ML Project - Image Classification on Fashion MNIST

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1. Introduction

This study evaluates the performance of various machine learning models on the Fashion MNIST dataset, which includes 28x28 pixel grayscale images of fashion items across ten categories. Models such as K-Nearest Neighbors (KNN), Random Forests, and Support Vector Machines (SVM) are compared against a Convolutional Neural Network (CNN) to identify their strengths and weaknesses in image classification.

2. Dataset

The Fashion MNIST dataset contains 28x28 pixel grayscale images of fashion items across ten categories. It serves as a challenging benchmark for evaluating image classification algorithms in computer vision and machine learning.

3. Models

This project employs K-Nearest Neighbors (KNN), Random Forests, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) for image classification. Each model is discussed in detail below.

3.1. KNN

K-Nearest Neighbors (KNN) captures local patterns in image data and is assessed using accuracy, precision, recall, and F1-score. KNN's simplicity makes it a good starting point, but it may struggle with high-dimensional data like images.

Table 1. KNN Model Performance

Metric	Value
Accuracy	0.8554
Precision	0.8578
Recall	0.8554
F1-score	0.8546

3.2. Random Forest

Random Forest handles high-dimensional data, captures complex patterns, and mitigates overfitting through ensemble learning. It is robust to noisy data and effective for classifying diverse fashion items. This approach aims to improve upon KNN by providing better generalization and robustness.

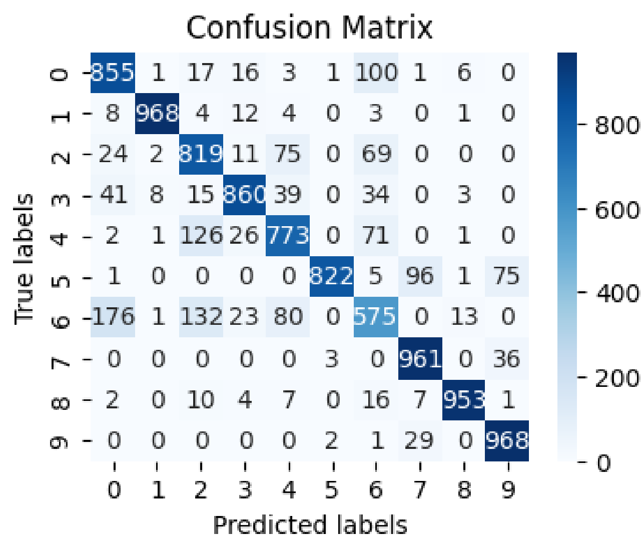

Figure 1. Confusion Matrix of a KNN Model

Table 2. Random Forest Model Performance

Metric	Value
Accuracy	0.8762
Precision	0.8753
Recall	0.8762
F1-score	0.8749

3.3. SVM

Support Vector Machines (SVM) are effective in high-dimensional spaces and find optimal decision boundaries between classes, making them suitable for handling complex image data. SVMs aim to address the limitations of Random Forests by potentially offering better performance in finding precise class boundaries.

3.4. CNN

Convolutional Neural Networks (CNNs) automatically learn hierarchical features from raw pixel values. The CNN

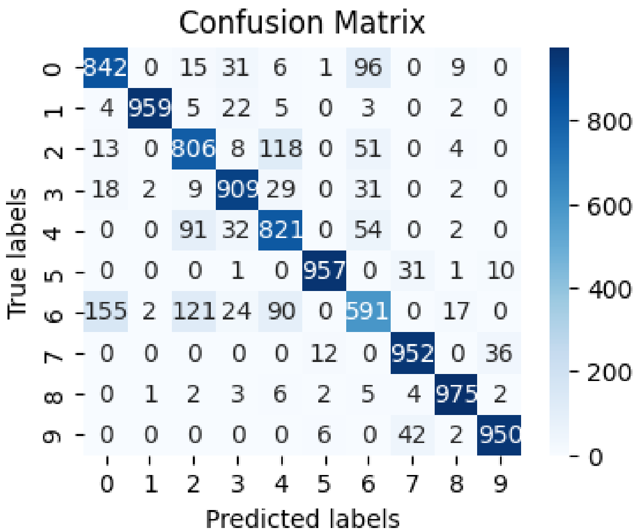

Figure 2. Confusion Matrix of a Random Forest Model

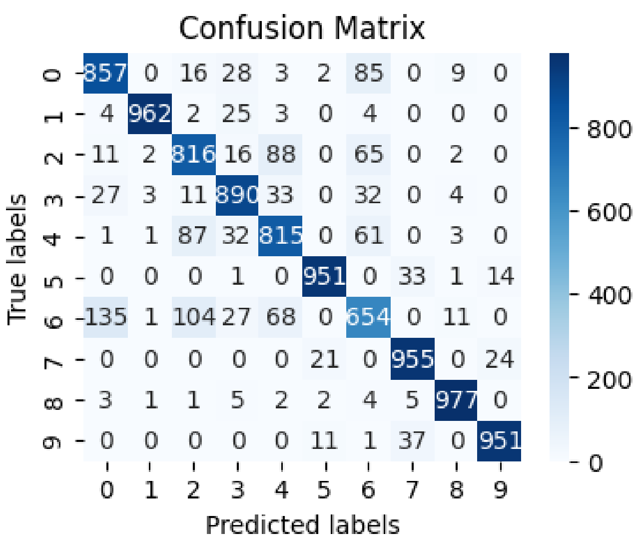

Figure 3. Confusion Matrix of a SVM Model

Table 3. SVM Model Performance

Metric	Value
Accuracy	0.8828
Precision	0.8823
Recall	0.8828
F1-score	0.8822

model includes three Conv2D layers with 32, 64, and 128 filters, each followed by LeakyReLU activation, max pooling, and dropout layers. The final convolutional output is flattened and passed through a dense layer with 128 units, followed by another dropout layer. The model ends with a dense output layer using softmax activation to produce class probabilities. This deep learning approach aims to overcome the limitations of SVMs by providing superior feature extraction and handling complex image data more effectively.

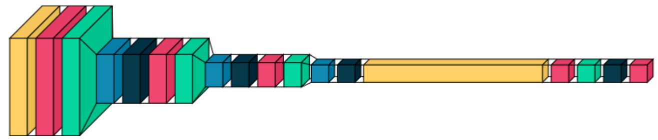

Figure 4. CNN Model Architecture

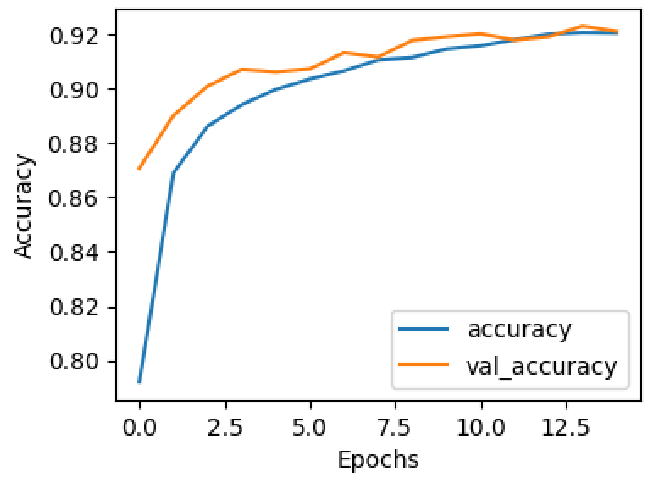

Figure 5. Training vs Validation Accuracy

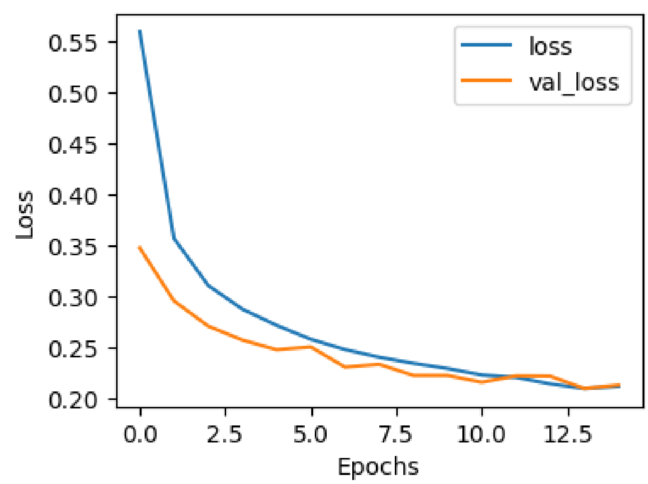

Figure 6. Training vs Validation Loss

4. Conclusion

This study evaluated various machine learning models for classifying the Fashion MNIST dataset. The Convolu-

Table 4. CNN Model Performance

Metric	Value
Accuracy	0.921
Precision	0.920
Recall	0.921
F1-score	0.9206

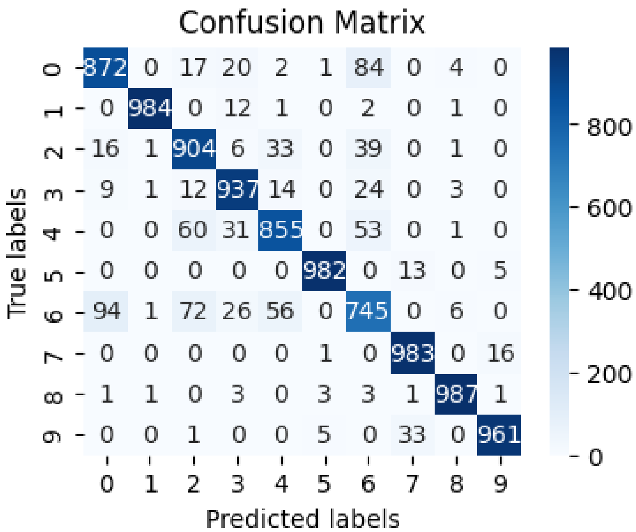

Figure 7. Confusion Matrix of a CNN Model

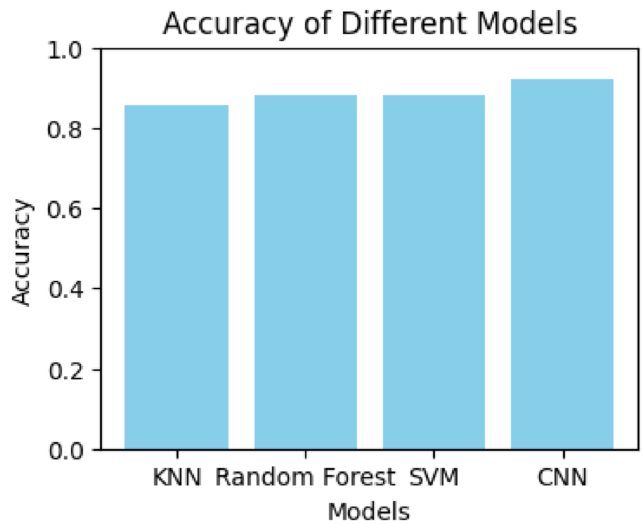

Figure 8. Models Comparison

tional Neural Network (CNN) achieved the highest accuracy of 92%, outperforming K-Nearest Neighbors (KNN), Random Forests, and Support Vector Machines (SVM). While KNN provided a simple baseline, Random Forests improved robustness and generalization. SVMs offered precise decision boundaries, but CNNs excelled by automatically learning hierarchical features. Although CNNs require more computational resources and training time, their superior performance highlights the potential of deep learning in fashion item recognition.

References

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