

Neural report

Part 1

Firstly, I called my `load_data` function with arguments batch size and number of workers which returns the `train_loader` and `test_loader`. The training pipeline included data augmentation, this was used to help with generalisation using a method of regularisation to help decrease overfitting. Looking at [\[1\]](#) Showed me how to correctly load and also to include normalize where I researched the best values and came across these which are the ones I use [\[2\]](#). The augmentations I used where found from here [\[3\]](#).

Part 2 (more detailed explanation found in the code comments)

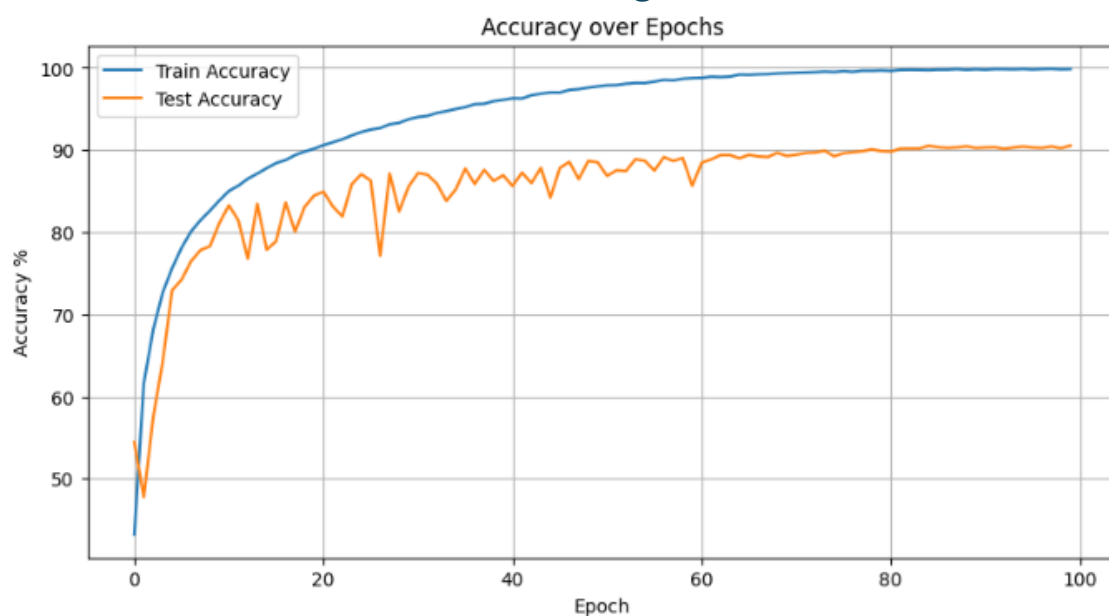
For creating the model, I firstly started by breaking each section down into its own class. The model itself is a class, this contains the initialisation of the stem, backbone and classifier, it returns the output of the classifier after going through the other components. I then create a class for the Stem, the Stem is a convolutional layer, that has BatchNorm to make the output of conv easier to learn from, next adding Relu for non-linearity to make features more complex (inspiration for the stem as a conv layer came from ECS659U TUTORIAL SHEET "conv_example.ipynb"). Then I have a class Backbone which initialises a list of Block modules for the desired amount [\[4\]](#). Block class is where the calculation for the output of each block happens, it also initialises the ExpertBranch and ConvLayers. ExpertBranch was implemented by following the CW guidelines (inspired by "conv_example.ipynb"). Next is the conv layers also implemented as CW guidelines say, but I found that adding BatchNorm and relu produced higher accuracies for me due to reasons stated earlier. Lastly the output is passed to the classifier where the required implementation is done, however SoftMax is done in the `train_one_epoch` method.

Part 3

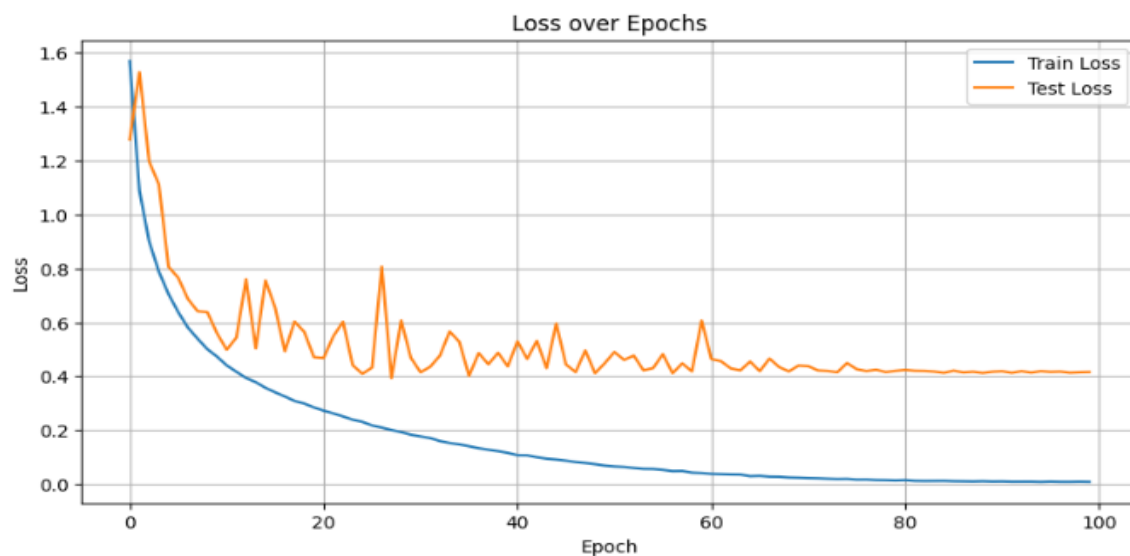
For my loss I used Cross Entropy and for my optimiser I used AdamW these were implemented in my `get_lossfunc_optimiser_scheduler`.

Part 4

The curves for the evolution of training and validation



The curves for the evolution of loss



All Training details including hyper-parameters used

num_blocks = 8

This refers to the number of blocks within my backbone, each block produces an output / feature map this is used as the next blocks input. This controls the depth of my network going beyond the initial stem, increasing the extraction of high-level features from an input image in the batch. I found that decreasing the number of blocks to 3-5 range makes my time per epoch much higher, however making accuracy much lower. Compared to increasing the number of blocks I found I get a higher accuracy on both training and testing, however it takes much longer per epoch.

output_channels or channels = 64

This hyper parameter was used as the amount of output channels for the stem, each conv layer in the convolution branch, and used as input for the classifier, conv branch and expert branch. This defines the number of channels a feature map has, increasing it means there is more capacity to learn more features. I found that having this too high meant epoch times increased by a large margin. Increasing the number of channels to 128 gave me lower accuracy peaks for my test data, I believe this is because this produced more features making the model memorise instead of generalising, leading to overfitting.

Reduction = 8

This controls how much the channels are reduced by in the expert branch. I initially played around with this value and found that having it too low meant there were more channels which lead to overfitting. I didn't really tune this parameter as much and kept it at 8 the majority of my time trying to improve test accuracy via other parameters. Looking back, I should have increased this reduction as I still have an aspect of overfitting.

K = 3

This determines how many convolutional branches there are in each block, and the output dimensions of the expert branch. I experimented with changing the k value between the ranges 2-5 and found that as I increased the k the initial accuracy also increased, reducing k decreased accuracy but made the time per epoch faster. With a small number of K I also observed that each jump in training per epoch initially was much lower compared to if I increased K to a specific point which was 3. When I set k=2 my model was stuck at a test accuracy of 89%, increasing it to 3 allowed me to achieve 90%.

learning rate = 0.0003

I found that increasing my learning rate also made my initial and final test and train accuracies much lower. Slowly decreasing it after many attempts, I landed on 0.0003 as the right balance to help me achieve 90%, however this may be too lower as my model gets stuck in the 89% test accuracy for a while .

weight_decay = 0.001

I added a small weight decay to help counteract overfitting I was getting into the mid 50 epochs, this slightly solved the issue.

AdamW, Cross Entropy Loss, Scheduler CosineAnnealingLR

Here I Used AdamW as my optimiser as I heard this pairs well with changing learning rates and decay, whereas Adam doesn't work as well with weight decay [5]. I used CrossEntropyLoss as it's the standard for classification models. I also used Cosine to help adjust the learning rate over time to.

Data augmentations (referenced in part 1)

Implementing these allowed to massively counteract memorisation and allow to model to generalise.

Overall

The classification process begins in the Stem class, where low level features from the input images are extracted. This output is then passed into the BackBone class which holds the 'n' number of blocks. Each block has a ExpertBranch and a Conv branch with 'k' conv layers. The expert branch outputs a vector 'a' of length 'k' for each input image. The output of the conv branch is then multiplied by the corresponding 'ak' and summed. Next this output feature map is passed to the classifier which produces logits for the 10 classes. Calling cross entropy loss applies SoftMax and calculates the probabilities for the logits that sum to 1.

Part 5

Final model accuracy was 90.53% over 100 epochs

Epoch [1/100] Train Loss: 1.5080 Train Acc: 43.31% Test Loss: 1.7070 Test Acc: 34.46% Time: 118.27s	Epoch [61/100] Train Loss: 0.0383 Train Acc: 98.78% Test Loss: 0.4642 Test Acc: 88.45% Time: 94.00s
Epoch [2/100] Train Loss: 1.3679 Train Acc: 48.87% Test Loss: 1.5767 Test Acc: 37.13% Time: 121.62s	Epoch [62/100] Train Loss: 0.0372 Train Acc: 98.92% Test Loss: 0.4560 Test Acc: 88.86% Time: 94.18s
Epoch [3/100] Train Loss: 1.2640 Train Acc: 52.46% Test Loss: 1.4567 Test Acc: 39.80% Time: 124.97s	Epoch [63/100] Train Loss: 0.0360 Train Acc: 98.88% Test Loss: 0.4295 Test Acc: 89.38% Time: 98.62s
Epoch [4/100] Train Loss: 1.1404 Train Acc: 56.15% Test Loss: 1.3403 Test Acc: 42.50% Time: 128.32s	Epoch [64/100] Train Loss: 0.0356 Train Acc: 98.94% Test Loss: 0.4239 Test Acc: 89.35% Time: 116.58s
Epoch [5/100] Train Loss: 1.0401 Train Acc: 59.12% Test Loss: 1.2327 Test Acc: 45.13% Time: 131.58s	Epoch [65/100] Train Loss: 0.0297 Train Acc: 99.18% Test Loss: 0.4548 Test Acc: 89.80% Time: 115.88s
Epoch [6/100] Train Loss: 0.9589 Train Acc: 60.40% Test Loss: 1.1347 Test Acc: 47.83% Time: 134.84s	Epoch [66/100] Train Loss: 0.0308 Train Acc: 99.15% Test Loss: 0.4198 Test Acc: 89.41% Time: 108.52s
Epoch [7/100] Train Loss: 0.8809 Train Acc: 62.43% Test Loss: 1.0457 Test Acc: 50.28% Time: 138.09s	Epoch [67/100] Train Loss: 0.0278 Train Acc: 99.21% Test Loss: 0.4659 Test Acc: 89.22% Time: 99.26s
Epoch [8/100] Train Loss: 0.8171 Train Acc: 63.87% Test Loss: 0.9597 Test Acc: 51.35% Time: 137.48s	Epoch [68/100] Train Loss: 0.0274 Train Acc: 99.23% Test Loss: 0.4343 Test Acc: 89.15% Time: 98.59s
Epoch [9/100] Train Loss: 0.7627 Train Acc: 65.08% Test Loss: 0.8805 Test Acc: 53.70% Time: 140.80s	Epoch [69/100] Train Loss: 0.0248 Train Acc: 99.32% Test Loss: 0.4182 Test Acc: 89.45% Time: 98.00s
Epoch [10/100] Train Loss: 0.7182 Train Acc: 67.13% Test Loss: 0.8030 Test Acc: 54.68% Time: 144.41s	Epoch [70/100] Train Loss: 0.0239 Train Acc: 99.36% Test Loss: 0.4399 Test Acc: 89.28% Time: 97.88s
Epoch [11/100] Train Loss: 0.6807 Train Acc: 68.41% Test Loss: 0.7306 Test Acc: 57.43% Time: 147.48s	Epoch [71/100] Train Loss: 0.0225 Train Acc: 99.41% Test Loss: 0.4377 Test Acc: 89.42% Time: 97.88s
Epoch [12/100] Train Loss: 0.6488 Train Acc: 69.45% Test Loss: 0.6588 Test Acc: 58.43% Time: 151.72s	Epoch [72/100] Train Loss: 0.0217 Train Acc: 99.44% Test Loss: 0.4219 Test Acc: 89.64% Time: 98.83s
Epoch [13/100] Train Loss: 0.6207 Train Acc: 70.45% Test Loss: 0.5901 Test Acc: 59.40% Time: 155.37s	Epoch [73/100] Train Loss: 0.0202 Train Acc: 99.48% Test Loss: 0.4199 Test Acc: 89.69% Time: 98.48s
Epoch [14/100] Train Loss: 0.5958 Train Acc: 71.32% Test Loss: 0.5248 Test Acc: 60.33% Time: 159.06s	Epoch [74/100] Train Loss: 0.0198 Train Acc: 99.53% Test Loss: 0.4152 Test Acc: 89.72% Time: 97.68s
Epoch [15/100] Train Loss: 0.5730 Train Acc: 72.05% Test Loss: 0.4687 Test Acc: 61.22% Time: 162.79s	Epoch [75/100] Train Loss: 0.0195 Train Acc: 99.50% Test Loss: 0.4493 Test Acc: 89.24% Time: 97.88s
Epoch [16/100] Train Loss: 0.5521 Train Acc: 72.73% Test Loss: 0.4031 Test Acc: 61.93% Time: 166.49s	Epoch [76/100] Train Loss: 0.0178 Train Acc: 99.60% Test Loss: 0.4264 Test Acc: 89.60% Time: 98.00s
Epoch [17/100] Train Loss: 0.5324 Train Acc: 73.37% Test Loss: 0.3454 Test Acc: 62.54% Time: 170.20s	Epoch [77/100] Train Loss: 0.0172 Train Acc: 99.52% Test Loss: 0.4195 Test Acc: 89.74% Time: 98.08s
Epoch [18/100] Train Loss: 0.5140 Train Acc: 73.98% Test Loss: 0.2907 Test Acc: 63.05% Time: 173.92s	Epoch [78/100] Train Loss: 0.0154 Train Acc: 99.60% Test Loss: 0.4245 Test Acc: 89.86% Time: 97.71s
Epoch [19/100] Train Loss: 0.4968 Train Acc: 74.57% Test Loss: 0.2393 Test Acc: 63.55% Time: 177.65s	Epoch [79/100] Train Loss: 0.0149 Train Acc: 99.63% Test Loss: 0.4159 Test Acc: 90.08% Time: 94.91s
Epoch [20/100] Train Loss: 0.4808 Train Acc: 75.14% Test Loss: 0.1933 Test Acc: 64.05% Time: 181.39s	Epoch [80/100] Train Loss: 0.0137 Train Acc: 99.69% Test Loss: 0.4203 Test Acc: 89.87% Time: 98.48s
Epoch [21/100] Train Loss: 0.4659 Train Acc: 75.69% Test Loss: 0.1487 Test Acc: 64.55% Time: 185.14s	Epoch [81/100] Train Loss: 0.0148 Train Acc: 99.64% Test Loss: 0.4237 Test Acc: 89.81% Time: 98.72s
Epoch [22/100] Train Loss: 0.4520 Train Acc: 76.22% Test Loss: 0.1062 Test Acc: 65.05% Time: 188.90s	Epoch [82/100] Train Loss: 0.0123 Train Acc: 99.75% Test Loss: 0.4208 Test Acc: 90.16% Time: 97.34s
Epoch [23/100] Train Loss: 0.4390 Train Acc: 76.73% Test Loss: 0.0678 Test Acc: 65.55% Time: 192.67s	Epoch [83/100] Train Loss: 0.0113 Train Acc: 99.77% Test Loss: 0.4199 Test Acc: 90.17% Time: 97.96s
Epoch [24/100] Train Loss: 0.4268 Train Acc: 77.22% Test Loss: 0.0322 Test Acc: 66.05% Time: 196.45s	Epoch [84/100] Train Loss: 0.0120 Train Acc: 99.76% Test Loss: 0.4377 Test Acc: 90.17% Time: 96.83s
Epoch [25/100] Train Loss: 0.4154 Train Acc: 77.69% Test Loss: 0.0252 Test Acc: 66.55% Time: 200.24s	Epoch [85/100] Train Loss: 0.0122 Train Acc: 99.73% Test Loss: 0.4138 Test Acc: 90.52% Time: 100.78s
Epoch [26/100] Train Loss: 0.4047 Train Acc: 78.14% Test Loss: 0.0202 Test Acc: 67.05% Time: 204.04s	Epoch [86/100] Train Loss: 0.0110 Train Acc: 99.78% Test Loss: 0.4211 Test Acc: 90.34% Time: 116.59s
Epoch [27/100] Train Loss: 0.3947 Train Acc: 78.57% Test Loss: 0.0167 Test Acc: 67.55% Time: 207.85s	Epoch [87/100] Train Loss: 0.0106 Train Acc: 99.78% Test Loss: 0.4145 Test Acc: 90.26% Time: 115.73s
Epoch [28/100] Train Loss: 0.3854 Train Acc: 78.98% Test Loss: 0.0140 Test Acc: 68.05% Time: 211.67s	Epoch [88/100] Train Loss: 0.0100 Train Acc: 99.85% Test Loss: 0.4170 Test Acc: 90.22% Time: 116.88s
Epoch [29/100] Train Loss: 0.3768 Train Acc: 79.37% Test Loss: 0.0120 Test Acc: 68.55% Time: 215.50s	Epoch [89/100] Train Loss: 0.0109 Train Acc: 99.77% Test Loss: 0.4325 Test Acc: 90.43% Time: 115.77s
Epoch [30/100] Train Loss: 0.3688 Train Acc: 79.74% Test Loss: 0.0107 Test Acc: 69.05% Time: 219.34s	Epoch [90/100] Train Loss: 0.0097 Train Acc: 99.83% Test Loss: 0.4171 Test Acc: 90.25% Time: 116.78s
Epoch [31/100] Train Loss: 0.3613 Train Acc: 80.09% Test Loss: 0.0094 Test Acc: 69.55% Time: 223.19s	Epoch [91/100] Train Loss: 0.0101 Train Acc: 99.78% Test Loss: 0.4198 Test Acc: 90.31% Time: 116.08s
Epoch [32/100] Train Loss: 0.3543 Train Acc: 80.42% Test Loss: 0.0087 Test Acc: 69.85% Time: 227.05s	Epoch [92/100] Train Loss: 0.0091 Train Acc: 99.85% Test Loss: 0.4138 Test Acc: 90.34% Time: 116.63s
Epoch [33/100] Train Loss: 0.3478 Train Acc: 80.73% Test Loss: 0.0082 Test Acc: 70.15% Time: 230.92s	Epoch [93/100] Train Loss: 0.0092 Train Acc: 99.84% Test Loss: 0.4192 Test Acc: 90.43% Time: 115.79s
Epoch [34/100] Train Loss: 0.3417 Train Acc: 81.02% Test Loss: 0.0078 Test Acc: 70.45% Time: 234.80s	Epoch [94/100] Train Loss: 0.0092 Train Acc: 99.82% Test Loss: 0.4136 Test Acc: 90.41% Time: 117.12s
Epoch [35/100] Train Loss: 0.3360 Train Acc: 81.29% Test Loss: 0.0074 Test Acc: 70.75% Time: 238.69s	Epoch [95/100] Train Loss: 0.0084 Train Acc: 99.86% Test Loss: 0.4192 Test Acc: 90.42% Time: 115.88s
Epoch [36/100] Train Loss: 0.3306 Train Acc: 81.54% Test Loss: 0.0070 Test Acc: 71.05% Time: 242.59s	Epoch [96/100] Train Loss: 0.0094 Train Acc: 99.81% Test Loss: 0.4166 Test Acc: 90.31% Time: 116.14s
Epoch [37/100] Train Loss: 0.3255 Train Acc: 81.78% Test Loss: 0.0066 Test Acc: 71.35% Time: 246.50s	Epoch [97/100] Train Loss: 0.0086 Train Acc: 99.85% Test Loss: 0.4177 Test Acc: 90.26% Time: 109.78s
Epoch [38/100] Train Loss: 0.3206 Train Acc: 82.00% Test Loss: 0.0062 Test Acc: 71.65% Time: 250.42s	Epoch [98/100] Train Loss: 0.0085 Train Acc: 99.88% Test Loss: 0.4134 Test Acc: 90.43% Time: 95.27s
Epoch [39/100] Train Loss: 0.3160 Train Acc: 82.20% Test Loss: 0.0058 Test Acc: 71.95% Time: 254.35s	Epoch [99/100] Train Loss: 0.0091 Train Acc: 99.82% Test Loss: 0.4151 Test Acc: 90.22% Time: 94.08s
Epoch [40/100] Train Loss: 0.3116 Train Acc: 82.38% Test Loss: 0.0054 Test Acc: 72.25% Time: 258.29s	Epoch [100/100] Train Loss: 0.0086 Train Acc: 99.85% Test Loss: 0.4160 Test Acc: 90.53% Time: 94.28s

References (corresponding code can be found by looking at the code comments)

- [1] https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html
- [2] <https://github.com/kuangliu/pytorch-cifar/issues/19>
- [3] <https://juliusruseckas.github.io/ml/lightning.html>
- [4] <https://pytorch.org/docs/stable/generated/torch.nn.ModuleList.html>
- [5] <https://www.datacamp.com/tutorial/adamw-optimizer-in-pytorch>
- [6] https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html
- [7] <https://pytorch.org/tutorials/beginner/introyt/trainingyt.html>
- [8] <https://discuss.pytorch.org/t/on-running-loss-and-average-loss/107890>