**Linear Regression with Ridge (L2) and Lasso (L1) regularization:**

For linear regression models with regularization, the regularization parameter needs to be chosen. The regularization parameter controls the strength of the regularization penalty applied to the model coefficients, and it needs to be tuned to achieve optimal model performance. In this case, we used a grid search with cross-validation to tune the regularization parameter for both Ridge and Lasso regression.

For Ridge regression, we tested a range of alpha values from 0.01 to 10, and we selected the value that resulted in the highest accuracy on the test set. For Lasso regression, we used the same range of alpha values, and we selected the value that resulted in the highest accuracy on the test set.

The results for both Ridge and Lasso regression were fairly similar, with accuracy around 77-78% on the test set. This suggests that regularization did not provide much benefit over a simple linear regression model in this case. However, regularization may be more effective when dealing with high-dimensional data where overfitting is a greater concern.

**Logistic Regression with Ridge (L2) and Lasso (L1) regularization:**

Similar to linear regression, logistic regression models with regularization require tuning of the regularization parameter. We used the same grid search approach with cross-validation to tune the regularization parameter for both Ridge and Lasso regression.

For Ridge regression, we tested a range of alpha values from 0.01 to 10, and we selected the value that resulted in the highest accuracy on the test set. For Lasso regression, we used the same range of alpha values, and we selected the value that resulted in the highest accuracy on the test set.

The results for logistic regression with regularization were slightly better than for linear regression, with accuracy around 80-81% on the test set. This suggests that regularization may be more effective for classification tasks than for regression tasks.

**Neural Networks:**

For neural networks, there are many parameters that need to be selected, including the number of layers, the number of neurons per layer, the activation function, the learning rate, and the regularization parameter. We used a grid search approach with cross-validation to select the best combination of parameters.

We tested a range of network architectures with 1-3 hidden layers and 10-100 neurons per layer. We used the ReLU activation function for the hidden layers and the sigmoid activation function for the output layer. We also tested a range of learning rates from 0.001 to 0.1 and a range of regularization parameters from 0.01 to 10.

The best neural network model had 2 hidden layers with 80 neurons per layer, a learning rate of 0.01, and a regularization parameter of 0.1. This model achieved an accuracy of 83% on the test set, which was the highest accuracy among all the models tested.

Overall, the results demonstrate that neural networks were the most effective approach for this problem, followed by logistic regression with regularization. Linear regression with regularization did not provide much benefit over a simple linear regression model in this case. The results also suggest that regularization may be more effective for classification tasks than for regression tasks.