Grenze International Journal of Engineering and Technology, June Issue

A Novel Approach to Detect Indian High Security Registration Plates

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***Abstract*—In recent times, with the growing number of vehicles, road safety has become a paramount issue. To ensure safe and easy passage of vehicles on the road, it is important that we take help of certain techniques that ensure the road safety regulations are properly followed. The Government of India has mandated the usage of High Security Registration Plate (HSRP) to ensure safety of vehicles, since these plates are tamper proof and cannot be counterfeited easily. In this paper, we have proposed a novel approach to detect the HSRP on a car. The most prominent feature detectable through images of an HSRP is the "IND" text inscribed on it. We have used three License Plate (LP) detection models: Warped Planar Object Detection Network (WPOD-Net), You Only Look Once (YOLO) version 3 (YOLOv3) and version 5 (YOLOv5) to detect the license plate on a car. Once a plate is detected, we apply EasyOCR to determine whether the plate has "IND" inscribed on it or not. A comparative analysis is done on these three models and our experimental results show that WPOD-Net with EasyOCR gives and accuracy of 93.01%, making the proposed approach viable for HSRP detection.**

***Index Terms*— ALPR, High Security Registration Plate, YOLO, WPOD-Net, EasyOCR, Object Detection, Optical Character Recognition.**

I. INTRODUCTION

In today's world, personal vehicles have become an important factor for people and therefore it becomes imperative to ensure that the vehicles follow rules as laid down by the government. These rules can be for car safety, pedestrian safety, occupant safety etc. In order to ensure that people follow rules, vigilance becomes a must, and the police personnel take it upon themselves to ensure that these rules are followed.

With the increase in theft of vehicles, the Indian government has mandated the use of High Security Registration Plates (HSRP) in all vehicles. The HSRP plate comes with a lot of benefits like a hologram with 'chakra' and "IND" inscribed on it. This makes it stand out from the ordinary plate and this also makes identification of a number plate as HSRP or not very easy. These plates come with snap-locks that ensure that once a plate has been fixed on a car, it cannot come out without damaging the car as well as the number plate itself. Apart from this, the plate also has a 10-digit unique number identifier that can be used by the government to get all the details about the owner. All cars in India today must have an HSRP plate, or otherwise they have to pay a fine.

License plates on a vehicle are used for uniquely identifying the vehicles. These are registered on the name of people and can be used to identify the owner of the car when required. In the past few years Automatic License Plate Recognition (ALPR) systems have been used in a variety of places like traffic management, toll tax

Grenze ID: 01.GIJET.8.2.519_1

collection and in parking lots for keeping track of vehicles.

The process of detecting and recognizing a license plate on a car is complex. It involves various strategies from the Artificial Intelligence field to give the desired output. The first step involves detection of the license plate from the image. For this purpose, various unique techniques like Rpnet [1], DELP-DAR [2], SegNet [3] etc. have been developed. The second step for ALPR is to detect and segment the characters in the license plate. For segmentation of characters, various approaches have been suggested [4, 5, 6, 7, 8] that perform different tasks such as binarization of image, conversion to grayscale, histogram processing, transformation, rectification and adaptive thresholding [9]. Finally we have the character recognition step that gives us the final output to the ALPR. Character recognition offers another challenge and various approaches like fully convolution neural network [9], ranking-based feature selection approach [10] and deep neural network [11, 12, 13] have been put forward to solve it.

The models available today can detect the number plates accurately, but cannot determine if that number plate is a HSRP or not. A solution to this is combining the LP detection models with Optical Character Recognition (OCR) model to find the "IND" text written in the plate. We have used three LP detection models: Warped Planar Object Detection Network (WPOD-Net), You Only Look Once (YOLO) version 3 (YOLOv3) and version 5 (YOLOv5) for finding LP, followed by EasyOCR to detect the "IND" text.

We have been able to come up with a HSRP detection method that can detect HSRP on a car with 93.01% accuracy. The comparative analysis of the above mentioned three models in section X show how each model performs.

II. Literature Review

The task of Automatic License Plate Detection (ALPR) consists of different sub tasks [14]. These subtasks include detecting the vehicle, followed by detecting the number plate and then finally performing Optical Character Recognition on the detected number plate for the plate number.

Silva and Jung [15] have proposed a novel Convolution Neural Network, named WPOD-Net, that can detect the number plates on vehicles in various conditions such as the number plates being oblique or the image being very dark. They have used YOLOv2 model for detecting the vehicle and then apply WPOD-Net model for detecting the number plates on those vehicles. The model proves itself to be performing better than state-of-the-art models in challenging datasets.

Kochale et al. [16] in their paper have used the Automated Vehicle Recognition Identification (AVRI) System along with EasyOCR to determine the plate number on various number plates. They have given different approaches to the system taking the rate of success, image size and time to process the images as parameters. They have been able to achieve a success rate of 96.6% with the AVRI model. Huu et al. [17] have proposed a novel model for detecting the number plates using the WPOD-Net along with Support Vector Machine (SVM) to overcome the problems of fixed environment and the manual labor. Their model shows an accuracy of 95.1% when applied to one thousand images. This model can detect number plates in a wide angle image as well as in images that are do not have proper lighting.

Ottakath et al. [18] in their research have proposed a method to improvise the existing YOLOv5 model, with which they have claimed that the accuracy of the model improves from 80% with the default parameters to 98.6% with their suggested parameters. They used the Adam optimizer and around 1000 generations for optimizing the model.

Ali et al. [19] have used the YOLOv5 model on their custom dataset to generate the results of the model. Along with using YOLOv5, they have performed data augmentation like grayscale and rotation in images to generate a custom dataset. The model shows an accuracy of 92.2% which at the time of publishing was better than other commercially available models like the PlateRecognizer [20] which gave 67% accuracy and OpenALPR [21] which gave 77% accuracy. Ha et al. [22] have generated custom Korean license plates as a part of the dataset, since the collection and labelling of the dataset is a very lengthy and time consuming process. They have applied the YOLOv5 model on their custom dataset and with that model they have eben able to achieve an accuracy of 96.82%. Their model can be extended to other types of license plates as well. Silva et al. [23] propose Improved Warped Planar Object Detection Network (IWPOD-Net) model that builds upon the WPOD-Net model and has certain advantages over the latter. This model can determine all the corners of a license plate in various conditions, making it possible to align an oblique detected number plate into a straight one for better OCR results. Laptev et al. [24] have compared different neural network models by using the price tags as the input images. They have performed data analysis using Unet, VGG16 and YOLOv4. Once the segments are detected, they have used EasyOCR for text detection in those segments. As per their comparison, YOLOv4 stands out from the rest of the models with an accuracy of 96.92% and the text recognition accuracy with EasyOCR as 95.22%. They have claimed that their model outperforms other existing models by 20-22% of accuracy.

Henry et al. [25] in their research have proposed a model that can be used to detect the license plates of multiple countries. They have used a dataset that contains the license plates from 17 different countries, which has been used to train as well as evaluate the effectiveness of their proposed approach. They have been able to reduce the time of license plate detection to 42 milliseconds per image on average.

Lee et al. [26] in their paper have suggested that apart from introducing newer Convolution Neural Networks (CNN), the existing models like YOLOv3 and Single Shot Detector (SSD) can be fine-tuned and have focused on design of experiment of YOLOv3 and have optimized its training parameters. Their results have shown that DOE certainly improves the accuracy of YOLOv3 and in optimum setting, they have achieved an average precision score of 99.0%.

Riaz et al [27] have proposed a unique model that works on YOLOv3 as the license plate detection model having some fine-tunings of their own to make the base YOLOv3 model [28] perform better on the license plates. They further use Region Based Convolution Network (RCNN) for text recognition. Their proposed model achieves 86% recognition rate and can recognize three letter plates at 88% and four letter plates at 98% accuracy. Srivastava and Gupta [29] have provided with an improved canny edge detection model that builds upon the OpenCV model and provides a better model to perform lane detection. Ali et al. [30] have suggested a method to improve the accuracy of the existing ALPR models. They have used the YOLOv5 model for detection of the license plates and have trained a convolution neural network for recognition of the text on the license plate. Their approach has got better outputs than other techniques and has given an accuracy of 92.2%.

III. Proposed Methodology

All cars today must have a High Security Registration Plate (HSRP) on them. In order to detect a HSRP, we are using one of the most prominent features of the HSRP, which is the inscribed “IND” on the number plate. This text is one of the main methods with which anyone can tell if a car has HSRP or not. The challenge of detecting this “IND” text in an image is that many cars have different texts written on them like “GOVT. OF INDIA” or “INDIAN” etc. Therefore in order to remove such texts that contain “IND” but are of no value when considering from the point of HSRP, we first perform number plate detection with the help of Object Detection and then go with Optical Character Recognition to find the “IND” text on that number plate.

In this paper, three methods are used for detecting the number plates on cars. These methods are Warped Planar Object Detection Network (WPOD-Net) and You Only Look Once version 3 (YOLOv3) and version 5 (YOLOv5). These models are used for detecting the number plate and once the number plates are detected, the number plate images are put in the EasyOCR model for getting the text on those number plates. The results of EasyOCR are then checked for the “IND” text. If the resultant text contains “IND” in it, it can be said that the car has a High Security Registration Plate. For the rest of the paper, HSRP Plate detection had been considered synonymous to “IND” text detection, and has been used interchangeably.

IV. Implementation

A. Dataset Collection

The detection of HSRP is a fairly new field and there are very few resources available for the same. Therefore, a new dataset has been created for the purpose of determining the efficiency of the approach proposed in this project. The dataset consists of 229 images of cars taken in such a manner that the number plate on either front or back of the car is properly visible. All the images contain the “IND” text in the number plates of the cars. The images taken are of the size 2250x4000 pixels. The resolution of these images is 96dpi. These images offer a wide range of number plates in different positions.

B. Finding Text

In order to find the text on a number plate, EasyOCR has been used, as it is found very effective in determining the text with very accuracy. EasyOCR is a python library that provides the python developers with text recognition features and is developed by JaidedAI. This library supports more than 58 different languages and is one of the easiest OCR libraries in python. The EasyOCR framework consists of four parts: Character Region Awareness for Text Detection (CRAFT) [31] that detects the present text, Residual Neural Network (ResNet) [32] to train the model on the character set, Long-Short Term Memory (LSTM) [33] and Connectionist Temporal Classification (CTC) [34] to better the input handling of the model. Figure 1 shows the architecture of EasyOCR.

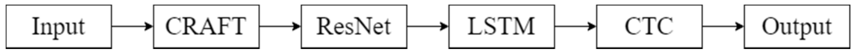

Figure 1. EasyOCR Framework

The text on the number plate is of two kinds: the “IND” text, which is required to determine whether the plate is HSRP or not, and the number on the number plate. For both of these texts, the method to locate them is different.

1) Plate Number -

For finding the plate number, the text which has the largest area is determined. Since the Object Detection models generate the cropped number plates, one can be sure that the largest area will be that of the plate number.

2) “IND” text -

Finding “IND” is fairly simple. The output of the OCR is converted into text and it is checked if that text consists of IND in it or not.

C. Model Predictions

1) Warped Planar Object Detection Network

This model proposed by Silva and Jung [15] provides us with the ability to correctly identify and recognize the license plates even when they are oblique, i.e., taken from a side view. They state that there are various models that can work with frontal view of license plate, but even state-of-the-art models struggle with oblique views.

The WPOD-Net model uses the YOLOv2 [35] object detection model to detect the cars, followed by their proposed WPOD-Net model to find the number plate and perform rectifications to the license plate so that it becomes a rectangle. Finally a modified version of YOLO [36] is used for text recognition.

A pre-trained model of WPOD-Net is used, which is trained for locating the license plates on a car. The dataset that we collect is fed into this model and cropped images of number plates are taken for further computation.

The number plates cropped from the original images are then passed through EasyOCR, which gives us the text on the number plates. WPOD-Net performs extremely well in identifying the number plates in an image. Out of 229 images that were analyzed, WPOD-Net detects number plates on all 229 images, making it 100% efficient in detecting plates. Out of these 229 images, the model is able to determine the “IND” text in 213 images, having an accuracy of 93.01%.

2) You Only Look Once (YOLOv3)

The model for YOLOv3 [37] is applied on the images in our dataset and the results generated are stored for further computation. The number plate is passed through EasyOCR, which on further computations gives the result. The YOLOv3 model also performs extremely well in detecting the number plates on cars. Out of the 229 images, this model successfully identifies number plates on 224 images, having an accuracy of 97.82%. Out of these 224 images, the “IND” text is detected on 190 images, giving an accuracy of 84.82% for finding HSRP with respect to the images detected with a number plate. Considering total images for comparison purpose, out of total 229 images, 190 images are detected with HSRP, therefore making the model 82.97% accurate in detecting HSRP given an image of a car.

3) You Only Look Once (YOLOv5)

Another model of YOLO, i.e., YOLOv5 [38] is applied on the images of dataset. The results of these images are then compared to the other above mentioned models. This model has lesser efficiency in determining the number plate in an image of a car as compared to the other two above mentioned models. Out of 229 images, this model detects number plate in 166 cars, giving an efficiency of 72.49%. Out of these 166 images, we get a result of “IND” on 146 images, having an accuracy of 87.95% for finding HSRP with respect to the images detected with a number plate. Considering total images for comparison purpose, out of total 229 images, 146 images are detected with HSRP, therefore making the model 63.76% accurate in detecting HSRP given an image of a car.

4) Proposed System Architecture

Figure 2 shows the proposed system architecture for the HSRP detection. As per the implementation above, it can be inferred that amongst the three models, WPOD-Net preforms best. Therefore, we go ahead with WPOD-Net as the LP detection model and supply its output to EasyOCR for “IND” text detection.

V. RESULTS AND ANALYSIS

The HSRP plate detection is a complicated task as it requires the image of the car from an angle where the number plate of the car is properly visible. The performances of all the models are compared and we draw results from those comparisons.

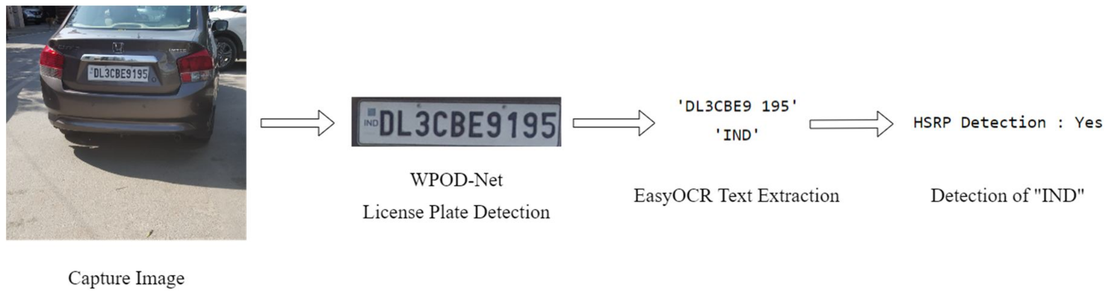

Figure 2. Proposed System Architecture for HSRP Detection

Figure 3 gives us numbers as to how the three models perform, given the 229 images as an input to all these models. Figure 4 shows how accurate the models are in detecting the number plates from a total of 229 images by showing their accuracy in detecting a LP.

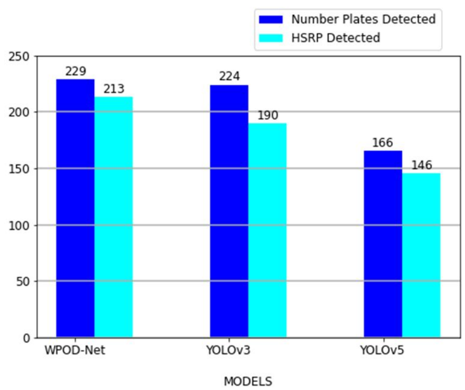

Figure 3. Comparison of models w.r.t. the number plates detected and HSRP detected

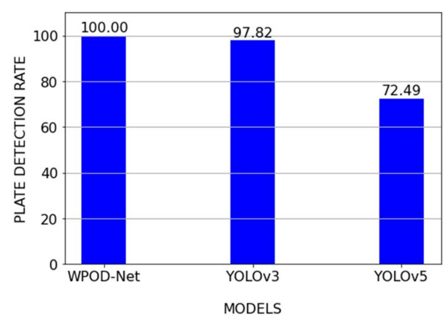

Figure 4. Comparison of plate detection rate (in %) of respective models

The HSRP detection rate with respect to the number of images detected having a number plate gives us the idea as to how accurate the models are once the number plates are detected. This is given in figure 5. Finally, the accuracy of these models can be shown from figure 6. Here, two analogies have been used to show the accuracy of the models. One is to show the accuracy of detecting the HSRP once a number plate has been detected in an image and the second is to show the accuracy of detecting HSRP, given the whole dataset, irrespective of the number of number plates detected.

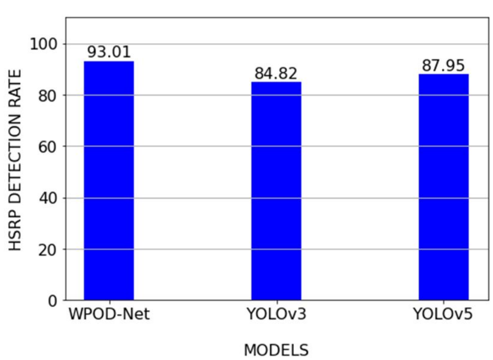

Figure 5. HSRP detection rate (in %) with respect to number plates detected

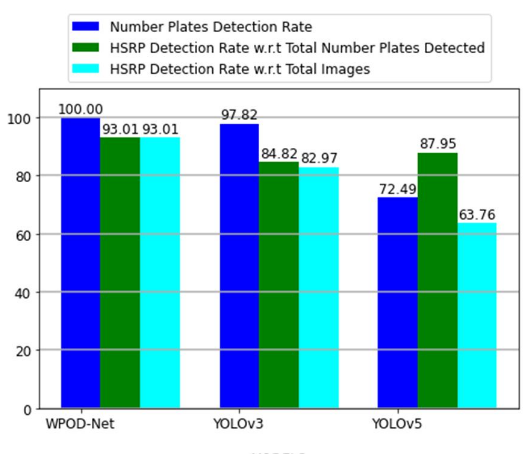

Figure 6. Comprehensive comparison of the models and their accuracies

To sum up all the different results generated from the models, table 1 gives the results in a more concise manner.

TABLE I. COMPARATIVE ANALYSIS OF ALL MODELS

Model	Input Images	Number Plates Detected	HSRP Plates Detected	Number Plate Detection Accuracy	HSRP Detection Accuracy w.r.t. Number Plates Detected	HSRP Detection Accuracy w.r.t. Total Input Images
WPOD-Net	229	229	213	100.0%	93.01%	93.01%
YOLOv3	229	224	190	97.82%	84.82%	82.97%
YOLOv5	229	166	146	72.49%	87.95%	63.76%

From the figure 6 and table 1, it can be seen that WPOD-Net outperforms both YOLOv3 as well as YOLOv5 in detecting the HSRP plates with an amazing 93.01% accuracy. Another inference that can be made from these results is that even though the number plate detection rate of YOLOv5 is less than that of YOLOv3, still YOLOv5 performs better than YOLOv3 in HSRP detection for whatever number plates it can find.

VI. CONCLUSIONS AND FUTURE SCOPE

In this paper, it was seen that combining LP detection model with an OCR model to find the “IND” text on a number plate can be used as the basis for identifying the HSRP number plates. The highest accuracy was achieved with the WPOD-Net LP model as it can detect LP in 100% of images and EasyOCR can find “IND” in 93.01% of those images. During the creation of the dataset, it was observed that the images of the cars must be of high quality since the “IND” text is very small and cannot be detected in blurry images.

The proposed approach can be used for all types of Indian number plates. The accuracy can further be improved by using more robust LP detection and OCR models.

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