Multiclass Classification Using Deep Learning and Machine Learning (Fashion-MNIST)

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Date : 12/07/2025

1. Introduction

This report presents a comprehensive theoretical explanation of the multiclass classification workflow applied to the Fashion-MNIST dataset. The project focuses on understanding dataset characteristics, preprocessing steps, exploratory analysis, and the conceptual foundations of both traditional machine learning models and deep learning architectures used for image classification. The report is fully theoretical and does not include code; instead, it provides conceptual explanations, methodology, and interpretation of each stage in a typical supervised learning pipeline.

2. Dataset Description

The Fashion-MNIST dataset is a benchmark dataset created to replace the classic MNIST digit dataset. It consists of 70,000 grayscale images of fashion items, each of size 28×28 pixels. The dataset contains 10 classes, representing everyday clothing categories such as T-shirt/top, trouser, pullover, dress, coat, sandal, shirt, sneaker, bag, and ankle boot.

Each image corresponds to a single label. The dataset is widely used to evaluate image classification models, as it introduces greater complexity than handwritten digits while remaining computationally manageable.

Class Labels

The 10 output classes are:

0. T-shirt/top
1. Trouser
2. Pullover
3. Dress
4. Coat
5. Sandal
6. Shirt
7. Sneaker
8. Bag
9. Ankle boot

3. Data Preprocessing

Data preprocessing is a critical step that ensures the dataset is clean, consistent, and suitable for training classification models. In the context of image datasets, preprocessing typically includes the following activities:

• Handling missing values: The dataset is examined for missing or null values. Image datasets such as Fashion-MNIST usually do not contain missing entries, but the check

ensures integrity.
• Removing duplicates: Duplicate entries can bias the learning process. Any repeated images or labels must be identified and removed.
• Normalization: Pixel values originally range from 0 to 255. Normalization rescales values to the range 0–1, stabilizing gradient descent and improving model convergence.
• Reshaping: Machine learning algorithms may require flattened vectors, while deep learning models expect 2D or 3D structures with channel dimensions.

Importance of Preprocessing
Proper preprocessing reduces noise, improves training efficiency, prevents model bias, and ensures that learning algorithms correctly interpret pixel intensities. In deep learning, normalization is especially important because it significantly enhances training stability and prevents exploding or vanishing gradients.

4. Exploratory Data Analysis (EDA)

Exploratory Data Analysis provides insights into dataset structure, distributions, and patterns. In image classification tasks, EDA commonly includes inspecting sample images, evaluating class distributions, and understanding feature intensities.

Typical visualizations used during EDA include:
• Random sample images from each class
• Class frequency bar charts
• Pixel intensity histograms
• Correlation heatmaps (though less meaningful for raw pixel data)

These visuals help identify class imbalance, detect unusual patterns, and understand dataset complexity.

5. Machine Learning Classifiers

Traditional machine learning models such as Logistic Regression, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Random Forest, and Gradient Boosting are often applied to image classification. However, because these models do not inherently capture spatial patterns in images, they require flattened (1D) representations of pixel data.

Advantages of machine learning models:
• Fast training on small datasets
• Lower computational requirements
• Useful baseline models

Limitations:
• Loss of spatial information when flattening images
• Less effective on complex datasets
• Sensitive to high dimensionality

Expected Performance
On Fashion-MNIST, machine learning classifiers generally achieve accuracy in the range of 75–88%. SVM and Random Forest typically perform better than logistic regression due to their ability to capture non-linear decision boundaries.

6. Deep Learning Models
Deep learning approaches, particularly neural networks and convolutional neural networks (CNNs), are significantly more effective for image classification. Unlike traditional models, CNNs learn spatial hierarchies and extract local patterns from images through convolutional filters.

Key components of a CNN:
• Convolutional layers: Extract visual features such as edges, textures, and shapes.
• Pooling layers: Reduce dimensionality and help prevent overfitting.
• Fully connected layers: Combine extracted features for final decision-making.
• Softmax output layer: Produces probabilistic predictions for each of the 10 classes.

Training Process
Training a deep learning model involves:
• Forward propagation to compute predictions
• Loss calculation (typically categorical cross-entropy)
• Backpropagation to update weights
• Optimization using algorithms like Adam or SGD
• Iterative refinement across multiple epochs

CNNs typically achieve 88–93% accuracy on Fashion-MNIST, depending on architecture depth and regularization techniques such as dropout or batch normalization.

7. Model Evaluation
Model evaluation focuses on assessing predictive performance using metrics such as:
• Accuracy: Proportion of correctly classified images
• Precision, Recall, F1-score: Useful for interpreting model behavior across classes
• Confusion Matrix: Visual summary showing correct and incorrect classifications
• Loss curves and accuracy curves: Used to identify overfitting and training stability

A strong model exhibits high accuracy, balanced class-wise performance, and stable training curves with minimal gap between training and validation metrics.

8. Conclusion

This theoretical report outlines the end-to-end workflow for performing multiclass image classification on the Fashion-MNIST dataset using machine learning and deep learning techniques. While machine learning models provide useful baselines, deep learning—particularly CNNs—delivers superior performance due to its ability to learn sophisticated spatial patterns. A complete analysis includes thorough preprocessing, visual exploration, model development, and quantitative evaluation to ensure robust and reliable predictions.