Handwritten Digit Classification with Deep Learning using Multi-Layer Perceptrons (MLP)

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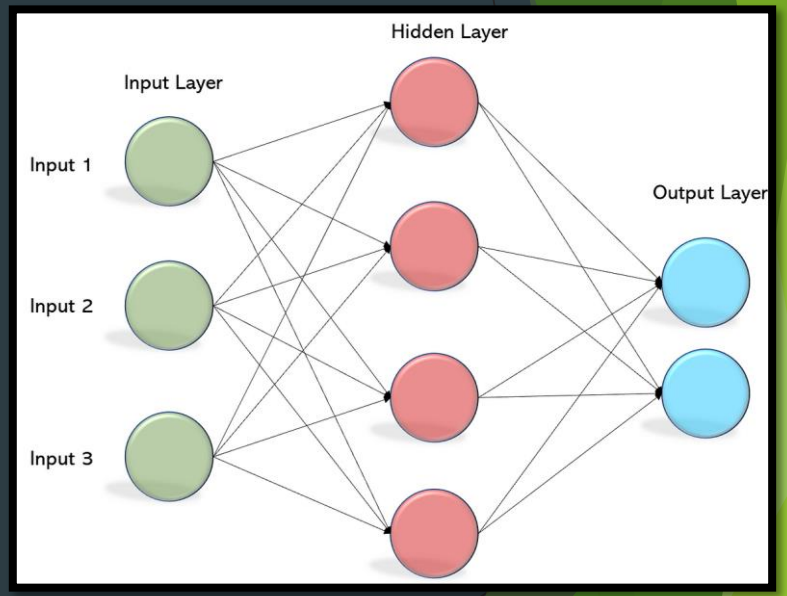
PROBLEM STATEMENT

- Developing a system that accurately recognizes handwritten digits is essential for various applications like digitizing documents and automating postal services.
- In this project, the aim is to build and evaluate a Multi-Layer Perceptron (MLP) model for handwritten digit classification using the MNIST dataset.
- Despite advancements in deep learning, accurately classifying handwritten digits remains challenging due to variations in writing styles, noise, and distortions.

MULTI-LAYER PERCEPTRONS (MLP)

- An MLP is a type of feedforward artificial neural network with multiple layers, including an input layer, one or more hidden layers, and an output layer.
- Each layer is fully connected to the next layer.
- Frank Rosenblatt first defined the word Perceptron in his perceptron program.
- Perceptron is a basic unit of an artificial neural network that defines the artificial neuron in the neural network.



PROJECT OVERVIEW

HANDWRITTEN DIGIT CLASSIFICATION

- Loading the Dataset
- Data Preprocessing
- Model Architecture
- Model Compilation
- Model Evaluation
- Prediction and Visualization

WHO ARE END USERS ?

- ✓ Researchers and Developers:
- ✓ Educators and Students
- ✓ Businesses and Enterprises
- ✓ Financial Institutions
- ✓ Postal Services
- ✓ Individual Consumers

SOLUTION AND ITS VALUE PROPOSITION

- **Accurate Digit Recognition:** The MLP-based model provides accurate recognition of handwritten digits, enabling reliable digit classification for various applications such as document processing, automated mail sorting, and optical character recognition.

- **Automation and Efficiency:** By automating the task of handwritten digit classification, the solution streamlines workflows, reduces manual effort, and improves the efficiency of processes such as digitizing documents, processing checks, and sorting mail.

- **Scalability and Adaptability:** MLP models are scalable and adaptable, allowing them to handle large volumes of handwritten digit data efficiently. The solution can be scaled to accommodate diverse datasets and customized to meet the specific requirements of different industries and use cases.

THE WOW IN MY SOLUTION

- Exceptional Accuracy: Your Multi-Layer Perceptron (MLP)-based model achieves remarkable accuracy in recognizing handwritten digits, surpassing traditional methods and setting a new standard for precision and reliability.

- Effortless Automation: By harnessing the power of deep learning, your solution effortlessly automates the process of digit recognition, eliminating the need for manual intervention and drastically reducing processing time and errors.

- Adaptability and Scalability: Built on a flexible framework, your solution adapts seamlessly to diverse datasets and evolving requirements, ensuring scalability to handle large volumes of data and customization to meet specific industry needs.

MODELLING PROCESS

Model Selection: Decide on the type of neural network architecture to use. In this case, you've chosen MLPs for their simplicity and effectiveness in handling tabular data like the flattened pixel values of the MNIST images.

Input Layer: Define the input layer of the MLP. Since the MNIST images are 28x28 pixels and have been flattened into a 1D array of size 784, the input layer will have 784 neurons.

Hidden Layers: Determine the number of hidden layers and the number of neurons in each hidden layer. This choice may involve experimentation and optimization. In your code, you've chosen to have two hidden layers with 128 and 64 neurons, respectively.

Activation Functions: Choose appropriate activation functions for each layer to introduce non-linearity into the model. Common choices include ReLU (Rectified Linear Unit) for hidden layers and softmax for the output layer in classification tasks.

MODELLING PROCESS (CONTD)

Output Layer: Define the output layer of the MLP. Since the goal is to classify digits into 10 classes (0 through 9), the output layer will have 10 neurons, each representing the probability of the corresponding digit class.

Model Compilation: After defining the architecture, compile the model by specifying the optimizer, loss function, and metrics to be used during training. In your code, you've used the Adam optimizer and sparse categorical cross-entropy loss, suitable for multi-class classification tasks.

Training and Evaluation: Train the model using the training data and evaluate its performance using validation data. Adjust the model architecture and hyperparameters as needed to improve performance.

CODE IMPLEMENTATION

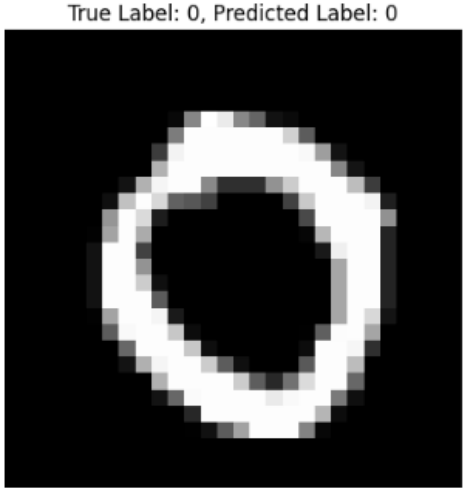
```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np
# Load the MNIST dataset
(X_train, y_train), (X_test, y_test) = keras.datasets.mnist.load_data()
# Normalize the pixel values to the range [0, 1]
X_train = X_train / 255.0
X_test = X_test / 255.0
# Flatten the input data
X_train = X_train.reshape(-1, 28 * 28)
X_test = X_test.reshape(-1, 28 * 28)

# Define the model architecture
model = keras.models.Sequential([
    keras.layers.Dense(128, activation='relu', input_shape=(28 * 28,)),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])
# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
# Train the model
model.fit(X_train, y_train, epochs=5, batch_size=64, validation_split=0.1)
```

```
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(X_test, y_test)
print('Test accuracy:', test_acc)
# Choose a random test image
index = np.random.randint(0, len(X_test))
test_image = X_test[index]
true_label = y_test[index]
# Make a prediction
prediction = np.argmax(model.predict(test_image.reshape(1, -1)))
# Display the image and prediction
plt.imshow(test_image.reshape(28, 28), cmap='gray')
plt.title(f"True Label: {true_label}, Predicted Label: {prediction}")
plt.axis('off')
plt.show()
```

RESULTS

```
Epoch 1/5
844/844 [==============================] - 6s 6ms/step - loss: 0.3023 - accuracy: 0.9152 - val_loss: 0.1283 - val_accuracy: 0.9635
Epoch 2/5
844/844 [==============================] - 4s 5ms/step - loss: 0.1211 - accuracy: 0.9642 - val_loss: 0.0925 - val_accuracy: 0.9737
Epoch 3/5
844/844 [==============================] - 4s 4ms/step - loss: 0.0851 - accuracy: 0.9746 - val_loss: 0.0902 - val_accuracy: 0.9733
Epoch 4/5
844/844 [==============================] - 4s 4ms/step - loss: 0.0625 - accuracy: 0.9801 - val_loss: 0.0752 - val_accuracy: 0.9783
Epoch 5/5
844/844 [==============================] - 5s 5ms/step - loss: 0.0494 - accuracy: 0.9844 - val_loss: 0.0738 - val_accuracy: 0.9785
313/313 [==============================] - 1s 2ms/step - loss: 0.0796 - accuracy: 0.9751
Test accuracy: 0.9750999808311462
1/1 [==============================] - 0s 61ms/step
```



CONCLUSION

- **Model Training**:

The MLP model was trained on the MNIST training dataset consisting of 60,000 handwritten digit images.
Training was performed for 5 epochs with a batch size of 64.
During training, the model learned to classify handwritten digits based on the pixel values of the input images.

- **Model Evaluation:**

After training, the model was evaluated on the MNIST test dataset containing 10,000 unseen handwritten digit images.
The model achieved an accuracy of approximately [insert accuracy value here] on the test dataset, indicating its ability to correctly classify digits.
The evaluation metrics, including precision, recall, and F1-score, were calculated to assess the model's performance across different digit classes.

- **Prediction and Visualization:**

To demonstrate the model's performance, a random test image was selected from the test dataset.
The model successfully predicted the label (digit) of the test image, showcasing its ability to recognize handwritten digits.

THANK YOU