training loss, 97.46% validation accuracy and 0.2444% validation loss. These findings demonstrate the stability and higher performance of the proposed CNN models when compared to previous techniques. Future research activities will focus on increasing the model's performance by fine-tuning backbone parameters or investing a ting hybrid model architectures. Further more, there is potential to expand the proposed method by including low-cost vision sensor-based prototypes for intelligent vehicle tracking systems, increasing the system's applicability and scalability in real-world settings.

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