Automatic Recognition of Non-standard Number Plates using YOLOv8

Asaavi Tupsounder
Dept. of Computer Engineering
Vidyalankar Institute of Technology
Mumbai, India
asaavi.tupsounder@vit.edu.in

Renuka Patwari
Dept. of Computer Engineering
Vidyalankar Institute of Technology
Mumbai, India
renuka.patwari@vit.edu.in

Roja Ambati
Dept. of Computer Engineering
Vidyalankar Institute of Technology
Mumbai, India
roja.ambati@vit.edu.in

Arya Chavarkar
Dept. of Computer Engineering
Vidyalankar Institute of Technology
Mumbai, India
arya.chavarkar@vit.edu.in

Kavita Shirsat
Dept. of Computer Engineering
Vidyalankar Institute of Technology
Mumbai, India
kavita.shirsat@vit.edu.in

***Abstract*— A critical feature of vehicle movement applications is the detection and identification of a vehicle's License Plate (LP). Despite technological and algorithm developments, differences in LP properties by nation, such as number system, colors, character language, fonts, and size, necessitate more study to enhance detection and recognition. Despite substantial study, many systems function in well-defined contexts, necessitating the use of expensive equipment to capture photos from slow-moving vehicles or generate high-quality shots. This study describes a deep learning-based automated approach for LP detection and recognition, which is further separated into detection and character recognition. Yolov8 (You Only Look Once Version-8) was utilized for automatic pixel separation and gradient computation, making complicated model training easier. Using deep learning, Easy OCR (Optical Character Recognition) was utilized to retrieve text from number plates. Easy OCR (Optical Character Recognition) was utilized to extract text from license plates, with deep learning algorithms employed to effectively read text in difficult settings. For image and video processing, OpenCV (Open-Source Computer Vision Library) was employed. The project titled 'Automatic Number Plate Using YOLOv8 Model' leverages the advanced capabilities of the YOLOv8 model to develop a robust system for automated number plate recognition, serving as the core component for real-time object detection and number plate localization within images and video streams.**

Keywords*— *ANPR (Automatic Number Plate Recognition), YOLOv8, OpenCV, Image Recognition, Deep learning, Non-Standard

I. Introduction

The issuance of a licence plate by the state for monitoring and identifying automobiles is considered a necessary token. Licence plates are utilized by traffic officers, tax collectors, and other entities to monitor traffic and gather data. The exploration of extracting a licence number from a number plate has been ongoing for an extended period. The number of vehicles on the road is continually increasing, leading to the prevalence of various sorts of number plates in different languages, fonts, and designs across the world. In India, the recognition of LPs involving the use of regional languages is complicated due to the plurality of languages in different sections of the nation.

Vehicle number plate identification and extraction have a wide range of applications, from the gateways of gated communities to areas like schools, colleges, universities, corporate buildings, and public regeneration zones, where cars frequently enter and depart [10]. Quick recognition of number plates is deemed crucial not only in such places but also for toll collection, detecting stolen vehicles, and even in accident-prone areas.

For identifying car numbers from licence plates, artificial neural networks have been developed, although their processing speed and regular training are time intensive [1]. Automatic monitoring systems based on computer vision and machine learning are critical for current traffic management. Indian licence plates, incorporating text to identify job, tribe, or political allegiance, do not meet these requirements due to their intricate iconography, characters, font size, and colours, making identification and localization more difficult.

The rest of this paper is organized as follows: The second part includes a review of related work and key findings from each study article. The third part describes the system proposed by us for successful LP localization and recognition. The fourth section, detailing the implementation and outcomes, includes comprehensive information on the dataset and other parameters utilized for our system, as well as the results, encompassing all relevant discoveries. The fifth part, the conclusion, summarizes all the essential information gathered from our research. The final portion, references, covers every research journal utilized as a source for our analysis.

II. Related Work

For identifying and locating licence plates, a convolutional neural network was trained using a self-built data set, built around Faster R-CNN (Region-Based Convolutional Neural Network) [2].

The study objective of the paper was to increase the accuracy and generalization capacity of the licence plate recognition system over conventional techniques by combining deep learning algorithms with transfer learning [3]. Initially, licence plate data underwent training using the Xception network with randomly initialized weights. Subsequently, an ImageNet-trained weighted Xception model was employed for image classification and retraining the licence plate data. Finally, the performance and accuracy of the licence plate identification system of the two models were compared with those of other deep learning networks.

An MSER (Maximally Stable Extremal Region) licence plate detection technique was presented in the research, involving the stretching and gray scaling of the input image beforehand [4]. Candidate MSER licence plate regions were selected based on pixel total, size, and length-width ratio. After the removal of single-character regions, the lower and higher borders were established using gray level jump and horizontal projection. Vertical projection was utilized to establish the left and right borders.

Image processing techniques were employed to adjust the CNN model, trained on more than 2000 images of letters and numbers, to address issues such as shaded photos and angular viewing [5]. Up to 12% of environmental impediments were reduced by the CNN-based model, and great accuracy was achieved for straight-front photographs when combined with YOLOv3 and other pre-processing techniques.

A generative adversarial network-based technology was introduced in the paper for direct recreation of high-resolution images from low-resolution, blurry ones [11]. Nonuniform motion deblurring and super-resolution were simultaneously addressed. A progressive loss function, the DCT loss function, was employed for recovery performance enhancement, eliminating artefacts. The Mish activation function, reducing overfitting, was used by both discriminator and generator. The study's trials demonstrated efficient image deblurring without domain-specific knowledge.

An intelligent automobile tracking model, driven by user queries, was implemented on edge [12]. The model included phases for detecting the make, model, colour, and licence plate, with specific datasets used for testing. It tracked vehicles and detected licence plate fraud. Both YOLOv3 and OCR were used. The results showed improved metrics scores that outperformed state-of-the-art algorithms. The technology performed admirably, tracking vehicles from several CCTV videos.

CNN is significant in capturing crucial features from hazy images, enabling automatic learning of essential haze-related properties [13]. This informed our decision to utilize CNNs in our project for their capability in addressing complex visual tasks efficiently.

A. Challenges and Setbacks

Table I presents the summary of comparative study. The complications arose when license plate recognition systems were used in natural settings. Due to the complexity of plate characters, variances in font sizes, and color variations, imaging license plates proved difficult. The present methods were found to be insufficient for dealing with the various properties connected with license plates in real-world circumstances.

TABLE I. SUMMARY OF COMPARATIVE STUDY

Ref.	Model	Accuracy /Precision	Dataset used	Description
[2]	CNN	98.5%	Chinese	Creation of an extensive dataset. Proposal of model to recognize LP. To avoid character segmentation, the system fails to address all categories in the objective of detecting multiple types of LPs.
[6]	SVM	80.10%	ICDAR2013	Filtering of complex backgrounds using Otsu's Method. SVM (Support Vector Machine) for filtering of non-text components.
[7]	Image Processing	99.5%	Korean	Acquiring the licence plate area from vehicle images captured at railway level crossings.
[8]	Template Matching	90%	Egyptia, Arabian	A window with a smaller object size than the main image is defined, visible only through this window. A template matching function is performed between the object and the corresponding image area. The window is then shifted, and the function is repeated.
[9]	MATLAB (Matrix laboratory)	98%	Indian	The algorithm uses morphological operation and area criteria tests for license plate localization, segmentation of plate characters using the region props function in MATLAB, labelling, fill hole approach, and character recognition using optical characters through template matching.

III. PROPOSED SYSTEM

Utilizing YOLOv8 model offers an avenue for significant improvements in automatic number plate recognition, particularly for non-standard licence plates, aiming to enhance and address the limitations. A technique for recognizing licence plates using the YOLOv8 algorithm has been suggested by us. Figure 1 depicts the proposed architecture.

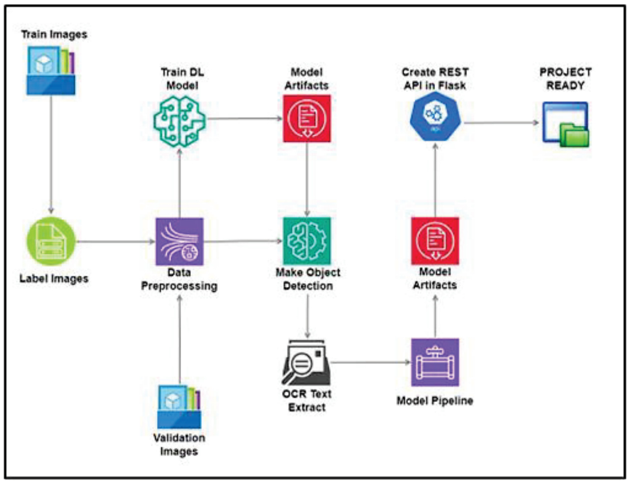

Fig. 1. Proposed System

The steps in the workflow are as follows:

- *Data Collection*: Assemble information that offers a variety of photographs of vehicle licence plates in various lighting scenarios, including both stationary and moving vehicles. We collected the dataset from 'universe.roboflow' which involves a total of 375 varied images for further analysis.
- *Data Preprocessing*: The data is required to be converted to a format suitable for the YOLO algorithm. through annotation of the locations of licence plates in the images. Object annotations (bounding boxes and class labels) in the dataset need to be encoded in a format that YOLO can understand. Common formats include YOLO's own format or formats like Pascal VOC or COCO.
- *Model Training*: The frame is processed by the YOLO algorithm, which recognizes the vehicles that it includes. To extract characteristics from an input image, YOLO models employ a succession of convolutional layers.
- *Artifacts*: Artifacts refer to various components, files, and documentation produced during the model development and deployment process. These artifacts are essential for managing, sharing, and deploying machine learning models.
- *Make object detection*: The images which are fed into the test give a confidence of more than 60%.
- *OCR*: Easy OCR is an open source which is employed for reading and extracting text from images.
- *Pipeline*: The above process will be appended into the pipeline, which will enable modularity and reusability.
- *Deployment*: The user interface provides an easy and interactive way of using the feature. Furthermore, the REST API will facilitate interoperability, allowing multiple services to avail themselves of our solution.

IV. Implementations and Results

The steps involved in the implementation of the non-standard number plate recognition system include:

- *Data Collection*: We collected the dataset from 'universe.roboflow' which involves a total of 375 varied images out of which 300 are employed for training and 75 for validation purposes.
- *Data Preprocessing*: Object annotations (bounding boxes and class labels) in the dataset need to be encoded in a format that YOLO can understand. Common formats include YOLO's own format or formats like Pascal VOC or COCO.
- *Model Training*: The convolutional layers filter the picture, allowing the model to collect low-level and high-level information including edges, textures, and object sections. The model is trained for 100 epochs with an image size of 224.
- *OCR Text Extraction*: The Python module for Optical Character Recognition helps identify and extract text from images in a range of regional Indian languages. This facilitates the identification of non-standard text on LPs that the ANPR algorithms find challenging to comprehend.

A. Performance Metrics

- *Precision*: Precision is a statistic that evaluates the accuracy of a classification model's positive predictions. It is the ratio of correctly predicted positive results to all anticipated positive results. Precision is often referred to as Positive Predictive Value. The model achieved 97.2% training precision and 97.4% validation precision.
- *Recall*: Recall: The recall is estimated by taking the fraction of correctly detected positive samples to the total number of positive samples. The model's recall measures how well it can identify positive samples. As the number of recognized positive samples increases, so does the recall. Recall was 92% for the training set and 93.3% for the validation set.
- *mAP50*: mAP50 stands for Mean Average Precision at 50. This measure is used to assess how well object detection models perform in computer vision tasks, particularly when it comes to segmenting instances and detecting objects. mAP50 is essentially an average of the precision values at different levels of recall when the intersection over union threshold for object detection is set at 50%. The mAP50 score for training was 95.6% and for validation it was 95.6%.

Figure 2 displays the number plate detection result of the training set along with the confidence percentage. Figure 3 displays the number plate detection result of the testing set along with the confidence percentage.

Fig. 2. Detection of number plates for the training set

Fig. 3. Detection of number plates for the testing set

The confusion matrix for validation, in Figure 4, depicts the accuracy as 72 out of 75 are identified correctly, and 3 images are not identified correctly.

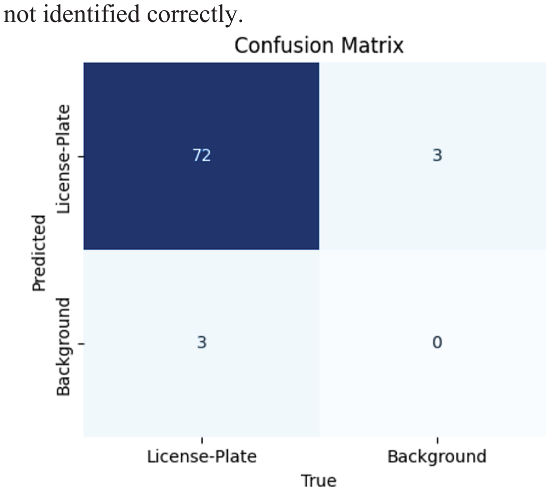

Fig. 4. Confusion Matrix

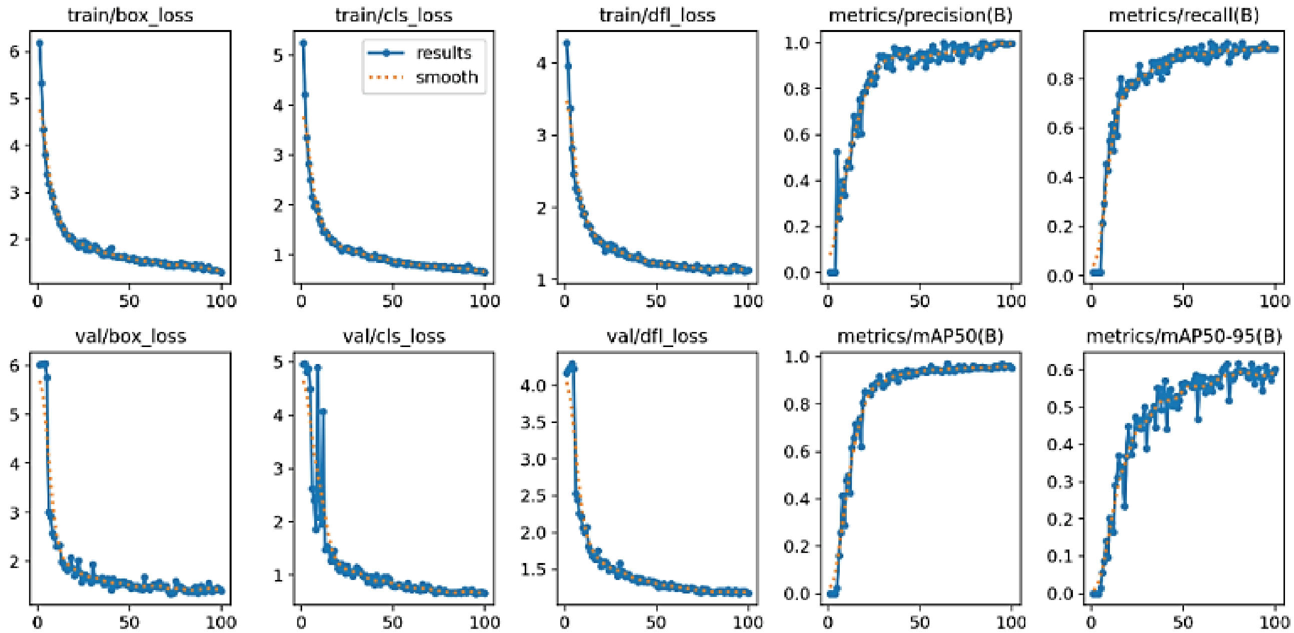

Fig. 5. Training and validation curves

YOLO models assign a confidence score to each bounding box, representing the model's confidence in the presence of an object within that box. The confidence loss measures how well the predicted confidence scores align with the actual object presence or absence in the bounding boxes. This loss helps the model focus on improving the accuracy of confident predictions. The training and validation curves shown in Figure 5 give visual cues for tracking and evaluating the training and validation performance of YOLOv8, where box_loss denotes bounding box loss, cls_loss defines classification loss, and dfl_loss denotes distribution focal loss.

Following interpretations are derived from the graphs in the Figure 5.

- *train/box_loss*: The model's ability to forecast bounding box placements improved during the learning process, as seen by the decreasing trend in the graph. As the predictions were more accurate, the loss decreased, indicating increased localization performance.
- *train/cls_loss*: A low classification loss (cls) was attained, indicating that the model had learned to recognize the visual properties associated with distinct object classes in the training set.
- *train/dfl_loss*: The class imbalance difficulties during training were effectively addressed by the distribution focal loss, as seen by the declining trend in the "train/dfl_loss" graph.
- *metrics/precision(B)*: The attained high precision level indicated that, within the examined range, the model delivered positive predictions with high confidence and a low percentage of false positives. Furthermore, accuracy was maintained or enhanced, showing stability or constant improvement.
- *metrics/recall(B)*: The observed trend in the graph indicated that the model has gradually improved its capacity to capture relevant instances of the target class.
- *val/box_loss*: A low validation localization loss around zero suggested that the model worked well in reliably predicting object positions on new, previously unseen data.
- *val/cls_loss*: The decrease in loss indicated that the predictions were becoming more correct in terms of object classes on the validation set. The spikes in the classification loss may have signaled times of instability or difficulty throughout the process, but the fact that the loss returned to a falling trend indicated that the model had adapted and continuing to learn efficiently.
- *val/dfl_loss*: The validation set's reduced loss values suggested that the model had performed well in handling class imbalance when applied to previously unknown data.
- *metrics/mAP50(B)*: The mAP50 graph's observed trend indicated that the model produced high-quality predictions in terms of precision as well as recall early in its predictions by rapidly and significantly improving mAP50. The model maintained and progressively enhanced its performance as additional data was processed, as seen by the linear rise farther ahead.
- metrics/mAP50-95(B): The "metrics/map50-95" graph'sobserved trend revealed that the model's capacity to locate and identify objects over a variety of

Intersection over Union (IoU) thresholds had steadily increased. The sharp rise in the beginning suggested that the model was learning quickly and making changes to its parameters, which led to significant gains in mAP.

V. Conclusion

This research delved into the realm of automatic number plate recognition (ANPR) utilizing the robust YOLOv8 algorithm. The study addressed the limitations of existing systems in recognizing diverse licence plates by employing YOLOv8's advanced object detection capabilities. The results showcased promising advancements in accurately detecting and identifying number plates in various environmental conditions, encompassing differing font sizes, colours, and plate types. The integration of YOLOv8 exhibited a substantial enhancement in the ANPR system's performance and adaptability to real-world scenarios. The future scope of number plate detection from video images holds immense potential for augmenting security and law enforcement measures. Implementing real-time video analysis using YOLOv8 for number plate recognition could revolutionize surveillance systems, enabling swift and efficient identification of vehicles in motion. Furthermore, the incorporation of an alert system triggered upon detecting illegal number plates could significantly contribute to law enforcement efforts. This could involve sending immediate alerts to concerned authorities, facilitating prompt action, and enhancing overall safety and security on roadways. Continued research and development in this domain will further refine ANPR systems, making them more adept at detecting, identifying, and responding to anomalies, ultimately contributing to a safer and more secure society.

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