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Automatic Two Wheeler License Plate Recognition Using Deep Learning Techniques

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***Abstract*—Nowadays, two-wheeler vehicles are often considered less safe for traveling due to a rising number of accidents attributed to the disregard of traffic rules. To address this issue, governments have implemented various plans aimed at ensuring better adherence to these rules. One significant measure has been the increase in penalty amounts, which has played a role in maintaining better control over road safety.However, this has also presented challenges for traffic authorities in effectively monitoring the substantial volume of traffic. The introduction of Automatic License Plate Recognition (ALPR) allowed the real-time monitoring of rule breakage. This enabled parking management, toll collections, tracking stolen cars, detecting law breakage, etc. This paper provides proper understanding of different methodologies used for recognition of license plates. In addition, we implemented a vehicle plate recognitionframework using ConvolutionNeural Network that compared to previous research work excelled in overall performance.**

Keywords: Number plate, review, machine learning, deep learning, non-helmet rider, Yolo

I. Introduction

ALPR systems have various applications including tracking rules broken, parking management, tracking stolen cars, traffic flow control, tracking deliveries, user billing and many other vital services. These systems may also be referred to as Optical Character Recognition of Number Plates or Vehicle Identification.[1].

ALPR combines various computer vision and image processing techniques to identify and extract License Plate (LP) information from images of vehicles. It involves object detection which is used to locate license plates on the vehicle. Image processing is used to enhance the quality of image to amplify the important features and pattern recognition uses these important features to detect characters on LP and differentiate between characters i.e it helps recognize individual characters and produce the final LP in text form.

The process of reading LP involves 3 main phases:

Phase1: License Plate Detection: It is the process of detecting and locating the LP within the given image.

Phase2: Segmentation of Characters on LP: Each character is isolated and cropped and fed to OCR.

Phase 3: Optical Character Recognition (OCR): Here all the characters are identified and converted to text [2].

Currently, there are many ALPR systems but due to variable environmental conditions such as lighting conditions, distorted LP images, dirt or nails on LPs, etc., their accuracy will be greatly reduced. This survey highlighted some major challenges encountered as ALPR technologies became more and more widely used. Some of the main challenges were changes in the LP datasets from images containing the frontal view of a single car to images containing oblique views of multiple cars, noisy or blurry images. Due to physical obstacles like bad lighting or weather conditions like snow or rain, LPs are hindered or due to fast movement of vehicles in real time LP images are fuzzy, etc. These factors greatly affect the accuracy and reliability of these systems [3].

These systems generally consist of stationary cameras located at different locations which capture the video or the image frames in the required format, then detect the vehicle if present and finally produce the LP in text form as output. There are numerous techniques used for detecting & reading the LP such as image processing to enhance patterns, object detection and classification based on these patterns in the image, etc. This survey addresses various evaluation metrics pertaining to the ALPR system such as model accuracy, speed and frames per second [4].

This survey provides a comprehensive overview of various ALPR techniques used in license plate recognition, segmentation and character recognition. These techniques range from simple image processing to advanced neural network-based techniques. Some common advanced techniques used in ALPR include Head On Generation (HOG), Convolution Neural Network (CNN) and AI powered ALPR software. The level of sophistication of the ALPR system depends on its intended application and desired accuracy of its results. The performance of these techniques is evaluated based on factors such as accuracy, speed, robustness to variations in license plate such as lightening condition, orientation and font style. The paper also discussed the challenges faced in implementing ALPR systems such as character occlusion, image distortion and character variability [5].

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Research work carried out earlier makes the use of image processing, machine learning and deep learning approaches. This research uses CNN models and in particular the YOLOv7 approach for object detection. When compared to other models it excels in performance. After result analysis it is observed that the proposed system excels in performance compared to other machine learning and deep learning approaches.

This paper has been further divided into sections where: Section II briefly surveys previous research, Section III presents our proposed research methodology, Section IV includes the result analysis of our proposed research and lastly, Section V gives the conclusion of the paper.

II. Literature Review

Over the years many research works have been done on the solutions for this problem.

A. Deep Learning Based Techniques

Reference [7] introduces a Hybrid KNN-SVM model that achieves an accuracy of 97.03% and decreases OCR phase cost and time and decreases training rate. It is also able to better recognize similar characters of the LP as the SVM was modeled specifically for similar character recognition.

In [9], the proposed model makes use of regional CNNs. It aimed to focus on the frontal view of the cars which was challenging due to its small size, out of all methods like faster RCNN, YOLO was found to be fast and able to detect small objects. Therefore YOLO was used for detection of license plates as well as recognition of characters.

In [11], the proposed approach is based on a CNN model. It utilizes a YOLOv2 model in 2 stages: detecting the vehicle and then detecting the helmet. The training of this model involved using both the COCO dataset and a custom dataset containing images of people wearing helmets, each in its corresponding stage. It utilizes detection of person class compared to the motorcycle to achieve a higher helmet accuracy. Furthermore, the license plate information was extracted using OpenALPR. This model gave an overall accuracy of 94.70%.

The methodology in [12] comprises a Warped Planar Object Detection Network for detecting the LP and a customized variant of YOLOv2 for recognizing the characters. It could recognize and correct oblique views of LPs and had an accuracy of 89.33%.

In [13] the model used Fast-YOLO and YOLOv2 for extraction and CNN for segmentation.With the exception of character recognition, letters and digits were recognised separately, a separate neural network was trained for every stage of the ALPR process.The overall accuracy was 93.53%.

In [14], a system is proposed that uses CNN classifiers to identify motorcyclists and helmets. They also employ Canny edge detection and Morphological Operations for object detection and segmentation. The system uses Tesseract to recognize the LP characters. Overall model accuracy for detection is 98.72% & for recognition is 96.36%.

In [16], the system proposed a CNN network to extract LP information. The key advantage of utilizing CNN lies in its ability to automatically learn and extract relevant features without relying on any previous knowledge of the distinct features. This independence from pre-defined features enhances its efficiency while processing data. To ensure optimal performance, the CNN model required a substantial amount of training data. As no publicly available dataset was suitable for their purpose, they took the initiative to create their own dataset specifically for the detection and recognition of Bangla LP.

Identification and recognition of multinational and multilingual LPs with various formats were the main topics of the [18] study. Using YOLOv2, LP detection was carried out. A CNN model was suggested for categorizing the LP's nation, language, and layout. These strategies could be categorized as international and multilingual LPD techniques.

Faster-RCNN and CNN are used in the proposed methodology in [20] for LP detection and character segmentation, and for character recognition respectively. A method for building a character recognition network specific to India is also introduced, leveraging the data generated by the network thus improving the training even further. Additionally, a dataset for Indian Plates has also been introduced.

In [21], a CNN model was proposed. To increase system efficiency, the input image was enhanced by applying a combination of morphological operations and pre-processing techniques. The superiority of this system was that it was able to recognise skewed LP's, multiple line LP's and various fonts for different vehicle types and also could detect in the night. It provided an accuracy of 98.13%.

In [22], the model used YOLOv2 for extraction and CNN for OCR. The proposed system used multiple datasets and applied various augmentation techniques to train the network, ensuring their ability to perform well under diverse conditions. Over 8 public datasets, the system attained a recognition rate of 96.9% on average.

The research work discussed in this subsection is summ-arized in Table 2.

Table I: Deep Learning Based Techniques

Ref. No.	Dataset	Image Resolution	No. of Images	LP Detection	Segmentation	OCR	Tools / Software	Accuracy	Real Time	Country	Cons
[6]	Own Dataset	20x16	2548	CNN	-	-	NA	95.60%	No	Brazil	Performance varies on different dataset.
[7]	Own Dataset	-	257	Hybrid KNN-SVM	Morphology Based	Hybrid KNN-SVM	NA	97.03%	No	Iran	-
[8]	Own Dataset	224x224	5000	SNoW Classifiers & Strong CNN	Probabilistic Inference Method using HMM's	Hidden Markov Models(HMMs) using Viterbi Algorithm	NA	-	-	US	-
[9]	Own Dataset	1920x1080		YOLO, Fast-YOLO	-	LPS-CR Network	NA	63%	-	Brazil	-
[10]	Own Dataset	-	380	CNN	-	CNN	TensorFlow	F1score=0.84	-	Brazil	-
[11]	Own Dataset & COCO Dataset	-	3054	OpenALPR	-	-	OpenCV, Darknet	94.70%	No	India	-
[12]	Cars Dataset, SSIG Database, AOLP Dataset	-	693	WPOD-NET	-	Modified Yolo-v2	TensorFlow framework, DarkNet framework, Python wrapper	89.33%	Yes	Europe, USA, Brazil	Similar characters misjudged.
[13]	Own Dataset	20x17	1500	Fast-YOLO, YOLOv2	CNN	-	NA	93.53%	Yes	Brazil	Couldn't detect LP in one vehicle
[14]	Indian car plates		2010	Canny Edge Detection	Morphology Based	Tesseract OCR	OpenCV, Keras, Tensorflow	98.72%	Yes	India	
[15]	Own Dataset	-	713	CNN	-	SSD	NA	96.94%	No	Thailand	-
[16]	Own Dataset	416x416	200	YOLOv3/ CNN	-	-	NA	99.50%	No	Bangladesh	Speed decreased for images with Multiple LP.
[17]	Own Dataset	-	100	The CogniMem neural network chip	-	-	CogniMem chip	91.20%	-	China	-
[18]	LPDC 2020 Dataset	224x224	29030	YOLOv2	-	-	MATLAB	99.33%	-	Turkey	-
[19]	Own Dataset	544x544	1365	Yolov2	-	-	Darknet-19, LabelImg, Google Collab	98.52%.	Yes	Thailand	-
[20]	Own Dataset	-	-	Faster-RCNN	-	CNN	TensorFlow	88.50%	-	Indian	Misjudged nail as 'O'.
[21]	-	-	-	Gray scaling, Median filter, Masking, Thresholding	-	CNN	MATLAB	98.13%	No	Indian, Saudi Arabia	Couldn't detect multiple LPs in image. Couldn't differ between LP area and vehicle grills.
[22]	ChineseLP, Open ALPR-EU, SSIG-SegPlate, UFPR-ALPR	-	6239	YOLOv2	-	CNN	NA	96.90%	No	China	Misclassification of characters, alignment of

III. Proposed Approach

Most previous ALPR research focuses only on car LPs. Our proposed approach aims at recognizing 2-wheeler motorcycle LPs. We have proposed a model using YOLOv7 for detection, Hough Transform lines for rotation, Segmentation using contours and CNN for OCR.

The workflow is depicted in Fig. 1.

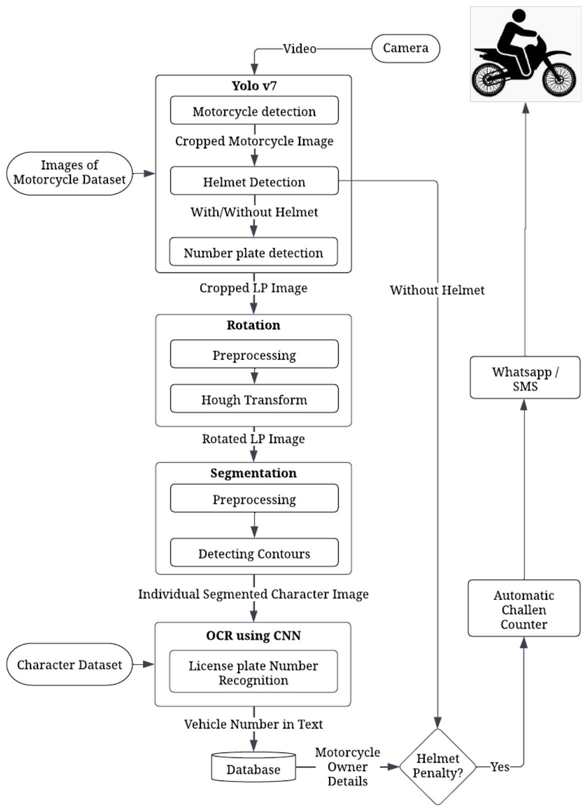

Fig. 1: Conceptual Framework For LP Detection

The main focus of our model is to extract the license plate of riders with/without helmet and recognise the characters accordingly. License plates of those without helmets, will trigger helmet penalty to the owner via SMS to register mobile number. We train the YOLOv7 model with the motorcycle image dataset and CNN model with character image dataset. The input to our system would be a video feed from which images are extracted and fed to the YOLO model. From the input image we detect the Motorcycle, Helmet and License Plate.

The cropped LP is then preprocessed to better facilitate Hough Transform for rotation. This includes: Gray Scaling, Contrast Enhancement, Smoothing using Gaussian Blur, Thresholding using Adaptive Threshold to get a binary image and edge detection using Canny Edge algorithm. Then, Hough Transform is performed on this preprocessed image and LP edges are detected. Using these lines the inclination of the LP is determined and the original LP image is rotated.

Next, the rotated LP undergoes preprocessing to facilitate Segmentation. This includes: Gray Scaling and Thresholding to get a binary image. Then the contours are detected in the LP and the characters filtered out.

Individual characters are then cropped and passed one by one to a CNN network to predict the characters. The output is then given in text format for further processing. The LP number integrated with non helmet riders is queried to the database and owner's details are forwarded to automatic challan counter where fine is generated and sent via Whatsapp or SMS of registered mobile number.

IV. Result Analysis

We collected a dataset consisting of 1069 images that feature motorcycles, some with helmets and others without taken at 5 locations in Goa, India. Each image was carefully annotated by outlining bounding boxes around the motorcycles, the head of the person, and the LP. The annotated dataset was then used to train the YOLOv7 model. A few images from our dataset are shown in Fig 2.

Fig. 2: Motorcycle Image Dataset

For training the CNN model we used an existing dataset from Kaggle consisting of around 1000 images for each character as shown in Fig 3.

Fig. 3: Character Image Dataset

After detection of the LP using Yolov7, it was cropped based on the detected boundary coordinates and underwent some preprocessing. This includes: Gray Scaling, Contrast Enhancement, Gaussian Blurring and Adaptive Thresholding to get a binary image to facilitate the detection of lines using Hough Transform. Then the edges in the image were detected using the Canny Edge algorithm. The outputs of the preprocessing steps are shown in Fig. 4.

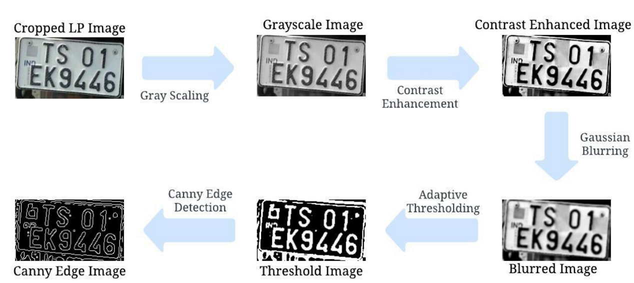

Fig. 4: Preprocessing

Next, the 4 largest lines i.e the boundary of the LP were determined from the preprocessed image using Hough Transform as shown in Fig. 5. The average inclination of these lines gives the angle by which the LP is to be rotated as shown in Fig. 6.

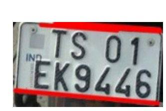

Fig. 5: Hough Transform Lines

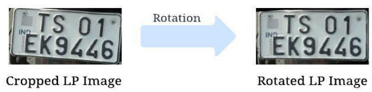

Fig. 6: Rotation

Next the rotated LP image was preprocessed using gray scale conversion and thresholding to get a binary image. The output of these preprocessing steps are shown in Fig. 7.

Fig. 7: Preprocessing

Next we found the contours i.e boundaries within the image and extracted the 30 largest contours in terms of area. The detected contours are shown in Fig. 8.

Fig. 8: Contours

Next we filtered out the screws from the contours based on their contours height compared to the LP height and we filtered out possible character contours based on their area compared to the LP areas and based on their aspect ratio. The segmented character output in show in Fig. 9.

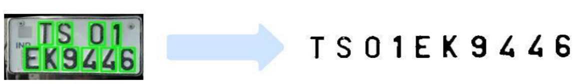

Fig. 9: Segmented Characters

Our YOLOv7 model achieved an overall Precision of 0.949, an overall Recall of 0.901 and a Mean Average Precision(mAP) of 0.926 on training it using a batch size of 16 for around 50 epochs.

Table II: Mean Average Precision

Epochs	Motorcycle	With Helmet	Without Helmet	License Plate	Overall mAP@.5
50	0.965	0.862	0.901	0.975	0.926

Fig. 10 shows the relationship between precision and the confidence threshold for our model. The curve shows a high precision of 1 across a range of confidence thresholds. This indicates accurate positive predictions and a low rate of false positives.

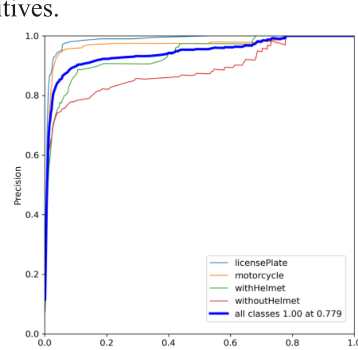

Fig. 10: Precision Curve

Fig. 11 shows the relationship between recall and confidence scores or probabilities assigned to predictions in a binary classification problem. The curve exhibits a steep initial rise with 0.95 recall, indicating that even at relatively low confidence thresholds, the model can capture a significant proportion of positive instances.

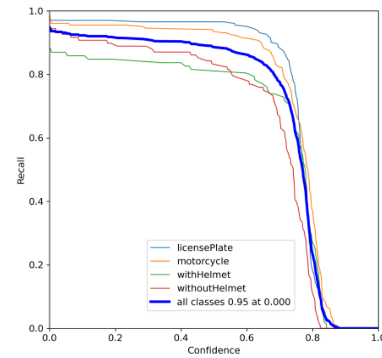

Fig. 11: Recall Curve

Fig. 12 shows the relationship between the F1 score and the confidence threshold for our model. The curve shows a high F1 score of 0.92 across a range of confidence thresholds. This indicates a good balance between precision and recall, with accurate positive predictions and minimal false positives and false negatives.

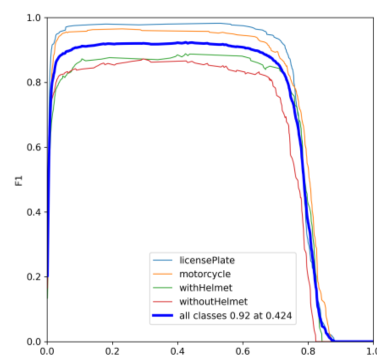

Fig. 12: F1 Curve

Fig. 13 shows the trade-off between precision and recall for our model. We obtained a high precision and high recall which indicates accurate positive predictions.

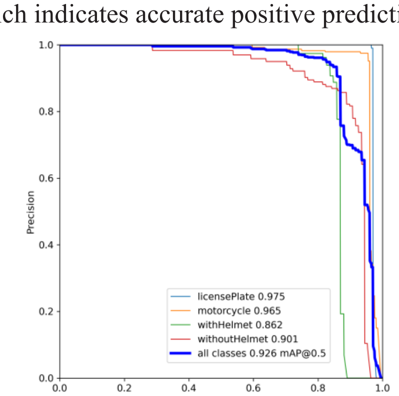

Fig. 13: Precision-Recall Curve

Our CNN model achieved an accuracy of 0.99 with a loss of 0.01 on training it using a batch size of 128 for around 50 epochs.

In this research on ALPR for Indian roads, we compared our model to a previous approach that utilized Rest-Net-50 for license plate detection. Their model achieved an accuracy of 90.08%. However, our model, which utilized YOLOv7, outperformed their method with a higher accuracy of 92.6% on our dataset. Our model demonstrated faster prediction capabilities in comparison with other techniques.

Furthermore, our CNN model for OCR obtained an accuracy value of 99%, surpassing the value of 98.6% achieved by the CNN used in the OCR network. It is worth noting that the accuracy of 99% achieved by our model is notably higher than previous OCR models.

An important advantage of our approach is that it effectively handles oblique views of license plates by utilizing the Hough Transform lines for rotation. Our project was capable of recognizing both single and double line license plates, providing flexibility for different plate formats and also it could detect and ignore screws present on the license plate, which is an improvement over previous research in this area.

Overall, our research showcased good performance of our ALPR model. In our work, we addressed the challenge of motorcycle license plate recognition, which received comparatively less attention in existing research. Moreover, we extended our research to include the detection of motorcyclists wearing helmets, which is an important practical application. In this aspect, we achieved a good accuracy rate.

V. Conclusion

The paper provides a detailed overview and compares several technologies utilized for vehicle license plate recognition. The outdated conventional approaches were substituted by contemporary technologies for this goal. Every technique has benefits and drawbacks. Tables displaying some frequently used methods for image processing and deep learning are shown. It has been demonstrated that deep learning approaches are more accurate than conventional image processing techniques.

In this research paper, we presented a helmet detection and two-wheeler number plate recognition framework that utilizes the YOLOv7, Hough Transform Lines for rotation, Segmentation using contours and a CNN model. Our YOLO model obtained a precision of 92.6% while the CNN 99%. Our model was able to successfully rotate inclined LPs and also distinguish screws on the LP from characters which is an improvement over previous models.

The future scope of our project includes improving the accuracy, efficiency and speed of our system. Additionally, we can explore further possibilities in the field of ALPR such as detecting violations such as exceeding the maximum passenger limit on a motorcycle or identifying license plates that are in poor condition.

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