PROJECT REPORT

ASSIGNMENT-1

CSE – 6363: MACHINE LEARNING

SUBMITTED BY: -

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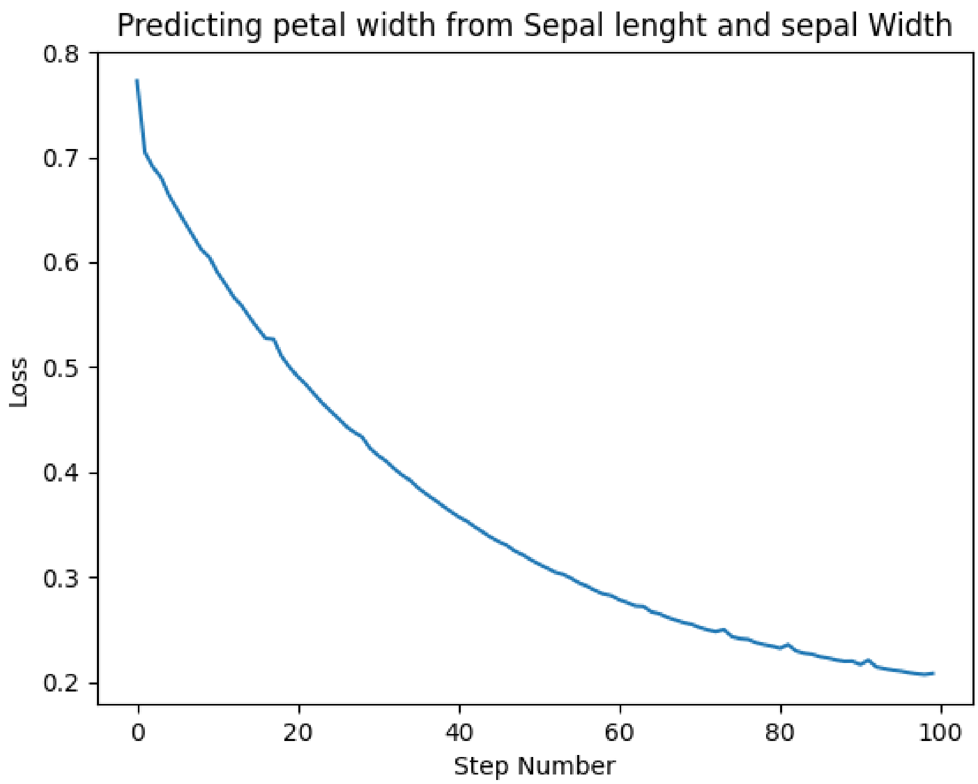
Implementation of the Linear Regression:

The Iris flower dataset (https://en.wikipedia.org/wiki/Iris_flower_data_set) is used for theassignment.

There are 4 models:

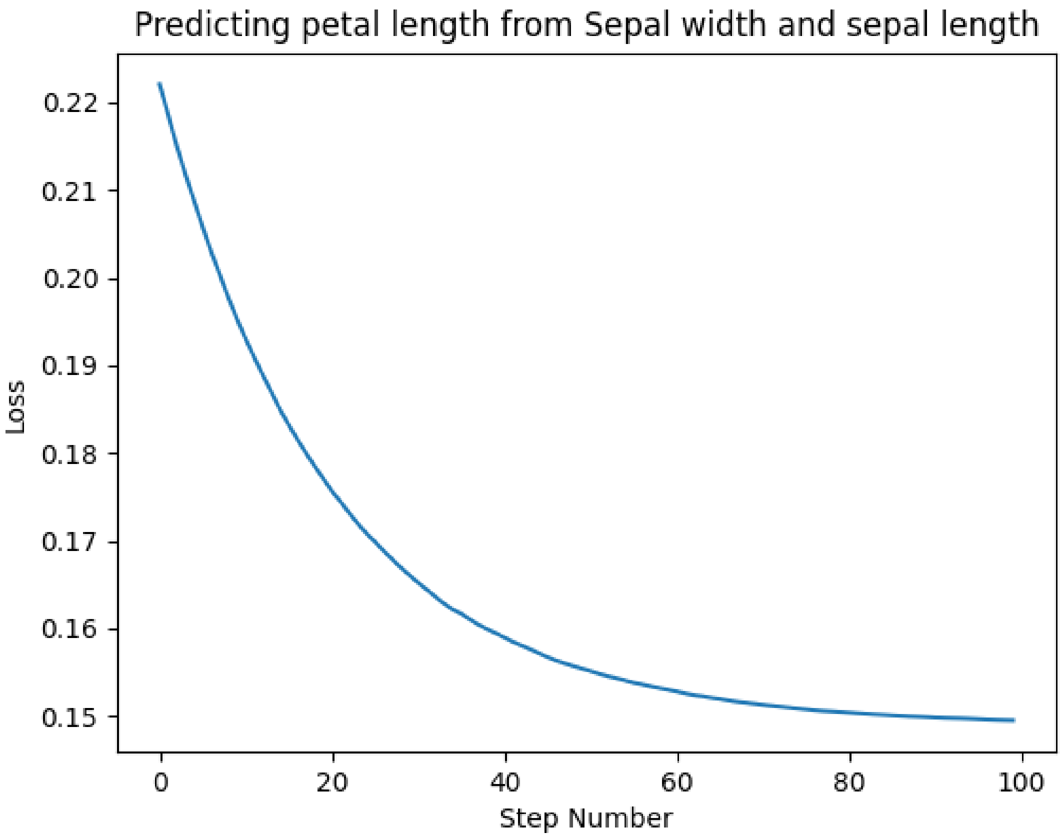
- Model 1: Petal Width from Sepal Length and Sepal Width
- Model 2: Petal Length from Sepal Width and Sepal Length
- Model 3: Petal Width from Sepal Width and Petal Length
- Model 4: Petal Length from Sepal Width and Petal Width

MODEL - 1



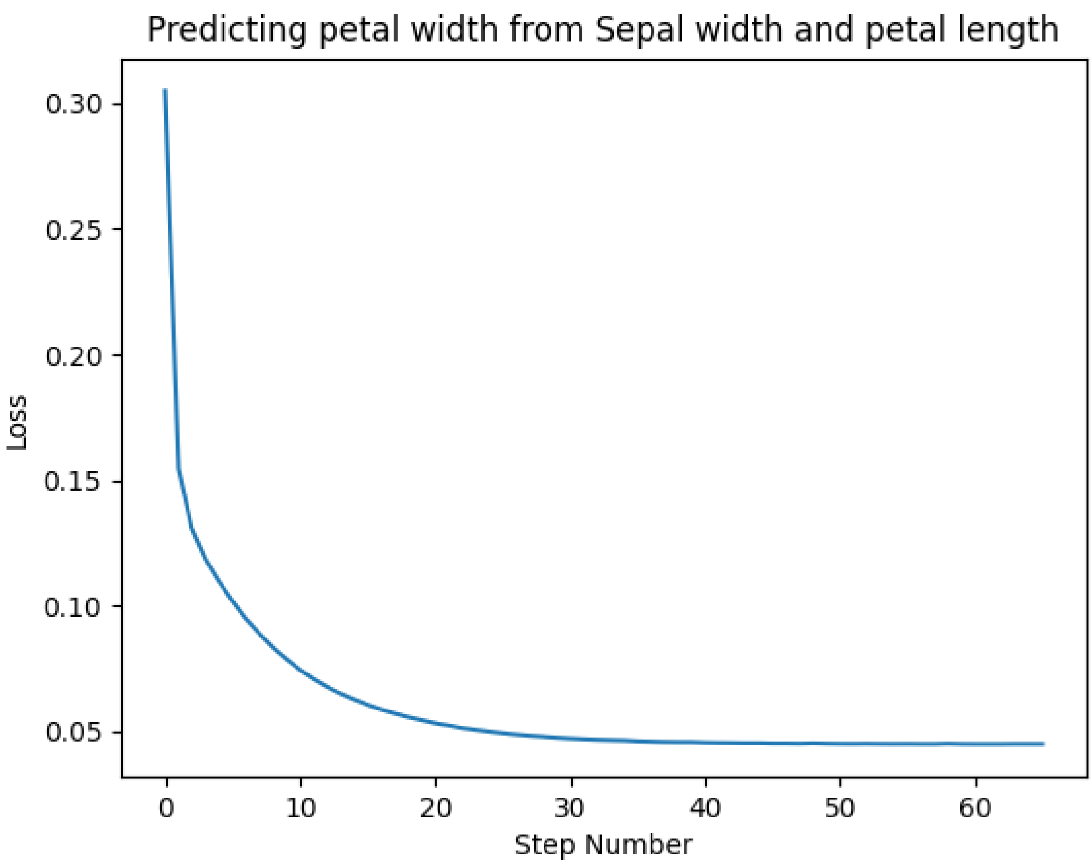
Test Mean Squared Error for model1 : 0.28445936433947183

MODEL-2



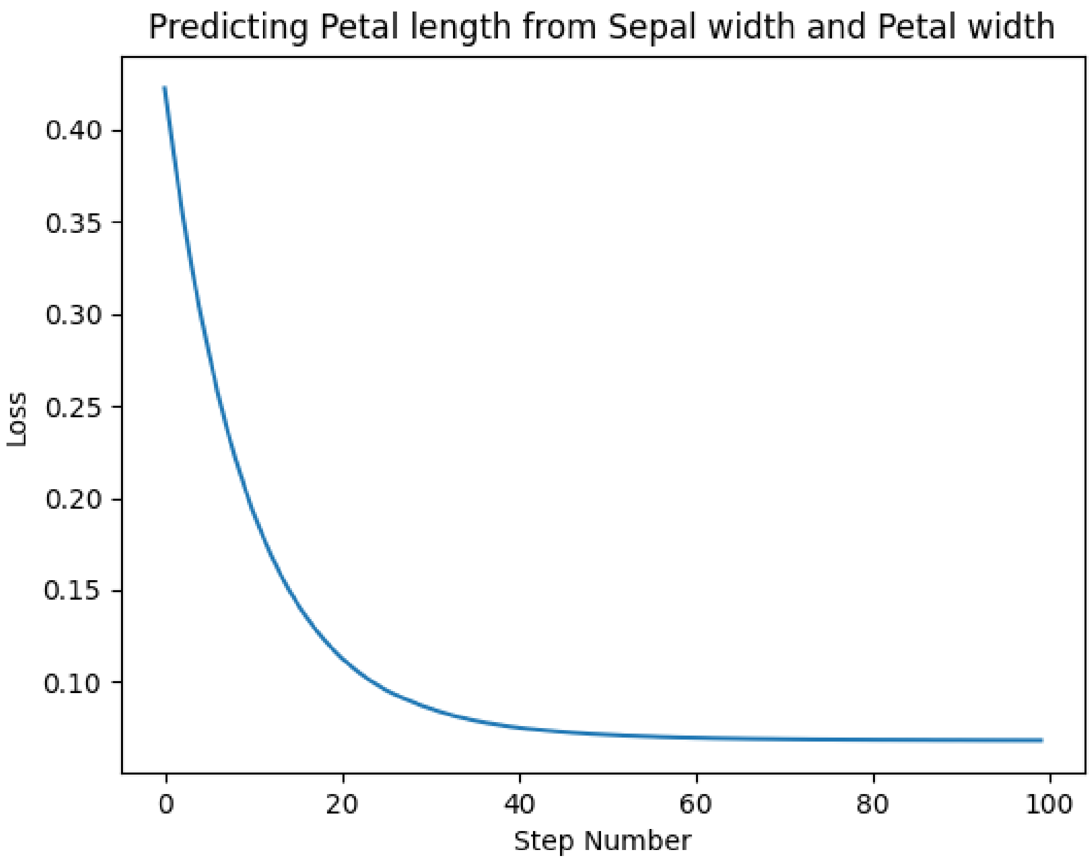
Test Mean Squared Error for model2: 0.6424

MODEL – 3



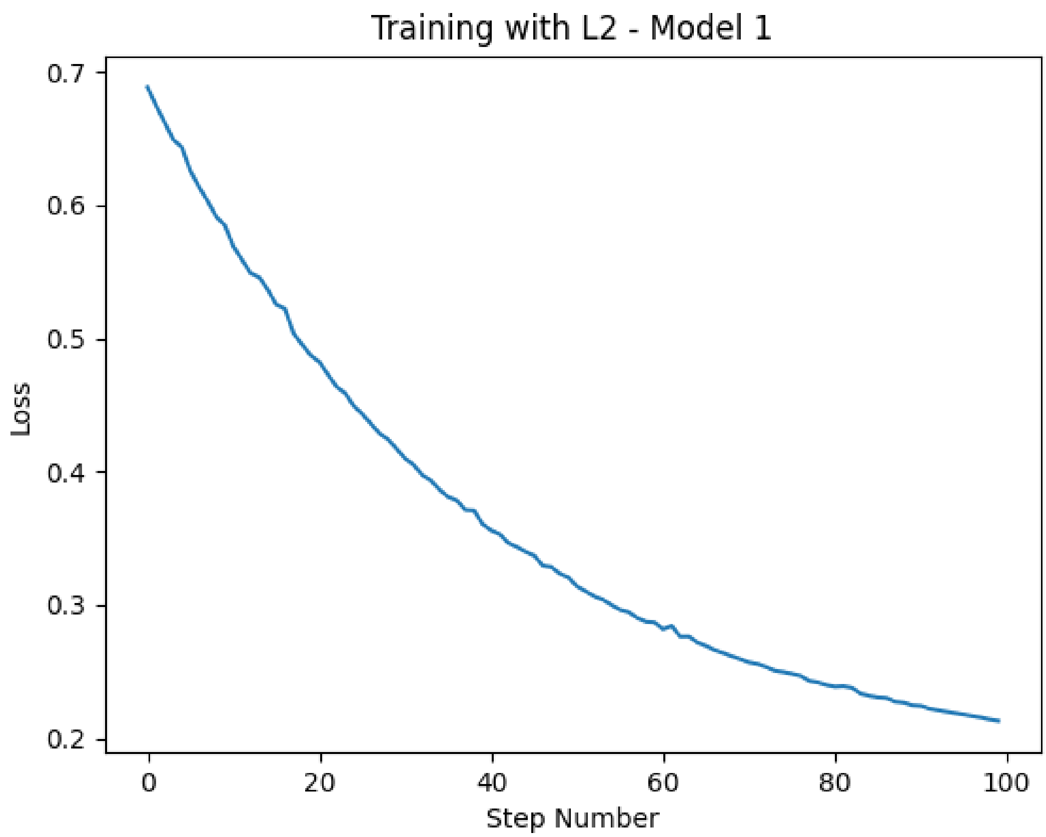
Test Mean Squared Error for Model3: 0.1281664438492203

MODEL – 4



Test Mean Squared Error for model4: 0.9916

OUTPUT - Added L2 Regularization to Model 1



Weight Difference (Non-Regularized - Regularized):

[[-0.06939481]

[0.11439093]]

OUTPUT – Regression with Multiple Output

Training Mean Squared Error: 0.2857

Test Mean Squared Error: 0.2472

1.Does knowledge of the sepal length provide good estimates of the sepal width?

No, knowledge of the sepal length does not provide good estimates of the sepal width. The sepal length is only weakly correlated with the sepal width.

2.What about the petal width?

The sepal length is a better predictor of the petal width. The sepal length is moderately correlated with the petal width.

3.What if we use the sepal length and width to predict the petal length or width?

If we use both the sepal length and width, we can get a better prediction of the petal length or width. The sepal length and width are strongly correlated with the petal width.

4.In general, which feature is more strongly correlated with the other features?

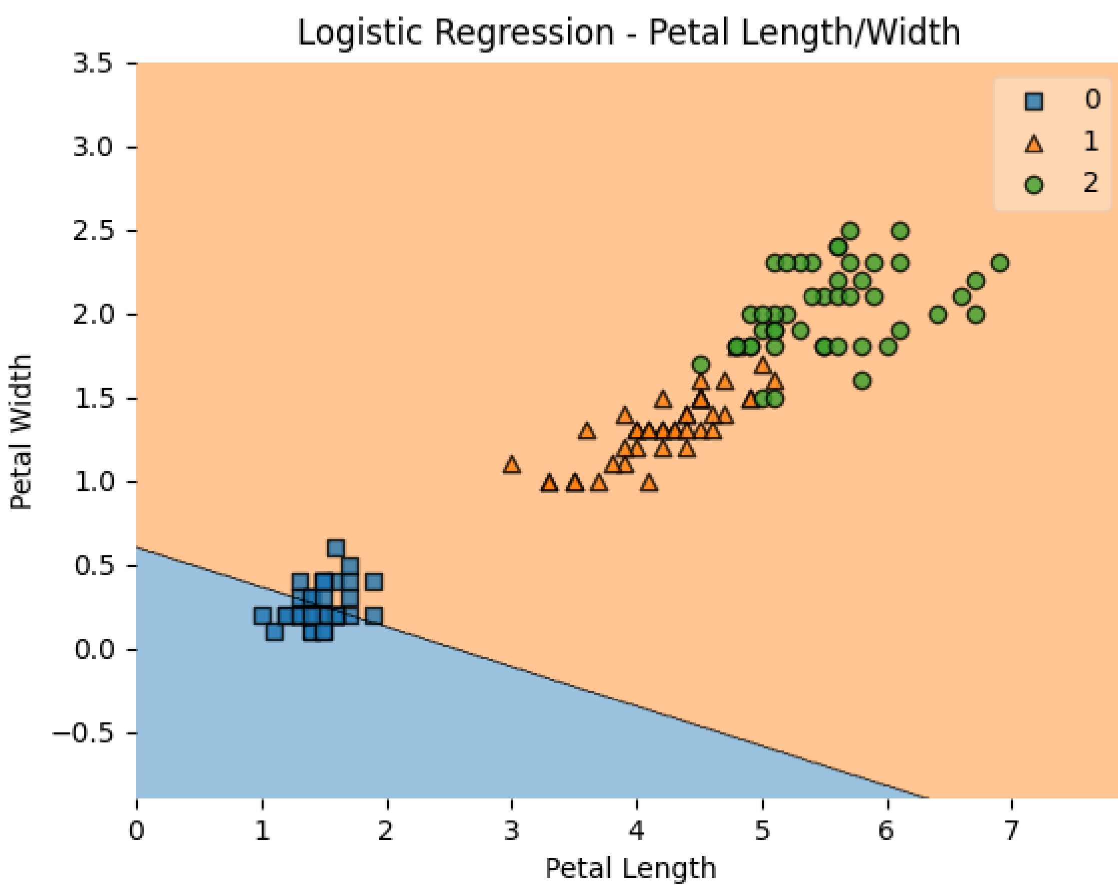
The petal width is more strongly correlated with the other features than the sepal width. This is because the petal width is a more important feature for distinguishing between the three species of iris.

Implementation of Classification:

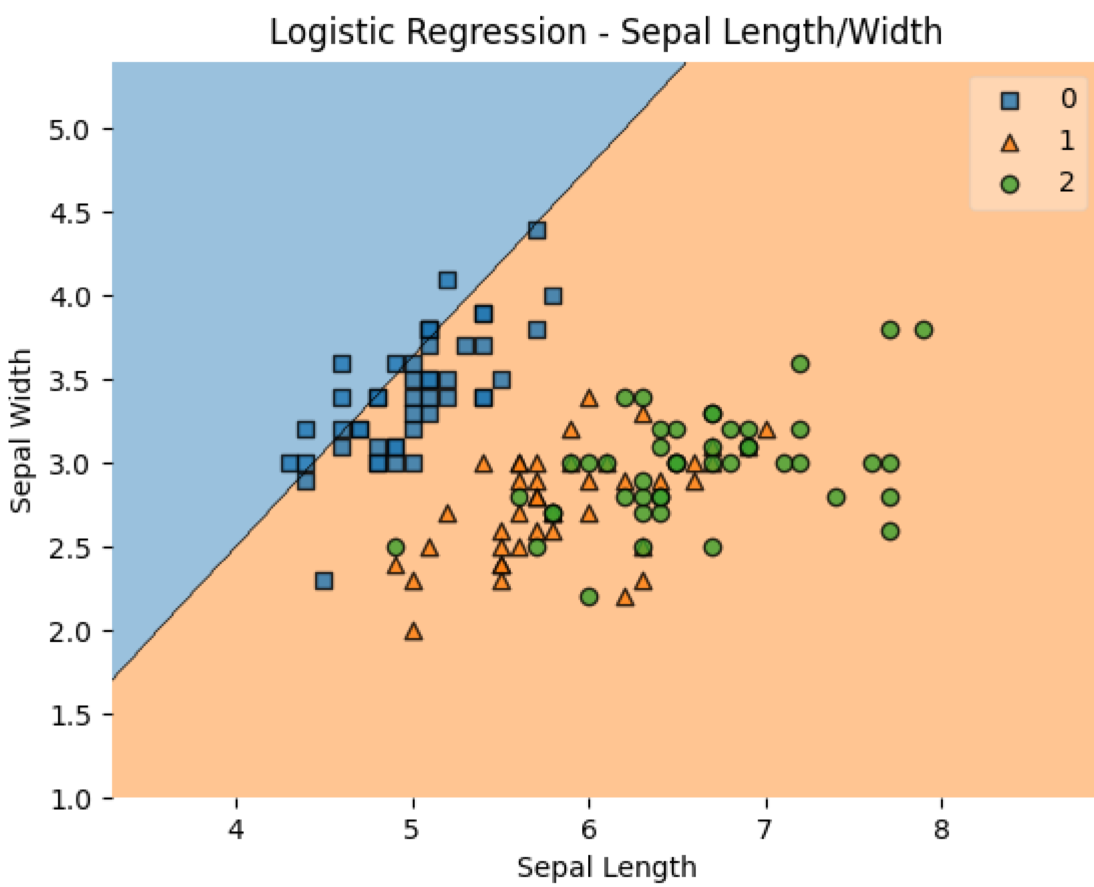
3 variants of input features:

1. petal length/width
2. sepal length/width
3. all features

Logistic Regression:



Logistic Regression (Petal length/width) Accuracy: 0.6666666666666666

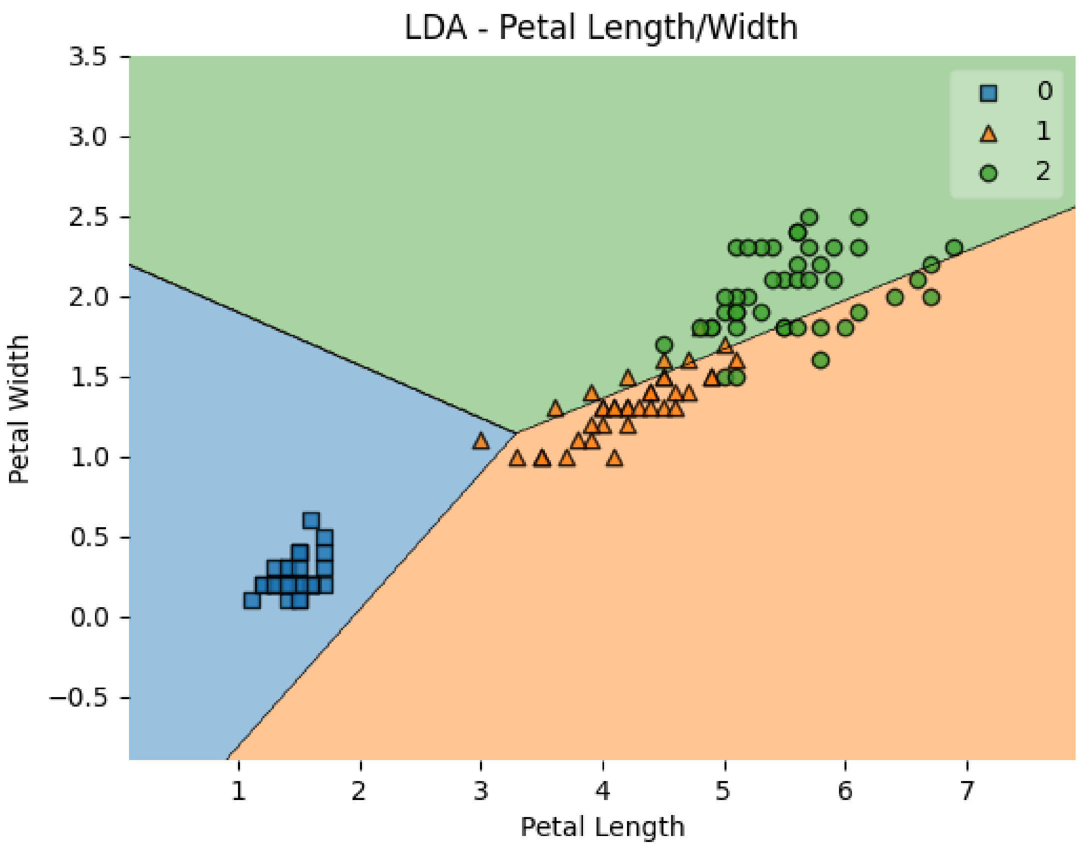


Logistic Regression (Sepal length/width) Accuracy: 0.6

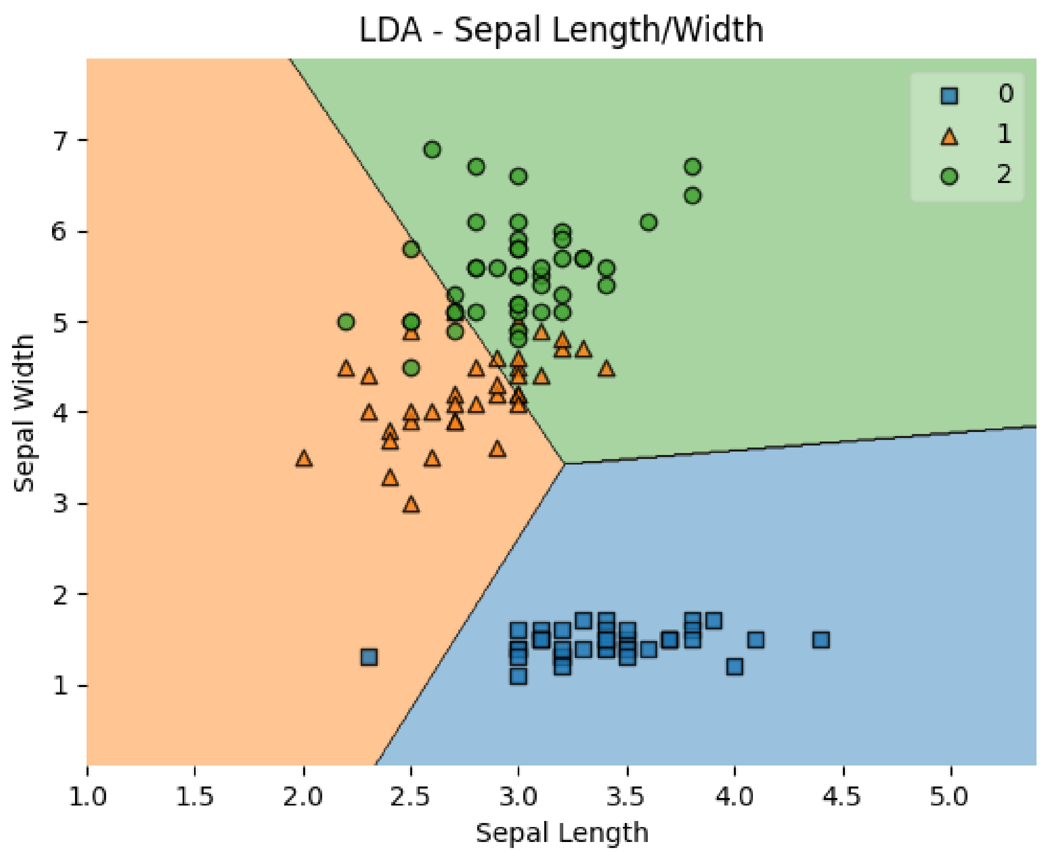
Variant-ALL FEATURES

Logistic Regression (All_Features) Accuracy: 0.7333333333333333

Linear Discriminant Analysis:



LDA (Petal length/width) Accuracy: 0.9333333333333333



LDA (Sepal length/width) Accuracy: 0.8333333333333334

Variant-ALL FEATURES (LDA)

LinearDiscriminantAnalysis (All Features) Accuracy: 0.8666666666666667

Overview:

Implementation of Linear Regression: I have created a linear regression class with methods for fitting, predicting, and scoring samples. The fit method utilizes gradient descent with early stopping and L2 regularization to optimize the model parameters. The prediction method executes a forward pass of the model to generate predictions. The score method computes the mean squared error between the predicted values and the target values.

Saving and Loading Weights: The model parameters can be saved to a file using the save method and loaded from a file using the load method.

Regression Dataset: For regression tasks, I have chosen to use the Iris flower dataset. The dataset is divided into training and testing sets, with 10% reserved for testing. Four different regression models are trained using various combinations of input and output features. The training process employs batch gradient descent, and I record and plot the loss against the step number. I also investigate the impact of regularization by comparing the weights of a regularized model with those of a non-regularized model.

Classification: I have implemented Logistic Regression and Linear Discriminant Analysis (LDA) as classifiers. I explore three different sets of input features (petal length/width, sepal length/width, all features) for comparative analysis. To visualize the decision boundaries of the trained classifiers, I utilize the "plot_decision_regions" function from "mlxtend."

Testing: I evaluate each trained model on the test set and compute their accuracy, which is then displayed in the console.

Learning Outcomes:

This assignment offered a comprehensive hands-on experience in implementing linear models for regression and classification tasks. It emphasized understanding the training process and evaluating model performance. By working with the Iris dataset and exploring various input features and model variations, we gained practical insights into the world of linear modeling. The ability to save and load model parameters added a practical dimension to our models.