Transfer Learning For Bangladeshi Vehicles Classification

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***Abstract*—Bangladesh Has different kinds and large number of vehicles. To classify them correctly it needs to have a good data set and classification algorithm. In this paper we proposed to use different Transfer Learning models to classify them correctly. Transfer learning uses its previous knowledge to solve the current one. By using different Transfer Learning models we are able to classify different vehicles and also we compare them that which model can give more accurate result.**

***Index Terms*—Transfer Learning, Image Data set, Vehicle Classification, Deep Learning.**

I. Introduction

Bangladesh is a very populated country. It also has a large number and different kinds of vehicles. So it is quite taught to classify those vehicles correctly. Machine Learning can do this kinds of classification. From Machine Learning, Transfer Learning [1] and Deep Learning can do classification very well. Transfer Learning means it can use its previous knowledge to solve current problem. When Transfer Learning solves a problem it stores gained knowledge of the current problems to reuse this knowledge in future problems.

In this paper [3], author says that image classification is one of the core problems in computer vision field with large number of practical applications. He also mentioned Convolutional Neural Network (CNN) has top accuracy in image classification. In that paper they are trying to figure out is it work best in terms of accuracy and efficiency with new dataset. In this paper [4], they use a learning approach based on training convolutional neural network for traffic signal classification. They explore the transfer learning technique called fine tuning technique to determine the appropriate architecture. They reuse trained layer on the ImageNet dataset to provide solution for four class classification on a new dataset. In this paper [5], author says that breast cancer is one of the leading cancers and it is detectable using patient's imagery data. Convolutional Neural Network known as deep learning architecture achieved impressive result in this field. Here they use pre trained CNN model. They use VGG16 for feature extraction and AlexNet for fine tuning. They use histopathologic breast cancer dataset and evaluate the result. Finally, they make a complement which is transfer learning provides better result than others. In this paper [6], author says that convolutional neural network (CNN) has the power of robust feature extraction and information mining. Here they use transfer learning to fine tune the pre trained network parameter of VGG19. After that they compare the architecture with AlexNet and VGG16. They evaluate the performance and fine tuned VGG19 architecture out forms the other CNN and Hybrid learning approach for image classification task.

To classify different kinds of vehicles we are proposed to use different Transfer Learning Models. In this paper, we are using VGG16, ResNet152V2, DenseNet201, EfficientNetB7 and EfficientNetV2L. Those all are Transfer Learning model with good accuracy. In this paper, we will see what will be the performance of those high performing model in our complex ParibahanBD [2] Dataset. We will also compare them in terms of performance, recall, f1 score and accuracy.

II. Proposed Method

A. Dataset Details

In this paper, we will use ParibahanBD [2] Dataset. It is a large dataset where Bangladeshi vehicles data are available. It has information about 15 native vehicles in Bangladesh. The vehicles are : Bicycle, Boat, Bus, Car, CNG, Easy-bike, Horse-cart, Launch, Leguna, Motorbike, Rickshaw, Tractor, Truck, Van and Wheelbarrow. The dataset contains a total of 9058 images reftab:data with a high diversity of poses, angles, lighting conditions, weather conditions, backgrounds. This dataset is divided into 16 folders I.

B. Features

Our dataset has large number of images and it has 16 different classes of vehicles. From those data we will consider some parameter as features. First we will take shape as a feature. Different vehicles have different body shape. So it can be a good feature. Then we can take color. Different vehicle can have different so it will be easy to classify them correctly. We can take wheel type as a feature. It can help to differentiate between vehicles.

C. Transfer Learning Models

Here are are doing classification of different vehicles of Bangladesh. So we will use Machine Learning. From Machine Learning we will use Transfer Learning. Transfer Learning can perform very well in image classification. We use different

TABLE I
DATA DESCRIPTION OF 'PORIBOHON-BD' DATASET

Classes	Total Appearance
Bicycle	707
Boat	613
Bus	452
Car	708
CNG	533
Easy-bike	616
Horse-cart	256
Launch	662
Leguna	218
Motorbike	864
Rickshaw	495
Tractor	433
Truck	736
Van	615
Wheelbarrow	237
Multi Class	913
Total	9058

Transfer Learning Algorithms like VGG16, ResNet152V2, DenseNet201, EfficientNetB7 and EfficientNetV2L. Those are all pre-trained model. They can use their previous knowledge and also they will be train with new data. After that we will test their accuracy. Here is the used models summary :

1) VGG16: It has total 14,845,776 parameters. From them 131,088 are trainable parameters and 14,714,688 are non trainable parameters.

2) ResNet152V2: It has total 59,150,864 parameters. From them 819,216 are trainable parameters and 58,331,648 are non trainable parameters.

3) DenseNet201: It has total 18,813,520 parameters. From them 491,536 are trainable parameters and 18,321,984 are non trainable parameters.

4) EfficientNetB7: It has total 65,121,703 parameters. From them 1,024,016 are trainable parameters and 64,097,687 are non trainable parameters.

5) EfficientNetV2L: It has total 118,258,864 parameters. From them 512,016 are trainable parameters and 117,746,848 are non trainable parameters.

D. Epoch

Epoch means how times the training data will passes in Machine Learning Algorithm. Due to limited computation power we set the value of epoch in 10.Our model has 228 steps per epoch.

E. Prepossessing

We divide our dataset in 3 parts.We have 3 folders as training, validation and test datasets. In train part we have 80 percent data, in validation part we have 10 percent data and test part we have 10 percent data.In training dataset we have 7251 images. In validation dataset we have 873 images and in test dataset we have 910 images. After loading those data from drive we define the image size of batch size of those data. we use image size as 150*150 and batch size as 32. After that we re-scale the images. After that we have done label mapping of the classes.

III. RESULT ANALYSIS

We use different types of Transfer Learning Models in this project. Here is the details result of all the models :

A. VGG16

In Figure 1(a), we can see the accuracy curve and loss curve. In Figure 1(b), we can see the confusion matrix. In Figure 1(c), we can see the classification report. From those we can see that VGG16 has 0.7099 accuracy and 0.9995 loss.

B. ResNet152V2

In Figure 2(a), we can see the accuracy curve and loss curve. In Figure 2(b), we can see the confusion matrix. In Figure 2(c), we can see the classification report. From those we can see that ResNet152V2 has 0.6912 accuracy and 13.0936 loss.

C. DenseNet201

In Figure 3(a), we can see the accuracy curve and loss curve. In Figure 3(b), we can see the confusion matrix. In Figure 3(c), we can see the classification report. From those we can see that DenseNet201 has 0.7354 accuracy and 0.530 loss.

D. EfficientNetB7

In Figure 4(a), we can see the accuracy curve and loss curve. In Figure 4(b), we can see the classification report. From those we can see that EfficientNetB7 has 0.0493 accuracy and 32.0639 loss.

E. EfficientNetV2L

In Figure 5(a), we can see the accuracy curve and loss curve. In Figure 5(b), we can see the confusion matrix. In Figure 5(c), we can see the classification report. From those we can see that EfficientNetV2L has 0.2231 accuracy and 3.4736 loss.

IV. CONCLUSION

In this paper, we work with different transfer learning models to classify Bangladeshi vehicles. We talked about every models accuracy and loss curve, confusion matrix and classification report. From those models we can see DenseNet201 has the highest accuracy which is 0.1354 and lowest loss which is 0.530 in ParibahanBD [2] Dataset. In future if we make fine tune this model and use augmented dataset then it can achieve better performance and accuracy.

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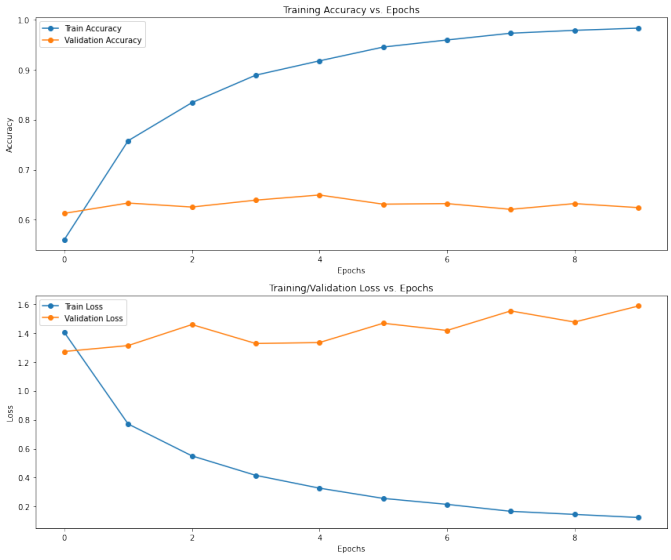
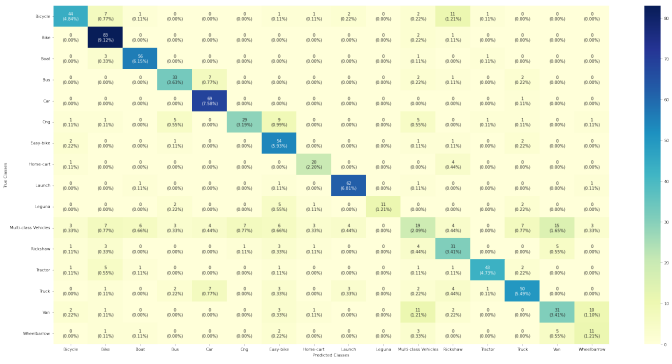


(a) Accuracy and Loss Curve

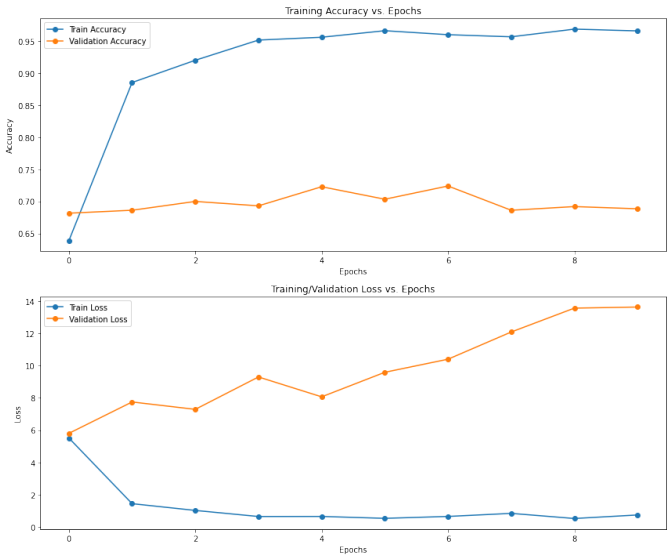


(b) Confusion Matrix

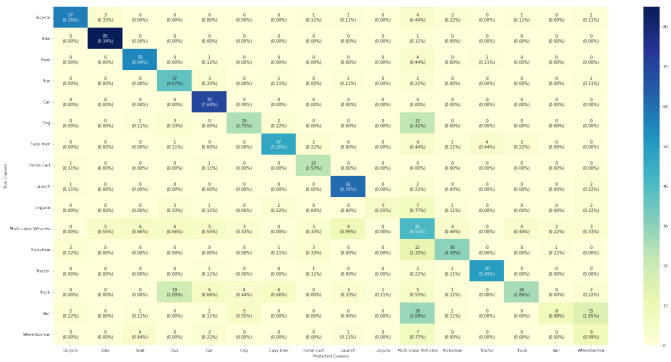
	precision	recall	f1-score	support
Bicycle	0.80	0.63	0.70	70
Bike	0.74	0.97	0.84	86
Boat	0.85	0.92	0.88	61
Bus	0.72	0.73	0.73	45
Car	0.79	0.99	0.88	70
Cng	0.78	0.55	0.64	53
Easy-bike	0.61	0.89	0.72	61
Horse-cart	0.74	0.80	0.77	25
Launch	0.87	0.94	0.91	66
Leguna	1.00	0.52	0.69	21
Multi-class Vehicles	0.35	0.21	0.26	91
Rickshaw	0.52	0.63	0.57	49
Tractor	0.91	0.78	0.84	55
Truck	0.75	0.68	0.71	73
Van	0.55	0.51	0.53	61
Wheelbarrow	0.42	0.48	0.45	23
accuracy			0.71	910
macro avg	0.71	0.70	0.70	910
weighted avg	0.70	0.71	0.70	910

(c) Classification Report

Fig. 1. VGG16 Result Analysis



(a) Accuracy and Loss Curve

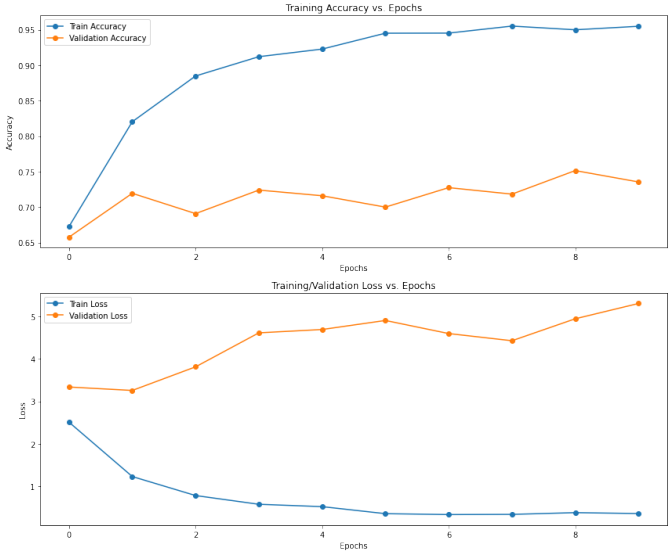


(b) Confusion Matrix

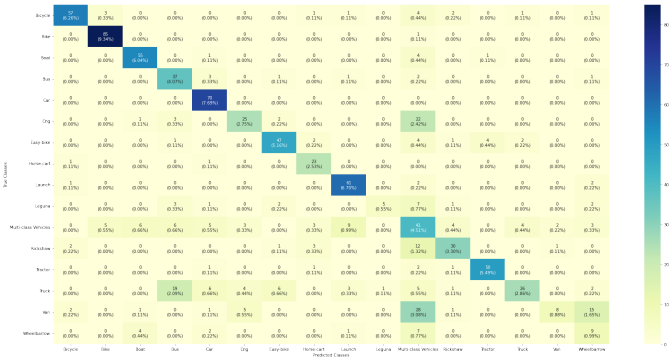
	precision	recall	f1-score	support
Bicycle	0.90	0.81	0.86	70
Bike	0.91	0.99	0.95	86
Boat	0.82	0.90	0.86	61
Bus	0.54	0.82	0.65	45
Car	0.77	1.00	0.87	70
Cng	0.68	0.47	0.56	53
Easy-bike	0.80	0.77	0.78	61
Horse-cart	0.70	0.92	0.79	25
Launch	0.80	0.92	0.86	66
Leguna	0.83	0.24	0.37	21
Multi-class Vehicles	0.29	0.45	0.35	91
Rickshaw	0.73	0.61	0.67	49
Tractor	0.91	0.91	0.91	55
Truck	0.79	0.36	0.49	73
Van	0.73	0.13	0.22	61
Wheelbarrow	0.26	0.39	0.31	23
accuracy			0.69	910
macro avg	0.72	0.67	0.66	910
weighted avg	0.73	0.69	0.68	910

(c) Classification Report

Fig. 2. ResNet152V2 Result Analysis



(a) Accuracy and Loss Curve

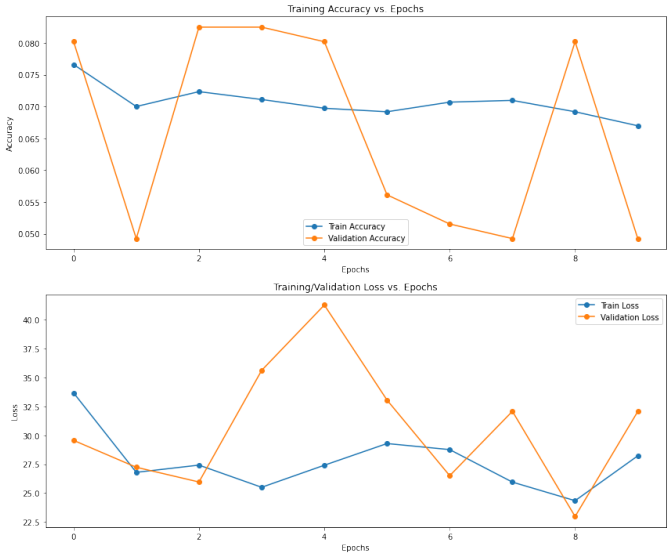


(b) Confusion Matrix

	precision	recall	f1-score	support
Bicycle	0.95	0.76	0.84	70
Bike	0.80	0.95	0.87	86
Boat	0.88	0.95	0.91	61
Bus	0.93	0.62	0.75	45
Car	0.71	1.00	0.83	70
Cng	0.90	0.72	0.80	53
Easy-bike	0.84	0.77	0.80	61
Horse-cart	0.95	0.72	0.82	25
Launch	0.81	0.91	0.86	66
Leguna	0.75	0.57	0.65	21
Multi-class Vehicles	0.36	0.40	0.38	91
Rickshaw	0.64	0.76	0.69	49
Tractor	0.98	0.96	0.97	55
Truck	0.77	0.81	0.79	73
Van	0.67	0.54	0.60	61
Wheelbarrow	0.50	0.26	0.34	23
accuracy			0.76	910
macro avg	0.78	0.73	0.74	910
weighted avg	0.77	0.76	0.75	910

(c) Classification Report

Fig. 3. DenseNet201 Result Analysis



(a) Accuracy and Loss Curve

	precision	recall	f1-score	support
Bicycle	0.00	0.00	0.00	70
Bike	0.00	0.00	0.00	86
Boat	0.00	0.00	0.00	61
Bus	0.00	0.00	0.00	45
Car	0.00	0.00	0.00	70
Cng	0.00	0.00	0.00	53
Easy-bike	0.00	0.00	0.00	61
Horse-cart	0.00	0.00	0.00	25
Launch	0.00	0.00	0.00	66
Leguna	0.00	0.00	0.00	21
Multi-class Vehicles	0.00	0.00	0.00	91
Rickshaw	0.00	0.00	0.00	49
Tractor	0.06	1.00	0.11	55
Truck	0.00	0.00	0.00	73
Van	0.00	0.00	0.00	61
Wheelbarrow	0.00	0.00	0.00	23
accuracy			0.06	910
macro avg	0.00	0.06	0.01	910
weighted avg	0.00	0.06	0.01	910

(b) Classification Report

Fig. 4. EfficientNetB7 Result Analysis

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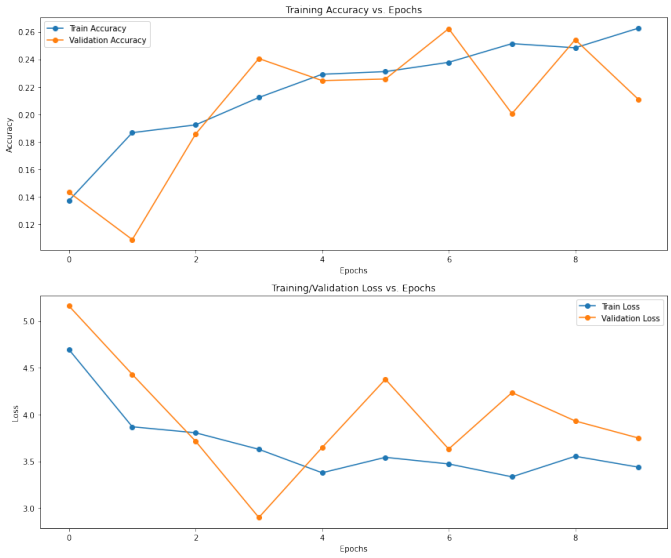
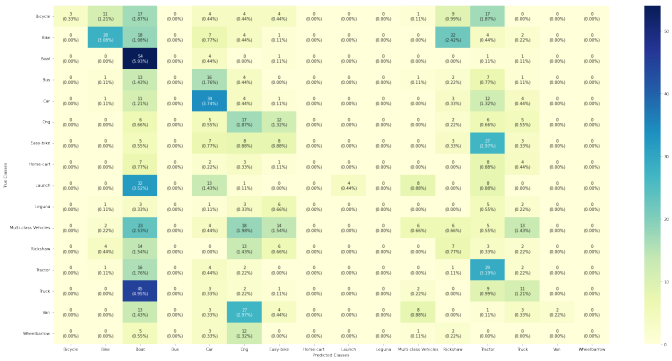


(a) Accuracy and Loss Curve



(b) Confusion Matrix

	precision	recall	f1-score	support
Bicycle	1.00	0.04	0.08	70
Bike	0.57	0.33	0.41	86
Boat	0.19	0.89	0.31	61
Bus	0.00	0.00	0.00	45
Car	0.31	0.49	0.38	70
Cng	0.14	0.32	0.19	53
Easy-bike	0.14	0.13	0.13	61
Horse-cart	0.00	0.00	0.00	25
Launch	1.00	0.06	0.11	66
Leguna	0.00	0.00	0.00	21
Multi-class Vehicles	0.22	0.07	0.10	91
Rickshaw	0.12	0.14	0.13	49
Tractor	0.20	0.53	0.29	55
Truck	0.21	0.15	0.17	73
Van	1.00	0.03	0.06	61
Wheelbarrow	0.00	0.00	0.00	23
accuracy			0.22	910
macro avg	0.32	0.20	0.15	910
weighted avg	0.38	0.22	0.18	910

(c) Classification Report

Fig. 5. EfficientNetV2L Result Analysis