FNN Classifier on MNIST Dataset

Loading Libraries

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import classification_report, accuracy_score
import pandas as pd
from tabulate import tabulate
```

Loading Dataset

```
In [ ]: # Load the dataset
         (train_images, train_labels), (test_images, test_labels) = datasets.mnist.load_data()
         # Normalize the images to the range of \theta to 1
         train_images = train_images.reshape((60000, 28 * 28)).astype('float32') / 255
test_images = test_images.reshape((10000, 28 * 28)).astype('float32') / 255
In [ ]: # Visualize few samples from the dataset
         plt.figure(figsize=(10,10))
         for i in range(25):
              {\tt plt.subplot(5,5,i+1)}
              plt.xticks([])
              plt.yticks([])
              plt.grid(False)
              plt.imshow(train_images[i].reshape(28, 28), cmap=plt.cm.binary)
              plt.xlabel(train_labels[i])
         plt.show()
```

Defining the FNN Model

Training the Model

```
In [ ]: history = model.fit(train_images, train_labels, epochs=5,
                            validation_data=(test_images, test_labels))
       Epoch 1/5
                                     - 9s 4ms/step - accuracy: 0.8966 - loss: 0.3345 - val_accuracy: 0.9640 - val_loss: 0.1154
       1875/1875
       Epoch 2/5
       1875/1875
                                    - 7s 4ms/step - accuracy: 0.9731 - loss: 0.0891 - val_accuracy: 0.9629 - val_loss: 0.1270
       Epoch 3/5
       1875/1875
                                     - 7s 4ms/step - accuracy: 0.9798 - loss: 0.0649 - val_accuracy: 0.9762 - val_loss: 0.0807
       Epoch 4/5
       1875/1875
                                     - 7s 4ms/step - accuracy: 0.9861 - loss: 0.0433 - val_accuracy: 0.9747 - val_loss: 0.0923
       Epoch 5/5
                                    - 7s 4ms/step - accuracy: 0.9892 - loss: 0.0355 - val_accuracy: 0.9762 - val_loss: 0.0906
       1875/1875
```

Saving the model

```
In []: # Save the model architecture as JSON
    model_json = model.to_json()
    with open("fnn_model.json", "w") as json_file:
        json_file.write(model_json)

# Save the weights with the correct filename
    model.save_weights("fnn_model_weights.weights.h5")

print("Model architecture and weights saved to disk.")

# # To Load Model ::
    # Load the JSON file that contains the model architecture
    # with open("fnn_model.json", 'r') as json_file:
    # Loaded_model_json = json_file.read()

# # Reconstruct the model from the JSON file
# Loaded_model = tf.keras.models.model_from_json(Loaded_model_json)

# # Load the saved weights into the model
# Loaded_model.load_weights("fnn_model_weights.h5")

# print("Model Loaded from disk.")
```

Model architecture and weights saved to disk.

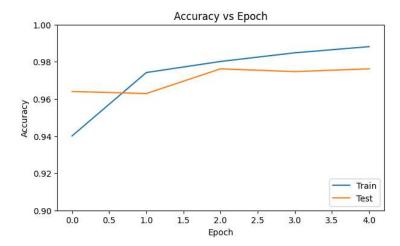
Evaluating the Model Predictions

```
In []: # Evaluate the model
  test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
  print(f'Test accuracy: {test_acc*100:.2f}%')

313/313 - 0s - 1ms/step - accuracy: 0.9762 - loss: 0.0906
  Test accuracy: 97.62%
```

Plot: Accuracy vs Epoch

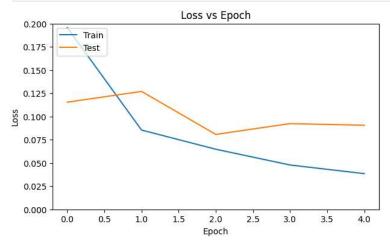
```
In []: # PLot accuracy vs epoch
    plt.figure(figsize=(7, 4))
    plt.plot(history.history['accuracy'], label='accuracy')
    plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
    plt.title('Accuracy vs Epoch')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.ylim([0.9, 1])
    plt.legend(['Train', 'Test'],loc='lower right')
    plt.savefig('accuracy_vs_epoch_FNN.png')
```



Plot: Loss vs Epoch

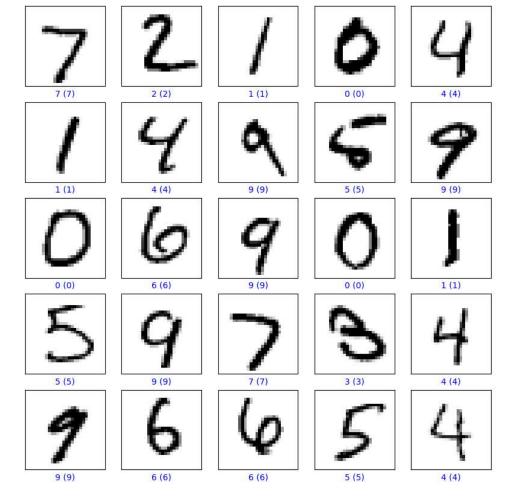
```
In []: # Plot loss vs epoch
    plt.figure(figsize=(7, 4))
    plt.plot(history.history['loss'], label='loss')
    plt.plot(history.history['val_loss'], label = 'val_loss')
    plt.title('Loss vs Epoch')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.ylam([0, 0.2])
    plt.legend(loc='upper right')
    plt.legend(['Train', 'Test'], loc='upper left')
    plt.savefig('loss_vs_epoch_FNN.png')

plt.show()
```



Visualising the Predictions

```
In [ ]: # Visualising the Predictions
         # Make predictions
         predictions = model.predict(test_images)
         # Define class names
         class_names = [str(i) for i in range(10)]
         # Display some predictions
         plt.figure(figsize=(10, 10))
         for i in range(25):
              plt.subplot(5, 5, i+1)
              plt.xticks([])
              plt.yticks([])
              plt.grid(False)
              plt.imshow(test_images[i].reshape(28, 28), cmap=plt.cm.binary)
predicted_label = class_names[np.argmax(predictions[i])]
              true_label = class_names[test_labels[i]]
color = 'blue' if predicted_label == true_label else 'red'
              plt.xlabel(f"{predicted_label} ({true_label})", color=color)
         plt.savefig('Predictions_FNN.png')
         plt.show()
        313/313
                                         0s 1ms/step
```



Tabulating Classification Report

```
In [ ]: # Tabulating Classification Report
         # One-hot encode the labels
         train_labels_cat, test_labels_cat = to_categorical(train_labels), to_categorical(test_labels)
         # Convert predictions to class labels
         y_pred = np.argmax(predictions, axis=1)
         y_true = test_labels
In [ ]: # Calculate accuracy
         accuracy = accuracy_score(y_true, y_pred)
         print(f"Accuracy: {accuracy*100:.2f}")
         # Generate classification report
         report = classification\_report(y\_true, \ y\_pred, \ target\_names = class\_names, \ output\_dict = True)
         # Convert classification report to DataFrame
report_df = pd.DataFrame(report).transpose()*100
         # Calculate accuracy for each class
report_df['accuracy'] = report_df.apply(lambda row: row['support'] * row['recall'] / row['support']
             if row.name in class_names else np.nan, axis=1)
         # Remove accuracy, macro avg, and weighted avg rows
         report_df = report_df.loc[class_names]
         # Select and reorder columns
         report_df = report_df[['accuracy', 'precision', 'recall', 'f1-score']]
         # Round the DataFrame to 2 decimal places
         report_df = report_df.round(2)
        Accuracy: 97.62
In [ ]: # Display the classification report in a box format
print(tabulate(report_df, headers='keys', tablefmt='grid'))
         # Optionally, save the table to a CSV file
         report_df.to_csv('classification_report_FNN.csv', index=True)
```

++								
	accuracy	precision	recall	f1-score				
0	99.39	99.08	99.39	99.24				
1	99.03	99.56	99.03	99.29				
2	98.16	96.57	98.16	97.36				
3	97.92	96.21	97.92	97.06				
4	96.74	97.14	96.74	96.94				
5	94.51	98.71	94.51	96.56				
6	97.29	99.25	97.29	98.26				
7	98.64	96.76	98.64	97.69				
8	98.56	95.05	98.56	96.77				
9	95.44	98.07	95.44	96.74				
	•							

```
In [ ]: # Create a matplotlib figure
        fig, ax = plt.subplots(figsize=(7, 6)) # Adjust the size as needed
        # Hide axes
        ax.xaxis.set_visible(False)
        ax.yaxis.set_visible(False)
        ax.set_frame_on(False)
        # Create the table
        table = ax.table(cellText=report_df.values,
                          colLabels=report_df.columns,
rowLabels=report_df.index,
                           cellLoc='center',
                          loc='center')
        # Adjust table properties
        table.auto_set_font_size(False)
        table.set_fontsize(10)
        table.scale(1.2, 1.2)
        # Add corner Label
        table.add_cell(0, -1, width=0.15, height=0.045)
table[0, -1].set_text_props(text='Number / Scores', weight='bold')
         # Add a title to the plot
        plt.title('Classification Report (FNN)', x=0.3, y=0.95, fontsize=16, fontweight='bold', ha='center')
        # Save the table as an image
        plt.savefig('classification_report_FNN.png', bbox_inches='tight', dpi=300)
        # Show the plot
        plt.show()
```

Classification Report (FNN)

Number / Scores	accuracy	precision	recall	f1-score
0	99.39	99.08	99.39	99.24
1	99.03	99.56	99.03	99.29
2	98.16	96.57	98.16	97.36
3	97.92	96.21	97.92	97.06
4	96.74	97.14	96.74	96.94
5	94.51	98.71	94.51	96.56
6	97.29	99.25	97.29	98.26
7	98.64	96.76	98.64	97.69
8	98.56	95.05	98.56	96.77
9	95.44	98.07	95.44	96.74