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Deep Learning Approach for Vehicle Number Plate Recognition System with Image Enhancement Technique

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Abstract. The number of automobiles and trucks on the road is continually rising, particularly in direct connection to the emergence of the industrial revolution and the expansion of the economy. Because of the proliferation of motor vehicles, there is a greater potential for the violation of traffic laws, which in turn increases the risk of both unintended collisions and criminal activity on the road. In order to address these problems, a sophisticated traffic monitoring system is required. The intelligent technology has the ability to significantly contribute to traffic management via the recognition of licence plates. As part of this work, we use convolutional neural networks (CNNs) based Alexnet and MobileNetV2 framework, a subset of the deep learning technology known as convolutional neural networks, to build a system for the automatic identification and recognition of licence plates. We also propose to improve both the frameworks by applying image enhancement techniques. Both the detection and identification of licence plates are integral parts of this system. A digital camera is used to capture the image of the vehicle during the detection phase. The Alexnet and MobileNetV2 framework then isolates only the licence plate from the whole image. After the licence plate number region has been removed, the low-resolution image is converted into a high-quality one by a process called super resolution. The convolutional layer of a CNN is used in conjunction with a super resolution technique to restore the original image's pixel quality. To separate the characters of a licence plate number, we employ a bounding box method. Features are extracted and labelled using the CNN technique during the recognition stage.

Keywords: *CNN, Alexnet, MobileNetV2, recognition, detection, convolutional.*

1. Introduction

Manually directing and monitoring traffic in an urban environment with an increasing number of vehicles is not only challenging, but also time-consuming, costly, and prone to mistake. It could even be impossible sometimes. As a result, research on automatic licence plate recognition has been ongoing[1]. Given that licence plates are the only reliable means to identify a specific car, ALR has several practical uses. Traffic management, ticketing offenders, speed estimate, self-driving cars, and surveillance are just a few of the many uses for this technology. To this end, a vast network of surveillance cameras has been installed throughout the country's towns, roads, and highways, as well as at its borders, parking lots, and other secure locations, to keep track of vehicles with greater accuracy[2]. Pictures taken by these cameras of passing vehicles are monitored continuously. It is difficult to find automobiles and identify licence plates without first processing and analysing these photos.

Image processing and machine learning are needed to create a system that can identify vehicles and pull out further information, such as licence plate numbers[3]. The speed and reliability of licence plate recognition systems are closely related to the quality of the images used to make the recognitions. Environmental and climatic conditions such as light projection angle, light intensity, rain, fog, dust, humidity, darkness, glare, occlusion, precipitation, tilt, and blurriness may all have an impact on the quality of the collected images[4].

Detecting vehicle number plates in an efficient manner has been approached from a number of different angles. In order to improve the speed at which this step is completed as well as its overall efficiency, "denoising" and "quality-enhancing preprocessing" operations are carried out. The next step involves positioning the plates shown in the image that has been provided[5-9]. Recent research on plate identification has led to the categorization of existing approaches into the following five main groups: edge-based methods, color-based methods, texture-analysis methods, methods based on image global properties, and hybrid methods. In every one of these domains, machine vision and image processing have been implemented in a variety of guises [10-16]. The segmentation of the plate comes next in this procedure. The binary form is used in the first stage of processing the picture of the observed plate. The methods of morphology [17], the linked component analysis algorithm [18], and histogram-based methodologies are then used in order to extract the character-related

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components. This stage is troublesome since the majority of binarization algorithms can only provide adequate results on plates that are completely free of spots. When these procedures are carried out on plates that are not clean, considerable portions of the information are discarded. To be more exact, the sections of the plate that are designated as character parts are not always always labelled as character parts, and vice versa[19].

2. Literature Survey

Using Hough Lines and Matching Template Models,[20] created a complete licence plate identification and recognition system with a primary emphasis on Hough Transformation. The canny detector was used to perform the investigation, and the accuracy rate for the extraction of vehicle licence plates was 95.67 percent. New Extreme Learning Method (ELM) recognition software was created[21]. The Thai licence plate was used for the purposes of preprocessing and extracting features by using the ELM classifier and the Histogram of oriented Gradients (HOG). With an accuracy of 91.26 percent, the system was able to detect licence plates that included both the identification number of the automobile registration as well as the province. In their paper [22], introduced a unique hierarchical character recognition system that centred on supervised K-means and SVM in order to recognise licence plates that were blurry and slanted. This system attained an accuracy of 96.75 percent when compared to the state-of-the-art techniques to plate identification, which is an average rise of 4.5 percent higher than those approaches23.

In order to investigate the ANPR system using a deep learning strategy, [24] employed the first CNN model for licence plate identification and pre-processing methods to identify licence plates and nonlicense plates. The classification and identification tasks were carried out with the assistance of the second CNN model. The investigation was conducted using a tensorflow architecture, and it made use of 45 different classes of the second CNN model. Following this,[25] devised a three-stage plate recognition system based on the Mask-RCNN algorithm. Mask R-CNN was used both for the purpose of character recognition as well as for the detection purpose of YOLOv2. According to the results, car number plates with bevel angles greater than 0 to 75 degrees may be identified, and a mAP value of around 93 percent was also reached. An automatic number plate reader (ANPR) system that uses CNN-GRU fusion has been suggested[26]. In this method, an optical character recognition technology is used to retrieve vehicle plates. An ANPR framework that incorporates morphological image processing and deep learning for edge detection and Connected Component Analysis (CCA) for regional extraction was suggested[27]. As the feature extractor, a pre-trained CNN "Alex-Net" was used, and the results showed a success rate of 92.7 percent. In [28] proposed a method for the identification of licence plates that included the use of classifiers. These classifiers included Random Forest Classifiers, Rep tree, IBK, and K-star. The use of Kstar ML algorithms, which provide an accuracy rate of 98.75 percent in the data collecting, helped achieve effective accuracy[29].

An ANPR system that is capable of fooling CNN's learning feature capabilities was created[30]. Because it is able to differentiate between vehicle states that have been arranged in a feature detector echelon network, CNN's self-synthesized function was selected for this task. The results showed an accuracy rate that was 95 percent greater despite their being less training samples overall. In [31] proposed the use of a GPU to power an automated system for identifying the licence plate numbers of motor vehicles. This investigation was carried out with the assistance of NVIDIA Jetson TX1 boards and CNN-based plate identification by making use of the AlexNet LP database, which demonstrated recognition accuracy rates of 97.2 percent.

3. Proposed Methodology

When there are a large number of plates present in the frame that is being processed, the majority of techniques for plate identification are unable to detect all of the plates. This renders these approaches inapplicable for use non real-time scenarios, when there may be a large number of plates in each frame and the amount of time available for reaction may be restricted. In order to solve this problem, the suggested method Alexnet and MobileNetV2, which boosts the processing performance to a level that enables real-time licence plate identification. The initial step of the proposed strategy is the detection of automobiles. After that, based on the architecture of deep learning, plates are first recognised, and then the text of the plates is extracted using a deep network that consists of both convolutional layers and recurrent layers. This process takes place in two stages. The solution that has been suggested is an end-to-end system that can concurrently detect cars and licence plates and identify the plates. The many stages of this process are broken down into their respective parts below**.**

a. Vehicsle Detection:

Real-time applications benefit from beginning with vehicle detection for a higher detection rate. When searching for a plate, traditional deep learning-based algorithms often examine the whole image. The current method is time-consuming due to the fact that plates make up such a minute percentage of a frame. To save time analysing irrelevant areas of the picture, the suggested technique begins with vehicle detection. Taking this measure saves time and effort by reducing the number of repetitions required to complete the procedure. Multiple convolutional layers of a deep network are used to identify vehicles.

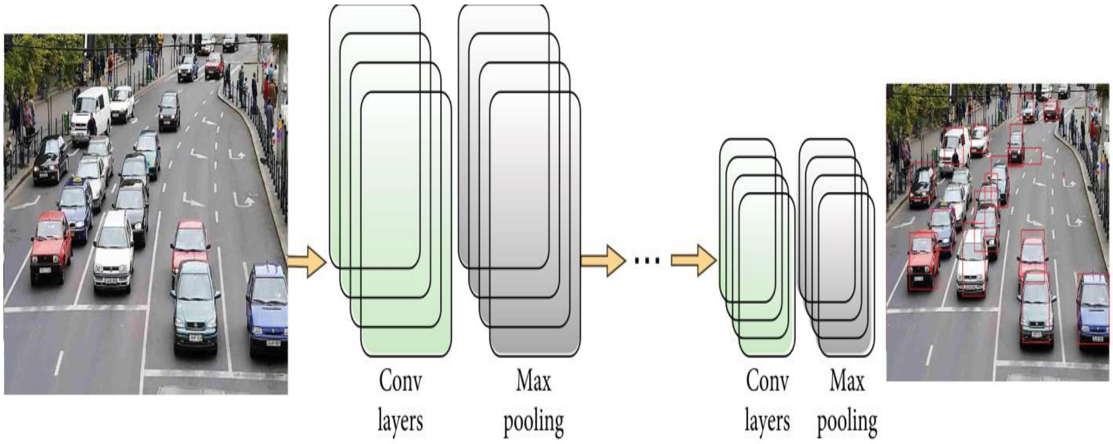

Fig. 1. Vehicle Detection

The constructed convolutional network extracts high-level characteristics for use in vehicle detection. The suggested technique really utilises a combination of high-level data retrieved by a convolutional and recurrent network and low-level features in the main convolutional layer to identify automobiles. In addition, many layers are used to extract distinct features from input photos. Features are retrieved with varying degrees of precision between layers due to the varying sizes of the kernels used. This aids in having pictures rich in detail, allowing for the extraction of useful and distinguishing elements. As shown in Figure 1, the proposed design includes components for identifying the presence of vehicles.

b. Dataset:

Fig. 2. Sample Images of Indian Vehicles with Number Palates

c. Steps of Number plate recognition:

First, the ANPR camera takes still photos or movies that include one or more licence plates. This may be done either individually or in groups (video stream or photo). It is feasible to utilise ANPR at any time of the day because to the widespread usage of infrared illumination, which enables cameras to read the licence plates of passing vehicles even after the sun has set.

Detect and crop number plate: In the picture, the licence plate was found using machine learning and computer vision techniques. This was followed by the number plate being cropped. There are a variety of approaches, each of which varies considerably from the others in terms of the amount of computer resources required, level of complexity, amount of time required, and degree of precision. Using object detection to identify the cars first and then locating the licence plate inside the bounding boxes generated is a frequent approach. In most cases, this may be accomplished by searching for regions of contrast between the backdrop and the numberplate. Following the successful recognition of the licence plate, the image is further cropped and normalised (sharpened, distorted, and enhanced).

The next step is to apply OCR software to the identified plate region in order to retrieve the licence plate number in text format. This allows the number to be extracted and read. The OCR software may be customised to work with a variety of character sets, which enables the ANPR system to be used in several countries without modification. The output of an ANPR system is normally the number of the licence plate, often accompanied by the area or nation.

Use the information from the licence plate Once the information has been transformed into plain text format, the licence plate number of the vehicle is saved in a database so that it may be integrated with other IT systems. The licence plate may be compared to a database of registered plates, whitelist and blacklist databases, or both. The programme searches for the car in a database and, if successful, provides information that has been saved about it, such as the name and address of the registered owner.

d. Alexnet Model

Alexnet features eight layers with trainable parameters. There are a total of five layers in the model, with Relu activation used in all except the final output layer. The first two levels make use of max pooling, followed by three fully connected layers.

Researchers discovered that by using the relu as an activation function, training durations might be cut by as much as a factor of six. Because of their usage of dropout layers, their model was not overfit. In addition, the Imagenet dataset is used for training the model. Almost 14 million photos from 1,000 different types may be found in the Imagenet collection.

Figure 10 depicts the CNN AlexNet architecture that is being considered. Five convolutional layers, three max-pooling layers, two fully connected layers, and one Softmax layer made up the AlexNet model. The model also included one Softmax layer. Convolutional filters and a nonlinear activation function known as ReLU were used at each stage of the network's training process. The maximum pooling that could be done was achieved by using the pooling layers. The first convolution layer included 96 filters, each of which had a size of 11 by 11 and a Stride of 4. On the other hand, the dimensions of Layer 2 were 55 by 55, and there were 256 filters in all. Filter sizes of 13 by 13 were distributed throughout Layers 3 and 4, totaling 384 individual filters. In the final convolutional layer, the filter size was 13 by 13, and there were 256 filters total. The output of the Softmax layer was categorised using the 1 4096 characteristics that were supplied by the two fully linked layers. After that, the photos of the licence plates were segmented in order to find the city, kind, and number of the vehicles. By converting the visual text to characters, CNN was able to extract attributes from these photographs and use them to identify the city, kind, and number of vehicles individually. For the purpose of feature extraction, a 224-by-224-by-1-pixel picture was employed. The system implemented AlexNet as its model for CNN. The steps involved in recognising each character are shown in Figure 3.

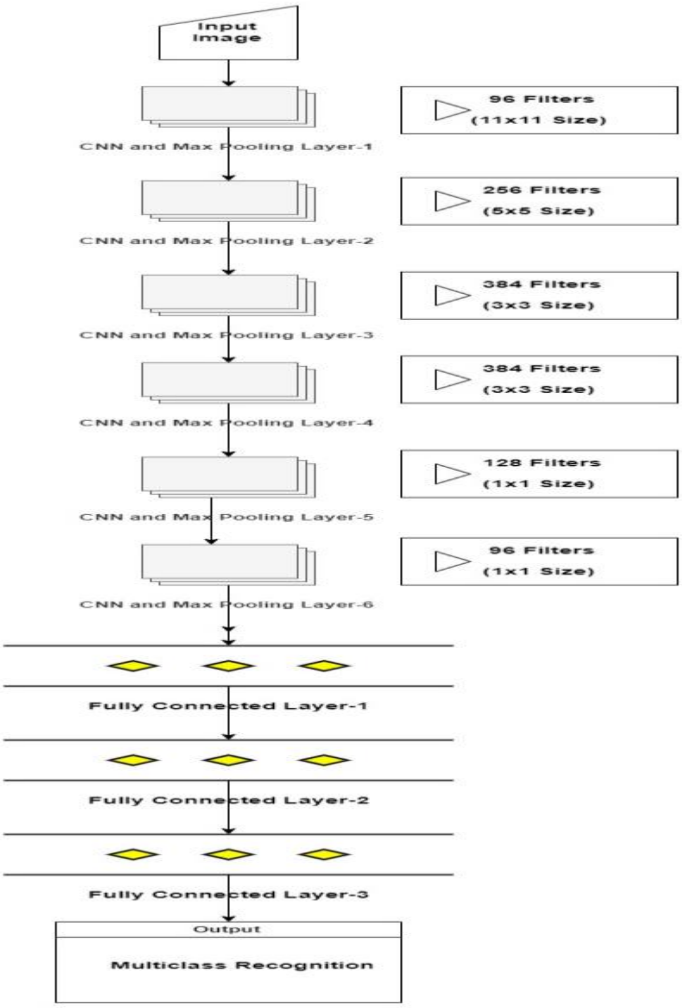

Fig. 3. Architecture for Alexnet Model

e. MobileNetV2 Model

MobileNetV2 is an attempt to design a convolutional neural network that can function effectively on mobile devices. It is predicated on a backwards residual structure, with the bottleneck layers acting as the links between the residual layers. A source of non-linearity is filtered out in the intermediate expansion layer by use of light-weight depthwise convolutions applied to features. To summarise, MobileNetV2's architecture is made up of a 32-filter fully convolutional first layer, followed by 19 layers of residual bottlenecks.

Because of its generic design, MobileNetV2 may be used to a wide variety of scenarios. It has a wide range of input layer sizes and width factors to choose from. As a result, the inference cost for mobile devices may be lowered by using a model with a different width. MobileNetV2 is almost identical to the original, except that it makes use of inverted residual blocks and bottlenecking characteristics. When compared to the original MobileNet, it has a much less number of parameters. MobileNets accept inputs of any size above 32x32, and the performance improves with bigger images.

Five convolutional layers, three max-pooling layers, two fully connected layers, and one Softmax layer made up MobileNetV2. Convolutional filters and the nonlinear activation function ReLU were used in each convolutional layer. Maximum pooling was accomplished with the aid of the pooling layers. There were 96 filters in the first convolution layer, and the Stride was 4. The filter size was 11 by 11, and the Stride was 4. Meanwhile, Layer 2's parameters were 55 by 55 pixels and 256 filters. The filter sizes in layers 3 and 4 were 13 by 13, and there were a total of 384 filters. The 256 filters in the final convolutional layer have a filter size of 13 by 13. A total of 1 4096 features were produced by the two fully linked layers for use in the Softmax layer's output classification. The photos of licence plates were then segmented in order to determine the location, make, and registration of the vehicles. By converting visual text to characters, the CNN was able to extract elements from these photos and identify the city, car type, and vehicle number. To extract features from the images, a size of 224 x 224 x 1 was employed. MobileNetV2 was the CNN model employed by the system in question. The steps used to identify each character are shown in Figure 4.

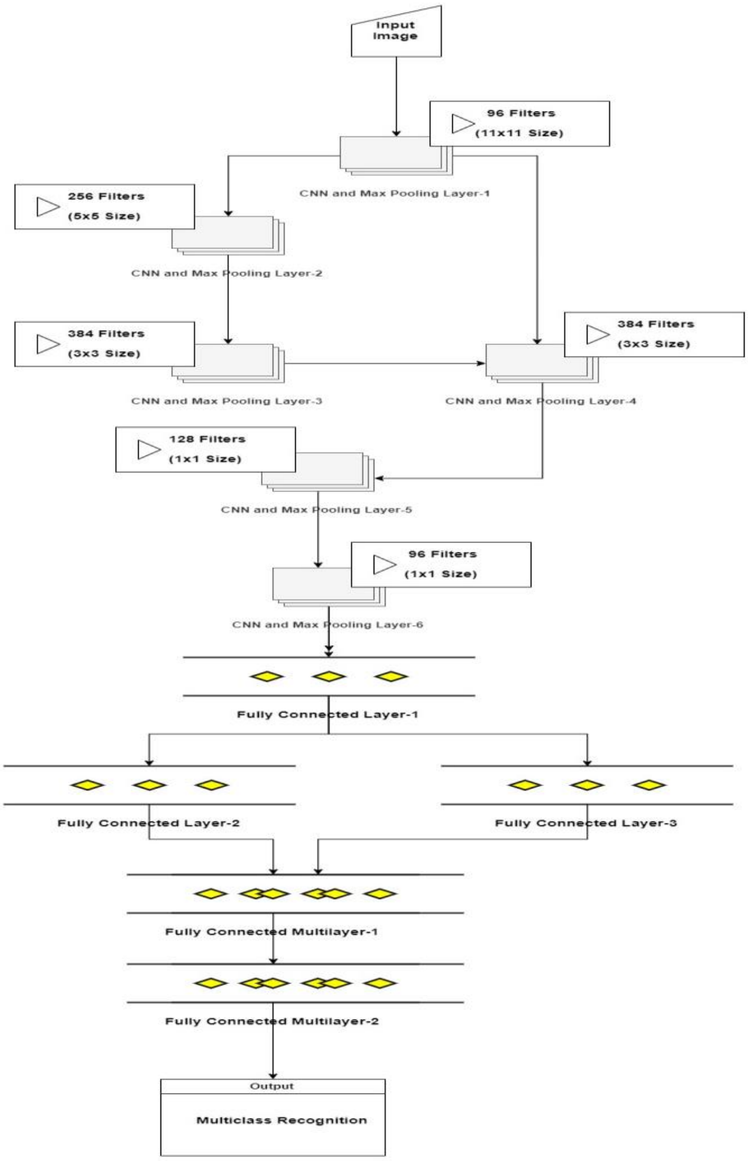

Fig. 4. Architecture for MobileNetV2 Model

4. Experimental Results

In this experiment, we implemented two models namely, Alexnet and MobileNetV2 for identification of the vehicle Number Plates. Both the models are implemented with and without image enhancement method. The implementation results are analysed on the basis of accuracy and Loss. We obtained the results by implementing it for 1 to 10 epochs. Following are the results obtained for Alexnet model. Figure 5 and 6 represents the Accuracy of Alexnet model without image enhancement and Accuracy Loss respectively.

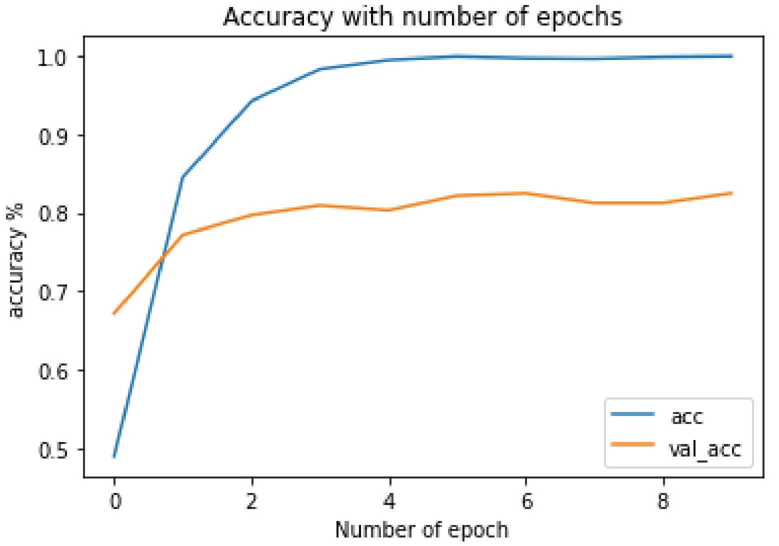

Fig. 5. Accuracy Comparison Plot for AlexNet

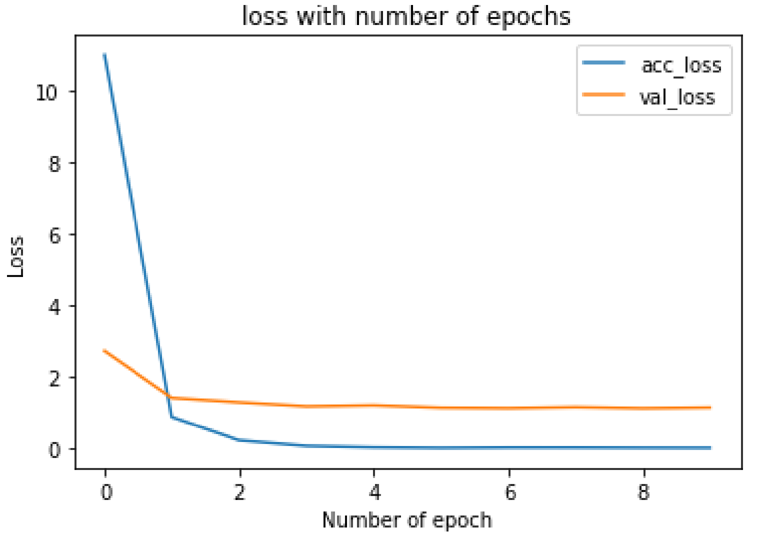

Fig. 6. Loss Comparison Plot for AlexNet

Figure 7 and 8 represents the Accuracy of Alexnet model and Accuracy Loss with image enhancement respectively.

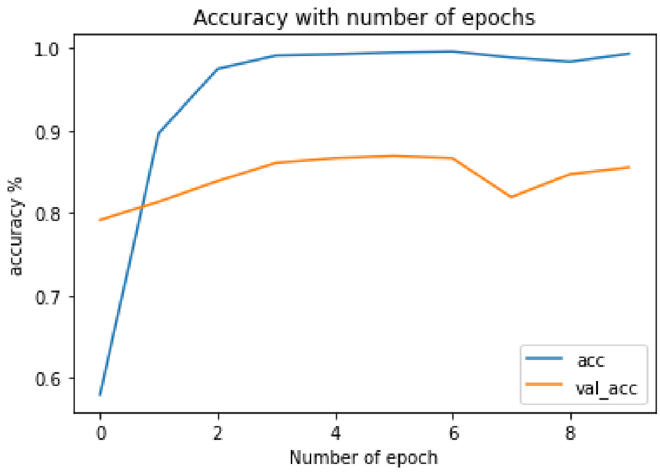

Fig. 7. Accuracy Comparison Graph AlexNet with Image Enhancement Technique Accuracy

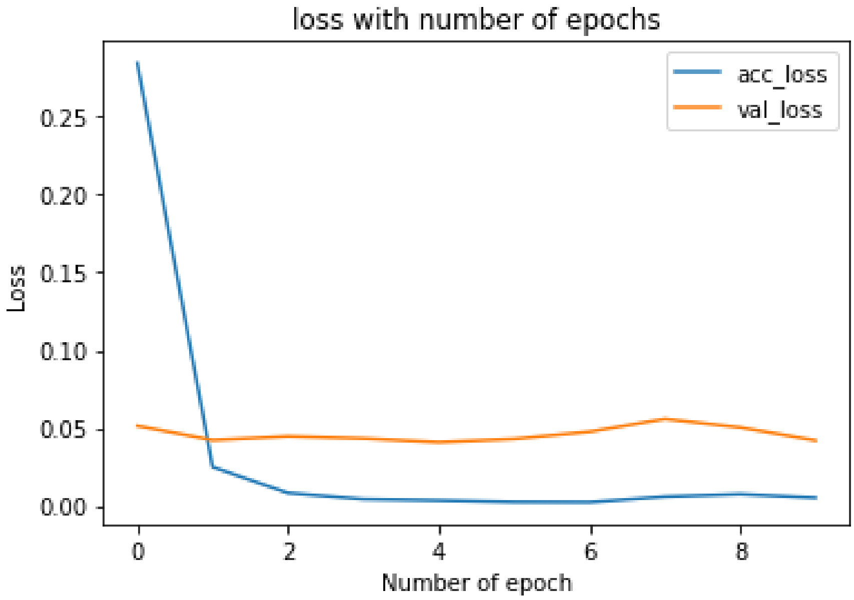

Fig. 8. Loss Comparison Graph for AlexNet with Image Enhancement Technique

Figure 9 and 10 represents the Accuracy of MobilNetV2 model and Accuracy Loss without image enhancement respectively.

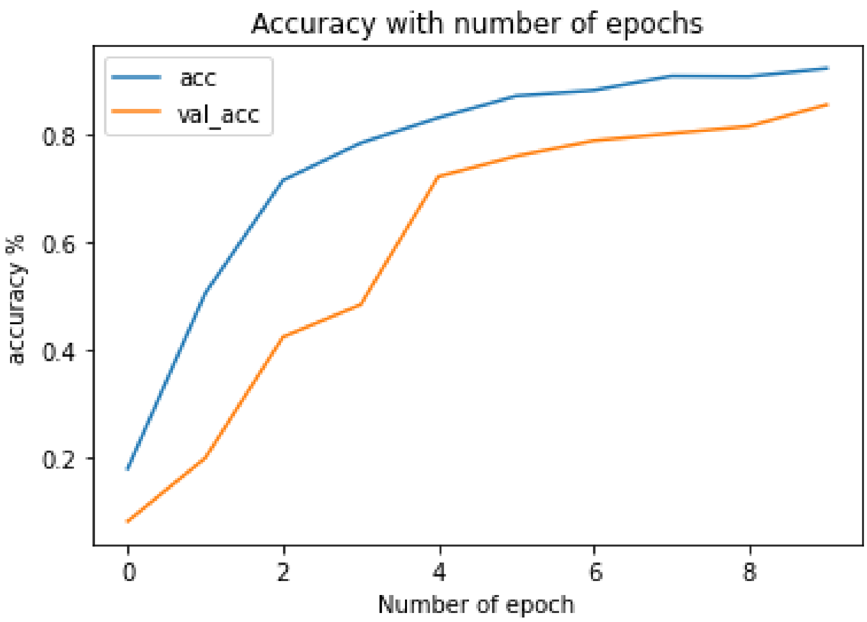

Fig. 9. Accuracy Comparison Graph MobilNetV2 without Image Enhancement

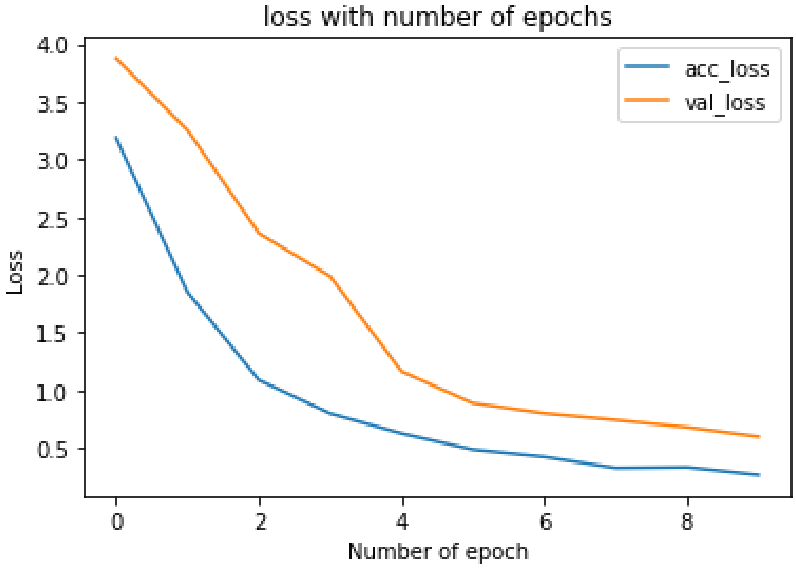

Fig. 10. Loss Comparison Graph MobilNetV2 without Image Enhancement

Figure 11 and 12 represents the Accuracy of MobilNetV2 model and Accuracy Loss with image enhancement respectively.

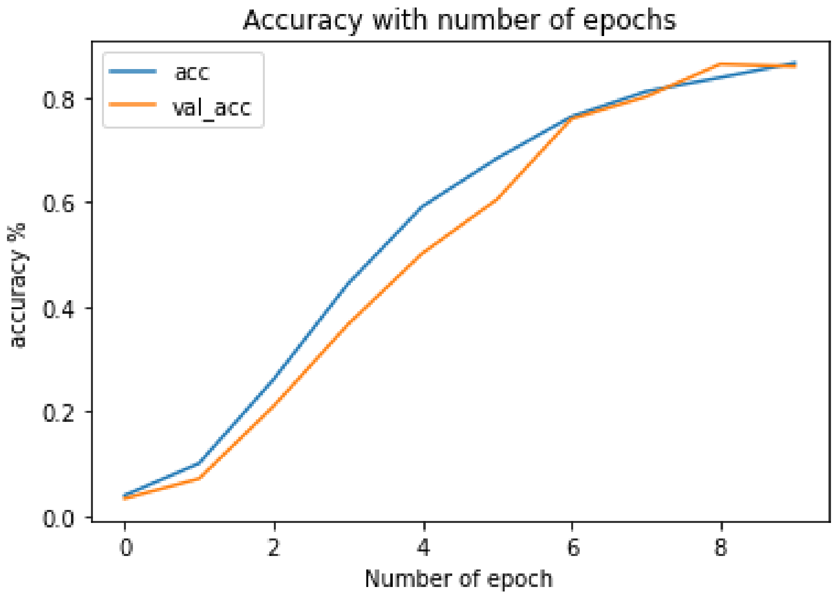

Fig. 11. Accuracy Comparison Graph for MobilNetV2 with Image Enhancement Technique

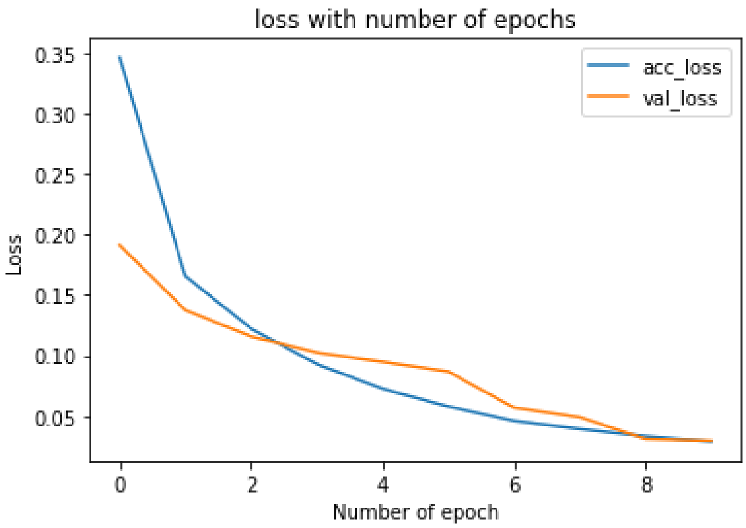

Fig. 12. Loss Comparison Graph for MobilNetV2 with Image Enhancement Technique

The comparative analysis of both the models i.e AlexNet with and without Image enhancement and MobileNetV2 with and without Image enhancement is presented in figure 13 and 14. The comparison is on the basis of accuracy and Loss

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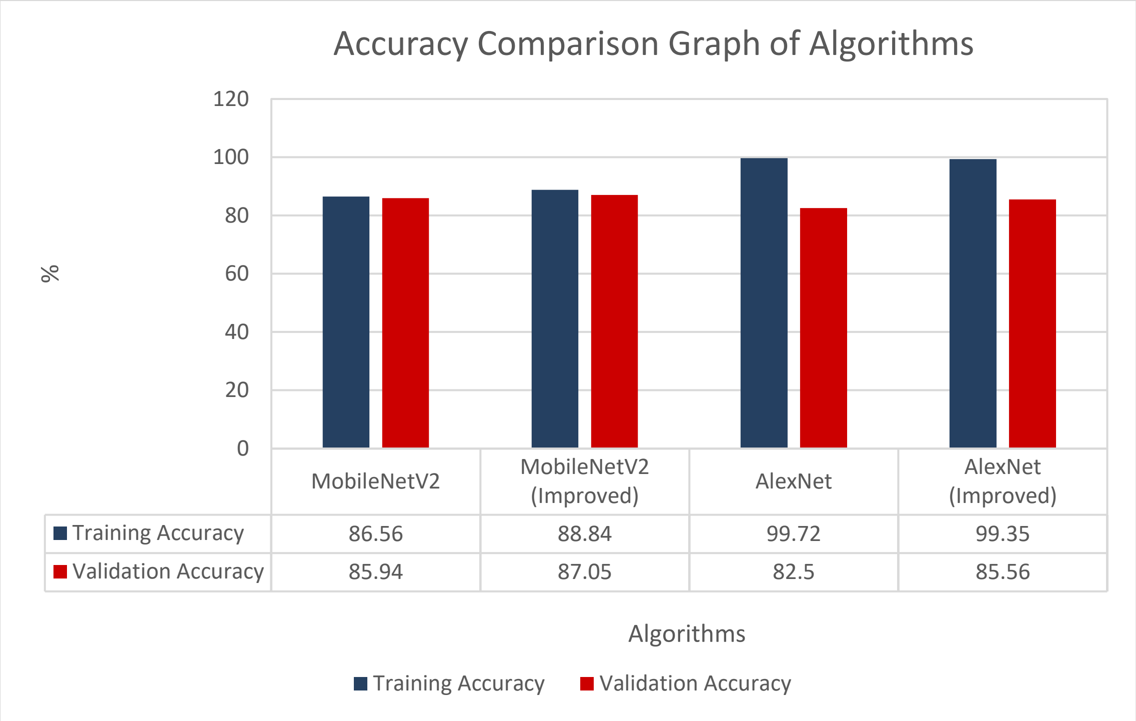

Fig. 13. Accuracy Comparison Graph of MobilNetV2 and AlexNet with Image Enhancement Technique

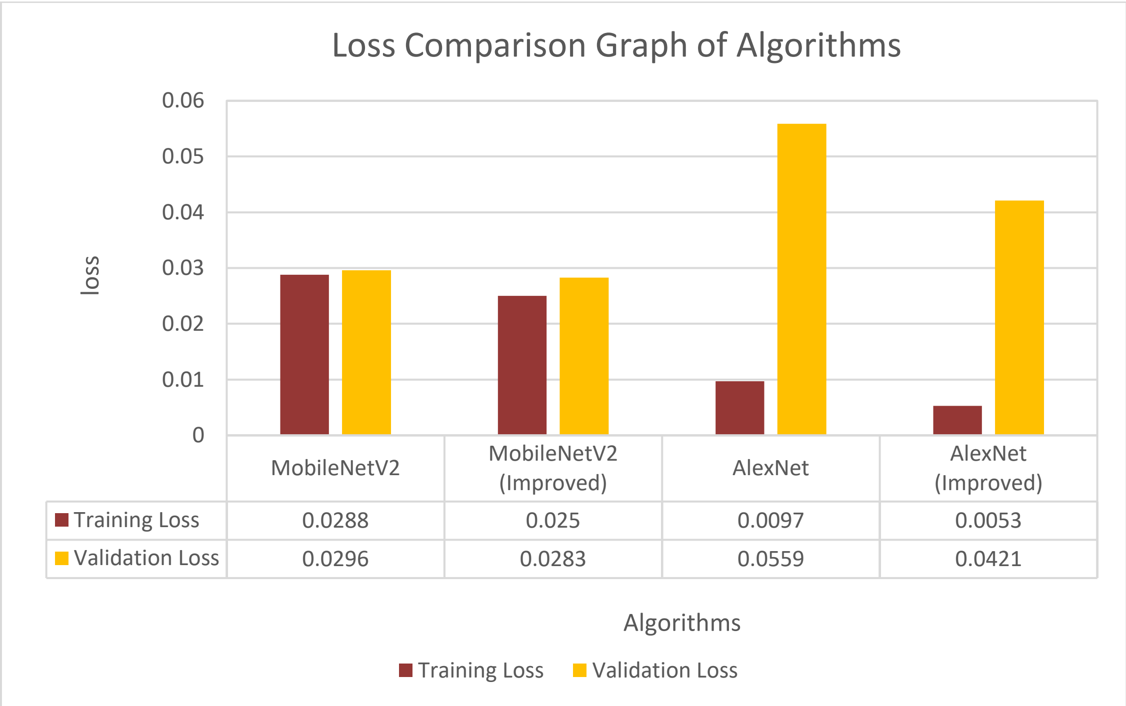

Fig.s 14. Loss Comparison Graph of MobilNetV2 and AlexNet with Image Enhancement Technique

5. Benefits of Automatic Number Plate Recognition

a. **Automatization**: The automated identification of licence plates enables automatic warnings and controls to be implemented at facilities. Therefore, automatic number plate recognition (ANPR) is an essential technology for smart cities or toll stations. Accuracy: Automatic Number Plate Recognition (ANPR) systems are capable of achieving a very high level of accuracy and can swiftly and readily identify cars based on the licence plates they are equipped with.

b. **Analytics**: The data that was created may be put to use analysing the flow of traffic. This is especially critical for the operation of Intelligent Transportation Systems (ITS), which use data processing technologies to enhance the movement of people and commodities, control demand, boost safety, decrease traffic congestion, and efficiently handle problems.

c. **Identification**: The reconition of a vehicle's licence plate in a short amount of time is the foundation for a quick and painless identification of a vehicle. This identity may either be used to enable access to certain cars or to locate and monitor individual vehicles.

d. **Low Footprint**: An automatic numberplate recognition system has a low overall footprint, and it is very inexpensive to instal and run. There is a large variety of cameras that may be used for ANPR.

e. **Convenience**: ANPR is often integrated with other information technology systems and functions within an ecosystem to give end-users with an experience that is both smooth and trouble-free. As a result, the technology is utilised to improve the overall experience for customers and to provide new services and goods, such as payment systems for automated parking lots.

f. **Automated** vehicle identification has a wide range of potential applications, including parking management, security, traffic enforcement, logistics optimization in manufacturing, and many more. Its adaptability allows it to be used for all of these purposes and more.

g. **Security**: Automatic Number Plate Recognition (ANPR) systems are very important for the many different security and surveillance applications that use computer vision. These kinds of systems provide a means for automatically identifying and following a number of cars, which contributes to an improvement in overall safety.

6. Conclusion

The innovative technology has the capability to considerably help to traffic management through licence plate recognition. We proposed AlexNet and MobileNetV2 frameworks, a subset of deep learning technology referred as convolutional neural networks, in this paper to construct a method for automatic recognition and classification of licence plates. We also recommend that picture enhancing techniques be used to improve both frameworks. The experimental results shows that both the models work significantly for the licence plate recognition. Also the accuracy further improves by implementing image enhancement techniques. The accuracy of AlexNet model comes to be 99.72% without image enhancement whereas the loss stays at 0.0097. The accuracy of AlexNet with image enhancement comes to be 99.35% with Loss at 0.0053. The results shows that there is not much improvement in the accuracy but validation accuracy of the AlexNet model with image enhancement improves to 85.56% from 82.5% which was of AlexNet without Image Enhancement. Similarly, the accuracy of MobileNetV2 model comes to be 86.56% without image enhancement whereas the loss stays at 0.0288. The accuracy of MobileNetV2 with image enhancement comes to be 88.84% with Loss at 0.0250. From the results, it can be concluded that AlexNet model works with better accuracy as compared to MobieNetV2. In Future, some new hybrid deep learning models or Ensemble models can be used for Licence Plate recognition.

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