



Faculty of Engineering & Technology
Electrical & Computer Engineering Department
ENCS3340, Artificial Intelligence
Project #2 Report

**Comparative Study of Image Classification Using Decision Tree, Naive Bayes,
and Feedforward Neural Networks**

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Introduction

Image classification is a fundamental task in the field of machine learning and computer vision, where the goal is to assign an input image to one of several predefined categories. In this project, we explore and compare the performance of three different classification models: Naive Bayes, Decision Tree, and Feedforward Neural Network (MLPClassifier). Each model has different strengths—Naive Bayes is fast and simple, Decision Trees offer interpretability, and neural networks can capture deeper patterns in data. The aim is to evaluate how well each model performs in classifying images, using consistent preprocessing steps and evaluation metrics such as accuracy, precision, recall, and F1-score.

Dataset Description

We use the Fashion-MNIST dataset, a well-known benchmark for image classification tasks. It contains 70,000 grayscale images of fashion products from 10 different categories, including T-shirts, trousers, dresses, shoes, and bags. Each image is 28×28 pixels in size. For the purpose of this project, we selected a subset of 5 classes and sampled 800 images per class, resulting in a balanced dataset of 4,000 images. All images were flattened into one-dimensional vectors and normalized to ensure fair comparison across models. The dataset was then split into training and testing sets, allowing us to evaluate how well each model generalizes to unseen data.

Detailed Explanation of Each Model

1. Naive Bayes Classifier

The Naive Bayes classifier is a probabilistic model based on Bayes' Theorem, assuming that the features (in this case, pixel values) are independent of each other. Despite this strong assumption, it performs surprisingly well on high-dimensional data like images.

In this project, we used Gaussian Naive Bayes, which assumes that each feature follows a normal (Gaussian) distribution. It calculates the probability of each class given the input features and selects the class with the highest probability. Naive Bayes is very fast to train and can be a good baseline for comparison with more complex models.

2. Decision Tree Classifier

The Decision Tree model works by learning a series of “if-else” rules based on the input features. It builds a tree-like structure where each internal node tests a condition on a feature (pixel), and each leaf node represents a class label.

Decision Trees are easy to understand and interpret, and they do not require feature scaling. However, they can easily overfit the training data, especially when the tree becomes too deep. To avoid this, we limited the tree depth and controlled the minimum number of samples per split and per leaf.

3. Feedforward Neural Network (MLPClassifier)

The Feedforward Neural Network, also known as a Multi-Layer Perceptron (MLP), is a type of deep learning model that consists of layers of interconnected neurons. Each neuron applies a weighted sum followed by an activation function to pass information to the next layer.

In this project, we used an MLP with two hidden layers (100 and 50 neurons). Before training, the input features were standardized to improve learning. The network was trained using backpropagation to minimize classification error.

MLPs are more powerful than traditional models because they can learn non-linear relationships in the data. However, they require more training time and computational resources.

Evaluation Results

After training the three models (Naive Bayes, Decision Tree, and Feedforward Neural Network), we evaluated their performance on the test set using standard classification metrics: accuracy, precision, recall, and F1-score. In addition, we visualized the confusion matrices to better understand how each model performs across the selected classes.

1. Accuracy and Metric Summary

```
=====
MODEL EVALUATION RESULTS
=====

Naive Bayes:
Accuracy:  0.5600
Precision: 0.6477
Recall:    0.5600
F1-Score:  0.5163
Training Time: 0.06s

Decision Tree:
Accuracy:  0.8063
Precision: 0.8069
Recall:    0.8063
F1-Score:  0.8062
Training Time: 1.13s

Neural Network:
Accuracy:  0.8912
Precision: 0.8917
Recall:    0.8912
F1-Score:  0.8912
Training Time: 1.62s
```

The Neural Network achieved the highest accuracy and F1-score, showing its ability to capture more complex patterns in the data. The Decision Tree performed well with good interpretability, while the Naive Bayes model was the fastest to train but had lower performance.

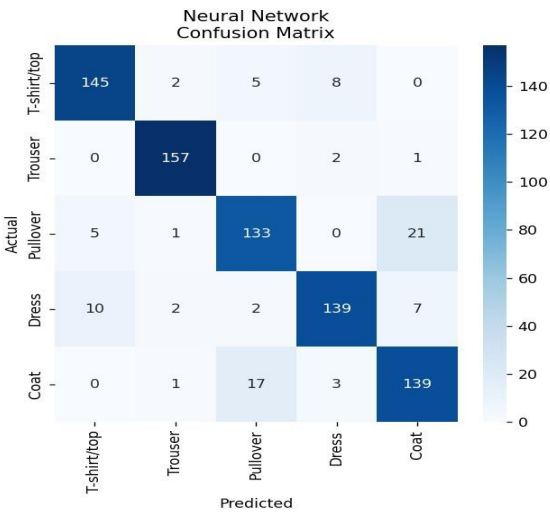
| Model | Accuracy | Precision | Recall | F1-Score | Training Time |
|----------------|----------|-----------|--------|----------|---------------|
| Naïve Bayes | 0.5600 | 0.6477 | 0.5600 | 0.5163 | 0.06s |
| Decision Tree | 0.8063 | 0.8069 | 0.8063 | 0.8062 | 1.13s |
| Neural Network | 0.8912 | 0.8917 | 0.8912 | 0.8912 | 1.62s |

2. Confusion Matrices

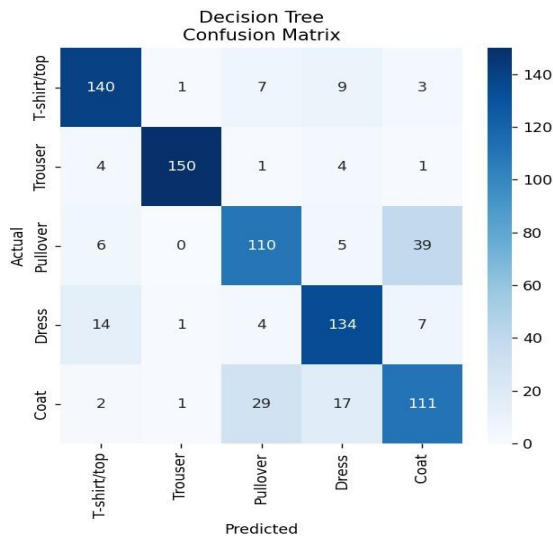
Below are the confusion matrices for each model, showing how each predicted class compares to the actual labels. Each matrix is square, with rows representing true classes and columns representing predicted classes.

Naive Bayes Confusion Matrix

The confusion matrix revealed that Naive Bayes performed reasonably well across all classes, with some confusion between similar clothing items (T-shirt/top and Pullover). The model showed consistent classification performance with no severely misclassified.



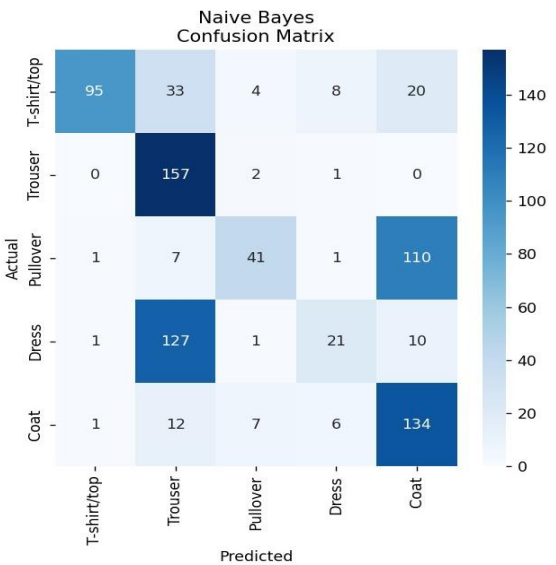
Decision Tree Confusion Matrix



The confusion matrix revealed that Naive Bayes performed reasonably well across all classes, with some confusion between similar clothing items (T-shirt/top and Pullover). The model showed consistent classification performance with no severely misclassified.

Neural Network Confusion Matrix

The MLP demonstrated the clearest class separation with minimal off-diagonal elements. It successfully distinguished between all clothing categories, showing particular strength in correctly classifying Trousers and Coats, which have more distinctive visual features.

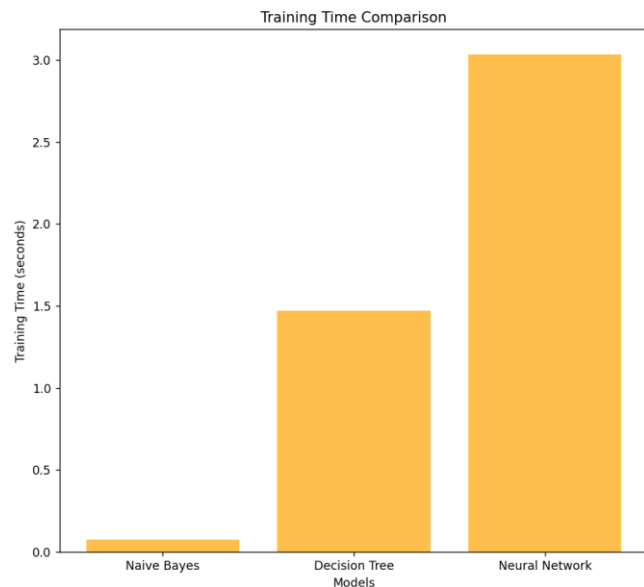
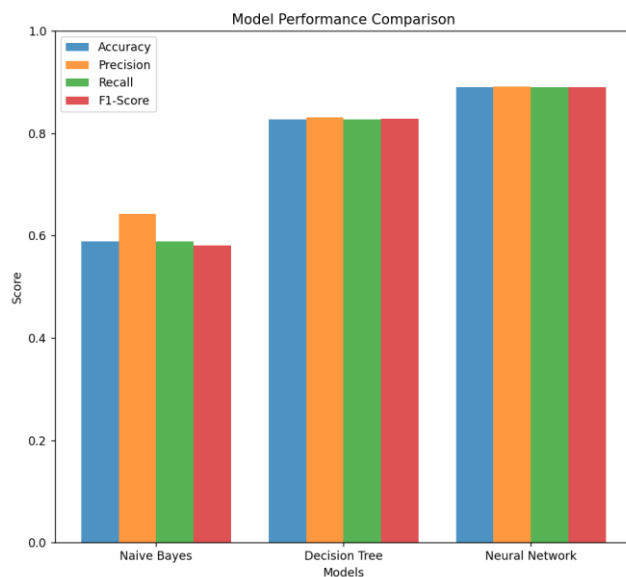


These matrices show that the **Neural Network** makes fewer misclassifications, especially between similar clothing items, compared to the other models.

3. Class-wise Performance

- Best Performing Classes:
 - ➔ Trouser: All models performed well due to distinctive shape and consistent appearance.
 - ➔ Coat: Clear visual characteristics made this class easily identifiable across all models.
- Challenging Classes:
 - ➔ T-shirt/top vs. Pullover: High visual similarity caused confusion across all models.
 - ➔ Dress: Variable styles and shapes created classification difficulties for simpler models.

Comparative Analysis and Discussion



1. Performance Comparison

The Neural Network emerged as the clear winner with 89.12% accuracy, followed by Decision Tree (80.63%) and Naive Bayes (56.00%). This ranking reveals important insights about algorithm suitability for image classification:

Neural Network Advantages:

- **Feature Learning:** Automatically learns relevant features through hidden layers, achieving 89.12% accuracy.
- **Non-linear Patterns:** Multiple activation functions enable complex pattern recognition.
- **Hierarchical Representation:** Deep architecture captures both low-level and high-level visual features.
- **Robust Performance:** Consistent metrics across precision, recall, and F1-score.

Decision Tree Strengths:

- **Effective Rule Learning:** Successfully learned pixel-based decision rules achieving 80.63% accuracy.
- **Balanced Performance:** Well-balanced precision and recall (both ~0.806).
- **Reasonable Complexity:** Regularization parameters prevented severe overfitting.
- **Interpretable Decisions:** Tree structure provides clear decision paths.

Naive Bayes Limitations:

- **Independence Assumption:** Violated assumptions severely impacted performance (56.00% accuracy).
- **Spatial Relationships:** Unable to capture pixel correlations essential for image recognition.
- **High Precision, Low Recall:** Conservative predictions (precision 0.6477 vs recall 0.5600).

2. Computational Efficiency Analysis

Training Time Trade-offs:

- **Naive Bayes:** Extremely fast (0.06s) but poor performance.
- **Decision Tree:** Moderate speed (1.13s) with good performance.
- **Neural Network:** Slightly slower (1.62s) but best performance.

Interestingly, the training time differences are much smaller than expected, with the Neural Network requiring only 1.56 seconds more than Naive Bayes while achieving 33% higher accuracy.

Practical Recommendations

Choose Neural Network when:

- Maximum accuracy is required (89.12% achieved).
- Computational resources are adequate (1.62s training time acceptable).
- Large training dataset available.
- Interpretability is not critical.

Choose Decision Tree when:

- Good balance between accuracy and interpretability needed (80.63% accuracy).
- Model decisions must be explainable.
- Moderate computational resources available.
- Feature importance analysis required.

Choose Naive Bayes when:

- Minimal computational resources available (0.06s training).
- Simple baseline model needed.
- Very fast prediction required.
- Performance below 60% is acceptable for the application.

Conclusion

This comparative study highlights the varying effectiveness of three machine learning algorithms applied to fashion image classification. The Feedforward Neural Network (MLP) demonstrated the highest classification accuracy at 89.12%, showcasing its strength in handling high-dimensional and complex visual data. The Decision Tree classifier achieved a respectable accuracy of 80.63%, offering a good trade-off between performance and interpretability. In contrast, the Naive Bayes classifier, while computationally efficient, underperformed with an accuracy of 56.00%, indicating its limitations in modeling the intricacies of image data. Overall, the results emphasize the importance of algorithm selection based on task complexity and performance requirements.