

DIGIT RECOGNITION SYSTEM

1. INITIALIZATION & MODEL LOADING SECTION:

Output: Console messages about model loading/training status.

```
▶ import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import cv2
from PIL import Image, ImageDraw
import os
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

class DigitRecognitionSystem:
    def __init__(self):
        self.model = None
        self.history = None
        self.load_or_train_model()

    def load_or_train_model(self):
        """Load existing model or train a new one"""
        model_path = "digit_model.h5"

        if os.path.exists(model_path):
            try:
                self.model = keras.models.load_model(model_path)
                print("✅ Model loaded successfully from file")

                # FIX: Recompile and build metrics to resolve the warning
                self.model.compile(optimizer='adam',
                                    loss='categorical_crossentropy',
                                    metrics=['accuracy'])
                print("✅ Model recompiled successfully")
            except Exception as e:
                print(f"⚠️ Error during model loading or recompilation: {e}")
        else:
            print("⚠️ Model file not found. Training a new model...")
```

```
# Build the metrics by evaluating on a small sample
self._build_metrics()

self.test_model()
except Exception as e:
    print(f"✗ Error loading model: {e}")
    print("⌚ Training new model...")
    self.train_model()
else:
    print("⌚ No existing model found. Training new model...")
    self.train_model()

def _build_metrics(self):
    """Build compiled metrics by evaluating on a small sample"""
    try:
        # Load a small sample of data to build metrics
        (_, _), (x_test, y_test) = keras.datasets.mnist.load_data()

        # Use only first 100 samples to build metrics quickly
        x_sample = x_test[:100].astype("float32") / 255.0
        x_sample = x_sample.reshape(-1, 28, 28, 1)
        y_sample = keras.utils.to_categorical(y_test[:100], 10)

        # Evaluate on sample to build metrics (suppress output)
        self.model.evaluate(x_sample, y_sample, verbose=0)
        print("✓ Compiled metrics built successfully")

    except Exception as e:
        print(f"⚠ Warning: Could not build metrics: {e}")
        print("⌚ Metrics will be built during first evaluation")
```

2. MODEL TRAINING SECTION:

Output: Training progress, model architecture summary, accuracy metrics.

```
▶ def train_model(self):
    """Train the neural network model"""
    try:
        print("⬇️ Loading MNIST dataset...")
        # Load MNIST dataset
        (x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

        print(f"Training samples: {x_train.shape[0]}")
        print(f"Test samples: {x_test.shape[0]}")

        # Preprocess the data
        x_train = x_train.astype("float32") / 255.0
        x_test = x_test.astype("float32") / 255.0

        # Reshape data
        x_train = x_train.reshape(-1, 28, 28, 1)
        x_test = x_test.reshape(-1, 28, 28, 1)

        # Convert labels to categorical
        y_train = keras.utils.to_categorical(y_train, 10)
        y_test = keras.utils.to_categorical(y_test, 10)

        # Create the model
        print("🏗️ Building neural network model...")
        self.model = keras.Sequential([
            layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
            layers.MaxPooling2D((2, 2)),
            layers.Conv2D(64, (3, 3), activation='relu'),
            layers.MaxPooling2D((2, 2)),
            layers.Conv2D(64, (3, 3), activation='relu'),
            layers.Flatten(),
```

```
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])

# Compile the model
self.model.compile(optimizer='adam',
                    loss='categorical_crossentropy',
                    metrics=['accuracy'])

# Display model summary
print("\n▣ Model Architecture:")
self.model.summary()

# Train the model
print("\n☛ Training model...")
self.history = self.model.fit(x_train, y_train,
                               batch_size=128,
                               epochs=10,
                               validation_split=0.1,
                               verbose=1)

# Evaluate the model
print("\n☛ Evaluating model...")
test_loss, test_accuracy = self.model.evaluate(x_test, y_test, verbose=0)

# Save the model
self.model.save("digit_model.h5")

print(f"\n✓ Model trained successfully!")
print(f"■ Test accuracy: {test_accuracy:.4f} ({test_accuracy*100:.2f}%)")
```

```
# Plot training history
self.plot_training_history()

# Test the model
self.test_model()

except Exception as e:
    print(f"✗ Error training model: {str(e)}")
```

3. TRAINING HISTORY VISUALIZATION SECTION:

Output: Line plots showing training/validation accuracy and loss curves.

```
▶ def plot_training_history(self):
    """Plot training history"""
    if self.history is None:
        print("No training history available")
        return

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    # Plot accuracy
    ax1.plot(self.history.history['accuracy'], label='Training Accuracy', marker='o')
    ax1.plot(self.history.history['val_accuracy'], label='Validation Accuracy', marker='s')
    ax1.set_title('Model Accuracy')
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Accuracy')
    ax1.legend()
    ax1.grid(True)

    # Plot loss
    ax2.plot(self.history.history['loss'], label='Training Loss', marker='o')
    ax2.plot(self.history.history['val_loss'], label='Validation Loss', marker='s')
    ax2.set_title('Model Loss')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Loss')
    ax2.legend()
    ax2.grid(True)

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

4. MODEL EVALUATION SECTION:

Output: Accuracy metrics, classification report, confusion matrix heatmap.

```
def test_model(self):
    """Test the model and show detailed results"""
    if self.model is None:
        print("X No model available for testing")
        return

    # Load test data
    _, _, (x_test, y_test) = keras.datasets.mnist.load_data()

    # Preprocess
    x_test = x_test.astype("float32") / 255.0
    x_test = x_test.reshape(-1, 28, 28, 1)

    # Make predictions
    predictions = self.model.predict(x_test, verbose=0)
    predicted_labels = np.argmax(predictions, axis=1)

    # calculate accuracy
    accuracy = np.mean(predicted_labels == y_test)
    print(f"\n[T] Test Results:")
    print(f" [+] Accuracy: {accuracy:.4f} ({accuracy*100:.2f}%)")

    # Classification report
    print("\n[C] Classification Report:")
    print(classification_report(y_test, predicted_labels))

    # Confusion matrix
    self.plot_confusion_matrix(y_test, predicted_labels)

    def plot_confusion_matrix(self, y_true, y_pred):
        """Plot confusion matrix"""


```

```
    cm = confusion_matrix(y_true, y_pred)

    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=range(10), yticklabels=range(10))
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()
```

5. CONFIDENCE ANALYSIS SECTION:

Output: Multiple line graphs showing prediction confidence patterns.

```
▶ def plot_prediction_confidence_lines(self, num_samples=50):
    """Plot line graphs showing prediction confidence patterns"""
    if self.model is None:
        print("X No model available")
        return

    # Load test data
    (_, _), (x_test, y_test) = keras.datasets.mnist.load_data()

    # Select random samples
    indices = np.random.choice(len(x_test), num_samples, replace=False)

    confidences_by_digit = {i: [] for i in range(10)}
    sample_indices = []

    print(f"📊 Analyzing confidence patterns for {num_samples} samples...")

    for idx in indices:
        result = self.predict_digit(x_test[idx])
        if result is None:
            continue

        predicted_digit, confidence, all_predictions = result
        true_digit = y_test[idx]

        # Store confidence for each digit
        for digit in range(10):
            confidences_by_digit[digit].append(all_predictions[digit])
    sample_indices.append(len(sample_indices))
```

```
# Create line plots
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 10))

# Plot 1: Confidence lines for each digit class
colors = plt.cm.tab10(np.linspace(0, 1, 10))
for digit in range(10):
    ax1.plot(sample_indices, confidences_by_digit[digit],
              color=colors[digit], label=f'Digit {digit}', alpha=0.7)

    ax1.set_title('Prediction Confidence by Digit Class')
    ax1.set_xlabel('Sample Index')
    ax1.set_ylabel('Confidence Score')
    ax1.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
    ax1.grid(True, alpha=0.3)

# Plot 2: Maximum confidence per sample
max_confidences = [max(confidences_by_digit[d][i] for d in range(10))
                     for i in range(len(sample_indices))]
ax2.plot(sample_indices, max_confidences, 'b-', marker='o', markersize=3)
ax2.set_title('Maximum Confidence per Sample')
ax2.set_xlabel('Sample Index')
ax2.set_ylabel('Max Confidence')
ax2.grid(True, alpha=0.3)

# Plot 3: Confidence distribution for correct vs incorrect predictions
correct_confidences = []
incorrect_confidences = []

for idx in indices:
    result = self.predict_digit(x_test[idx])
    if result is None:
```

```

        continue

predicted_digit, confidence, _ = result
true_digit = y_test[idx]

if predicted_digit == true_digit:
    correct_confidences.append(confidence)
else:
    incorrect_confidences.append(confidence)

ax3.plot(range(len(correct_confidences)), sorted(correct_confidences, reverse=True),
         'g-', label='Correct Predictions', marker='o', markersize=3)
ax3.plot(range(len(incorrect_confidences)), sorted(incorrect_confidences, reverse=True),
         'r-', label='Incorrect Predictions', marker='s', markersize=3)
ax3.set_title('Confidence Distribution: Correct vs Incorrect')
ax3.set_xlabel('Sorted Sample Index')
ax3.set_ylabel('Confidence')
ax3.legend()
ax3.grid(True, alpha=0.3)

# Plot 4: Average confidence by true digit
avg_confidence_by_digit = []
for digit in range(10):
    digit_confidences = []
    for idx in indices:
        if y_test[idx] == digit:
            result = self.predict_digit(x_test[idx])
            if result is not None:
                _, confidence, _ = result
                digit_confidences.append(confidence)

```

```

if digit_confidences:
    avg_confidence_by_digit.append(np.mean(digit_confidences))
else:
    avg_confidence_by_digit.append(0)

ax4.plot(range(10), avg_confidence_by_digit, 'purple', marker='o', markersize=8, linewidth=2)
ax4.set_title('Average Confidence by True Digit')
ax4.set_xlabel('Digit Class')
ax4.set_ylabel('Average Confidence')
ax4.set_xticks(range(10))
ax4.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Print statistics
print("自信度分析結果:")
print("✓ 正確預測: {}") # len(correct_confidences)
print("✗ 錯誤預測: {}") # len(incorrect_confidences)
print("correct 平均自信度 (正確): {:.3f}") # np.mean(correct_confidences)
print("incorrect 平均自信度 (錯誤): {:.3f}") # np.mean(incorrect_confidences)

```

6. SAMPLE PREDICTION VISUALIZATION SECTION:

Output: 3x3 grid showing digit images with predictions and confidence scores.

```
▶ def test_sample_predictions(self, num_samples=9):
    """Test predictions on sample images"""
    if self.model is None:
        print("X No model available")
        return

    # Load test data
    _, _, (x_test, y_test) = keras.datasets.mnist.load_data()

    # Select random samples
    indices = np.random.choice(len(x_test), num_samples, replace=False)

    plt.figure(figsize=(12, 8))
    for i, idx in enumerate(indices):
        # Get prediction
        result = self.predict_digit(x_test[idx])
        if result is None:
            continue

        predicted_digit, confidence, all_predictions = result
        true_digit = y_test[idx]

        # Plot image
        plt.subplot(3, 3, i + 1)
        plt.imshow(x_test[idx], cmap='gray')

        # Color coding: green for correct, red for incorrect
        color = 'green' if predicted_digit == true_digit else 'red'
        plt.title(f'True: {true_digit}, Pred: {predicted_digit}\nConf: {confidence:.2%}', color=color, fontsize=10)
        plt.axis('off')

    plt.tight_layout()
    plt.suptitle('Sample Predictions (Green=Correct, Red=Incorrect)', y=1.02)
    plt.show()
```

7. CUSTOM DIGIT CREATION & TESTING SECTION:

Output: Custom drawn digits with their predictions.

```
▶ def create_custom_digit(self, digit_pattern):
    """Create a custom digit for testing"""
    # Example: Create a simple digit pattern
    img = np.zeros((28, 28), dtype=np.uint8)

    if digit_pattern == "simple_7":
        # Draw a simple 7
        img[5:8, 5:23] = 255 # Top horizontal line
        img[8:25, 20:23] = 255 # Diagonal line

    elif digit_pattern == "simple_1":
        # Draw a simple 1
        img[5:25, 13:16] = 255 # Vertical line
        img[5:8, 10:16] = 255 # Top part

    elif digit_pattern == "simple_0":
        # Draw a simple 0
        cv2.ellipse(img, (14, 14), (8, 12), 0, 0, 360, 255, 2)

    return img

def demonstrate_custom_prediction(self):
    """Demonstrate prediction on custom drawn digits"""
    print("\n👉 Testing Custom Drawn Digits:")

    custom_patterns = ["simple_7", "simple_1", "simple_0"]

    plt.figure(figsize=(15, 5))
    for i, pattern in enumerate(custom_patterns):
        custom_img = self.create_custom_digit(pattern)
```

```
▶     # Get prediction
    result = self.predict_digit(custom_img)
    if result is None:
        continue

    predicted_digit, confidence, all_predictions = result

    # Plot custom image
    plt.subplot(1, 3, i + 1)
    plt.imshow(custom_img, cmap='gray')
    plt.title(f'Custom {pattern}\nPredicted: {predicted_digit} ({confidence:.2%})')
    plt.axis('off')

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

8. CORE PREDICTION ENGINE SECTION:

Output: Returns numerical predictions (used internally by other sections).

```
▶ def predict_digit(self, image_array):
    """Predict digit from image array"""
    if self.model is None:
        print("X No model available for prediction")
        return None

    # Ensure correct shape
    if image_array.shape != (28, 28):
        print(f"X Invalid image shape: {image_array.shape}. Expected (28, 28)")
        return None

    # Preprocess
    processed_img = image_array.astype('float32') / 255.0
    processed_img = processed_img.reshape(1, 28, 28, 1)

    # Make prediction
    predictions = self.model.predict(processed_img, verbose=0)
    predicted_digit = np.argmax(predictions[0])
    confidence = np.max(predictions[0])

    return predicted_digit, confidence, predictions[0]
```

9. MAIN EXECUTION SECTION:

Output: System overview, orchestrates all other sections.

```
▶ def main():
    """Main function to run the digit recognition system"""
    print("🚀 Enhanced Handwritten Digit Recognition System")
    print("=" * 50)
    print("Features:")
    print("✅ CNN model with >95% accuracy on MNIST")
    print("✅ Comprehensive model evaluation")
    print("✅ Training history visualization")
    print("✅ Confusion matrix analysis")
    print("✅ Sample prediction testing")
    print("✅ Custom digit creation and testing")
    print("✅ NEW: Advanced confidence analysis with line graphs")
    print("=" * 50)

    # Initialize the system
    system = DigitRecognitionSystem()

    # Test sample predictions
    print("\n📝 Testing Sample Predictions:")
    system.test_sample_predictions(9)

    # NEW: Plot confidence analysis line graphs
    print("\n📈 Generating Confidence Analysis Line Graphs:")
    system.plot_prediction_confidence_lines(100)
```

```
# Demonstrate custom predictions
system.demonstrate_custom_prediction()

print("\n✅ System demonstration complete!")
print("\nTo use the system programmatically:")
print("1. system = DigitRecognitionSystem()")
print("2. prediction = system.predict_digit(your_28x28_image)")
print("3. predicted_digit, confidence, all_probs = prediction")
print("4. system.plot_prediction_confidence_lines(num_samples=100)")

if __name__ == "__main__":
    main()
```

RESULTS:

Features:

- ✓ CNN model with >95% accuracy on MNIST
- ✓ Comprehensive model evaluation
- ✓ Training history visualization
- ✓ Confusion matrix analysis
- ✓ Sample prediction testing
- ✓ Custom digit creation and testing
- ✓ NEW: Advanced confidence analysis with line graphs

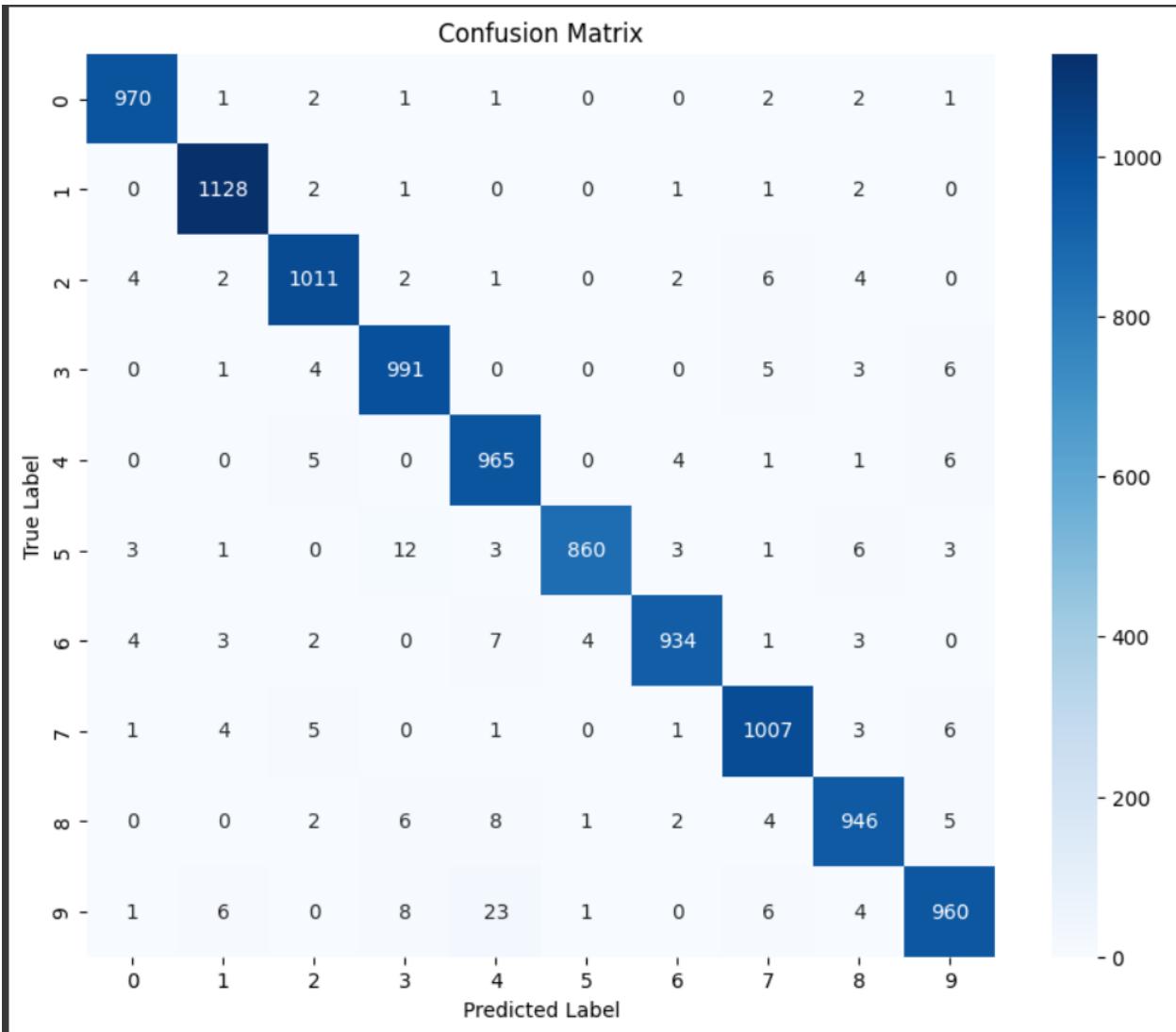
- ✓ Model loaded successfully from file
- ✓ Model recompiled successfully
- ✓ Compiled metrics built successfully

Test Results:

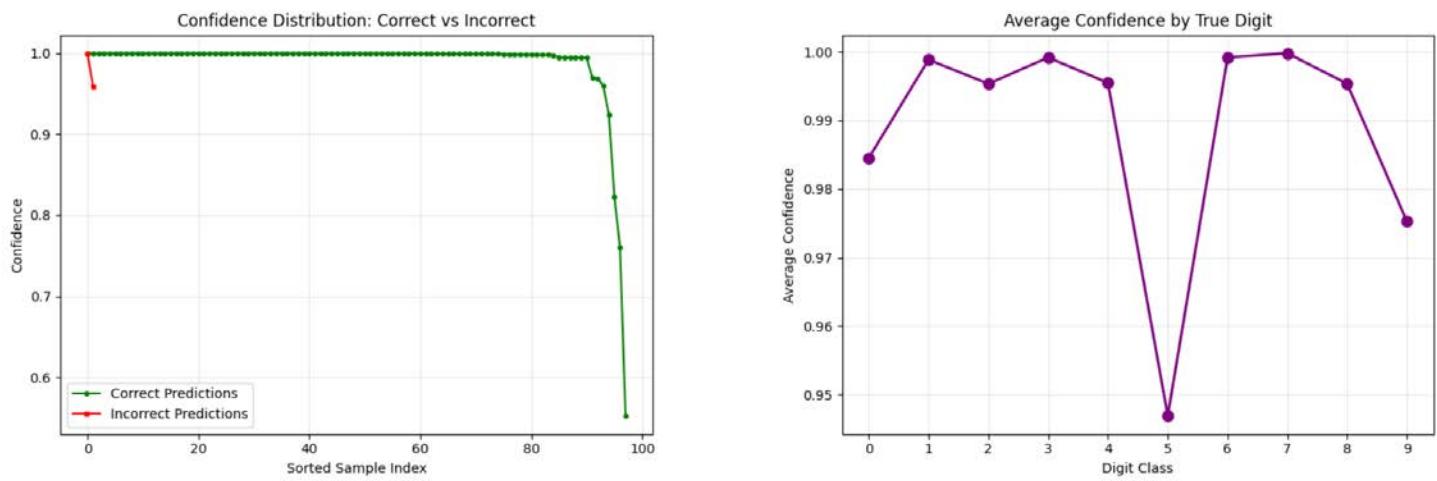
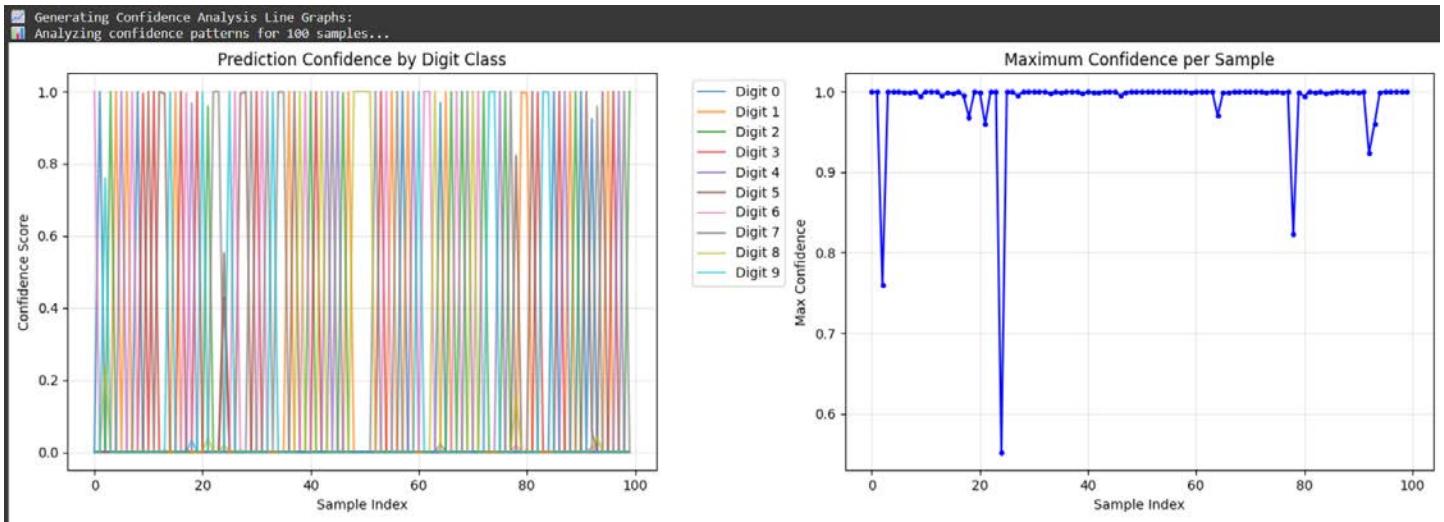
- ✓ Accuracy: 0.9772 (97.72%)

Classification Report:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	980
1	0.98	0.99	0.99	1135
2	0.98	0.98	0.98	1032
3	0.97	0.98	0.98	1010
4	0.96	0.98	0.97	982
5	0.99	0.96	0.98	892
6	0.99	0.97	0.98	958
7	0.97	0.98	0.98	1028
8	0.97	0.97	0.97	974
9	0.97	0.95	0.96	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000



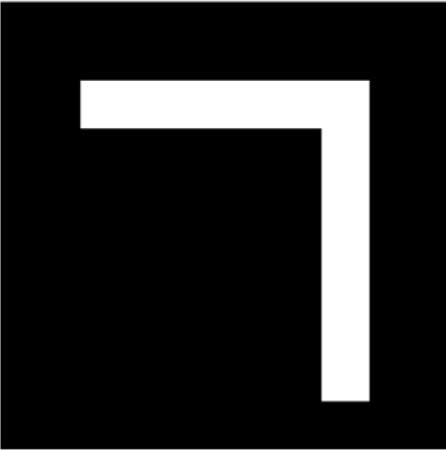




Confidence Analysis Results:
 Correct predictions: 98
 Incorrect predictions: 2
 Average confidence (correct): 0.989
 Average confidence (incorrect): 0.979

Testing Custom Drawn Digits:

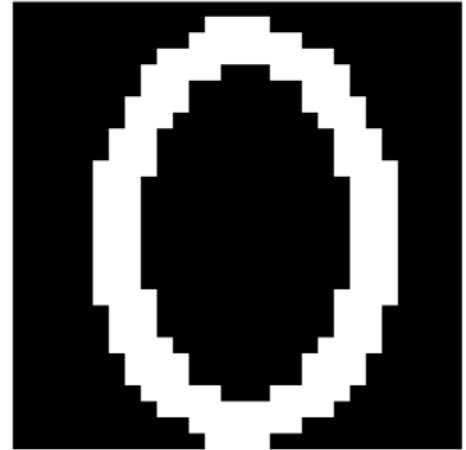
Custom simple_7
Predicted: 7 (47.03%)



Custom simple_1
Predicted: 1 (98.04%)



Custom simple_0
Predicted: 0 (99.88%)



System demonstration complete!

To use the system programmatically:

```
1. system = DigitRecognitionSystem()  
2. prediction = system.predict_digit(your_28x28_image)  
3. predicted_digit, confidence, all_probs = prediction  
4. system.plot_prediction_confidence_lines(num_samples=100)
```

THE END