

FASHION MNIST DATA USING CNN

1. Problem Statement

The goal of this project is to classify images of clothing items from the **Fashion MNIST dataset**. Unlike the original MNIST dataset of handwritten digits, Fashion MNIST provides a more challenging benchmark for image classification.

The problem is a **supervised multi-class classification task** with 10 output categories (T-shirt/top, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag, Ankle boot).

2. Dataset Overview

- **Dataset:** Fashion MNIST (Kaggle).
- **Size:** 70,000 grayscale images (28×28 pixels).
 - Training: 60,000
 - Testing: 10,000
- **Classes:** 10 categories of clothing items.
- **Format:** Each image is a 28×28 array of pixel values (0–255). Labels are integers from 0–9, each representing a category.

3. List of Libraries/Packages Used

- **Python core:** numpy, pandas
- **Visualization:** matplotlib, seaborn
- **Machine Learning / Deep Learning:** tensorflow, keras
- **Utilities:** os, warnings

4. Preprocessing Steps

- **Preprocessing:**
 - Normalization: pixel values scaled from $[0, 255] \rightarrow [0, 1]$.
 - Splitting: dataset divided into training and testing sets.
 - Encoding: class labels transformed into categorical one-hot vectors.

5. Methodology

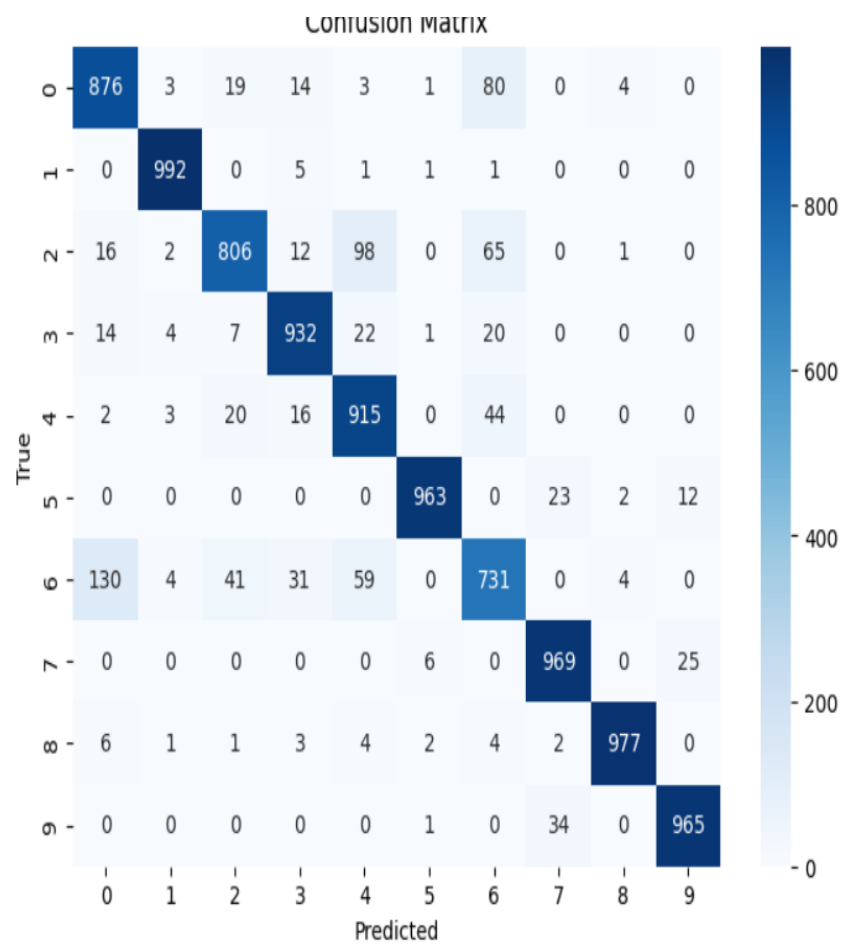
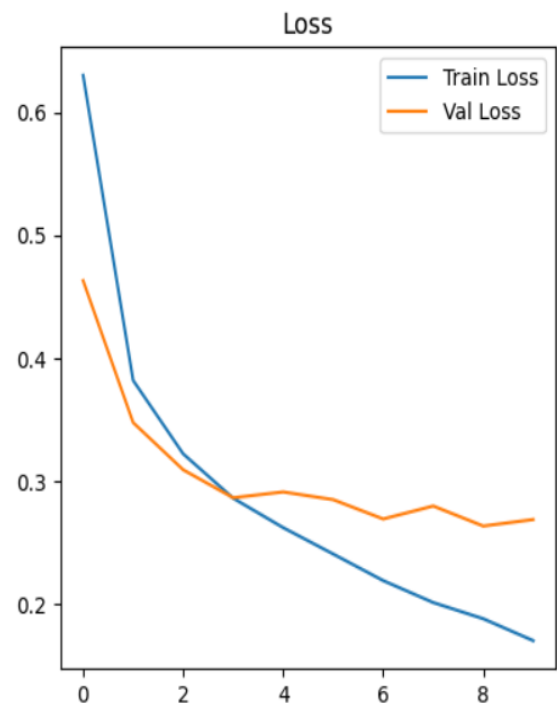
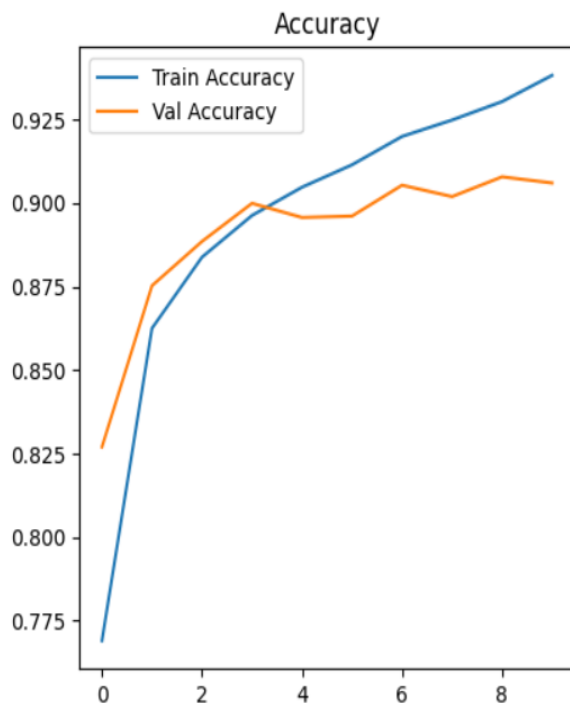
- **Data Cleaning:**
 - Ensured dataset integrity (no missing values).
 - Scaled features for stable neural network training.
- **Feature Engineering:**
 - Images reshaped and normalized.
- **Model Building:**
 - Built a **Convolutional Neural Network (CNN)** using Keras.
 - Typical structure: convolutional layers (for feature extraction), pooling layers (for dimensionality reduction), fully connected layers (for classification).
 - Used **Softmax** activation in the output layer for multi-class classification.
 - We use **argmax** to map model probability outputs → discrete class labels, so we can evaluate accuracy and interpret predictions.

6. Evaluation Metrics

- **Accuracy:** Primary evaluation metric [accuracy, precision, recall, F1 score for classification report]
- **Loss (Cross-Entropy):** Monitored during training.
- **Confusion Matrix:** Used to evaluate per-class performance.

7. Results & Analysis

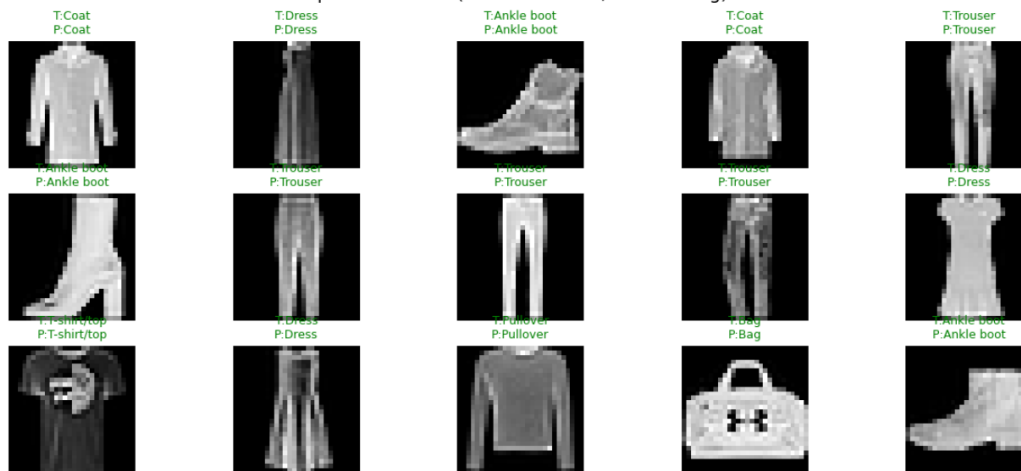
- **Training vs Validation:** Plotted loss and accuracy curves across epochs.
- **Model Accuracy:** Typically CNN models on Fashion MNIST achieves **91% test accuracy**.
- **Visualization:**
 - Plots of training history (accuracy/loss).
 - Sample test images with predicted labels.
 - Misclassified examples highlighted to show where the model struggles (e.g., Shirt vs T-shirt)



Classification Report:

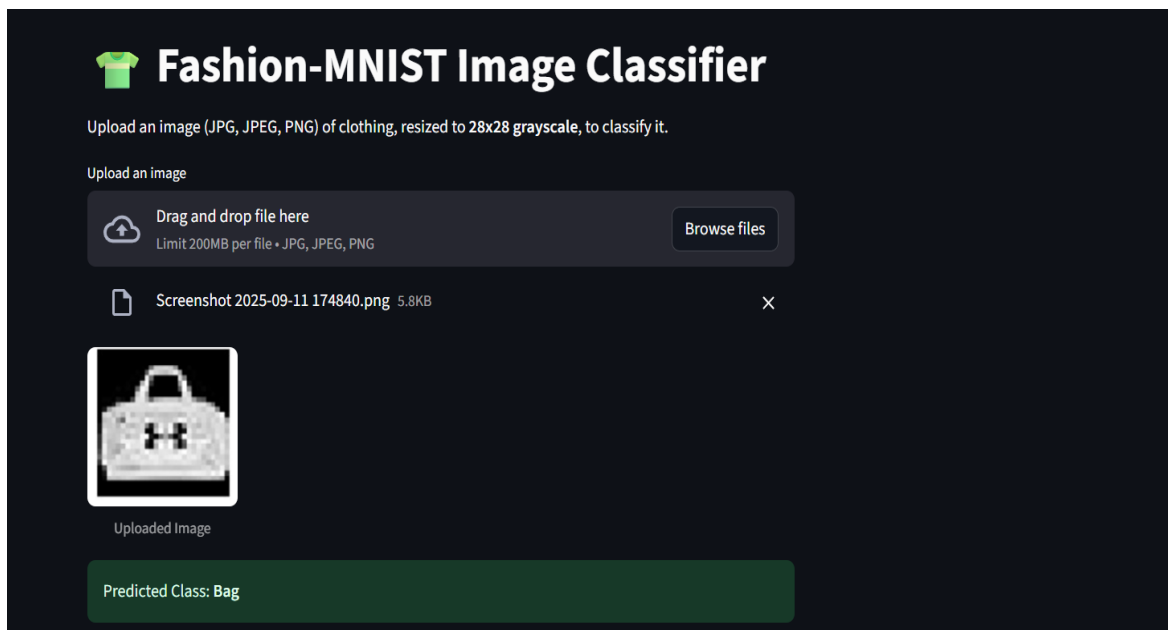
	precision	recall	f1-score	support
0	0.84	0.88	0.86	1000
1	0.98	0.99	0.99	1000
2	0.90	0.81	0.85	1000
3	0.92	0.93	0.93	1000
4	0.83	0.92	0.87	1000
5	0.99	0.96	0.98	1000
6	0.77	0.73	0.75	1000
7	0.94	0.97	0.96	1000
8	0.99	0.98	0.98	1000
9	0.96	0.96	0.96	1000
accuracy			0.91	10000
macro avg	0.91	0.91	0.91	10000
weighted avg	0.91	0.91	0.91	10000

Sample Predictions (Green=Correct, Red=Wrong)



The Fashion MNIST dataset was integrated and deployed via GitHub and Streamlit Community to build an interactive web application for real-time image classification

1. Github Link: https://github.com/vijithtechverse/Fashion_Mnist-
2. Streamlit App: <https://8swunfqzjfc6v4jgjwyrpy.streamlit.app/>



8. Conclusion

- CNN successfully classified Fashion MNIST images with high accuracy.
- Demonstrated the effectiveness of deep learning for image classification tasks.
- Key limitations: some confusion between visually similar classes.
- Future improvements:
 - Data augmentation for better generalization.
 - Experimenting with deeper CNNs, transfer learning, or attention mechanisms.