Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 9, August 2021: 3379 – 3391

# License Plate Recognition System using YOLO and Mask R-CNN

**Veena G.S.**, Assistant Professor, Dept. Computer Science and Engineering, Ramaiah Institute of Technology

Bangalore. veenags@msrit.edu

**Ashmitha. R**, Dept. Computer Science and Engineering, Ramaiah Institute of Technology , Bangalore. ashmithar167@gmail.com

**Dr.Divakar Harekal**, Assistant Professor, Dept. Computer Science and Engineering, Ramaiah Institute of Technology, Bangalore. divakar.h@msrit.edu

## ABSTRACT

License plate devices have been commonly used in parking lots in recent years. The Traditional plate recognition devices used on car park have fixed source of light and an angles for shooting in ordering to quickly distinguish license plates. Deformation oflicense recognition plate can also be especially extreme for tilted angles like for examplelicense plate images taken with ultra-widened angle lens or it can be fisheye lens, resulting in poor identification of standard license plate recognition systems. Mask RCNN Device that couldalso be useful for different angles of shooting as well as oblique pictures. Experimental findings have shown that proposed architecture will be able to classify license plates which have bevel angles of over 0/60. Proposed Mask R-CNN system hadalso made substantial progress in character recognizingwhich are inclined more than 45 degrees in comparison with approach of using the YOLOv2 model. Results from experiments also show that the system proposed in the open data plates collection is superior to other methods (known as AOLP dataset).

**Keywords -**deep learning,Mask R-CNN , license plate recognition systems.

## INTRODUCTION

Because of growth of smart towns, license plate recognition devices are planned as intelligent traffic monitoring, automatic charging or crime detection systems that can be built into intersection sensors or street lights. License plate recognition devices in the parking lots has recently been commonly used. The conventional parking lot license plate recognition device is equipped with a fixed shooting angle and light source to quickly distinguish license plates.The standard plate recognition device first detects license plate,then horizontally and vertically aligns, then segments the character to cut each and every individual characters.Finally, identification of characters takes place making use of template matching or machine learning (example SVM and KNN) or deep learning methods (example CNN, DNN).

On the other hand, on intersection display the operation of license plate recognition device is entirely different. In the parking lot, the license plate recognition system cannot fulfil intersectional monitor criteria, such as different shot angles, blurred license plates, light and shadow shifts, etc. For instance, the proportion of the license plates recognizedas well aslicense plate characters present in image is very low given the high-resolutioned wide-angle image as seen in Fig. 1. Moreover, for tilting angles especially, as seen in Fig 2: photographs of license plate which is taken using super wide-angle lens or of fisheye lens.License plate deformations can be especially severely affected, with the consequence that existing license plate identification systems are poorly recognized. Moreover, complex outdoor conditions can also impact the light source and cause excessive exposure or underexposure issues.

In proposed paper we already have established a 3-stage R-CNN[1] license plates method, which will be useful for different shooting angles, distancesas well as oblique images which helps in solving the problems mentioned above. The proposed architecture has 3 phases which includes vehicle detection, license plate localization as well as character recognition. Key benefit of 3-phase strategy is that it is not necessarily in order to implement the phases to be used.Since the portion of license plate of particularimage is quite closely linked to the shooting distance, one-phase architecture which isn't as helpfulfor training is difficult to match all samples. It is extremely hard to detect by making use of single-phase architecture consideringlicense plates which has longest shooting distance as well as small portion of frame. Three-stage architecture allow phased detection to improve percentage of license plate characteristics in photograph. It can be applied without taking the distance issue into account, facilitating and improving preparation.Mask R-CNN’s overlapping portions of large-angular shoots are exceptional at instance segmentation.Mask R-CNN can be described as multi-scale, pixel-pixel architecture, thus having strong object-to-fact recognition ability.

Therefore, although the picture on license plate is blurred, it could clearly distinguish, correctly identify the characteristics on the license plate. The proposed architecture will describe the license plate with angles of 0~60 degrees at which mAP rate is up to 91 percent can be achieved with experimental performance.The proposed Mask R-CNN system hadalready included considerable improvementby determining characters which are greater than 45 degrees compared to approach using YOLOv2[16]. The test results also demonstrate that approach proposed is much more superior thanall other methods that are in open plate dataset (known as AOLP dataset).

**Figure:1Example of the high-resolution widened-angle image**


**Figure:2 Deformed license plates caused due to the shooting angles**

## LITERATURE SURVEY

### *A)Traditional license plate recognition system*

Traditional license plate recognition system use image processing to remove appearancelike horizontal and vertical projection, edge detection from license plates. These characteristics are recognizable primarily by naked human naked eyes and modelled mathematically on algorithms directed towards generate characteristics which humans want. Finally, character grading is performed through contrast of features. The classification of character can be divided as follows into four methods.

### (*1) Template matching*

The matching template[8][9] is based on the distance from the regular templates calculated. Only basic screenplays including set light sources and shooting angles are required for template matches. Passing templates is fast, but changes in the shooting environment cannot be made.

### *(2) Machine learning classification*

Classifying characters directly by methods like SVM[10] as well as KNN[11]. For classification purposes, aforementioned approach use linear equation. Although the procedure is straightforward, nonlinear and multi-categories are difficult to distinguish and there is a considerable amount of estimation, that has progressively been substituted.

### *(3)Neural networks*

Neural network[12][13] is programmed via derived characteristics, as conventional approaches will, so computer can mimic human beings in order to understand these characteristics.

### *(4) Convolutional neural networks*

Conventional plate recognition devicethat can extract human characteristicswhich is used for training machine is not as simple to learn and classify, even though it appears intuitive to humans, and its effects are no better than the machine itself. The proposal for the formation of a system to remove functionality and identify objects by itself[14][14] is then made for convolutionary neural networks (CNN). While CNN can isolate the features itself, only photographs can be classified and the effect of object location cannot be achieved. It is only possible to identify one character each on a license plate in the final phase of the standard license plate recognition scheme.

***B)Object detection based license plate recognition system***

License plate recognition system based on object recognition [16][17] is used for locating and detecting characters present on license plates using object detection master-learning architecture. While the license plate identification systems focused upon object detection had significantly increased noise capability as well as broad-angle recognition capability compared with conventional license plate recognition system, segmentation capability of overlapping characters remains inadequate.

***(1) YOLOv2***

YOLO[7] also known as You Look Once, that implies for the whole picture, a one storey architecture, only one shot is detected. YOLOv2 has several anchor boxes of various sizes, with each picture split into s*s. Any centre of the grid is handled one at a time as an anchor, and all anchor boxes are then detected. YOLOv2 improves the generalisation through batch normalisation and increases YOLO's mAP rate with several anchor boxes, a high-resolution classifiers, a cluster of dimensions, a precise position predictor, training and sophisticated features. YOLOv2 is generally fasters and precise than YOLO, thus improving precise identification of small objects.

***(2) Mask R-CNN***

The mixture of ResNet[2] as well as FPN[4] could be contemplated loosely as mask of R-CNN. The Faster R-CN N[3] as well as FCN[5] combination and part of mask formed by FCN can be considered.

***a. ResNet***

ResNet's key benefit is the degradation solution Deeper neural teaching networks issues. ResNet is a multi-layered architecture consisting principally of four remaining blocks which match each other repeatedly Layers. - Layers. The remaining block creates an entry shortcut two convolutionary layers each with a sophisticated feature added to the outputs to maintain the power of initial entry and resolve the deep plain issue It is impossible to stably converge networks.

***b. Faster R-CNN***

Faster R-CNN known as2-stage method, with phase of proposal and phase of identification. Backbone of the Faster R-CNN is ResNet and the projected bounding boxes can be found with RPN.Faster R-CNN produces feature maps by ResNet in the proposal phase and that dispatches feature map for Region Proposal Network (RPN). RPN is comprehensive network that uses sliding window for defining zone proposals by usingthe anchor boxes of varying sizes.

Regions ideas are returned to the original ResNet performance charts in the detection stage, RoIPool is performed, the RoI is corrected, the final bounding box is retrieved, and classes as well as boxes are output.

***c. Feature Pyramid Network (FPN)***

For effects of convolution and pooling layers, FPN produces various scales of function maps. The bottom feature map makes the RPN performance forecast, samples up and adds to the previous feature map 4 times bigger than before, and generates the RPN projection output again. The same process is repeated by adding an element to the previous 4-fold function map and predicting the RPN performance then.

### *d. Fully Convolutional Networks (FCN)*

FCN is a network that is completely convolutionary. Unlike conventional CNN, FCN which is not completely bound to layer. Each pixel in the image is explicitly labelled and classified by FCN such that the semantic segmentation is possible.

e. RoIAlign

To optimise Faster R-CNN, RoIAlign is used. RCNN accomplishes pooled and quantized roI quicker. Since the RoI area does not actually land on the grid junction, spatial offsets are caused. This may not be a significant issue at first sight, but the precision of detection of small items has been significantly affected. Major contribution of Mask R-CNN is that to resolve problem which is caused due to pooled operation performed on RoI

RoIAlign is used to replace RoIPool with Mask R-CNN. RoIAlignwill not quantify RoI explicitly, but raises sampling point of each container and by bilinear interpolation measures the value of each and every sampling point, then extracts a total RoI value.Thus, RoIAlign prevents offsets and errors which are caused by quantization.

This is R-CNN mask definition. Since Mask R-CNN employs many different network optimization strategies, which has many benefits. For e.g., ResNetstabilises the R-CNN mask for best training performance.RPN can track objects and locate boxes in Faster R-CNN. To achieve instance segmentation, FCN will perform pixel-pixel training along with correction.

R-CNN mask attaches FCN to backside ofRPN moreover only executes FCN present on side of its bordering box for secure instance.RoIAlign is more exact than other methods of RoI of Mask R-CNN.The FPN allows the detection effect of small objects strong in multi-scale, significantly better than the detection effect.

## METHODOLOGY

In this segment we suggest a 3-phase license plate recognition scheme involving vehicle detection then license plate localization further more character recognition, as seen in Fig. 3.

### *A. Vehicle detection*

At initial stage, YOLOv2 is adopted for detecting vehicles. Vehicles listed includes cars, lorries, buses and trucks to meet real needs. Picture is split into a grid of 19*19. Since the car is of various proportions, the detection frame is made up of five types of anchor boxes. This phase is used to determine the vehicles to be included in a picture and then to mark the areas of the identified vehicles under the name RoI (area of interest).

### *B. License plate localization*

We also use YOLOv2 for license plate detection in the second round. In stage I, YOLOv2 division into the first 19 x 19 grid. In view of the skewed angle of license, five types of anchor boxes are applied, these anchor boxes are used for each and everylicense plate detection centre andafterwards for character identification, the license plate images are captured in the final process.

### *C. Character recognition*

In last stage, we make benefit of R-CNN mask to recognize character. On the grounds that R-CNN mask is architecture basically useful for each segmentation, the edges of each character must be labelled so that they can detect pixels by pixels. We have chosen ResNet-50 known as backbone of Mask R-CNN in ResNetwhich is based on trade-off in between speed alongside precision. The entire convolution network is useful for RoI masking after object recognition is done. Finally, the character on the license plates that were caught in the last phase is identified using Mask RCNN.

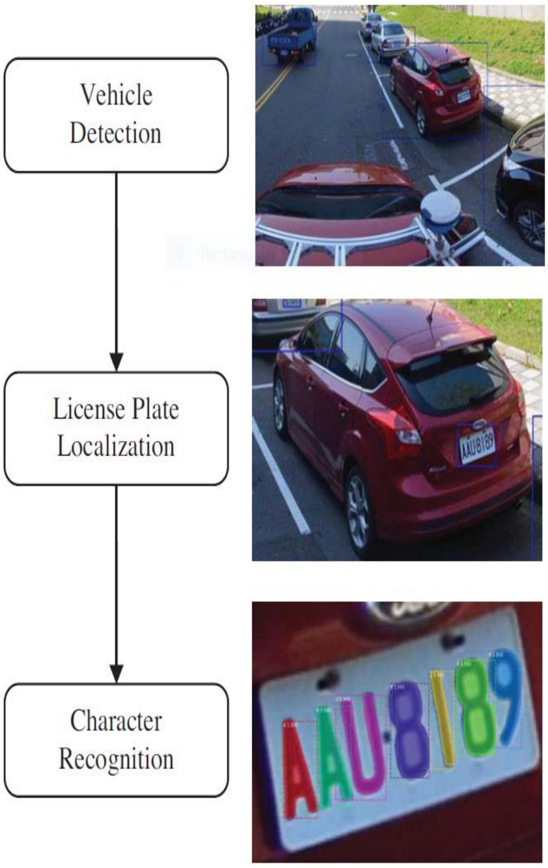


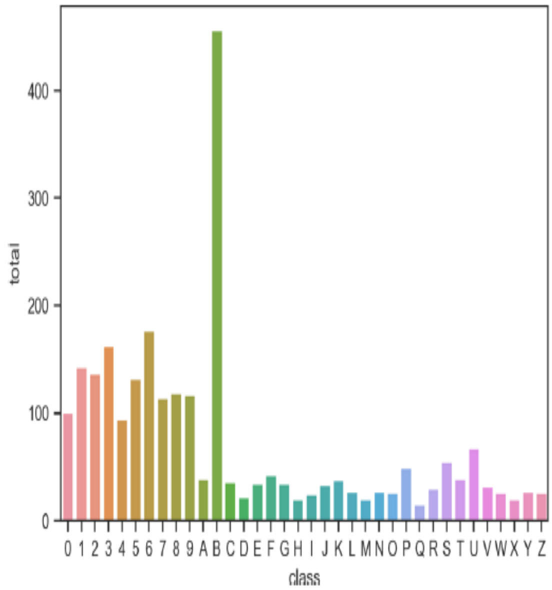

**Figure:3Stages of proposed license plate recognition system**

Generally speaking, proposedlicense plate identification device should no more have to be used together in three stages and can be efficiently deployed. For instance, Phase III could be useful in directly to recognize character even without locating the vehicle detected moreoverlicense plate if only license plate occupies more than 20% of the picture. If the license plate ratio for photographs range from 20% to 3%, PhaseII for the identification of license plates and PhaseIII for classification of characters without vehicles will be used. Entire three-phase scheme will be implemented if only ratio of license plate to photographs is lesser than 3%.

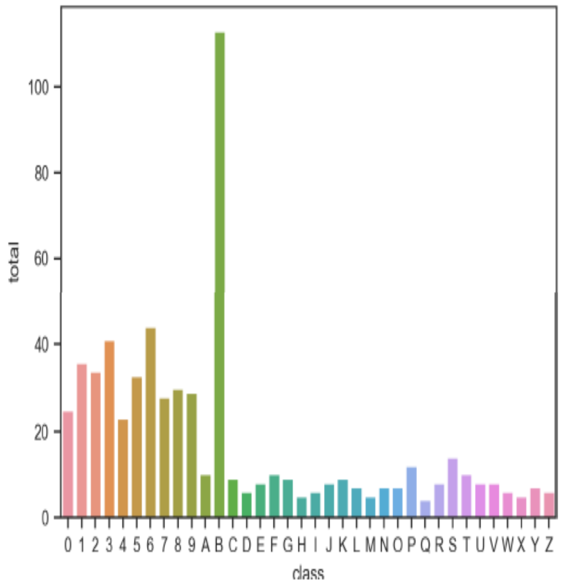
It should be noted that if ratio of license platform to picture is poor, it can be understood as simple to miss license platesalong with characters which contains one-stage profound learning architecture. In the phases I and II, YOLOv2 is used to collect vehicles and license plates, so that the character/image ratio is increased. Thus, in third step we will increase the reminder rate of the identification of the character and reduce significantly the problem that license plate characters cannot be detected.

## EXPERIMENTS

Fig. 4 shows extent of preparation along withapproval information required for ResNet model utilized in detection of License Plate digit classification.




**(a) Training**




**(b) Validation**

**Figure:4 Total amount of data perc class for training as well as validation of ResNet Model.**

The first step is to take the YOLOv4 Bounding Coordinates and simply take the region of the sub-image within the boundaries of the box. Since we utilize cv2.resize() for blowing the picture up to 3x its original size, most of the time it is incredibly tiny


We next transform the picture in grey and smooth it by applying a slight Gaussian blur.


After this, the image has black background threshold to white text and the Otsu technique has been applied. This black white writing helps to detect image contours.


The picture is then dilated using RCNN mask to increase the visibility of contours and to be taken in the future.


Then we use Mask-RCNN to detect all of the rectangular contours on the picture and sort them from left to right.

As we can see, several contours are contained inside the license plate number other than the contours of each character. We use a handful of characteristics to accept a contour in order to filter out the undesirable parts. These are height and width (i.e. the area height must be 1/6th the whole picture height) alone. These are height and width ratios. A few other characteristics are also set on the area etc. To view full details, check out the code. We are left with this filtering.


The only areas of interest remaining now are the individual characters of the license plate number. We segment and apply a bitwise not mask on the white backdrop of every picture in order to flip the picture into black text with which Tesseract is precise. A slight median blur on the image is the final stage, then the letter or number from it is given on to Tesseract. Example how letters would look when applied to tesseract.


Each letter or number will then only be joined together in a string and you will finally receive the entire recognized license plate.

The experimental equipment’s usedare  CPU of Intel Core i7-4790 alongside GPU of NVIDIA, GeForce GTX TITAN X. Intel Core i7-4790 which contains of cores operate at 3.60GHz while TITAN X which has 3,840 CUDA cores which operate at 1GHz. Operating system used is Linux Ubuntu 16.04 LTS.

Test item is general car license plate. The number plate consists of a mixture of A~Z (except I, O) and 0~9 for a total of 34 characters. In addition, the total number plate is 8. There are a minimum of 4 and a limit of 7 license plates on each license platform.

The license plate's background colour is white, black, red or green. However number of currently issued license plates vary somewhat based on the number of cars, the bulk of these are black and white license plates. In the sunny and snowy days, the pictures were taken.

There are two sections of the experimental findings. The pictures taken from roadside along with road bridge are usefulin training YOLOv2 model for vehicle identification and license plate detection. Multiple trails and multiple vehicles can include a picture. The size of the input image is 1920 pixels. The training data set which consists of 4,500 images and validation data set which consists of 500 images. These pictures include various vertical and horizontal offset and rotated angle. For license plate with angle range above 0~60 degrees, the characters recognition mAPconsidered for validation dataset is about 91%.

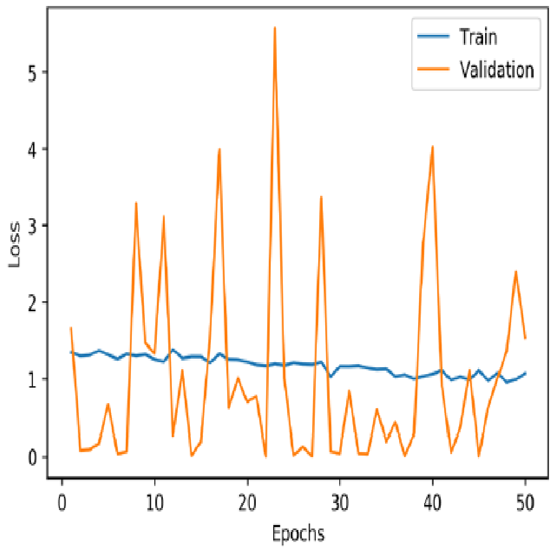

**Figure:4 License plate examples in training and testing dataset**

| Shooting angles | Example of license plates |
|---|---|
| 0° ~15° |  |
| 15° ~30° |  |
| 30° ~45° |  |
| 45° ~60° |  |
| 60° ~75° |  |

**Figure:5License plate patternswhich were taken from various angles**

## RESULTS

Figure:6 shows illustrations of misfortune as well as exactness of model. During preparation, we save loads which returns with best approval exactness as well as utilization for tag acknowledgment framework. The model has 0.80159 approval exactness.



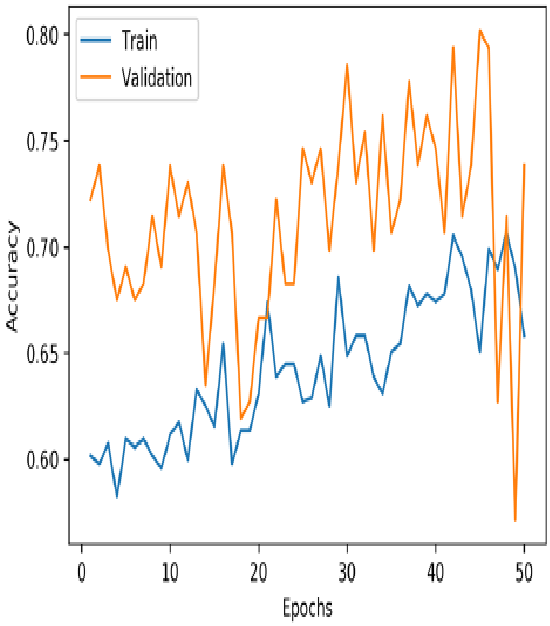



**Figure:6 The graphics for loss alongside accuracy of ResNet model**

In Table I, Recall rate for each and every angular range begins at the normal position of lens aligned to normal direction of centre plate, each of which is 15 degrees, according to figure 5. The reminder rate of each angled range. The study contains a left-hand side path and a right-hand path, each 50 percent. As the photographs are captured from real use, they can be concentrated at a distance of 150 ~ 200 cm, so the detection effect of 50cm is comparatively low. According to the real use, our data collection also contains a limited amount for samples from 60 to 75 degrees.The time of processing of each and every image is the result of image recognition. Detection time would be abnormally quick if image recognition effect is not successful. In Table I, for example, images of 45 to 60 and 60 to 75 degrees are processed in short periods than the images of less than 45 degree images. Processing time of 50 cm images is therefore less than the processed time of 100-200 cm images.

In Table I, the proposed approach with RCNN mask shows major advances when it comes to characters inclined above 45 degrees compared to method using the YOLOv2 model. For example proposed approach of Mask R-CNN achieves 76.8 per cent accuracy for photographs that are tilted from 45 directed towards 60 degrees over distance of about 200 cm, whereas YOLOv2 method is just 48 percent accurate.

| Model | A two-stage approach [16] using YOLOv2: License Plate Localization + Character Recognition | | | | The proposed approach with Mask R-CNN | | | | Average Improvement |
|---|---|---|---|---|---|---|---|---|---|
| Angle \ Distance | 50cm | 100cm | 150cm | 200cm | 50cm | 100cm | 150cm | 200cm | |
| 0 ~15 | 8.6% | 83.9% | 76.2% | 99.9% | 87.1% | 97.9% | 99.9% | 99.9% | 29% |
| 15 ~30 | 17.0% | 90.7% | 98.7% | 99.8% | 80.5% | 94.2% | 97.2% | 99.9% | 16% |
| 30 ~45 ġ | 0.4% | 85.7% | 84.1% | 93.1% | 63.7% | 85.6% | 93.6% | 98.6% | 19% |
| 45 ~60 ġ | 0.1% | 48.2% | 37.6% | 48.0% | 25.5% | 62.1% | 79.6% | 76.8% | 28% |
| 60 ~75 ġ | 0.0% | 0.1% | 4.0% | 4.2% | 6.4% | 13.1% | 26.7% | 22.1% | 15% |

**Table I: Comparison of recall rate of each and everyangular range.**

## CONCLUSION

In proposed paper we have introduced 3-stage R-CNN mask-based license platform recognition method which could be useful for different film angles as well asfor higher oblique images.Experimental findings indicate the design suggested will distinguish license plate which have radius angle of 0 to 60. In case of identification of characters inclined over 45 degrees, the proposed R-CNN mask process compared to the YOLOv2 model has made important progress.

## REFERENCES

[1] K. He, G. Gkioxari, P. Dollár and R. Girshick, "Mask R-CNN," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, 2017, pp. 2980-2988.
[2] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778.
[3] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017.
[4] T. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan and S. Belongie, "Feature Pyramid Networks for Object Detection," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 936-944.
[5] J. Long, E. Shelhamer and T. Darrell, "Fully convolutional networks for semantic segmentation," 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, 2015, pp. 3431-3440.
[6] J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 6517-6525.J. Redmon,

S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once:Unified, Real-Time Object Detection”, CVPR, LAS VEGAS, 2016, pp.1-10.
[7] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 779-788.
[8] M. Yu and Y. Kim. “An Approach to Korean License Plate Recognition Based on Vertical Edge Matching,” SMC, 2000 , pp.1-6.
[9] J. Wang, W. Zhou, J. Xue and X. Liu, "The research and realization of vehicle license plate character segmentation and recognition technology," 2010 International Conference on Wavelet Analysis and Pattern Recognition, Qingdao, 2010, pp. 101-104.
[10] Y. Wen, Y. Lu, J. Yan, Z. Zhou, K. M. von Deneen and P. Shi, “An Algorithm for License Plate Recognition Applied to Intelligent Transportation System,” IEEE Transactions on Intelligent Transportation Systems (T-ITS), vol. 12, no. 3, pp. 830-845, Sept. 2011.
[11] S. Karasu, A. Altan, Z. Sarac,and R. Hacioglu,“Histogram based vehicle license plate recognition with KNN method,” ICAT, Rifat, 2017, pp. 1-4.
[12] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos and E. Kayafas, “A License Plate-Recognition Algorithm for Intelligent Transportation System Applications,” IEEE Transactions on Intelligent Transportation Systems (T-ITS), vol. 7, no. 3, pp. 377-392, Sept. 2006.
[13] T. Nukano, M. Fukumi, and M. Khalid, "Vehicle license plate character recognition by neural networks," Proceedings of 2004 International Symposium on Intelligent Signal Processing and Communication Systems 2004 (ISPACS 2004), Seoul, South Korea, 2004, pp. 771-775.
[14] S. Li and Y. Li, "A Recognition Algorithm for Similar Characters on License Plates Based on Improved CNN," 2015 11th International Conference on Computational Intelligence and Security (CIS), Shenzhen, 2015, pp. 1-4.
[15] C. Lin, Y. Lin and W. Liu, "An efficient license plate recognition system using convolution neural networks," 2018 IEEE International Conference on Applied System Invention (ICASI), Chiba, 2018, pp. 224-227.
[16] C. Lin and Y. Sie, "Two-Stage License Plate Recognition System Using Deep learning, " ICASI, 2019, pp. 1-4.
[17] S. Abdullah, M. Mahedi Hasan and S. Muhammad Saiful Islam, "YOLO-Based Three-Stage Network for Bangla License Plate Recognition in Dhaka Metropolitan City," 2018 International Conference on Bangla Speech and Language Processing (ICBSLP), Sylhet, 2018, pp. 1-6.
[18] G. Hsu, J. Chen and Y. Chung, "Application-Oriented License Plate Recognition," in IEEE Transactions on Vehicular Technology, vol. 62, no. 2, pp. 552-561, Feb. 2013.
[19] J. Jiao, Q. Ye, and Q. Huang, “A configurable method for multi style license plate recognition, ”Pattern Recognit., 2009, pp.358–369.
[20] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos and E. Kayafas, "A License Plate-Recognition Algorithm for Intelligent Transportation System Applications," in IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 3, pp. 377-392, Sept. 2006.
[21] Z. Selmi, M. Ben Halima and A. M. Alimi, "Deep Learning System for Automatic License Plate Detection and Recognition," 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), Kyoto, 2017, pp. 1132-1138.ssss