Transfer Learning-Based CNN Models for Vehicle Image Classification

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Abstract.

Thi This paper describes a Convolutional Neural Network (CNN)-based platform that is created to identify vehicles and put them into seven different categories and they include: Auto Rickshaws, Bikes, Cars, Motorcycles, Planes, Ships, and Trains. As the influx of visual data processed by cameras and sensors has grown exponentially, quick and precise classification of vehicles has been demanded and is now important in the contemporary application of camera-related surveillance of traffic, autonomous driving, and intelligent transportation management. The data set involved in this piece is composed of 5,007 JPG images 3,504 of them to train and 1,503 to test.

Keywords. Artificial Intelligence, Deep Learning, Vehicle classification, Sustainable mobility.

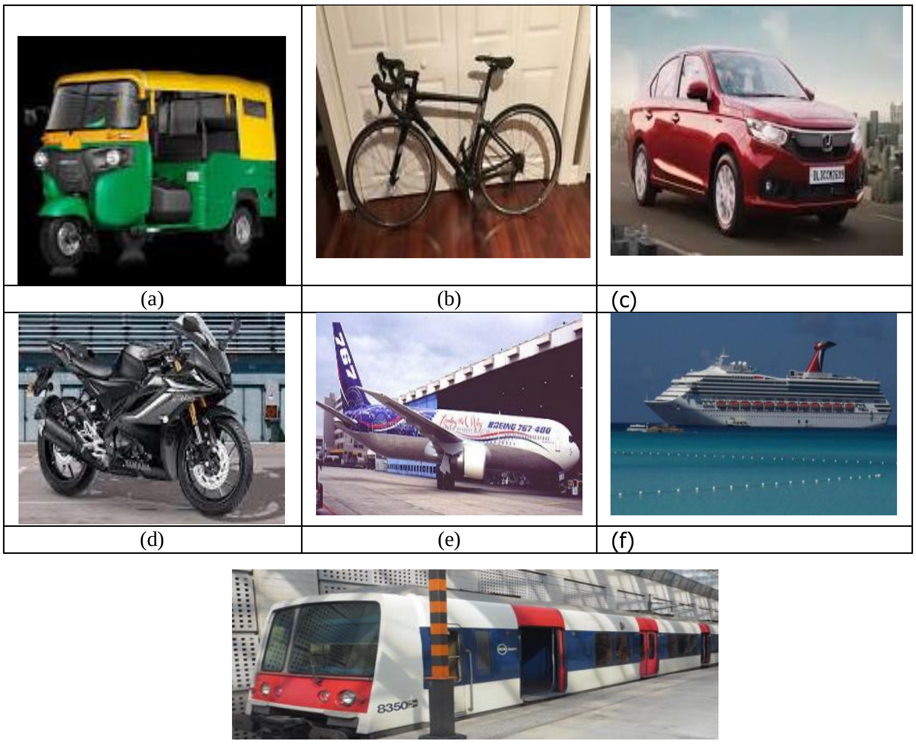
1. INTRODUCTION

The classification of vehicles is important in diverse fields including the monitoring of the traffic, autonomous vehicles, and smart transportation systems. As the digital platform develops fast and vehicle imagery proliferates, the necessity to find quick and accurate means of classification to the problem has grown. Maungmai and Nuthong [1] have defined the importance of deep learning in car classification and how the traditional fashion may be unable to cope with a large and tricky data set. In the same manner, Vijayaraghavan and Laavanya [2] showed that the Convolutional Neural Networks (CNNs) are better in terms of precision and performance as compared to conventional methods.

2. LITERATURE

Convolutional neural networks (CNNs) and deep learning methods have been extensively researched in the context of vehicle classification; they demonstrate high feature extractors and pattern recognition characteristics. Maungmai and Nuthong [1] created a CNN centered model that has the capacity to classify vehicles by their type and color and the model showed strong real world performance in four types of vehicles and seven colors. Vijayaraghavan and Laavanya [2] concentrated on bus detecting, cars, and bikes detection where capturing of the buses, cars, and bikes occurred by detection of bounding boxes followed by probability predictions to improve on detecting the objects. Tas et al. [3] introduced a CNN method that is specifically trained on low-resolution surveillance photographs, and compared it with VGG16 with focus on the scenario of efficiency versus accuracy.

II. INPUT DATASET



(a) (b) (c)

(d) (e) (f)

(g)

Fig. 1 Images from the proposed dataset.

The database that has been used in this study consists of 5,007 JPG images of vehicles that are grouped into seven different classes namely: Auto Rickshaws, Bikes, Cars, Motorcycles, Planes, Ships, and Trains. All of the pictures provide a visual depiction of each particular type of vehicle, taken at a variety of angles and resolutions to recreate real-life situations. The data is split into 3,504 images to be trained and 1,503 to be tested and the ratio of classes is kept so that there are no biases to evaluate the model. A variety of opinions will make the dataset more complex and realistic; thus making sure that the CNN model can effectively generalize with unknown data. The examples of such vehicle images are given in figure 1.

3. METHODOLOGY

A. Proposed Model:

The suggested Convolutional Neural Network (CNN) vehicle recognition model has combined various convolutional, pooling and dropout layers in order to attain efficient multi-class recognition. It has a Conv2D layer (conv2d_15) which filters feature maps with 32 filters with sizes 32-by-32-by-3 resulting to (126, 126, 32) feature maps. The next layer is the MaxPooling2D, which down-samples the result to (63, 63, 32), space dimension minimization but without the loss of important data.

B. Proposed Methodology:

The research also had a systematic methodology with the collection of data starting at the stage of data collection when 5007 JPG pictures of vehicles were collected and were divided into seven groups such as Auto Rickshaws, Bikes, Cars, Motorcycles, Planes, Ships and Trains. This dataset was also selected in a way that it is diverse and has a balanced address of all the types of vehicles, which is essential in the domain of creating a strong classification model.

IV. RESULTS

Conventional Neural Network (CNN) model showed good performance in vehicle classification in a dataset of 5007 images in seven categories namely Auto Rickshaws, Bikes, Cars, Motorcycles, Planes, Ships, and Trains. With a total test accuracy of 84, the model yielded extremely high results with Bikes (precision 0.95, recall 0.94) and Ships (F1 -score 0.94). Nevertheless, Trains had the least precision (0.68) and recall (0.76) which means that it needs additional improvement.

A. Classification Report Analysis

The model has an overall accuracy of 84, a macro and weighted average of 0.83, which has indicators of balanced but amenable classification abilities. As shown in Fig.2.

	precision	recall	f1-score	support
0	0.85	0.80	0.82	234
1	0.95	0.94	0.94	238
2	0.85	0.76	0.80	233
3	0.86	0.86	0.86	214
4	0.76	0.88	0.82	220
5	0.86	0.88	0.87	252
6	0.68	0.70	0.69	112
accuracy			0.84	1503
macro avg	0.83	0.83	0.83	1503
weighted avg	0.84	0.84	0.84	1503

Fig. 2 Classification Report Analysis

B. Confusion Matrix Analysis

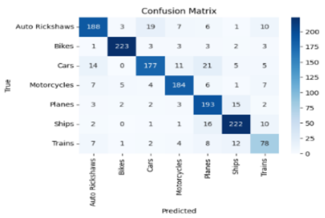
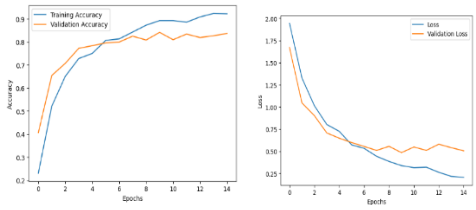


Fig. 3 Confusion Matrix Analysis

Although the Motorcycle and Plane detection achieved good outcomes, misclassification between other related-looking vehicles implies that the model should be improved with more distinction of features and the variety of data to become more accurate. As shown in fig.3.

C. Training VS Validation Accuracy and Loss Analysis

The model had a high-training accuracy-92.05% and validation-83.70% accuracy with low differences in loss at the final epoch. The results show that the model is robust and efficient during training with low overfitting, high levels of generalization, and stability of learning. As shown in fig.4(a) and fig.4(b).



(a) (b)

Fig. 4 (a) Training and Validation Accuracy Curve, (b) Training and Validation Loss Curve.

4. CONCLUSION

The categories of vehicle classified as a Convolutional Neural Network (CNN) model in this work are seven namely Auto Rickshaws, Bikes, Cars, Motorcycles, Planes, Ships and Trains. Through the tedious process of data collection and preparation, 5007 photos were selected and divided into training and test data which resulted in The model being trained and tested on the data and thus yielding an overall accuracy of 84% with regards to the test set. The test outcomes showed the ability of the CNN design to efficiently learn intricate characteristics of various types of vehicles, and thus emphasize on its likely application in traffic control and self-driving vehicle systems.

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