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Classification & Detection of Vehicles using Deep Learning

Madde Pavan Kumar, Dr. K. Manivel, N. Jayanthi

Department of Electronics and Communication, Mahendra Engineering College, Namakkal, Tamil Nadu, India

ABSTRACT

The vehicle classification and detecting its license plate are important tasks in intelligent security and transportation systems. The traditional methods of vehicle classification and detection are highly complex which provides coarse-grained results due to suffering from limited viewpoints. Because of the latest achievements of Deep Learning, it was successfully applied to image classification and detection of objects. This paper presents a method based on a convolutional neural network, which consists of two steps: vehicle classification and vehicle license plate recognition. Several typical neural network modules have been applied in training and testing the vehicle Classification and detection of license plate model, such as CNN (convolutional neural networks), TensorFlow, Tesseract-OCR. The proposed method can identify the vehicle type, number plate and other information accurately. This model provides security and log details regarding vehicles by using AI Surveillance. It guides the surveillance operators and assists human resources. With the help of the original (training) dataset and enriched (testing) dataset, the algorithm can obtain results with an average accuracy of about 97.32% in the classification and detection of vehicles. By increasing the amount of the data, the mean error and misclassification rate gradually decreases. So, this algorithm which is based on Deep Learning has good superiority and adaptability. When compared to the leading methods in the challenging Image datasets, our deep learning approach obtains highly competitive results. Finally, this paper proposes modern methods for the improvement of the algorithm and prospects the development direction of deep learning in the field of machine learning and artificial intelligence.

KEYWORDS: *Convolution neural network, Vehicle classification, Vehicle License plate Recognition*

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I. INTRODUCTION

Vehicle classification and detection have promising importance in the future. Because, it can be utilized in many aspects such as to analyze the urban traffic statistics, Advanced Driver Assistance System, against vehicle theft, large parking lot management, against vehicle escape, improvement of the road information acquisition and safety management of highway, electronic toll collection (ETC), traffic investigation and so on.

One of the most important applications for object recognition in the neural network is the image classification tasks. However, the vehicle classification and detecting its license plate still face a few great challenges because the number of vehicle classes are very large and that some attributions of the vehicle are too close to identify. So, the process of training the neural network requires a great number of parameters, which often accompanies by over-fitting problems. The recognition results can achieve a higher degree of accuracy in the training set, but a lower degree of accuracy in the test set.

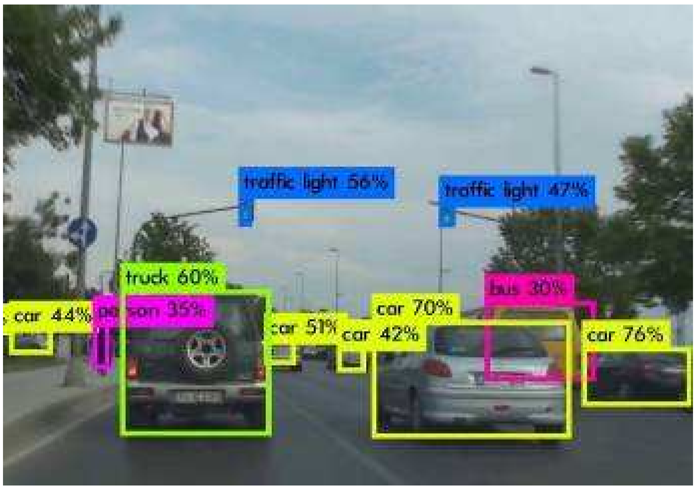

Fig 1: Classification of Vehicle

Although the training data set is modest in size, the neural network itself does not embody distinct advantages in evaluation systems of higher recognition accuracy and shorter training time than other models. The predominant motives for it are limited computing sources and lengthy processing time for even a small network. However, one of the keys to these issues is the feature extraction and classification of detection images for vehicle rearview. Because of Facing many practical problems, neural networks have been gradually integrated with some better methods emerging in the 21st century, such as Convolutional Neural Networks, ResNet Architecture, Tensor Flow. In this kind of model, aimed at different tasks, different systems are usually designed and respectively applied different manual design features.

Fig 2: License Plate Recognition

For example, the object recognition uses Feature extraction from CNN. License plate recognition uses Tesseract-OCR, and the pedestrian detection uses Histogram of Oriented Gradient (HOG) feature. Therefore, this paper aims at classifying and detecting the vehicles from different viewpoints under any circumstances.

II. EXISTING SYSTEMS

The traditional methods of vehicle classification and detection are mainly based on the following methods: 1) SIFT (Scale-invariant feature transform) feature matching and extraction; 2) the moving vehicle detection method of Gaussian mixture model; 3) the license plate classification method; 4) the monitoring video classification method of HOG (Histogram of Oriented Gradient) and SVM (Support Vector Machine). Based on these traditional methods, the neural network model gets the lower recognition reference to detect the objects. So, these methods give the inaccurate results in which accuracy is limited to 85% only.

The above traditional algorithms have already obtained good results. Several shortcomings in the traditional methods have limited its realization: (i) the high similarity between models naturally influence the accuracy, (ii) some models containing only a few images, and (iii) the unified direction like front, side or back in picture causes the inaccurate classification. (iv) the methods usually require the images are captured from certain viewpoints, (v) the vehicle recognition granularity just stays in the stage of the vehicle model classification. In this paper we address these limitations and providing techniques that are practical for vehicle classification problem. According to existing methods, this paper further optimized the classification and detection algorithms. It applies the Deep Neural Networks (DNNs) to the classification and License plate detection of the vehicles and obtained a better recognition performance under different viewpoints or traffic conditions.

III. LITERATURE SURVEY

[1] Chen, Z., Ellis, T., and Velastin, S. A., "Vehicle Type Categorization" A comparison of classification schemes In Intelligent transportation systems (ITSC), 14th international IEEE conference.

This Paper proposed the Vehicle detection and classification based on histogram of orientation gradients (HOG) approach which was presented by Zezhi Chen and Tim Ellis. This Classification model contains two parts: feature extraction and classifier selection. In their approach, measurement-based features (MBP) and the histogram of orientation gradients (HOG) features are used to classify the vehicles into four categories: car, van, bus, and motorcycle.

For this classification model, they have used two classifiers. They are Random Forest (RF) and Support Vector Machines (SVM). Due to the multiple classification problems, they decided to use one-vs-all strategy. With this approach, the best 3D model can be found that match with the original vehicle type. The model they have presented is a novel vehicle type classification, which provides an accurate and reliable performance. However, the features among the four vehicle types are very different. Sometimes 3D models of two vehicles such as hatchback and SUV may be similar. In this case, this system may be hard to detect the vehicle type.

[2] Chang, S.-L., Chen, L.-S., Chung, Y.-C., and Chen, S.-W., "Automatic license plate recognition" IEEE transactions on Intelligent Transportation Systems.

This paper proposed a license plate image technique consisting of two main models: a license plate locating model and a license number identification module. Specifically, the license plates extracted from the first model are examined in the identification model to reduce the error rate. They used color edge detection to compute edge maps.

But this is limited to only four types of edges. By using the unique formulas, the model can transform RGB space into HSI space that denote red, green, blue colors as hue, saturation, intensity parameter values of an image pixels, respectively. The identification module consists of two main stages, preprocessing and recognition. After this process, segmentation and recognition will be invoked sequentially. However, this identification model takes more time to recognize the characters and it is a complex process which needs to be modified. This model can detect the License plate, if and only if that license plate & characters are in specified color edges. This type of model can be useful in a particular region or place.

[3] Farhat, A., Al-Zawqari, A., Al-Qahtani, A., Hommos, O., Bensaali, F., Amira, A., and Zhai, X., "Tesseract-OCR Based Feature Extraction and Template Matching Algorithms For Number Plate Recognition" In Industrial Informatics and Computer Systems (CIICS), International Conference on IEEE.

A modified template matching Correlation algorithm was proposed by Ali Farhat et al. They have developed four algorithms for Numeric Automatic License Plate Recognition (ALPR) systems: Vector crossing, zoning and combined zoning-vector and template matching correlation. First three algorithms are based on feature extraction techniques and the last one is application of correlation technique. By using vector crossing algorithm, they distinguished the ten characters (0−9) except the characters "2", "3" and "5". Since these characters have the same number of the vectors. By using Zoning method, densities of the image in each zone are derived by the algorithm to determine the characters.

The third approach is the combination of the previous two methods. In that, density of the image is calculated. However, these three algorithms cannot determine a noise in the image. Hence, they developed a system based on template matching correlation as a fourth approach. This correlation indicates the linear relationship between each character with all other characters. However, the limitations of this approach are that, they can recognize only 10 numbers instead of the alphabets. If more templates are added to the system, the success rate may decline since some characters share the same density and vector.

[4] Casey, R. G. and, E., "A survey of methods and strategies in character segmentation", IEEE transactions on pattern evaluation and machine intelligence.

Lecolinet et al proposed a new algorithm for license plate identification. For faster detection of license plate regions, they developed a novel method called Sliding Concentric Windows (SCW), which can describe the irregularity in the image based on image statistics. The SCW segmentation algorithm involves following steps. (i) Two concentric windows A and B were created for the upper left corner pixel of the image. (ii) Mean values are obtained from both windows. In this approach, the RoI (Region of Interest) will be detected if the ratio of the statistical measurements (B to A) in the couple of windows reaches a threshold value.

Image masking, Binarization and connected components analysis (CCA) functions are employed in sequence. As a result, license plate region is detected. In license plate processing stage, they created an approach to segment the characters. The probabilistic neural network (PNN) is invoked to recognize the characters. As a result, possible character is determined in the output layer.

However, the proposed system relies highly on the lighting condition and the physical appearance of the plates. In some cases, the model cannot detect the plate due to the illumination condition or the quality of the plates.

IV. PROPOSED SYSTEM

This paper proposed an Advanced vehicle classification and detection method based on deep neural networks. In this system, vehicle classification task is accomplished by Convolutional Neural Networks. It extracts the vehicle region from its background area by pictures, in order to test the generalization ability about the domestic vehicle types of vehicle dataset. So, the vehicle region is segmented to remove background noise to improve the recognition accuracy. In this approach, the convolutional neural network is used to complete feature extraction and classification training of labeled image datasets of many vehicle types such as bus, car, bike, bicycle. In this way, the task of identifying vehicle types from different angles can be completed.

Fig 3: Input Image to the Model

Besides, this paper also focuses on automatic detection of the vehicle License plates which can be accomplished by Tesseract-OCR (optical character recognition). It is used to recognize the characters and provides the text from the given image. So, the extracted License Plate is given to the tesseract-OCR which in return provides the characters of number plate for license plate recognition.

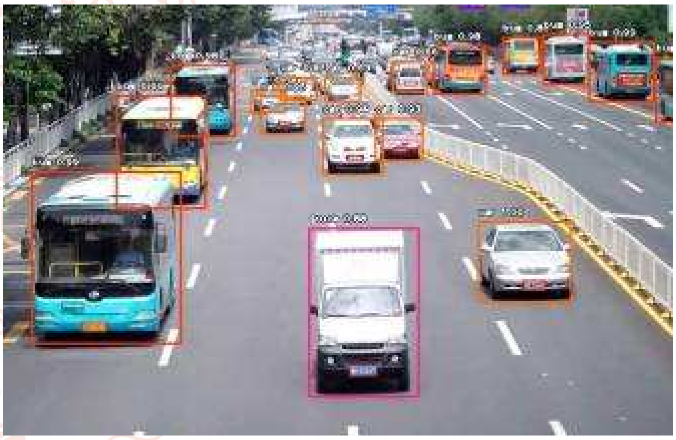

Fig 4: Output Image from Trained Model

Finally, the Proposed model is evaluated based on selection accuracy, recognition accuracy and real-time performance in the vehicle classification and detection process. While training the model for the detection of vehicle type and its number plate, the dataset must be split into train data and test data. The train and test data are statistically known as positive overlap range and negative overlap range respectively.

When we dataset the parameter "Negative Overlap Range" (where the overlap ratio between the candidate and the image labeled area is used as the interval for negative training samples) to [0, 0.3], and the parameter "Positive Overlap Range" (the overlap ratio between the candidate and the image labeled area as the interval of the positive training sample) to [0.7, 1.0], the accuracy of proposed vehicle detection model will be the highest.

V. SYSTEM ARCHITECTURE

Block Diagram of the Proposed System is represented as shown below in figure 5. This Proposed block diagram is categorized into three parts. They are (i) System Framework, (ii) Software Requirements, (iii) Methodology

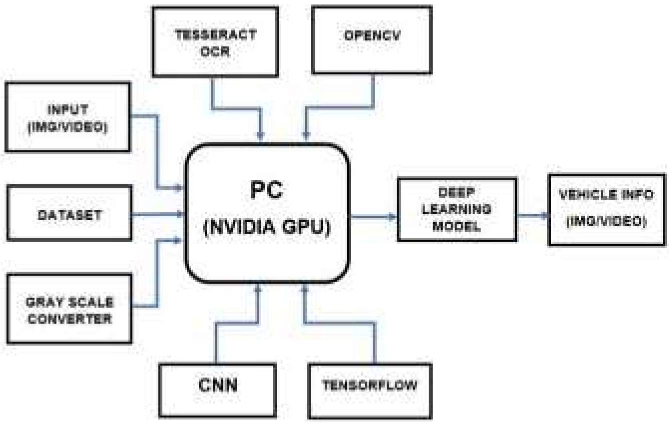

Fig 5: Block Diagram of Proposed System

A. SYSTEM FRAMEWORK

1. Vehicle Detection and Classification Based on Convolutional Neural Networks:

1.1. Vehicle Detection:

In this system, images of the training dataset are given as input and the foreground area of the target vehicle is detected by the convolutional neural network (CNN). But there are some issues to build a deep learning model by using CNN. The first problem while training the deeper networks is, accuracy should be increased with an increase in depth of the network as long as over-fitting is taken care of. However, the problem with increased depth is that the signal required to change the weights, which arises from the end of the network by comparing ground-truth and prediction becomes very small at the earlier layers, as a result of increased depth.

It essentially means that earlier layers are almost negligible to learn. This is called a **vanishing gradient.** The other problem while training the deeper networks is, executing the optimization on huge parameter space and therefore naively adding the layers which results in higher training error. This is called a **degradation** problem. In order to overcome these issues, Convolutional Neural Network uses ResNet Architecture to train the deeper networks.

ResNet architecture makes use of shortcut connections to solve the vanishing gradient and degradation problems. The basic building block of ResNet is a Residual block which is repeated throughout the network. The ResNet structure as shown in Figure 6.

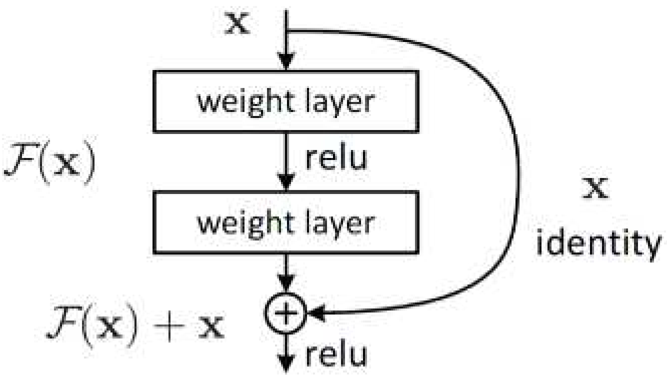

Fig 6: A Residual Block of Deep Residual Network

Instead of learning the mapping from x → F(x), the network learns the mapping from x → F(x)+G(x). When the dimension of the input x and output F(x) is same, the function G(x) = x is an identity function and the shortcut connection is called Identity connection. The identical mapping is learned by zeroing out the weights in the intermediate layer during training, since it's easier to zero out the weights than push them to one. For the case when the dimensions of F(x) differ from x, Projection connection is implemented rather than Identity connection. The function G(x) changes the dimensions of input x to that of output F(x).

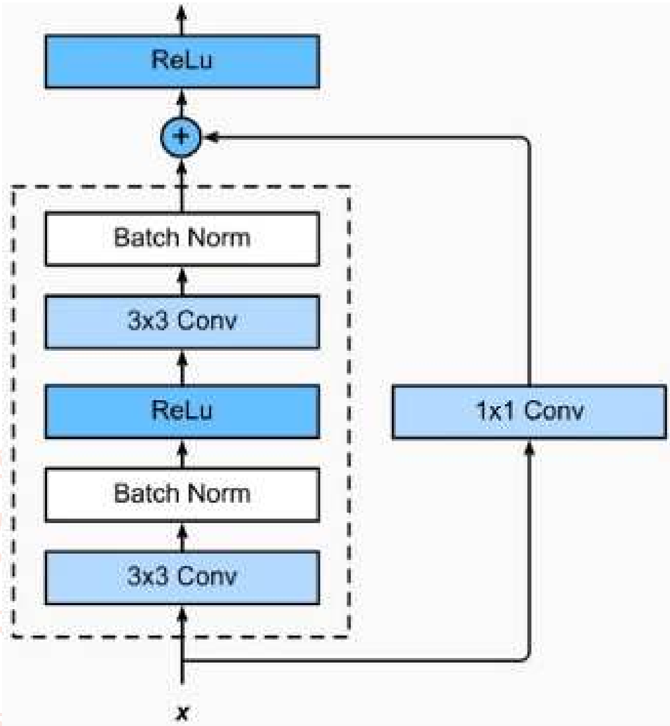

Fig 7: Projection connection of Residual Network

ResNet Architecture uses Rectified Linear Unit (ReLu) as an activation function of neural networks. This rectified Linear activation function is a piecewise linear function that gives the output as its input itself, if the input is positive. Otherwise, it gives output as zero if the input is negative. ReLu activation function reduces the large number of computations. It has become the default activation function for many types of neural networks because a model that uses ReLu is easier to train and often achieves better performance. The ReLu activation function is given as shown below.

$$\mathbf{F\ (x)} = \left\{ \begin{array}{ll} \mathbf{X} & \mathbf{if\ x > 0} \\ \mathbf{0} & \mathbf{if\ x \leq 0} \end{array} \right\} \quad \mathbf{for\ all\ x \in R}$$

By using ReLU as an excitation function instead of the traditional function, Logistics makes it easier to forward propagation and calculate the reverse gradient by using partial derivative. It also helps avoid complex algorithms such as exponent and division.

The hidden layer neurons with output less than 0 are discarded to increase the sparsity and reduces the overfitting effect. The ResNet network structure is adjusted while testing the data and the extracted vehicle area is outputted as shown in Figure 8.

Fig 8: Vehicle Detection

1.2. Vehicle Classification:

The foreground vehicle area obtained by vehicle detection algorithm is introduced into another convolutional neural network for vehicle recognition. Convolutional neural network uses a certain number of convolutional kernels to slide the input image with a certain step size to extract features in the convolution layer. Each convolution kernel focuses on different features, so the convolution obtains different feature maps.

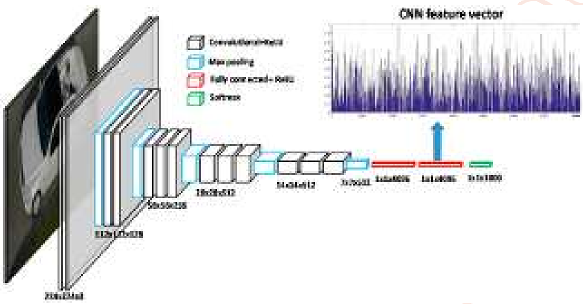

Fig 9: CNN Architecture

These obtained feature maps are passed into the lower convolution layer, and then the lower convolution layer uses a certain number of convolution kernels to extract the features of upper feature map, this operation will be repeated. The weighting parameter will be got after the features are processed for several times. Then the weighting parameter will be connected to the full connection layer, the full connection layer plays a role of classifier in the entire convolution neural network, namely a model to classify the extracted features.

By using the method of Deep Learning, the features ignored by the traditional methods can be extracted, the recognition accuracy can be improved obviously, and different convolution kernels are used to obtain convolution feature diagrams, as shown in Fig 10. This ResNet architecture is similar to the VGGNet which consists mostly of 3X3 filters or kernels.

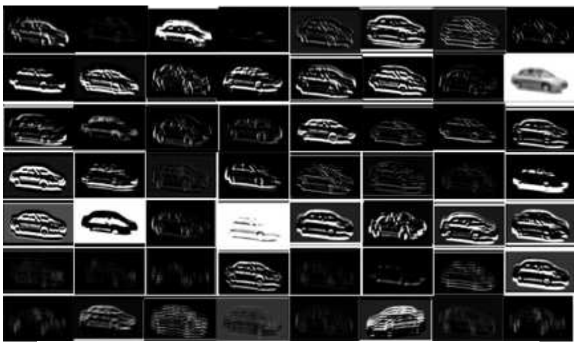

Fig 10: Feature Map of Convolution Layer

From the VGGNet, shortcut connection is inserted to form a residual network. In order to overcome the issues such as vanishing gradient and degradation problems of the deep learning model which occurs during training the model.

2. TENSORFLOW:

TensorFlow is an open source library which uses data flow graphs to build the models. This allows developers to create large-scale neural networks with many layers. TensorFlow is a neural network module which is mainly employed for Classification, Perception, Understanding, Discovering, Prediction and Creation. Tensors are the multidimensional arrays, an extension of 2-dimensional tables to data with a higher dimension. There are many features regarding TensorFlow which makes it appropriate for Deep Learning.

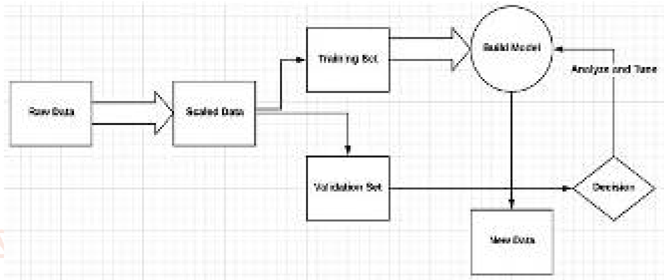

Fig 11: TensorFlow Architecture

TensorFlow architecture works in three parts. They are (i) Preprocessing the data, (ii) Build the model, (iii) To train and test the model. Initially, the raw data is scaled by normalizing the input and output features of a model. This preprocessed data splits into train and test dataset. This Building model is trained using train dataset. By comparing the prediction accuracy of test dataset with the ground-truth, loss function of the model can be analyzed and tuned with hyperparameters. TensorFlow is used for fast numerical computations of neural networks. It is a foundation library that can be used to provide Deep Learning models directly or perhaps by using wrapper libraries that simplify the process built on top of TensorFlow.

3. OpenCV:

OpenCV is also known as Open Source Computer vision. It is a cross-platform library of programming functions which mainly aims to develop the real-time computer vision applications. OpenCV was developed by Intel organization. This mainly focuses on image processing, video capture and analysis which include features such as face detection and object detection. It supports some models from deep learning frameworks such as tensor-flow, Tesseract-OCR, PyTorch modules to build an effective model.

By integrating the OpenCV with the Tesseract-OCR, it can extract the characters even from colored images with higher accuracy.

B. SOFTWARE REQUIREMENTS

1. TESSERACT-OCR:

The Character Recognition popularly referred as Optical Character Recognition (OCR). Tesseract-OCR is the software process of converting typed, handwritten, or printed text to machine-encoded text that we can access and manipulate via a string variable. The OCR has been one of the challenging and popular fields of research in pattern recognition. This can be used as one of the classifier in the image processing step since the most crucial step in OCR is identifying characters as one of 36 symbols (A-Z and 0-9). Therefore, for classification, we need to extract visual features from individual character image. Then, character can be classified with these features using machine learning. The most effective way for now is OCR-tesseract, which is originally developed by Hewlett Packard in the 1980s. It is one of the most accurate open source OCR engines currently available.

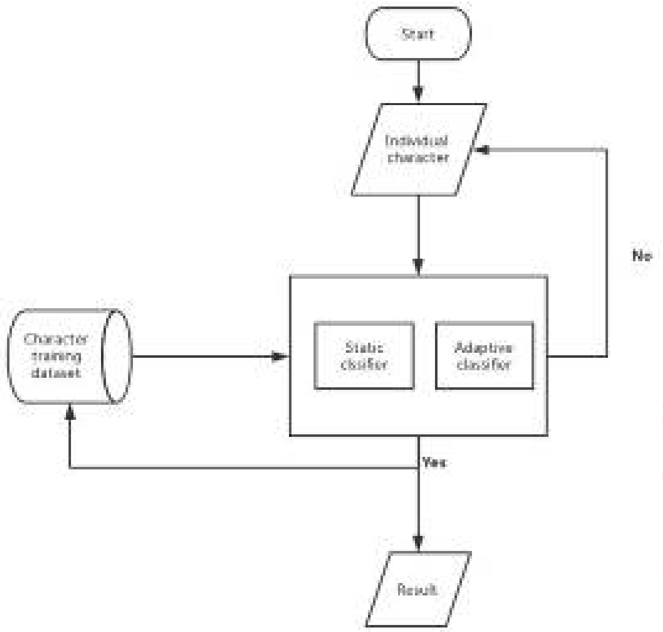

Fig 12: Flowchart of Tesseract-OCR Process

As other traditional procedures, this processing follow a step by step approach. As the most important part, recognition consists of two stages, which are adaptive classification and repeating recognition, respectively. In the first stage, each character is recognized sequentially. Additionally, the symbol that is classified is stored by the adaptive classifier as the training data. Then, the adaptive classifier will learn the information that classified characters provide, from which the characters that are not recognized in first step will be classified again. This two-stage process make this method accurate and efficient.

2. LabelIMG:

Labelimg is a graphical image annotation tool. It is designed in Python and uses Qt for its graphical interface. Annotations are saved as XML files in PASCAL VOC format which is employed by ImageNet. Image Annotation could be the process of building datasets for computer vision models. This helps machines to learn, how to automatically assign metadata into a digital image using captioning or keywords. This Labelimg tool is used to train our customized model.

This technique is used for image retrieval systems to organize and easily locate particular images from a database. Image labeling gives the insight into the content of images. When you use the API, you get a list of the entities that were recognized: people, things, places, activities, and so on. Each label found comes with a score that indicates the confidence or probability or accuracy of the ML model according to its relevance.

3. ANACONDA NAVIGATOR:

Anaconda Navigator is used to launch applications and to manage conda packages, virtual environments, and programs without the use of command line commands. In order to get the Navigator, download the Navigator Cheat Sheet and install Anaconda. It is a free open-source software which is associated with Python and R programming languages for scientific computing such as for data science, machine learning applications, large scale data processing, predictive analytics and so on. It aims to simplify package management and deployment.

Jupyter Notebook is a one of the IDE which have to be launched from the Anaconda Navigator to develop, execute, debug the algorithms which performs Artificial intelligence tasks. It provides you with an easy-to-use, interactive data science environment across many programming languages that doesn't only work as an IDE, but also as a presentation or education tool. It's perfect for those who are just starting out with data science. Because, it helps to debug the errors by specifying the type of error that was obtained.

C. METHODOLOGY

1. DATA COLLECTION & DATA PREPARATION:

In this Project, dataset is prepared by the collection of vehicle images from Open source, CCTV cameras and internet. To ensure the representativeness and the integrity of data, images are taken from different viewpoints under different traffic conditions. Most of the images in this dataset are rear views of the vehicle. Besides, the image dataset also covers most types of vehicles and noise images.

This involves collection of data by recording using a camera with auto iris function which keeps the average illumination of the view constant. It also uses i-LIDS dataset, then the input data is processed into a set of features before becoming suitable inputs for per frame vehicle detection and classification using 3D models.

2. EDGE DETECTION:

An edge based multi-stage detection is the main primary function to detect the vehicle and its license plate edges at their localization. In this paper, license plate edges are detected from its original image by edge detection. Localization of plate is undoubtedly a challenging task since there are significant variations in plate size, color, lighting condition and spatial orientations of license plate in images. So, three steps are employed at the preprocessing stage. They are (i) Gray Scale Conversion, (ii) Median Filtering, (iii) Contrast Enhancement.

2.1. Gray Scale Conversion:

By using following formula, the 24-bit color image can be converted into 8-bit gray image.

$$\textbf{Gray} = \mathbf{0.59 \times R + 0.30 \times G + 0.11 \times B}$$

2.2. Median Filtering:

As one of non-linear filter, it can calculate the median of the gray values of a pixel's neighbors. In this stage, they use 3×3 masks to get eight surrounding neighbors' gray value and replace the pixel value with the median value. As a result, the function could remove salt-and-peeper noise from the image.

2.3. Contrast Enhancement:

Histogram equalization technique is invoked to enhance contrast of the images. In the procedure of the conversion, the total number of pixels in the image is N and the number of pixels with the gray level k is n_k. Then the stretched gray level S_k is calculated by the following formula.

$$S_k = \sum_{j=0}^{k} \frac{n_j}{N} * 255$$

3. FUNCTIONAL PROCESS:

This paper proposed an Advanced vehicle classification and detection method based on the deep learning approach. In this system, the surveillance cameras are used for observing the vehicles at any specific region or area. These surveillance cameras are often connected to the Personal Computer (PC) or any recording device to provide those vehicle images or videos which are passing through that specific gateway or area. This vehicle data is taken as input to the Personal Computer (PC). By using the i-Lids, real time camera and open source data a dataset is created. With the help of this dataset, the Deep Learning model is trained up- to a specified epoch. With the Increase of number of epochs, the loss function of the model is reduced. Finally, the trained model is tested with the new vehicle data to check whether the model is working effectively in vehicle classification and detection of their number plates.

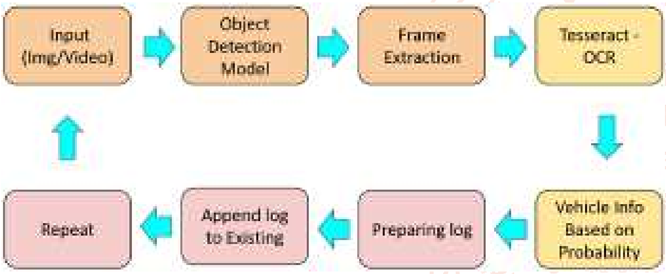

Fig 13: Functional Process of Proposed Scheme

In this system, Vehicle classification method is based on a convolutional neural networks and automatic license plate detection of vehicles method is based on Tesseract-ocr. This Deep neural network model will detect the vehicle from the given image or video by using frame extraction. It also provides the classified type of vehicle whether it is bus or bike or bicycle or any other type.

The model will detect the vehicle number plate if and only if there is number plate for that detected vehicle. The detected vehicle number plate is extracted as an image from the given data and simultaneously given to the Tesseract-OCR which is integrated with the OpenCV to recognize the characters present in that number plate. The model will be instructed to detect and classify the vehicles, only when their detection probability is more than 0.90. This Probability approach will be useful to get the accurate vehicle info or effective results of the model. A log is created in the PC, to note the details of the vehicles.

This Info includes type of vehicle, its number plate and other info like time in & time out are tabulated accurately in the log. Every vehicle info is appended to its log. Finally, this model provides the accurate info of log regarding the vehicles that are passed through this Artificial Intelligence Surveillance.

VI. FLOW CHART

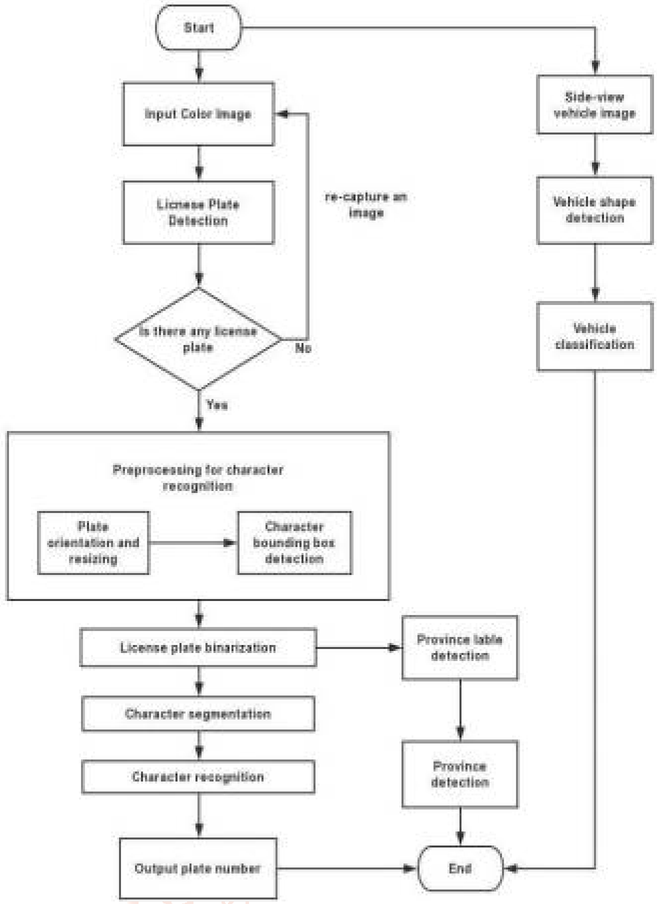

Fig 14: Flow Chart of Proposed System

The given flow chart of proposed system explains the procedure and sequence of Framework as shown above in figure 14.

VII. EVALUATION & DISCUSSION

For evaluating the proposed or implemented model, we must compare the performance of the proposed system to all other existing systems. After collecting the relevant training and testing experiment information, we analyzed and compared the accuracy rate of the different network structures such as AlexNet, Vggnet16, Vggnet19, Googlenet, Resnet50 and Resnet101. Currently, proposed system uses ResNet101 architecture to train and test the deep learning Algorithm for vehicle classification and detection. The accuracy for different network architectures shown below.

$$CR\,(\%) = \frac{CN\,(correct)}{TN(\,CN\,(correct) + EN\,(error)\,)}$$

In the equation, CN means for the number of correctly classified images and EN means for the number of incorrectly classified images indicates the correct rate. To compare the experimental results of various network results, the graphical representations of them are given below.

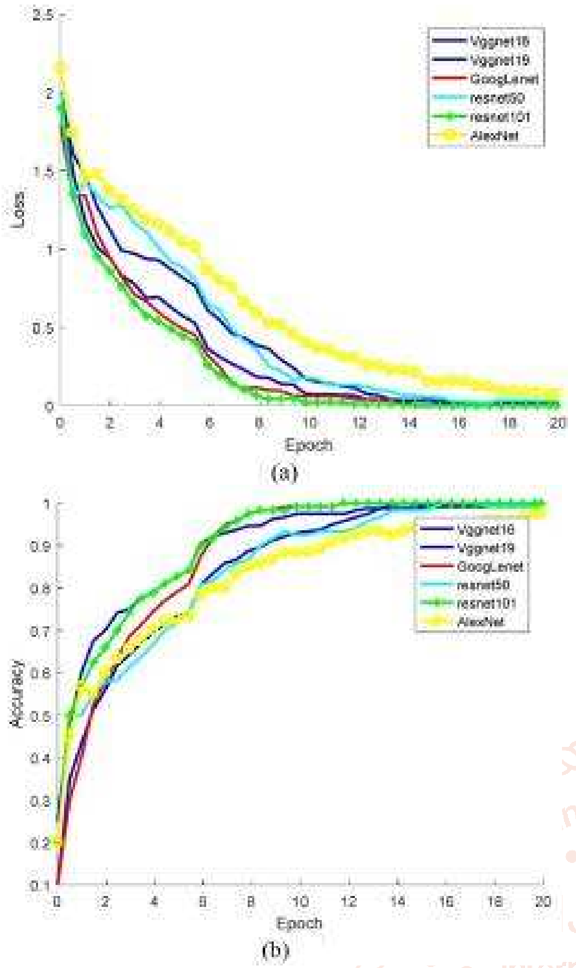

Fig 15: (a) loss curves of curves; (b) curves of accuracy

The dataset with 3500 pictures is collected and preprocessed with auto-iris function which is used to evaluate the trained models. We drew the loss curve and accuracy curve of every classification and recognition network structure, which are helpful to understand the training process of every model. From the comparison of the curves, it is clear that the Resnet-101 can get the fastest convergence and higher accuracy as shown in Fig 15.

Architecture	Accuracy	Year
Alex Net	82.6	2012
Inception-V1	88.4	2013
VGG	90.8	2014
ResNet-50	92.3	2016
ResNet-101	95.2	2018

Table 1: Comparision of Network Structures

We apply the proposed model which is trained by the image dataset into the real traffic road video or images collected by ourselves. The collection of real traffic vehicle pictures is also tested. We observed that for the recognition of the real traffic road image, the training image dataset obtains the higher accuracy.

The experimental results obtained from the training and testing dataset is shown in the below table. The figure 15 shows that, Resnet Network structure gives the higher accuracy for object detection and classification than the other network structures. By analyzing the testing performance with different number of layers in ResNet structure, the best performing one is the cascading of the ResNet101 network structure which achieves 95.27%.

VIII. RESULTS

In most of the cases, the experimental results of proposed system have obtained with higher accuracy. The proposed method has integrated feature extraction, object frame boundary generation, linear regression & classification and License plate recognition to provide a customized efficient model. By using this model, we can retrieve the vehicle info accurately. Even if there is background noise in the license plate, it will not affect the performance of the recognition. So, this system can recognize all the characters on the license plate successfully. Thus, the comprehensive performance has been greatly improved. When compared to existing models, the current deep learning vehicle classification and detection neural network model has the rate of accuracy as very high. Therefore, the proposed model gives standard results.

IX. CONCLUSION

Based on CNN, this paper proposed the vehicle type classification and license plate recognition in urban traffic video surveillance. This Deep Learning model can do both Classification and Detection of vehicles simultaneously. This reduces the complexity of the processing which helps to increase the performance of the system to train and test the model. With the increase of training dataset, the modification of parameters and replacement of the model; the proposed method becomes effective and validated by the relevant experiments. The experimental results show that the vehicle recognition rate is improved. In a comparative analysis, this vehicle classification & detection framework can get high accuracy with success rates which has been proposed to expose in a better performance than existing frameworks.

X. FUTURE WORK

In the future, we will implement this proposed model as a real-time hardware application with a deep learning Framework which further improves the accuracy and robustness for the traffic vehicle classification and detection. There are still mountains of work about deep learning to be studied. For example, it needs the other efficient and theory based deep learning model algorithms. It explores the new feature extraction models which are also worthy to do further research. Besides studying efficient parallel training algorithms, they need to be investigated. Regarding the applications of extending deep learning and how to make rational use of deep learning in enhancing the performance of traditional algorithms is still the focus of a variety of fields.

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