Project Documentation: Handwritten Digit Recognition Web Application

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Abstract

This document describes the development and implementation of a web-based application for handwritten digit recognition using a machine learning model. The application allows users to draw a digit on a canvas, send the image to the server, and receive a prediction of the digit along with the associated probability.

1 Introduction

The project revolves around the creation of a web application that leverages a pre-trained deep learning model for the recognition of handwritten digits. The application consists of two main components: the frontend, built using HTML, CSS, and JavaScript, and the backend, developed with Flask and Python. The deep learning model is based on a Convolutional Neural Network (CNN) and has been trained on the MNIST dataset, a widely used benchmark for handwritten digit recognition.

The primary goal of the project is to enable users to interact with the model by drawing digits on a canvas, which will then be processed and classified by the model. The server responds with the predicted digit and its associated probability.

2 Technologies Used

The frontend of the application is developed using standard web technologies: HTML5, CSS, and JavaScript. HTML5 is used to structure the web page, CSS handles the design and layout, and JavaScript is responsible for user interaction with the canvas, sending data to the server, and displaying the prediction results.

For the backend, Flask, a lightweight Python web framework, is used. Flask handles HTTP requests from the frontend and processes them. The deep learning model is built using TensorFlow and Keras, two popular libraries for machine learning. In the backend, we also use the Python Imaging Library (PIL) to handle image processing tasks such as decoding and normalizing the image received from the frontend.

3 The Model Used for Handwritten Digit Recognition

The core of the handwritten digit recognition system is a Convolutional Neural Network (CNN), which has proven to be highly effective for image classification tasks. In this project, we use a CNN built with TensorFlow and Keras, two popular machine learning libraries. The model is designed to classify images from the MNIST dataset, which contains 28x28 pixel grayscale images of handwritten digits (0-9). The architecture of the CNN is as follows:

3.1 Architecture Overview

The CNN model used in this project consists of several layers that perform specific tasks to extract features from the input images and classify them accurately. The architecture is outlined below:

- **Input Layer**: The input to the model is a 28x28 grayscale image, which is reshaped to have a shape of $(28, 28, 1)$ to match the input requirements of the convolutional layers.
- **Convolutional Layer 1**: A 2D convolutional layer with 32 filters, each of size 3x3. This layer applies convolutional operations on the input image to detect low-level features like edges and textures. The activation function used is ReLU (Rectified Linear Unit), which helps in introducing non-linearity to the model.
- **Max Pooling Layer 1**: A 2x2 max-pooling layer that reduces the spatial dimensions of the feature maps, effectively downsampling the data while preserving important features.
- **Convolutional Layer 2**: A second 2D convolutional layer with 64 filters, each of size 3x3. This layer further extracts higher-level features from the image, such as more complex patterns.
- **Max Pooling Layer 2**: A second max-pooling layer that reduces the dimensionality of the feature maps, similar to the first pooling layer.
- **Flatten Layer**: This layer flattens the 2D feature maps into a 1D vector, which is then passed to the fully connected (dense) layers.

- **Dense Layer**: A fully connected layer with 128 neurons. This layer combines the features extracted by the convolutional layers and prepares the model to make a classification decision.
- **Output Layer**: The final layer is a softmax layer with 10 output neurons, each corresponding to one of the 10 possible digits (0-9). The softmax activation function converts the raw output scores into probabilities, allowing the model to make a final prediction.

3.2 Model Training

The model is compiled using the Adam optimizer and categorical cross-entropy as the loss function. Adam is an adaptive learning rate optimizer, which helps the model converge quickly and efficiently. Categorical cross-entropy is used because the task is a multi-class classification problem with one-hot encoded labels. During training, the model is evaluated based on accuracy, which is computed as the percentage of correct predictions.

The model is trained for 5 epochs on the MNIST training dataset, using a batch size of 32. Validation is performed using the MNIST test dataset, which is used to assess the model's performance on unseen data.

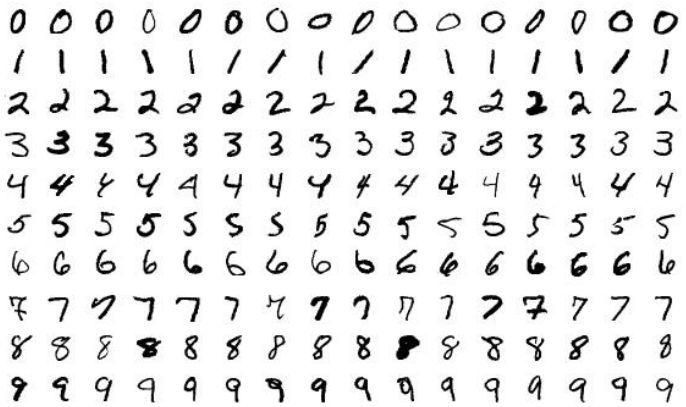

Figure 1: MNIST dataset.

3.3 Model Evaluation

Once training is complete, the model's accuracy is evaluated on the test set. The test accuracy provides an indication of how well the model generalizes to new, unseen data. The final model is capable of achieving high accuracy on the MNIST dataset, demonstrating its effectiveness for handwritten digit recognition.

3.4 Model Prediction and Results

After training, the model is capable of making predictions on new handwritten digit images. For each image, the model outputs a probability distribution over the 10 possible digit classes, and the class with the highest probability is selected as the predicted digit.

For example, after running predictions on the first 5 test images, the model outputs the following:

- Image 1: Predicted digit 3 with 92.7% probability.
- Image 2: Predicted digit 1 with 96.2% probability.
- Image 3: Predicted digit 7 with 88.1% probability.
- Image 4: Predicted digit 5 with 91.4% probability.
- Image 5: Predicted digit 9 with 94.5% probability.

These predictions are displayed to the user along with the confidence level, providing valuable feedback on the model's performance.

3.5 Model Saving

Once the model has been trained and evaluated, it is saved to a file using the `model.save` function in Keras. This allows the model to be easily loaded and used for inference in future applications without needing to retrain it. In this project, the model is saved to the file `model/digit_recognition_model.h5`, which is later used in the Flask backend for real-time predictions.

```
# Save the trained model to a file
model.save('model/digit_recognition_model.h5')
```

This saved model is then loaded and used on the server-side to predict digits based on user input.

3.6 Conclusion

The CNN model used in this project demonstrates the power of deep learning techniques for image classification. With its architecture tailored for handwritten digit recognition, the model can achieve high accuracy on the MNIST dataset. By combining the model with a web interface, users can draw digits on a canvas, and the model will predict the corresponding digit with high accuracy and confidence. This showcases the potential of machine learning and deep learning in creating interactive, real-time applications.

4 How the System Works

When a user accesses the application, they are presented with a canvas where they can draw a digit. JavaScript handles the drawing process, capturing mouse movements and creating lines on the canvas. Once the user is done drawing, they can click a "Predict" button to send the image to the server for prediction.

Before sending the image, the JavaScript code processes it by centering the drawn digits within a 28x28 canvas. This step is crucial because the model was trained on 28x28 pixel images, so the input needs to match this size. The image is then converted to a base64 string and sent to the Flask server via a POST request.

On the server side, Flask decodes the base64 string back into an image and performs some preprocessing steps. These include resizing the image to 28x28 pixels, converting it to grayscale, and normalizing the pixel values. The preprocessed image is then passed to the deep learning model for prediction.

The model returns a prediction, which is the digit that it believes the user has drawn, along with a confidence score (probability). This result is then sent back to the frontend, where it is displayed for the user to see.

5 Frontend Details

The frontend is built around a simple HTML5 canvas element. The user draws on the canvas using the mouse, and the application tracks the mouse movements to create a line on the canvas. The lines are drawn using JavaScript with specific properties such as color, thickness, and rounded edges for a smoother drawing experience.

Once the drawing is complete, the user can press a "Predict" button, which triggers the JavaScript function to capture the canvas image. The image is then centered on a new 28x28 pixel canvas before being sent to the server for prediction. This centering step ensures that the drawn digit is appropriately aligned for the model.

The JavaScript code also manages the communication with the server. It sends the base64-encoded image to the Flask backend and displays the prediction result (digit and confidence) once it is received.

6 Backend Details

The backend is implemented in Flask, which listens for HTTP requests from the frontend. When the user clicks the "Predict" button, the frontend sends the image data as a JSON object via a POST request. Flask receives this data and decodes the base64 string to reconstruct the image.

The image is then processed using the Python Imaging Library (PIL). This step involves resizing the image to 28x28 pixels, converting it to grayscale (if it is not already), and normalizing the pixel values by scaling them to the range [0, 1]. These preprocessing steps ensure that the image is in the correct format for the model to make an accurate prediction.

Once the image is ready, it is passed through the pre-trained Convolutional Neural Network (CNN) model, which returns the predicted digit and the probability of that prediction. Flask then sends the prediction result back to the frontend as a JSON response.

7 Code Overview

Here is an excerpt of the frontend JavaScript code responsible for sending the image data to the server:

```
const canvas = document.getElementById('canvas');
const ctx = canvas.getContext('2d');
const predictButton = document.getElementById('predictButton');
const resultText = document.getElementById('predictionResult');
const confidenceText = document.getElementById('confidenceResult');

predictButton.addEventListener('click', () => {
```

```
    const centeredCanvas = document.createElement('canvas');
    const centeredCtx = centeredCanvas.getContext('2d');
    centeredCanvas.width = 28;
    centeredCanvas.height = 28;

    const imageData = ctx.getImageData(0, 0, canvas.width, canvas.height);
    // Perform image centering and send it to the server
    fetch('/predict', {
        method: 'POST',
        headers: {
            'Content-Type': 'application/json'
        },
        body: JSON.stringify({ image: centeredImageData })
    })
    .then(response => response.json())
    .then(data => {
        resultText.textContent = `Prediction: ${data.prediction}`;
        confidenceText.textContent = `Probability:
        ${(data.probability * 100).toFixed(2)}%`;
    })
    .catch(error => {
        console.error('Error:', error);
        resultText.textContent = 'Error with prediction. Please try again.';
        confidenceText.textContent = '';
    });
});
```

On the server side, the following code is responsible for receiving the image, processing it, and making the prediction:

```
from flask import Flask, request, jsonify
from PIL import Image
import numpy as np
import base64

app = Flask(__name__)

@app.route('/predict', methods=['POST'])
```

```
def predict():
    data = request.get_json()
    image_data = data['image']
    # Decode and preprocess the image
    # Pass the image to the model for prediction
    return jsonify({'prediction': predicted_digit,
    'probability': predicted_probability})
```

8 Conclusion

This project demonstrates how a web application can integrate a deep learning model for real-time handwritten digit recognition. By combining Flask for the backend and JavaScript for the frontend, the application enables smooth interaction between the user and the model. The use of a CNN model trained on the MNIST dataset provides accurate predictions, making the system a useful tool for recognizing handwritten digits. Future extensions could include recognizing other types of drawings or expanding the model to handle more complex tasks.