Hybrid CNN-FNN Classifier on CIFAR-10 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

```
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
x_train, x_test = x_train / 255.0, x_test / 255.0

# One-hot encode the labels
y_train, y_test = to_categorical(y_train), to_categorical(y_test)
```

```
# Define class names for CIFAR-10 dataset
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
```

```
# Display some images from the dataset (optional)
plt.figure(figsize=(8,8))
for i in range(16):
    plt.subplot(4,4,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(x_train[i])
    plt.xlabel(class_names[np.argmax(y_train[i][0])])
plt.show()
```

Defining the Hybrid Model

In [ ]:
```
def create_hybrid_model():
    model = models.Sequential()

    # CNN part
    model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten the output for the fully connected part
    model.add(layers.Flatten())

    # FNN part
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(10, activation='softmax'))

    return model

model = create_hybrid_model()
```

In [ ]:
```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Training the Model

In [ ]:
```
history = model.fit(x_train, y_train, epochs=20,
                    validation_data=(x_test, y_test),
                    batch_size=64)
```

```
Epoch 1/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 20s 23ms/step - accuracy: 0.1996 - loss: 2.0747 - val_accuracy: 0.4685 - val_loss: 1.4487
Epoch 2/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - accuracy: 0.4427 - loss: 1.5046 - val_accuracy: 0.5474 - val_loss: 1.2260
Epoch 3/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.5487 - loss: 1.2687 - val_accuracy: 0.6165 - val_loss: 1.0864
Epoch 4/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.5977 - loss: 1.1428 - val_accuracy: 0.6558 - val_loss: 0.9779
Epoch 5/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.6423 - loss: 1.0385 - val_accuracy: 0.6623 - val_loss: 0.9646
Epoch 6/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - accuracy: 0.6713 - loss: 0.9610 - val_accuracy: 0.6836 - val_loss: 0.9091
Epoch 7/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.6935 - loss: 0.8960 - val_accuracy: 0.6841 - val_loss: 0.9160
Epoch 8/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.7218 - loss: 0.8281 - val_accuracy: 0.6988 - val_loss: 0.9039
Epoch 9/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 18s 23ms/step - accuracy: 0.7341 - loss: 0.7879 - val_accuracy: 0.6958 - val_loss: 0.9109
Epoch 10/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.7497 - loss: 0.7606 - val_accuracy: 0.7133 - val_loss: 0.8703
Epoch 11/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 19s 24ms/step - accuracy: 0.7630 - loss: 0.6998 - val_accuracy: 0.7159 - val_loss: 0.8830
Epoch 12/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 18s 23ms/step - accuracy: 0.7744 - loss: 0.6760 - val_accuracy: 0.7166 - val_loss: 0.8870
Epoch 13/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 18s 23ms/step - accuracy: 0.7843 - loss: 0.6485 - val_accuracy: 0.7317 - val_loss: 0.8433
Epoch 14/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.7971 - loss: 0.6105 - val_accuracy: 0.7136 - val_loss: 0.8998
Epoch 15/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.8029 - loss: 0.5917 - val_accuracy: 0.7237 - val_loss: 0.8915
Epoch 16/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.8101 - loss: 0.5593 - val_accuracy: 0.7370 - val_loss: 0.8801
Epoch 17/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.8231 - loss: 0.5286 - val_accuracy: 0.7299 - val_loss: 0.8983
Epoch 18/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 17s 22ms/step - accuracy: 0.8232 - loss: 0.5278 - val_accuracy: 0.7283 - val_loss: 0.9235
Epoch 19/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 18s 22ms/step - accuracy: 0.8315 - loss: 0.5022 - val_accuracy: 0.7211 - val_loss: 1.0048
Epoch 20/20
782/782 ━━━━━━━━━━━━━━━━━━━━ 18s 23ms/step - accuracy: 0.8373 - loss: 0.4881 - val_accuracy: 0.7280 - val_loss: 0.9925
```

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 [ ]:

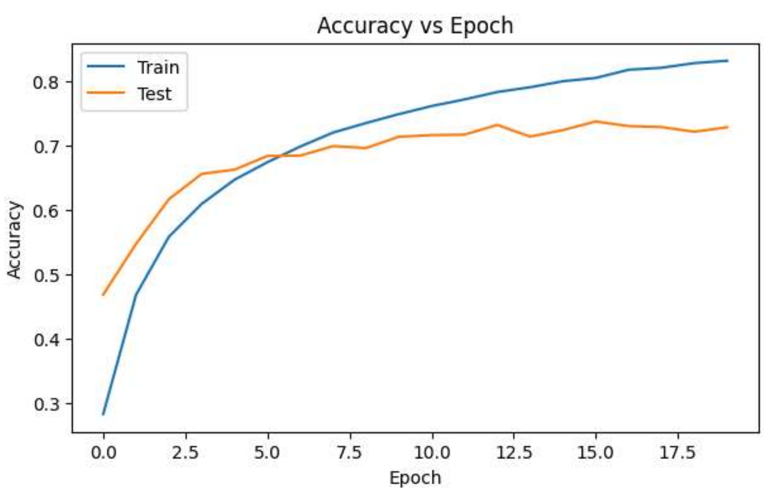
```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f'Test accuracy: {test_acc*100:.2f}%')
```

```
313/313 - 2s - 5ms/step - accuracy: 0.7280 - loss: 0.9925
Test accuracy: 72.80%
Test accuracy: 72.80%
```

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')
```

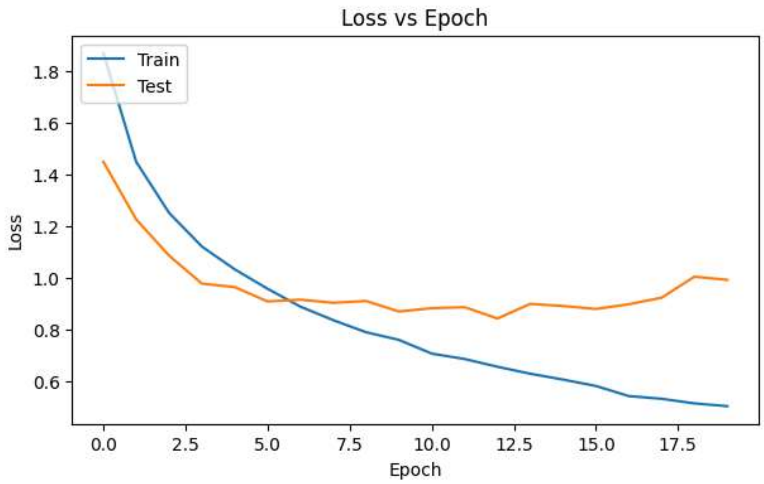


Plot: Loss vs Epoch

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

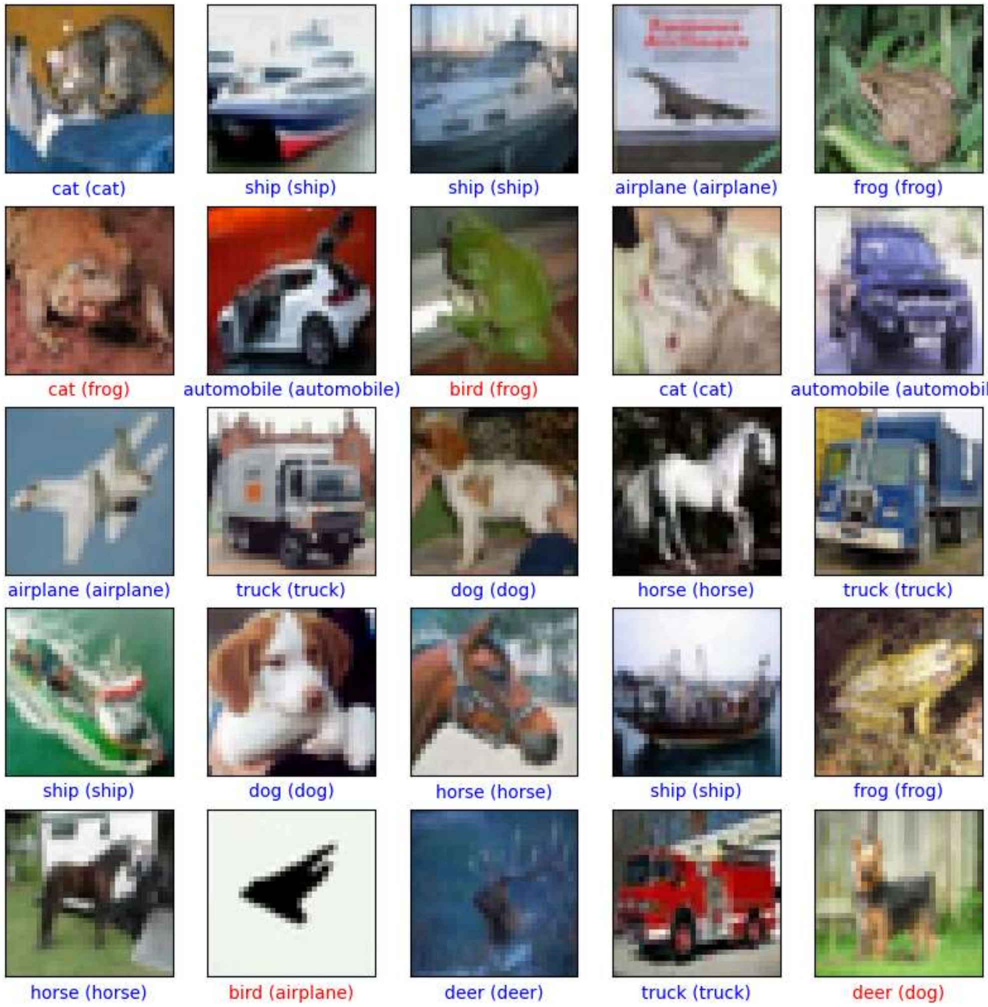
In [ ]:

```
# Make predictions
predictions = model.predict(x_test)

# 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(x_test[i])
    predicted_label = class_names[np.argmax(predictions[i])]
    true_label = class_names[np.argmax(y_test[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 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
```



Tabulating Classification Report

In [ ]:
```
# Convert predictions to class labels
y_pred = np.argmax(predictions, axis=1)
y_true = np.argmax(y_test, axis=1)

# 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: 72.80
```

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
airplane	81.6	71.64	81.6	76.3
automobile	80.5	91.06	80.5	85.46
bird	60	67.34	60	63.46
cat	54.8	48.62	54.8	51.53
deer	67.2	71.41	67.2	69.24
dog	65.2	60.26	65.2	62.63
frog	69.9	89.5	69.9	78.5
horse	80.3	73.2	80.3	76.59
ship	79.8	91.3	79.8	85.17
truck	88.7	74.92	88.7	81.23

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(True)
# table.set_fontsize(11)
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 Names / 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')

# Adjust plot layout
# plt.subplots_adjust(top=1)

# 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 Names / Scores	accuracy	precision	recall	f1-score
airplane	81.6	71.64	81.6	76.3
automobile	80.5	91.06	80.5	85.46
bird	60.0	67.34	60.0	63.46
cat	54.8	48.62	54.8	51.53
deer	67.2	71.41	67.2	69.24
dog	65.2	60.26	65.2	62.63
frog	69.9	89.5	69.9	78.5
horse	80.3	73.2	80.3	76.59
ship	79.8	91.3	79.8	85.17
truck	88.7	74.92	88.7	81.23