Perceptron & Adaline Report

CS_30

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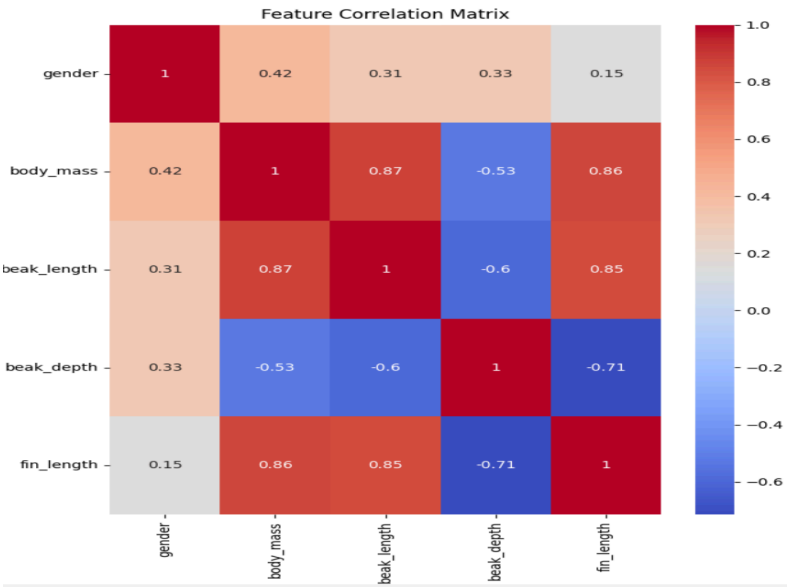
Dataset Overview

The dataset contains 150 samples, with 50 samples from each three bird species: A, B,C.
The dataset contains 6 columns:

- gender (categorical feature)
- body_mass, beak_length, beak_depth, fin_length (numerical features)
- Bird_category (categorical target column)

The dataset is balanced across the bird species, ensuring that classification algorithms are not biased toward any one class.

Data Correlation



Based on the correlation analysis, **body mass** and **beak length** would likely be the best two features for prediction as well as **beak_depth and beak_length (-0.6)**. These features show a strong positive correlation with each other (0.87) and are highly correlated with other relevant features (fin length and each other), suggesting they carry significant information.

Data Preprocessing

- **Train-Test Split:** Each class has been split into 30 training and 20 testing samples using train_test_split with stratified parameters.
- **Handling Missing Values:** Nulls were found only in the gender column, and have been imputed with the mode.
- **Encoding and Scaling:**
    - Gender column has been label encoded, 0 for female and 1 for male.
    - Numeric columns ('body_mass', 'beak_length', 'beak_depth', 'fin_length') have been scaled using minmax scaler.

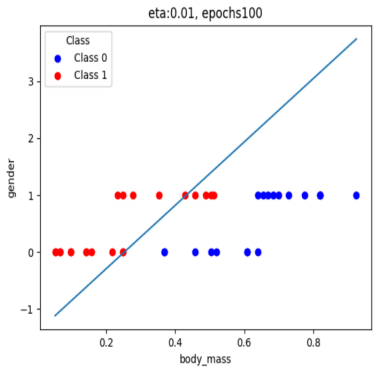
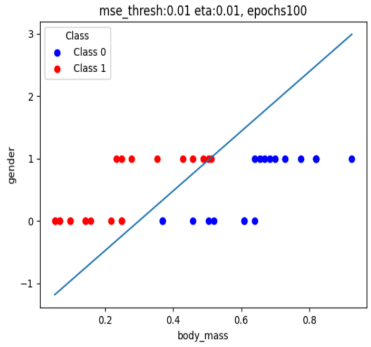
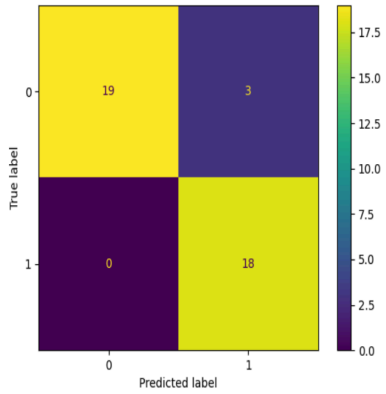
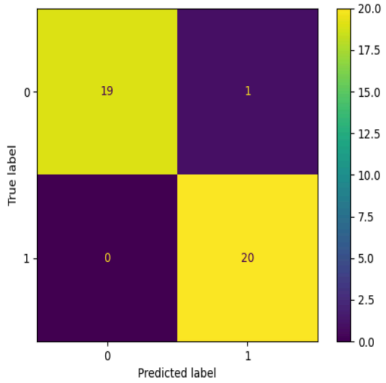
[Note] Training and testing sets have been processed separately to ensure that fitting of transformers and learning of preprocessing values is done on the training set only.

Modeling and Hyperparameters

We used the Preceptron and Adaline algorithms to be able to handle linearly separable data. The following tests have been conducted with these parameters:

- Learning rate=0.01
- Number of epochs=100
- MSE threshold=0.01 (adaline)
- Bias=true
- Weights and biases are initialized randomly

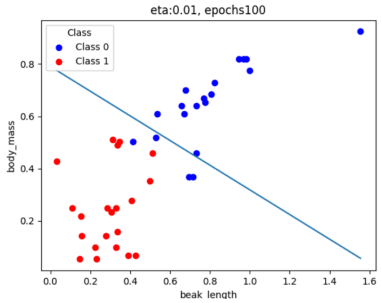
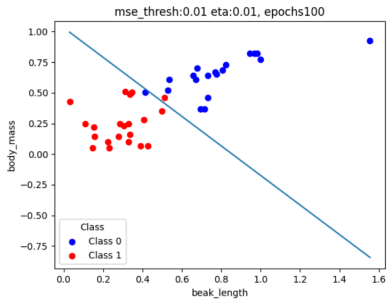
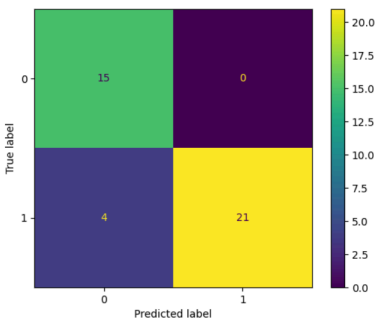
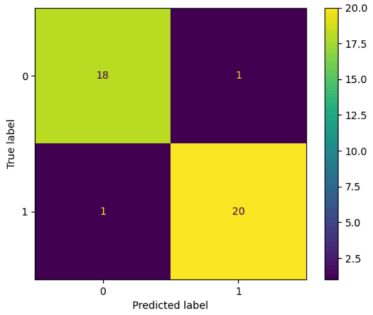
1. A vs B (Gender and body mass)

Algorithm	Perceptron	Adaline
Plot		
Confusion matrix		
Train accuracy	**0.9833**	**0.967**
Test accuracy	**0.925**	**0.975**
Weights , bias	**[0.0369253 -0.13894554] , [0.03386595]**	**[0.75995528 -3.63309102], [1.08704126]**

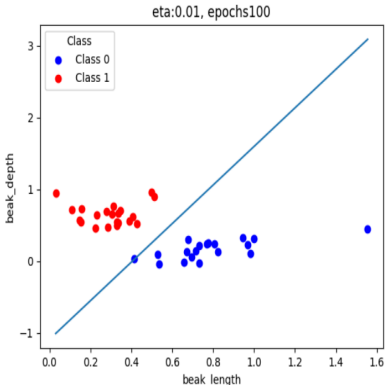
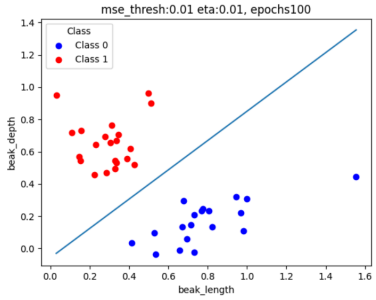
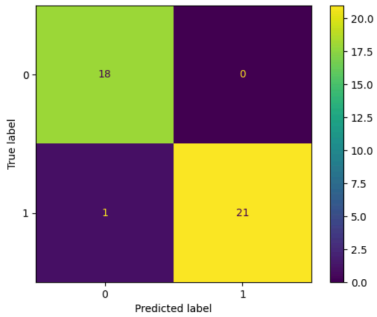
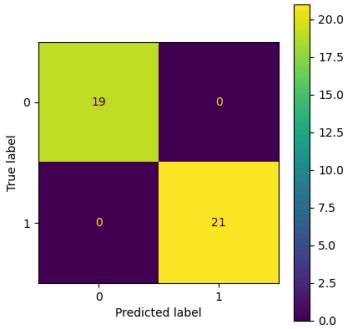
Performance Analysis

Gender does not seem to differentiate the features well, but body mass does a better job. The data is linearly separable along this feature pair.

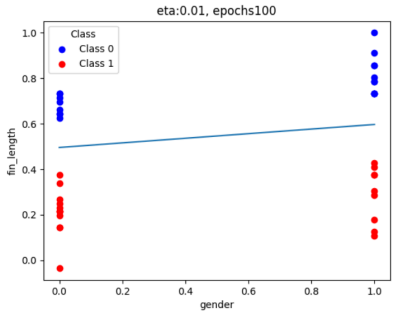
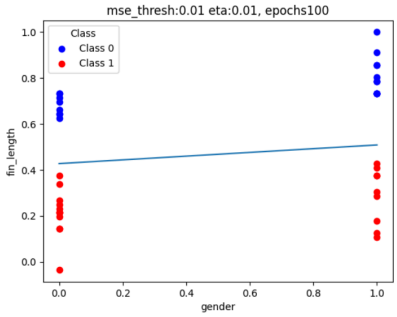
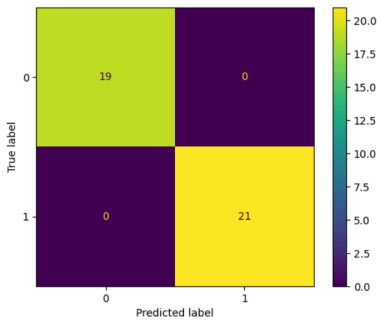
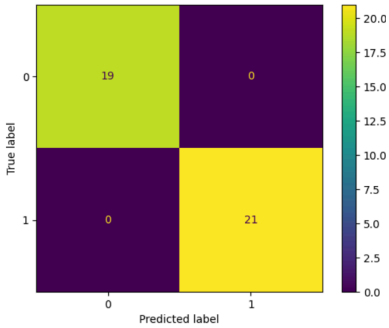
2. A vs C (Body mass and beak length)

Algorithm	Perceptron	Adaline
Plot		
Confusion matrix		
Train accuracy	**0.8833**	**0.9333333333333333**
Test accuracy	**0.9**	**0.95**
Weights , bias	**[-0.03910128 -0.08444439], [0.06638034]**	**[-1.78607336 -1.43035723], [1.5071363]**

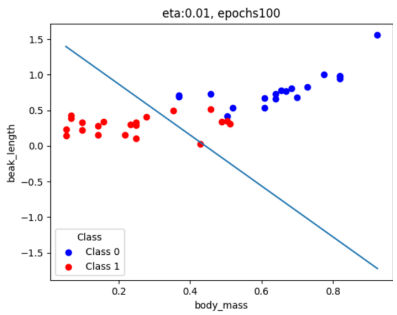
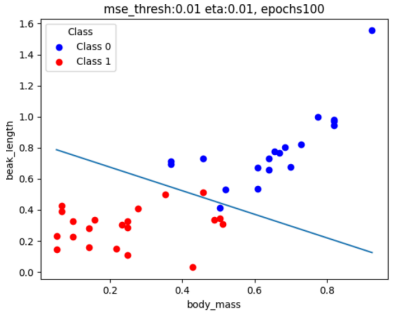
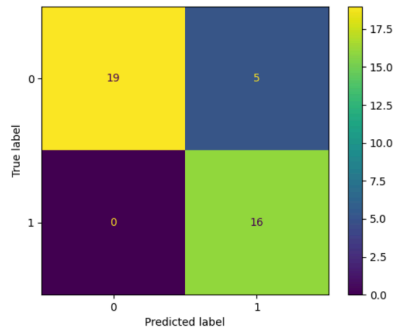
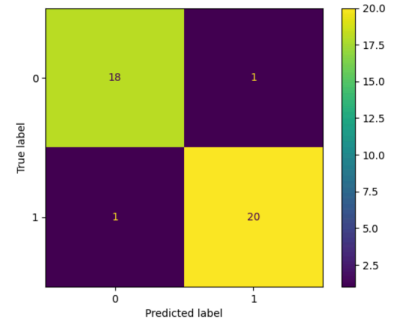
3. B vs C (Beak length and beak depth)

Algorithm	Perceptron	Adaline
Plot		
Confusion matrix		
Train accuracy	**1.0**	**1.0**
Test accuracy	**0.975**	**1.0**
weighs,bias	**[-0.18262686 0.06790361], [0.07413183]**	**[-1.78030688 1.96107718], [0.11313187]**

4. A vs B (Gender and fin length)

Algorithm	Perceptron	Adaline
Plot		
Confusion matrix		
Train accuracy	**1.0**	**1**
Test accuracy	**1.0**	**1**
Training weights,bias	**[0.01066537 -0.10538057], [0.05224796]**	**[0.27073244 -3.33741248], [1.42746889]**

5. A vs C (Body mass and beak length)

Algorithm	Perceptron	Adaline
Plot		
Confusion matrix		
Train accuracy	**0.9333333333333333**	**0.9333333333333333**
Test accuracy	**0.875**	**0.95**
Training weights,bias	**[-0.13706925 -0.03833908], [0.06072722]**	**[-1.38810132 -1.82880989], [1.51330172]**

Comparative Analysis of Learning Mechanisms:

ADALINE offers significant advantages over the Perceptron due to its use of the Least

Mean Squares (LMS) algorithm. This approach enables ADALINE to converge to the best possible solution, even when the data is not linearly separable, by minimizing the error effectively. where ADALINE avoids the infinite loops that the Perceptron encounters, as it halts once the error reaches a predefined threshold.

In contrast, the Perceptron rule guarantees convergence only for linearly separable data. However, it tends to overfit by reducing the training error to zero, leading to poor generalization and sensitivity to noise. This limitation makes it less reliable for handling noisy or non-separable datasets.

Performance Insights

- **Perceptron**: Accuracy ranges from **88.33% to 100%**, achieving perfect accuracy in two trials. It performs well on linearly separable data but is less stable in non-separable scenarios.
- **ADALINE**: Accuracy ranges from **93.33% to 100%**, demonstrating slightly greater stability and reliability in trials, especially with non-separable data, owing to its gradient-based optimization.

Conclusion

ADALINE's robust learning framework and superior generalization capabilities make it a preferred choice over the Perceptron for tasks involving noisy or non-linearly separable data.

Based on feature combinations, **Beak Length** and **Beak Depth** emerge as the most effective features for distinguishing between species, achieving the highest accuracy. This is particularly evident in distinguishing species B and C, where both Perceptron and ADALINE achieved 100% accuracy on the training and testing datasets.

On the test set, however, ADALINE outperformed the Perceptron (97.5% vs. 92.5%), indicating its superior ability to generalize to unseen data. ADALINE's consistent and accurate performance on the test set underscores its stability and effectiveness in real-world scenarios.