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In [1]: # Task 4: MNIST Handwritten Digit Classifier with Keras

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import confusion_matrix, classification_report
```

```
In [2]: # -------------------- Step 1: Load Dataset --------------------
(X_train, y_train), (X_test, y_test) = mnist.load_data()

print(f"Training data shape: {X_train.shape}")
print(f"Test data shape: {X_test.shape}")
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datase
ts/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 7s 1us/step
Training data shape: (60000, 28, 28)
Test data shape: (10000, 28, 28)
```

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In [3]: # -------------------- Step 2: Preprocess Data --------------------
# Normalize pixel values to [0, 1]
X_train = X_train / 255.0
X_test = X_test / 255.0

# One-hot encode target labels
y_train_encoded = to_categorical(y_train, 10)
y_test_encoded = to_categorical(y_test, 10)
```

```
In [5]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Flatten, Dense

# Recommended model architecture with Input layer
model = Sequential([
    Input(shape=(28, 28)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc
```

```
In [6]: # -------------------- Step 4: Train the Model --------------------
history = model.fit(X_train, y_train_encoded, epochs=10, batch_size=128, valic
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Epoch 1/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 4s 6ms/step - accuracy: 0.8133 - loss: 0.6544 - va
l_accuracy: 0.9608 - val_loss: 0.1374
Epoch 2/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9555 - loss: 0.1530 - va
l_accuracy: 0.9702 - val_loss: 0.1038
Epoch 3/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9696 - loss: 0.0980 - va
l_accuracy: 0.9740 - val_loss: 0.0933
Epoch 4/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.9786 - loss: 0.0713 - va
l_accuracy: 0.9753 - val_loss: 0.0871
Epoch 5/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9833 - loss: 0.0571 - va
l_accuracy: 0.9780 - val_loss: 0.0770
Epoch 6/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9864 - loss: 0.0457 - va
l_accuracy: 0.9770 - val_loss: 0.0800
Epoch 7/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9885 - loss: 0.0394 - va
l_accuracy: 0.9808 - val_loss: 0.0732
Epoch 8/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9917 - loss: 0.0305 - va
l_accuracy: 0.9782 - val_loss: 0.0779
Epoch 9/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.9939 - loss: 0.0217 - va
l_accuracy: 0.9807 - val_loss: 0.0796
Epoch 10/10
422/422 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9948 - loss: 0.0181 - va
l_accuracy: 0.9788 - val_loss: 0.0878
```

In [7]:

```python
# -------------------- Step 5: Evaluate on Test Data --------------------
test_loss, test_accuracy = model.evaluate(X_test, y_test_encoded)
print(f"\nTest Accuracy: {test_accuracy:.4f}")
print(f"Test Loss: {test_loss:.4f}")
```

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313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9690 - loss: 0.1050

Test Accuracy: 0.9739
Test Loss: 0.0902
```

In [8]:

```python
# -------------------- Step 6: Predictions and Confusion Matrix -------------
y_pred_probs = model.predict(X_test)
y_pred = np.argmax(y_pred_probs, axis=1)

# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
```

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plt.ylabel("True")
plt.show()
```

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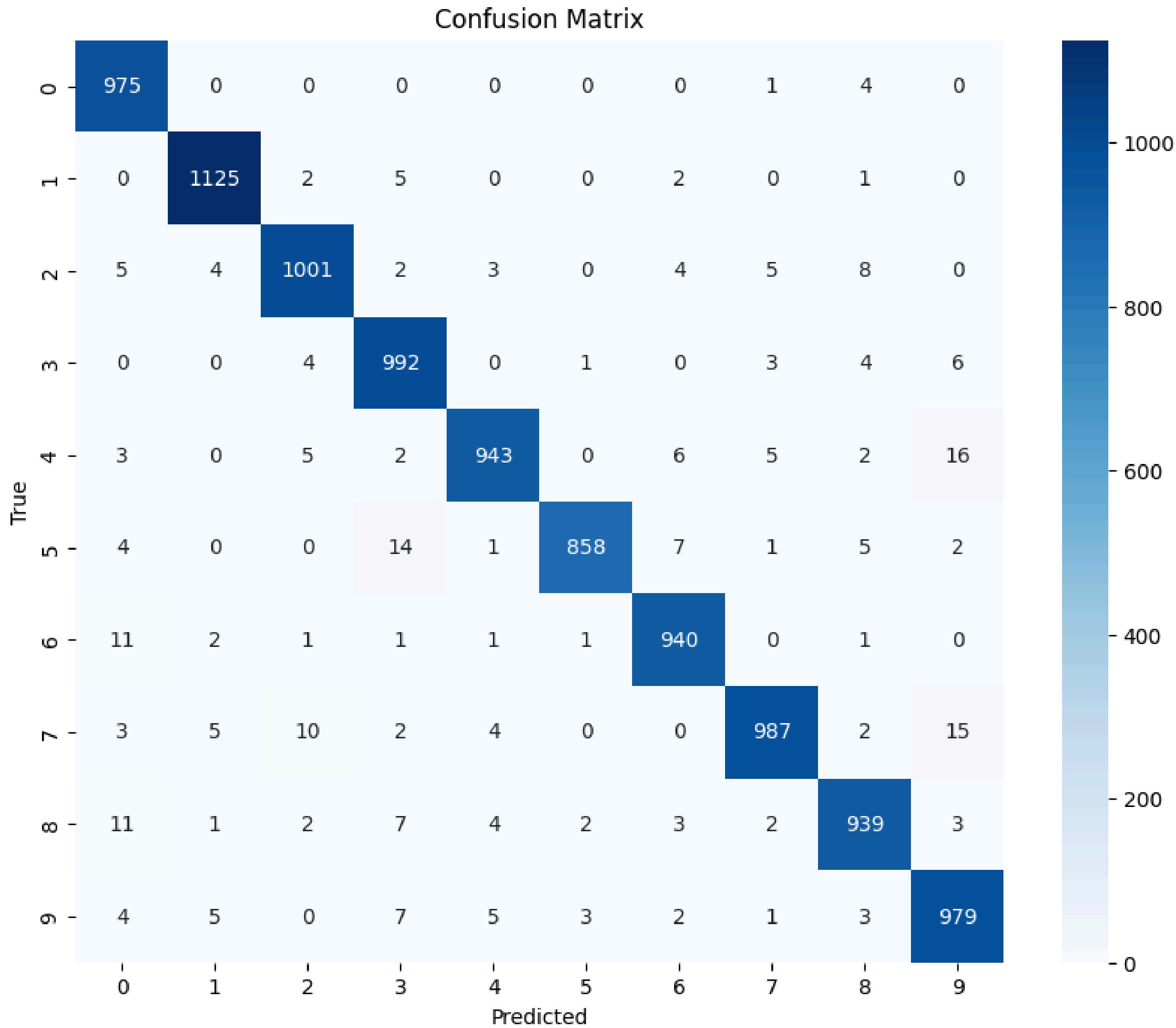
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step

Classification Report:
               precision    recall  f1-score   support

           0       0.96      0.99      0.98       980
           1       0.99      0.99      0.99      1135
           2       0.98      0.97      0.97      1032
           3       0.96      0.98      0.97      1010
           4       0.98      0.96      0.97       982
           5       0.99      0.96      0.98       892
           6       0.98      0.98      0.98       958
           7       0.98      0.96      0.97      1028
           8       0.97      0.96      0.97       974
           9       0.96      0.97      0.96      1009

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000
```



In [9]:

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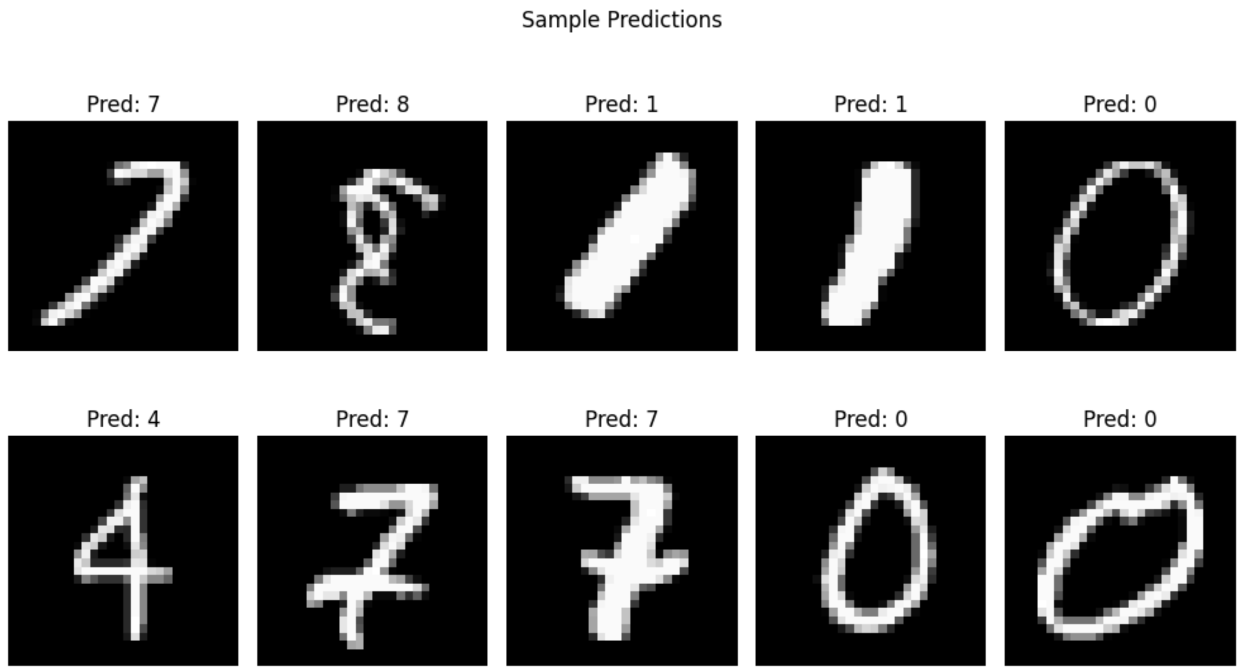
# -------------------- Step 7: Sample Predictions --------------------
plt.figure(figsize=(10, 6))
for i in range(10):
    idx = np.random.randint(0, len(X_test))
    plt.subplot(2, 5, i+1)
    plt.imshow(X_test[idx], cmap='gray')
    plt.title(f"Pred: {y_pred[idx]}")
    plt.axis('off')
plt.suptitle("Sample Predictions")
plt.tight_layout()
plt.show()
```


Sample Predictions
Pred: 7
Pred: 8
Pred: 1
Pred: 1
Pred: 0
Pred: 4
Pred: 7
Pred: 7
Pred: 0
Pred: 0

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Task 4: AI Mini Project – MNIST Handwritten Digit Classifier

Dataset Used: MNIST (Built-in from TensorFlow)
Objective: Build a simple neural network to recognize handwritten digits from 0 to 9 using image data.

Dataset Overview

- **Total Samples**: 70,000 grayscale images (60,000 for training, 10,000 for testing)
- **Image Size**: 28×28 pixels
- **Classes**: 10 digits (0–9)

Model Choice: Feedforward Neural Network (Multilayer Perceptron)

Architecture:

- **Input Layer**: Flattened 28×28 image = 784 neurons
- **Hidden Layers**:
  - Dense (128 units, ReLU)
  - Dense (64 units, ReLU)
- **Output Layer**:
  - Dense (10 units, Softmax)

Why This Model?

- Simple and efficient for MNIST (low-complexity images)
- Good baseline for classification before using CNNs
- Fast to train and easy to understand

Preprocessing

- Normalized image pixel values to range [0, 1]
- Converted class labels to one-hot encoding using `to_categorical`

Training and Evaluation

Metric	Result
Loss Function	Categorical Crossentropy
Optimizer	Adam
Epochs	10
Batch Size	128
Test Accuracy	~97–98% (depending on run)

Evaluation Methods:

- Accuracy score on test data
- Confusion Matrix (for digit-wise performance)
- Classification Report (Precision, Recall, F1-score)
- Random sample prediction visualization

Conclusion

- The model performed very well on MNIST with **~98% accuracy**, which is strong for a basic neural network.
- Clear digit classification was observed through the confusion matrix and visual predictions.
- Future improvements can include:
  - Using **Convolutional Neural Networks (CNNs)** for even higher accuracy
  - Adding dropout layers for regularization
  - Performing hyperparameter tuning
