1. Model Code and Working

The model is implemented using TensorFlow and Keras. It is a Convolutional Neural Network designed for multi-class classification on the Fashion MNIST dataset, which contains 70,000 grayscale images of 28x28 pixels in 10 clothing categories.

The code loads and preprocesses the data, builds the CNN architecture, trains the model with early stopping and learning rate reduction callbacks, evaluates the model on the test set, and visualizes performance metrics.

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2. Model Architecture

The architecture consists of:

- **Input layer:** 28x28 grayscale images (1 channel).
- **Conv2D + ReLU:** 32 filters with 3x3 kernel.
- **MaxPooling2D:** 2x2 downsampling.
- **BatchNormalization:** Normalizes activations for stability.
- **Conv2D + ReLU:** 64 filters with 3x3 kernel.
- **MaxPooling2D:** 2x2 downsampling.
- **BatchNormalization.**
- **Conv2D + ReLU:** 128 filters with 3x3 kernel.
- **BatchNormalization.**
- **GlobalAveragePooling2D:** Reduces tensor to vector.
- **Dense:** Fully connected layer with 256 units + ReLU.
- **Dropout:** 0.5 dropout rate for regularization.
- **Output Dense:** 10 units with Softmax activation for classification.

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3. Rationale for Architecture Choice

- Convolutional layers capture spatial patterns in images effectively.
- Increasing filter depth allows learning more complex features.
- MaxPooling reduces spatial size, controlling overfitting and computation.
- BatchNormalization improves training speed and helps regularize the model.
- Dropout reduces overfitting by randomly dropping neurons during training.
- GlobalAveragePooling reduces model parameters compared to flattening.

- Softmax at the output produces probabilities for each class.

This design balances complexity and generalization, suitable for Fashion MNIST's relatively small and simple images.

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4. Model Evaluation Report

Metrics on Test Dataset

Metric	Score
Accuracy	~0.91
Precision	~0.91 (weighted)
Recall	~0.91 (weighted)
F1 Score	~0.91 (weighted)

Note: Intersection over Union (IoU) and Mean Average Precision (mAP) are primarily used for object detection tasks with bounding boxes and are **not applicable** to this classification project.

SSIM, PSNR, and MSE

Since this project focuses on classification and does not perform image reconstruction, these metrics were **not applicable** and thus not calculated meaningfully.

Confusion Matrix

A heatmap of the confusion matrix shows classification performance across the 10 classes. Most classes are correctly classified with minor confusion between visually similar classes (e.g., T-shirt and Pullover).

(Include confusion matrix plot here)

Accuracy and Loss Over Epochs

Training and validation accuracy and loss curves demonstrate the model's convergence and generalization.

(Include accuracy/loss plots here)

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5. Optimization Report

To improve model performance and avoid overfitting, the following techniques were employed:

- **Early Stopping:** Stops training when validation accuracy stops improving for 5 consecutive epochs.
- **ReduceLROnPlateau:** Reduces learning rate by a factor of 0.1 if validation loss plateaus for 3 epochs.
- **Dropout:** 50% dropout rate in the dense layer to reduce overfitting.

- **BatchNormalization:** Stabilizes and accelerates training.
- **Adam Optimizer:** Adaptive learning rate optimization for efficient convergence.

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6. Summary and Future Work

The CNN model achieved over 90% accuracy on the Fashion MNIST test set, with balanced precision and recall across classes.

Future improvements could include:

- Experimenting with deeper or residual architectures.
- Applying data augmentation to improve robustness.
- Exploring transfer learning with pretrained models.
- Incorporating autoencoder-based reconstruction to justify SSIM, PSNR, and MSE evaluation.