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CNN based Vehicle Classification for Intelligent Transportation System in Unstructured Environments

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***Abstract* – One of the ideal tasks of road traffic monitoring is the vehicle classification system. It is an integral part of the Intelligent Transportation System (ITS) for the effective transportation planning, control, and for the development of driverless or autonomous vehicles. Very recently Convolution Neural Networks (CNN) and Deep Learnings have been widely used in vehicle classification systems. Although several CNN models exist, they are specialized to work well with delineated road environments. It remains a challenging research problem to classify the vehicles pertaining to unstructured environments. To address this problem, we propose a fine-tuned ResNet50 convolutional neural network based vehicle classification model. Initially, the ResNet50 is fine-tuned on NITCAD object dataset which comprises vehicle data collected from Indian roads. The proposed model is trained to run on a subset of the dataset to evaluate its performance in terms of accuracy, precision, recall and f1-score. To increase the diversity of the dataset, we applied data augmentation techniques and exemplified data augmentation improves the performance of the model. Finally, a comparison study has been carried out between the proposed and state of the art CNN models to evaluate the effectiveness of the proposed vehicle classification model.**

***Keywords:* Convolutional Neural Network, Vehicle classification, Data augmentation, ResNet50, NITCAD**

1. Introduction

With the rapid growth in the number of vehicles in developing countries, the road traffic violation is increasing day by day. This leads to frequent traffic congestion, traffic accidents and potential risk for the safety of commuters, pedestrians and for the vehicles also. An effective traffic monitoring system will be a solution to overcome these issues. One of the ideal functionality of road traffic monitoring is vehicle classification. It is an integral part of the Intelligent Transportation System (ITS) for the effective transportation planning, control, and for the development of driverless or autonomous vehicles. Especially, in an unstructured road environment where the traffic rules are lightly followed, vehicle classification is an essential task to track traffic flow control, signal jumping and over speed. It also helps to identify and plan for new road pavements depending on the quantity of types of vehicles passing, predict future transportation needs and improve road safety.

Numerous vehicle classification methods have been proposed in the literature. The older type of vehicle classification is an in-roadway-based system which uses sensors such as loop induction sensors [1], vibration sensors

[2], magnetic sensors and piezoelectric sensors [3]. These sensors have been deployed on the road pavements to collect information about the vehicles such as length of the vehicle and axle count to determine the type of vehicle. This methodology can accurately classify the vehicles because the sensors installed can have close contact with the moving vehicle. However, this methodology is rarely used nowadays due to undesired weather conditions which affects the sensors and also due to its high cost maintenance of breakages in the road pavement. With advancement in image processing and computer vision, many machine learning based vehicle classification systems have been proposed [4-6] in the literature. In traditional machine learning methodology, handcrafted feature extraction methods are used to extract important features to train the machine learning classifier to perform object level classification. This methodology works well in a controlled environment. However, with limited hand crafted features, this methodology is not suitable for generalization where prior knowledge is essential.

In recent years, Convolutional Neural Network (CNN), a class of deep learning is very popular for vehicle classification systems. we propose a vehicle classification model based on convolutional neural network and fine tuning of ResNet50. Following are the major contributions out of this research work.

(i) We proposed a fine-tuned ResNet50 convolutional neural network model to improve the robustness of vehicle classification in an unstructured environment.

(ii) We applied data augmentation and image transformation techniques to increase the diversity of the dataset. NITCAD dataset is used for training the proposed fine-tuned ResNet50 model.

(iii) A comparison of the proposed model with the state of the art CNN models like VGG16, DenseNet and InceptionV3 is performed and the results exemplify that our proposed fine-tuned ResNet50 CNN can classify vehicles in a more effective and efficient way.

The rest of the paper is organized as follows. In Section II, the existing vehicle classification models based on CNN are described. In Section III, the proposed methodology and fine tuned Resnet50 architecture is explained in brief. In Section IV, the dataset description and the performance metric for evaluation is explained. In Section V, the experimental result, discussion and comparison is explained. Section VI concludes the proposed work.

2. Literature study

The vehicle classification is an important task in traffic monitoring for the Intelligent Transportation System. Many different methodologies have been proposed in the literature for vehicle classification. The prominent one being convolutional neural networks which demonstrated better accuracy for vision based image classification tasks [7]. In this section we will review the state of the art models and architectures proposed for vehicle classification using CNN.

Dong et al. [8] have proposed a vehicle classification system. The presented model has been a semi – supervised model consisting of fully connected layer and softmax layer to classify real time vehicle data. The model has been tested on BIT-vehicle dataset on two different modes: the day and night with an accuracy of 96.01% and 89.6%. Maria et al. [9] have proposed a vehicle classification system using faster R-CNN and obtained an accuracy of 93% on their self-constructed dataset. In another work, Wang et al. [10] have proposed faster R-CNN based vehicle classification for real-time traffic monitoring systems. Their image dataset consists of more than 60, 000 images. Their model obtained an accuracy of 80.65%.

3. The Proposed Methodology and architecture

The CNNs adopts a supervised learning strategy with a feed forward network for large scale object classification. CNNs are proven to considerably increase the performance of the classifier when applied to real world applications. Traditional methods for image classification include ML classifiers[20-33] where the feature extractions are handcrafted. Compared to traditional ML classifiers, CNNs can automatically extract the learnable parameters from the input data to perform classification [11]. The architecture of CNN comprises three hierarchical layers, (i) Convolution layers, (ii) Pooling, and (iii) Fully connected layers.

Data augmentation is a technique to alleviate overfitting from networks by artificially increasing the dataset through label-preserving transformation methods. To increase the diversity of our dataset, we applied image transformation techniques during the training process. We employ techniques such as (i) Gaussian blur with a 5x5 filter that removes the high frequency noisy pixels while preserving the low frequency pixels. (ii) Rotation – we applied a ten degree rotation on the original dataset images to populate a varied view (iii) Horizontal flip – we employed a horizontal flip with a probability of 10% to increase the diversity of the images in the dataset for training the proposed CNN. (iv) Gaussian noise – we employed gaussian noise to make the training process more robust and to minimize the error.

In this work, a fine-tuned ResNet50 CNN for vehicle classification in an unstructured road scene is proposed. The layers of the ResNet50 are frozen as they learn more about simple features like edges and lines and these are common in all the objects. To perform transfer learning, the last fully connected layer, average pool, 1000-d fc, softmax is removed from the network, which was pre-trained to perform the classification of 1000 natural categories of ImageNet data. This layer is replaced with a classification block with three more layers: A fully connected layer with weight factor ‘’ as twenty and bias ‘β’ factor as twenty, the second layer is softmax layer and third layer is the classification layer that classifies six different vehicles in an unstructured Indian road scene. Fig. 1 depicts the proposed architecture of the fine-tuned CNN model. The input to the network layer is 224 X 224 pixels RGB images. The model uses 64 convolution kernels of 7 X 7 size with the stride of 2 in the first layer and followed by 3 X 3 max pooling with the stride of 2.

In ResNet50 architecture, from layer two to layer five, there are a block of identical layers having several kernels to 128, 256, 1024 and 2048, followed by a fully connected layer. The second convolution layer conv2_x has 64 kernels of 1 X 1 filter size followed by 3 X 3, 64 kernels and at as 1 X 1, 256 kernels. These layers are repeated a total of three, having 9 layers in the second convolution. Similarly, convolution layer conv3_x is repeated four times having 12 layers, conv4_x is repeated six times having a total of 18 layers and conv5_x is repeated 3 times having 9 layers. The total number of layers in ResNet is thus 50 layers. The ResNet model enables gradients to flow using skip connections. It uses shortcuts namely identity shortcut and projection shortcut.

The learning rate parameter or step size is a configurable hyper parameter which defines the number of weights updated at each epoch. We use a piecewise schedule to modify and reduce the step size with respect to the training progress [12]. The model uses an initial learning rate as 0.001. With the increase in epochs, the learning rate decreases using a piecewise schedule. It is defined as [13],

$$\eta\text{n+1} = \frac{\eta\text{n}}{1 + d\text{n}}$$

Where n is the epoch, ηn denotes the learning rate of the previous epoch, d is the decay rate. To calculate the learning rate of current epoch ηn+1, the piecewise scheduler updates the step size by reducing the denominator.

The training of CNN is based on optimizing the weights and coefficients and to minimize the loss. To optimize the weight, we use SGD with momentum as an optimizer. It is an optimizer method which helps accelerate gradient vectors in the right directions. This helps the model to converge fast. Applying SGD with momentum for training the model can average over the gradients. It is mathematically defined as [14],

$$mt = \beta mt\text{-1} + (1 - \beta)\nabla\text{w}L(W, X, y)$$
$$W = W - \alpha m\text{t}$$

Where, mt is the momentum gained at the tth recurrence, L is the learning rate, ∇ is the gradient with respect to weight w and learning rateα, the beta β is a hyper parameter that controls the momentum.

A loss function measures the performance of a CNN model based on calculating the difference between the target label(s) and prediction label(s). We use cross-entropy as loss function in our CNN model [15]. It takes the form,

$$l = \sum_{c=1}^{M} \sum_{i=1}^{N} yc, \text{n} \log(pc, \text{n})$$

l is loss, M is the number of classes, N is the number of images, yc, nis the binary indicator which is 1 if the image n belongs to the actual class c. log(pc, n) is the predicted probability image n is of class c.

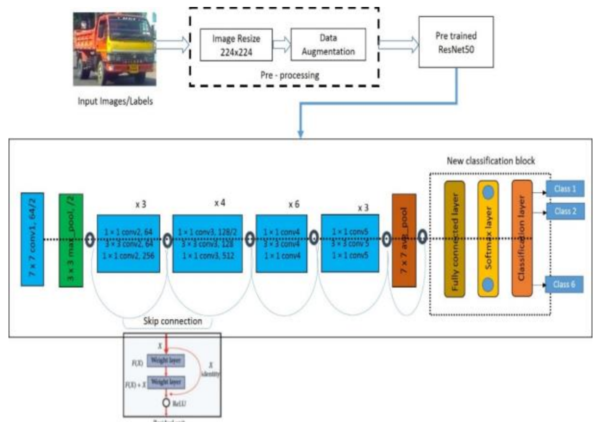

Fig. 1: Proposed Convolutional Neural Network Model for Vehicle Classification

4. Dataset Description

We use NITCAD dataset [16] to train the proposed CNN model to classify different vehicles in an unstructured road scene on an Indian road. The NITCAD dataset was developed by students of the National Institute of Technology, as an outcome of their major project. NITCAD object dataset comprises a total of 11000 images collected under different traffic conditions in and around Kottayam district, Kerala. Out of the total images, 4800 images are labelled and it has seven classes in the dataset namely auto-rickshaw, bus, car, pedestrians, truck, two-wheelers and van. It is observed from the original dataset that the number of cars, auto-rickshaws and two-wheelers are more than the number of vans, buses and trucks. It is also observed that the cars, auto-rickshaw and two-wheelers are present in almost all the frames.

For the implementation of our proposed model on NITCAD, the pedestrian class from the original dataset is not considered. The model is trained to classify the other six classes namely auto-rickshaw, bus, car, truck, two-wheelers and van. The images are cropped to extract individual classes and we use a subset of the labelled images from the dataset which consists of information about the location of various objects present in the corresponding frame. The images with the same content are avoided to reduce redundancy in the dataset. After this process, the subset of the dataset considered for implementation comprises 750 images with each class consisting of 125.

A limited dataset to train a deep learning model ends up in high risk of overfitting. So, we applied data augmentation such as gaussian blur, flipping, rotation, and gaussian noise to elaborate the data to fit in the dataset. Applying data augmentation introduced new images into our dataset by increasing the size of the dataset by a factor of four. In each iteration of the training process, we fetched a batch of images and for each image, we randomly applied data augmentation.

4.1 Evaluation Metrics

This section provides details of the evaluation metrics used to calculate the performance of the classification model. We use classification accuracy, precision, recall and f1-score to evaluate the performance of the classifier. Classification Accuracy (A) is defined as the total number of images correctly classified, divided by total number of images within the dataset. It is mathematically defined as,

$$A = \frac{tp + tn}{tp + tn + fp + fn} \tag{4}$$

Where tp denotes true positives, tn denotes true negatives, fp denotes false positives, and fn denotes false negatives.

Precision$P$ is the likeness of the percentage of correctly classified images to the total number of classified images. It is mathematically expressed as,

$$P = \frac{tp}{tp + fp} \tag{5}$$

tp denotes the correctly classified image and fp denotes the misclassified images.

The recall $R$is defined as the fraction of correctly classified images to the total number images. It is mathematically expresses as,

$$R = \frac{tp}{tp + fn} \tag{6}$$

F1-score is defined as the harmonic mean of precision and recall. It is mathematically expressed as,

$$f1 - score = 2 \times \frac{(P \times R)}{(P + R)} \tag{7}$$

5. Experiments and Results

To evaluate how well the proposed model performs, a subset of the labelled data from NITCAD is considered for training, validation and testing. The model is built upon tensorflow framework and the experiments are performed on Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz, and 32 GB RAM, Windows 10 pro operating system. The training of the proposed vehicle classification model is categorized into data preprocessing, training and evaluation. In the data pre – processing the images are cropped to extract all individual classes and subset of labelled data are considered and distributed into training, validation and testing sets.

The images are normalized to a size of 224 x 224 input size. A random split with 80:20 ratio is applied to generate the training, test set and the validation set is generated by a random selection of 20% images from the training set. The experiments on the dataset have been done in three aspects. They are (i) evaluation of the proposed fine-tuned resNet50 CNN model on NITCAD dataset without data augmentation, (ii) evaluation of the proposed fine-tuned resNet50 CNN model on NITCAD with data augmentation, (iii) comparison of the proposed CNN with state of the art CNNs with data augmentation.

Discussion

The proposed classification model has been compared with the existing models to validate the efficacy of the proposed network. The precision and recall of all six classes obtained by the models are shown in Table 3. It is observed that the proposed model performs well with an overall accuracy of 96.83 when compared to InceptionV3 [17] with 95.01%, DenseNet [18] with 93.83% and VGG16 [19] with 92.5%. The reason being the increase in the accuracy of the proposed model is that it has more depth layers than the other existing models compared. Though these existing models performed well on their dataset, the number of classes they considered for classification were minimal and cannot be used with real time vehicle classification.

	Auto-Rickshaw	Bus	Car	Truck	Two-Wheeler	Van
Auto-Rickshaw	98	0	1	0	1	1
Bus	0	96	0	3	0	0
car	1	1	97	0	0	3
Truck	0	2	0	96	0	0
Two-wheeler	0	0	0	0	98	0
van	1	1	2	1	0	96

Fig. 2: Confusion matrix of the classification results - without data augmentation

	Auto-Rickshaw	Bus	Car	Truck	Two-Wheeler	Van
Auto-Rickshaw	24	0	2	1	1	3
Bus	0	21	0	4	0	0
car	1	0	21	0	0	3
Truck	0	2	0	19	0	0
Two-wheeler	0	0	0	0	24	0
van	0	2	2	1	0	19

Fig. 3: Confusion matrix of the classification results - with data augmentation

Table. 1: Performance evaluation of fine-tuned ResNet50 CNN model on NITCAD without data augmentation

Class	Accuracy	Error Rate	Precision	Recall	F1-Score
Auto - rickshaw	94.67	5.33	0.77	0.96	0.86
Bus	94.67	5.33	0.84	0.84	0.84
Car	94.67	5.33	0.84	0.84	0.84
Truck	94.67	5.33	0.90	0.76	0.83
Two -Wheeler	99.33	0.67	1.0	0.96	0.98
Van	92.67	7.33	0.79	0.76	0.78

Table. 2: Performance evaluation of fine-tuned ResNet50 CNN model on NITCAD with data augmentation

CNN Models	Accuracy (%)
VGG16 [19]	92.5
DenseNet [18]	93.83
InceptionV3 [17]	95.01
Our Model	96.83

Table. 3: Comparison of fine-tuned ResNet50 CNN model with other CNN architectures

Class	Accuracy	Error Rate	Precision	Recall	F1-Score
Auto - rickshaw	99	1	0.96	0.98	0.97
Bus	98.83	1.17	0.97	0.96	0.96
Car	98.66	1.34	0.95	0.97	0.96
Truck	99	1	0.98	0.96	0.97
Two -Wheeler	99.67	0.33	1.0	0.98	0.99
Van	9.5	1.5	0.95	0.96	0.96

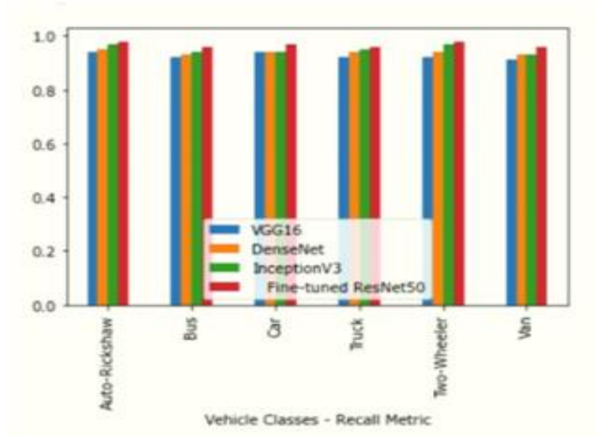

Fig. 4: Comparison of Recall Metric of all CNN models

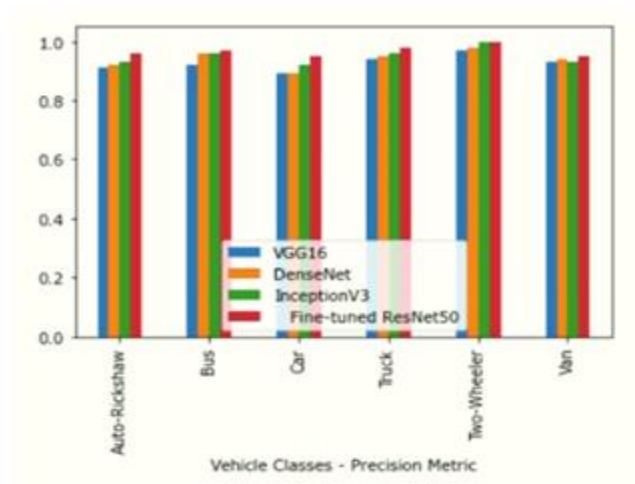

Fig. 5: Comparison of Precision Metric of all CNN models

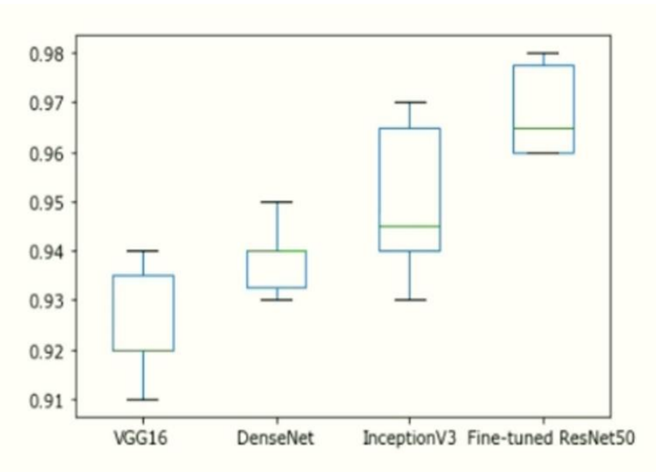

Fig. 6: Box plot of recall Metric of all CNN models

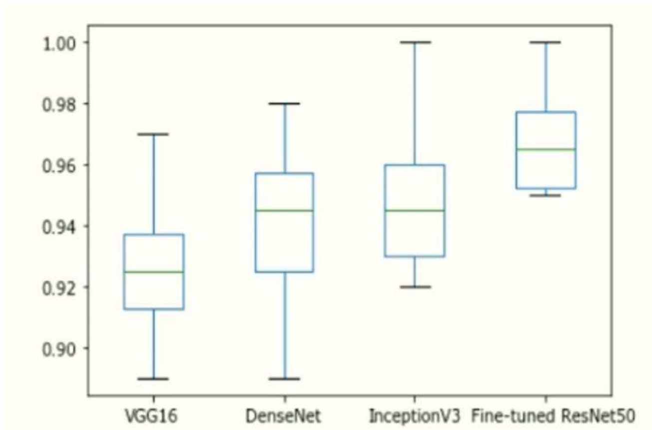

Fig. 7: Box plot of precision Metric of all CNN models

6. Conclusion

In this paper, a fine-tuned ResNet50 CNN is proposed to improve the effectiveness of vehicle classification in unstructured environments for intelligent transportation systems. A new classification block is added to the ResNet50 through transfer learning to ensure generalization. The proposed model is trained on a subset of NITCAD object dataset with six categories of vehicle classes that are pertinent to unstructured environments. To alleviate overfitting and to increase the diversity of our dataset, we applied data augmentation techniques and observed it improved the accuracy of the model. The proposed model is compared with InceptionV3, DenseNet and VGG16. Results exemplified that the proposed vehicle classification model achieved an accuracy of 96.83% compared to other models.

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