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Automatic Number Plate Character Recognition using Paddle-OCR

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***Abstract*—With increasing traffic on roads today, advanced technology is in great demand in order to monitor and manage traffic. Artificially intelligent systems are in demand for automated vehicle identification and number plate recognition. Automated number plate recognition (ANPR) uses machine learning and image processing techniques to perform tasks like counting vehicles, database management and parking violation alerts. They provide a lot of scope to abstain from human intervention since they provide real-time data on vehicle ingress and egress. This technology is a huge asset when it comes to traffic management, eliminating manpower requirements to a large extent. This paper proposes an image processing-based ANPR system using Paddle OCR. The system aims to automatically recognize unique number plates of vehicles, enabling intelligent traffic and vehicle management. The primary stages of this process is image capture, vehicle plate identification, the detection of edges, division of characters, and identification of characters in the number plates. PaddleOCR is one of the latest models for optical character recognition, hence it achieves a lot of efficiency in real-world scenarios.**

***Keywords*—Automatic Number Plate Recognition (ANPR), traffic management, vehicle monitoring, intelligent transportation systems, number plate recognition, deep learning, character segmentation.**

I. Introduction

Due to the increasing amount of traffic congestion on roadways, there is an increasing need for traffic control and surveillance technologies. Earlier methods of traffic monitoring were manual, which were inefficient, time-consuming and required excessive manpower. Thus, it is essential to develop automated systems for vehicle detection and identification of their number plates [1]. This is a step in the right direction when we think about smart cities. An effective solution to eliminate the manual process of vehicle recognition is the ANPR technology. It enables the above functionalities using machine learning and image processing techniques. Through this, there are many complex tasks that can be tackled such as vehicle counting, parking violation alerts, database management, and identification of blacklisted or stolen vehicles. Moreover, the increasing demand for secure and convenient parking spaces in urban areas necessitates effective parking management systems. ANPR technology plays a crucial role in these systems by registering authorized vehicles and capturing their number plates upon entry and exit. This real-time data aids in managing parking spaces and ensures the security and convenience of vehicle owners. Utilization of computer vision has made substantial progress in tackling real-life challenges in recent times [1] . Machine vision applications, including ANPR, have witnessed remarkable progress, enabling highly effective and practical techniques. However, ANPR faces challenges due to variations in viewpoint, similar color between vehicle bodies and license plates [2] , non uniform license plate designs, improper and varied lighting conditions during image capturing. To address these challenges, researchers have focused on developing efficient algorithms for localization of vehicle plates, identification and segmentation of characters [2] . The accurate localization of license plates is crucial, as it directly affects the subsequent steps of segmentation and recognition. Factors such as lighting conditions, weather, and backgrounds can affect license plate detection, highlighting the importance of precise and efficient localization techniques.

Deep learning has been a widely sought after technique for Automated Number plate recognition technologies. These models have demonstrated superior performance compared to traditional template matching techniques, thanks to their ability to be trained on many datasets.By combining deep learning algorithms with image processing techniques, ANPR systems can achieve higher accuracy and real-time implementation [3]. The primary goal of this paper is to propose an image processing-based ANPR system using Paddle OCR. The system aims to automatically recognize unique number plates of vehicles, enabling intelligent traffic and vehicle management.By leveraging Paddle OCR and deep learning models, the system achieves higher accuracy and efficiency in real-world scenarios. ANPR has found applications beyond traffic management, including industrial monitoring of vehicles, and security control in restricted areas. It greatly enhances the efficiency of vehicle management and contributes to the automation of various processes. Future advancements in ANPR are expected to further revolutionize the field of machine vision technology, supporting a wide range of community services and facilitating the maintenance of comprehensive databases of moving vehicles on the road. Thus, ANPR is indispensable for modern traffic management and vehicle monitoring. Its ability to automatically detect and recognize number plates offers numerous benefits in terms of efficiency, accuracy, and security. By leveraging advanced techniques such as image processing and deep learning, ANPR systems have the capability to impact the management and monitoring of vehicles on roads, providing a foundation for intelligent transportation systems of the future.

The major contributions of this paper are as follows :

- Automating Vehicle plate detection by applying machine learning methods to detect the characters of number plates.
- Using a dataset that is well processed, augmented and tested with a variety of scenarios.
- Applying a fine-tuned PaddleOCR model and comparing it with existing models which have shown better efficiency than the existing OCR methods.
- The model is well suited to work in a wide range of real world situations.

II. Literature Review

There has been various research and studies in the field of ANPR. In a research study by Liu et al., a methodology was proposed that combined Support Vector Machine (SVM) and supervised K-means to enhance the recognition of blurred license plate images. The supervised K-means algorithm segregates characters into subgroups, which SVM then classifies. This approach effectively handles challenges such as camera angle, vehicle speed, and lighting conditions, resulting in improved accuracy by reducing the complexity and workload of SVM classifiers [4] .In another research study, M.I. Khalil suggested the use of the Template Matching Method for Car Plate Recognition that involved matching similarity of recognized character and the provided templates [5] . The paper by Quiros et. al. [6] focuses on the use of the K-Nearest Neighbour algorithm for character classification in vehicle plates. A camera installed on a highway captures vehicle images for processing of images, and a contour analysis is performed to identify valid characters and segment the plates. The K-Nearest Neighbour algorithm is trained using a batch of 36 characters, including alphabets and numerical digits, and tested against other techniques of character identification such as artificial neural networks.In the study by Kumar Parasuraman, an license plate recognition system using Support Vector Machine (SVM) is proposed. SVM utilizes Statistical Learning Theory and structural risk minimization for optimal generalization.The system locates and extracts the number plate region using the mean shift method, performs simple segmentation using histogram projection, normalizes the image size, and generates high-dimensional features. Which are then used to train SVMs with RBF kernel [7] . The study by Subhadhira et.al. [8] employed an approach for training and accurately classifying license plates which were used. The system consists of two main components: preprocessing and feature extraction using HOG, followed by alphabet and number classification to analyze and separate the characters appearing on car's number plate. In [9], a machine learning-based vehicle plate identification methodology is developed. The technique utilizes input from an infrared camera and applies preprocessing steps such as contrast enhancement and noise reduction. It localizes the number plate by identifying the Region of Interest (RoI) and extracts salient features through contour tracing and Canny's edge detection. Character segmentation is then performed, and the letter or digit is recognized using pattern matching with deep learning methods like ANN .In [10], the Soble filter technique is adopted to accurately detect the edges of the vehicle resulting in its accurate identification. This technique proves effective in distinguishing the edges of the vehicle.The challenges of number plate recognition in India were studied in research by Singh, A. K., & Roy, S [11], such as varied style and size of fonts, colors, and vehicle plates present in double line, are addressed. The research tackles these issues in real Indian road conditions using ANN for character recognition and SVM for plate contour detection. In [12], a smart system is developed to accurately identify number plates of the Turkish region.This CNN model using Tensorflow and Keras was trained using these prepared dataset, and the extracted features were then used in an LSTM network with a decryption algorithm. The method achieved high accuracies: 96.36% for plates.The proposed system in a study by R.Panahi et.al. [13] addresses challenges related to unclear number plates caused by varying weather, lighting, speeding vehicles, and varied situation of traffic. By employing a robust hardware platform and innovative algorithms, the system handles differences in illumination, dimension, and image quality of the number plates, as demonstrated through a diverse dataset of images captured from different road conditions. In [14], a comprehensive review of vehicle plate detection methods is conducted. The system discussed in the study includes cameras, sensors, and various tools, aiming to prevent illegal entry of automobiles by matching them with a vehicle database already present. This image processing steps involve grayscale conversion, histogram adjustment for enhancement, morphological image processing, segmentation, and character recognition using a machine learning approach.In their proposal, S. Kranthi and K. Pranathi introduce Automatic License/Number Plate Detection/Recognition (ANPR) as a method for detecting and identifying vehicles by their license plate numbers. ANPR is widely utilized for identifying stolen or suspected vehicles involved in criminal activities [15] . These were a few of the research studies done in the field of automatic vehicle plate recognition.

III. Basic Concepts

A. PaddleOCR Model

The Optical Character Recognition, abbreviated as the OCR technology is used to extract text and interpret the characters present on the information. PaddleOCR is an open-source optical character recognition (OCR) model developed by PaddlePaddle, an AI research and development company.It is gaining popularity as it provides high accuracy along with a wide variety of language support like English, German, French, Chinese Japanese among the others. The PaddleOCR model can improve the accuracy of overall character recognition by capturing fine-grained text features. Version 2.6 of this model has several enhancements like performance optimization, real-time (or near real-time) on CPUs, GPUs and mobile devices. The model supports text information in several orientation, deformation and layout by adapting advanced techniques like geometric transform network (GTN). Thus, we can say that PaddleOCR is a valuable model for multiple cases allowing innovation in this field of study.

B. YoLo v8 Model

The YOLOv8 model provides a robust solution for object detection problems. The speed and accuracy for the results are the reason why the YOLOv8 model is widely used.

The given model uses a single deep neural network to predict the boundary boxes and class probabilities for the objects present in the image. So, the post-processing steps do not need to be applied since real-time detection is already facilitated here. To give a brief overview of the model architecture, it has a series of convolutional layers followed by a series of fully connected layers, which enables it to capture both the low-level and high-level features for accurate license plate detection. The model can be tweaked according to the problem statement that developers want to solve [16]. Due to its wide usage, there is a huge community support for anyone who wants to use it. There is extensive documentation available, along with pre-trained models and code examples to make the implementation process smoother. The real-time performance of the YOLOv8 model makes it suitable for autonomous vehicle applications, including surveillance systems and video analysis. The accuracy of the localisation performance is impressive, since it meticulously captures the license plate regions with precise bounding boxes. The orientations, lighting conditions and plate sizes are taken care of. For this paper, we have fine-tuned the YOLO-v8 model for our custom dataset, since license plate detection can differ for different regions and countries. This flexibility makes it adaptable to specific requirements and helps achieve higher accuracy for target applications. In a nutshell, the YOLO-v8 model is a very powerful and efficient model for object detection; and in this case - vehicle number plate recognition.

Its speed, accuracy, ease of use, and adaptability make it a top choice for developers and researchers working on object detection tasks, particularly in the context of license plate detection.

IV. PROPOSED METHODOLOGY

A. Data Collection

The dataset was collected from the Kaggle website and it consisted of a bunch of images as one shown in Figure 1 along with their corresponding .xml files that consisted of the dimensions of the bounding box corresponding to the license plate dimensions in the vehicle. This dataset originally consisted of a data.yaml file, an images folder - that consisted of the image files and their .xml files and a TEST folder that consists of a test.jpeg image file and an MP4 video file.

The images folder consisted of 225 images and .xml files.

Fig 1.One of the car image present in the dataset

B. License Plate Localisation

Since the bounding boxes of the license plates were given in the form of integer dimensions, their localisation was done by simply drawing a rectangular boundary around the number plates. The YOLO v8 algorithm was used for number plate detection since it is relatively easier to handle. It is an object detection algorithm which is very efficient in detecting license plates. YOLOv7 is mostly effective in locating a specific text class (customer name, price, etc.).

In video labeling, a 3% - 5% increase in accuracy is experienced.

Apart from the object detection part, since the dimensions were given, a separate folder was prepared that consisted of just the cropped images. After determining the dimensions for the number plate, the technique of image segmentation was applied to crop the desired region of interest. For this purpose, the 'clear_border'module of the scikit-learn library in Python.

The image folder was passed through the data augmentation process and some parts of it also passed through image preprocessing as displayed in one example of Figure 2.

Fig 2. Identification and localization of a car's license plate

C. Image Preprocessing

There were multiple methods and trials used for the image preprocessing portion. After each preprocessing attempt, the image was passed through the pre-trained PaddleOCR model and the accuracy was checked [17]. Most of the common computer vision techniques were applied such as Gaussian adaptive thresholding, and Otsu's thresholding on binary images. Some morphological transformations like erosion and dilation were also applied. Contour edge detection and canny edge detection were also applied. All of the techniques were carried out through the OpenCV library in Python.

D. Data Augmentation

In order to increase the training and testing data for our model, the upsampling method was applied in order to generate varied and fake images from the original images given. The parameters specified for upsampling were as follows:

(i) rotation_range=20
Function: Randomly rotated images in the range of 0 to 20

degrees.

(ii) width_shift_range=0.2
Function: Shifts the photos horizontally at random, where 0.2 is a fraction of the overall width.

(iii) height_shift_range=0.2
Function: Vertically adjusts the photos at random, where 0.2 is a proportion of the entire height.

(iv) shear_range=0.2
Function: Applies shearing transformations in random order.

(v) zoom_range=0.2
Function: Randomly zooms in on the images.

(vi) horizontal_flip=True
Function: Flips the photos horizontally at random.

(vii) fill_mode='nearest'
Function: This function puts in the newly generated pixels.

The above was done with the ImageDataGenerator module of the keras.preprocessing.image library.
For each image, a batch of three other images was generated using the upsampling technique. It was done in an iterative manner by navigating the images in the original folder one by one. The steps followed for this were loading the image, converting it to a numpy array and reshaping the array into the dimensions (1, height, width, channels).
The final augmented dataset consisted of 1106 images in total.

E. Fine-tuning of PPOCR Model

Fine-tuning a PaddleOCR model using TensorFlow involves taking a pre-trained PaddleOCR model and training it further on a custom dataset or task-specific data to improve its performance or adapting it to a different task. This technique allows you to make utilisation of the pre-trained model's expertise gained from a huge dataset and transfer it to a new domain or specific task.
Firstly, for the fine-tuning part, we have split our custom dataset into separate chunks of data with an 80:20 ratio, for training and testing respectively. After the split, the image files were randomly shuffled. The train data folder consisted of 884 images and the test data folder consisted of 222 images. That was our annotated dataset with the ground truth values specified. Fine-tuning was done with Tensorflow[18]. The environment was further set up by installing the required dependencies of PaddleOCR and installing a compatible version of Tensorflow. We have used the transformation technique to fine-tune our model. The subsequent step was to create a custom dataset class. The weights of the pre-trained PaddleOCR Models were downloaded which are usually available in '.pdparams' or '.pdmodel' formats. The pre-trained model was loaded using the PaddleOCR library in Tensorflow. After loading the images and annotations from the dataset, we modified the model architecture. By creating a separate class for defining the model architecture, we have carried out the above-mentioned task. The base model used was ResNet50 and the subsequent forward layers were added through the paddle library. The resnet50 model was imported from the paddle.vision.models library. We have flattened the layers and reshaped the tensors into 1000 Linear class tensors.

The most crucial step is to set up the fine-tuning pipeline. Training parameters used are as follows:

batch_size = 16
num_epochs = 10
learning_rate = 0.001

We have further created custom datasets for the training and validation processes and their corresponding data loaders of the current batch size. On the basis of the particular task, it is important to define an appropriate loss function. The Cross-Entropy Loss Function is the loss function accountable for evaluation. It is employed in the optimization of classification models. Understanding Cross-Entropy is dependent on comprehending the Softmax activation function.

Random variable entropy X represents the degree of uncertainty in the variable's probable result.

For p(x) — probability distribution and a random variable X, entropy is defined as follows:

Equation (i) shows probability distribution and a random variable X for continuous values.

$$H(X)=-\int_{1}^{n} p(x)log\,x\ p(x),\ \text{if X is continuous} \qquad (i)$$

Equation (ii) shows probability distribution and a random variable X for discrete values.

$$H(X)= -\sum_{1}^{n} p(x)log\,p(x)\ p(x),\ \text{if X is discrete} \qquad (ii)$$

Then we have set up an optimizer and learning rate scheduler. The Adam optimizer is used along with the Step Decay learning rate and a gamma value of 0.1. After setting up the training loop, forward pass, backward pass and optimization are applied. Finally, the average loss of the epoch is calculated. Accuracy is computed for each epoch.

The total time taken for the model to train on 1106 images was 2 hours and 5 minutes on the CPU. The training results were as follows:

Epoch [1/10], Loss: 0.0731, Accuracy: 1.0000

Epoch [2/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [3/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [4/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [5/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [6/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [7/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [8/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [9/10], Loss: 0.0000, Accuracy: 1.0000

Epoch [10/10], Loss: 0.0000, Accuracy: 1.0000

The model was finally saved to our directory using the '.pdparams' extension and employed for testing. Figure 3 displays the block diagram of the methodology.

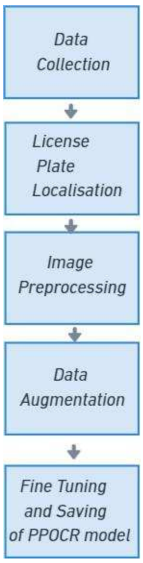

Fig 3. Block diagram of the proposed methodology

V. TESTING AND ANALYSIS

The saved model path is used for loading the model and it is set to the evaluation model. We took a sample of 5 images from our augmented dataset and tested it for the fine-tuned PaddleOCR model and two existing OCR models that are EasyOCR and TesseractOCR as shown in Figure 4.

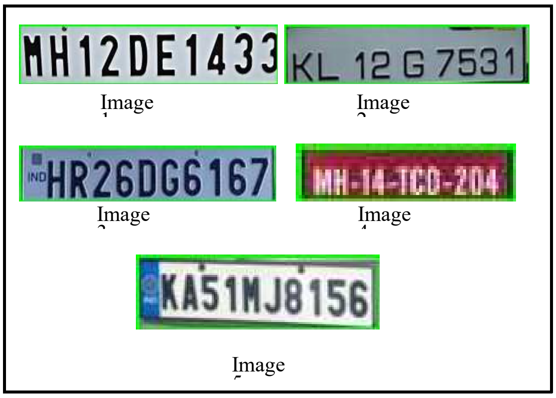

Fig 4. Images of the License Plate from the Augmented dataset

In Table 1, we have tested the five images using Fine-Tuned PaddleOCR.

TABLE 1. Fine-Tuned Paddle Model Prediction

Image	Actual Number Plate	Predicted Number Plate	Confidence Percentage	Percentage of characters recognized correctly
1	MH12DE14 33	MH12DE14 33	97.91%	100%
2	KL12G7531	KL12G753 1	99.28%	100%
3	HR26DG61 67	PHR26DG6 167	91.06%	90.09%
4	MH-14-TC D-204	MH-14-TC D-204	97.87%	100%
5	KA51MJ815 6	KA51MJ81 56	99.11%	100%

In Table 2, we have tested the same data using the EasyOCR model.

TABLE 2. EasyOCR Model Prediction

Image	Actual Number Plate	Predicted Number Plate	Confidence Percentage	Percentage of characters recognized correctly
1	MH12DE14 33	HHI2DE14 33	75.02%	70%
2	KL12G7531	KL 12 G 7535	47.42%	88.89%
3	HR26DG61 67	HR26DG6 167	22.6%	100%
4	MH-14-TC D-204	MhII-IcD-2 04	7.83%	50%
5	KA51MJ815 6	KA51J8156	58.86%	90%

Table 3 indicates prediction using TesseractOCR Model where five distinct images were used and the correctly recognized characters were detected.

TABLE 3. Tesseract Model Prediction

Image	Actual Number Plate	Predicted Number Plate	Confidence Percentage	Percentage of characters recognized correctly
1	MH12DE14 33	MH12DE14 33	46%	100%
2	KL12G7531	KL 126 7531	84%	88.89%
3	HR26DG61 67	HR26DG66 167	41%	90.09%
4	MH-14-TC D-204	PREE-ELE	24%	0%
5	KA51MJ815 6	EKAS1MJ8 156	64%	81.82%

From the above Tables 1, 2 and 3 we can clearly see that the Fine-Tuned PaddleOCR model provided a much better character recognition performance with high confidence percentage even in blurred images like image 4 shown in figure 4 whereas the other two OCR models that is EasyOCR and TesseractOCR could not perform well especially when the quality of image is low, dimensions are small and the background is not well-lit. Also we can see that the PPOCR model gave a consistent result whereas a high variation was observed in the case of EasyOCR and TesseractOCR. Figure 5 displays the comparison of the Percentage of characters recognized correctly from the five images taken in Table I, II and III.

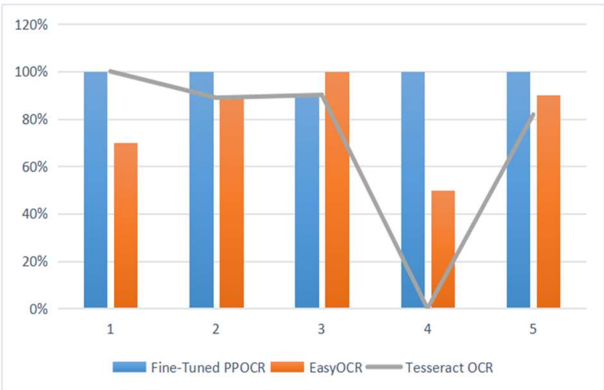

Fig 5. Combined line-bar graph comparing characters recognized correctly of the three OCR models

In Figure 6, we have taken 100 images from our augmented and compared the confidence score across the three models.

Fig 6. Comparing average confidence % of the three OCR models

From the above analysis and results, we can clearly see that Paddle-OCR is the one of the most suitable models to be applied for identification of characters in ANPR giving an average accuracy of almost 98-99% in most cases.

VI. Conclusion and Future Scope

ANPR is an indispensable tool for modern traffic management and vehicle monitoring. Its ability to automatically detect and recognize number plates offers numerous benefits in terms of efficiency, accuracy, and security. By leveraging a Fine-Tuned Paddle OCR and deep learning models, the system achieves higher accuracy and efficiency in real-world scenarios as compared to the existing OCR models.

Although our model displayed a promising results, there are also scope of improvement like enhancing the robustness of the system while capturing videos and images in challenging conditions, such as variations in viewpoint, lighting conditions, and license plate formats, increasing the size and diversity of the dataset can also help to improve the system's performance and generalization.

References

[1] Ghadage , Shraddha. “A Review Paper on Automatic Number Plate Recognition System Using Machine Learning Algorithms”.2020, International Journal of Engineering Research and. V8. doi: https://dx.doi.org/10.17577/IJERTV8IS120398

[2] Kaushik Deb, Ibrahim Khan, Anik Saha, and Kang-Hyun Jo. "An Efficient Method of Vehicle License Plate Recognition Based on Sliding Concentric Windows and Artificial Neural Network" Procedia Technology, vol. 4, 2012. doi:https://doi.org/10.1016/j.protcy.2012.05.133

[3] V Gnanaprakash, N Kanthimathi and N Saranya “Automatic number plate recognition using deep learning” 2021 IOP Conf. Ser.: Mater. Sci. Eng. 1084 01202, doi:http://dx.doi.org/10.1088/1757-899X/1084/1/012027

[4] Liu, W.-C., &Lin, C.-H. “A hierarchical license plate recognition system using supervised K-means and Support Vector Machine”, 2017 International Conference on Applied System. Innovation(ICASI). doi:https://doi.org/10.1109/ICASI.2017.7988244

[5] M. I. Khalil, "Car Plate Recognition Using the Template Matching Method," International Journal of Computer Theory and Engineering vol. 2, no. 5, pp. 683-687, 2010. doi:http://www.ijcte.org/show-32-273-1.html

[6] Quiros,A.R.F.,Bedruz,R.A.,Uy,A.C.,Abad,A.,Bandala,A.,Dadios, E.P.,Sa lle, D.L.(2017),"A kNN-based approach for the machine vision of character recognition of license plate numbers", TENCON 2017 - 2017 IEEE Region 10 Conference doi:https://doi.org/10.1109/TENCON.2017.8228018

[7] Kumar Parasuraman, "SVM Based License Plate Recognition System" 2010 IEEE International Conference on Computational Intelligence and Computing Research doi:http://itfrindia.org/ICCIC/Vol2/9024ICCIC.pdf

[8] Subhadhira,S., Juithonglang, U., Sakulkoo, P., &Horata, P. (2014). "License plate recognition application using extreme learning machines",2014Third ICT International Student Project Conference (ICT-ISPC). doi:https://doi.org/10.1109/ICT-ISPC.2014.6923228

[9] Atul Patel Chirag Patel Dipti Shah "Automatic Number Plate Recognition System (ANPR): A Survey International Journal of Computer Applications" 2013 Volume 69– No.9 pp. (0975 – 8887). doi:http://dx.doi.org/10.5120/11871-7665

[10] SaeidRahati, ReihanehMorvejian, Ehsan M. Kazemi and Farhad M. Kazem "Vehicle Recognition Using Contourlet Transform and SVM," Proceedings of the Fifth International Conference on Information Technology, 2008. doi:https://doi.ieeecomputersociety.org/10.1109/ITNG.2008.136

[11] Singh, A. K., & Roy, S. (2015). "ANPR Indian system using surveillance cameras",2015 Eighth International Conference on Contemporary Computing (IC3). doi:http://dx.doi.org/10.3390/technologies9010009

[12] İrfan Kılıç, Galip Aydin (2018) "Turkish Vehicle License Plate Recognition Using Deep Learning International Conference on Artificial Intelligence and Data Processing" pp.1-5 doi:https://doi.org/10.1109/IDAP.2018.8620744

[13] Rahim Panahi and Iman Gholampour "Accurate Detection and Recognition of Dirty Vehicle Plate Numbers for High-Speed Applications",IEEE Transactions on intelligent transportation systems, vol. 18, 2017 doi:https://doi.org/10.1109/TITS.2016.2586520

[14] Marko Arsenovic Srđan Sladojevic Andras Anderla Darko Stefanovic 2017 Deep Learning Driven Plates Recognition System XVII International Scientific Conference on Industrial Systems Novi Sad Serbia. doi:https://www.researchgate.net/publication/320911914_Deep_Lear n ing_Driven_Plates_Recognition_System

[15] Kumar, Ravi, et al. "Reverse Engineering A Generic Software Exploration Environment Is Made Of Object Oriented Frame Work And Set Of Customizable Tools." International Journal of Advanced Research in Computer Science 2.5 (2011).

[16] M. Rout, D. Bhattarai and A.K. Jena, "Recurrent Neural Network-Based Long Short-Term Memory Deep Neural Network Model for Forex Prediction", In Artificial Intelligence and Machine Learning in Business Management, 2021, pp. 205-221, CRC Press, doi: 10.1201/9781003125129-13.

[17] U. Singh, A. K. Jena and M. T. Haque, "An Ensemble Learning Approach and Analysis for Stroke Prediction Dataset". In 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), 2022, pp. 1-8, doi: 10.1109/ASSIC55218.2022.10088363.

[18] C.N. Aher and A.K. Jena, "Heart Disease Detection from Gene Expression Data Using Optimization Driven Deep Q-Network", In International Conference on Frontiers of Intelligent Computing: Theory and Applications, 2022, pp. 601-611. Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-7524-0_53