```
#import necessary library


import warnings


warnings.filterwarnings('ignore')


import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import mnist
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import to_categorical
from tensorflow.keras import regularizers
import keras_tuner as kt
```

```
2025-01-21 17:53:25.916973: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly di
2025-01-21 17:53:25.927852: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register cuFFT fact
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1737460405.940361    7045 cuda_dnn.cc:8310] Unable to register cuDNN factory: Attempting to register factory
E0000 00:00:1737460405.943952    7045 cuda_blas.cc:1418] Unable to register cuBLAS factory: Attempting to register facto
2025-01-21 17:53:25.956614: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the app
```

Step 1: Load and preprocess the MNIST dataset

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

Normalize the data to [0, 1]

```
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0
```

Reshape data to be in the form (batch_size, height, width, channels)

```
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
```

```
x_train.shape,x_test.shape
```

```
((60000, 28, 28, 1), (10000, 28, 28, 1))
```

One-hot encode the labels

```
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

```
y_train,y_test
```

```
(array([[0., 0., 0., ..., 0., 0., 0.],
        [1., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 1., 0.]]),
 array([[0., 0., 0., ..., 1., 0., 0.],
        [0., 0., 1., ..., 0., 0., 0.],
        [0., 1., 0., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.]]))
```

Step 2: Define the model with hyperparameters for tuning

```
def build_model(hp):
    model = models.Sequential()

    # Convolutional Layer 1
    model.add(layers.Conv2D(filters=hp.Int('conv_1_filters', min_value=32, max_value=96, step=32),
                            kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1),
                            kernel_regularizer=regularizers.l2(hp.Float('conv_1_l2', min_value=0.0, max_value=0.05, step=0.0
    model.add(layers.MaxPooling2D((2, 2)))

    # Convolutional Layer 2
    model.add(layers.Conv2D(filters=hp.Int('conv_2_filters', min_value=64, max_value=192, step=64),
                            kernel_size=(3, 3), activation='relu',
                            kernel_regularizer=regularizers.l2(hp.Float('conv_2_l2', min_value=0.0, max_value=0.05, step=0.0
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten the output
    model.add(layers.Flatten())

    # Fully Connected Layer 1
    model.add(layers.Dense(units=hp.Int('dense_1_units', min_value=128, max_value=384, step=128),
                           activation='relu', kernel_regularizer=regularizers.l2(hp.Float('dense_1_l2', min_value=0.0, max_v
    model.add(layers.Dropout(hp.Float('dropout_1', min_value=0.3, max_value=0.5, step=0.1)))

    # Fully Connected Layer 2
    model.add(layers.Dense(units=hp.Int('dense_2_units', min_value=64, max_value=192, step=64),
                           activation='relu', kernel_regularizer=regularizers.l2(hp.Float('dense_2_l2', min_value=0.0, max_v
    model.add(layers.Dropout(hp.Float('dropout_2', min_value=0.3, max_value=0.5, step=0.1)))

    # Output Layer
    model.add(layers.Dense(10, activation='softmax'))

    # Compile the model
    model.compile(optimizer=Adam(learning_rate=hp.Float('learning_rate', min_value=1e-4, max_value=1e-3, sampling='LOG')),
                  loss='categorical_crossentropy', metrics=['accuracy'])

    return model
```

Step 3: Set up the Hyperparameter Tuner with reduced trials

```
tuner = kt.Hyperband(build_model,
                     objective='val_accuracy',
                     max_epochs=6,           # Fewer epochs
                     hyperband_iterations=1, # Fewer iterations
                     directory='my_dir',
                     project_name='mnist_tuning_reduced_trials')
```

```
Reloading Tuner from my_dir/mnist_tuning_reduced_trials/tuner0.json
2025-01-21 17:53:27.418628: E external/local_xla/xla/stream_executor/cuda/cuda_driver.cc:152] failed call to cuInit: INT
```

Step 4: Set up Early Stopping

```
early_stopping = EarlyStopping(monitor='val_loss', patience=2, restore_best_weights=True)
```

Step 5: Start the Hyperparameter Search

```
tuner.search(x_train, y_train, epochs=10, validation_data=(x_test, y_test), callbacks=[early_stopping])
```

Step 6: Get the Best Model and Hyperparameters

```
best_model = tuner.get_best_models(num_models=1)[0]
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print(f"Best Hyperparameters: {best_hps.values}")
```

```
Best Hyperparameters: {'conv_1_filters': 64, 'conv_1_l2': 0.04, 'conv_2_filters': 64, 'conv_2_l2': 0.0, 'dense_1_units':
```

Step 7: Evaluate the Best Model

```
test_loss, test_acc = best_model.evaluate(x_test, y_test, verbose=2)
print(f'Test accuracy: {test_acc}')
```

```
313/313 - 1s - 4ms/step - accuracy: 0.9797 - loss: 0.1844
Test accuracy: 0.9797000288963318
```

```
# Get the training history
history = best_model.history.history
```

```
# Retrain the best model to capture training history
retrain_history = best_model.fit(
    x_train, y_train,
    epochs=10,  # Adjust epochs as needed
    validation_data=(x_test, y_test),
    callbacks=[early_stopping]
)

# Retrieve the training history
history = retrain_history.history
```

```
Epoch 1/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 25s 13ms/step - accuracy: 0.9693 - loss: 0.2102 - val_accuracy: 0.9801 - val_loss: 0.1774
Epoch 2/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 26s 14ms/step - accuracy: 0.9735 - loss: 0.2048 - val_accuracy: 0.9832 - val_loss: 0.1605
Epoch 3/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 26s 14ms/step - accuracy: 0.9740 - loss: 0.1969 - val_accuracy: 0.9841 - val_loss: 0.1557
Epoch 4/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 26s 14ms/step - accuracy: 0.9750 - loss: 0.1848 - val_accuracy: 0.9808 - val_loss: 0.1644
Epoch 5/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 26s 14ms/step - accuracy: 0.9760 - loss: 0.1819 - val_accuracy: 0.9788 - val_loss: 0.1585
```

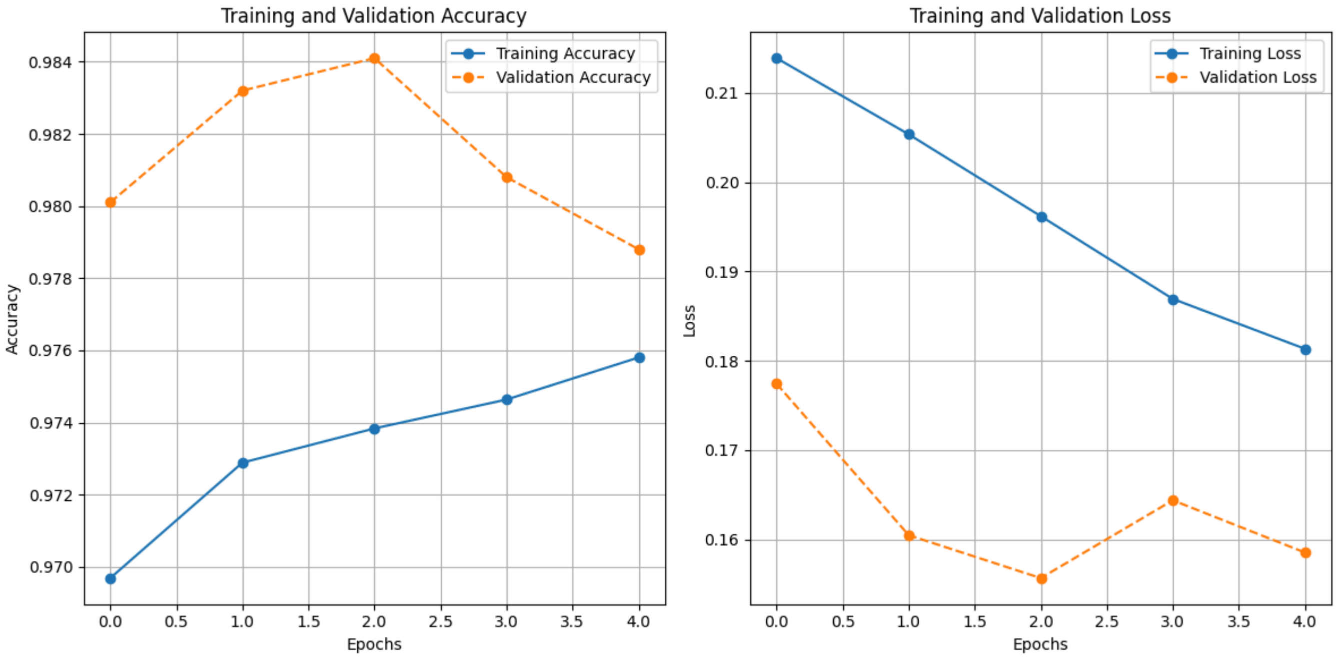
Step 8: Plot Training and Validation Accuracy & Loss

```
# Plot Training and Validation Accuracy & Loss
plt.figure(figsize=(12, 6))

# Plotting training and validation accuracy
plt.subplot(1, 2, 1)
plt.plot(history['accuracy'], label='Training Accuracy', marker='o')
plt.plot(history['val_accuracy'], label='Validation Accuracy', marker='o', linestyle='--')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Plotting training and validation loss
plt.subplot(1, 2, 2)
plt.plot(history['loss'], label='Training Loss', marker='o')
plt.plot(history['val_loss'], label='Validation Loss', marker='o', linestyle='--')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

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



Start coding or generate with AI.