Deferral CSC8635 Machine Learning Project

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1 Introduction

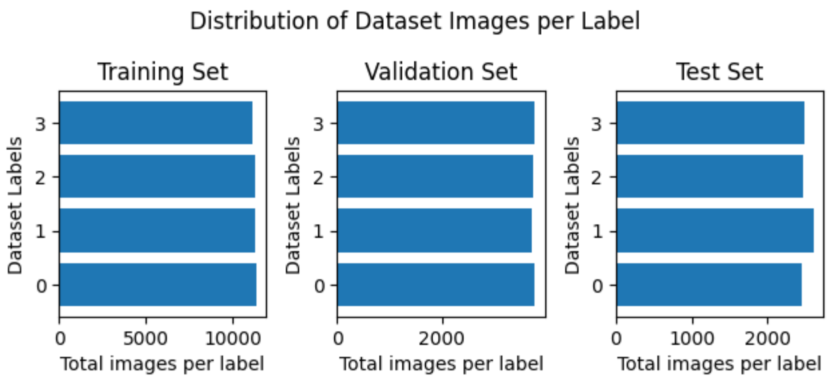
This report is about the image dataset task 2 in the CSC8635 Machine Learning Project. It will be structured in the typical machine learning pipeline workflow, that is exploration, preprocessing, model training, model interpretation and evaluation.

2 Exploration

The dataset being investigated is called CIFARTile, a 64x64 size images dataset which consist of 4 CIFAR-10 32x32 images as "tiles" in the images. The labels corresponds to the number of unique CIFAR-10 classification in an image minus 1, example images are in Figure 1.

Figure 1: Examples of CIFARTile

Investigating the distribution of labels across the dataset in Figure 2 shows that the data is well balanced which avoids instances of over-fitting or under-fitting.



Label	Frequency
0	11359
1	11250
2	11264
3	11127

Label	Frequency
0	3764
1	3714
2	3741
3	3781

Label	Frequency
0	2443
1	2602
2	2473
3	2482

Figure 2: The distribution of labels across the dataset

However, for the images in the dataset, the training and validation data contain noise as in ”empty black margins” between the CIFAR-10 images in the CIFARTile (see Figure 3). On the other hand the test data does not contain the same noise (see Figure 4). Furthermore, the images have non-standard colour range scaling of -1.9892120361328125 to -1.9892120361328125.

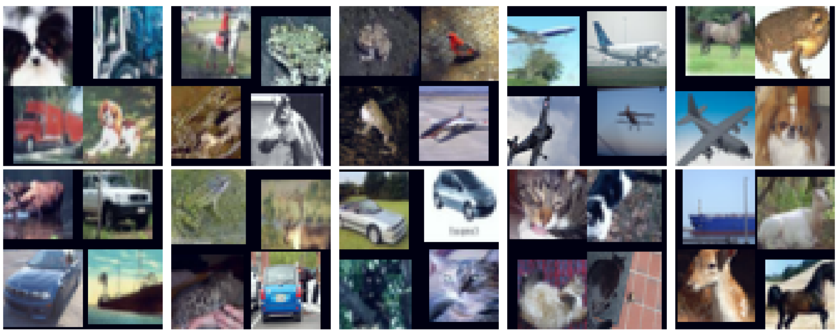


Figure 3: Example of the dataset images that contain ”empty black margins”

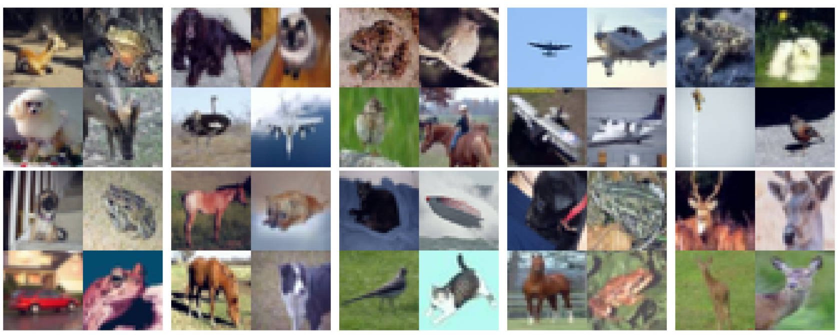


Figure 4: Example of the test image which seems to not contain noise

2.1 Finding the values of the noise

In this subsection, the methodology took to identify the colour values of the "empty black margins" noise.

First, use an image with the noise as the basis to finding the colour values. The example used is the first image in the training data (see Figure 5). The image is then temporary converted to 8-bit 0 to 255 RGB colour values (see section 3 Preprocessing for more details).

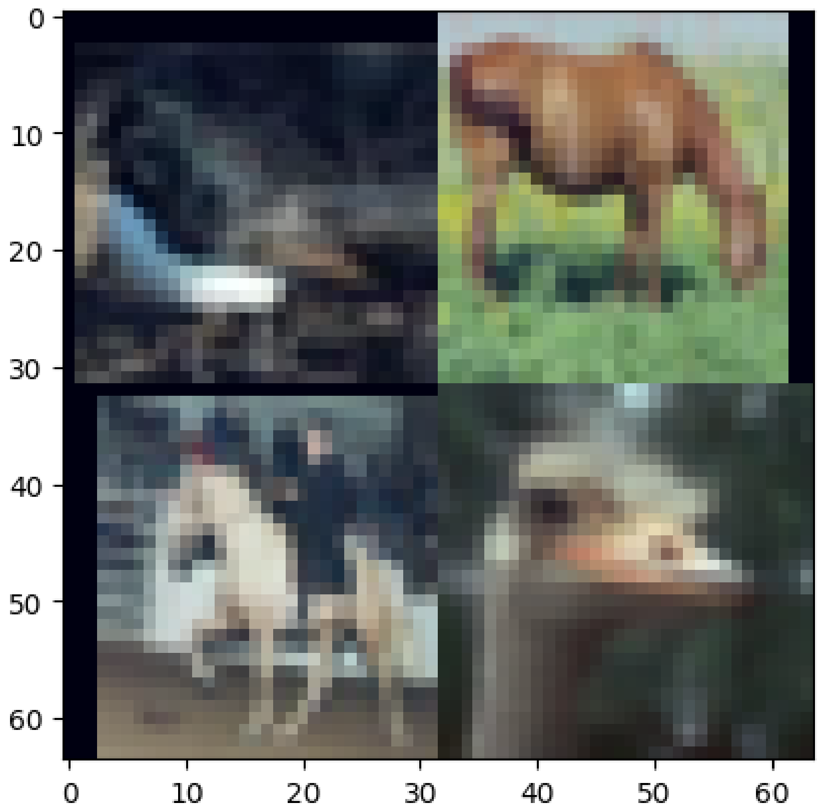


Figure 5: Base image used to identify the RGB 8-bit colour values of "empty black margins" noise

Second, using the base image in Figure 5, the first row (top of the image), column (left vertical line) and last column (right vertical line) are retrieved then the mode is calculated to determine the 3 channel colours which was determined to be `[0, 0, 17]`.

Last, to determine that the value is consistent with the other images in the dataset, 10 images are randomly selected which then have every pixels set to white beside the pixels containing the value `[0, 0, 17]`, see Figure 6 - you can see other pixels that are not noise have the same value as `[0, 0, 17]`, this is handled in the section 3 Preprocessing.

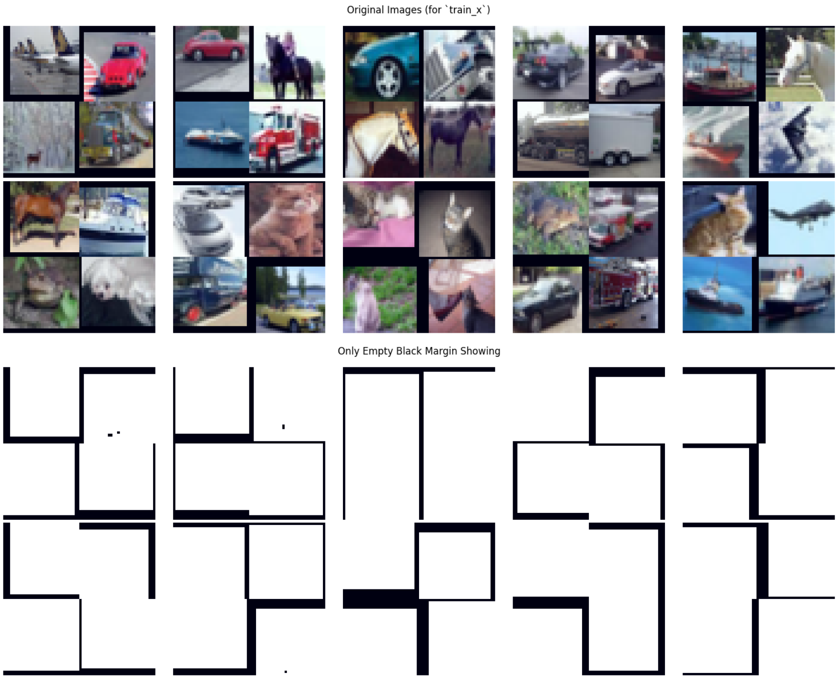


Figure 6: 10 random images that shows the original images compare to only keeping the values `[0, 0, 17]`

3 Preprocessing

In this section, it will discuss how is the noise removed in the images (subsection 3.1) and how are the labels handled (subsection 3.2).

3.1 Removing noise in the images

First, the image is normalised from the colour range scaling of -1.9892120361328125 to -1.9892120361328125, to a 0 to 1 scaling. Then it will be further scaled to unsigned 8-bit integer scaling of 0 to 255 which done in the reason of simplify the preprocessing preprocess of removing the noise in images.

Second, a Python class called `EmptyMarginRemover` which contain the functions `split_tiles()`, `remove_empty_margins()`, `combine_tiles()` and `preprocess()`.

The `preprocess()` is the main function that runs the `EmptyMarginRemover` class, which takes 64x64 unsigned 8-bit RGB channel CIFARTile images and it will be fed to other functions of the class in this order: `split_tiles()`, `remove_empty_margins()`, `combine_tiles()`.

As discussed in section Exploration, the CIFARTile dataset consists of 4 CIFAR-10 images which is divided into 32x32 images in the 64x64 image - this is further confirmed by looking at the test data, see Figure 4. Thus, the CIFARTile images are split into 4 images by the `split_tiles()` function to simplify the preprocessing methodology.

The 4 images are then fed individually into the `remove_empty_margins()` function. This function takes each row and column of the images and calculates the average of each colour values to determine if the row or column pixels only contain the values of `[0, 0, 17]` which has the average of 6 when rounded as a whole number (see Figure 7).

$$row\_or\_column\_of\_pixels\_in\_a\_tile = 32 \tag{1}$$

$$colour\_channel\_of\_empty\_margin = (0 + 0 + 17) \tag{2}$$

$$rgb\_colour\_channel\_size = 3 \tag{3}$$

$$total\_pixels\_with\_colour\_channels = row\_or\_column\_of\_pixels\_in\_a\_tile \times rgb\_colour\_channel\_size \tag{4}$$

$$\frac{row\_or\_column\_of\_pixels\_in\_a\_tile \times colour\_channel\_of\_empty\_margin}{total\_pixels\_with\_colour\_channels} = 5.6666666\ldots \tag{5}$$

$$\frac{32 \times (0 + 0 + 17)}{(32 \times 3)} = 5.6666666\ldots \tag{6}$$

Figure 7: Equations related to tile processing

Once each of the 4 images are preprocessed under `remove_empty_margins()` function, it will then be combined back into 64x64 CIFARTile using `combine_tiles()` and returned - see examples of before and after the preprocessing in Figure 8

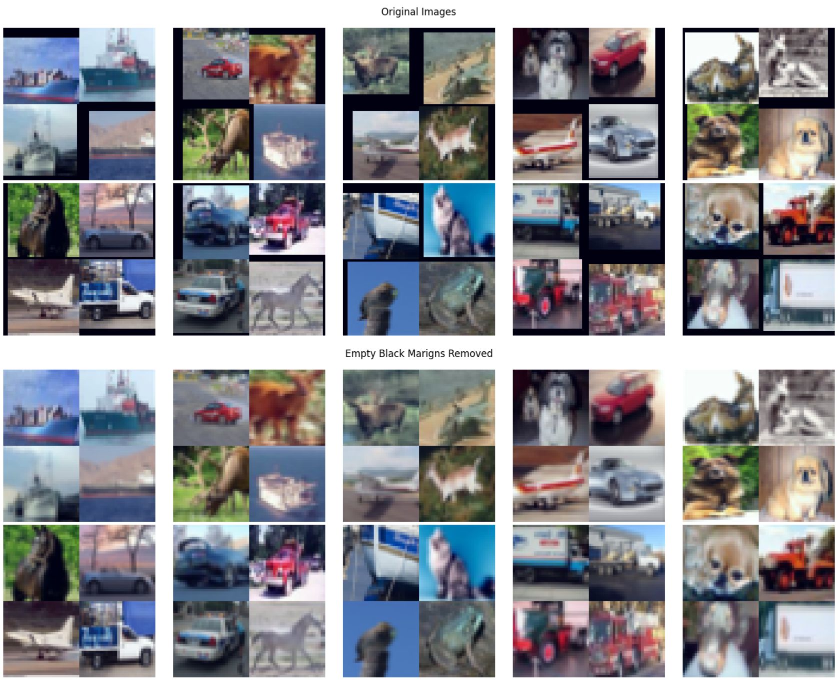


Figure 8: Example of image before and after the `EmptyMarginRemover` preprocess class

3.2 Handling labels

Due to this being a image classification problem, one-hot encoding is performed on the labels to provide the model more information of the categorical variables.

4 Model Training

4.1 Why ResNet50v2?

ResNet50v2 is well-suited for the CIFARTile image classification problem due to its architectural strengths and proven performance in complex image tasks [1, 2].

Firstly, the depth of ResNet50v2, comprising 50 layers, enables it to learn and represent complex patterns effectively. This depth is crucial for the CIFARTile dataset, where each 64x64 image consists of four tiled CIFAR-10 images, creating a more complex classification challenge than standard single-image tasks.

A key feature of ResNet architectures, including ResNet50v2, is residual connections. These connections help prevent the vanishing gradient problem, facilitating efficient training even with many layers. This is particularly beneficial for CIFARTile images, where capturing intricate features across the tiled sub-images is essential.

ResNet50v2 is designed to capture hierarchical features, starting from low-level features such as edges and textures to high-level features like shapes and objects. This ability to capture and integrate features at different scales is crucial for accurate classification of CIFARTile images, which contain multiple smaller images.

ResNet50v2 has a strong track record in image classification benchmarks, demonstrating high accuracy and robustness across diverse datasets. Its proven performance on the CIFAR-10 dataset, which forms the basis of the CIFARTile dataset, underscores its reliability for extending to the more complex CIFARTile problem.

In summary, ResNet50v2's depth, residual connections, hierarchical feature learning, proven effectiveness, and adaptability make it an excellent choice for the CIFARTile classification task.

4.2 Hyperparameter tuning

For the Hyperparameter tuning, a grid-search is used to iterate to all possible hyperparameter combinations. The hyperparameters chosen are the following:

Pooling	**Optimizer**	**Learning Rate**
avg	adam	0.1
max	rmsprop	0.01
	sgd	0.001

Table 1: Configuration hyperparameters for the model

The choice of hyperparameters for ResNet50v2 aims to optimise its performance for the CIFARTile image classification task by exploring various configurations.

For pooling methods, average pooling (avg) smooths feature maps by averaging values within a pooling window, reducing noise and retaining prominent features. This helps stabilise the learning process. On the other hand, max pooling (max) selects the maximum value in a pooling window, capturing dominant features and preserving important spatial hierarchies, which is useful for well-defined features.

Regarding optimisers, Adam combines the benefits of AdaGrad and RMSProp, adapting learning rates for each parameter, making it robust and efficient for training deep networks. RMSprop adjusts learning rates based on an exponentially decaying average of squared gradients, which stabilises training and speeds up convergence. Stochastic Gradient Descent (SGD) updates model parameters in the direction of the negative gradient and is effective with momentum for large-scale problems, helping to escape local minima and converge to the global minimum.

The learning rates chosen are 0.1, 0.01, and 0.001. A high learning rate of 0.1 allows for faster convergence but carries the risk of overshooting. A moderate rate of 0.01 balances speed and accuracy, providing stable updates. A low rate of 0.001 ensures precise convergence, reducing the risk of overshooting, making it ideal for fine-tuning.

This systematic exploration of pooling methods, optimisers, and learning rates helps identify the best hyperparameter combination, ensuring robust and accurate classification for the CIFARTile dataset.

5 Model Interpretation and Evaluation

5.1 Interpreting the hyperparameter tuning

Trial	Pooling	Optimizer	Learning Rate	Validation Accuracy
0002	avg	adam	0.001	0.525
0005	avg	rmsprop	0.001	0.524
0003	avg	rmsprop	0.01	0.449
0000	avg	adam	0.01	0.435
0016	max	sgd	0.1	0.424
0007	avg	sgd	0.1	0.421
0011	max	adam	0.001	0.403
0015	max	sgd	0.01	0.386
0006	avg	sgd	0.01	0.386
0017	max	sgd	0.001	0.277

Table 2: Summary of the 10 Best Trials

The results of the best 10 trials indicate that the optimal configuration for the ResNet50v2 model on the CIFARTile dataset involves specific combinations of hyperparameters.

The most successful trial (0002) used an Adam optimiser with a learning rate of 0.001 and average pooling, achieving the highest score of 0.525. This suggests that Adam with a low learning rate and average pooling is highly effective.

Trial 0005, with similar settings but using RMSprop instead of Adam, achieved a nearly equivalent score of 0.524, indicating that RMSprop is also a strong choice when paired with average pooling and a low learning rate.

Scores declined notably when the learning rate was increased to 0.01, as seen in trials 0003 and 0000, regardless of whether Adam or RMSprop was used, showing the importance of a lower learning rate for optimal performance.

Trials with max pooling generally performed worse than those with average pooling. For instance, trial 0011, which used max pooling with Adam and a learning rate of 0.001, had a lower score of 0.403.

SGD as an optimiser, regardless of the pooling method or learning rate, consistently yielded lower scores compared to Adam and RMSprop. The best SGD result (trial 0016) with max pooling and a learning rate of 0.1 scored 0.424, further emphasising that SGD is less effective for this task.

Overall, the results highlight that using the Adam optimiser with a learning rate of 0.001 and average pooling provides the best performance for the ResNet50v2 model on the CIFARTile dataset.

5.2 Evaluating the best 2 models

two best models from the trials, namely Trial 0002 and Trial 0005, Both models exhibit similar performance, but there are slight differences in their metrics. Trial 0005 achieves a marginally higher test accuracy (50.58%) compared to Trial 0002 (50.37%). This indicates that Trial 0005 correctly classifies a slightly higher percentage of test samples.

However, when considering precision, Trial 0002 (0.4995) outperforms Trial 0005 (0.4896). Precision measures the accuracy of positive predictions, suggesting that Trial 0002 is somewhat better at ensuring that predicted positives are actual positives.

In terms of recall, which measures the ability to capture actual positives, Trial 0005 (0.5058) is marginally better than Trial 0002 (0.5037). This means Trial 0005 is slightly more effective at identifying true positive cases.

For confusion matrix, see Figure 9, The confusion matrix indicatesstrong performance in label class `1` and `2` for Trail 0002, however, it is worser classification for labels `0` and more worse `4` compare to Trail 0005.

The F1 Score, which balances precision and recall, is slightly higher for Trial 0002 (0.4988) compared to Trial 0005 (0.4878). This indicates that Trial 0002 has a more balanced performance between precision and recall despite, Trial 0002 having a weaker classification for class label `4` than Trial 0005.

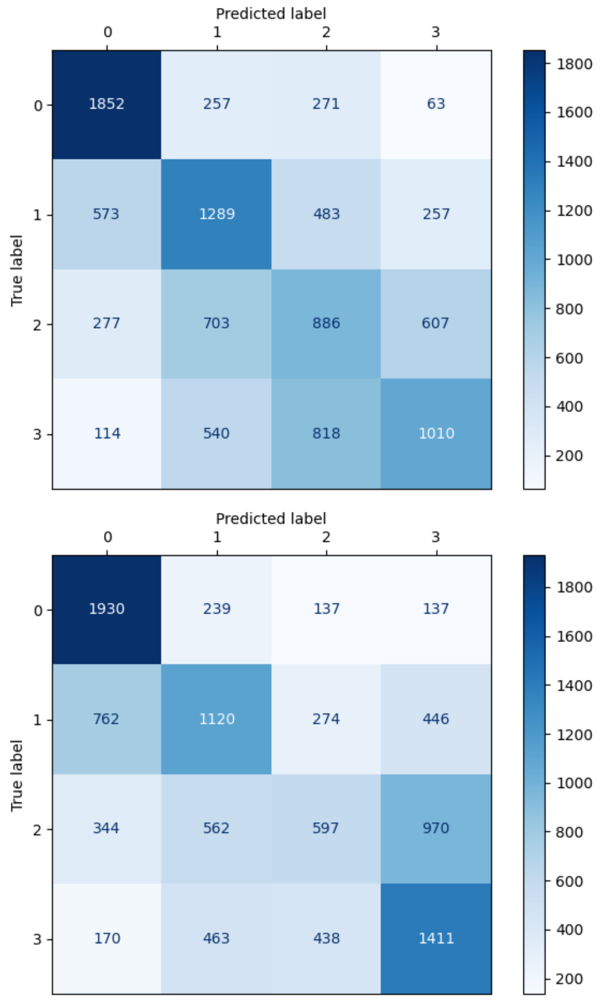


Figure 9: Confusion matrix for Trail 0002 (top) and Trail 0005 (bottom)

References

[1] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[2] ——, "Identity mappings in deep residual networks," *CoRR*, vol. abs/1603.05027, 2016. [Online]. Available: http://arxiv.org/abs/1603.05027