CSC345/M45 Big Data and Machine Learning
Coursework: Object Recognition
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Introduction.

Classification is a type of supervised learning whereby the data is labelled with predefined classes. The goal was to use Machine Learning (ML) methodologies to perform image multi-classification. The CIFAR100 dataset was used to classify in the challenge. The dimensions of each image used are (32,32,3), which correspond to the height, width, and colour channel (RGB). The dataset was used to train and assess the performance of the models. According to Ray (2015), using multiple machine learning algorithms is a good way to improve ML accuracy because some algorithms are better suited for certain datasets than others. The classification methods used for this assignment are Support Vector Classifier (SVC), Neural Network (NN), and Convolutional Neural Network (CNN). CNN According to the experimental results shown below, CNN is a better classifier than the other two approaches.

Method.

Task1: Download the *CIFAR100* dataset.

To accomplish this, imported the tensor flow package, which is utilised in model development. The downloaded dataset is divided into four NumPy array variables, which is why the NumPy package was imported to store our datasets. The dataset consists of 50000 training datasets and 10,000 testing datasets. Another NumPy array is declared to store the image target class names.

Task2: Computing Features and Visualizing Images

Slice data:

The training dataset was sliced from 50000 to 500, and the testing dataset was sliced from 10000 to 100. Because the hog functions accept image input, as (32,32,3) the data was transposed to be shown as (samples, height, width, color_channels) rather than (height, width, color_channels, samples)

Feature Extraction

The extracted features are a simplified representation of the image that incorporates only the most significant information about the image. Imported the skimage.feature package to use the *hog function*. As stated by Singh (2019), the *hog function* computes the histogram of oriented gradients. Had to loop through the entire dataset and extract features for each image when using the Hog function, which took a long time for 50000 dataset it took 30 minutes. Instead of using the Hog function, decided to flatten and then normalise the dataset, as implemented in lab4. Before normalising the pixels by dividing them by 255, the training and testing datasets were reshaped to (50000,3072) and (10000,3072), respectively. This was done to convert the dataset from 4D to 2D and create a single long continuous linear vector that could be fed into neural network models. Ray (2015) claims that this is one of the methods used to improve model performance. However, it did not seem to be useful for SVC and Linear SVC since the dataset size was too enormous, requiring a long time to fit the dataset into the object, despite LSVC's documentation promising support for larger datasets.

Task3: Learning Algorithms

Build ML Models

First, defined the ML. model by selecting the type of model needed, followed by determining the network topology, in this case a sequential model. By doing so, the model's layers are configured, each with numerous nodes and activation functions, and the levels are integrated into a cohesive model. The second stage is model compilation, which involves running a method to compile the model with the supplied configuration, which will build the necessary data structures for efficient model usage. To archive this, select an optimization loss function (Sparse Categorical Cross entropy or binary cross entropy). This involves the selection of an

optimisation strategy (Adam) as well as metrics (accuracy) to monitor during the model training process. Following that, the model is evaluated using the validation dataset, which is 20% of the training dataset. This is done to ensure that the model fulfils its intended purpose and to assess the loss and metrics. Finally, predict the test picture dataset class labels from our dataset's 20 target classes to determine if the model is classifying images correctly.

Neural Network

A fully connected neural network is composed of many densely connected layers that connect every neuron in one layer to every neuron in the next using input from the hog function or flattened data and the ReLU action, which aids in learning non-linear correlations between components and makes the network more resilient to detecting diverse patterns.

Create SVC and Linear SVC

To modify image characteristics to be on a same scale, used the Standard Scaler class to standardise the dataset. The dataset was then modified to match the destination system (SVC). Created a SCV object and fitted the training dataset and its labels into it. SVC is typically used to work with small complex datasets. Finally, the object was evaluated once the classes of the testing dataset were predicted.

Build CNN.

CNN is a deep learning method that assumes the inputs are images and allows certain features to be encoded into the model architecture for image classification. Each layer of a CNN uses a differentiable function (ReLU) to transform one volume of activations to another. CNNs are effective because they can do automatic feature extraction at a large scale. SoftMax is used at the output to interpret raw classifier scores as probabilities.

Results.

Task 4: Evaluate the Models

Evaluation measure performance of independent blind test data. This was done using the confusion matrix, accuracy score, and classification report. In machine learning according to Bharathi (2021), a confusion matrix is a table used to assess the effectiveness of a classification model. Imported pandas and seaborn packages to display the results in the Appendices section as a heat map. In multilabel classification, the accuracy score computes the subset accuracy. The precision, recall, and f1-score for each target class are displayed in the classification report. Precision indicates how well the model predicts a certain class, recall indicates how many times the model detected a specific class, and the f1-score weighted average of precision and recall.

Refer to Appendices for screenshots of results.

	SVC (500 dataset)	NN	CNN1	CNN2	CNN3	2nd CNN1	2nd CNN2	2nd CNN3
Accuracy Score %	12	10.34	5	19.09	25.18	44.98	49.2	53.56
Time lapse for training for 50000 image datasets	> 1hour	9.45s	1m 52.7s	2m 2.9s	4m 54.7s	1m 51s	3m 45.2s	5m 56s
Classification Bias towards target name	Medium sized mammals	Fruit and vegetables	Large outdoor scenes	Insects, large carnivores	Insects	People	Household furniture	Large outdoor scenes

Lowest Classification towards target name	Most target classes except people, large man-made outdoor things, and household electrical devices	fish, flowers, household furniture, large carnivores, non-insect invertebrates, people, reptiles, small mammals	Every target class	vehicles2	Small mammals	Small mammals	reptiles	non-insect invertebrates
Correct Classification	-	-	-	Some target classes	some target classes	Most target classes	Most targets classes	Most targets

Improvement Method

Image Data Generator, according to PyImageSerach (2019), can be used to improve model accuracy since it allows for image augmentation to reduce the possibility of overfitting data by loading the image dataset into memory and generating batches of augmented data. This method allows us to artificially increase the dataset's size and diversity, which improves model generalisation and the CNN's ability to learn more robust features.

Conclusion.

Task5: Benchmark and Discussion

There is enough evidence to conclude that SVC is not an appropriate classification methodology for large datasets, which is why the data was sliced. However, using smaller datasets is not a good model training methodology because the model may have biased outliers due to noticing patterns that do not exist, resulting in overfitting. More training data, according to Ray (2015), allows the "data to tell for itself" rather than relying on assumptions and weak correlations. According to the SVC documentation, linear SVC is supposed to work for large datasets, but fitting the 50000-image dataset took more than an hour, which is inefficient.

To try to solve the problem raised by SVC objects, NN was used to classify since it can handle large datasets. Even though using simple NN reduced model training time and allowed us to use the entire dataset, the model's accuracy score was very low. One significant reason for this poor performance is that NN does not automatically extract features like CNN when training models, resulting in large losses when training model. The image features had to be extracted manually first using the hog function, but the function was taking too long, so the method from lab4 was used. However, none of the images were correctly classified in the end, indicating that the model was not performing its intended function.

Another classification method, deep learning with CNN, was used to improve the classification. Deep learning automatically learns features from data, eliminating the need for manual extraction of image features. The results show that the more layers you add to the CNN, the better the model performs. The results show that more images are being classified correctly, something that the SVC and NN models did not do. Used the Image Data Processed methodology proposed by Ray (2015) and GeeksforGeeks (2023) to further improve our model performance. Image augmentation is one of the methods to be used to improve model accuracy. The model's performance increased from 25% to 53%, and the training and validation accuracy increased after 2 epochs for the 2nd CNN in the 1st CNN it increased after 6 epochs. In conclusion, CNN is the most effective ML methodology for multi-classification of images for large datasets; however, there is a need to investigate Transfer learning methodology to see how it improves model precision in the future.

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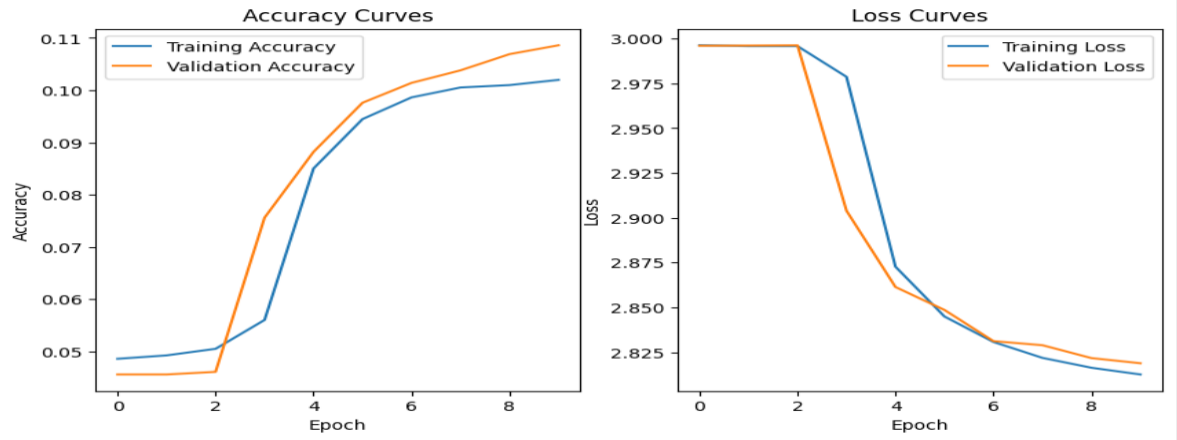
Appendices.

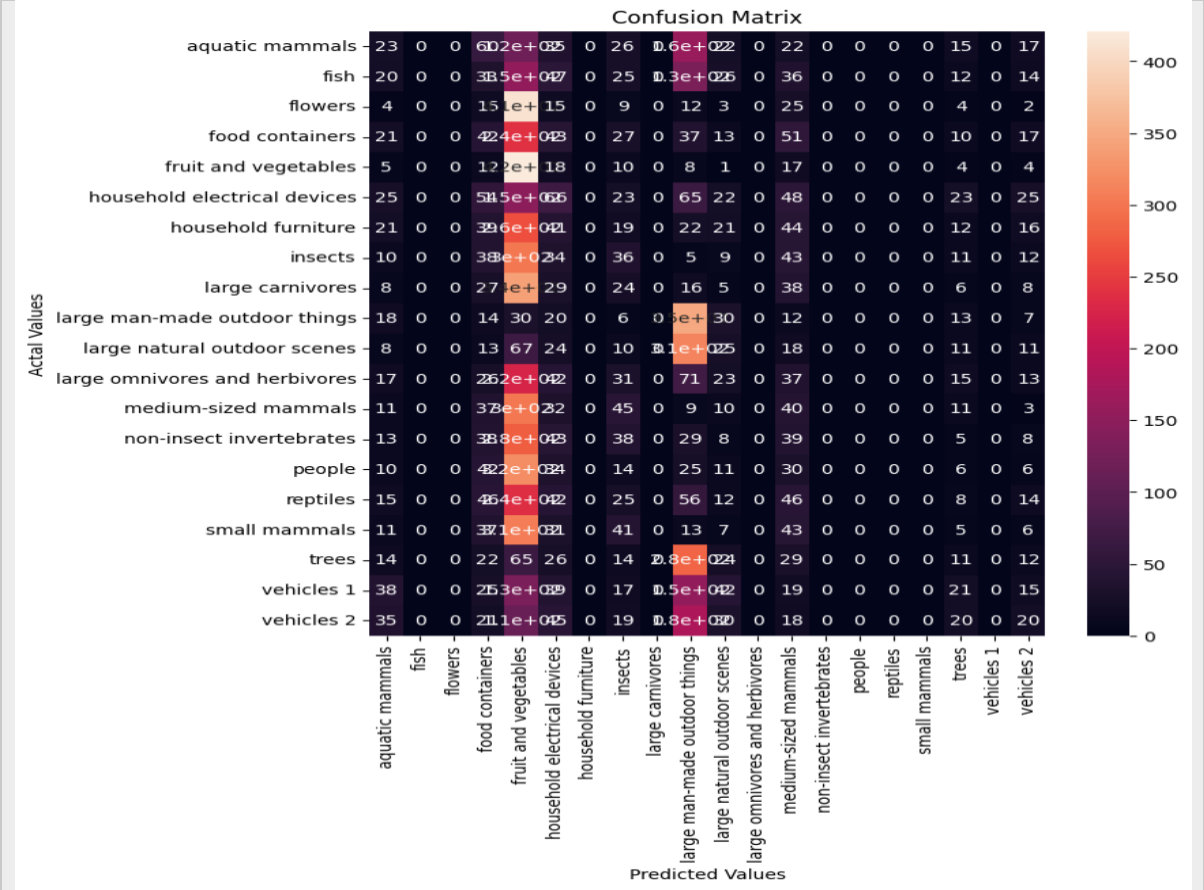
NN Classification Report

```
313/313 [==============================] - 0s 559us/step
NN Accuracy: 10.340
                                  precision    recall  f1-score   support

                 aquatic mammals       0.07      0.05      0.06       500
                            fish       0.00      0.00      0.00       500
                         flowers       0.00      0.00      0.00       500
                food containers       0.07      0.08      0.07       500
          fruit and vegetables        0.09      0.84      0.17       500
  household electrical devices       0.09      0.13      0.11       500
       household furniture           0.00      0.00      0.00       500
                         insects       0.08      0.07      0.08       500
               large carnivores       0.00      0.00      0.00       500
 large man-made outdoor things        0.18      0.70      0.29       500
 large natural outdoor scenes         0.07      0.05      0.06       500
large omnivores and herbivores        0.00      0.00      0.00       500
         medium-sized mammals         0.06      0.08      0.07       500
      non-insect invertebrates        0.00      0.00      0.00       500
                        people        0.00      0.00      0.00       500
                       reptiles       0.00      0.00      0.00       500
                small mammals         0.00      0.00      0.00       500
                         trees        0.05      0.02      0.03       500
                  vehicles 1          0.00      0.00      0.00       500
                  vehicles 2          0.09      0.04      0.05       500

                      accuracy                              0.10     10000
                     macro avg        0.04      0.10      0.05     10000
                  weighted avg        0.04      0.10      0.05     10000
```

NN Accuracy and Loss Results



NN Confusion Matrix Heatmap

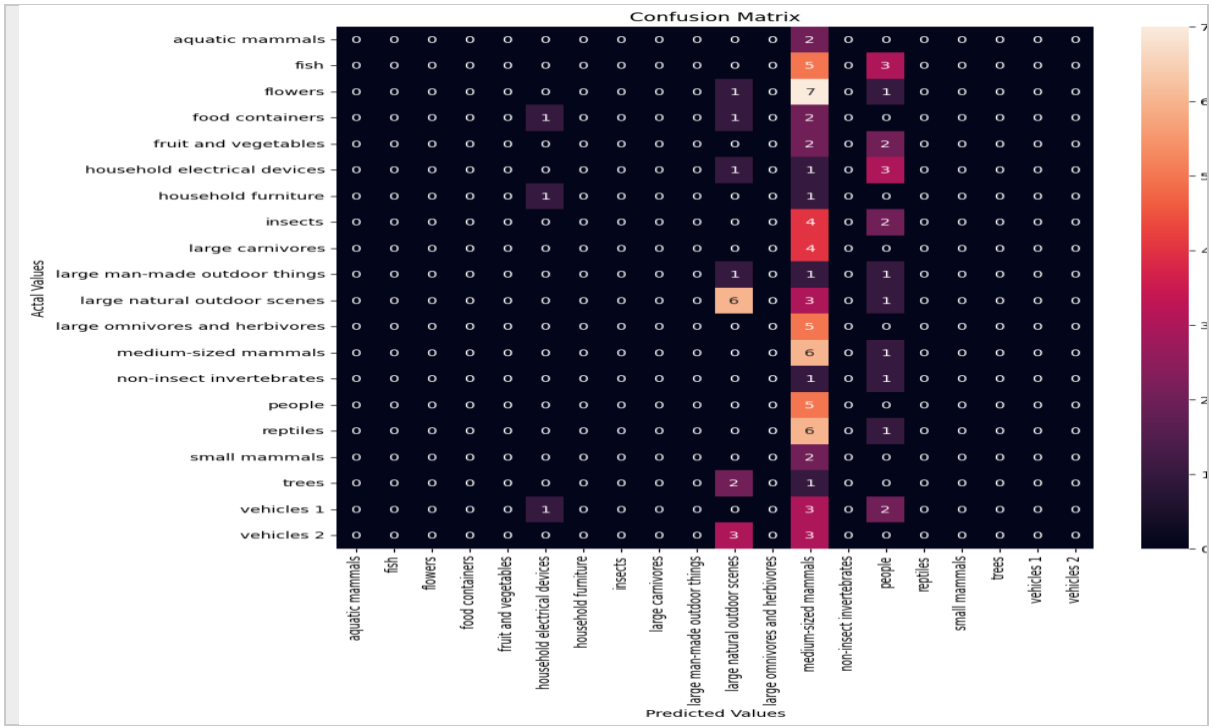


SVC Classification Report

SVC Accuracy: 12.000

	precision	recall	f1-score	support
aquatic mammals	0.00	0.00	0.00	2
fish	0.00	0.00	0.00	8
flowers	0.00	0.00	0.00	9
food containers	0.00	0.00	0.00	4
fruit and vegetables	0.00	0.00	0.00	4
household electrical devices	0.00	0.00	0.00	5
household furniture	0.00	0.00	0.00	2
insects	0.00	0.00	0.00	6
large carnivores	0.00	0.00	0.00	4
large man-made outdoor things	0.00	0.00	0.00	3
large natural outdoor scenes	0.40	0.60	0.48	10
large omnivores and herbivores	0.00	0.00	0.00	5
medium-sized mammals	0.09	0.86	0.17	7
non-insect invertebrates	0.00	0.00	0.00	2
people	0.00	0.00	0.00	5
reptiles	0.00	0.00	0.00	7
small mammals	0.00	0.00	0.00	2
trees	0.00	0.00	0.00	3
vehicles 1	0.00	0.00	0.00	6
vehicles 2	0.00	0.00	0.00	6
accuracy			0.12	100
macro avg	0.02	0.07	0.03	100
weighted avg	0.05	0.12	0.06	100

SVC Confusion Matrix Heatmap



CNN Classification Report

313/313 [==============================] - 1s 3ms/step
CNN Accuracy: 5.000

	precision	recall	f1-score	support
aquatic mammals	0.00	0.00	0.00	500
fish	0.00	0.00	0.00	500
flowers	0.00	0.00	0.00	500
food containers	0.00	0.00	0.00	500
fruit and vegetables	0.00	0.00	0.00	500
household electrical devices	0.00	0.00	0.00	500
household furniture	0.00	0.00	0.00	500
insects	0.00	0.00	0.00	500
large carnivores	0.00	0.00	0.00	500
large man-made outdoor things	0.00	0.00	0.00	500
large natural outdoor scenes	0.05	1.00	0.10	500
large omnivores and herbivores	0.00	0.00	0.00	500
medium-sized mammals	0.00	0.00	0.00	500
non-insect invertebrates	0.00	0.00	0.00	500
people	0.00	0.00	0.00	500
reptiles	0.00	0.00	0.00	500
small mammals	0.00	0.00	0.00	500
trees	0.00	0.00	0.00	500
vehicles 1	0.00	0.00	0.00	500
vehicles 2	0.00	0.00	0.00	500
accuracy			0.05	10000
macro avg	0.00	0.05	0.00	10000
weighted avg	0.00	0.05	0.00	10000

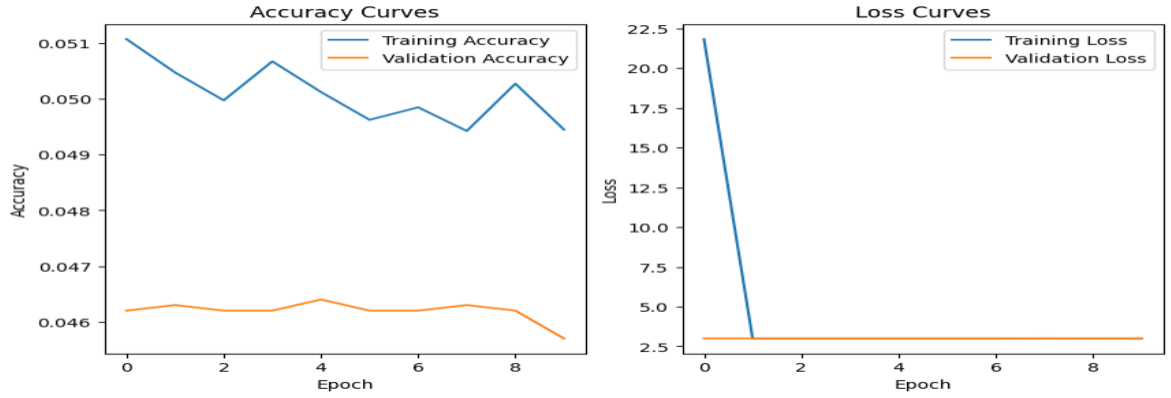
313/313 [==============================] - 2s 6ms/step
CNN Accuracy: 19.090

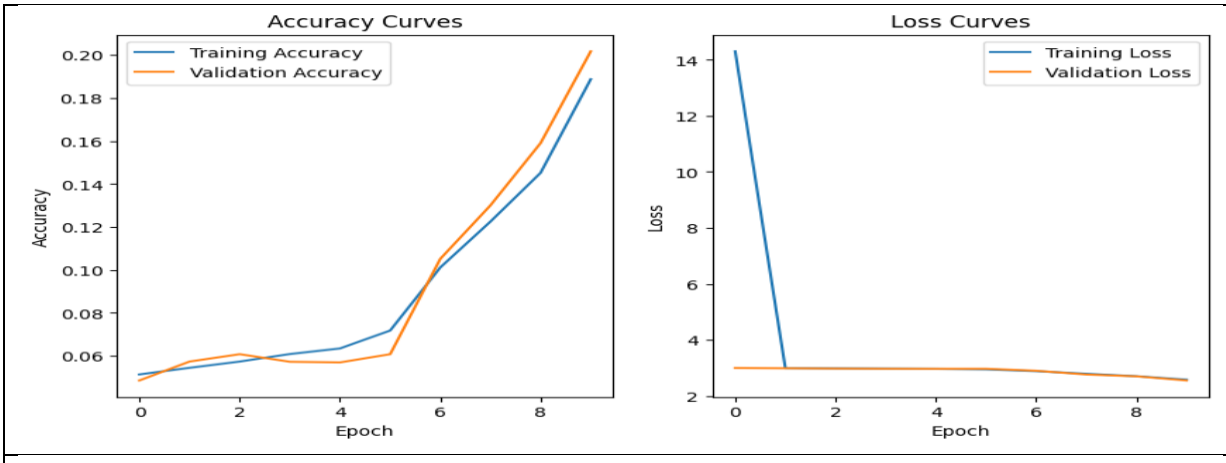
	precision	recall	f1-score	support
aquatic mammals	0.26	0.15	0.19	500
fish	0.18	0.12	0.15	500
flowers	0.49	0.58	0.53	500
food containers	0.35	0.08	0.12	500
fruit and vegetables	0.45	0.38	0.41	500
household electrical devices	0.08	0.01	0.02	500
household furniture	0.21	0.17	0.19	500
insects	0.10	0.50	0.16	500
large carnivores	0.06	0.21	0.10	500
large man-made outdoor things	0.24	0.42	0.31	500
large natural outdoor scenes	0.30	0.27	0.29	500
large omnivores and herbivores	0.10	0.12	0.11	500
medium-sized mammals	0.10	0.02	0.03	500
non-insect invertebrates	0.15	0.01	0.03	500
people	0.23	0.22	0.23	500
reptiles	0.13	0.02	0.03	500
small mammals	0.06	0.00	0.01	500
trees	0.74	0.36	0.49	500
vehicles 1	0.14	0.16	0.15	500
vehicles 2	0.05	0.01	0.01	500
accuracy			0.19	10000
macro avg	0.22	0.19	0.18	10000
weighted avg	0.22	0.19	0.18	10000

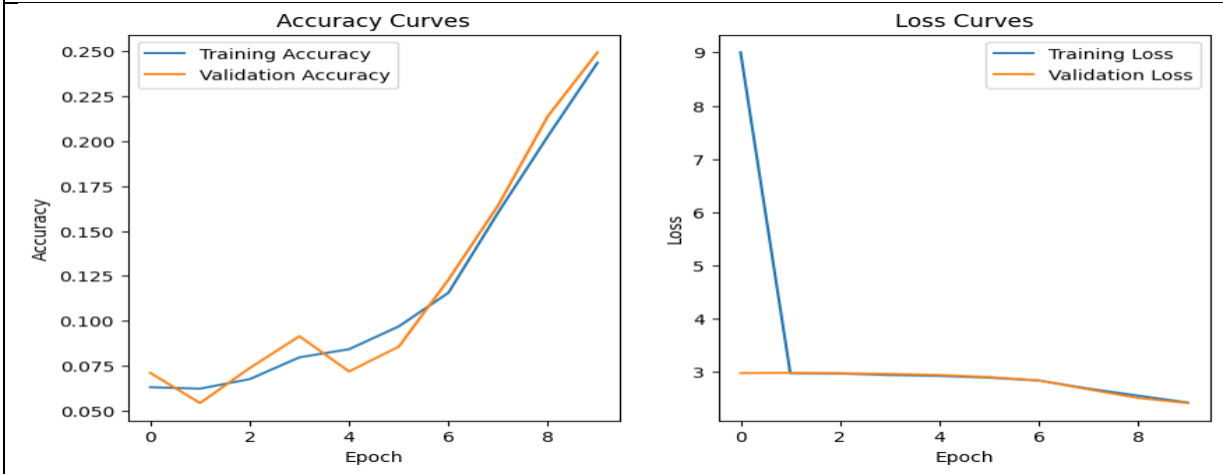
313/313 [==============================] - 3s 9ms/step
CNN Accuracy: 25.180

	precision	recall	f1-score	support
aquatic mammals	0.28	0.26	0.27	500
fish	0.35	0.17	0.23	500
flowers	0.55	0.59	0.57	500
food containers	0.33	0.13	0.19	500
fruit and vegetables	0.48	0.40	0.43	500
household electrical devices	0.09	0.06	0.07	500
household furniture	0.23	0.16	0.19	500
insects	0.14	0.51	0.22	500
large carnivores	0.09	0.03	0.04	500
large man-made outdoor things	0.29	0.43	0.35	500
large natural outdoor scenes	0.56	0.54	0.55	500
large omnivores and herbivores	0.12	0.08	0.09	500
medium-sized mammals	0.13	0.18	0.15	500
non-insect invertebrates	0.08	0.00	0.00	500
people	0.21	0.43	0.28	500
reptiles	0.11	0.01	0.02	500
small mammals	0.33	0.00	0.00	500
trees	0.49	0.70	0.58	500
vehicles 1	0.12	0.31	0.18	500
vehicles 2	0.09	0.03	0.05	500
accuracy			0.25	10000
macro avg	0.25	0.25	0.22	10000
weighted avg	0.25	0.25	0.22	10000

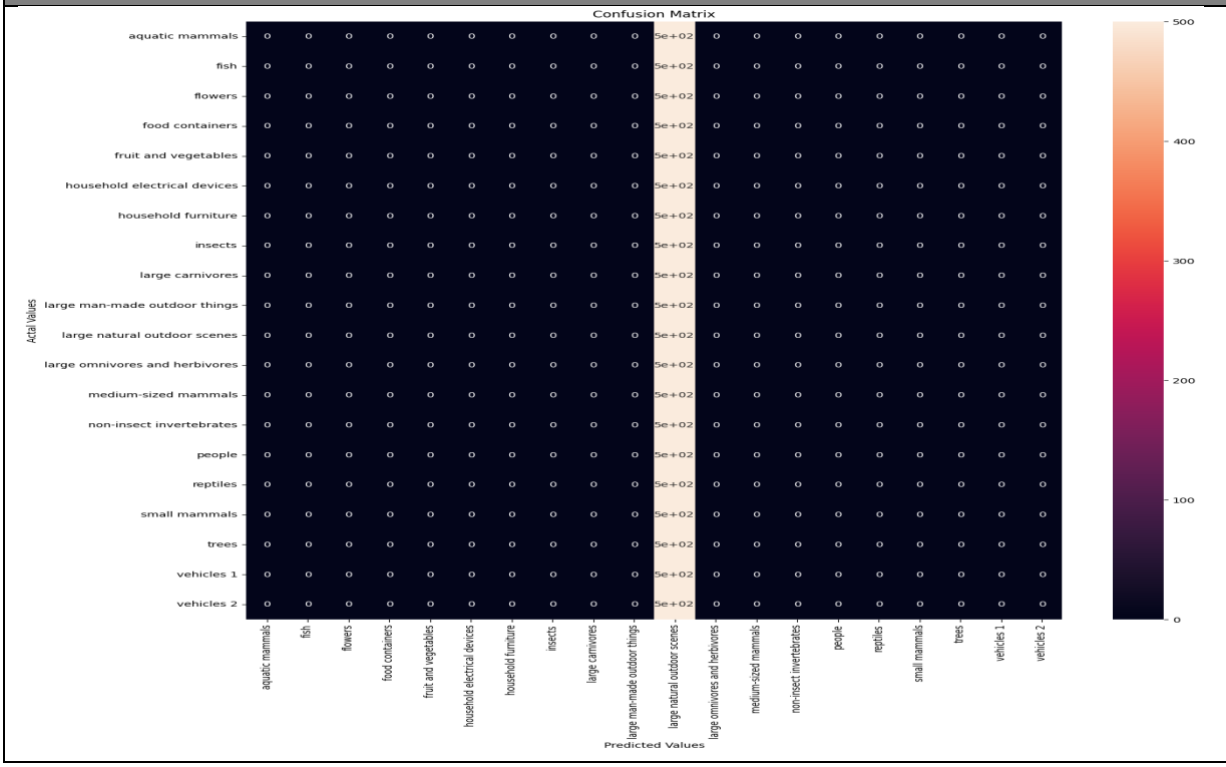
CNN Accuracy and Loss Results

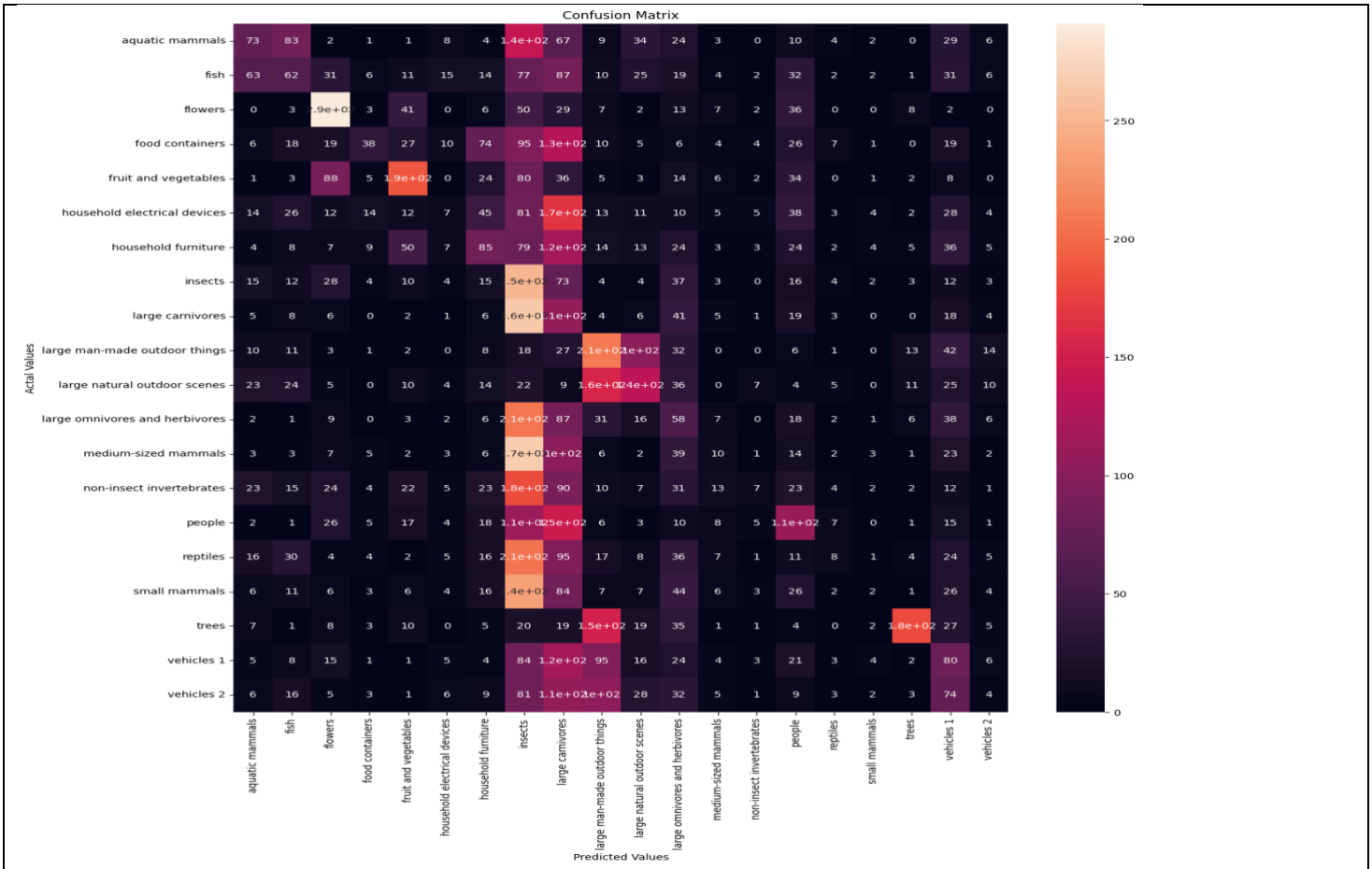


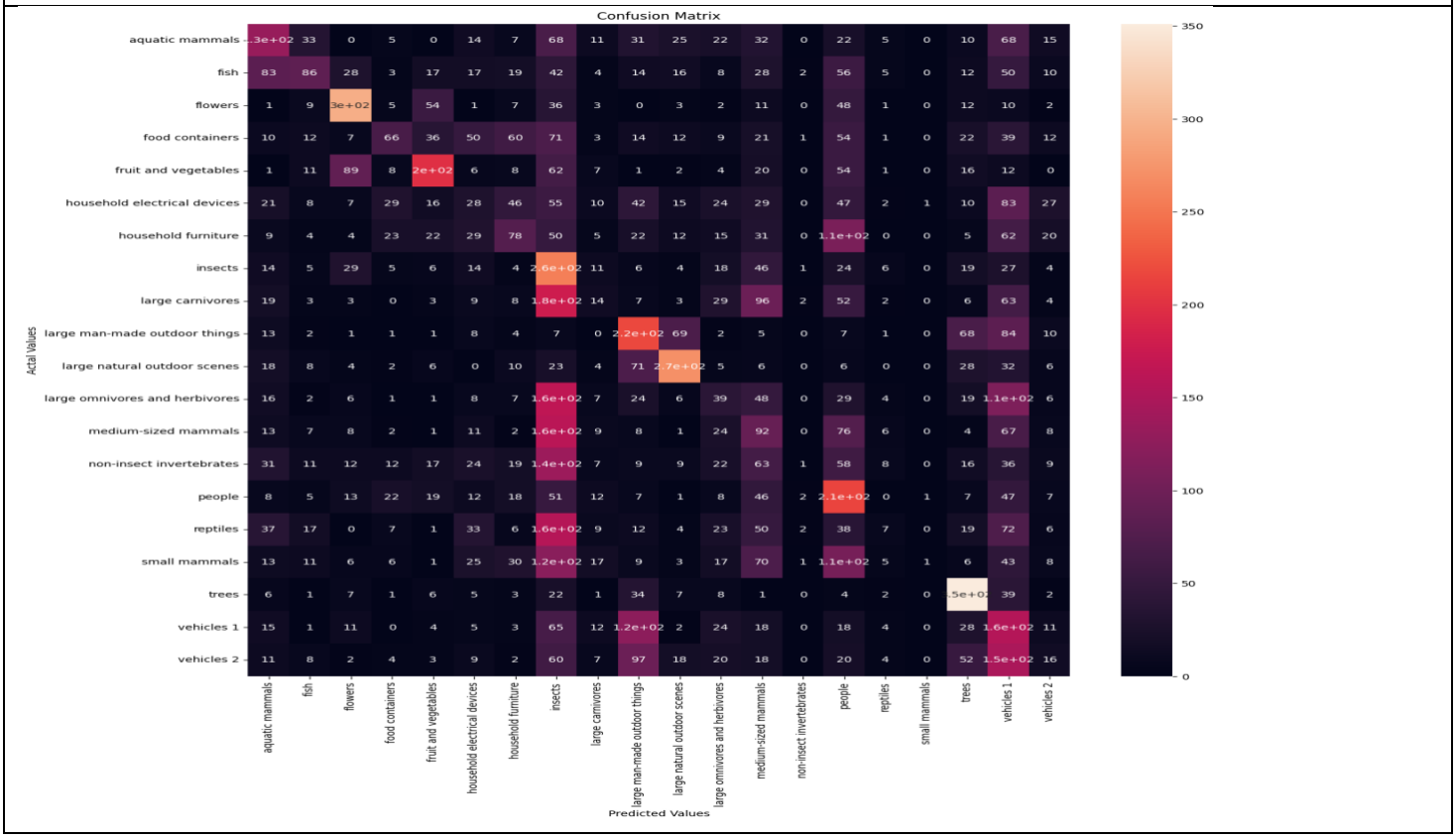




Confusion Matrix HeatMap




Confusion Matrix
aquatic mammals
fish
flowers
food containers
fruit and vegetables
household electrical devices
household furniture
insects
large carnivores
large man-made outdoor things
large natural outdoor scenes
large omnivores and herbivores
medium-sized mammals
non-insect invertebrates
people
reptiles
small mammals
trees
vehicles 1
vehicles 2
Actal Values
Predicted Values
0
50
100
150
200
250


Confusion Matrix
aquatic mammals
fish
flowers
food containers
fruit and vegetables
household electrical devices
household furniture
insects
large carnivores
large man-made outdoor things
large natural outdoor scenes
large omnivores and herbivores
medium-sized mammals
non-insect invertebrates
people
reptiles
small mammals
trees
vehicles 1
vehicles 2
Actal Values
Predicted Values
0
50
100
150
200
250
300
350

2nd CNN Classification Report

CNN2 Accuracy: 44.980

	precision	recall	f1-score	support
aquatic mammals	0.06	0.08	0.07	500
fish	0.05	0.04	0.05	500
flowers	0.04	0.05	0.04	500
food containers	0.03	0.03	0.03	500
fruit and vegetables	0.06	0.05	0.05	500
household electrical devices	0.06	0.04	0.05	500
household furniture	0.03	0.02	0.02	500
insects	0.06	0.07	0.06	500
large carnivores	0.06	0.07	0.06	500
large man-made outdoor things	0.05	0.06	0.06	500
large natural outdoor scenes	0.06	0.04	0.05	500
large omnivores and herbivores	0.04	0.04	0.04	500
medium-sized mammals	0.05	0.03	0.04	500
non-insect invertebrates	0.05	0.04	0.05	500
people	0.05	0.08	0.06	500
reptiles	0.06	0.06	0.06	500
small mammals	0.03	0.02	0.02	500
trees	0.04	0.04	0.04	500
vehicles 1	0.03	0.02	0.02	500
vehicles 2	0.05	0.07	0.06	500
accuracy			0.05	10000
macro avg	0.05	0.05	0.05	10000
weighted avg	0.05	0.05	0.05	10000

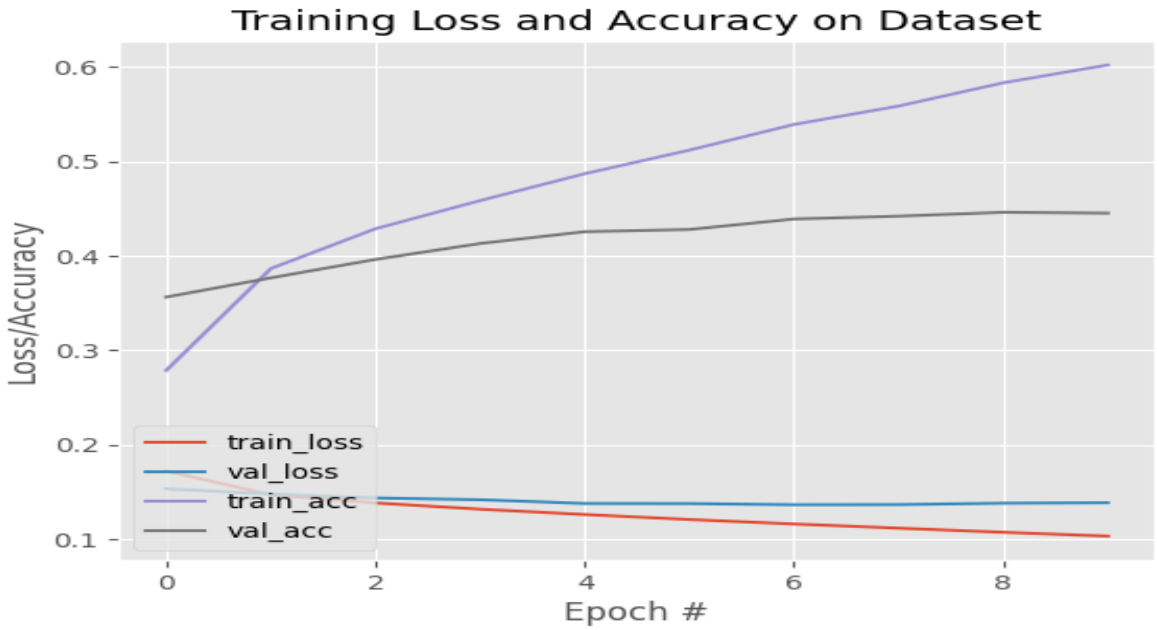
CNN2 Accuracy: 49.300

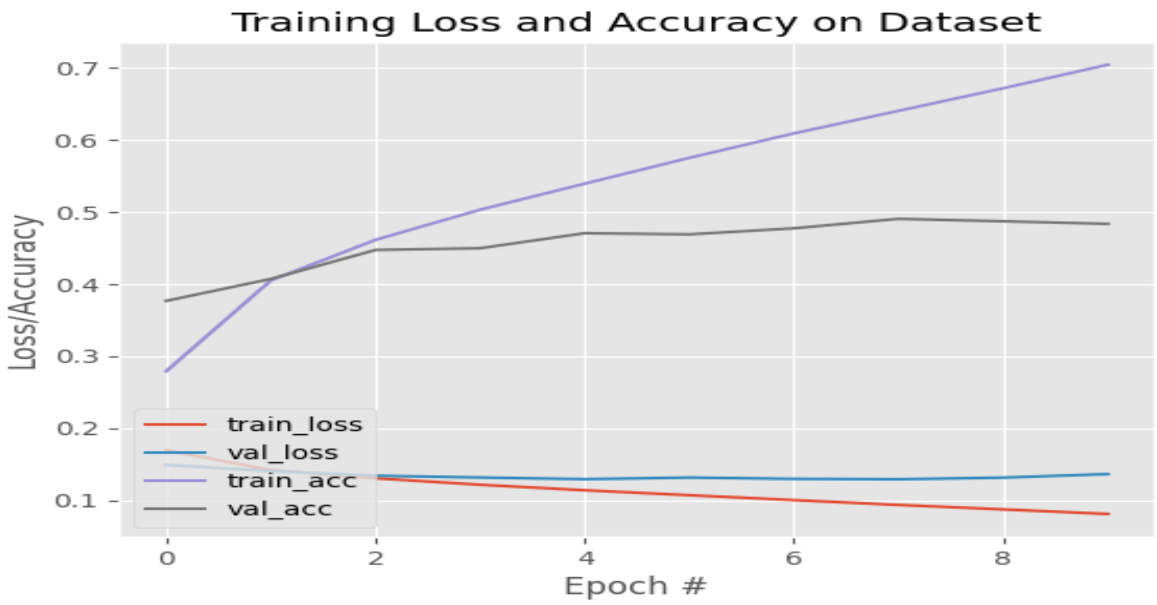
	precision	recall	f1-score	support
aquatic mammals	0.05	0.04	0.05	500
fish	0.06	0.04	0.05	500
flowers	0.05	0.07	0.06	500
food containers	0.05	0.07	0.06	500
fruit and vegetables	0.05	0.05	0.05	500
household electrical devices	0.06	0.07	0.06	500
household furniture	0.05	0.08	0.06	500
insects	0.06	0.04	0.05	500
large carnivores	0.06	0.08	0.07	500
large man-made outdoor things	0.04	0.05	0.05	500
large natural outdoor scenes	0.06	0.05	0.05	500
large omnivores and herbivores	0.07	0.06	0.06	500
medium-sized mammals	0.04	0.02	0.03	500
non-insect invertebrates	0.04	0.02	0.03	500
people	0.05	0.07	0.06	500
reptiles	0.04	0.02	0.03	500
small mammals	0.05	0.03	0.04	500
trees	0.04	0.05	0.04	500
vehicles 1	0.05	0.04	0.05	500
vehicles 2	0.05	0.06	0.05	500
accuracy			0.05	10000
macro avg	0.05	0.05	0.05	10000
weighted avg	0.05	0.05	0.05	10000

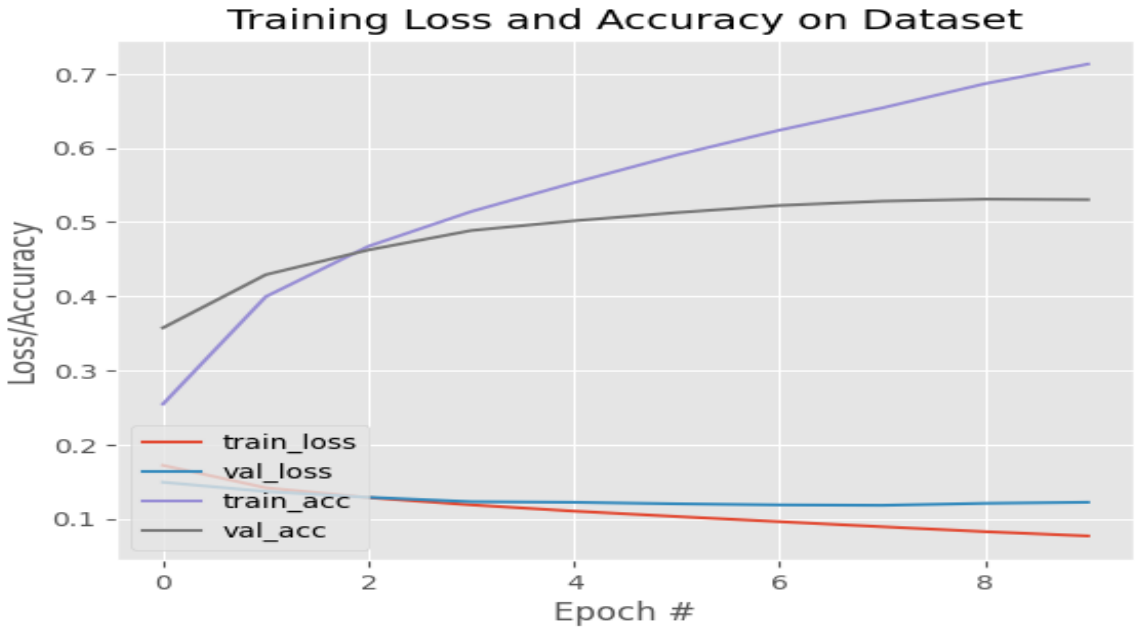
CNN2 Accuracy: 53.560

	precision	recall	f1-score	support
aquatic mammals	0.05	0.05	0.05	500
fish	0.07	0.06	0.06	500
flowers	0.05	0.04	0.05	500
food containers	0.04	0.03	0.03	500
fruit and vegetables	0.05	0.07	0.06	500
household electrical devices	0.06	0.05	0.05	500
household furniture	0.05	0.05	0.05	500
insects	0.04	0.05	0.05	500
large carnivores	0.04	0.04	0.04	500
large man-made outdoor things	0.06	0.10	0.07	500
large natural outdoor scenes	0.04	0.04	0.04	500
large omnivores and herbivores	0.06	0.05	0.05	500
medium-sized mammals	0.06	0.08	0.07	500
non-insect invertebrates	0.06	0.04	0.05	500
people	0.04	0.05	0.04	500
reptiles	0.05	0.04	0.04	500
small mammals	0.05	0.05	0.05	500
trees	0.06	0.06	0.06	500
vehicles 1	0.04	0.04	0.04	500
vehicles 2	0.05	0.05	0.05	500
accuracy			0.05	10000
macro avg	0.05	0.05	0.05	10000
weighted avg	0.05	0.05	0.05	10000

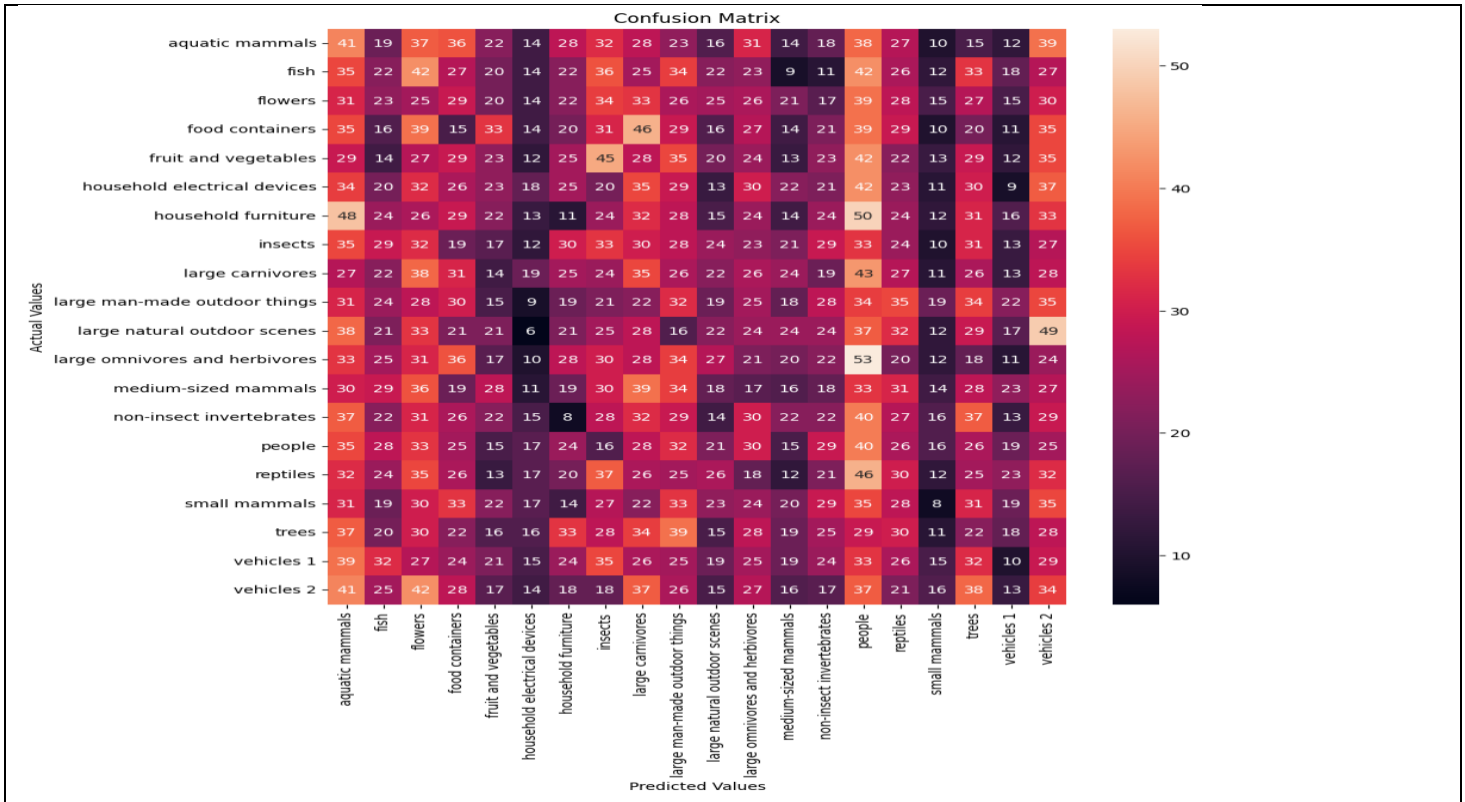
2nd CNN Accuracy and Loss Results

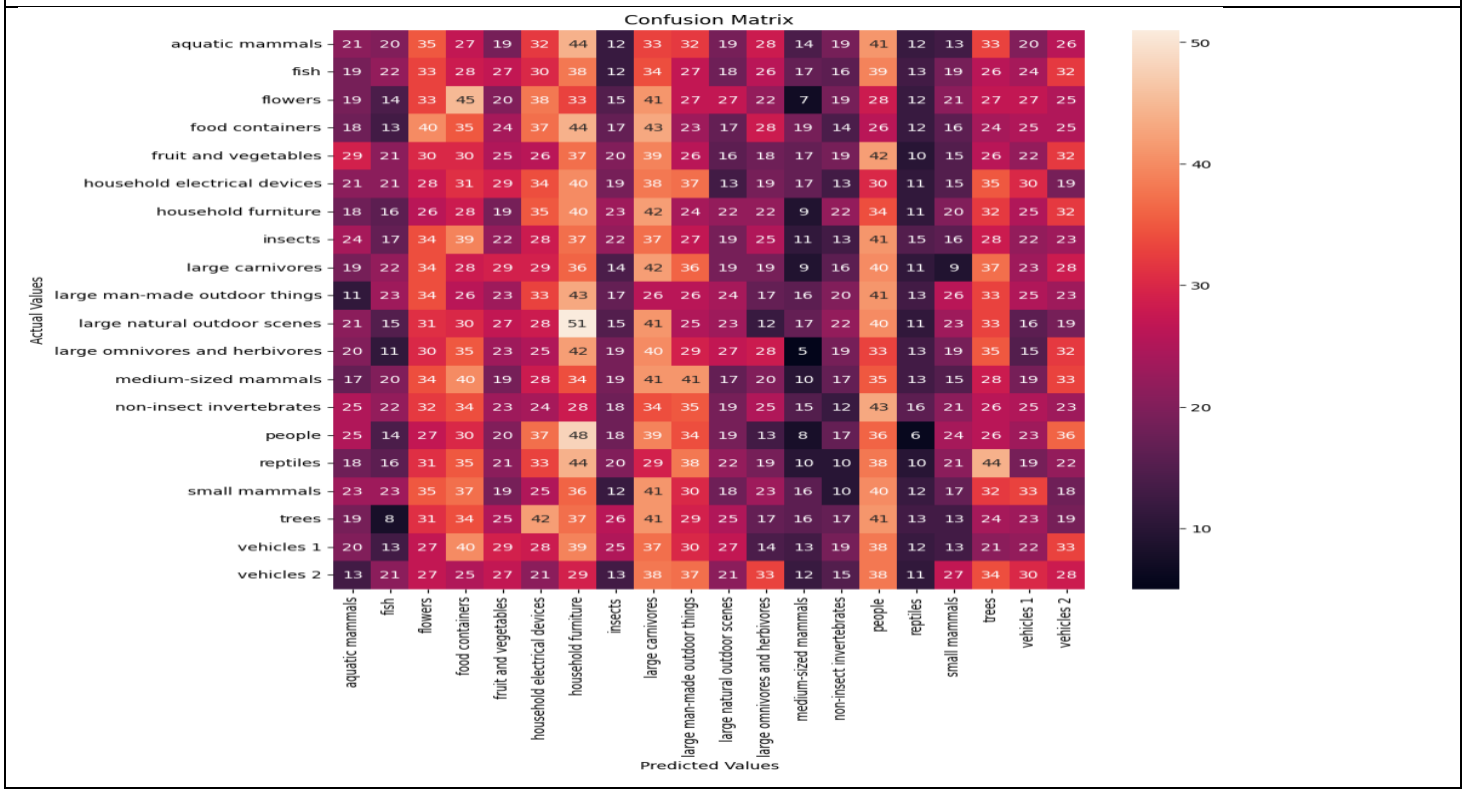


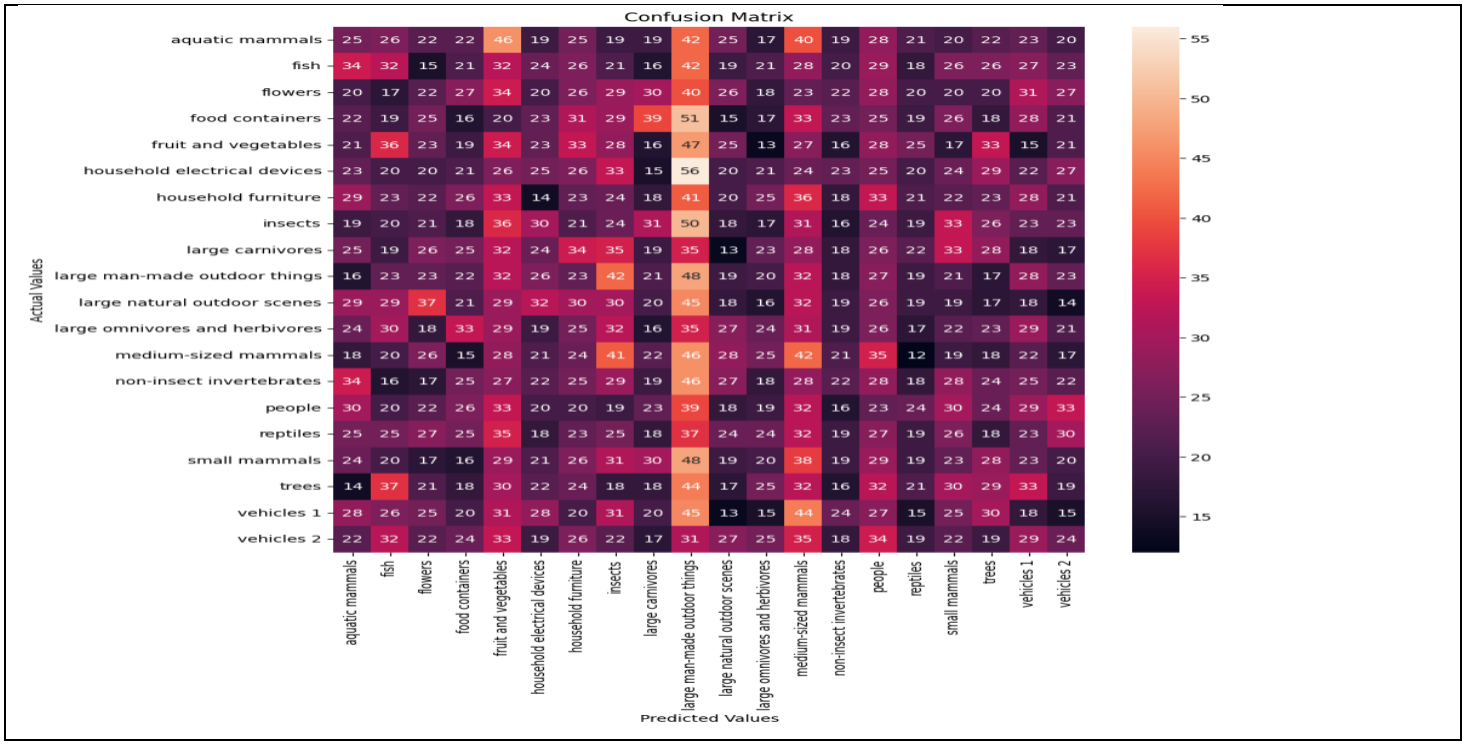




2nd CNN Confusion Matrix HeatMap


Confusion Matrix
aquatic mammals 41 19 37 36 22 14 28 32 28 23 16 31 14 18 38 27 10 15 12 39
fish 35 22 42 27 20 14 22 36 25 34 22 23 9 11 42 26 12 33 18 27
flowers 31 23 25 29 20 14 22 34 33 26 25 26 21 17 39 28 15 27 15 30
food containers 35 16 39 15 33 14 20 31 46 29 16 27 14 21 39 29 10 20 11 35
fruit and vegetables 29 14 27 29 23 12 25 45 28 35 20 24 13 23 42 22 13 29 12 35
household electrical devices 34 20 32 26 23 18 25 20 35 29 13 30 22 21 42 23 11 30 9 37
household furniture 48 24 26 29 22 13 11 24 32 28 15 24 14 24 50 24 12 31 16 33
insects 35 29 32 19 17 12 30 33 30 28 24 23 21 29 33 24 10 31 13 27
large carnivores 27 22 38 31 14 19 25 24 35 26 22 26 24 19 43 27 11 26 13 28
large man-made outdoor things 31 24 28 30 15 9 19 21 22 32 19 25 18 28 34 35 19 34 22 35
large natural outdoor scenes 38 21 33 21 21 6 21 25 28 16 22 24 24 24 37 32 12 29 17 49
large omnivores and herbivores 33 25 31 36 17 10 28 30 28 34 27 21 20 22 53 20 12 18 11 24
medium-sized mammals 30 29 36 19 28 11 19 30 39 34 18 17 16 18 33 31 14 28 23 27
non-insect invertebrates 37 22 31 26 22 15 8 28 32 29 14 30 22 22 40 27 16 37 13 29
people 35 28 33 25 15 17 24 16 28 32 21 30 15 29 40 26 16 26 19 25
reptiles 32 24 35 26 13 17 20 37 26 25 26 18 12 21 46 30 12 25 23 32
small mammals 31 19 30 33 22 17 14 27 22 33 23 24 20 29 35 28 8 31 19 35
trees 37 20 30 22 16 16 33 28 34 39 15 28 19 25 29 30 11 22 18 28
vehicles 1 39 32 27 24 21 15 24 35 26 25 19 25 19 24 33 26 15 32 10 29
vehicles 2 41 25 42 28 17 14 18 18 37 26 15 27 16 17 37 21 16 38 13 34
aquatic mammals
fish
flowers
food containers
fruit and vegetables
household electrical devices
household furniture
insects
large carnivores
large man-made outdoor things
large natural outdoor scenes
large omnivores and herbivores
medium-sized mammals
non-insect invertebrates
people
reptiles
small mammals
trees
vehicles 1
vehicles 2
Actual Values
Predicted Values
50
40
30
20
10


Confusion Matrix
aquatic mammals 21 20 35 27 19 32 44 12 33 32 19 28 14 19 41 12 13 33 20 26
fish 19 22 33 28 27 30 38 12 34 27 18 26 17 16 39 13 19 26 24 32
flowers 19 14 33 45 20 38 33 15 41 27 27 22 7 19 28 12 21 27 27 25
food containers 18 13 40 35 24 37 44 17 43 23 17 28 19 14 26 12 16 24 25 25
fruit and vegetables 29 21 30 30 25 26 37 20 39 26 16 18 17 19 42 10 15 26 22 32
household electrical devices 21 21 28 31 29 34 40 19 38 37 13 19 17 13 30 11 15 35 30 19
household furniture 18 16 26 28 19 35 40 23 42 24 22 22 9 22 34 11 20 32 25 32
insects 24 17 34 39 22 28 37 22 37 27 19 25 11 13 41 15 16 28 22 23
large carnivores 19 22 34 28 29 29 36 14 42 36 19 19 9 16 40 11 9 37 23 28
large man-made outdoor things 11 23 34 26 23 33 43 17 26 26 24 17 16 20 41 13 26 33 25 23
large natural outdoor scenes 21 15 31 30 27 28 51 15 41 25 23 12 17 22 40 11 23 33 16 19
large omnivores and herbivores 20 11 30 35 23 25 42 19 40 29 27 28 5 19 33 13 19 35 15 32
medium-sized mammals 17 20 34 40 19 28 34 19 41 41 17 20 10 17 35 13 15 28 19 33
non-insect invertebrates 25 22 32 34 23 24 28 18 34 35 19 25 15 12 43 16 21 26 25 23
people 25 14 27 30 20 37 48 18 39 34 19 13 8 17 36 6 24 26 23 36
reptiles 18 16 31 35 21 33 44 20 29 38 22 19 10 10 38 10 21 44 19 22
small mammals 23 23 35 37 19 25 36 12 41 30 18 23 16 10 40 12 17 32 33 18
trees 19 8 31 34 25 42 37 26 41 29 25 17 16 17 41 13 13 24 23 19
vehicles 1 20 13 27 40 29 28 39 25 37 30 27 14 13 19 38 12 13 21 22 33
vehicles 2 13 21 27 25 27 21 29 13 38 37 21 33 12 15 38 11 27 34 30 28
aquatic mammals
fish
flowers
food containers
fruit and vegetables
household electrical devices
household furniture
insects
large carnivores
large man-made outdoor things
large natural outdoor scenes
large omnivores and herbivores
medium-sized mammals
non-insect invertebrates
people
reptiles
small mammals
trees
vehicles 1
vehicles 2
Actual Values
Predicted Values
50
40
30
20
10


Confusion Matrix
Actual Values
Predicted Values
aquatic mammals 25 26 22 22 46 19 25 19 19 42 25 17 40 19 28 21 20 22 23 20
fish 34 32 15 21 32 24 26 21 16 42 19 21 28 20 29 18 26 26 27 23
flowers 20 17 22 27 34 20 26 29 30 40 26 18 23 22 28 20 20 20 31 27
food containers 22 19 25 16 20 23 31 29 39 51 15 17 33 23 25 19 26 18 28 21
fruit and vegetables 21 36 23 19 34 23 33 28 16 47 25 13 27 16 28 25 17 33 15 21
household electrical devices 23 20 20 21 26 25 26 33 15 56 20 21 24 23 25 20 24 29 22 27
household furniture 29 23 22 26 33 14 23 24 18 41 20 25 36 18 33 21 22 23 28 21
insects 19 20 21 18 36 30 21 24 31 50 18 17 31 16 24 19 33 26 23 23
large carnivores 25 19 26 25 32 24 34 35 19 35 13 23 28 18 26 22 33 28 18 17
large man-made outdoor things 16 23 23 22 32 26 23 42 21 48 19 20 32 18 27 19 21 17 28 23
large natural outdoor scenes 29 29 37 21 29 32 30 30 20 45 18 16 32 19 26 19 19 17 18 14
large omnivores and herbivores 24 30 18 33 29 19 25 32 16 35 27 24 31 19 26 17 22 23 29 21
medium-sized mammals 18 20 26 15 28 21 24 41 22 46 28 25 42 21 35 12 19 18 22 17
non-insect invertebrates 34 16 17 25 27 22 25 29 19 46 27 18 28 22 28 18 28 24 25 22
people 30 20 22 26 33 20 20 19 23 39 18 19 32 16 23 24 30 24 29 33
reptiles 25 25 27 25 35 18 23 25 18 37 24 24 32 19 27 19 26 18 23 30
small mammals 24 20 17 16 29 21 26 31 30 48 19 20 38 19 29 19 23 28 23 20
trees 14 37 21 18 30 22 24 18 18 44 17 25 32 16 32 21 30 29 33 19
vehicles 1 28 26 25 20 31 28 20 31 20 45 13 15 44 24 27 15 25 30 18 15
vehicles 2 22 32 22 24 33 19 26 22 17 31 27 25 35 18 34 19 22 19 29 24
aquatic mammals
fish
flowers
food containers
fruit and vegetables
household electrical devices
household furniture
insects
large carnivores
large man-made outdoor things
large natural outdoor scenes
large omnivores and herbivores
medium-sized mammals
non-insect invertebrates
people
reptiles
small mammals
trees
vehicles 1
vehicles 2
55
50
45
40
35
30
25
20
15