Automatic Number Plate Detection in Vehicles using Faster R-CNN

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Abstract-**The paper is aimed to identify the number plate in the vehicles during difficult situations like distorted, high/low light and dusty situations. The paper proposes the use of the Faster R-CNN to detect the number plate in the vehicle from the surveillance camera which is placed on the traffic areas etc. The created system is used to capture the video of the vehicle and then detect the number plate from the video using frame segmentation and image interpolation for better results. From the resulted image using the technique called optical character recognition is applied on that image for number recognition. These number are given as input to the database to retrieve data like vehicle's name, owner name, address, owner mobile number, etc. The performance of this system is measured using in a graph model. The proposed system is able to achieve a 99.1% accuracy to detect the number plate of the vehicle and show the vehicle's owner information.**

***Keywords*- Faster R-CNN; number plate detection; vehicle detection; optical character recognition; number recognition; image segmentation; image interpolation.**

I. INTRODUCTION

Automatic number plate detection is well hot topic in the machine leaning and image processing domains. This number plate detection is applied on the surveillance camera on the traffic areas. This system is used to increase the accuracy of the detection of the number plate over the manual conditions. The core area of this system is frame separation from the input video to convert to image and then technique like image segmentations, image interpolation and OCR are applied on the image to get the information about the number plate in that image. Some of the important factors in the number plate detection is frame separation and feature extraction.

The frame separation is the combination of the many technique like separation of foreground and background objects. where foreground objects are modelled by sparse matrix and background objects are modelled by low-rank matrix. The anchor frames are then selected to overcome the difficulty in detection of slow-motion objects. The background and foreground object detection are of two types namely local and global methods. In the local method, the video is detected on each pixel separately. Some of the available methods are Gaussian average, temporal median filtering and first-order low pass filtering. In some times we can have difficulty in detecting in the black grounds with multi-level intensity. the separation of the frames quality or clarity is based on the surveillance camera. It is difficult to detect the objects in the black or low light conditions. The distance of the camera and angle of the camera toward the vehicle also plays major role in the detection of the object in the video. If the distance is less between the camera and the vehicle than the clarity of the number plate image is less and accuracy in the detection of the number plate reduces. The frames per sec in the camera should be minimum 20FPS for a good amount of accurate for detection of the number plate.

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Fig 1. Various Conditions of number pates.

It is very difficult in handling in varying lighting conditions. So non-parametric model based on the kernel density estimation are used. Hoffmann based model is used which is by assigning adaptive randomness of parameters. The Principal component analysis is a powerful method in the background separation.

Global methods are contrast to the local method; this method can exploit more spatial correlation information. Markov random filed methods are more used in background extraction. In the old methods motor blur can occur in frame separation which can reduce the detection of number plate in the vehicles. To reduce that motion blur, we are using optical flow estimator to some extent. Sometimes we can use in the image interpolation. The feature selection process plays the major role in number plate detection after all the image processing methods. During the rainy conditions blur of the video can mostly occur and this system is heavy trained for that critical time. This system is based on the latest method across all the machine learning and image processing like IR camera datasets.

Dense Motion Estimation with Anchor, Selection is used to reduced interfacing with other pixels for increasing the detection process by using below method.

$$e_k = \frac{\sum_{m\in M, n\in N} \left| i_k^{m,n} - i_{anchor}^{m,n} \right|}{M \times N}$$

We set first frame i_0 in the starting anchor frame. The remain anchor frames are selected according to the difference to the pervious nearest anchor frame. The difference between the current frame $i_k$and the previous nearest anchor frame *ianchor* is calculated for each frame. The difference e_k is defined as mean absolute difference between two frames. Where *m, n* are the two-dimension pixel indexes in a frame. If the difference is larger than a threshold *T*, this frame is selected as a new anchor frame.

II. Related work

Many old studies are done on older CNN and YOLO methods which are less accuracy and also has less performance. This is system has image processing and frame separation with advanced machine learning models. In the deep neural networks, which are based on the large number of controlling parameters. In side also has hidden multi-level layer structure. The features are based on the grey level statistics to describe the textures to high features dimensions. For YOLO similar to other region proposal classification networks (fast RCNN) which perform detection on various region proposals network and end up with performing prediction multiple times for various regions in an image, yolo architecture is more like FCNN (fully convolutional neural network) and passes the image once through the FCNN and output is prediction. This architecture is evaluating the input image in maximum grid and to each grid peer group 2
bounding boxes and class probabilities for those bounding boxes.

$$\lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2 \right]$$

$$+ \sum_{i=0}^{s^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} (C_i - \hat{C}_i)^2 + \lambda_{noobj} \sum_{i=0}^{s^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{noobj} (C_i - \hat{C}_i)^2$$

$$+ \sum_{i=0}^{s^2} \mathbb{1}_{ij}^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)$$

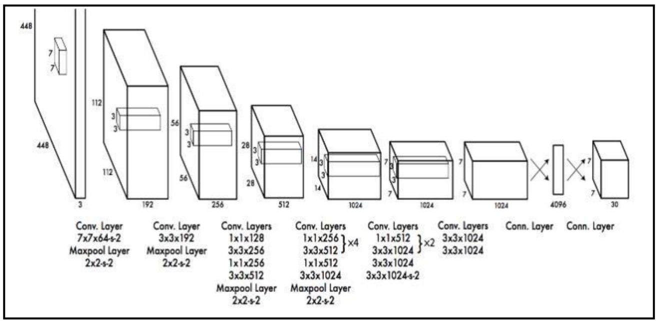

Fig 2. YOLO v2

The Yolo is good for image processing and others are doing their work in this model. YOLO divides each image into a grid of S x S and each grid predicts N bounding boxes and confidence. The assurance reproduces the exactness of the bounding box and whether the bounding box actually contains an object (regardless of class). YOLO also calculates the arrangement score for each box for every class in training. This can combine both the modules to calculate the likelihood of each class being present in a predicted box. Some are also using the Fast R-CNN for detection, but it has slow comparing the Faster R-CNN. The drawbacks of R-CNN to develop a fast object detection algorithm and it named as Fast R-CNN. Approach is almost similar to the R-CNN object detection. But, instead of feeding the region proposals to the CNN, we feed the input image to the CNN to generate a convolutional feature map. Since from the convolutional feature map, it identifies the section of suggestions and wrap them into squares and by using a RoI pooling layer we reshape them into a fixed scope so that it can be fed into another fully associated layer. From the Region of Interest (ROI) feature vector, it can use a SoftMax layer to predict each class of the proposed region and offset.

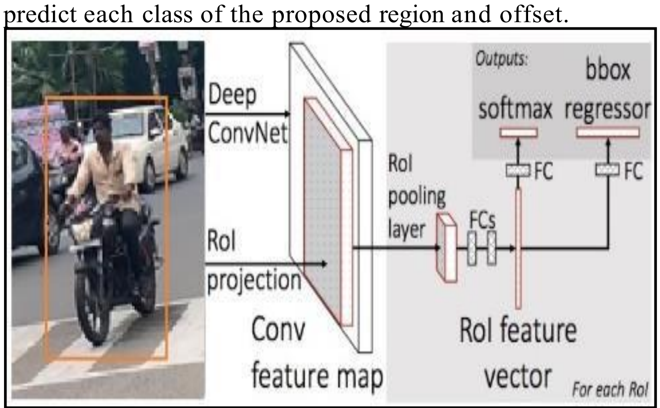

Fig 3. Working of Fast R-CNN

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III. Proposed method

In this system we used the Faster R-CNN, OCR, and advanced machine leaning models with latest image get processing methods available. The video is capture from the camera the sent to Faster R-CNN models and then resulted image is sent to OCR and then resulted numbers are checked with the database to show information. So, in the Faster R-CNN,

Both of the previous algorithms (R-CNN & Fast R-CNN) uses selective search to find out the region proposals. But our designed Faster RCNN didn't uses selective search for object identification. When using Selective search-based model progress is very slow and time-consuming which may affect rewrites into disk for every output and performance of the network. Similar to Fast R-CNN, the image is provided as an input to a convolutional network which provides a convolutional feature map. In spite of using selective search algorithm on the feature map to identify the region proposals, a separate network is used to predict the region proposals. The expected region suggestions are then reshaped using a Region of Interest (ROI) pooling layer.

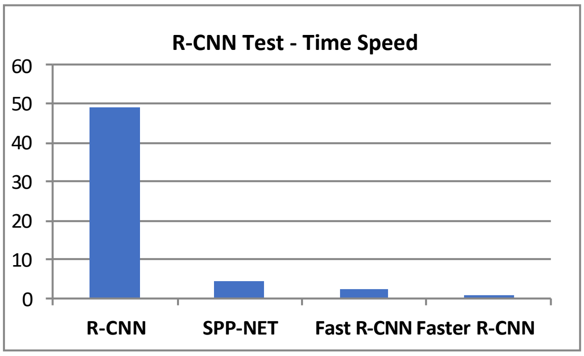

Fig 4. Comparison of Faster R-CNN

If we elect one position at each stride of sixteen, there'll be 1989 (39x51) positions. This results in 17901 (1989 x 9) boxes to contemplate. The sheer size is hardly smaller than the mixture of window and pyramid. Or you will reason this is often why it's a coverage nearly as good as alternative state of the art ways. The bright facet here is that we will use region proposal network, the method in Fast RCNN, to significantly reduce number. These anchors work well for Pascal VOC dataset likewise because the coconut palm dataset. However, you have got the liberty to style completely different types of anchors/boxes. For example, you're coming up with a network to count passengers/pedestrians, you'll not got to contemplate the terribly short, very big, or square boxes. A neat set of anchors might increase the speed likewise because the accuracy. The output of a part proposal network (RPN) could be a bunch of boxes/proposals which will be examined by a classifier and regression to eventually check the incidence of objects. To be supplementary exact, RPN predicts the possibility of an anchor being background or foreground, and refine the anchor. The 600x800 image shrinks 16 times to a 39x51 feature map after applying CNNs. Every location inside the feature map has nine anchors, and every anchor has two possible labels (background, foreground). If we make the depth of the feature map as 18 (9 anchors x 2 labels), we will make every anchor have a vector with two values (normal called logit) representing foreground and background. If we tend to feed the logit into a SoftMax/logistic regression activation perform, it will predict the labels. Now the coaching knowledge is complete with options and labels.

Fig 5. Working of image interpolation.

Interpolation Formula:

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1}(x - x_1)$$

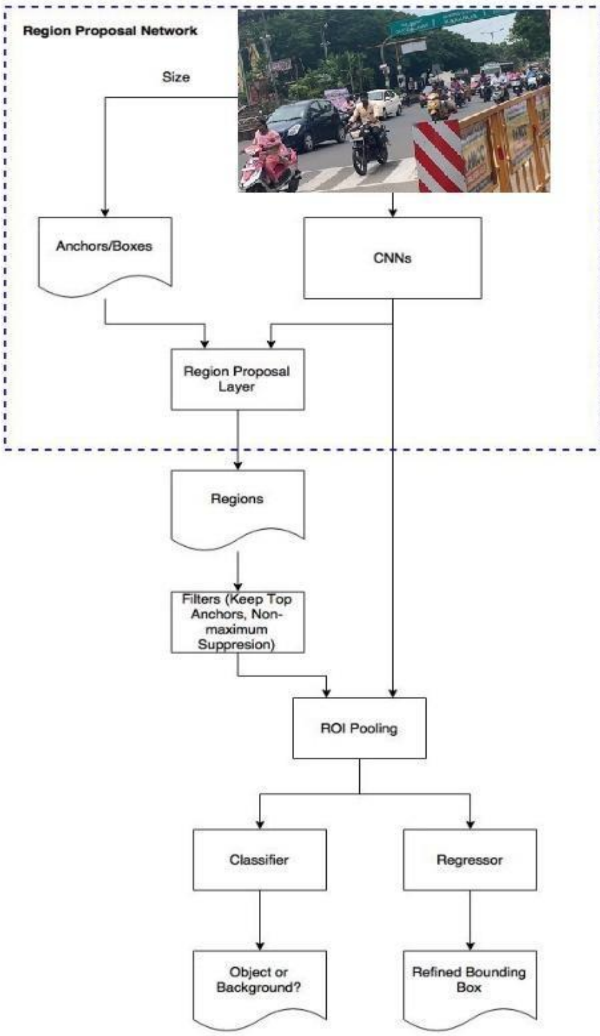

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Fig 6. Working of Faster R-CNN.

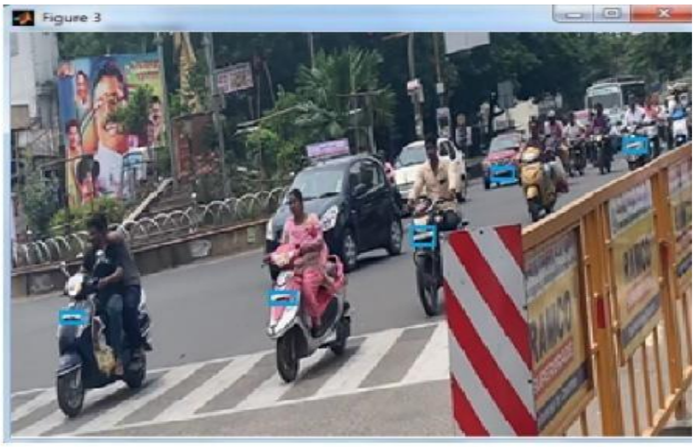

Fig 7. Output of Faster R-CNN.

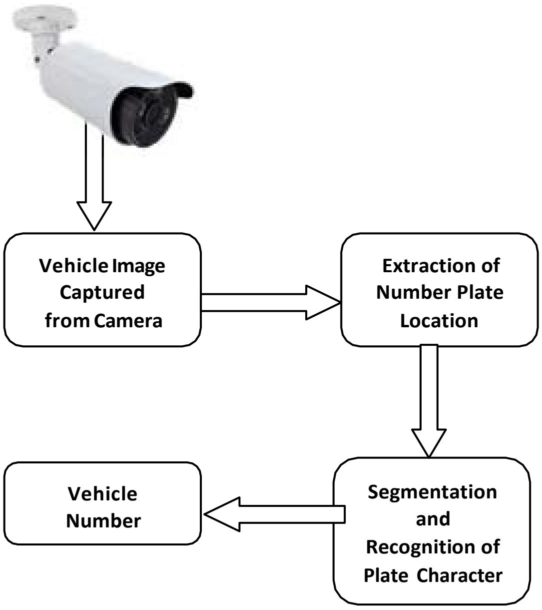

Fig 8. Step before OCR

During the OCR, the number plate is extracted in the image get processing form the object.

3.1 Character Segmentation

Characters are further extracted from the number plate. From the input image cropping is done on that image with from start to ending leaving out all the white spaces. Then the comparison process starts with image to database to normalized into character set in the database.

3.2 Optical Character Recognition

It is used to convert the string in the image to string of character. OCR separates each character from each other's. The template matching is one method in OCR. In that method, the cropped image is compared with the existing template database. OCR can automatically and recognizes the characters without any indirect input. Characters in the number plate is uniform pattern so, OCR for number plate is less complex than other methods. Template matching moves the precision of automatic number plate recognition.

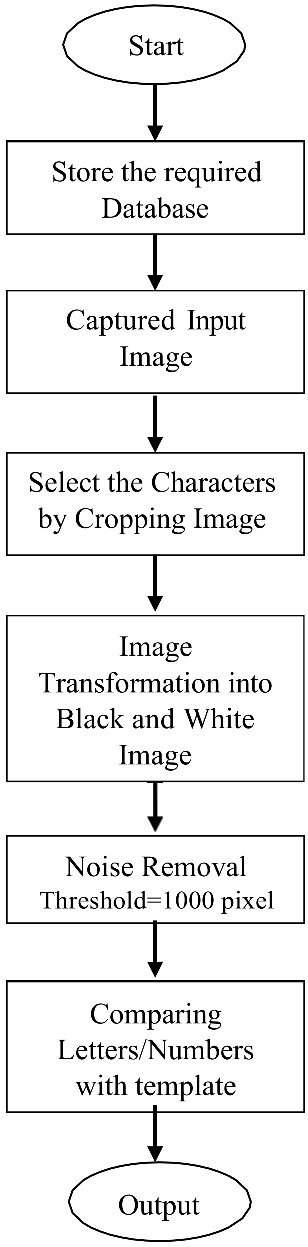

Fig 9. Working of OCR

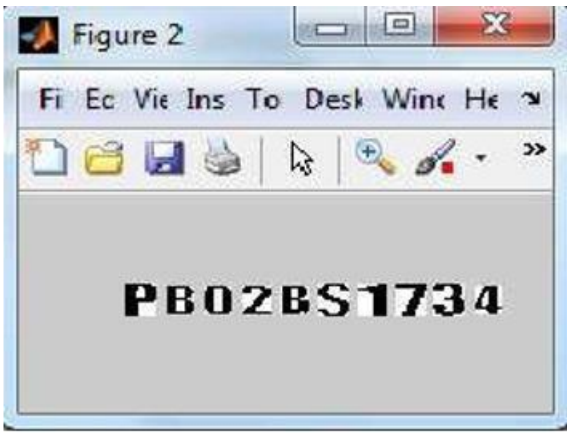

Fig 10. Output of OCR.

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It requires to have six algorithm processes to detect the plate data properly. The initial algorithm would be the plate localization, which is the process of responsibly finding the plate on the image captured on the screen. The second would be the plate orientation and sizing. This is the process that will compensate for the skew and adjust the dimensions to get the desired image size. Moreover, originate in the automatic number plate recognition with OCR, is the normalization, character segmentation and geometrical analysis algorithms. The preceding algorithm and system would be the optical character recognition. To detect an object in an image we first study its general characteristics and how it is different from
other objects within the image, general characteristics of a plate number include:

1. Plates have high contrast; this is designed for humans to be able to read easily, which is bliss for a computer vision problem.

2. The shape of the plate is a horizontal rectangle, the aspect ratio and the size of this rectangle is standard within one country.

3. The location is usually towards the bottom and middle of the car.

4. Some other local characteristics, i.e. country/state dependent.

It is an easy task to develop your filters and image pre-process to detect the plate using the image processing toolbox in resolution. All the rectangular regions of an image where the colors are predominantly white near the edges and black in the middle. This phase will eradicate most of the redundant data, but areas which have similar color with the same aspect ratio of the plate are present. These, once passed through filters which detect the high contrast will work in most of the cases except when the image background contains patterns similar to plates, such as numbers stamped on a vehicle and textured floors.

By used a Faster region-convolutional neural network (Faster R-CNN) which is trained to detect the alphabets and numerals. As the font is standard, on the License plate training of the ANN is easy. The primary 2 characters of a license plate are symbols, representing the state code, and the next two are numbers for the zone code. Defining these letters will increase the efficiency of the algorithm.

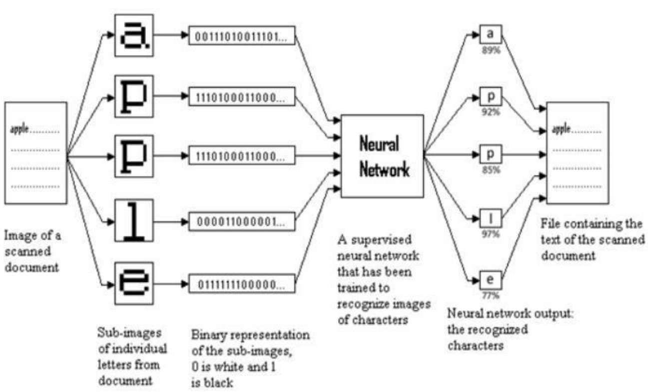

Fig 11. Detection of number in image.

The letters width for each row can be calculated from the boundary feature set. The width of the character is basically the distance between leftmost dark pixels to the rightmost dark pixel which is extracted in boundary feature set. This way a feature set of (1xh) is obtained. This stage is very important as it normalizes the character width feature set. Normalization is required as we have resized the segment keeping the aspect ratio constant. Thus, the height of each and every character is same but width varies depending on the type of the character. E.g., the characters M and H have maximum width, whereas the characters I and 1 have minimum width, thus normalizing the feature set gives character width feature between 0 and 1.

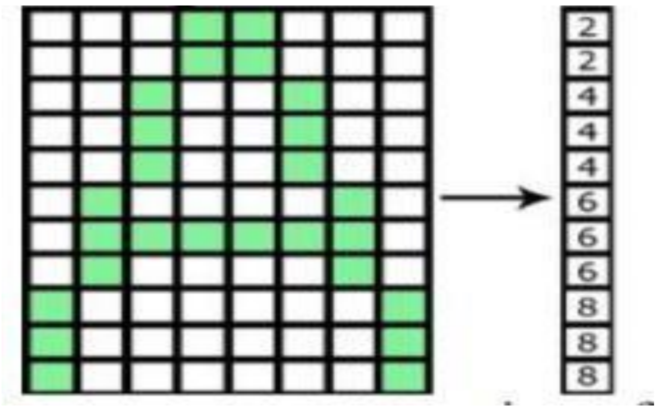

Fig.12 Detection of character in OCR.

IV. Conclusions

We increased the number of training vehicle images for the pre-processing stage. Vehicle images with different styles and difficult condition, it is helped to improve the accuracy of the NPD system. The ELM classifier was used to classify and learn the ML-ELBP features in order to produce an ensemble of strong features vectors or trained network models as a detector to detect different NPs. This work used a feature vector of 710 dimensions to represent the NP regions the output neurons depend on the number of NP classes in the training dataset. The proposed method was tested on further distorted images (unseen data) taken under difficult conditions, such as low/high contrast, foggy, and rotated NPs. The overall performance evaluation for the detection, precision and F-measure rate is 99.10%, 98.2%, and 98.86%, respectively, with an FP rate of 5%. The experimental results of the proposed method were also compared with several existing NPD methods that used the same database. It outperformed those methods in terms of the detection rate and efficiency. The average detection time per vehicle image was 0.98s. Many existing methods used only the testing phase with the pre-processing stage under some assumptions. This proposed method works well without assumptions due to the use of two separate phases of testing and learning.

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