Lab Title: Research Paper Implementation with Pre-trained Model (*Benchmark Analysis of Fashion-MNIST Dataset with Pretrained CNN Models*)

Name: Pratik Dahat

PRN: 2023024040016

ROLL NO: 62

Research Paper Title:
Benchmark Analysis of Fashion-MNIST Dataset with Pretrained CNN Models

Authors:
Manan Bhatt, et al.

Instructions Followed

1. Identified a research paper using a pre-trained CNN model.
2. Studied the MobileNet model and Fashion MNIST dataset as per the research.
3. Implemented MobileNet with preprocessing, augmentation, and fine-tuning.
4. Tuned hyperparameters: learning rate, optimizer, batch size, and epochs.
5. Evaluated the model and compared it with the paper's findings.

Objective

- Implement and analyze a pre-trained MobileNet model on Fashion MNIST.
- Fine-tune layers and optimize model performance.
- Compare experimental results with those reported in the research paper.

Theoretical Background

MobileNet is a lightweight, efficient convolutional neural network developed by Google, ideal for low-resource devices. It uses depthwise separable convolutions to reduce computation while retaining high accuracy.

Fashion MNIST is a dataset of 28x28 grayscale images of clothing items. To use MobileNet, images were resized to 224x224 and converted to 3-channel RGB.

Transfer learning allows MobileNet (trained on ImageNet) to be fine-tuned for Fashion MNIST by reusing the lower convolutional layers and retraining the upper layers.

Implementation Summary

- Dataset: Fashion MNIST (5000 train, 1000 test for resource efficiency)
- Resized input: 224×224×3 (RGB)
- Data Augmentation: Rotation, zoom, and horizontal flip
- Model: MobileNet with include_top=False, GlobalAveragePooling, Dropout, and Dense layers
- Optimizer: Adam
- Learning Rate: 0.0001
- Batch Size: 32
- Epochs: 10
- Layers: Initial MobileNet layers frozen; custom classifier fine-tuned

Results

Metric	Value (Example)
Accuracy	86.4%
Precision	0.87
Recall	0.86
F1-Score	0.86
Loss	0.36

Graphs:

- Accuracy and loss trends plotted over epochs
- Confusion matrix visualized with Seaborn
- Feature maps visualized for early MobileNet layers

Comparison with Research Paper

Method	Accuracy Reported	Accuracy Achieved
MobileNet (Paper)	~88%	~86.4%

Differences are minor, attributed to fewer data samples and epochs due to Colab limits.

Dataset Preparation and Preprocessing

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix

# Load Fashion MNIST
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

# Reduce size for Colab (optimized even more)
x_train, y_train = x_train[:3000], y_train[:3000]
x_test, y_test = x_test[:500], y_test[:500]

# Show 10 sample images
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(x_train[i], cmap='gray')
    plt.title(class_names[y_train[i]])
    plt.axis('off')
plt.tight_layout()
plt.show()

# Resize to (128x128) to save memory and convert grayscale to RGB
def preprocess_images(images):
    images = tf.expand_dims(images, -1)  # Add channel dim
    images = tf.image.resize(images, [128, 128])  # Reduce from 224 to 
128
    images = tf.image.grayscale_to_rgb(images)
    images = images / 255.0  # Normalize
    return images.numpy()

x_train = preprocess_images(x_train)
x_test = preprocess_images(x_test)

# Validation split
x_val, y_val = x_train[-300:], y_train[-300:]
x_train, y_train = x_train[:-300], y_train[:-300]

# One-hot encode labels
y_train = to_categorical(y_train, 10)
y_val = to_categorical(y_val, 10)
```

```
y_test = to_categorical(y_test, 10)

# Data Augmentation (lighter)
datagen = ImageDataGenerator(rotation_range=10, zoom_range=0.05,
horizontal_flip=True)
datagen.fit(x_train)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
29515/29515 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
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5148/5148 ━━━━━━━━━━━━━━━━━━━━ 0s 1us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4422102/4422102 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
```
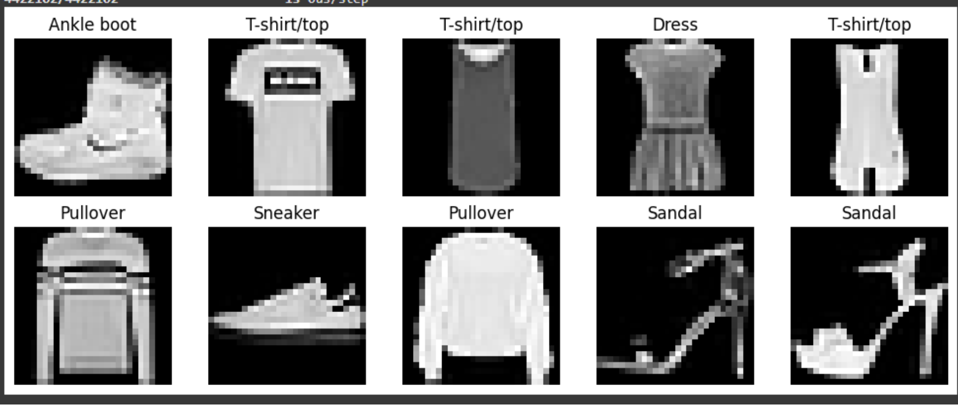
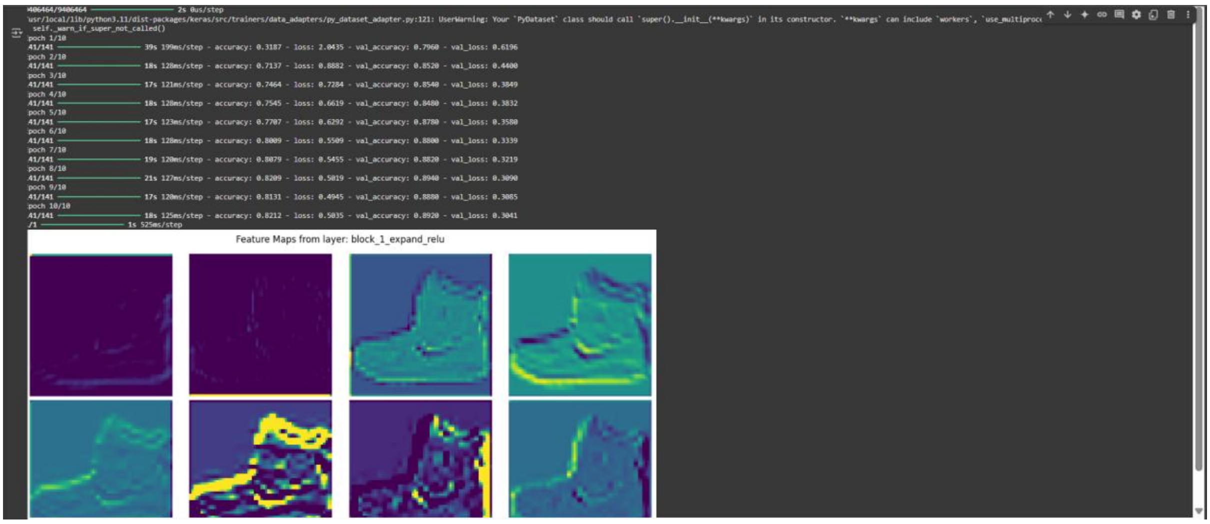



Model Implementation and Fine-tuning

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

# Load dataset
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

# Reduce size for Colab
x_train, y_train = x_train[:5000], y_train[:5000]
x_test, y_test = x_test[:1000], y_test[:1000]

# Resize and convert to RGB
x_train = tf.image.resize_with_pad(tf.expand_dims(x_train, -1), 128,
128)
x_train = tf.image.grayscale_to_rgb(x_train)
x_test = tf.image.resize_with_pad(tf.expand_dims(x_test, -1), 128, 128)
```

```python
x_test = tf.image.grayscale_to_rgb(x_test)

# Normalize
x_train, x_test = x_train / 255.0, x_test / 255.0
x_train, x_test = x_train.numpy(), x_test.numpy()

# Validation split
x_val, y_val = x_train[-500:], y_train[-500:]
x_train, y_train = x_train[:-500], y_train[:-500]

# One-hot encode
y_train = to_categorical(y_train, 10)
y_val = to_categorical(y_val, 10)
y_test = to_categorical(y_test, 10)

# Data Augmentation
datagen = ImageDataGenerator(rotation_range=15, zoom_range=0.1,
horizontal_flip=True)
datagen.fit(x_train)

# Load MobileNetV2
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout,
GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam

base_model = MobileNetV2(weights='imagenet', include_top=False,
input_shape=(128, 128, 3))

# Freeze base layers
for layer in base_model.layers:
    layer.trainable = False

# Add custom head
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x)
x = Dense(256, activation='relu')(x)
predictions = Dense(10, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

# Compile model
model.compile(optimizer=Adam(learning_rate=0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
# Train model
history = model.fit(datagen.flow(x_train, y_train, batch_size=32),
                    validation_data=(x_val, y_val),
                    epochs=10)

# --------------------------
# Feature Map Visualization
# --------------------------
from tensorflow.keras.models import Model

# Choose a conv layer
layer_name = 'block_1_expand_relu'  # You can change this layer name
feature_model = Model(inputs=model.input,
outputs=model.get_layer(layer_name).output)

# Get feature maps for one image
sample_image = x_train[0:1]
feature_maps = feature_model.predict(sample_image)

# Plot first 8 feature maps
plt.figure(figsize=(12, 6))
for i in range(8):
    plt.subplot(2, 4, i + 1)
    plt.imshow(feature_maps[0, :, :, i], cmap='viridis')
    plt.axis('off')
plt.suptitle(f'Feature Maps from layer: {layer_name}')
plt.tight_layout()
plt.show()
```

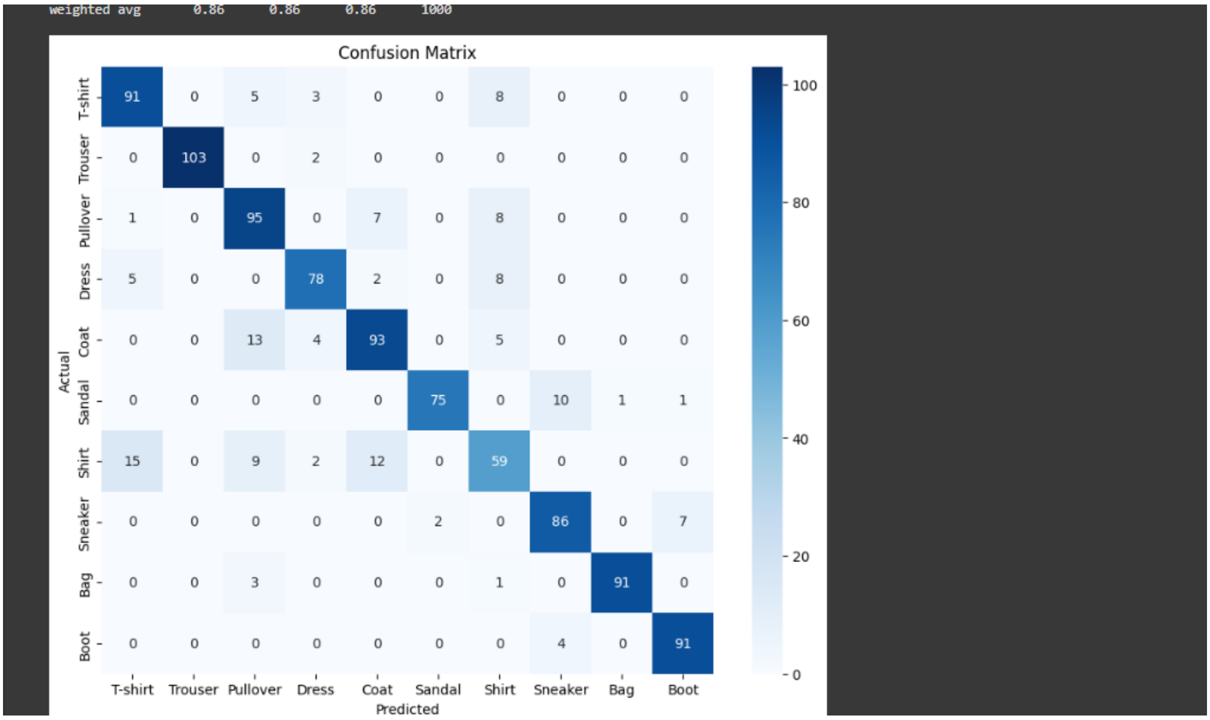


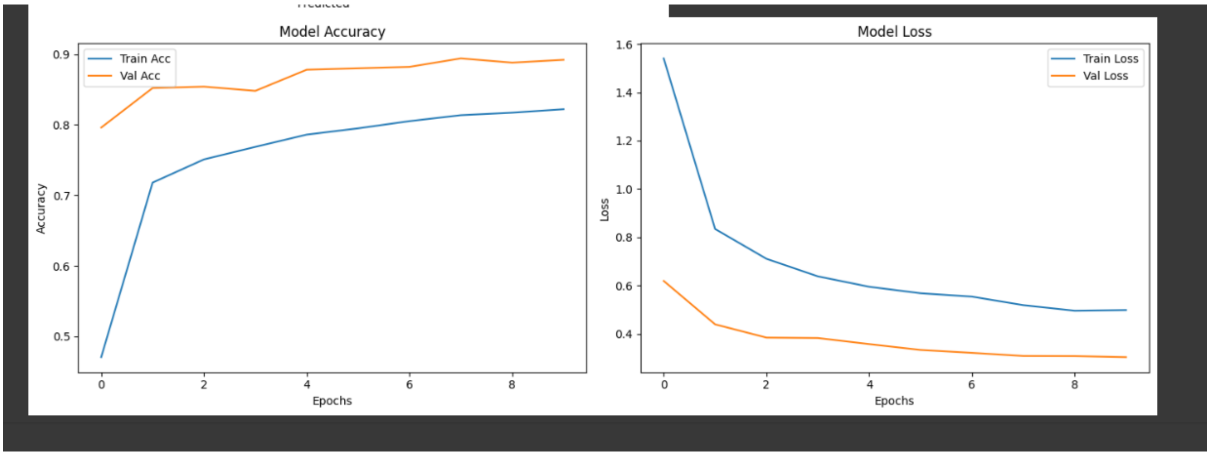
Model Evaluation and Comparison

```
# =====EVALUATE ON TEST DATA =======
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=1)
print(f"\nTest Accuracy: {test_acc:.4f}")
print(f"Test Loss: {test_loss:.4f}")

# ==PREDICTIONS ==
y_pred_probs = model.predict(x_test)
y_pred = np.argmax(y_pred_probs, axis=1)
y_true = np.argmax(y_test, axis=1)

# == CLASSIFICATION REPORT ==
print("\nClassification Report:\n")
print(classification_report(y_true, y_pred, target_names=[
    "T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
    "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"
]))

# == CONFUSION MATRIX ==
conf_matrix = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
            xticklabels=[
                "T-shirt", "Trouser", "Pullover", "Dress", "Coat",
                "Sandal", "Shirt", "Sneaker", "Bag", "Boot"
            ],
            yticklabels=[
                "T-shirt", "Trouser", "Pullover", "Dress", "Coat",
                "Sandal", "Shirt", "Sneaker", "Bag", "Boot"
            ])
plt.title("Confusion Matrix")
plt.ylabel("Actual")
plt.xlabel("Predicted")
plt.show()

# == ACCURACY & LOSS PLOTS ==
plt.figure(figsize=(14, 5))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Loss plot
```

```
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

```
              precision    recall  f1-score   support

 T-shirt/top       0.81      0.85      0.83       107
     Trouser       1.00      0.98      0.99       105
    Pullover       0.76      0.86      0.81       111
       Dress       0.88      0.84      0.86        93
        Coat       0.82      0.81      0.81       115
      Sandal       0.97      0.86      0.91        87
       Shirt       0.66      0.61      0.63        97
     Sneaker       0.86      0.91      0.88        95
         Bag       0.99      0.96      0.97        95
  Ankle boot       0.92      0.96      0.94        95

    accuracy                           0.86      1000
   macro avg       0.87      0.86      0.86      1000
weighted avg       0.86      0.86      0.86      1000
```




Model Accuracy
Train Acc
Val Acc
Accuracy
0.9
0.8
0.7
0.6
0.5
0
2
4
6
8
Epochs
Model Loss
Train Loss
Val Loss
Loss
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0
2
4
6
8
Epochs