Artificial Intelligence-Homework 1

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Introduction

1. In this assignment, I disign experiments to compare the test perforamnce of 4 loss functions in multi-class classification task. And loss functions are given specifically below:
   - MAE(L1) loss: `nn.L1Loss()`
   - CE (Cross-Entropy) Loss: `nn.CrossEntropyLoss()`
   - Focal Loss (gamma=0.5): `FocalLoss(gamma=0.5, alpha=None)`
   - Focal Loss (gamma=2): `FocalLoss(gamma=2, alpha=None)`

```
class FocalLoss(nn.Module):
    def __init__(self, gamma=2, alpha=None):
        super(FocalLoss, self).__init__()
        self.gamma = gamma
        self.alpha = alpha

    def forward(self, output, target):
        # 计算交叉熵损失
        ce_loss = F.cross_entropy(output, target, reduction='none')

        # 计算概率
        pt = torch.exp(-ce_loss)

        # 计算Focal Loss
        focal_loss = ((1 - pt) ** self.gamma) * ce_loss

        # 加权Focal Loss
        if self.alpha is not None:
            assert len(self.alpha) == output.size(1), "Alpha must have the same length as the number of classes."
            alpha = self.alpha[target]
            focal_loss = focal_loss * alpha

        return focal_loss.mean()
```

2. To quantify the performance, here is some metrics for each loss function.
   - Accuracy: Computes the accuracy rate of the model on the test set to assess the predictive power of the model.
   - Model Convergence Speed: Evaluated by monitoring the loss value changes by function at each training epoch. Here I use function `.pct_change()` to get percentage change between each element in the list and its preceding element, and the more it nears zero, the closer to convergence of the loss function.
   - Overfitting and Generalization: If the difference between training loss and test loss is small, then the model has good generalization ability. Conversely, if the difference between training loss and test loss is large, then the model may have an overfitting problem, i.e., it performs well on the training set but poorly on the test set. In addition, we can evaluate the generalization ability of the model by observing the trend of test loss. If the test loss remains stable or decreases after the training rounds increase, the model has good generalization ability. On the other hand, if the test loss starts to rise after the number of training rounds increases, then the model may have an overfitting problem.
   - Sensitivity: Introducing noise(in norm distribution) into the input data by `image_noise = image + torch.randn(image.size())` and then observing the change in testing loss values. The degree of fluctuation of the loss value can indicate the sensitivity of the model to noise.

3. Some hyperparameters: For every loss functions, they have same hyperparameters in one comparative experiment.
   - `NUM_EPOCHS = 40` : The number of epochs, here is constant in 40 as the model can get converged.
   - `BATCH_SIZE = 128` : The number of examples in each mini-batch, which is set to be 128 by default.

- `LEARNING_RATE = 1e-1`

4. Optimizer: I use 2 optimizers to train and test the data for each loss functions respectively.
   - SGD: `optimizer = optim.SGD(model.parameters(), lr=LEARNING_RATE, momentum=MOMENTUM)`
   - Adam: `optimizer = optim.Adam(model.parameters())`

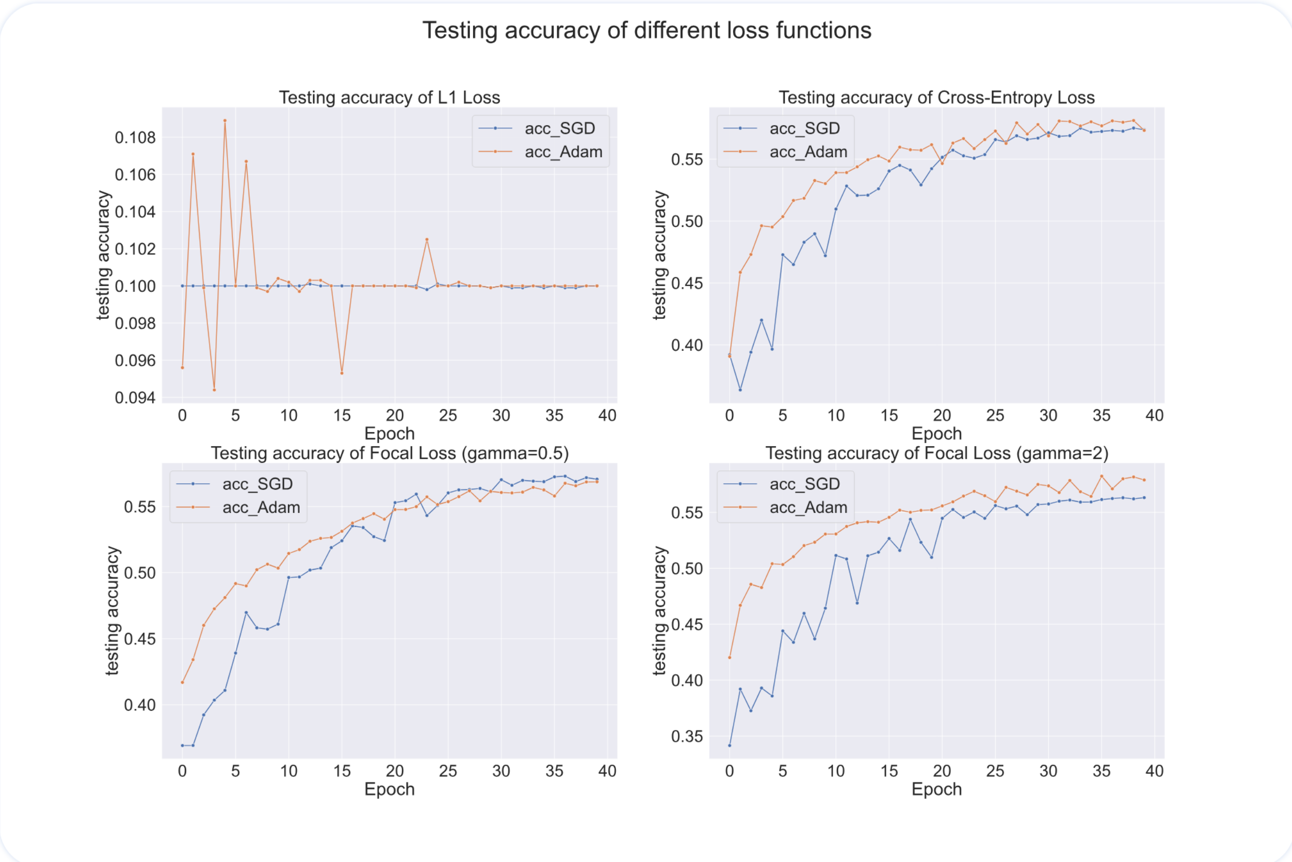
Data analyse

For each loss function, we have 12 lists to storage their expression abilities:

List Name	
`training_loss_SGD`	The value of loss function in SGD optimizer while training
`training_acc_SGD`	The accuracy rate of model in SGD optimizer while training
`testing_loss_SGD`	The value of loss function in SGD optimizer while testing
`testing_acc_SGD`	The accuracy rate of model in SGD optimizer while testing
`testing_loss_SGD_S`	The value of loss function in SGD optimizer while testing after adding noise to input image
`testing_acc_SGD_S`	The accuracy rate of model in SGD optimizer while testing after adding noise to input image
`training_loss_Adam`	The value of loss function in Adam optimizer while training
`training_acc_Adam`	The accuracy rate of model in Adam optimizer while training
`testing_loss_Adam`	The value of loss function in Adam optimizer while testing
`testing_acc_Adam`	The accuracy rate of model in Adam optimizer while testing
`testing_loss_Adam_S`	The value of loss function in Adam optimizer while testing after adding noise to input image
`testing_acc_Adam_S`	The accuracy rate of model in Adam optimizer while testing after adding noise to input image

Accuracy

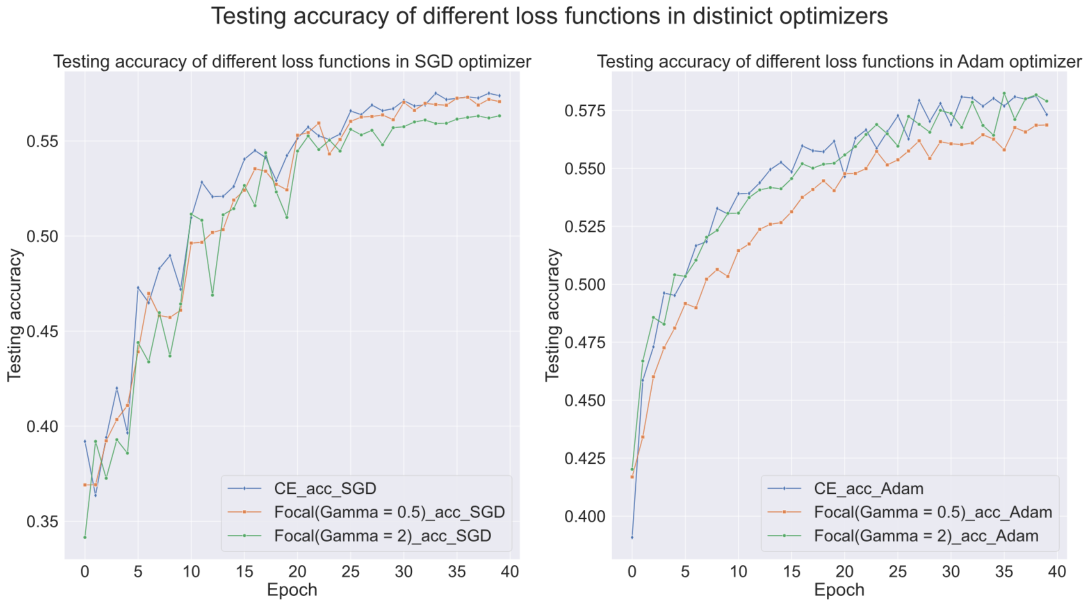
1. From the picture below, except for `L1 Loss`, the testing accuracy of other 3 loss fucntions have an overall increasing trend. In addition, we can also find that, to some extent, Adam optimizer has great advantages in improving the accuracy of the model.



> According to the figure, after referring some materials, I find that `L1 Loss` is not good at multi-classification. So I will not

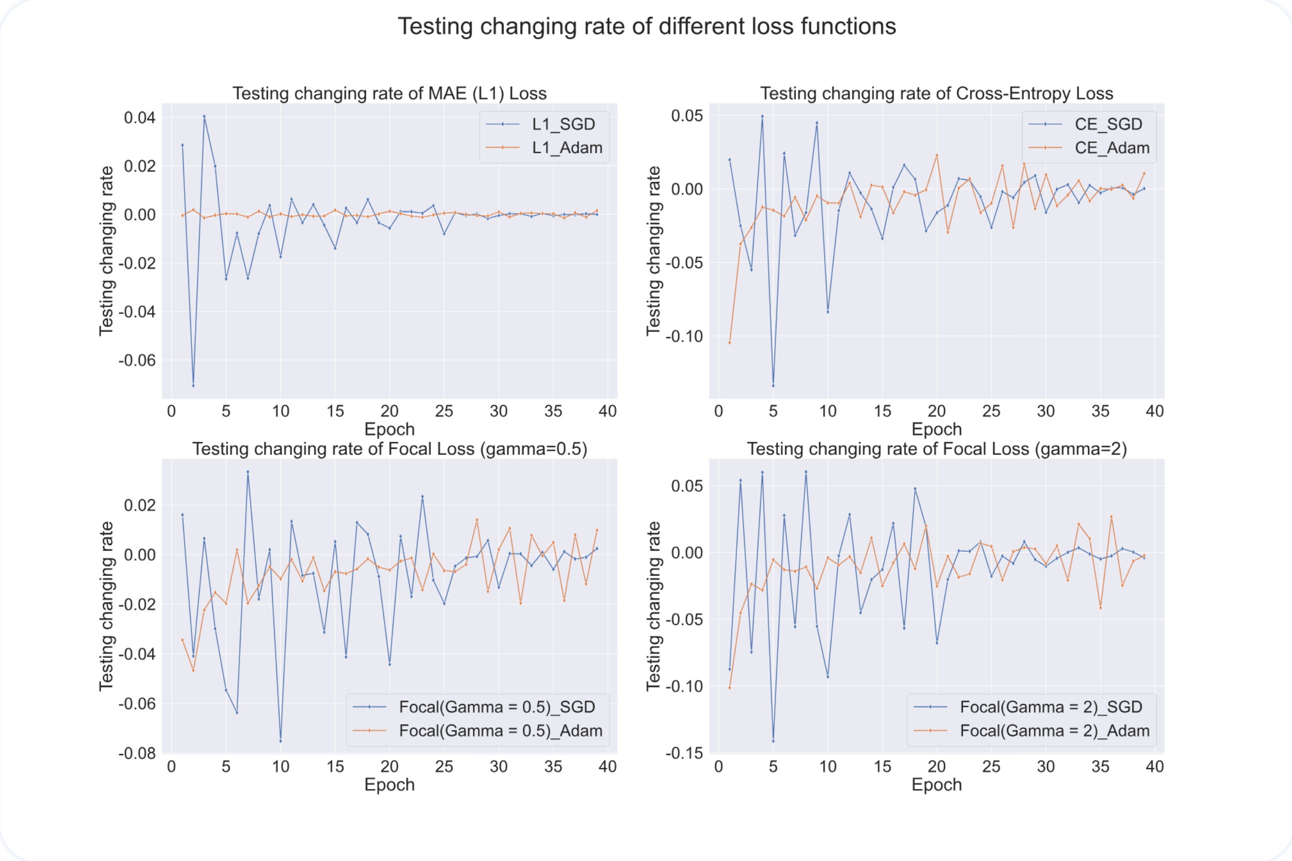
> talk much about it in the second half of the report.

2. Inspecting the picture, there are different performances in distinict optimizers.
    - In SGD optimizer, the accuracy rate of `Cross Entropy Loss` and `Focal Loss(Gamma = 0.5)` are larger than `Focal Loss(Gamma = 2)` .
    - And in Adam optimizer, `Cross Entropy Loss` and `Focal Loss(Gamma = 2)` have same expression power. Both of them have higher acceracy than `Focal Loss(Gamma = 0.5)` .



Convergence Speed

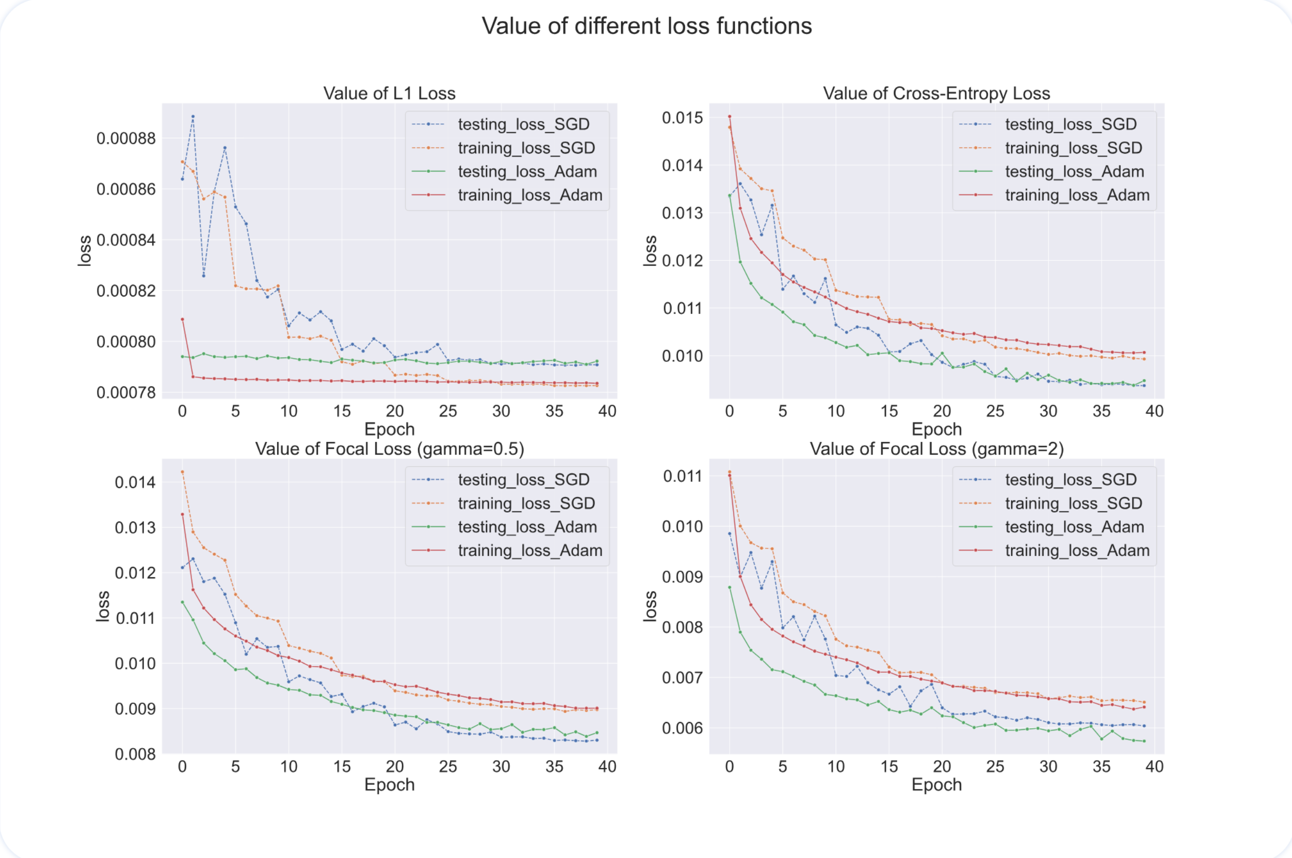
1. As presented in the diagram, for 3 loss functions, Adam optimizer has a better performance in convergence speed than SGD optimizer, which can make loss functions converge faster. More specifically, loss fucntion in Adam can be approximatelty converged in 5 epochs instead of nearly 15 epochs in SGD. However, the Adam comes to be more fluctuated than SGD in the second half of the epoches.



2. In SGD optimizer, It can be found from the figure that the `Cross-Entropy Loss` is conveging fastest, then `Focal Loss(Gamma = 2)` and `Focal Loss(Gamma = 0.5)` .

Overfitting and Generalization

1. In each subgraph, the training loss and test loss decrease gradually with the increase of training rounds. This is because as the model is trained, the model gradually learns better feature representations, resulting in lower loss values. And for 3 distinct loss function, it is clear that all the testing losses are lower than the training loss, meaning that models have good performance in the generalization instead of overfitting.



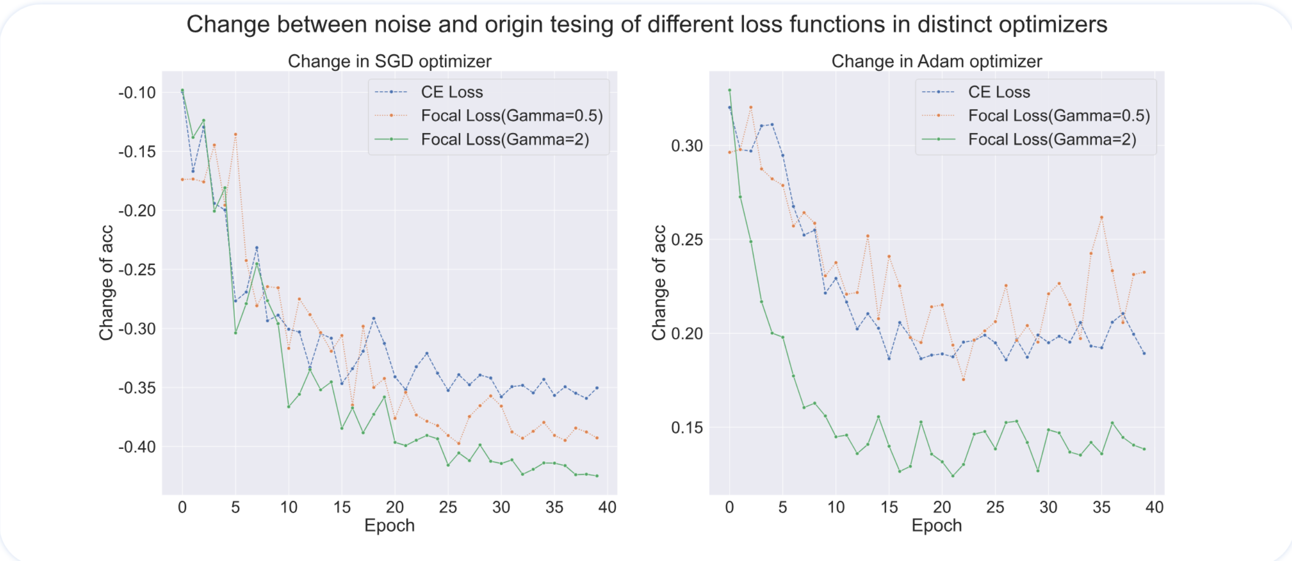
2. Then we need to note the difference between training losses and testing losses. The closer distance can get to 0, the more model will generalize. Hence, in SGD optimizer, the generalization of `CE Entropy Loss` is remarkable, then `Focal Loss(Gamma = 2)` and `Focal Loss(Gamma = 0.5)` follow. However, as for Adam optimizer, all three performed pretty well, none of them were particularly bad in generalization.

Sensitivity

1. The picture below shows the changes between testing output from noise input and testing output from original input, which are calculated by `loss_noise - loss_no_noise` and `acc_noise - acc_no_noise` . Even though all 3 loss functions have inconsistent performance in value, they have same expression that change of testing accuracy in SGD optimizer is always negative while in Adam optimizer it is always postive.

> To some degree, model in Adam optimizer have a excellent ability of generalization.

2. To test the sensitivity of model, I compute changes of accuracy of loss function between noise and no-noise. So the bigger variation (the change of acc is smaller) indicates the model is more sensitive to noise. Then, in this figure, we can distinguish that , in SGD optimizer `Cross Entropy Loss` is the most sensitive, then `Focal Loss(Gamma = 0.5)` , and `Focal Loss(Gamma = 2)` the last. While in Adam optimizer, the sensitivity from high to low is `Focal Loss(Gamma = 0.5)` , `Cross Entropy Loss` , `Focal Loss(Gamma = 2)` .



Summary

In this assignment, I conducted experiments to compare the test performance of four different loss functions in a multi-class classification task. The loss functions evaluated are MAE (L1) loss, CE (Cross-Entropy) loss, Focal Loss with gamma equal to 0.5, and Focal Loss with gamma equal to 2. Besides, I employed two optimizers, namely SGD and Adam, to train and test the models for each loss function.

The evaluation metrics used to quantify the performance of the models include accuracy, model convergence speed, overfitting and generalization, and sensitivity to noise. Here's a summary of the findings:

- **Accuracy:** `Cross-Entropy Loss` achieved the highest testing accuracy among the four loss functions, while L1 Loss performed poorly in multi-class classification.

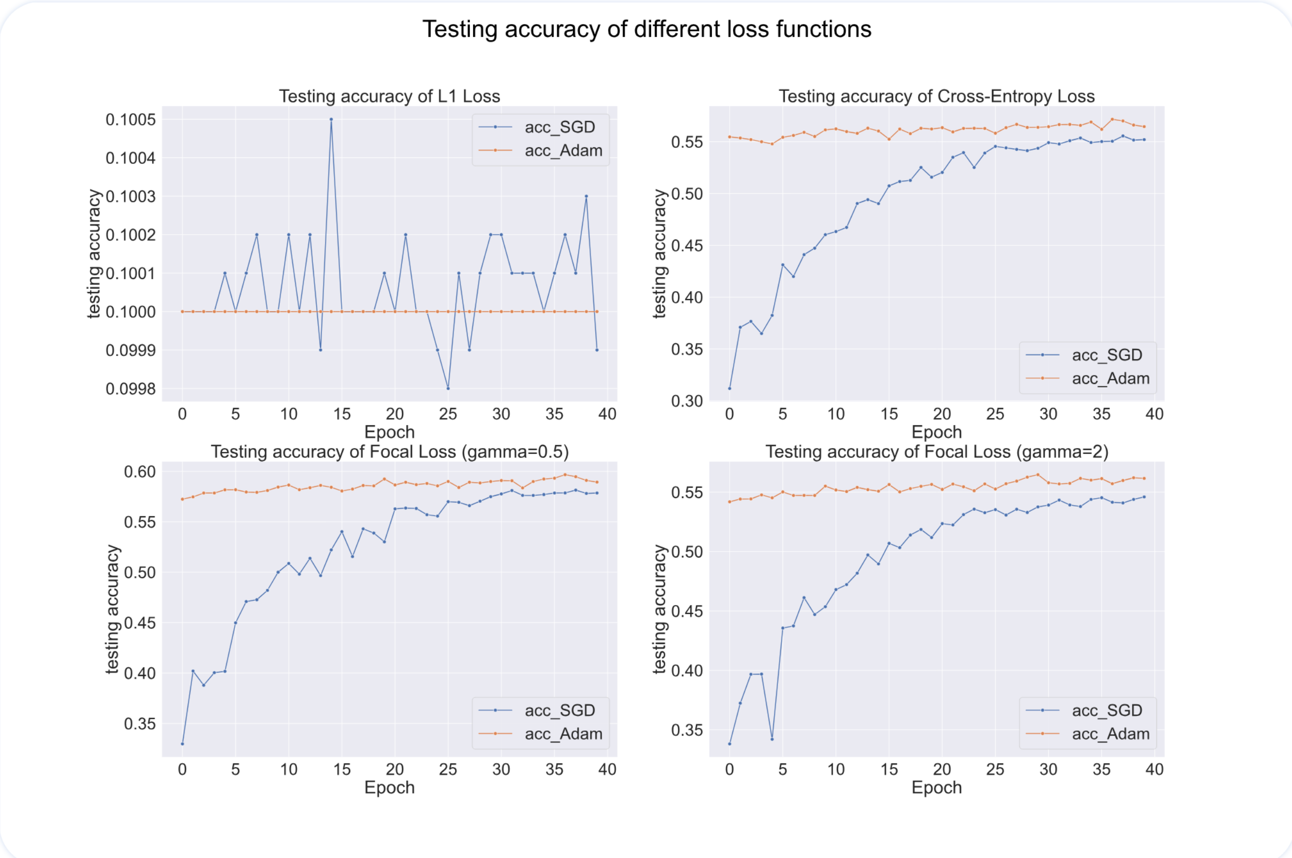
- **Convergence Speed:** Adam showed faster convergence compared to SGD. Among the loss functions in SGD, `Cross-Entropy Loss` converged the fastest, followed by `Focal Loss (Gamma = 2)` and `Focal Loss (Gamma = 0.5)` .
- **Overfitting and Generalization**:
  - All three loss functions demonstrated good generalization as the testing losses were consistently lower than the training losses.
  - In SGD optimizer, `Cross-Entropy Loss` exhibited the best generalization, followed by `Focal Loss (Gamma = 2)` and `Focal Loss (Gamma = 0.5)` . In Adam optimizer, all three loss functions showed strong generalization.
- **Sensitivity to Noise**:
  - In SGD optimizer, the models were sensitive to noise, with `Cross-Entropy Loss` being the most sensitive, followed by `Focal Loss (Gamma = 0.5)` , and `Focal Loss (Gamma = 2)` .
  - In Adam optimizer, the models showed less sensitivity to noise, with `Focal Loss (Gamma = 0.5)` being the most sensitive, followed by `Cross-Entropy Loss` , and `Focal Loss (Gamma = 2)` .

> The sensitivity experiment needs improving much as I only introduce one kind of noise in normal distribution due to the time limit and more researches need to be conducted.

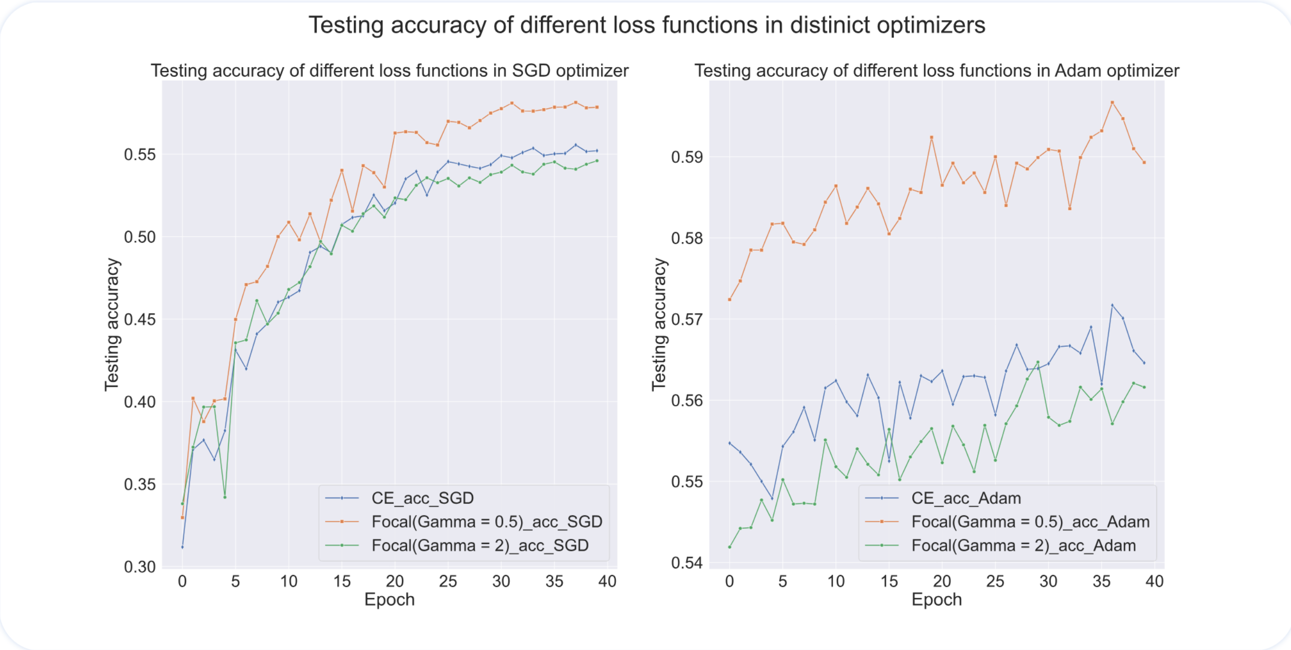
The results suggest that `Cross-Entropy Loss` is generally more suitable for multi-class classification tasks, with Adam as the preferred optimizer due to its faster convergence and better generalization.

A mistake I made

After traing the model in SGD optimizer, I forgot to update model parameters so that the result in Adam optimizer is prominent. Adam is the optimizer that follows training. For this situation, I use two different optimizers, training on the same model, it seems to work better, as if model in SGD optimizer falls into a local optimum.



What' s more, the performance of `Focal Loss(Gamma = 0.5)` is extremely exceptional. It seems that `Focal Loss(Gamma =0.5)` is more suitable for the multi-classification task, which is contradict to the conclusion above. Anyway, more researches need to be conducted.



Testing accuracy of different loss functions in distinict optimizers
Testing accuracy of different loss functions in SGD optimizer
Testing accuracy of different loss functions in Adam optimizer
Testing accuracy
Epoch
CE_acc_SGD
Focal(Gamma = 0.5)_acc_SGD
Focal(Gamma = 2)_acc_SGD
CE_acc_Adam
Focal(Gamma = 0.5)_acc_Adam
Focal(Gamma = 2)_acc_Adam