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Recognition and Detection of Vehicle License Plates Using Convolutional Neural Networks

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ABSTRACT

The rise in toll road usage has sparked a lot of interest in the newest, most effective, and most innovative intelligent transportation system (ITS), such as the Vehicle License Plate Recognition (VLPR) approach. This research uses Convolutional Neural Networks to deliver effective deep learning principally based on Automatic License Plate Recognition (ALPR) for detection and recognition of numerous License Plates (LPs) (CNN). Two fully convolutional one-stage object detectors are utilized in ALPRNet to concurrently identify and categorize LPs and characters, followed by an assembly module that outputs the LP strings. Object detectors are typically employed in CNN-based approaches such as You Only Look Once (YOLO), Faster Region-based Convolutional Neural Network (Faster R-CNN), and Mask Region-based Convolutional Neural Network (Mask R-CNN) to locate LPs. The VLPR model is used here to detect license plates using You Only Look Once (YOLO) and to recognize characters in license plates using Optical Character Recognition (OCR). Unlike existing methods, which treat license plate detection and recognition as two independent problems to be solved one at a time, the proposed method accomplishes both goals using a single network. Matlab R2020a was used as a tool.

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1. INTRODUCTION

An automobile registration plate, also known as a number plate in the UK, a license plate in the US, or a license plate in Canada, is a metal or plastic plate that is attached to a motor vehicle or trailer for the purpose of official identification [1-3]. Avenue motors, which include automobiles, trucks, and motorbikes, are required to have registration plates in all worldwide places. In the car register of the issuing region, the registration identification-which may be numeric or alphanumeric-uniquely identifies a vehicle or its owner. In certain foreign locations, the identifier is unique to the entire country, whereas in others, it is unique to a single state or province and digital license plates are also available. All motorized autos on Indian roadways must be registered with the RTO and have a license plate, according to The Motor Vehicles Act, 1988.

(Number plate). There are numerous varieties of license plates in India. Unregistered vehicles are in direct violation of the law and may face severe penalties. A registration number is formed by a combination of alphabets and digits on a license plate. The registration code is obtained from the district RTO (Regional Transport Office) and must be displayed on both the front and rear of the vehicle with provision. For the purpose of illuminating India's international license plate is IND. The first two letters on a number plate (DL, KL, HR, MH, etc.) indicate where the vehicle is registered. The initials CG will appear on a vehicle registered with the Chhattisgarh RTO. The next digits indicate the district in which the vehicle is registered. The third section of the license plate consists of a set of numbers (usually four) that are unique to the vehicle. Vanity numbers, like as 0001, 0786, and 1111, appear to be VIP numbers and can be sold in RTO auctions for top dollar. The remaining portion of the registration code displays the India IND global license plate.

2. EXISITING METHOD

The Block Diagram of Existing Method is shown in figure 1. License plate recognition is a method for automatically finding and extracting license Plate Information. (LPR).

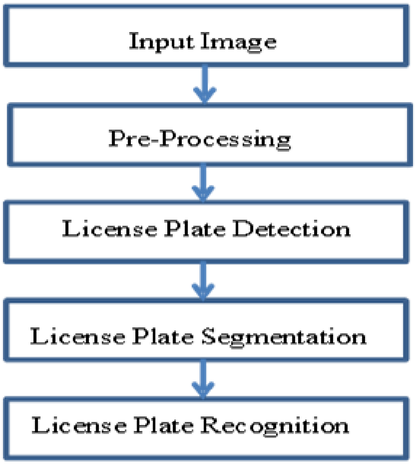

Figure 1. Block Diagram of Existing Method

License plate detection is the most important stage of the LPR system. Most algorithms for detecting license plates can only be used under certain circumstances, such as fixed backdrops, known colors, and fixed license plate sizes. This algorithm is built around the detection step, which determines the zone. The system processes the acquired image in order to identify the license plate, and the result is based on geometrical features and mathematical morphological techniques. The license plate photos are generated from the vehicle images that were taken using a variety of backgrounds, lighting, licence plate orientations, camera distances from the vehicles, light conditions, and vehicle sizes and types [4-6].

An image undergoes pre-processing to enhance its quality, which involves converting the image to grayscale and smoothing it. The pre-processing section processed images captured by the camera. These images are fed into the license plate detection module. The pre-processing output is provided to another module for rectangle detection; But the system has stated that it will test several levels to find rectangles in photographs, and if level is zero, the image will be passed to the canny edge detector and converted to an edge image. We used mathematical morphology to the image once it was converted to the edge. The image is first dilated to strengthen the edges and fill in any gaps between the lines, and then it is eroded to eliminate the excess thickness from the edge image and distinguish the desired edges from the undesired edges, which might influence overall detection performance.

Finally, the image is subjected to closure morphology to fill in gaps in the regions while retaining region sizes. In contrast, the system employs binary thresholding if the level is higher than zero, rather than the smart and morphological operators to select a probable plate region. Each closed morphological and threshold picture is subjected to a contour procedure in order to identify the quadrilateral with four vertices. The system further assessed the discovered candidate by examining the angle, which should roughly equal 90 degrees, in order to constrain the quadrilateral to be more precisely a rectangle derived using the contour technique to segregate the region. and additionally, some incorrect regions were also found. In order to filter out candidates who provided misleading information, a mechanism was put in place to assess whether a candidate was a valid or not.

Disadvantages of existing method

- Segmentation / Detection of license plate is not up to level best.
- There is no feature of character segmentation.
- There is no feature of character recognition.
- Not fit for all conditions (depends on environment light).

3. PROPOSED METHOD

The Block Diagram of proposed Method is shown in figure 2.

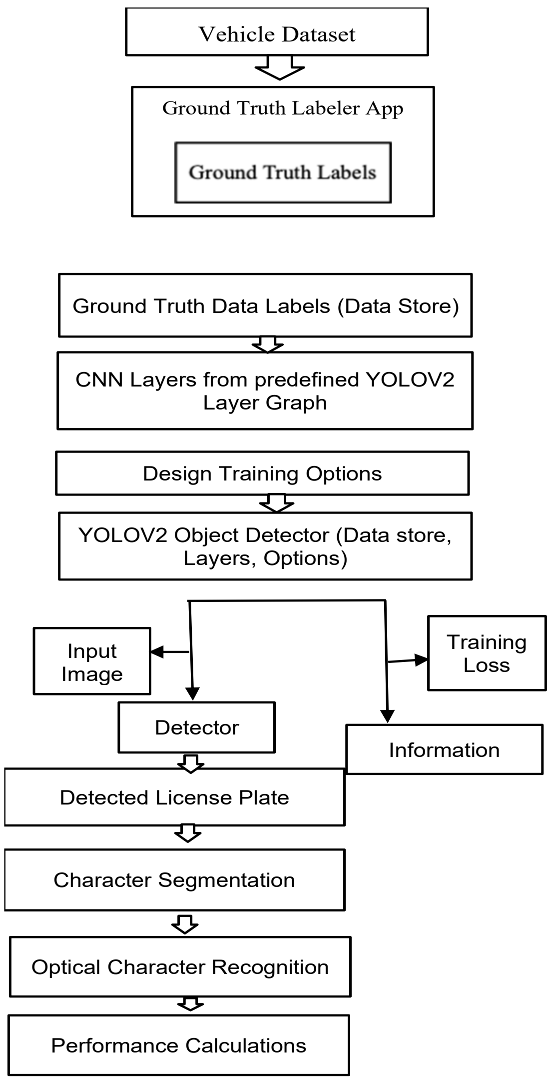

Figure 2. Block diagram of Proposed Method

In this proposed method, VLPR based YOLOv2 algorithm is employed. Hovering over each block in the display in YOLOv2 reveals the specifics of that block. Except for the final Convolution block, each Convolution block features Batch Norm normalization followed by Leaky ReLU activation. By using an S*S grid, YOLO divides the source image. In each grid cell, a single object is expected.

Each grid cell is anticipated to have a specific number of border boxes. The one-object rule, on the other hand, limits how near detected items can be. No matter how many boundary boxes are used, it only detects one object, forecasts conditional class probabilities, and forecasts boundary boxes for each grid cell with a single box confidence score. The boundary boxes' box confidence score infers how precise each boundary box is. The image's width and height are used to normalize the bounding box's dimensions [7-9].

The class confidence score is computed as follows for each prediction box:

It assesses the accuracy of both categorization and localization (where an object is located).

$$box\ confidence\ score\ \equiv Pr(object).\ IoU \tag{1}$$

$$conditional\ class\ probability\ \equiv Pr\ (class\mid object) \tag{2}$$

$$class\ confidence\ score \equiv Pr(class\ ).IoU$$

$$\equiv \text{box confidence score} * \text{conditional class probability} \tag{3}$$

where,

$\Pr(object)$ is the likelihood that an object is in the box.

IoU stands for the intersection over union of the anticipated box and the actual data.

$\Pr\ (class\mid object)$ is the probability that the object belongs to class conditioned on an object.

$Pr(class\ )$ is the probability that the object belongs to class.

Every grid cell, YOLO predicts numerous bounding boxes. To determine the actual positive's loss, it is necessary for one of them to be in charge of the object. For this reason, choose the one that has the highest IoU with the actual data. The bounding box forecasts get more specialized as a result of this method. The ability to predict specific sizes and aspect ratios gets better with each forecast.

The sum-squared error analyzed by YOLO between the forecasts and the actual data to determine loss. The components of the loss function are as follows:

1.The loss of classification.

2.Localization loss (errors between ground truth and the predicted boundary box).

3.The confidence loss (the objectness of the box).

3.1 Loss of Classification

If an item is detected, each cell classification loss equals the squared error of the class conditional probability for each class.

$$\sum_{i=0}^{s^2} 1_i^{obj} \sum_{c\in classes}(p_i(c) - \hat{p}_i(c))^2 \tag{4}$$

where,

1_i^{obj} =1 if an object appears in cell I, otherwise 0.

$\hat{p}_i(c)$ denotes the conditional class probability for class c in cell i.

The localization loss is used to determine how inaccurately border box locations and sizes are predicted. The only box that counts is responsible for finding the object.

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

$$\lambda coord \sum_{i=0}^{s^2}\sum_{j=0}^{B} 1_{ij}^{obj}[\left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2] \tag{5}$$

where,

1_{ij}^{obj} =1 if the j th boundary box in cell I is responsible for detecting the object, otherwise 0.

$\lambda coord$ increase the weight for the loss in the boundary box coordinates.

As a result, absolute inaccuracies in large and small boxes are not divided proportionally. A 2-pixel error in a large box is equivalent to a 2-pixel error in a small box. To address this, instead of predicting the width and height of the bounding box, YOLO predicts its square root. In addition, we double the loss by cord to emphasize the precision of the border box (default: 5).

3.2 Convolutional Neural Network (CNN)

A Convolutional Neural Network is a type of neural network with one or more convolutional layers that is frequently used for auto-correlated data processing, segmentation and classification. Thus, every convolutional layer employs a collection of filters denoted as convolutional kernels. The filter is a subset of the input pixel values that is applied to a matrix of integers of the same size as the kernel. For simplicity, each pixel is multiplied by the kernel's corresponding value, and the result is added together to form a grid cell [10-12], Each convolution is a linear transformation that resembles an affine function. Three-channel RGB images are widely used as the input for computer vision. For the sake of simplicity, take into account a grayscale image with a single channel and a 3x3 convolutional kernel. The kernel slides/scans across the starting rows of the matrix holding the picture pixel values as it goes horizontally, column by column, across the input matrix of integers. The kernel then descends vertically to the next rows. After the input has been fed into the model, the output from each layer is then obtained. This is referred to as feedforward. The error is then calculated using an error function. After that, the derivatives are computed and back-propagated into the model. This process is known as "backpropagation", which is used to minimize the loss.

3.3 Character Segmentation

Global thresholding binary approaches, such as Otsu and average grayscale value, uses a histogram that shows a bi-modal pattern of images to help differentiate the target and background [13-15], which produce the best results when used with the BA (Bensen Algorithm), Since noise and other sources are present in real-world photos, the picture histogram was unable to construct a bimodal pattern. At this stage, traditional binary models are unable to produce the desirable results. Local threshold techniques, such as the (BA) and the Niblack technique, are commonly used to detect important interference in a picture. The BA, which is the local binary model's optimal output, is typically the best way to deal with the problem of inadequate illumination.

3.4 Optical Character Recognition (OCR)

OCR technology converts any image containing written text, whether it is typed, printed or handwritten into text data that computers can understand.

3.5 Training Details

Training, validation, and testing are the three processes that make up the real AI training phase. In order to provide a certain forecast with each cycle, the computer system is trained by being fed data. To ensure that the predictions get better with each training stage, the parameters can be changed. The technique is then verified by contrasting the validation data with the training model [16-20]. It could now be necessary to change new variables. Following the validation phase, the device can be examined using real-world information devoid of tags or labels. Checking if the algorithm is prepared for usage at this point is important. Training of license plate images is depicted in figure 3.

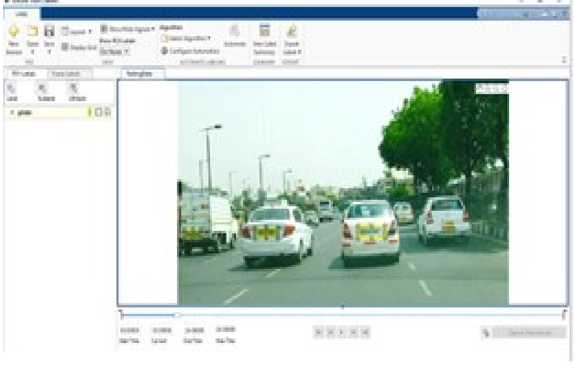

Figure 3. Training of license plate images

3.6 Layers of the Proposed Model

Figure 4 shows the layers of the proposed model.

1	'input'	Image Input	128x128x3 images
2	'conv_1'	Convolution	16 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
3	'BN1'	Batch Normalization	Batch normalization
4	'relu_1'	ReLU	ReLU
5	'maxpool1'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
6	'conv_2'	Convolution	32 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
7	'BN2'	Batch Normalization	Batch normalization
8	'relu_2'	ReLU	ReLU
9	'maxpool2'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
10	'conv_3'	Convolution	64 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
11	'BN3'	Batch Normalization	Batch normalization
12	'relu_3'	ReLU	ReLU
13	'maxpool3'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
14	'conv_4'	Convolution	128 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
15	'BN4'	Batch Normalization	Batch normalization
16	'relu_4'	ReLU	ReLU
17	'yolov2Conv1'	Convolution	128 3x3 convolutions with stride [1 1] and padding 'same'
18	'yolov2Batch1'	Batch Normalization	Batch normalization
19	'yolov2Relu1'	ReLU	ReLU
20	'yolov2Conv2'	Convolution	128 3x3 convolutions with stride [1 1] and padding 'same'
21	'yolov2Batch2'	Batch Normalization	Batch normalization
22	'yolov2Relu2'	ReLU	ReLU
23	'yolov2ClassConv'	Convolution	24 1x1 convolutions with stride [1 1] and padding [0 0 0 0]
24	'yolov2Transform'	YOLO v2 Transform Layer.	YOLO v2 Transform Layer with 4 anchors.
25	'yolov2OutputLayer'	YOLO v2 Output	YOLO v2 Output with 4 anchors.

Figure 4. Layers of the proposed model

Image is fed through Image Input Layer, Convolutional layer, Batch Normalization Layer, Rectified Linear Unit, Max and Average Pooling Layers, and finally classification layer of Convolutional Neural Networks [21-26]. The classification layer's training network makes use of the values from the softmax function.

3.7 Advantages of Proposed Method

- Fast. It is suitable for real-time processing.
- A single network produces predictions (object locations and classes). Accuracy can be improved through end-to-end training.
- The more general word is "YOLO." It outperforms earlier methods when extrapolating from natural photographs to different fields. Approaches for limiting the classifier to a certain region are available. In order to forecast limits, YOLO uses the whole image. With the new information, YOLO produces fewer false positives in the background.
- One item is detected by YOLO per grid cell. In creating forecasts, it imposes spatial variety.

4. RESULTS AND DISCUSSIONS

In this research, to improve appearance of the license plate, a deep learning technique CNN, YOLO, OCR are employed. The models are then assessed against the validation set in order to identify the best model. After much improvement and validation, testing data comes into play. However, the test set is used to assess how effectively the final model generalizes to fresh, unreported data. The existing and proposed model results are shown below from figure 5 to figure 13.

Existing Method

Figure 5. Input Image

Proposed Method

Figure 9. Input Image

Figure 6. Detection of License Plate

Figure 7. Conversion to Grayscale image

Figure 8. Detected license Plate

Figure 10. Detection of License Plate

Figure 11. Conversion of Grey Scale

Figure 12. Detected License Plate

Figure 13. Character Segmentation

5. CONCLUSION

A deep learning technique for the effective detection and recognition of License Plates is utilized. For this model, CNN and YOLO are used for the detection of license plates and OCR for character recognition on license plates. Experimental findings demonstrate that our planned model correctly recognizes the number plate region from an image, and provides sophisticated results compared to existing work.

6. FUTURE SCOPE

In the future, results of the OCR phase (improving character recognition) can be improved, and also this concept of classifying can be extended to whether the vehicle is stolen or not/authorized or not using deep learning techniques.

REFERENCES

[1] Irina Valeryevna Pustokhina, Denis Alexandrovich Pustokhin, Joel J.P.C. Rodrigues, Deepak Gupta et al. "Automatic Vehicle License Plate Recognition Using Optimal K-Means with Convolutional Neural Network for Intelligent transportation Systems", *IEEE Access*, vol.8, pp.92907-92917, 2020.

[2] P. Geetha, B.Senthil Kumar, H.D.Praveena, K.Sudha, "Modeling of hollow cylinder for carbon absorption," *Solid State Technology*, vol. 63, Issue No.06, pp. 12667-12673, Dec 2020.

[3] K. Yamaguchi, Y. Nagaya, K. Ueda, H. Nemoto, and M. Nakagawa, "A method for identifying specific vehicles using template matching," in *Proc. IEEE Int. Conf. Intell. Transp. Syst*., pp. 8–13, 1999.

[4] Q. Zuo and Z. Shi, "A real-time algorithm for license plate extraction based on mathematical morphology," *J. Image Graph*., vol. 8, no. 3, pp. 281–285, 2003.

[5] L. Salgado, J. M. Menendez, E. Rendon, and N. Garcia, "Automatic car plate detection and recognition through intelligent vision engineering," in *Proc. IEEE Int. Carnahan Conf. Security Technol*., pp. 1–76, 1999.

[6] H.D. Praveena, "Finite Element Method based Modeling and Study of the Electrical Characteristics of Nano MOSFET for Carbon Capture," *Design Engineering*, vol.2021, Issue No.8, pp.4073-4087, October 2021.

[7] K. M. Babu and M. V. Raghunadh, ''Vehicle number plate detection and recognition using bounding box method,'' in *Proc. Int. Conf. Adv. Commun. Control Comput. Technol*. (ICACCCT), pp. 106–110, May 2016.

[8] H.D. Praveena, Nirmala S. Guptha, Afsaneh Kazemzadeh, B. D. Parameshachari, K. L. Hemalatha, "Effective CBMIR System Using Hybrid Features-Based Independent Condensed Nearest Neighbor Model," *Journal of Healthcare Engineering*, Vol. 2022, pp.1-9, March 2022.

[9] I. Ullah and H. J. Lee, ''An approach of locating Korean vehicle license plate based on mathematical morphology and geometrical features,'' in *Proc. Int. Conf. Comput. Sci. Comput. Intell. (CSCI)*, pp. 836–840, Dec. 2016.

[10] C.-H. Lin, Y.-S. Lin, and W.-C. Liu, ''An efficient license plate recognition system using convolution neural networks,'' in Proc. *IEEE Int. Conf. Appl. Syst. Invention (ICASI),* pp. 224–227, Apr. 2018.

[11] Y. P. Huang, S. Y. Lai, and W. P. Chuang, "A template-based model for license plate recognition," in Proc. *IEEE Int. Conf. Netw., Sens. Control*, Taipei, Taiwan, pp. 737–742, Mar. 21–23, 2004.

[12] N. Rana and P. K. Dahiya, ''Localization techniques in ANPR systems: A-state-of-art,'' Int. J. Adv. Res. Comput. Sci. Softw. Eng., vol. 7, no. 5, pp. 682–686, May 2017.

[13] Liang, G., Shivakumara, P., Lu, T., & Tan, C. L, "A new wavelet-Laplacian method for arbitrarily-oriented character segmentation in video text lines," In *Proceedings of the 13th international conference on document analysis and recognition (ICDAR)* pp. 926–930. IEEE. Netw., Sens. Control, Taipei, Taiwan4, pp. 737–74, Mar 21–23, 2015.

[14] K. Sudha, H.D. Praveena, Sai Raja Narendra and R. Anjaneya Srujit," Design and Simulation of Bow-Tie Shaped Hexagonal Rings Quasi Fractal Antenna for Satellite Applications" *Indian Journal of Science and Technology*, vol.12, No.6, pp.1-5, February 2019.

[15] Dhar, P., Guha, S., Biswas, T., & Abedin, M. Z, "A system design for license plate recognition by using edge detection and convolution neural network," In *Proceedings of the IC4ME2,* pp. 1–4, 2018.

[16] Radchenko, A., Zarovsky, R., & Kazymyr, V, "Method of segmentation and recognition of Ukrainian license plates," In *Proceedings of the YSF,* pp. 62–65, 2017.

[17] H.D. Praveena, K. Sudha, and P. Geetha, "Support Vector Machine Based Melanoma Skin Cancer Detection," *Journal of University of Shanghai for Science and Technology*, vol. 22, Issue 11, pp.1075-1081, Nov 2020.

[18] Morasa, Balaji, and Padmaja Nimmagadda. "Low Power Residue Number System Using Lookup Table Decomposition and Finite State Machine Based Post Computation." *Indonesian Journal of Electrical Engineering and Computer Science*, vol.6, No.1, pp. 127–134, 2022.

[19] Raghunandan, K. S., Shivakumara, P., Jalab, H. A., Ibrahim, R. W., Kumar, G. H., Pal, U., et al." Riesz fractional

based model for enhancing license plate detection and recognition," *IEEE Transactions on Circuits and Systems for Video Technology,* vol.28 No.9, pp.2276–2288, 2017.

[20] Yasmine Begum, A., Balaji, M., Vishnuvardhan, G., Harshavardhan, G., & Lazer Mathew, T, "Development of animal collar for state of health determination of livestock," *Journal of Information and Optimization Sciences*, vol.41, no.2, pp.489-497, 2020.

[21] Al-Shemarry, M. S., Li, Y., & Abdulla, S, "Ensemble of adaboost cascades of 3L-LBPs classifiers for license plates detection with low quality images," *Expert Systems with Applications,* vol.92, pp.216–235, 2018.

[22] Dong, M., He, D., Luo, C., Liu, D., & Zeng, W, "A CNN-based approach for automatic license plate recognition in the wild," In *Proceedings of the BMCV,* pp. 1–12, 2017.

[23] Satyanarayana, V., M. Balaji, and K. Neelima. "Optimal of 1-bit Comparator design and Energy Estimation using Quantum Dot Cellular Automata." *International Journal of Engineering and Applied Physics*, vol.1. No.2, pp. 103-110, May 2021.

[24] Bulan, O., Kozitsky, V., Ramesh, P., & Shreve, M. "Segmentation-and annotation-free license plate recognition with deep localization and failure identification," *IEEE Transactions ITS,* vol.18, No.9, pp. 2351–2363, 2017.

[25] Yang, Y., Li, D., &Duan, Z, "Chinese vehicle license plate recognition using kernel-based extreme learning machine with deep convolutional features," *IET Intelligent Transport System,* vol. 12, No.3, pp. 213–219, 2018.

[26] Akshat Ajeya, "Types of Number Plates in India & HSRP Explained", *Go Mechanic informative*, May 16 2019.

[27] Tallapragada, V.V., Alivelu Manga, N., Nagabhushanam, M.V. and Venkatanaresh, M., 2022." Greek Handwritten Character Recognition Using Inception V3". *In Smart Systems: Innovations in Computing (pp. 247-257).* Springer, Singapore.

[28] Tallapragada, V.V., Manga, N.A., Kumar, G.V. and Naresh, M.V., 2020. "Mixed image denoising using weighted coding and non-local similarity". *SN Applied Sciences*, 2(6), pp.1-11.