MLFA Assignment-3

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- **Experiment 1:**

- After Implementation of gradient descent approach towards logistic regression for multiple classes [LOG_MUL_GRAD] with Minibatch, I Trained the logistic regression model with learning_rate = 0.1, num_epochs = 50, batch_size = 30 and evaluated the model on the validation set. The evaluation metrics came out to be

Before feature scaling:

```
Accuracy on validation set: 83.33%
Confusion Matrix:
               [[12  0  0]
                [ 0  1  5]
                [ 0  0 12]]
Precision: 0.90
Recall: 0.72
F1-Score: 0.70
```

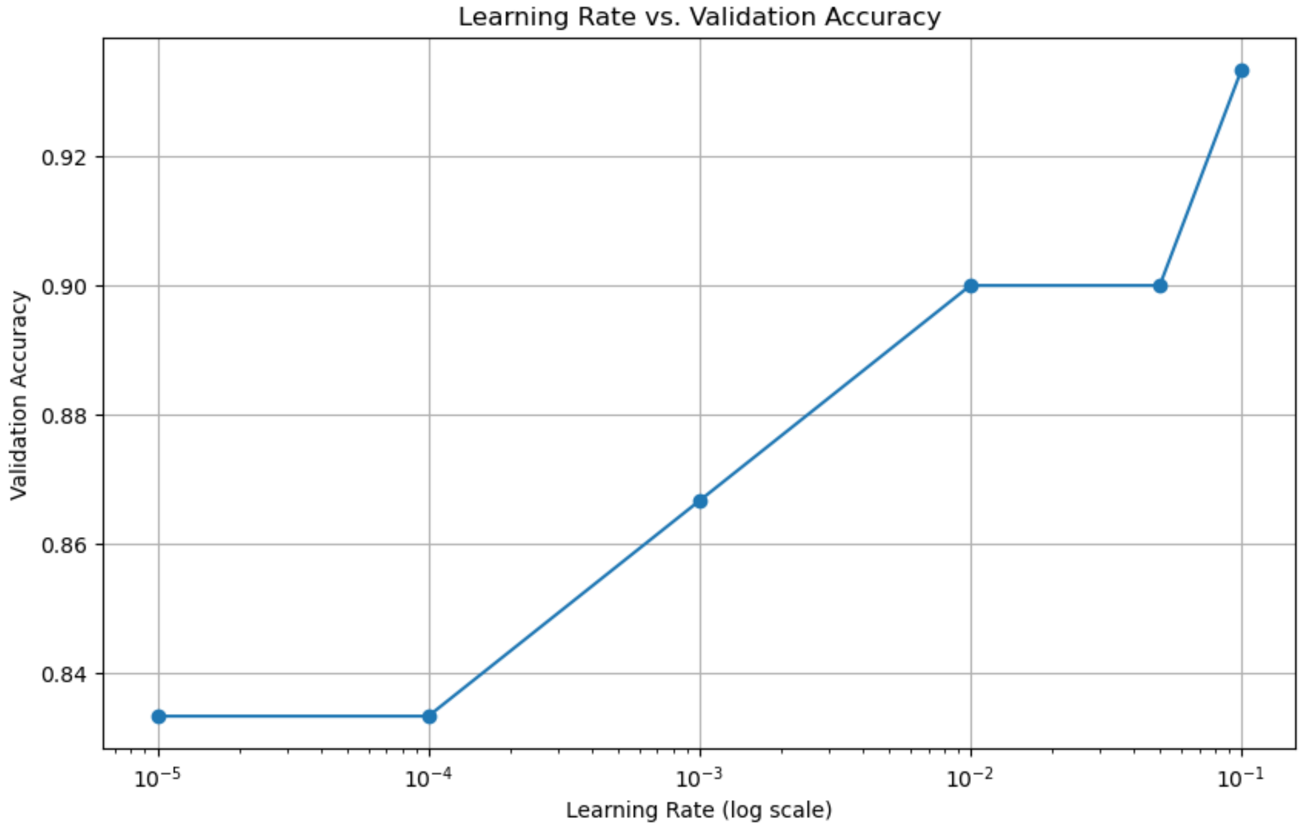
After feature scaling:

```
Accuracy on validation set: 93.33%
Confusion Matrix:
               [[12  0  0]
                [ 0  4  2]
                [ 0  0 12]]
Precision: 0.95
Recall: 0.89
F1-Score: 0.91
```

- **Experiment 2:**

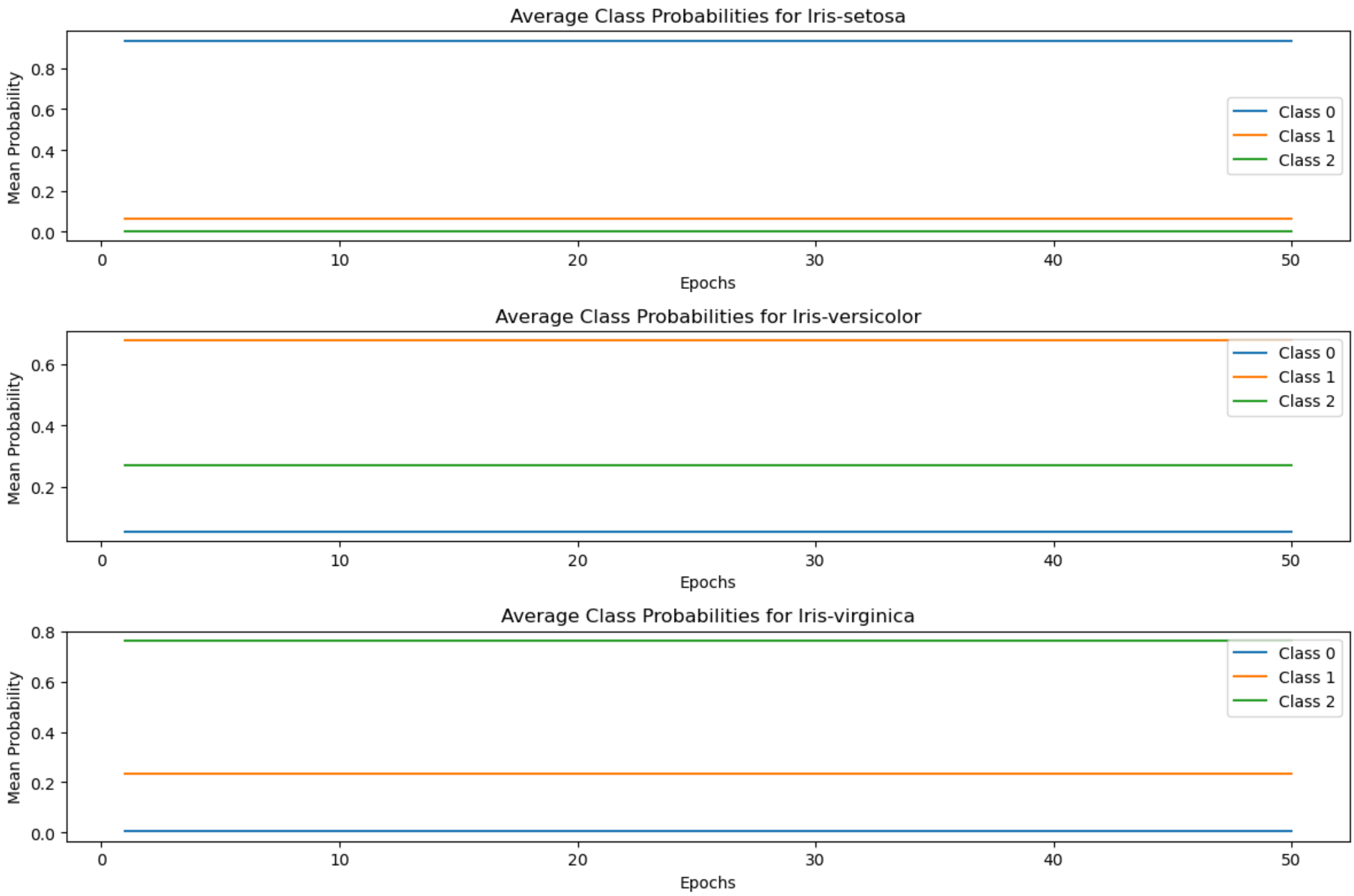
Learning Rate vs. Validation Accuracy:

```
Learning Rate: 0.000010, Accuracy: 0.8333
Learning Rate: 0.000100, Accuracy: 0.8333
Learning Rate: 0.001000, Accuracy: 0.8667
Learning Rate: 0.010000, Accuracy: 0.9000
Learning Rate: 0.050000, Accuracy: 0.9000
Learning Rate: 0.100000, Accuracy: 0.9333
```



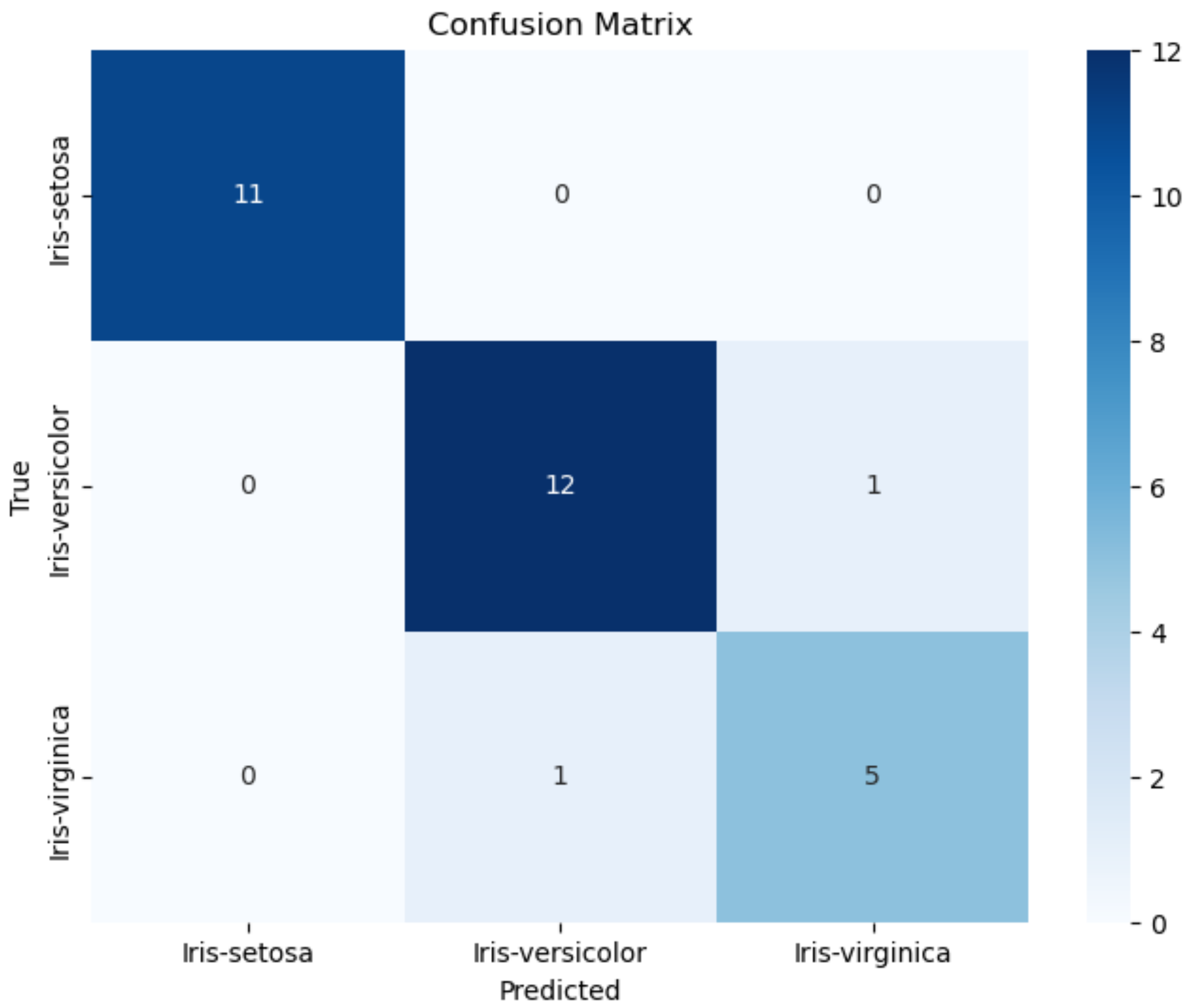
Best Learning Rate: 0.100000, Best Accuracy: 0.9333

- **Experiment 3:**



- **Experiment 4:**

Confusion matrix as heatmap:



Confusion matrix is:

```
[[11  0  0]
 [ 0 12  1]
 [ 0  1  5]]
```

Representing confusion matrix in form of table:

	Iris-setosa	Iris-versicolor	Iris-virginica
Iris-setosa	11	0	0
Iris-versicolor	0	12	1
Iris-virginica	0	1	5

Representing Precision/Recall/f1-score in form of table:

	Precision	Recall	f1-score
Iris-setosa	1	1	1
Iris-versicolor	0.92	0.92	0.92
Iris-virginica	0.83	0.83	0.83

Classification Report:

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        11
Iris-versicolor       0.92      0.92      0.92        13
 Iris-virginica       0.83      0.83      0.83         6

       accuracy                           0.93        30
      macro avg       0.92      0.92      0.92        30
   weighted avg       0.93      0.93      0.93        30
```

The classification report provides valuable insights into the model's performance for each class in our dataset. Here are some observations and explanations based on the classification report:

- **Precision, Recall, and F1-Score for Each Class:**
    - **Iris-setosa:** The precision, recall, and F1-score for Iris-setosa are all very high, indicating that the model performs exceptionally well on this class. This could suggest that Iris-setosa flowers have distinct features that make them easy to classify.
    - **Iris-versicolor**: Precision, recall, and F1-score for Iris-versicolor are also quite good but slightly lower than Iris-setosa. This suggests that the model performs well on this class, but there may be some instances of misclassification.
    - **Iris-virginica:** The model's performance on Iris-virginica is the lowest among the three classes. Precision, recall, and F1-score are all lower. This could imply that Iris-virginica might have features that make it more similar to the other classes, leading to misclassification.

- **Support:** The "support" column represents the number of samples in each class. In our dataset, Iris-setosa has the highest support, followed by Iris-versicolor, and then Iris-virginica. This indicates that there are more samples available for Iris-setosa, which might have contributed to the better performance metrics for this class.

- **Accuracy:** The overall accuracy of the model is 93%, which means that it correctly predicts the class labels for 93% of the samples in the test dataset.

- **Macro Avg and Weighted Avg:** These metrics provide an average of precision, recall, and F1-score across all classes. The macro average gives equal weight to each class, while the weighted average considers class imbalances. In our case, both macro and weighted averages are close to 0.92 and 0.93, respectively, indicating a balanced performance across classes.

- **Observations**: Based on this classification report, we can observe that the model performs exceptionally well on the class with the highest support (Iris-setosa) and relatively well on the other two classes. The differences in performance could be due to differences in the distinctiveness of class features, sample sizes, or the presence of noise in the data.

In summary, the class-specific information in the classification report reflects how well the model can distinguish between different classes in our dataset. It indicates that the model might have more difficulty distinguishing Iris-virginica due to similarities with other classes or a smaller sample size for this class. These insights can help us understand the model's strengths and weaknesses in handling different classes and guide for further improvements if needed.