Hybrid CNN-FNN Classifier on FMNIST Dataset

Loading Libraries

In [ ]:
```
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 Fashion MNIST dataset
(train_images, train_labels), (test_images, test_labels) = datasets.fashion_mnist.load_data()

# Normalize the images to a range of 0 to 1
train_images, test_images = train_images / 255.0, test_images / 255.0

# Reshape the data to add a color channel dimension
train_images = train_images.reshape((train_images.shape[0], 28, 28, 1))
test_images = test_images.reshape((test_images.shape[0], 28, 28, 1))
```

In [ ]:
```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

In [ ]:
```
# Visualize a few samples from the dataset
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(train_images[i].reshape(28, 28), cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()
```

Defining the Hybrid CNN-FNN Model

In [ ]:
```
# Build the hybrid CNN-FNN model
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Flatten())

model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_5 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten_2 (Flatten)	(None, 1600)	0
dense_6 (Dense)	(None, 128)	204,928
dense_7 (Dense)	(None, 64)	8,256
dense_8 (Dense)	(None, 10)	650

Total params: 232,650 (908.79 KB)

Trainable params: 232,650 (908.79 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:
```
# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

In [ ]:
```
# Train the model
history = model.fit(train_images, train_labels, epochs=10, batch_size=64,
            validation_data=(test_images, test_labels))
```

```
Epoch 1/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 12s 11ms/step - accuracy: 0.7330 - loss: 0.7360 - val_accuracy: 0.8687 - val_loss: 0.3731
Epoch 2/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 10s 11ms/step - accuracy: 0.8753 - loss: 0.3449 - val_accuracy: 0.8746 - val_loss: 0.3428
Epoch 3/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 9s 10ms/step - accuracy: 0.8924 - loss: 0.2948 - val_accuracy: 0.8976 - val_loss: 0.2865
Epoch 4/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 9s 10ms/step - accuracy: 0.9040 - loss: 0.2588 - val_accuracy: 0.8968 - val_loss: 0.2818
Epoch 5/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 9s 10ms/step - accuracy: 0.9141 - loss: 0.2318 - val_accuracy: 0.9018 - val_loss: 0.2767
Epoch 6/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 10s 11ms/step - accuracy: 0.9253 - loss: 0.2021 - val_accuracy: 0.9068 - val_loss: 0.2501
Epoch 7/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 9s 10ms/step - accuracy: 0.9295 - loss: 0.1870 - val_accuracy: 0.8979 - val_loss: 0.2750
Epoch 8/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 10s 11ms/step - accuracy: 0.9343 - loss: 0.1733 - val_accuracy: 0.9071 - val_loss: 0.2590
Epoch 9/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 10s 11ms/step - accuracy: 0.9445 - loss: 0.1476 - val_accuracy: 0.9115 - val_loss: 0.2456
Epoch 10/10
938/938 ━━━━━━━━━━━━━━━━━━━━ 9s 10ms/step - accuracy: 0.9484 - loss: 0.1363 - val_accuracy: 0.9149 - val_loss: 0.2600
```

Saving the model

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

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

print("Model 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 weights saved to disk.
```

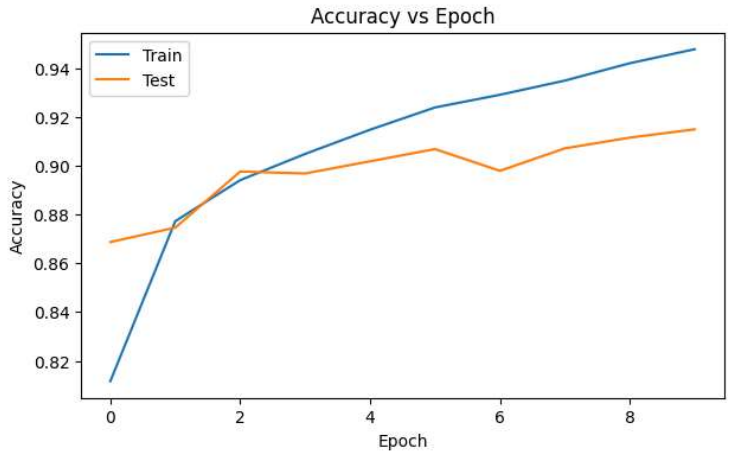
Evaluating the Model Predictions

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 - 1s - 2ms/step - accuracy: 0.9149 - loss: 0.2600
Test accuracy: 91.49%
Test accuracy: 91.49%
```

Plot: Accuracy vs Epoch

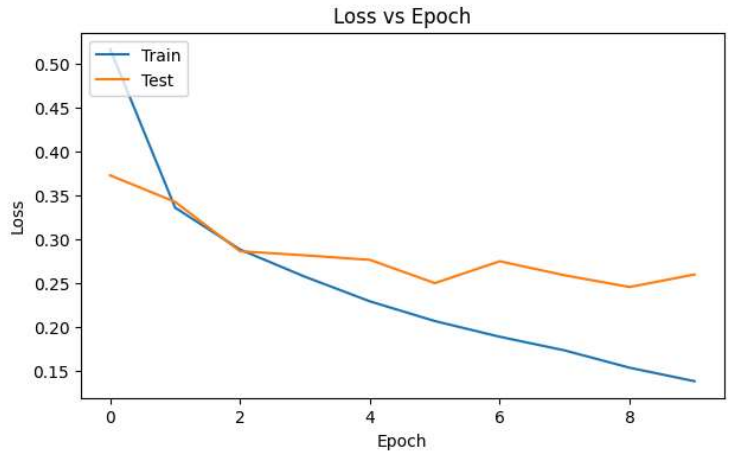
In [ ]:
```
# Plot training & validation accuracy values
plt.figure(figsize=(7, 4))
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Accuracy vs Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Test'], loc='upper left')
plt.savefig('accuracy_vs_epoch_Hybrid.png')
```



Plot: Loss vs Epoch

In [ ]:
```
# Plot training & validation loss values
plt.figure(figsize=(7, 4))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Loss vs Epoch')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Test'], loc='upper left')
plt.savefig('loss_vs_epoch_Hybrid.png')


plt.show()
```



Visualising the Predictions

In [ ]:
```
# Make predictions
predictions = model.predict(test_images)

# 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_Hybrid.png')
plt.show()
```

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

Tabulating Classification Report

In [ ]:
```
# One-hot encode the labels
train_labels, test_labels = to_categorical(train_labels), to_categorical(test_labels)

# Convert predictions to class labels
y_pred = np.argmax(predictions, axis=1)
y_true = np.argmax(test_labels, axis=1)
```

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: 91.49
```

Display the Table

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_Hybrid.csv', index=True)
```

```
+-------------+------------+-------------+----------+------------+
|             |   accuracy |   precision |   recall |   f1-score |
+=============+============+=============+==========+============+
| T-shirt/top |       90.5 |       83.18 |     90.5 |      86.69 |
+-------------+------------+-------------+----------+------------+
| Trouser     |       98.3 |       99.19 |     98.3 |      98.74 |
+-------------+------------+-------------+----------+------------+
| Pullover    |       82.6 |       90.97 |     82.6 |      86.58 |
+-------------+------------+-------------+----------+------------+
| Dress       |       92.9 |       90.99 |     92.9 |      91.93 |
+-------------+------------+-------------+----------+------------+
| Coat        |       88.1 |       85.45 |     88.1 |      86.76 |
+-------------+------------+-------------+----------+------------+
| Sandal      |       98.5 |       97.24 |     98.5 |      97.86 |
+-------------+------------+-------------+----------+------------+
| Shirt       |       72.4 |       77.77 |     72.4 |      74.99 |
+-------------+------------+-------------+----------+------------+
| Sneaker     |       97.1 |       95.48 |     97.1 |      96.28 |
+-------------+------------+-------------+----------+------------+
| Bag         |       98.4 |       96.28 |     98.4 |      97.33 |
+-------------+------------+-------------+----------+------------+
| Ankle boot  |       96.1 |       98.26 |     96.1 |      97.17 |
+-------------+------------+-------------+----------+------------+
```

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='Class Name / Scores', weight='bold')

# Add a title to the plot
plt.title('Classification Report (Hybrid CNN-FNN)', x=0.3, y=0.95, fontsize=16, fontweight='bold', ha='center')

# Save the table as an image
plt.savefig('classification_report_Hybrid.png', bbox_inches='tight', dpi=300)

# Show the plot
plt.show()
```

Classification Report (Hybrid CNN-FNN)

Class Name / Scores	accuracy	precision	recall	f1-score
T-shirt/top	90.5	83.18	90.5	86.69
Trouser	98.3	99.19	98.3	98.74
Pullover	82.6	90.97	82.6	86.58
Dress	92.9	90.99	92.9	91.93
Coat	88.1	85.45	88.1	86.76
Sandal	98.5	97.24	98.5	97.86
Shirt	72.4	77.77	72.4	74.99
Sneaker	97.1	95.48	97.1	96.28
Bag	98.4	96.28	98.4	97.33
Ankle boot	96.1	98.26	96.1	97.17