

<sup>1</sup>Raja Rao PBV<sup>2</sup>Kiran Sree  
Pokkuluri<sup>3</sup>M. Prasad<sup>4</sup>P T Satyanarayana  
Murthy<sup>5</sup>Asapu Satyamallesh<sup>6</sup>G Ramesh Babu<sup>7</sup>CH Phaneendra  
Varma

## Generic Framework for Vehicle Identification System with Deep Learning Models



**Abstract:** - In contemporary vehicle scenario, different kinds of vehicles are playing vital role for the customers. Day by day, vehicles are increasing with different properties and identifications. Monitoring and maintain the records of vehicles in digital platform is the challenging task as well as a crucial task for the countries. Here, we have to take the scenario of digitalization of vehicles with deep learning network models for identification and maneuvering process. In our country, different states are following multiple vehicle identification like numbering, coloring and imaging. Many researchers were contributing towards this identification mechanism like supervised, unsupervised models for getting optimum accuracy. Text and Image classification are not sufficient to solve this vehicle identification problem. We are incorporating text, image and video related unstructured data set to solve this problem. We have framed a generic architecture for all kind of vehicles analyze the data. For instance, a vehicle is moving towards CCTV camera and it has been recorded as video content. In this paper, we come across video to still pictures and image segmentation and all the identification parameters like White, Yellow and green. We performed both text classification and image classification algorithms to acquire effective result compared to existing algorithms. Bi Directional RNN (LSTM/GRU) and LeNet, Alex Net, Inception, VggNet and ResNet algorithms are analyzed for this entire process. This is one of the globally challenging scenarios for identification with feature extraction, data cleaning and processing. At the end of the result, we achieved 98.94 % accuracy compare than other existing systems.

**Keywords:** RNN, LeNet, AlexNet, DBN

### I. INTRODUCTION

Identification of vehicles using sensors and other traditional methods are the vital task for Transport Management System (TMS) for all the regions of the country. They have performed with classification, Identification, Transport monitoring and Transport management for security with societal purpose. Since this process has been discussing by many researchers for past three decades and they have provided lot of solutions for vehicle identification process. Noise detection and multiple sensors handling are the crucial task for classify the vehicles. One strategy for utilising strain data to identify and categorise cars is data-driven methodology [1]. Under the scaffold deck, the sensors are arranged extremely neatly and without any obstruction from traffic. For transportation observation, vehicle characterisation and detection [2] are crucial throughout the board. The purpose of gathering vehicle data is to examine and repair vehicles, investigate information, portray it, and enhance the transportation system. For example, vehicle data is necessary for weight restriction checks. Decision tree Algorithm, Support Vector Machine (SVM) are the optimum solutions for small vehicles. Artificial Neural Network (ANN) was suggested [4] for Multi axel vehicle classification with high volume of datasets. Federal Highway [3] Administration have been accomplished with K-nearest neighbor (KNN) and ANN [25] for multiple classification of heavy vehicles. Autonomous driving and astute transportation research have led to remarkable progress in car discovery innovation. Deep learning [5],[22] is used for utilizing the technique for profound figuring out how to concentrate on the vehicle discovery calculation, in which essential stage target recognition calculations, to be specific, YOLOv3 calculation and SSD calculation, are taken on. In the automated driving framework, the PC vision advancements are utilized to see the climate predominantly by distinguishing the general climate through the objective identification

<sup>1\*</sup>Corresponding author: Raja Rao PBV, rajaraopbv@gmail.com

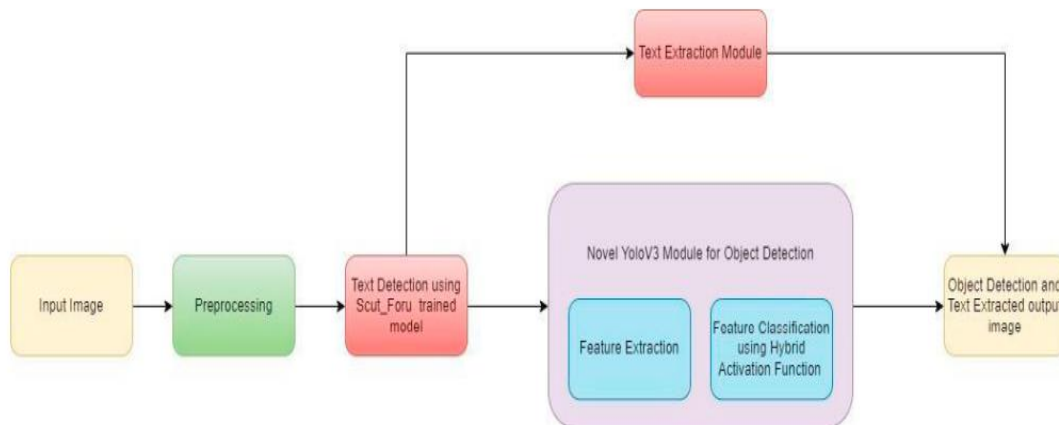
<sup>1-7</sup> Department of Computer Science and Engineering, Shri Vishnu Engineering College for Women, Bhimavaram, India.

innovation. Conventional vehicle [6] identification strategies likewise incorporate vehicle recognition innovation in light of shallow AI, which acknowledges vehicle location by joining AI calculation based on vehicle attributes.

An increasing proportion of people possess private vehicles as a result of rising material demands for daily comforts, leading to the development of new and higher criteria for automobiles. People are so growing more concerned about autonomous driving technologies. The increase of automobiles not only makes it easier for people to move, but it also raises some concerns. Travel is now not favorable due to street blockages, and the need for smart mobility has garnered widespread attention. The emergence of deep learning and its extensive applications in computer vision have propelled the amazing expansion of CV Technology in the contemporary digital environment [7]. Real-world applications of computer vision innovation include facial recognition, image processing, and programmed driving.

## II. LITERATURE SURVEY

Convolutional neural networks, or CNNs, have made a substantial contribution to computer vision's progress. The ability to recognise things might be crucial as it is a component of computer vision. For the detection and classification phases, CNNs offer a one-step implementation with better results. Proper object temporal monitoring will be undertaken in both of these stages by looking at the video sequences and noting the form, size, existence, and placement of the objects. The authors of this work have attempted to extract text from a photograph of a scene and provide a novel application of the Object Detection method.



**Figure 1. Process of CNN**

The process of extracting text from a picture involves three phases.

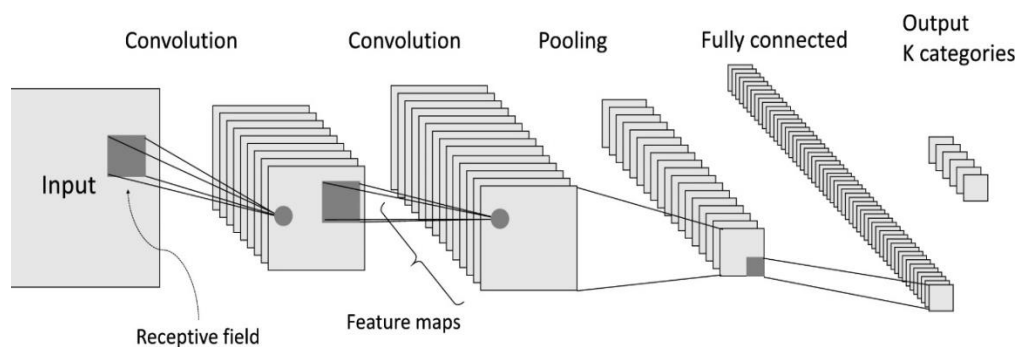
- Pre-processing the image taken as input
- Marking each location for the text
- Text extraction

You can submit a colour picture into this procedure. Preprocessing is consequently required for the submitted picture. At first, the picture is split into two smaller copies. A little amount of text will be lost if the image is not broken up into smaller parts, and noise will still be present in the final text image that is recovered. Following that, two sub-pictures are transformed into two grayscale images, which are further translated into two binary images. Each sub-image was subjected to the text extraction process before we created two sub-images [26]. After that, a second grayscale picture has the text copied and pasted into it. If the provided image is grayscale, no preparatory steps are required.

Text identification and recognition for natural situations and character recognition for commercial promotion photographs are developed using prior research on OCR-based systems [12]. After the necessary character identification system is finished, an unacceptable words detection system will be implemented to help decrease the amount of legal challenges that might result from the use of wrong words in ads.

Redmon et al. presented a one-stage object detector as a replacement for Faster RCNN [8],[24]. Real-time detection of complete photos and webcams is the primary contribution. One of the most significant and difficult applications of computer vision is object detection, which is used in many aspects of daily life to find instances of semantic objects of a particular class. Examples of these applications include autonomous driving, security [27],[28] monitoring, and more. Object detectors are doing much better now that deep learning networks for detecting tasks are being developed quickly. To gain a comprehensive understanding of the object detection pipeline's development state, it is necessary to first examine the methodologies used by typical detection models that are now in use and provide a description of the benchmark datasets. One of the most significant and difficult jobs in computer vision is visual saliency identification, which seeks to identify the areas of a picture that contain the most prominent object regions. Visual saliency is used in many applications to enhance performance, including object identification, picture retrieval, and cropping and segmentation. In general, there are two schools of thought in salient object detection [10], which are top-down (TD) and bottom-up (BU).

### III. IMPLEMENTATION



**Figure 2. Basic Operational Principles of CNN**

A type of CNN, or Deep Neural Network, is a computational method that utilizes a wide range of brain units [12]. Unlike the classic MLP models, each layer of the CNN is composed of a rectangular 3D lattice of neurons. Rather of connecting with every neuron in the population, the neurons inside a layer are essentially connected to the neurons within a receptive field, which is a tiny region within the layer that comes before it quickly. Using open fields, CNNs [23] use the spatially local connectedness of data. CNNs can provide effective representations of tiny pieces of the data thanks to the responsive fields, which they then use to assemble representations of larger regions.

In this scenario, video, image and text classifications are needed to classify the vehicles. As displayed in the stream outline in Figure 3.2, this study utilizes the three-outline contrast calculation to identify the moving objective as follows: (1) first, the caught video picture is preprocessed, and afterward, the gained picture is handled with grayscale level to change over the picture into grayscale space. (2), separated picture is sifted for three successive edges. Here, the middle separating technique is embraced to process the picture. (3), contrast activity is done on the three continuous casing pictures extricated. (4) After picture binarization, the burr and commotion in the picture are taken out, to acquire an ideal frontal area target. (5) , got two casings of distinction pictures were utilized for stage estimation, also, the burr and commotion were eliminated and the void was filled, to accomplish the ideal impact.

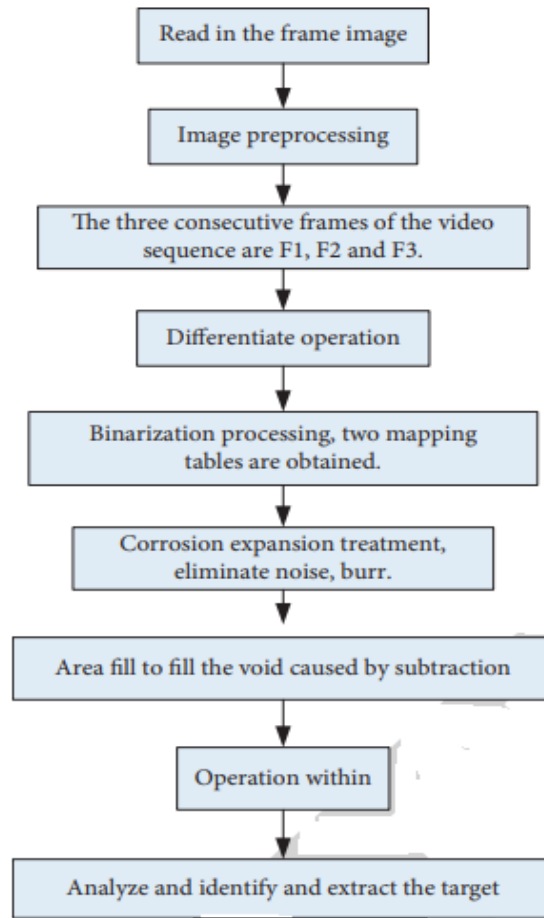
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**Figure 3 Video segmentation**

Algorithm:

1. Given I/P: NO.OF FRAMESETS  $\{It | t = 0, \dots, T - 1\}$ ,
2. Frame = f
3. Expected Output: S (Sequential set)
4. for f = 0; f < f; f  $\leftarrow$  f + 1 do
5. t = g(f);
6. sk(t)  $\leftarrow$  Detect (It);
7. M  $\leftarrow$  {Sf(t)};
8. for i = t + 1; i < T; i  $\leftarrow$  i + 1 do
9. Sf(i)  $\leftarrow$  Propagate (M, Ii);
10. M  $\leftarrow$  M  $\cup$  Sf(i);
11. end
12. M  $\leftarrow$  {Sf(t)};

13. for  $j = t - 1; j \geq 0; j \leftarrow j - 1$  do
14.  $Sf(j) \leftarrow \text{Propagate}(M, I_j)$ ;
15.  $M \leftarrow M \cup Sf(j)$ ;
16. end
17.  $Sf \leftarrow (Sf(0), Sf(1), \dots, Sf(T - 1))$ ;
18.  $f \leftarrow f + 1$ ;
19. end
20.  $S \leftarrow S_0 \cup S_1 \cup \dots \cup S_{f-1}$ ;
21. Get  $S$ ;

Key frame selection, CNN, and frame reduction were implemented

#### IV. RESULT AND DISCUSSION

As we stated, Bi-directional RNN and LeNet, AlexNet, VggNet and ResNet algorithms were used for analyzing the image processing scenario.

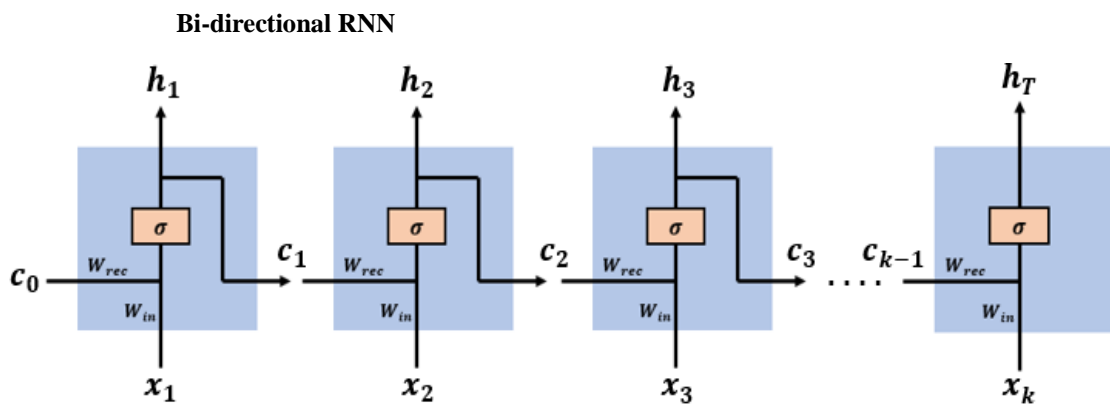


Figure 4 Hidden layers in Bi-directional RNN

To solve this issue RNN came into the image. which tackles this issue by utilizing hidden layers. what's more, covered up layers are the principal highlights of RNN. hidden layers assist RNN with recollecting the grouping of words (information) and utilize the succession design for the expectation.

#### LeNet

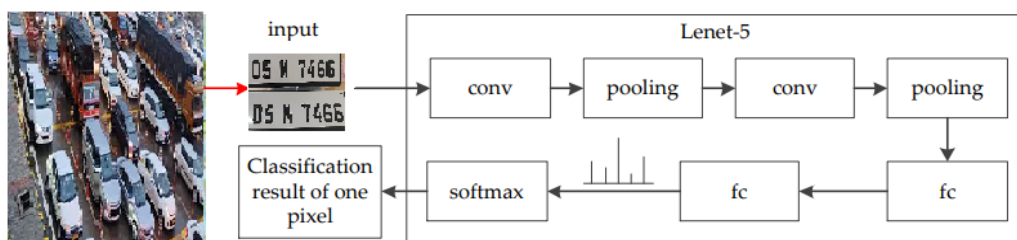


Figure 5 Hidden layers in Bi-directional LeNet

In unique LeNet design, they have utilized tanh actuation in light of the fact that around then tanh was more well known. In any case, presently we can utilize ReLu here since it will in general give much better arrangement exactness. It utilized normal pooling. Rather than normal pooling we use max pooling by and large [14].

Table 1 AlaxNet implementation parameters

Layer	Neurons	Filters	Stride	Padding	Feature Map	ReLU / Activated
Input					227 X 227 X 3	
Convolutional 1	96	11x11	4		55 X 55 X 96	Activated
Max Pooling 1		3 X 3	2		27 X 27 X 96	
---- N						
Dropout 1	0.5				6 X 6 X 256	

### AlexNet

Eight layers with learnable boundaries make up the Alexnet. The model consists of five layers, each of which uses a combination of max pooling, three fully associated layers, and Relu enactment in all except the result layer.

They discovered that the preparation cycle might be accelerated by merely few times by using the Relu as a starting capability. They also made use of the dropout layers, which prevented their model from becoming overfit. Additionally, the Image Net dataset is used to create the model. There are very nearly 14 million images in 1,000 classifications in the Image Net collection. Since Alexnet is a DL design, the creators acquainted cushioning with forestall the size of the component maps from diminishing radically. The contribution to this model is the pictures of size 227X227X3.

### VGG-16

In their publication "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman from the University of Oxford presented the convolutional neural network model VGG16.

VGG-16 model architecture (Fig. 1): 2 fully connected layers, 1 SoftMax classifier, and 13 convolutional layers The VGG-16 architecture was first presented by Karen Simonyan and Andrew Zisserman in their 2014 publication, "Very Deep Convolutional Network for Large Scale Image Recognition." A 16-layer network made up of completely linked and convolutional layers was designed by Karen and Andrew. For simplicity, just 3x3 convolutional layers layered on top of one another are used.

"The VGG-16 networks depicted in Figure 1 have the exact structure as follows:

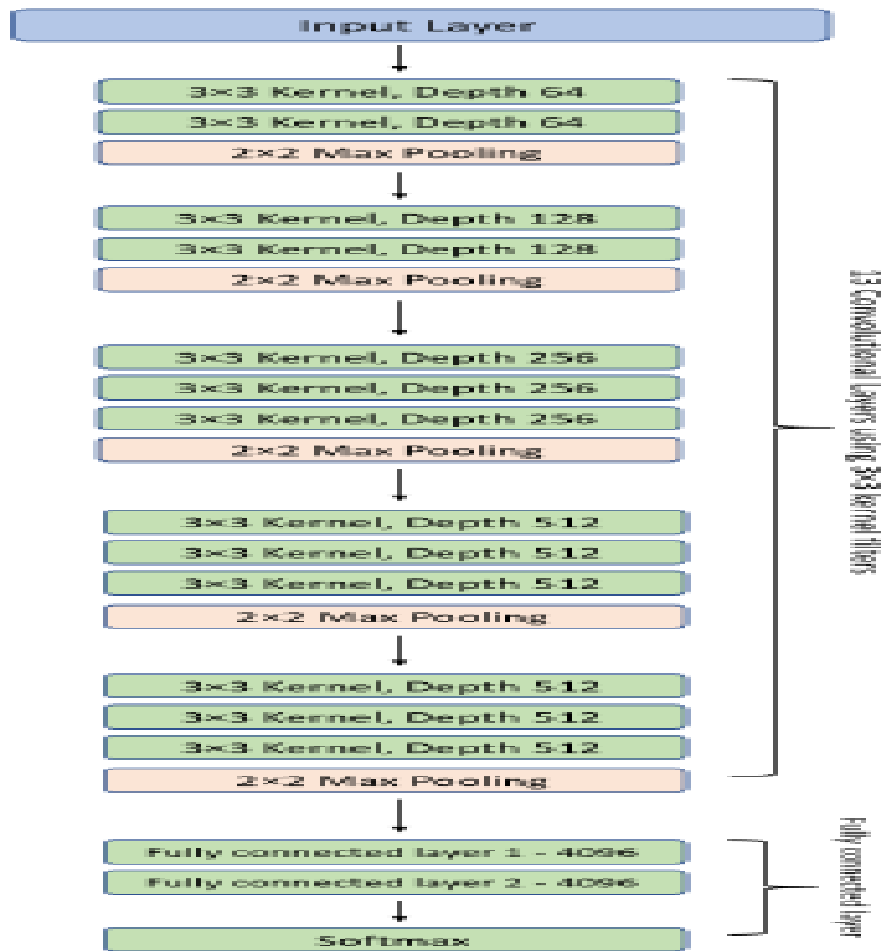
The 64 feature kernel filters that make up the first and second convolutional layers have a 3x3 filter size. The dimensions of the input picture (a RGB image with depth of 3) change to 224x224x64 as it passes through the first and second convolutional layers. Next, with a stride of 2, the output is sent to the max pooling layer.

The 124 feature kernel filters that make up the third and fourth convolutional layers have a 3x3 filter size. A max pooling layer with stride 2 comes after these two layers, reducing the final output to 56x56x128.

Three-by-three kernel size convolutional layers make up the fifth, sixth, and seventh layers. Three utilise 256 feature maps each. There is a max pooling layer with stride 2 after these layers.

There are two sets of convolutional layers with kernel sizes ranging from eight to thirteen. There are 512 kernel filters in each of these sets of convolutional layers. After these layers comes the max pooling layer with a stride of one.

A SoftMax output layer (the sixteenth layer) of 1000 units comes after the completely linked hidden levels of 14 and 15.



**Figure 6 VGG – 16 Implementation**

CS-MHC ResNet

The "brood parasitic" cuckoo species, together with certain birds and fruit flies, are the source of inspiration for the Cuckoo Search Algorithm (CSA). Levy flying has been used for international exploration and has produced positive outcomes, demonstrating its effectiveness. As a consequence, the proportion of exploration to extraction in CSA was balanced. Occasionally, though, it takes advantage of solutions that converge slowly and poorly. Because of this, the suggested algorithm strikes a compromise between the MHC's deep exploitation and the CSA's worldwide exploration.

Using the normal cuckoo search for the number of iterations, CSMHC begins the search. The HC is then given the best result to expedite the search and get around the traditional Cuckoo search algorithm's sluggish convergence.

The MHC is an iterative method that, as Figure 4.4 illustrates, begins with an arbitrary solution to a problem and then iteratively modifies one piece of the solution at a time in an effort to find a better solution. If the modification yields an improved answer, incremental modifications are made to the new solution and this process is continued until no further gains are possible. Subsequently, the result is sent back to the CSA for verification using the fraction probability  $P_{\alpha}$

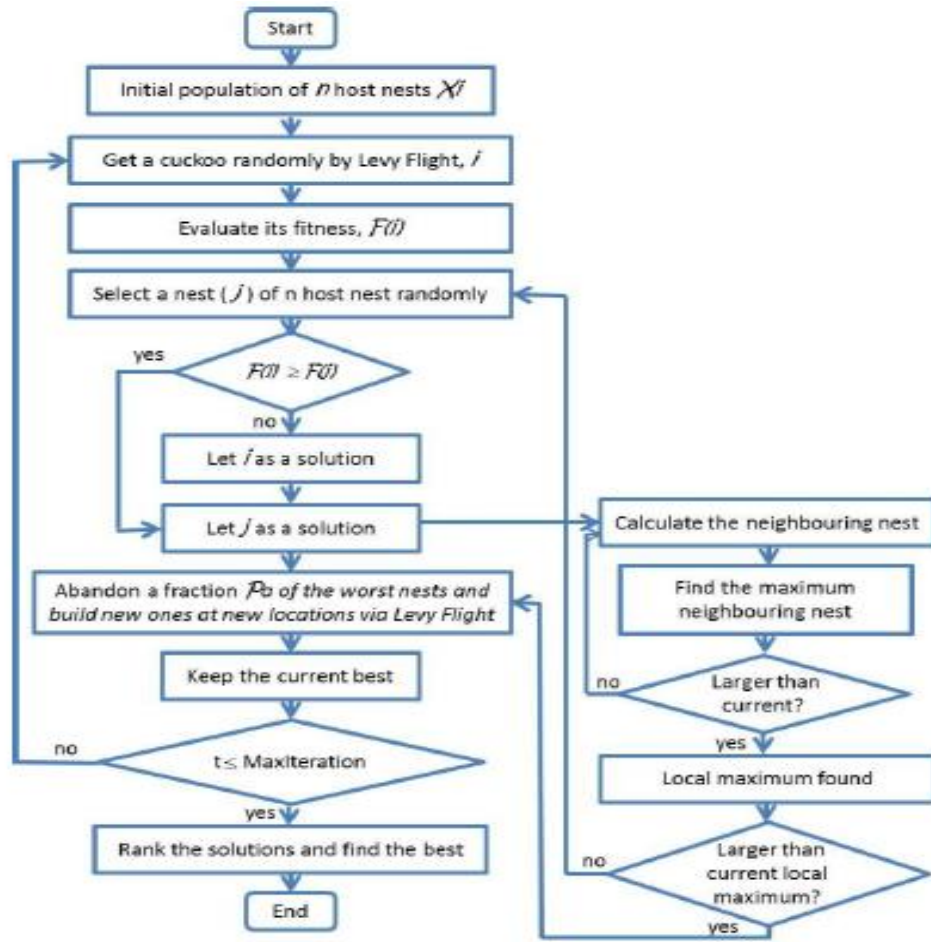


Figure 7 CS-MHC ResNet



Figure 8 Different Identifies in Datasets

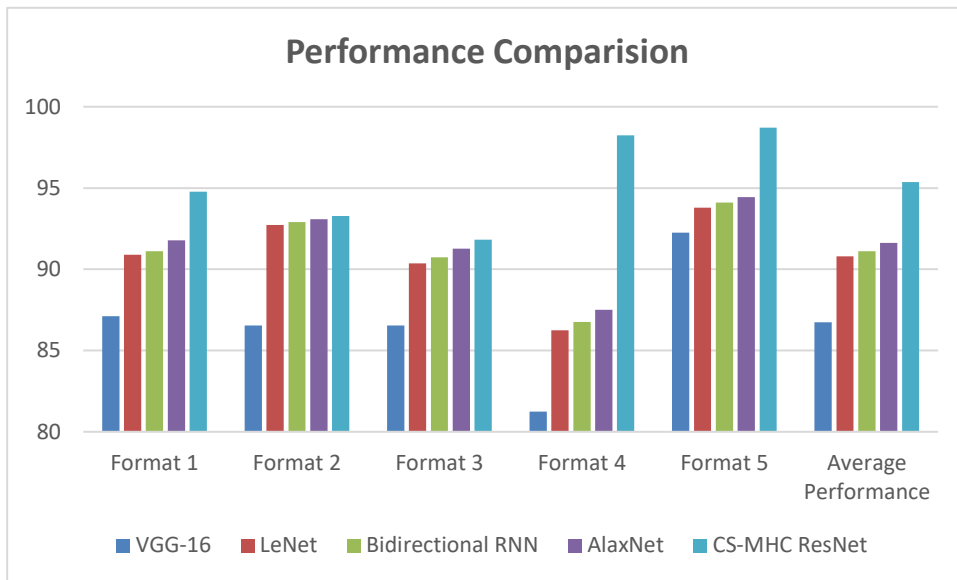
We have collected different types of vehicle name plates and analysed with trained model. Here VGG16, Lent, Bidirectional RNN, AlaxNet and CS-MHC ResNet algorithms are implemented and measured each format's performance and average is taken

Table 2 Algorithms Performance

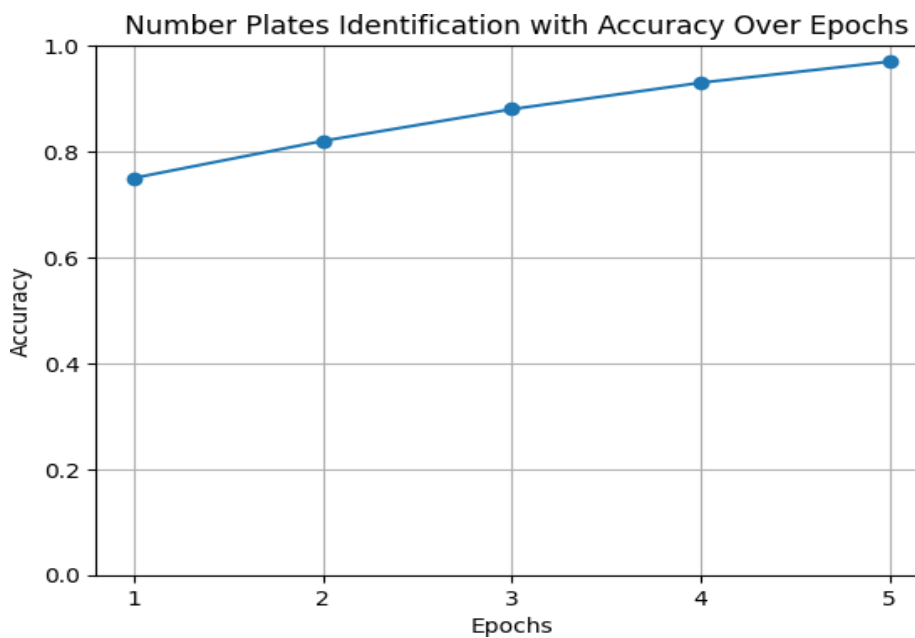
Types / Vehicles	VGG-16	LeNet	Bidirectional RNN	AlaxNet	CS-MHC ResNet



Format 1	87.11	90.89	91.11	91.78	94.78
Format 2	86.55	92.73	92.91	93.09	93.27
Format 3	86.55	90.36	90.73	91.27	91.82
Format 4	81.25	86.25	86.75	87.5	98.25
Format 5	92.25	93.78	94.11	94.44	98.72
Average Performance	86.74	90.80	91.12	91.62	95.37



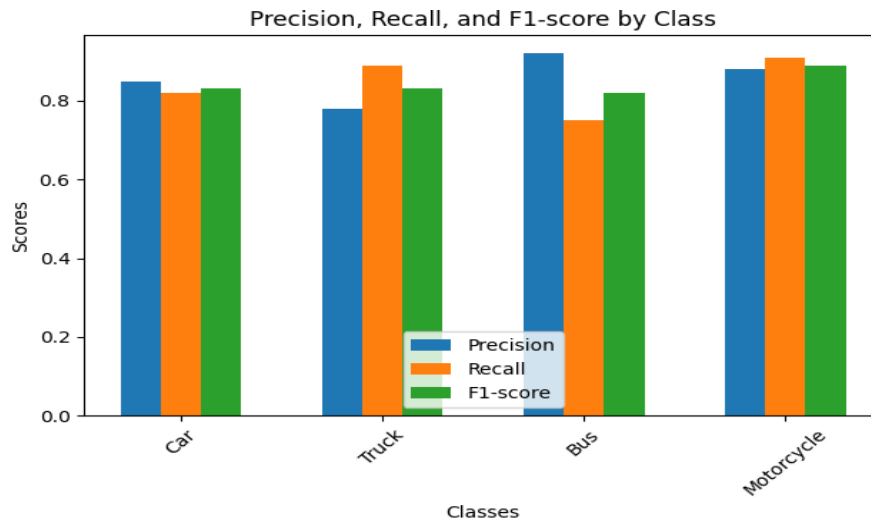
**Figure 9 Comparison performance**



**Figure 10. Number Plate Identification with Number of Epochs**

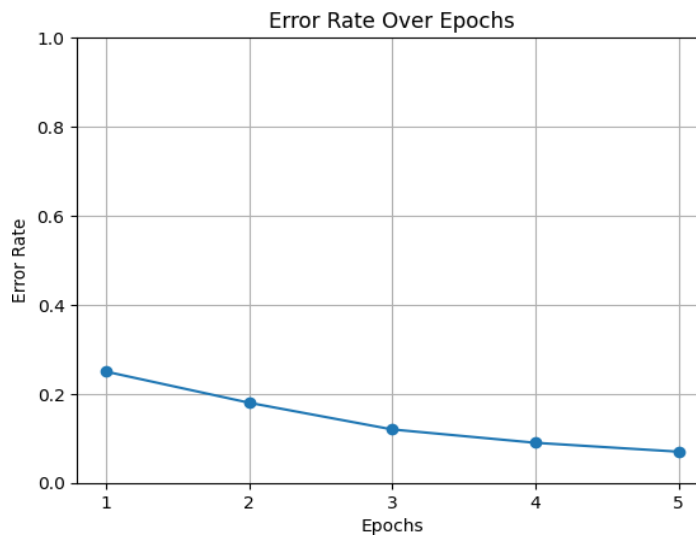
THE vehicle identification system, employing deep learning, demonstrates increasing accuracy over epochs. Beginning at 75% in the first epoch, accuracy steadily rises, reaching 93% by the fifth epoch. This trend signifies the model's improving capability in identifying vehicles from images as training progresses. The system's performance refinement showcases the effectiveness of deep learning techniques in tackling complex classification

tasks like vehicle identification, offering promising implications for real-world applications such as traffic management and surveillance as shown in figure 4.7.



**Figure 11. Number Plate Identification with Different Classes**

Precision, recall, and F1-score are essential metrics for evaluating the performance of a vehicle identification system based on deep learning. Precision measures the accuracy of positive predictions, indicating the proportion of correctly identified vehicles among all vehicles predicted. Recall, also known as sensitivity, assesses the system's ability to identify all relevant vehicles, measuring the proportion of correctly identified vehicles among all actual vehicles. F1-score combines precision and recall into a single metric, providing a balanced measure of a system's overall performance



**Figure 12. Error rate over the Epochs**

The error rate graph for a vehicle identification system with deep learning illustrates the system's performance evolution over epochs. Utilizing Matplotlib in Python, epochs and corresponding error rates are plotted using plt.plot(). Features like titles, labels, and gridlines enhance clarity. It's essential to set y-axis limits to reflect error rates (0 to 1) and align x-axis ticks with epochs. Customization options ensure a clear depiction, aiding in performance assessment and guiding system refinement as shown in 4.9

## V. CONCLUSION

In contemporary machinery world, vehicle identification and classification is the crucial task for the researchers as well as Developers. But we are having the responsibility to serve the organization to improve their Vehicle Classification So we have analysed five different formats were used for vehicle identification system and its

classification. We have implemented average performance for this system for above discussed algorithm and CS-MHC ResNet algorithm is giving high accuracy of this research.

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