A hybrid model could involve using traditional machine learning algorithms for feature engineering or dimensionality reduction, followed by a deep learning model for more complex pattern recognition or representation learning.

Alternatively, it could involve incorporating deep learning layers within a traditional machine learning pipeline.

In this example:

- 1. We first train a Random Forest classifier on the reduced data obtained through PCA.
- 2. We then train a simple neural network on the original standardized data.
- 3. Finally, we create an ensemble model by combining the predictions from both the Random Forest and Neural Network.

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.datasets import load iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy score
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# Load the Iris dataset
iris = load_iris()
data = iris.data
target = iris.target
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data, target, test_size=0.3, random_state=42)
# Standardize the data
scaler = StandardScaler()
X_train_standardized = scaler.fit_transform(X_train)
X_test_standardized = scaler.transform(X_test)
PCA reduction
# Apply PCA for dimensionality reduction
num_components = 2
pca = PCA(n_components=num_components)
X_train_pca = pca.fit_transform(X_train_standardized)
X_test_pca = pca.transform(X_test_standardized)
print("Standarized train PCA data:", X_train_pca[:2, :])
print("
            ")
print("Standarized test PCA data:", X_test_pca[:2, :])
print("
            ")
→ Standarized train PCA data: [[-0.16752092 1.52763072]
     [ 1.02089353 0.2868919 ]]
     Standarized test PCA data: [[ 0.5226002    0.37959608]
      [-1.94983374 -1.69481837]]
Random Forest Classifier
# Train a Random Forest classifier on the reduced data
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train_pca, y_train)
# Make predictions on the test set
y_pred_rf = clf.predict(X_test_pca)
# Evaluate the accuracy of the Random Forest classifier
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print(f'Accuracy of Random Forest Classifier: {accuracy_rf:.2f}')
print("
```

Neural Network Architecture

plt.title('Original Data Distribution')

plt.xlabel('Feature 1') plt.ylabel('Feature 2')

```
# Convert target labels to one-hot encoding for neural network
encoder = OneHotEncoder(sparse=False)
y_train_encoded = encoder.fit_transform(y_train.reshape(-1, 1))
y_test_encoded = encoder.transform(y_test.reshape(-1, 1))
# Build a simple neural network
model = Sequential()
model.add(Dense(16, input_dim=num_components, activation='relu'))
model.add(Dense(3, activation='softmax')) # Output layer with 3 neurons for Iris dataset classes
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
print("Model Architecture:", model.summary())
print("
              ")
# Train the neural network on the reduced data obtained through PCA
model.fit(X_train_pca, y_train_encoded, epochs=50, batch_size=8, verbose=0)
# Evaluate the neural network on the test set
_, accuracy_nn = model.evaluate(X_test_pca, y_test_encoded)
print(f'Accuracy of Neural Network: {accuracy_nn:.2f}')
print("
              ")
→ Model: "sequential_2"
     Layer (type)
                                Output Shape
                                                         Param #
     _____
     dense_4 (Dense)
                                (None, 16)
                                                         48
     dense_5 (Dense)
                                (None, 3)
                                                         51
    ______
    Total params: 99 (396.00 Byte)
    Trainable params: 99 (396.00 Byte)
    Non-trainable params: 0 (0.00 Byte)
    Model Architecture: None
     /usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_outpu
    2/2 [========= ] - 0s 7ms/step - loss: 0.3174 - accuracy: 0.8444
    Accuracy of Neural Network: 0.84
# Combine predictions from Random Forest and Neural Network (Ensemble)
y_pred_ensemble = np.argmax(model.predict(X_test_pca) + clf.predict_proba(X_test_pca), axis=1)
accuracy_ensemble = accuracy_score(y_test, y_pred_ensemble)
print(f'Accuracy of Ensemble Model: {accuracy_ensemble:.2f}')
    2/2 [======] - 0s 5ms/step
    Accuracy of Ensemble Model: 0.98
print(f'Accuracy\ of\ Random\ Forest\ Classifier:\ \{accuracy\_rf:.2f\}')
print("
         ")
\label{lem:print}  \texttt{print}(\texttt{f'Accuracy of Neural Network: } \{\texttt{accuracy\_nn:.2f}\}') 
print(f'Accuracy of Ensemble Model: {accuracy_ensemble:.2f}')
→ Accuracy of Random Forest Classifier: 0.96
    Accuracy of Neural Network: 0.84
    Accuracy of Ensemble Model: 0.98
# Visualize the distribution of points in the reduced feature space
plt.figure(figsize=(12, 6))
# Plot original data before PCA
plt.subplot(1, 2, 1)
for label in np.unique(y_test):
   indices = y_test == label
   plt.scatter(X_test[indices, 0], X_test[indices, 1], label=f'Class {label}', alpha=0.7)
```

```
pit.iegena()
# Plot points with true labels
plt.subplot(1, 2, 2)
for label in np.unique(y_test):
    indices = y_test == label
    plt.scatter(X_test_pca[indices, 0], X_test_pca[indices, 1], label=f'Class {label}', alpha=0.7)
# Plot points with ensemble predictions
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_pred_ensemble, marker='X', s=100, cmap='viridis', edgecolor='k', label='Ensemble Pred
\verb|plt.title('Distribution of Points After PCA and Ensemble Predictions')|\\
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()
\overline{\Rightarrow}
                            Original Data Distribution
                                                                                 Distribution of Points After PCA and Ensemble Prediction
         4.5
                                                                Class 0
                                                                Class 1
                                                            Class 2
                                                                                  1
         4.0
                                                                      \approx
                                                                              Principal Component 2
                                                                                  0
         3.5
      Feature 2
                                                                                 -1
         3.0
```

-2

-3

2.5

4

4.5

5.0

5.5

6.0

Feature 1

6.5

7.0

7.5

8.0

Class 0

Class 1

Class 2

0

Principal Component 1

Ensemble Predictions

1

•

-1

-2

 \approx

3