ECGR-5106 Homework 1

Student Information

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Homework Number: 1

GitHub Repository

https://github.com/xuy50/ecgr5106-hw1

Problem 1: Multi-Layer Perceptron for CIFAR-10

1.a Training from Scratch

I implemented a multi-layer perceptron (MLP) with three hidden layers and trained it from scratch on the CIFAR-10 dataset. The training results for 20 epochs and 100 epochs are shown below:

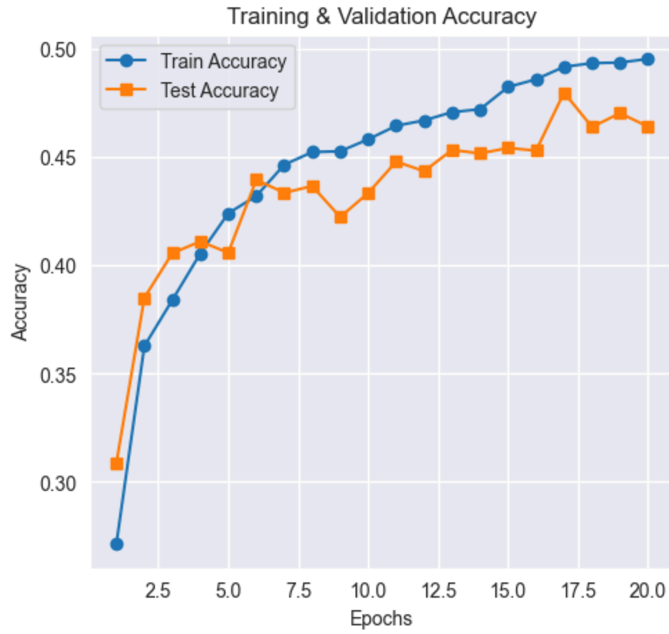
Training and Validation Results (3-Layer MLP)

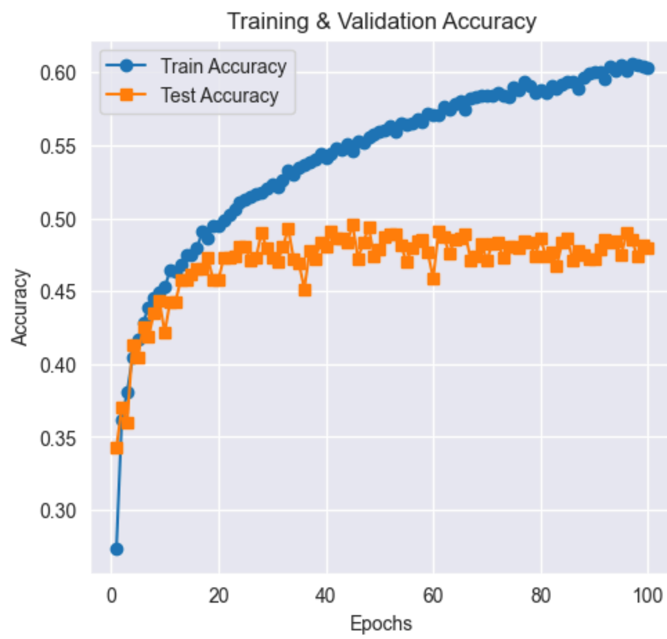
- **20 Epochs:** Train Loss: **1.4112**, Train Acc: **0.4955**, Test Loss: **1.5260**, Test Acc: **0.4642**
- **100 Epochs:** Train Loss: **1.1130**, Train Acc: **0.6031**, Test Loss: **1.6629**, Test Acc: **0.4796**

Evaluation Metrics

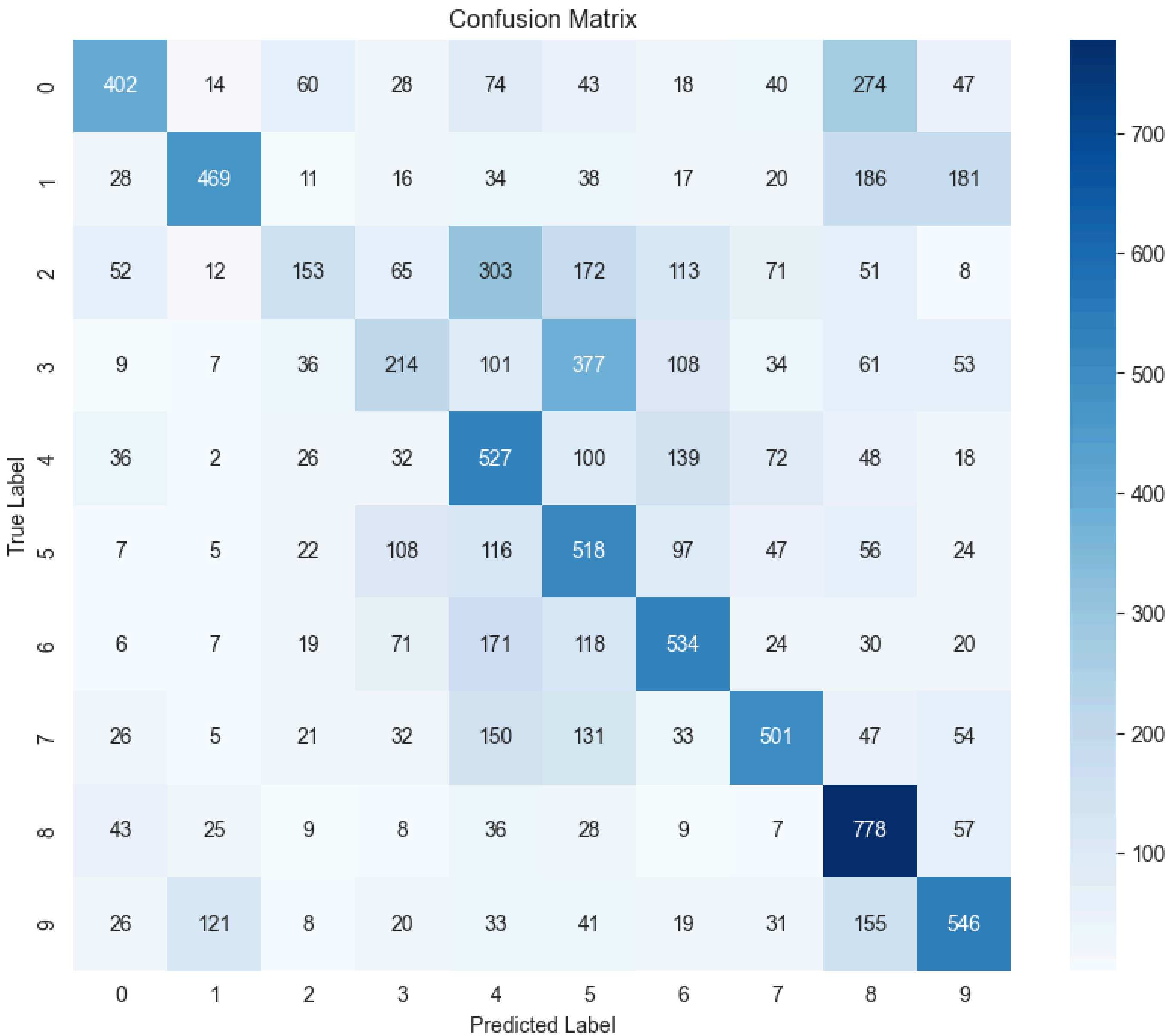
Epochs	Precision	Recall	F1 Score
20	0.4873	0.4642	0.4542
100	0.4842	0.4796	0.4764

Training and Validation Loss & Accuracy





Confusion Matrix (20 Epochs)



Observations:

- The network shows slight overfitting after around 20 epochs, so I think it achieves full training within 20 epochs.
- Increasing epochs leads to better training accuracy, but validation performance does not improve significantly.
- The model achieves reasonable performance but struggles with generalization.

1.b Increasing Network Complexity

I tested models with 4 and 5 hidden layers to analyze the effect of network depth on performance.

Training and Validation Results

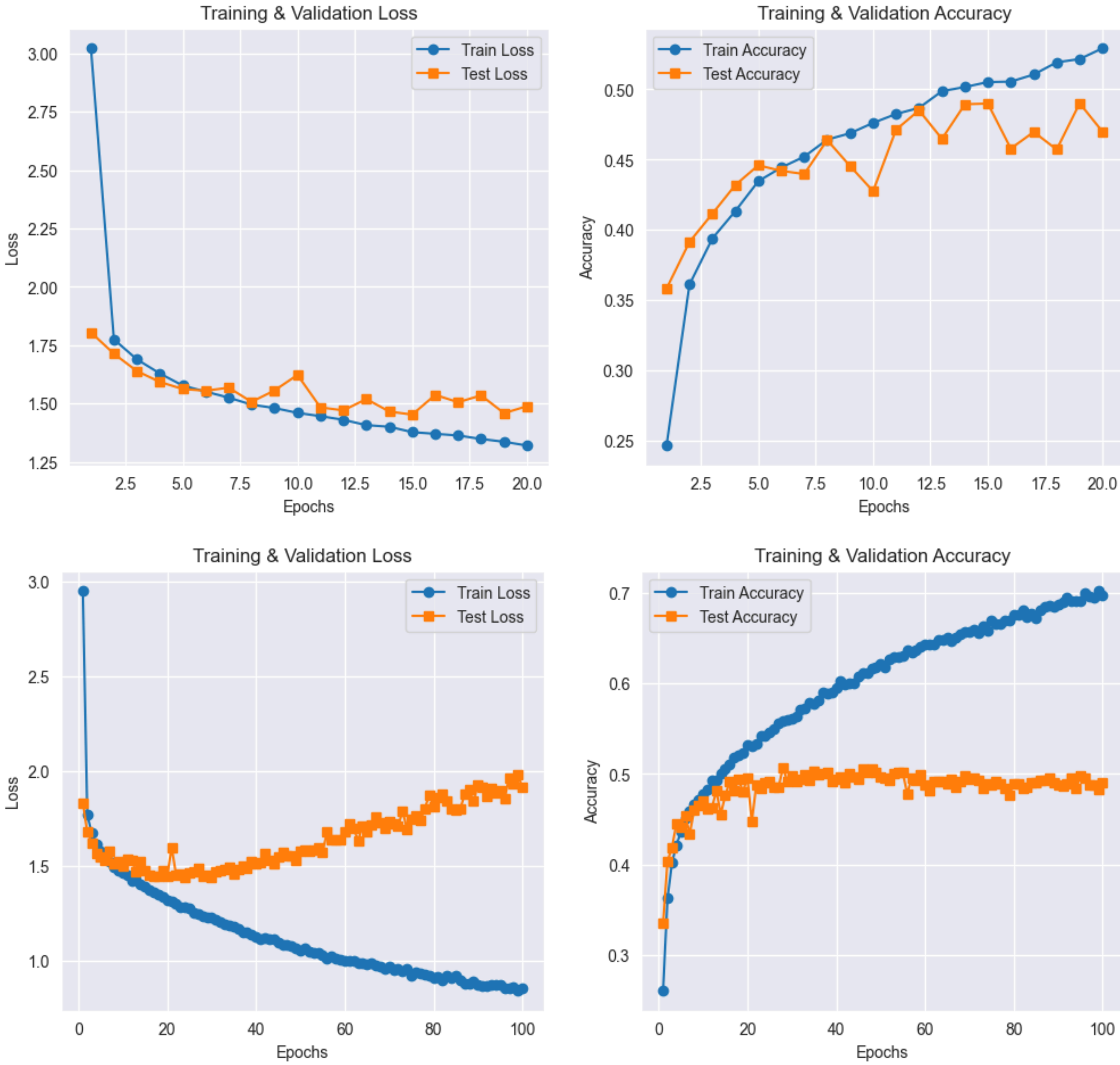
Model	Epochs	Train Loss	Train Acc	Test Loss	Test Acc
4-Layer	20	1.3201	0.5292	1.4888	0.4698
4-Layer	100	0.8533	0.6976	1.9120	0.4909

Model	Epochs	Train Loss	Train Acc	Test Loss	Test Acc
5-Layer	20	1.2729	0.5445	1.4969	0.4854
5-Layer	100	0.4833	0.8365	2.9720	0.4582

Evaluation Metrics

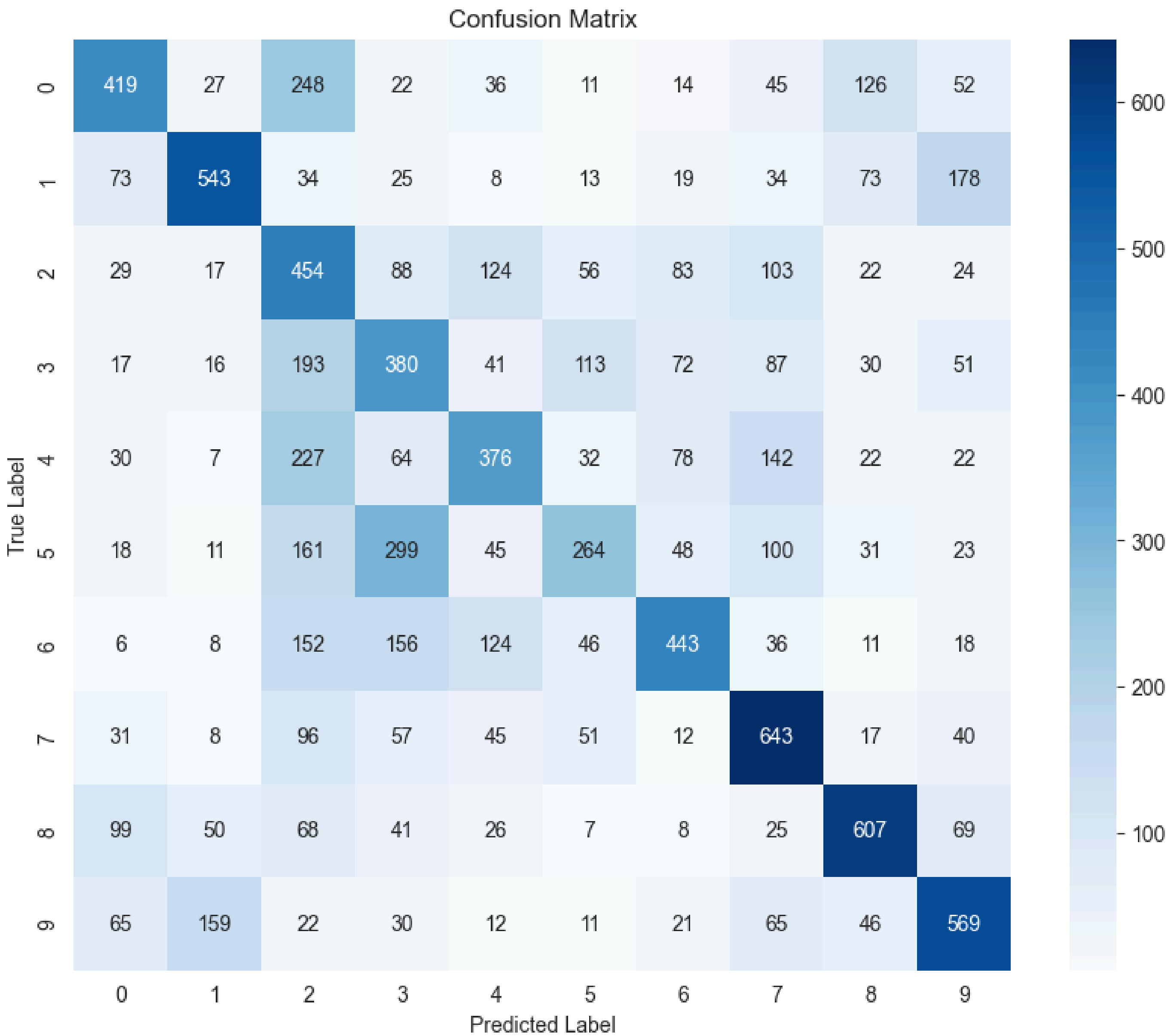
Model	Epochs	Precision	Recall	F1 Score
4-Layer	20	0.4880	0.4698	0.4714
4-Layer	100	0.5024	0.4909	0.4891
5-Layer	20	0.4886	0.4854	0.4782
5-Layer	100	0.4621	0.4582	0.4565

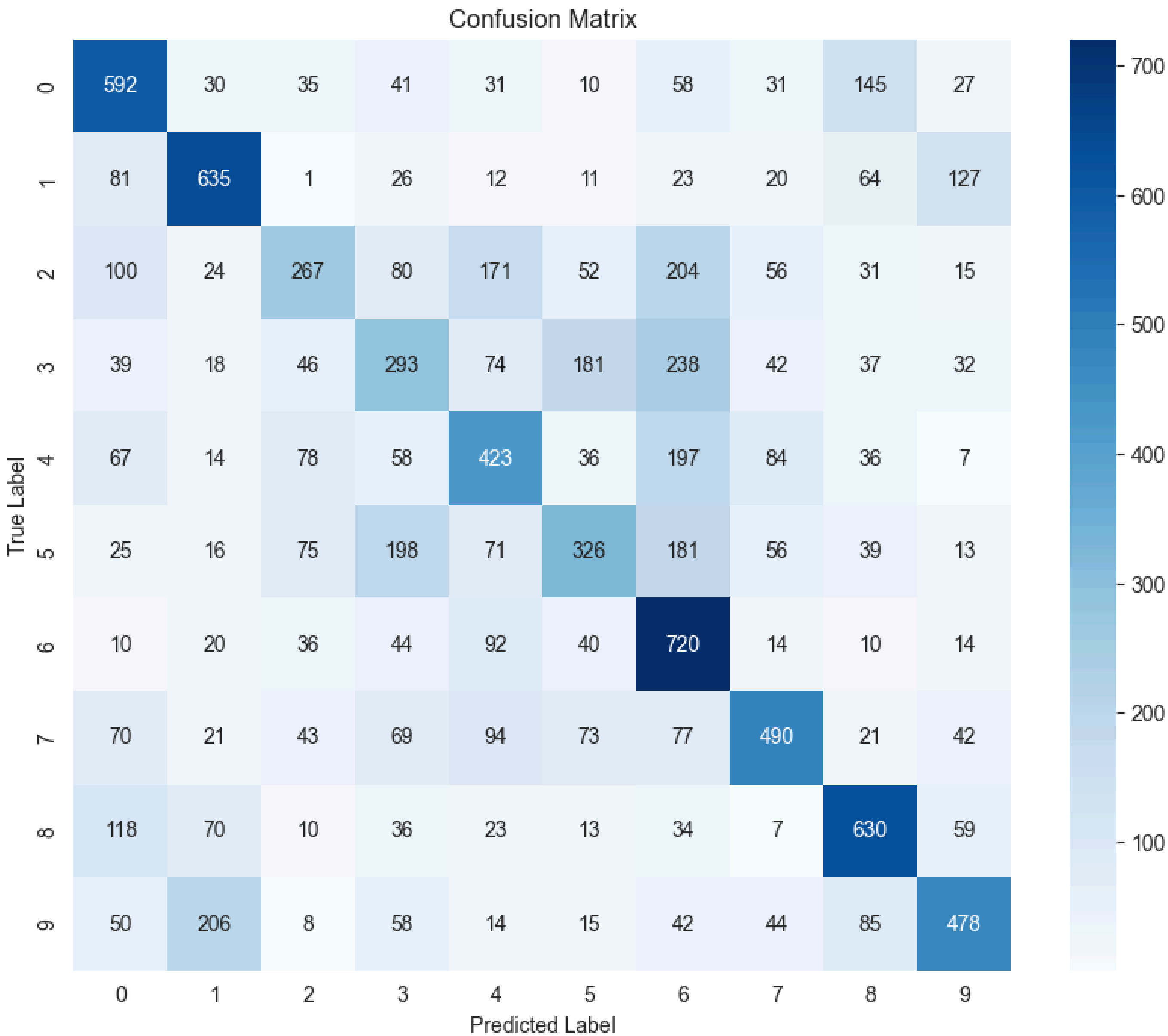
Training and Validation Loss & Accuracy (4-Layer)



Training and Validation Loss & Accuracy (5-Layer)

Confusion Matrices (20 Epochs)


Confusion Matrix
True Label
Predicted Label
0
1
2
3
4
5
6
7
8
9
419 27 248 22 36 11 14 45 126 52
73 543 34 25 8 13 19 34 73 178
29 17 454 88 124 56 83 103 22 24
17 16 193 380 41 113 72 87 30 51
30 7 227 64 376 32 78 142 22 22
18 11 161 299 45 264 48 100 31 23
6 8 152 156 124 46 443 36 11 18
31 8 96 57 45 51 12 643 17 40
99 50 68 41 26 7 8 25 607 69
65 159 22 30 12 11 21 65 46 569
600
500
400
300
200
100



Observations:

- Increasing depth slightly improves early training performance but leads to noticeable overfitting after 20 epochs.
- The 4-layer & 5-layer model performs well on training data but generalizes poorly, with a significant increase in test loss.
- Overfitting starts appearing in all models after approximately 20 epochs, indicating that the network has already reached full training by this point.

Conclusion

- A 3-layer MLP provides a good balance between accuracy and generalization.
- Increasing depth beyond 3 layers leads to diminishing returns and more overfitting.
- Overfitting becomes noticeable after 20 epochs in all cases, confirming that the network has already achieved full training and further training does not provide significant benefits.

Problem 2: Multi-Layer Perceptron for Housing Price Regression

2.a Training without One-Hot Encoding

I implemented a multi-layer perceptron (MLP) to predict housing prices using a standard dataset without one-hot encoding for categorical features. The training and validation results for 60 and 100 epochs are shown below:

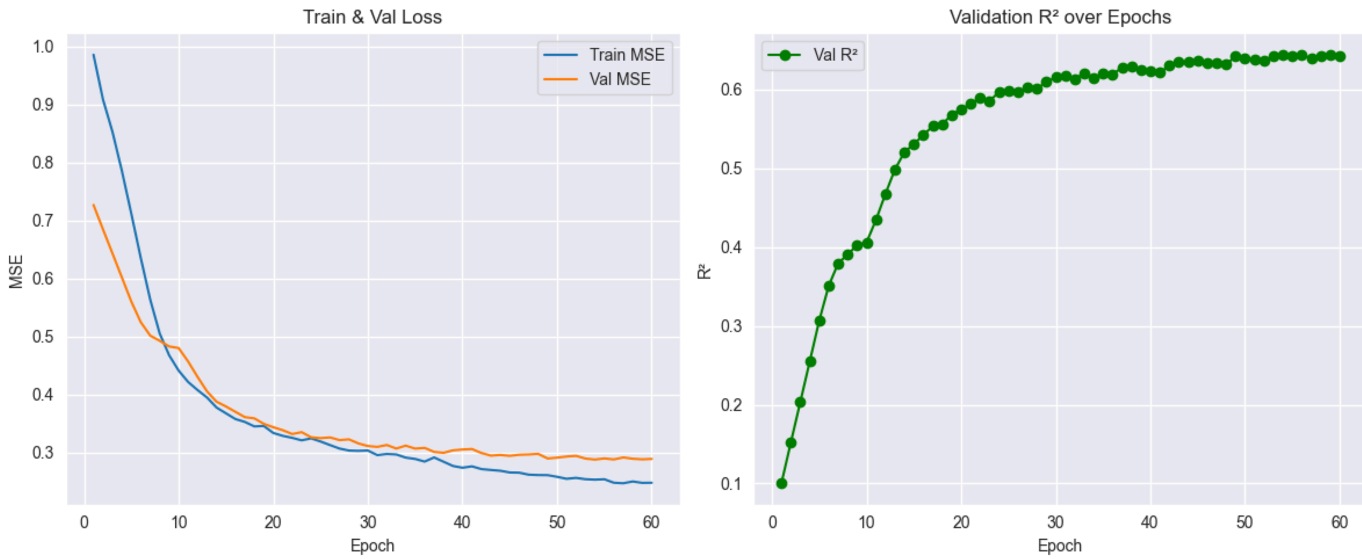
Training and Validation Results (Without One-Hot Encoding)

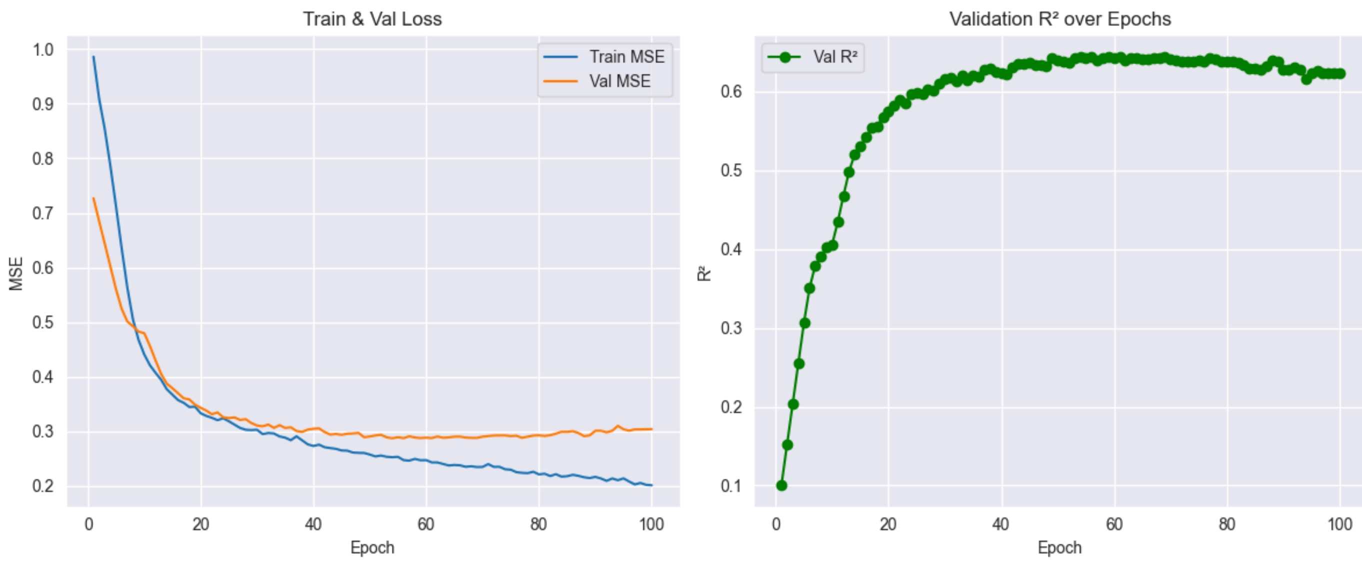
- **60 Epochs:** MSE: **0.29**, MAE: **0.41**, R^2: **0.64**
- **100 Epochs:** MSE: **0.30**, MAE: **0.42**, R^2: **0.62**

Model Complexity

- Hidden layers: **[64, 32]**
- Total trainable parameters: **2945**

Training and Validation Loss & R^2





Observations:

- The model shows slight overfitting after **60 epochs**, meaning training beyond this does not yield significant validation improvement.

2.b Training with One-Hot Encoding

Next, I trained an MLP using one-hot encoding for categorical features. The training and validation results for 60 and 100 epochs are:

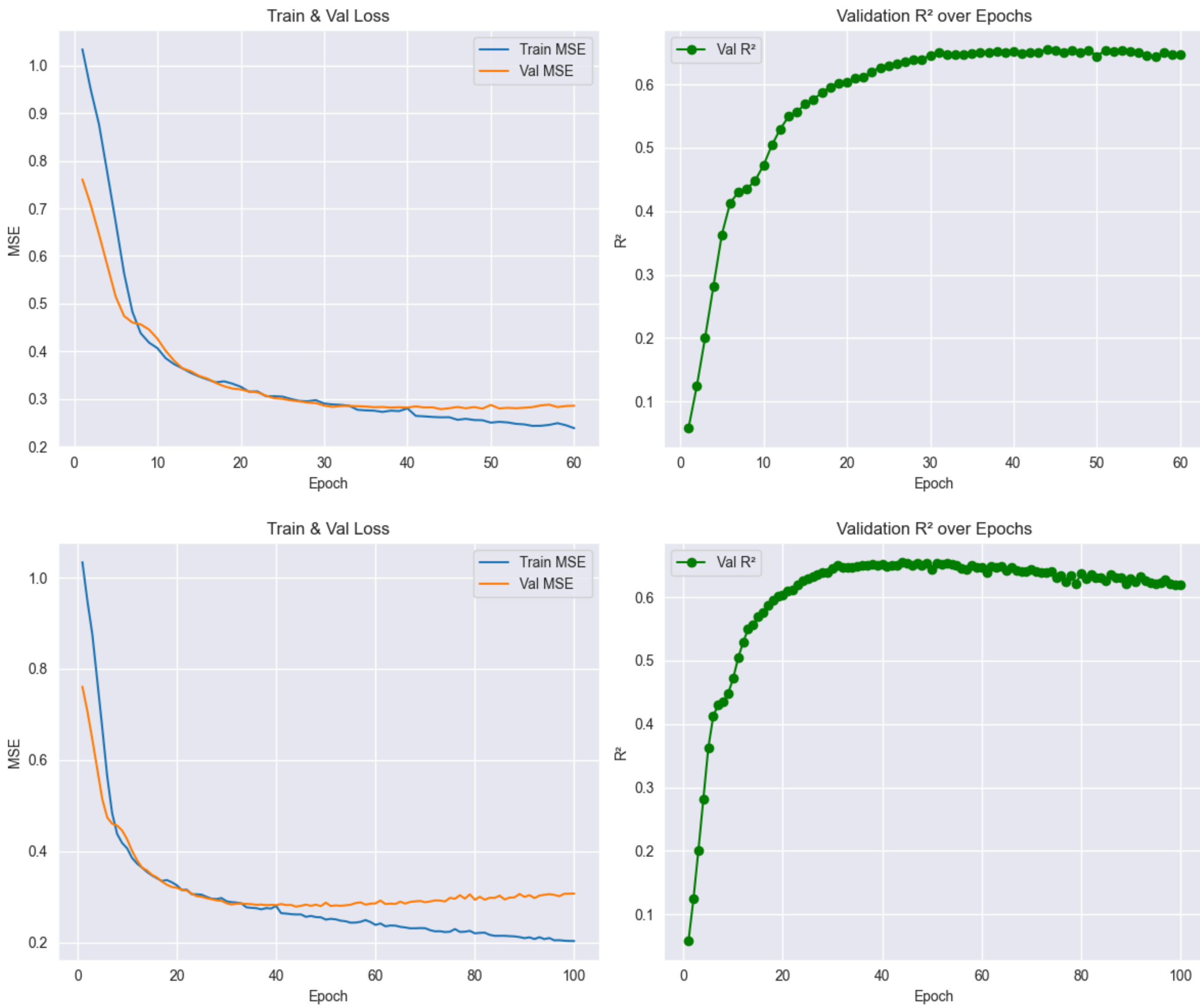
Training and Validation Results (With One-Hot Encoding)

- **60 Epochs:** MSE: **0.29**, MAE: **0.42**, R^2: **0.65**
- **100 Epochs:** MSE: **0.31**, MAE: **0.43**, R^2: **0.62**

Model Complexity

- Hidden layers: **[64, 32]**
- Total trainable parameters: **3073**

Training and Validation Loss & R^2



Observations:

- One-hot encoding slightly improves performance (**R^2 increased from 0.64 to 0.65** in 60 epochs).
- Overfitting starts appearing after **60 epochs**.
- The improvement from one-hot encoding is relatively small, possibly because the instance and the network structure are not highly complex, limiting the impact of additional categorical feature representation.

2.c Increasing Model Complexity

I experimented with increasing network complexity by adding more layers and neurons.

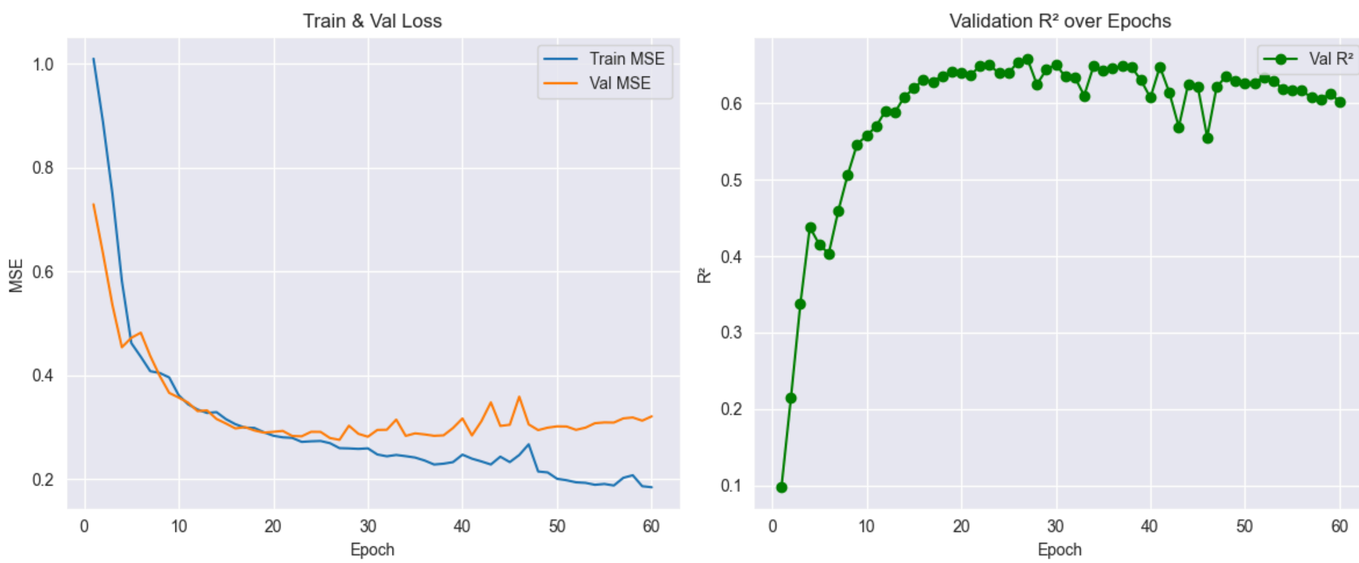
Training and Validation Results (3-Layer Network)

- **50 Epochs:** MSE: **0.30**, MAE: **0.42**, R^2: **0.63**
- **60 Epochs:** MSE: **0.32**, MAE: **0.42**, R^2: **0.60**

Model Complexity

- Hidden layers: **[128, 64, 32]**
- Total trainable parameters: **12289**

Training and Validation Loss & R²



Observations:

- Overfitting appears **after 50 epochs**, meaning deeper networks require earlier stopping.

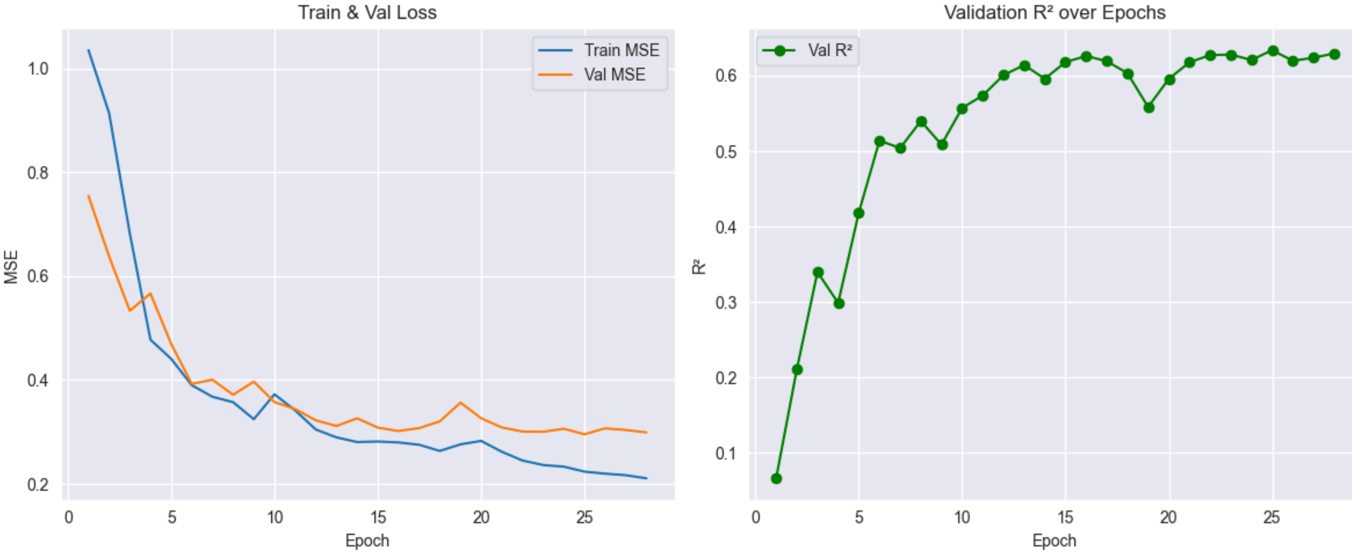
Training and Validation Results (4-Layer Network)

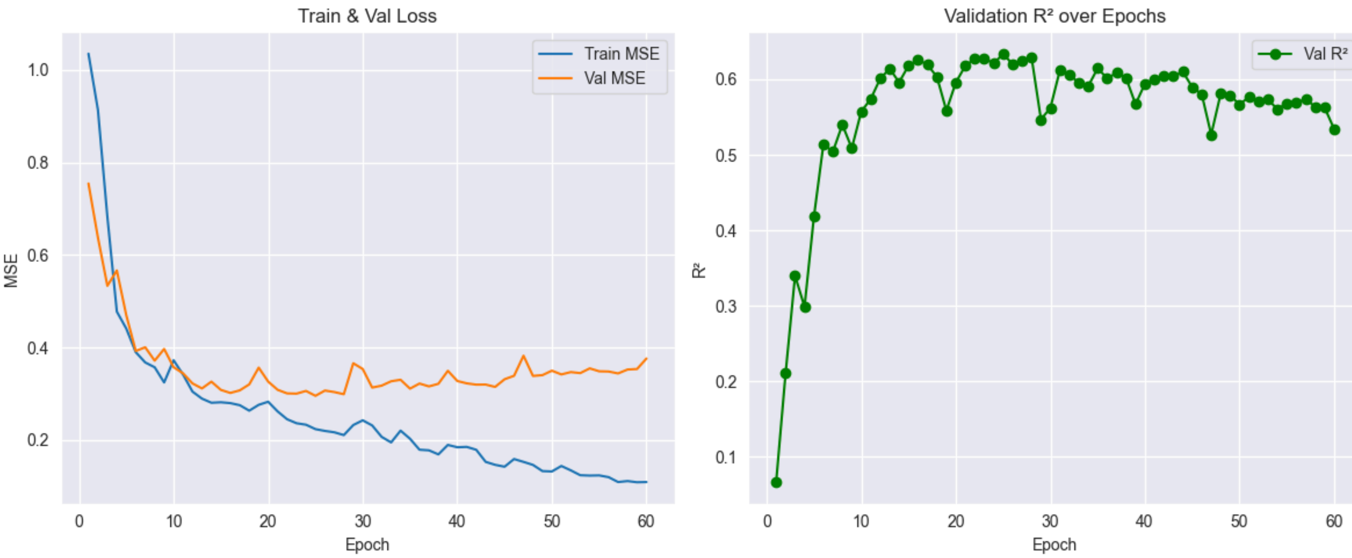
- **28 Epochs:** MSE: **0.30**, MAE: **0.41**, R^2: **0.63**
- **60 Epochs:** MSE: **0.38**, MAE: **0.44**, R^2: **0.53**

Model Complexity

- Hidden layers: **[256, 128, 64, 32]**
- Total trainable parameters: **47105**

Training and Validation Loss & R²





Observations:

- Overfitting starts appearing earlier (**after 28 epochs**).
- Increasing depth **does not significantly improve performance**, and actually reduces generalization beyond **60 epochs**.

Conclusion

- One-hot encoding improves model performance slightly but does not drastically change results, possibly due to the relatively simple instance and network architecture.
- Increasing network complexity leads to earlier overfitting, suggesting **smaller architectures may be better for this dataset**.
- The best balance of performance and generalization occurs **at 60 epochs** for 2.a and 2.b, and **around 28-50 epochs** for 2.c.