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Automatic Number Plate Recognition Using Deep Learning Under Night time and Low-Illumination Conditions

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Abstract Intelligent traffic management relies heavily on the recognition and localization of license plate numbers of moving vehicles, making it a critical task in this field. Numerous methods have been proposed to automate this procedure, utilizing computer vision and image processing algorithms to extract the number and characters from the detected license plate in surveillance photos and videos. However, these methods have primarily focused on daytime photographs and films, neglecting the challenges posed by difficult weather conditions or dim lighting settings. As a result, identifying the position of license plates and interpreting the characters from them remains an understudied area, particularly in low-light environments and night time photography. In response, we present a Night Time number plate detector and recognizer model in this paper. The model begins with a YOLOv5-based detector that has been trained to detect license plates in dark and hazy vehicle photos, generating a polygon bounding box around the number plate. The second phase of the process comprises an improvement module, where the retrieved picture of the license plate undergoes a variety of filters. Lastly, Easy OCR is employed to read the characters on the license plate. Our experimental results demonstrate that training the detector on dark and low illumination photographs, along with precise bounding box generation, significantly improves detection and recognition accuracy. Specifically, our model achieved a mAP score of 97%, highlighting the efficacy of our approach. In conclusion, our Night Time number plate detector and recognizer model represents a significant step forward in the recognition and localization of license plate numbers, particularly in low-light conditions. Our approach provides a powerful and effective tool for intelligent traffic management systems, and we believe that our results will pave the way for further research in this field.

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1 Introduction

ALPR(Automatic Licence Plate Recognition) or ANPR (Automatic Number Plate Recognition), is an automated system that identifies and records characters from video frames or images for the purposes of traffic and security analysis. Despite the fact that numerous effective solutions utilising image processing algorithms and computer vision technologies have been put forth in the past [1–3], it remains to be a significant study area in the field of intelligent transportation systems [4–7]. One of the key reason behind this ongoing research is the significance it holds in the traffic management and monitoring.

In recent years, the rapid growth of urban populations and the increasing number of vehicles on roads have further intensified the need for efficient and intelligent traffic monitoring systems. Traditional manual monitoring approaches are no longer sufficient due to their limited scalability, higher operational costs, and susceptibility to human error. As a result, automated systems such as ALPR have become an essential component of modern smart city infrastructures, enabling real-time monitoring, faster decision-making, and improved law enforcement efficiency.

For vehicle management operations like illegal parking identification [8], ticket-less parking [9], tolling, gathering traffic flow statistics [10], detecting stolen vehicles [11], spotting vehicles at crime scenes and suspect tracking, smart billing, spotting signal and speed violation on highways and streets [12], and many other applications, a smart, automated detection and recognition system is crucial. Figure 1 highlights some of the key areas where the system is applicable.

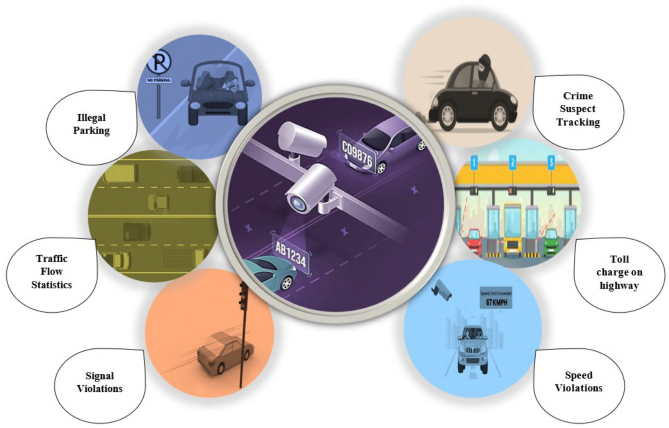


Figure 1. Advantages of Automatic License Plate Detection And Recognition

These applications not only improve traffic efficiency but also enhance public safety by enabling rapid identification of suspicious or unauthorized vehicles. Furthermore, the integration of ALPR systems with large-scale databases and surveillance networks allows authorities to perform predictive analysis, detect traffic patterns, and respond proactively to potential risks. This makes ALPR a key enabling technology for intelligent transportation ecosystems.

To recognise the licence plate in an image accurately in the first place, the system traditionally requires that the image captured be screened using some detector filter. The Optical Character Recognition (OCR) is then applied to the detected bounding box after the region of interest has been localised and extracted in order to recognise the characters on the number plate and to print the characters in the same sequence in text format. The result can either be plotted on the image for display or saved in a database for further analysis and processing. The general pipeline for an ALPR or ANPR system is shown in Figure 2.

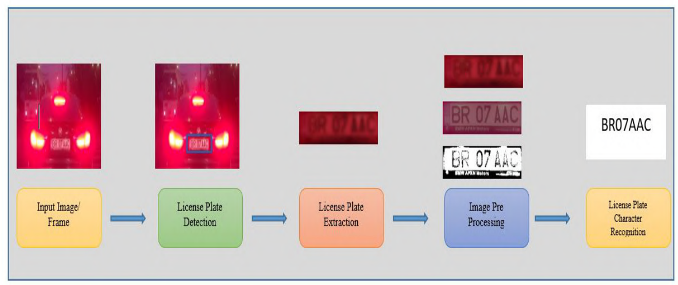


Figure 2. General Pipeline for Vehicle License Plate Detection and Recognition

Although this pipeline appears straightforward, each stage introduces its own set of challenges that can significantly affect the overall system performance. For instance, inaccurate localisation of the licence plate region can propagate errors to the recognition stage, ultimately reducing the reliability of the system. Therefore, improving each component of the pipeline is essential to achieving robust and consistent results in real-world scenarios.

Over the past 20 years, a variety of techniques have been put out for the goal of automatically detecting and recognising licence plates, albeit few have undoubtedly achieved great success. However, the majority of the techniques used up until now only work well in day time acquired images with normal weather conditions. Nevertheless, there are a number of challenges when it comes to taking photos of fast-moving vehicles on the road, including blurring or distortion of the image, problems brought on by shifting viewpoints and occlusion, complex backgrounds as a result of shifting road conditions, and the presence of numerous licence plates in a single image. Additionally, external factors like harsh weather, such as smog, rain, fog, or snow, make things more difficult. And, when a licence plate has to be detected at night, the situation gets even worse. Deep learning has made a significant contribution by enhancing our capacity for recognition and providing highly accurate detection. We therefore present a licence plate detection and recognition system keeping the aforementioned difficulties in mind.

In particular, low-light and night-time conditions introduce severe visibility constraints, including reduced contrast, increased noise, glare from vehicle headlights, and partial occlusion of characters. These factors make it difficult for conventional algorithms to accurately detect and recognise licence plates. Even modern deep learning-based approaches may struggle if they are not specifically trained on such challenging conditions. This highlights the necessity of designing specialised models and preprocessing techniques that can effectively handle illumination variations and degraded image quality.

Some of the key contributions of our work are as follows;

1. We used the YOLOv5 object detector to train on blur and night time vehicle photos with polygon bounding boxes around them.
2. We improved the accuracy of recognition using Easy OCR through our enhancement module including Black Hat transformation and Global Threshold.
3. Our proposed method outperformed the existing benchmark methods by more than 10

In addition to these contributions, our work emphasises the importance of combining accurate detection with effective preprocessing to achieve reliable recognition in challenging environments. The proposed approach demonstrates that even lightweight models can achieve high performance when trained on appropriately curated datasets and supported with suitable enhancement techniques.

The rest of this papers is organised as follows. The state-of-the-art methodologies for character recognition and licence plate detection, including conventional techniques and contemporary deep learning based systems, are reviewed in Section 2. The methods and algorithms used during training procedure is described in full in Section 3 along with our proposed methodology. The experimental findings and results are presented in Section 4. The paper is concluded in Section 5, which also suggests areas for future research.

2 Literature Review

As we briefly mention in the following part, the application of deep neural networks and computer vision techniques has considerably stimulated research in the automatic license plate detection and recognition.

In recent years, the transition from traditional image processing techniques to deep learning-based approaches has significantly improved the robustness and accuracy of ALPR systems. Earlier methods relied heavily on handcrafted features and edge-based techniques, which were highly sensitive to noise, illumination variations, and background complexity. However, the introduction of deep neural networks has enabled automatic feature extraction, making these systems more adaptive to real-world scenarios. Despite these advancements, achieving consistent performance under challenging conditions such as low illumination and motion blur remains a critical research problem.

In a study [13] used a simple CNN-based model to train the dataset to produce a multi-scale feature vector. They used a different technique that involved stacking five convolution layers on top of an Inception Resnet layer. This feature vector, which represents the character sequence on a licence plate, is sent into the predictor layer, where three different prediction methods using one, three, and seven convolution layers were used to output the license plate number.

Such CNN-based approaches demonstrate strong feature extraction capabilities; however, they often require carefully designed architectures and large annotated datasets to generalize well across different environments. Additionally, these models may struggle when dealing with complex backgrounds or degraded image quality, which limits their applicability in uncontrolled outdoor conditions.

A new age of target identification algorithms is introduced by the YOLO (You Only Look Once) [14] algorithm proposal. The most recent development in the YOLO series algorithms is the single-stage YOLOv5 target detection method [15]. It keeps the benefits of earlier algorithms' quick detection speeds and can finish various target detection jobs very instantly. Many researchers used YOLOv5 as detector including [16, 17] and [18]. In [19] authors used a two-stage detection and recognition method to complete the task. To detect licence plates, they employed a proprietary transfer learning model first, and to recognise them, they trained an OCR engine based on LSTM. On a mixed dataset from Google and Kaggle, their model's mean average precision was 87.2

The popularity of YOLO-based approaches is mainly due to their ability to perform real-time detection with high accuracy. These models combine speed and efficiency, making them suitable for deployment in real-world traffic systems. However, their performance can still degrade when dealing with small objects, low contrast regions, or images captured under poor lighting conditions, which highlights the need for further optimisation.

For the purpose of detection and recognition in different weather conditions, [20] suggested a two stage process [21–23]. Prior to extracting the licence plate from the image, YOLOv3 is taught to recognise the licence plate's location. Then, a module by the name of ILPRNET is utilised as a recognition network. It is made up of an encoder decoder CNN enhanced with a 2D attention-based licence plate recognizer [24–26] that pays attention to the spatial information of the characters.

Attention-based mechanisms have shown promising results by focusing on relevant regions of the image, thereby improving recognition accuracy. Nevertheless, these approaches often increase computational complexity and may not be suitable for real-time applications without optimisation.

To detect individual characters from the licence plate, [27] lowered the YOLO model's 27 to 10 layers. When instead of using 24 convolution layers to identify 36 class labels, including digits and alphabets, the model uses 12 convolution layers. Their technique makes use of a sliding-window device for detection. In order to determine whether characters from the sliding window-based YOLO belong on the licence plate or not, their model applies a localization step after the characters have been recognised. [28] uses YOLOv4 for detecting 6 vehicle types and korean license plates with 80

These studies collectively indicate that while significant progress has been made, most approaches are still evaluated under relatively controlled conditions. The lack of diverse datasets representing real-world challenges such as night-time environments, occlusions, and extreme weather limits the generalisation capability of these models.

However, the majority of the research that has been discussed so far focuses on clear images that were taken in broad daylight under typical meteorological conditions. But occasionally the image quality affects how well and accurately detection and recognition work. Images that are warped and of low resolution are one of the biggest problems that ALPDR systems confront. As a result, when we work with low resolution, dark or low illumination, distorted, rotated number plate images, the results suffer. Some of the work deal with this issue use involvement of a deep generative network. Like by reconstructing a detailed version of the localised image, [33, 34] and [35] all used the super-resolution generative adversarial network (SR-GAN) to enhance the system's performance and provide recognition with high accuracy. Similar work was done by [36] using generated counter network. But, training a GAN itself is a complex and time consuming task.

Although GAN-based approaches improve image quality, they introduce additional computational overhead and require careful training to avoid instability. This makes them less practical for real-time systems where speed and efficiency are critical factors.

Hence, we propose fast and accurate detection [37] of license plate using YOLOv5 and improving the character recognition by first passing the detected number plate through our image restoration module.

Our approach is motivated by the need to balance accuracy and computational efficiency, particularly in challenging environments where both detection and recognition tasks are affected simultaneously. By integrating lightweight detection with targeted preprocessing, the proposed method aims to address the limitations observed in existing literature.

3 Materials and Methods

The following section explains the tools and techniques that have been used in our proposed NTNPDR model.

3.1 You only Look Once

YOLO is a regression based algorithm which detects object in one stage [14]. DarkNet serves as the backbone of YOLO's fundamental architecture. DarkNet is a CUDA- and C-based open source neural network implementation framework. In this work, we use the YOLOv5 architecture which has three important parts.

1. Backbone: Extracts the features
2. Neck: Construct the feature pyramid
3. Head: Final Detection

The baseline architecture of YOLOv5 is shown in Figure 3.

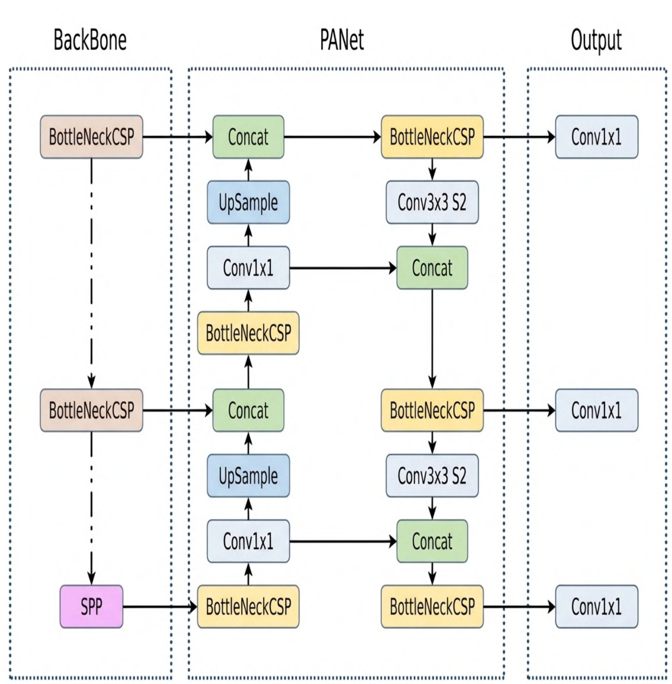


Figure 3. The Architecture of Yolov5 [38]

3.2 OpenCV - Thresholding

The simplest segmentation technique is thresholding. It seeks to distinguish areas of an image that match to the things we wish to investigate. The difference in intensity between the object pixels and the background pixels is the basis for this division.We compare each pixel's intensity value with regard to a threshold in order to distinguish the pixels we are interested in from the others (which will eventually be discarded). After properly separating the crucial pixels, we can give them a predetermined value to help us identify them (for example, we can give them a value of 0 (black), 255 (white), or any other value that works for you) [39].

3.2.1 Adaptive Thresholding

If there are various lighting conditions across an image. Adaptive thresholding can be useful in the situation. Here, a pixel's threshold is calculated by the algorithm using a small area around it. As a result, we obtain various thresholds for various areas inside the same image, which produces superior outcomes for photos with changing lighting. Figure 4(a-c) shows the results of applying adaptive threshold to an input image.

1. Adaptive Mean Thresholding: The neighbourhood area's mean less the constant C determines the threshold value.

2. Adaptive Gaussian Thresholding: A gaussian-weighted sum of the neighbourhood values less the constant C determines the threshold value.

3.3 Black Hat Transformation

Enhancing dark items of interest against a bright background is done with the black-hat technique. It is the distinction between an image's input and opening.

3.4 Label Studio

An open source tool for data labelling is called Label Studio. With a clear and simple user interface, it enables you to label a variety of data kinds, including audio, text, photos, videos, and time series, and export to several model formats. To create more accurate machine learning models, it can be used to prepare raw data or enhance current training data [40]

3.5 EasyOCR

EasyOCR, a library for optical character recognition, can read short texts (such as serial numbers, part numbers and dates). It uses a template matching algorithm and font files (pre-defined OCR-A, OCR-B, and semi-standard fonts, or other learned fonts) to identify characters of any size that have been misprinted, broken, or linked. The four steps involved in character recognition are as follows:

(a) Original (b) Adaptive Mean Thresholding (c) Adaptive Gaussian Thresholding

Figure 4. The Results of Applying Thresholding on an image

1. Raw Image
2. Object Segmentation
3. Character isolation
4. Character recognition

3.6 Our proposed Methodology

We explain our proposed Methodology in the following section as depicted in Figure 5.

Following are the architectural innovations in our methodology.

- Unlike the other ANPR systems which so far mainly uses rectangular bounding boxes we modified the dataset so as to utilize polygon-based localization within the YOLOv5 framework. This gives us the precise alignment with the natural shape and orientation of license plates.
- We also removed completely or minimized the irrelevant background regions so as to improve the detection accuracy.
- To handle challenging visual conditions we introduced a dedicated preprocessing stage particularly in cases of perspective distortion, occlusion, or tilted views.
- The Black Hat transformation enhances dark regions on bright backgrounds, making license plate characters more distinguishable in low illumination.
- The global thresholding, which binarizes the image to improve contrast between characters and the plate surface.
- The detected plate region is finally processed by EasyOCR, which accurately recognizes characters despite noise, blur, or illumination inconsistencies.

3.7 Step 1: Data Annotation on Label Studio

The dataset named CCPD was used in this study. CCPD is a large and detailed License Plate dataset. A roadside parking management company's employees manually capture each image, and each one is meticulously tagged. With over 250k unique automobile photos with filename bearing the annotation. Figure 6 shows some of the images from this dataset with their bounding box coordinates. And Figure 7 shows some of the very challenging images from the same dataset. The dataset was split into training, validation, and testing sets in a 70:15:15 ratio to ensure unbiased model evaluation as shown in table 1.

Table 1. Summary of Data Split

Annotation Type	Bounding boxes
Train Set	70%
Validation Set	15%
Test Set	15%

However, as seen in Figure 6, the bounding boxes encompass a larger area and also include a zone that is devoid of the licence plate. We re-annotated the dataset

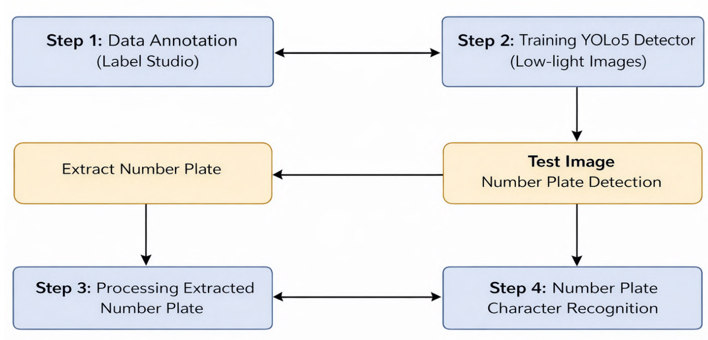


Figure 5. Our Proposed Methodology

using closed region polygon bounding boxes as shown in Figure 8 since the accuracy and quality of your bounding boxes define the performance of your model. We utilised Label Studio on the Anaconda platform for annotation.

3.8 Step 2: Training Yolov5 Detector

The training was conducted on Google Colab environment on Tesla T4 GPU. The summary of the Yolov5 model is shown in Figure 9. For our training we chose the smallest, fastest base model of YOLOv5 i.e. YOLOv5s.

3.9 Step 3: Processing Extracted Number Plate

As our study mainly focuses images at night time where the detected number plate has low illumination and unknown depth. To enhance the image we used OpenCV toolbox and applied the filters as shown in Figure 10. Enhancing black objects of interest against a bright background is done with the BlackHat transform.

The $morphologyEx(image, cv2, MORPHBLACKHAT, kernel)$ function is employed.

Where kernel is defined as $kernel = np.ones((5, 5), np.uint8)$

3.10 Step 4: Number Plate Character Recognition

Finally, once the image is ready we used EasyOCR to read the characters of the number plate. A sample result from EasyOCR is shown in Figure 11.

4 Results and Discussion

After training, we analyzed the experimental losses using TensorBoard visualisations. Figures 12 and 13 show the training and validation loss curves, respectively. It can be observed that both curves follow a consistent decreasing trend throughout the training process, indicating that the model effectively learns the underlying features even under low-light conditions.

For evaluation of our proposed model, we considered the following standard evaluation metrics to assess both detection and recognition performance.

4.0.1 Mean Average Precision

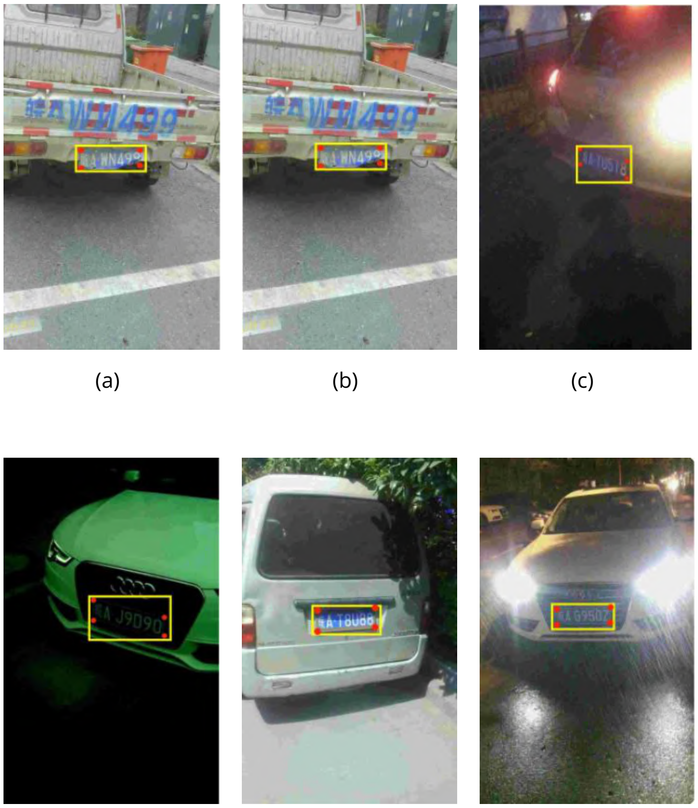
Models for object identification such as R-CNN and YOLO are evaluated using a measurement called mean average precision (mAP). By comparing the detected bounding box with the ground-truth bounding box, mAP determines a score. The objective of object detection tasks is to find the relevant object in the images and categorise it according to its properties. In these tasks, predictions are produced in the form of bounding boxes and labels indicating the object's class.

The model's performance, or mAP, is evaluated by combining the two key measures of precision and recall. For understanding, it is essential to comprehend precision and recall [41, 42]. Precision is simply how often the model makes a correct prediction, while recall is the measure of how consistently the model identifies the correct instances.

5 Detection Results

Figure 14 shows the sample detection results with confidence score. It can be seen that the model is able to detect the number plates clearly even in low-light and night-time conditions. The bounding boxes are properly aligned with the number plates and the confidence scores show that the detections are reliable.

In some images, the number plates are slightly tilted or not very clear, but the model is still able to detect them correctly. This shows that the model is able to handle



(a) (b) (c)

(d) (e) (f)

Figure 6. Sample challenging images with low number plate characters visibility

different conditions such as blur, low visibility and angle variations. The results also show that the detected region is good enough to be passed to the next stage for recognition.

Figure 15 shows the precision and recall curve. It shows that the model maintains a good balance between precision and recall. The curve does not drop suddenly, which means the model is consistent in its predictions and does not produce many false detections.

Figure 16 shows the mAP curve of our model. It shows that the model achieves high average precision. The curve remains stable, which indicates that the model is trained properly and performs well on unseen data.

5.0.1 Comparison with Existing Work

We compared our results with [19], which also used YOLOv5 for detection and EasyOCR for recognition. This shows that both approaches follow a similar method, so the comparison is fair.

(a) a (b) b

(c) c (d) d

Figure 7. Some of the most challenging images from dataset

Table 2. Comparison of our results with baseline paper

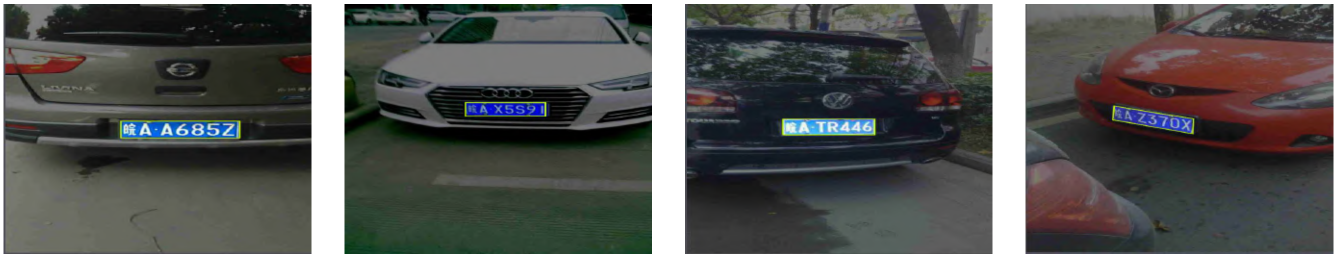
Model	mAP	Avg Detection Time (ms)	Precision	Recall	F1-Score
Baseline Model [19]	87.2	4.8	0.882	0.822	0.851
Our Model	97.4	2.3	0.998	1.0	0.999
Improvement	+10.2	-2.5	+0.998	+1.0	+0.999

The main difference is in the training. Their model used transfer learning with weights from the Microsoft COCO dataset. Our model, however, was trained on the CCPD dataset which contains a large number of vehicle images, including low-light images. This helps our model to perform better in night-time conditions.

Another difference is in the bounding boxes. The baseline model used rectangular boxes, while we used polygon-based bounding boxes. This gives better alignment with the number plate and reduces unnecessary background.

We also applied an enhancement step before recognition. The use of Black Hat transformation and global thresholding improves the visibility of characters, which helps EasyOCR to read the number plate more accurately.

On their validation and test sets, their model achieved



(a) (b) (c) (d)

Figure 8. Re-Annotating using Label Studio for more accurate Bounding Boxes using Yolo Format as output.

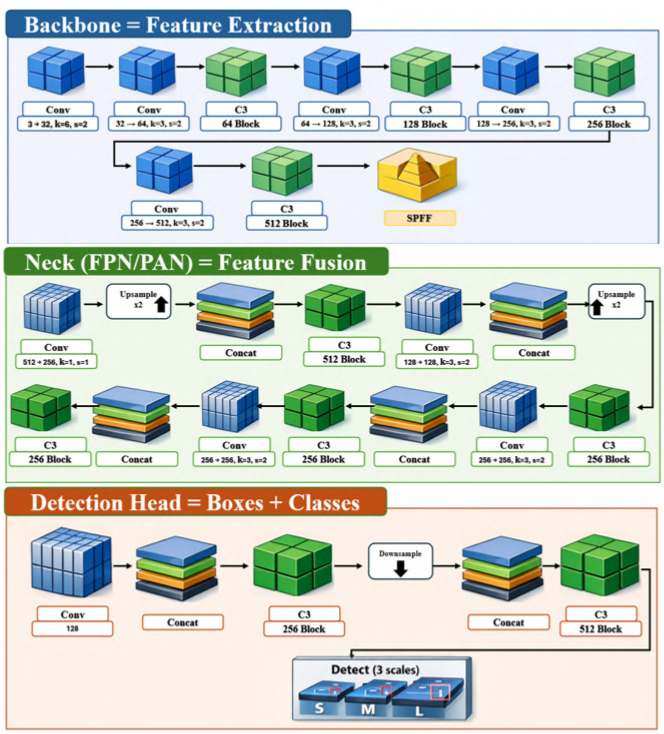


Figure 9. The Summary of YOLOv5 Model Layers

Figure 10. The Results of Applying OpenCV Image Enhancements

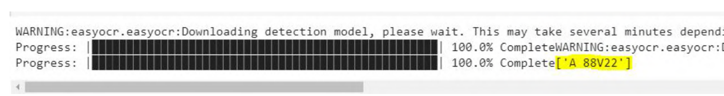


Figure 11. Sample Result From EasyOCR

mAP scores of 88.4% and 87.2%. In comparison, our model achieved 99% on the validation set and 97% on the testing set. This shows a clear improvement in performance.

Table 2 shows the comparison of our model with the selected baseline model.

6 Conclusions

The goal of this project was to provide a framework for recognising and identifying licence plates in images taken at night or in poor light. We used Yolov5 to train our model using 25k pictures after re-annotating the dataset with the polygon tool to create bounding boxes. We were able to achieve 98 percent accuracy and a 97 percent mAP score as a result. Thus, we can say that training with night time photos that have already been processed and a good, exact bounding box improved detection accuracy. Furthermore, our results suggest that while Yolov5 is a speedy and efficient approach, deep learning-based OCR struggled to distinguish the characters on the number plate since they were so weakly lit and were first recognised incorrectly. The Easy OCR was able to identify them after they had simply been processed using our enhancement module. Our identification accuracy was high when we used the black hat picture filter, the inverse of the grey scale, and global thresholding. However, our model's inability to accurately recognise broken and incomplete number

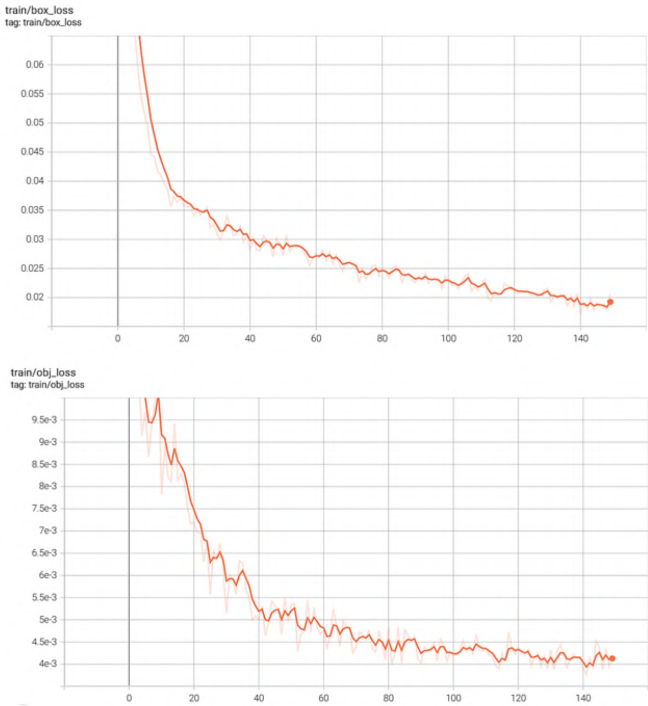


Figure 12. Training Loss Curves

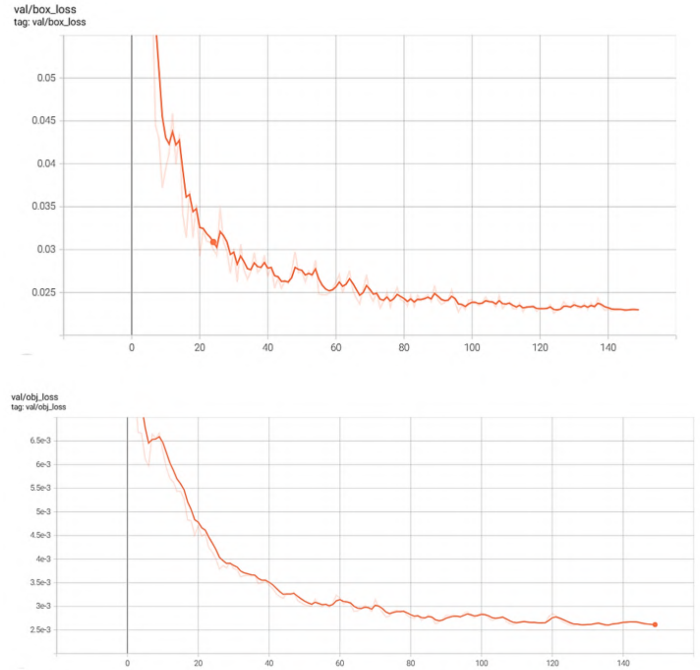


Figure 13. Validation Loss Curves

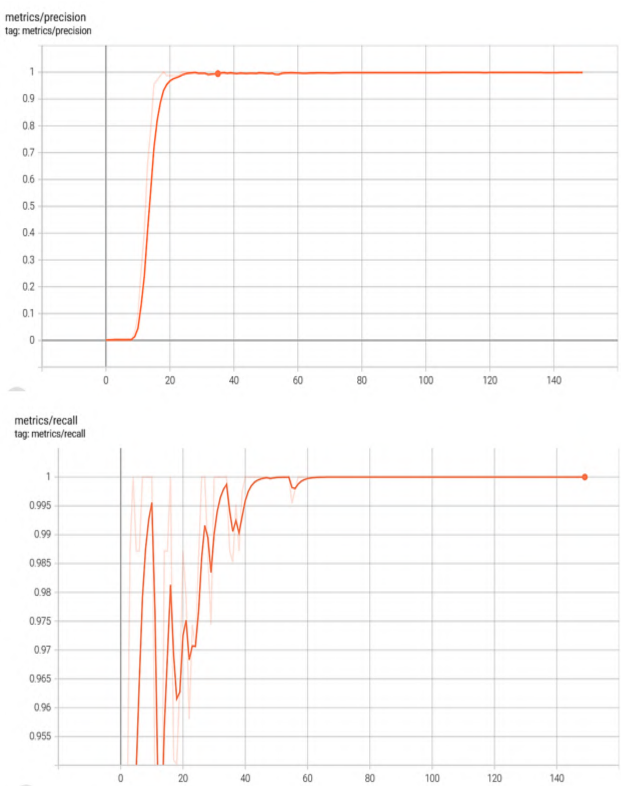


Figure 15. Precision/Recall Curve

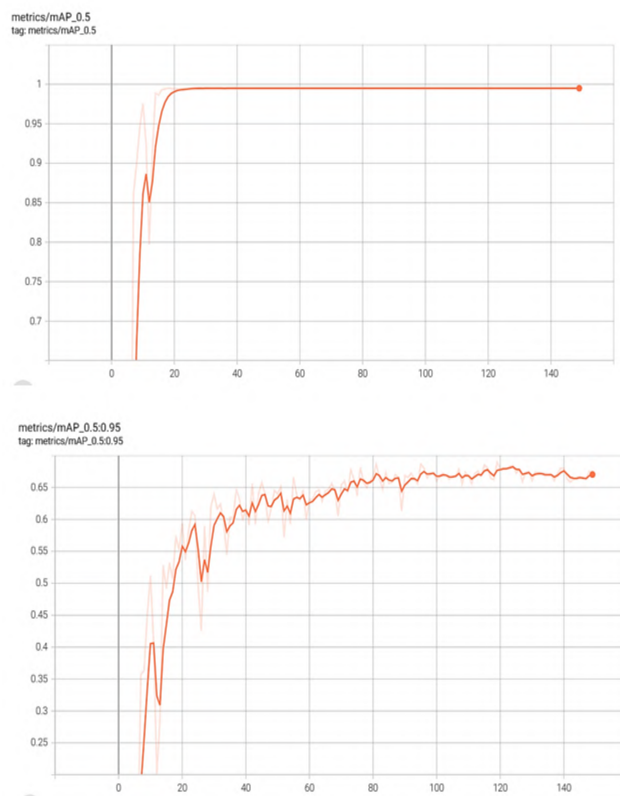


Figure 16. Mean Average Precision

(a) (b) (c) (d)

Figure 14. Sample Results with Confidence Score.

plates is one of its limitations. In the future, we intend to replace OpenCV filters with SRGAN (Super-Resolution Generative Adversarial Networks) to upsample low-resolution images into higher resolutions with the least amount of information distortion.

Author Contributions

F.A. contributed to conceptualization, methodology, investigation, data curation, and writing – original draft. N.Z.J. contributed to conceptualization, methodology, review, visualization, and supervision. H.M.A. contributed to project administration, resources, and manuscript review. All authors approved the final manuscript.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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