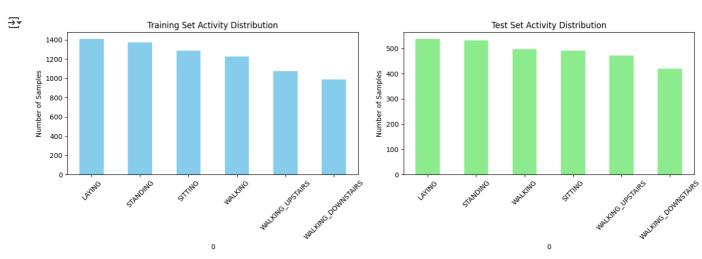
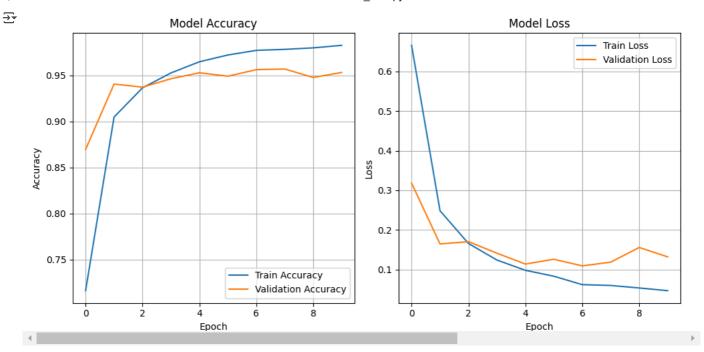
```
from google.colab import drive
drive.mount('/content/drive')
Fr Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force remount=True).
import pandas as pd
import numpy as np
import os
# Set the dataset path
dataset_path = "/content/drive/MyDrive/UCI HAR Dataset/UCI HAR Dataset"
# Load features and activity labels
features = pd.read_csv(os.path.join(dataset_path, 'features.txt'),
                       delim_whitespace=True, header=None)
feature names = features[1].values
activity_labels = pd.read_csv(os.path.join(dataset_path, 'activity_labels.txt'),
                              delim_whitespace=True, header=None, index_col=0)
activity_labels_dict = activity_labels[1].to_dict()
# Load training and testing data
X_train = pd.read_csv(os.path.join(dataset_path, 'train', 'X_train.txt'),
                      delim_whitespace=True, header=None)
y_train = pd.read_csv(os.path.join(dataset_path, 'train', 'y_train.txt'),
                      delim_whitespace=True, header=None)
X_test = pd.read_csv(os.path.join(dataset_path, 'test', 'X_test.txt'),
                     delim_whitespace=True, header=None)
y_test = pd.read_csv(os.path.join(dataset_path, 'test', 'y_test.txt'),
                     delim_whitespace=True, header=None)
# Add feature names for clarity (optional)
X_train.columns = feature_names
X_test.columns = feature_names
# Convert labels to one-hot encoding for classification
from tensorflow.keras.utils import to_categorical
y_train = to_categorical(y_train - 1) # Labels are 1-based
y_test = to_categorical(y_test - 1)
⇒ <ipython-input-4-93679bd03e77>:9: FutureWarning: The 'delim whitespace' keyword in pd.read csv is deprecated and will be removed in
       features = pd.read_csv(os.path.join(dataset_path, 'features.txt'),
     <ipython-input-4-93679bd03e77>:13: FutureWarning: The 'delim_whitespace' keyword in pd.read_csv is deprecated and will be removed ir
       activity_labels = pd.read_csv(os.path.join(dataset_path, 'activity_labels.txt'),
     <ipython-input-4-93679bd03e77>:18: FutureWarning: The 'delim_whitespace' keyword in pd.read_csv is deprecated and will be removed ir
       X_train = pd.read_csv(os.path.join(dataset_path, 'train', 'X_train.txt'),
     <ipython-input-4-93679bd03e77>:20: FutureWarning: The 'delim_whitespace' keyword in pd.read_csv is deprecated and will be removed ir
       y_train = pd.read_csv(os.path.join(dataset_path, 'train', 'y_train.txt'),
     <ipython-input-4-93679bd03e77>:23: FutureWarning: The 'delim_whitespace' keyword in pd.read_csv is deprecated and will be removed ir
     X_test = pd.read_csv(os.path.join(dataset_path, 'test', 'X_test.txt'),
<ipython-input-4-93679bd03e77>:25: FutureWarning: The 'delim_whitespace' keyword in pd.read_csv is deprecated and will be removed in
       y_test = pd.read_csv(os.path.join(dataset_path, 'test', 'y_test.txt'),
    4
os.listdir("/content/drive/MyDrive/UCI HAR Dataset/UCI HAR Dataset")
    ['features.txt',
       'features_info.txt'
      'activity_labels.txt',
      'README.txt',
      '.DS_Store',
       'test',
      'train']
import os
import pandas as pd
# 🔽 Correct nested path
dataset path = "/content/drive/MyDrive/UCI HAR Dataset/UCI HAR Dataset"
# Use sep='\s+' instead of deprecated delim_whitespace
features = pd.read_csv(os.path.join(dataset_path, 'features.txt'), sep='\s+', header=None)[1].values
activity_labels = pd.read_csv(os.path.join(dataset_path, 'activity_labels.txt'), sep='\s+', header=None, index_col=0)
# Load train data
X_train = pd.read_csv(os.path.join(dataset_path, 'train', 'X_train.txt'), sep='\s+', header=None)
```

```
y_train = pd.read_csv(os.path.join(dataset_path, 'train', 'y_train.txt'), sep='\s+', header=None)
# Load test data
X_test = pd.read_csv(os.path.join(dataset_path, 'test', 'X_test.txt'), sep='\s+', header=None)
y_test = pd.read_csv(os.path.join(dataset_path, 'test', 'y_test.txt'), sep='\s+', header=None)
import pandas as pd
import\ matplotlib.pyplot\ as\ plt
import os
# Define dataset path
dataset_path = "/content/drive/MyDrive/UCI HAR Dataset/UCI HAR Dataset"
# Load activity labels
activity_labels = pd.read_csv(
    os.path.join(dataset_path, 'activity_labels.txt'),
    sep='\s+', header=None, index_col=0
).to_dict()[1]
# Load y_train and y_test
y_train = pd.read_csv(os.path.join(dataset_path, 'train', 'y_train.txt'), header=None)[0]
y_test = pd.read_csv(os.path.join(dataset_path, 'test', 'y_test.txt'), header=None)[0]
# Map labels to activity names
y_train_named = y_train.map(activity_labels)
y_test_named = y_test.map(activity_labels)
# Plotting
fig, ax = plt.subplots(1, 2, figsize=(14, 5))
# Training set distribution
y\_train\_named.value\_counts().plot(kind='bar', ax=ax[0], color='skyblue')
ax[0].set_title('Training Set Activity Distribution')
ax[0].set_ylabel('Number of Samples')
ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation=45)
# Test set distribution
y_test_named.value_counts().plot(kind='bar', ax=ax[1], color='lightgreen')
ax[1].set_title('Test Set Activity Distribution')
ax[1].set_ylabel('Number of Samples')
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation=45)
plt.tight_layout()
plt.show()
```



```
dataset path = "/content/drive/MyDrive/UCI HAR Dataset/UCI HAR Dataset"
features = pd.read_csv(os.path.join(dataset_path, 'features.txt'), sep='\s+', header=None)[1].values
X_train = pd.read_csv(os.path.join(dataset_path, 'train', 'X_train.txt'), sep='\s+', header=None).values
y_train = pd.read_csv(os.path.join(dataset_path, 'train', 'y_train.txt'), sep='\s+', header=None).values
X_test = pd.read_csv(os.path.join(dataset_path, 'test', 'X_test.txt'), sep='\s+', header=None).values
y_test = pd.read_csv(os.path.join(dataset_path, 'test', 'y_test.txt'), sep='\s+', header=None).values
# Preprocessing
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
y_train = to_categorical(y_train - 1)
y_test = to_categorical(y_test - 1)
num_classes = y_train.shape[1]
input_shape = (X_train.shape[1], 1)
# ----- CBAM MODULE -----
def cbam block(input tensor, ratio=8):
    # Channel Attention
    channel = input_tensor.shape[-1]
    shared_dense_one = Dense(channel // ratio, activation='relu', kernel_initializer='he_normal', use_bias=True)
    shared_dense_two = Dense(channel, kernel_initializer='he_normal', use_bias=True)
    avg_pool = GlobalAveragePooling1D()(input_tensor)
    avg pool = Reshape((1, channel))(avg pool)
    avg_pool = shared_dense_one(avg_pool)
    avg_pool = shared_dense_two(avg_pool)
    max_pool = GlobalMaxPooling1D()(input_tensor)
    max_pool = Reshape((1, channel))(max_pool)
    max_pool = shared_dense_one(max_pool)
    max_pool = shared_dense_two(max_pool)
    cbam_feature = Add()([avg_pool, max_pool])
    cbam_feature = Activation('sigmoid')(cbam_feature)
    cbam_feature = Multiply()([input_tensor, cbam_feature])
    # Spatial Attention
    avg_pool = Lambda(lambda x: K.mean(x, axis=2, keepdims=True))(cbam_feature)
    max_pool = Lambda(lambda x: K.max(x, axis=2, keepdims=True))(cbam_feature)
    concat = Concatenate(axis=2)([avg_pool, max_pool])
    spatial_attention = Conv1D(filters=1, kernel_size=7, padding='same', activation='sigmoid')(concat)
    refined_feature = Multiply()([cbam_feature, spatial_attention])
    return refined_feature
# ----- SELECTIVE KERNEL BLOCK -----
def selective_kernel_block(input_tensor, filters):
    branch_3 = Conv1D(filters, kernel_size=3, padding='same', activation='relu')(input_tensor)
    branch_5 = Conv1D(filters, kernel_size=5, padding='same', activation='relu')(input_tensor)
    branch_7 = Conv1D(filters, kernel_size=7, padding='same', activation='relu')(input_tensor)
branch_9 = Conv1D(filters, kernel_size=9, padding='same', activation='relu')(input_tensor)
    merged = Add()([branch_3, branch_5, branch_7, branch_9]) # Could also try Concatenate()
    return merged
# ----- BUILD ASK-HAR MODEL -----
input_layer = Input(shape=input_shape)
x = selective_kernel_block(input_layer, filters=64)
x = cbam_block(x)
x = MaxPooling1D(pool size=2)(x)
x = selective kernel block(x, filters=128)
x = cbam_block(x)
x = MaxPooling1D(pool_size=2)(x)
x = Flatten()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
output_layer = Dense(num_classes, activation='softmax')(x)
model = Model(inputs=input_layer, outputs=output_layer)
```

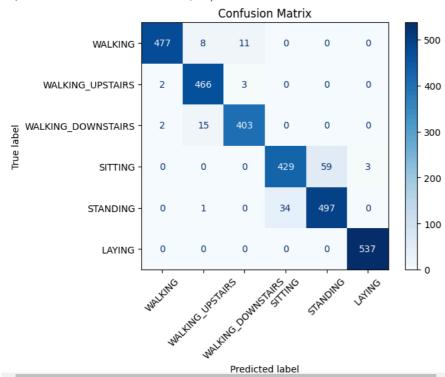
```
# Compile
model.compile(optimizer=Adam(learning rate=0.001), loss='categorical crossentropy', metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10, batch_size=64, validation_data=(X_test, y_test))
→ Epoch 1/10
     115/115
                                — 118s 955ms/step - accuracy: 0.5547 - loss: 1.0187 - val accuracy: 0.8697 - val loss: 0.3181
     Epoch 2/10
     115/115 -
                                - 134s 891ms/step - accuracy: 0.8873 - loss: 0.2842 - val_accuracy: 0.9406 - val_loss: 0.1646
     Epoch 3/10
                                – 136s 840ms/step - accuracy: 0.9379 - loss: 0.1726 - val_accuracy: 0.9372 - val_loss: 0.1704
     115/115 -
     Epoch 4/10
     115/115 -
                                — 95s 822ms/step - accuracy: 0.9488 - loss: 0.1352 - val_accuracy: 0.9464 - val_loss: 0.1413
     Epoch 5/10
                                — 137s 787ms/step - accuracy: 0.9645 - loss: 0.0944 - val_accuracy: 0.9528 - val_loss: 0.1139
     115/115
     Epoch 6/10
     115/115 -
                                - 143s 799ms/step - accuracy: 0.9725 - loss: 0.0836 - val accuracy: 0.9491 - val loss: 0.1260
     Epoch 7/10
     115/115 -
                                — 139s 776ms/step - accuracy: 0.9790 - loss: 0.0608 - val_accuracy: 0.9562 - val_loss: 0.1094
     Epoch 8/10
                                — 144s 799ms/step - accuracy: 0.9755 - loss: 0.0673 - val_accuracy: 0.9569 - val_loss: 0.1188
     115/115 -
     Epoch 9/10
     115/115 -
                                – 141s 787ms/step - accuracy: 0.9799 - loss: 0.0493 - val_accuracy: 0.9477 - val_loss: 0.1558
     Epoch 10/10
     115/115
                                — 146s 822ms/step - accuracy: 0.9809 - loss: 0.0509 - val_accuracy: 0.9532 - val_loss: 0.1321
import matplotlib.pyplot as plt
# Plot accuracy and loss
def plot_training_history(history):
   plt.figure(figsize=(10, 5))
   # Accuracy
   plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
   plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
   plt.title('Model Accuracy')
   plt.xlabel('Epoch')
   plt.ylabel('Accuracy')
   plt.legend()
   plt.grid(True)
   # Loss
   plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Train Loss')
   plt.plot(history.history['val_loss'], label='Validation Loss')
   plt.title('Model Loss')
   plt.xlabel('Epoch')
   plt.ylabel('Loss')
   plt.legend()
   plt.grid(True)
   plt.tight_layout()
   plt.show()
# Call the function
plot_training_history(history)
```



```
from sklearn.metrics import confusion_matrix, {\tt ConfusionMatrixDisplay} import numpy as {\tt np}
```

```
# Predict
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = np.argmax(y_test, axis=1)
# Confusion matrix
\label{eq:cm} \mbox{cm = confusion\_matrix}(\mbox{y\_true, y\_pred\_classes})
labels = [
    'WALKING', 'WALKING_UPSTAIRS', 'WALKING_DOWNSTAIRS',
    'SITTING', 'STANDING', 'LAYING'
]
# Plot
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot(cmap=plt.cm.Blues, xticks_rotation=45)
plt.title("Confusion Matrix")
plt.grid(False)
plt.show()
```





```
from sklearn.metrics import classification_report

# Assuming y_true and y_pred_classes are already defined
labels = [
    'WALKING', 'WALKING_UPSTAIRS', 'WALKING_DOWNSTAIRS',
    'SITTING', 'STANDING', 'LAYING'
]

# Generate and print the classification report
report = classification_report(y_true, y_pred_classes, target_names=labels)
print("Classification Report:\n")
print(report)
```

→ Classification Report:

	precision	recall	f1-score	support
WALKING	0.99	0.96	0.98	496
WALKING_UPSTAIRS	0.95	0.99	0.97	471
WALKING_DOWNSTAIRS	0.97	0.96	0.96	420
SITTING	0.93	0.87	0.90	491
STANDING	0.89	0.93	0.91	532
LAYING	0.99	1.00	1.00	537
accuracy			0.95	2947
macro avg	0.95	0.95	0.95	2947
weighted avg	0.95	0.95	0.95	2947