Fisher Linear Discriminant and PCA analysis for Breast Cancer Detection.

Task 1: Fisher Linear Discriminant and PCA Analysis with 10 Components

- Apply Fisher linear discriminant to the first 2/3rd of the data (the training set) after reducing its dimensionality to 10 using PCA.
- Apply the same PCA transform to the remaining 1/3rd of the data (testing set) and then use the
 previously derived Fisher LDA to produce testing scores.
- Repeat this process without PCA shortening and produce all the training and validation ROC curves (4 altogether) and
- Also present the training and testing AUCs and d primes, and
- Plot the Scree graph.

Results:

With PCA (10 Components):

Explained variance by each principal component (10 components):

[0.44629805 0.1926257 0.09980873 0.05816819 0.0512186 0.0397819 0.0214634 0.01622204 0.0141189 0.01160413]

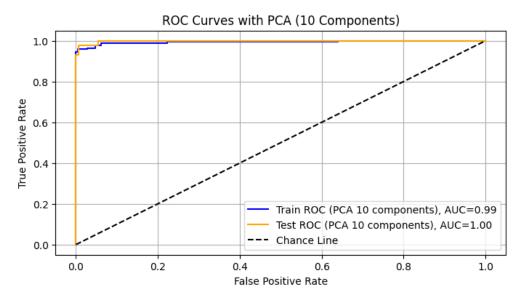
AUCs for PCA - reduced Data (10 components)

AUC (Train with PCA) = 0.993AUC (Test with PCA) = 0.998

d-prime for PCA-reduced data (10 components) :

d-prime (Train with PCA) = 3.126 d-prime (Test with PCA) = 3.124

ROC Curves : PCA 10 components



- The 10-component PCA reduction preserved a significant portion of variance, leading to strong classification performance. The ROC curves showed good separation, and AUC values for both training and testing were high, indicating reliable model accuracy.
- The d-prime values were also high, confirming excellent class separability.

• Overall, the 10-component PCA reduction was effective in maintaining model performance while simplifying the feature space.

• Without PCA:

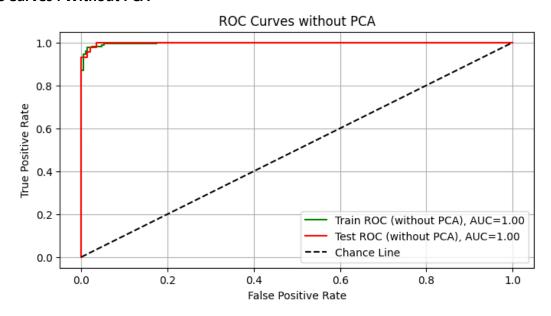
• AUCs for Original Data (Without PCA)

AUC (Train without PCA) = 0.997 AUC (Test without PCA) = 0.998

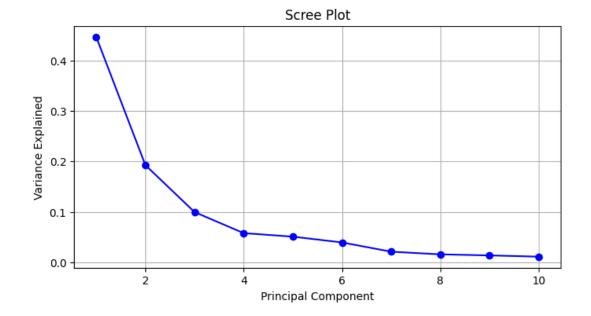
• d-prime for full data without PCA:

d-prime (Train without PCA) = 3.699 d-prime (Test without PCA) = 3.674

ROC Curves : Without PCA



- Using LDA on the full dataset (without PCA) served as a baseline and showed comparable AUC and d-prime values to the 10-component PCA-reduced model.
- This indicates that PCA did not significantly impact the classification power, while it did help reduce data complexity.
- **Scree Plot**: A Scree plot is generated to show variance explained by each principal component, useful for selecting an optimal number of components.



Task 2: Repeat with PCA to 2 and 5 components

AUC values for both PCA - Reduced Data (2 and 5 Components)

AUC (Train with 2 PCA components) = 0.988 AUC (Test with 2 PCA components) = 0.996 AUC (Train with 5 PCA components) = 0.993 AUC (Test with 5 PCA components) = 0.998

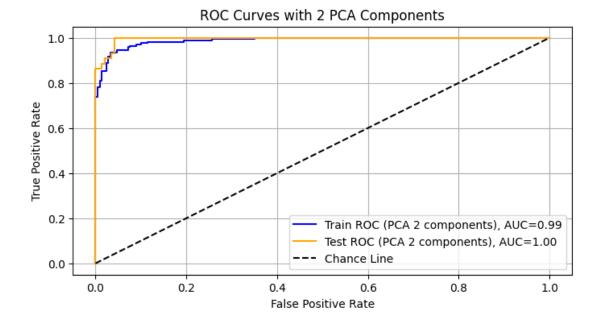
d-prime values for both PCA-Reduced Data (2 and 5 Components)

d-prime (Train with 2 PCA components) = 2.650 d-prime (Test with 2 PCA components) = 2.583 d-prime (Train with 5 PCA components) = 3.042 d-prime (Test with 5 PCA components) = 2.972

• PCA with 2 Components:

Train AUC = 0.99 Test AUC = 1.00 Train d-prime = 2.65 Test d-prime = 2.58

• ROC Curves : for PCA with 2 Components

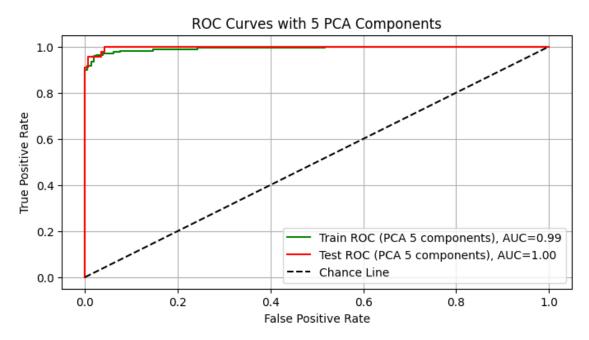


- Reducing the dataset to only 2 components resulted in a noticeable loss of variance, which negatively impacted model accuracy. The AUC and d-prime values were lower, reflecting limited class separability and reduced performance.
- The 2-component PCA reduction was insufficient to retain critical information for effective classification.

• PCA with 5 Components:

Train AUC = 0.99 Test AUC = 1.00 Train d-prime = 3.04 Test d-prime = 2.97

• ROC Curves : for PCA with 5 Components



• Using 5 components provided a better balance, retaining more variance than the 2-component reduction while still simplifying the dataset.

• Although the performance improved over the 2-component reduction, the AUC and d-prime values were still somewhat lower than with 10 components, indicating that some discriminative information was lost.

Conclusion: The results suggest that reducing the dimensionality to 5 components offers a moderate improvement over 2 components but does not perform as well as the 10-component reduction.