

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_wine
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

# Loading the Wine dataset
wine_data = load_wine()
X = pd.DataFrame(wine_data.data, columns=wine_data.feature_names) # Features
y = wine_data.target # Target classes
X
y

# Check for missing values and descriptive statistics
print("Missing values per column:\n", X.isnull().sum())
print("\nDescriptive statistics:\n", X.describe())

# Normalize the data to ensure all features are on the same scale
scaler = StandardScaler()
X_normalized = scaler.fit_transform(X)
X_normalized

# Dimensionality reduction using PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X_normalized)
pca_result

# Visualizing PCA results
plt.figure(figsize=(10, 7))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=y, cmap='viridis', alpha=0.7, edgecolor='k')
plt.title('PCA Visualization')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Class')
plt.grid(True)
plt.show()

# Dimensionality reduction using t-SNE
tsne = TSNE(n_components=2, perplexity=30, random_state=0)
tsne_result = tsne.fit_transform(X_normalized)

# Visualizing t-SNE results
plt.figure(figsize=(10, 7))
plt.scatter(tsne_result[:, 0], tsne_result[:, 1], c=y, cmap='viridis', alpha=0.7, edgecolor='k')
plt.title('t-SNE Visualization')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.colorbar(label='Class')
plt.grid(True)
plt.show()

# Import necessary libraries for second part of the project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_normalized, y, test_size=0.3, random_state=42)

# Define a function to evaluate and display results for each model
def evaluate_model(model, model_name):
    # Train the model
    model.fit(X_train, y_train)
    # Predict on the test set
    y_pred = model.predict(X_test)
    # Calculate accuracy
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Results for {model_name}:\n")

```

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print(f"Accuracy: {accuracy:.2f}\n")
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("-----\n")

# 1. Distances
# k-Nearest Neighbors (kNN)
knn = KNeighborsClassifier(n_neighbors=5)
evaluate_model(knn, "k-Nearest Neighbors (kNN)")

# Nearest Centroid Classifier
from sklearn.neighbors import NearestCentroid
centroid = NearestCentroid()
evaluate_model(centroid, "Centroid Classifier")

# 2. Probabilistic Models
# Gaussian Naive Bayes (GNB)
gnb = GaussianNB()
evaluate_model(gnb, "Gaussian Naive Bayes (GNB)")

# Linear Discriminant Analysis (LDA)
lda = LinearDiscriminantAnalysis()
evaluate_model(lda, "Linear Discriminant Analysis (LDA)")

# 3. Rule-Based Models
# Decision Trees (DTs)
decision_tree = DecisionTreeClassifier(random_state=42)
evaluate_model(decision_tree, "Decision Tree")

# Bagging with kNN
bagging_knn = BaggingClassifier(base_estimator=KNeighborsClassifier(), n_estimators=10, random_state=42)
evaluate_model(bagging_knn, "Bagging with kNN")

# Random Forest
random_forest = RandomForestClassifier(n_estimators=100, random_state=42)
evaluate_model(random_forest, "Random Forest")

# 4. Hyperplane-Based Models
# Support Vector Machines (SVM)
# Linear Kernel
svm_linear = SVC(kernel='linear', random_state=42)
evaluate_model(svm_linear, "SVM (Linear Kernel)")

# Polynomial Kernel
svm_poly = SVC(kernel='poly', degree=3, random_state=42)
evaluate_model(svm_poly, "SVM (Polynomial Kernel)")

# RBF Kernel
svm_rbf = SVC(kernel='rbf', random_state=42)
evaluate_model(svm_rbf, "SVM (RBF Kernel)")

# Perceptron
from sklearn.linear_model import Perceptron
perceptron = Perceptron(max_iter=1000, random_state=42)
evaluate_model(perceptron, "Perceptron")

# Hyperparameter Tuning Example: kNN
knn_params = {'n_neighbors': [3, 5, 7, 10]}
grid_search = GridSearchCV(KNeighborsClassifier(), knn_params, cv=5)
grid_search.fit(X_train, y_train)
print("Best parameters for KNN:", grid_search.best_params_)
evaluate_model(grid_search.best_estimator_, "Tuned k-Nearest Neighbors (kNN)")

# Import necessary libraries for the third part
import numpy as np
import pandas as pd
from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report, confusion_matrix

# Load the Wine dataset
wine_data = load_wine()
X = pd.DataFrame(wine_data.data, columns=wine_data.feature_names)
y = wine_data.target

```

```

# One-hot encode the target variable
encoder = OneHotEncoder(sparse_output=False) # Corrected argument
y_encoded = encoder.fit_transform(y.reshape(-1, 1))

# Normalize the data
scaler = StandardScaler()
X_normalized = scaler.fit_transform(X)

# Split the dataset into training, validation, and testing sets
X_train, X_temp, y_train, y_temp = train_test_split(X_normalized, y_encoded, test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

# Define a function to create and compile the model
def create_model(input_dim, hidden_layers=[64, 32], dropout_rate=0.2, learning_rate=0.001):
    model = Sequential()
    model.add(Dense(hidden_layers[0], input_dim=input_dim, activation='relu'))
    for units in hidden_layers[1:]:
        model.add(Dense(units, activation='relu'))
        model.add(Dropout(dropout_rate))
    model.add(Dense(3, activation='softmax')) # Output layer for 3 classes
    optimizer = Adam(learning_rate=learning_rate)
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
    return model

# Experiment 1: Baseline Model
print("\n--- Experiment 1: Baseline Model ---")
baseline_model = create_model(input_dim=X_train.shape[1], hidden_layers=[64, 32])
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
history = baseline_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=100, batch_size=16, callbacks=[early_stopping], verbose=0)
baseline_results = baseline_model.evaluate(X_test, y_test, verbose=0)
print(f"Baseline Test Accuracy: {baseline_results[1]:.4f}")

# Experiment 2: Deeper Network
print("\n--- Experiment 2: Deeper Network ---")
deeper_model = create_model(input_dim=X_train.shape[1], hidden_layers=[128, 64, 32], dropout_rate=0.3)
history_deeper = deeper_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=100, batch_size=16, callbacks=[early_stopping])
deeper_results = deeper_model.evaluate(X_test, y_test, verbose=0)
print(f"Deeper Network Test Accuracy: {deeper_results[1]:.4f}")

# Experiment 3: Lighter Network
print("\n--- Experiment 3: Lighter Network ---")
lighter_model = create_model(input_dim=X_train.shape[1], hidden_layers=[32, 16], dropout_rate=0.5)
history_lighter = lighter_model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=100, batch_size=16, callbacks=[early_stopping])
lighter_results = lighter_model.evaluate(X_test, y_test, verbose=0)
print(f"Lighter Network Test Accuracy: {lighter_results[1]:.4f}")

# Compare all configurations
print("\n--- Comparison of Models ---")
print(f"Baseline Model Accuracy: {baseline_results[1]:.4f}")
print(f"Deeper Network Accuracy: {deeper_results[1]:.4f}")
print(f"Lighter Network Accuracy: {lighter_results[1]:.4f}")

# Generate classification report for the best model
y_pred = np.argmax(baseline_model.predict(X_test), axis=1)
y_true = np.argmax(y_test, axis=1)
print("\n--- Classification Report for Baseline Model ---")
print(classification_report(y_true, y_pred))

# Generate confusion matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_true, y_pred))

```

```
→ Missing values per column:
alcohol           0
malic_acid       0
ash               0
alcalinity_of_ash 0
magnesium         0
total_phenols    0
flavonoids        0
nonflavanoid_phenols 0
proanthocyanins 0
color_intensity   0
hue               0
od280/od315_of_diluted_wines 0
proline          0
dtype: int64
```

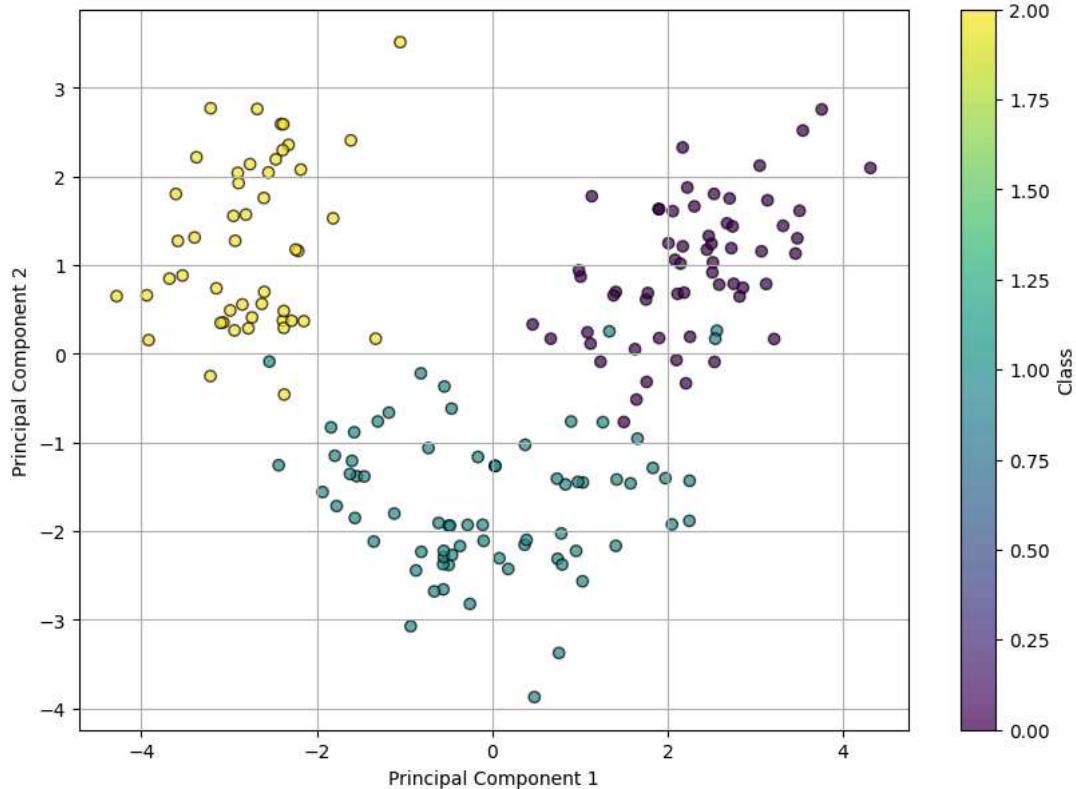
Descriptive statistics:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	\
count	178.000000	178.000000	178.000000	178.000000	178.000000	
mean	13.000618	2.336348	2.366517	19.494944	99.741573	
std	0.811827	1.117146	0.274344	3.339564	14.282484	
min	11.030000	0.740000	1.360000	10.600000	70.000000	
25%	12.362500	1.602500	2.210000	17.200000	88.000000	
50%	13.050000	1.865000	2.360000	19.500000	98.000000	
75%	13.677500	3.082500	2.557500	21.500000	107.000000	
max	14.830000	5.800000	3.230000	30.000000	162.000000	

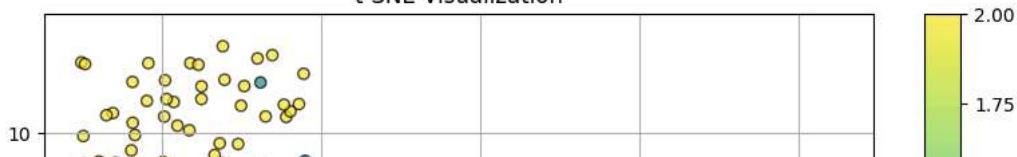
	total_phenols	flavonoids	nonflavanoid_phenols	proanthocyanins	\
count	178.000000	178.000000	178.000000	178.000000	
mean	2.295112	2.029270	0.361854	1.590899	
std	0.625851	0.998859	0.124453	0.572359	
min	0.980000	0.340000	0.130000	0.410000	
25%	1.742500	1.205000	0.270000	1.250000	
50%	2.355000	2.135000	0.340000	1.555000	
75%	2.800000	2.875000	0.437500	1.950000	
max	3.880000	5.080000	0.660000	3.580000	

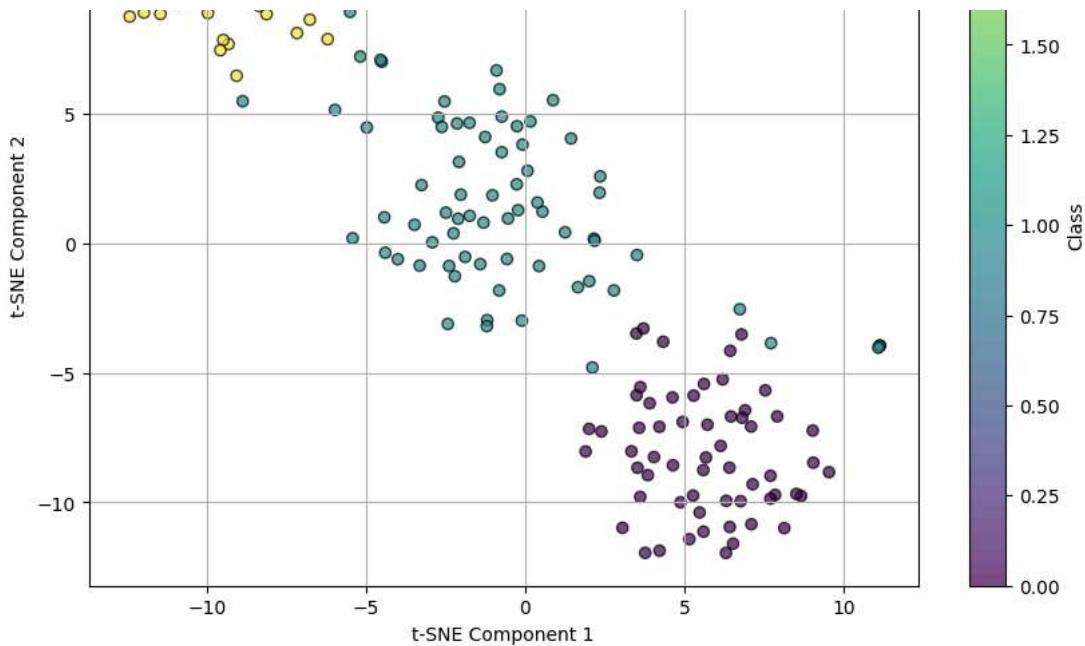
	color_intensity	hue	od280/od315_of_diluted_wines	proline	\
count	178.000000	178.000000	178.000000	178.000000	
mean	5.058090	0.957449	2.611685	746.893258	
std	2.318286	0.228572	0.709990	314.907474	
min	1.280000	0.480000	1.270000	278.000000	
25%	3.220000	0.782500	1.937500	500.500000	
50%	4.690000	0.965000	2.780000	673.500000	
75%	6.200000	1.120000	3.170000	985.000000	
max	13.000000	1.710000	4.000000	1680.000000	

PCA Visualization



t-SNE Visualization





Results for k-Nearest Neighbors (kNN):

Accuracy: 0.96

Classification Report:

	precision	recall	f1-score	support
0	0.95	1.00	0.97	19
1	1.00	0.90	0.95	21
2	0.93	1.00	0.97	14
accuracy			0.96	54
macro avg	0.96	0.97	0.96	54
weighted avg	0.97	0.96	0.96	54

Confusion Matrix:

```
[[19  0  0]
 [ 1 19  1]
 [ 0  0 14]]
```

Results for Centroid Classifier:

Accuracy: 0.98

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	0.95	0.98	21
2	0.93	1.00	0.97	14
accuracy			0.98	54
macro avg	0.98	0.98	0.98	54
weighted avg	0.98	0.98	0.98	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 20  1]
 [ 0  0 14]]
```

Results for Gaussian Naive Bayes (GNB):

Accuracy: 1.00

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	21
2	1.00	1.00	1.00	14
accuracy			1.00	54
macro avg	1.00	1.00	1.00	54
weighted avg	1.00	1.00	1.00	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 21  0]
 [ 0  0 14]]
```

Results for Linear Discriminant Analysis (LDA):

Accuracy: 1.00

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	21
2	1.00	1.00	1.00	14
accuracy		1.00	1.00	54
macro avg	1.00	1.00	1.00	54
weighted avg	1.00	1.00	1.00	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 21  0]
 [ 0  0 14]]
```

Results for Decision Tree:

Accuracy: 0.96

Classification Report:

	precision	recall	f1-score	support
0	0.95	0.95	0.95	19
1	0.95	1.00	0.98	21
2	1.00	0.93	0.96	14
accuracy		0.96	0.96	54
macro avg	0.97	0.96	0.96	54
weighted avg	0.96	0.96	0.96	54

Confusion Matrix:

```
[[18  1  0]
 [ 0 21  0]
 [ 1  0 13]]
```

Results for Bagging with kNN:

Accuracy: 0.94

Classification Report:

	precision	recall	f1-score	support
0	0.95	1.00	0.97	19
1	1.00	0.86	0.92	21
2	0.88	1.00	0.93	14
accuracy		0.94	0.94	54
macro avg	0.94	0.95	0.94	54
weighted avg	0.95	0.94	0.94	54

Confusion Matrix:

```
[[19  0  0]
 [ 1 18  2]
 [ 0  0 14]]
```

Results for Random Forest:

Accuracy: 1.00

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	21
2	1.00	1.00	1.00	14
accuracy		1.00	1.00	54
macro avg	1.00	1.00	1.00	54
weighted avg	1.00	1.00	1.00	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 21  0]
 [ 0  0 14]]
```

Results for SVM (Linear Kernel):

Accuracy: 0.98

Classification Report:

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	1.00	1.00	1.00	19
1	1.00	0.95	0.98	21
2	0.93	1.00	0.97	14
accuracy			0.98	54
macro avg	0.98	0.98	0.98	54
weighted avg	0.98	0.98	0.98	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 20  1]
 [ 0  0 14]]
```

Results for SVM (Polynomial Kernel):

Accuracy: 0.96

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.89	0.94	19
1	0.91	1.00	0.95	21
2	1.00	1.00	1.00	14
accuracy			0.96	54
macro avg	0.97	0.96	0.97	54
weighted avg	0.97	0.96	0.96	54

Confusion Matrix:

```
[[17  2  0]
 [ 0 21  0]
 [ 0  0 14]]
```

Results for SVM (RBF Kernel):

Accuracy: 0.98

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	0.95	1.00	0.98	21
2	1.00	0.93	0.96	14
accuracy			0.98	54
macro avg	0.98	0.98	0.98	54
weighted avg	0.98	0.98	0.98	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 21  0]
 [ 0  1 13]]
```

Results for Perceptron:

Accuracy: 0.98

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	0.95	0.98	21
2	0.93	1.00	0.97	14
accuracy			0.98	54
macro avg	0.98	0.98	0.98	54
weighted avg	0.98	0.98	0.98	54

Confusion Matrix:

```
[[19  0  0]
 [ 0 20  1]
 [ 0  0 14]]
```

Best parameters for kNN: {'n_neighbors': 5}
Results for Tuned k-Nearest Neighbors (kNN):

Accuracy: 0.96

Classification Report:

	precision	recall	f1-score	support
0	0.95	1.00	0.97	19
1	1.00	0.90	0.95	21
2	0.93	1.00	0.97	14
accuracy			0.96	54

	0.96	0.97	0.96	54
macro avg	0.96	0.97	0.96	54
weighted avg	0.97	0.96	0.96	54

Confusion Matrix:

```
[[19  0  0]
 [ 1 19  1]
 [ 0  0 14]]
```

--- Experiment 1: Baseline Model ---

Epoch 1/100

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

8/8 2s 34ms/step - accuracy: 0.2304 - loss: 1.2847 - val_accuracy: 0.4444 - val_loss: 1.1135

Epoch 2/100

8/8 0s 9ms/step - accuracy: 0.4745 - loss: 0.9680 - val_accuracy: 0.7037 - val_loss: 0.9067

Epoch 3/100

8/8 0s 6ms/step - accuracy: 0.6565 - loss: 0.8249 - val_accuracy: 0.9259 - val_loss: 0.7333

Epoch 4/100

8/8 0s 7ms/step - accuracy: 0.8350 - loss: 0.6979 - val_accuracy: 0.9630 - val_loss: 0.5930

Epoch 5/100

8/8 0s 9ms/step - accuracy: 0.8936 - loss: 0.5773 - val_accuracy: 0.9630 - val_loss: 0.4784

Epoch 6/100

8/8 0s 7ms/step - accuracy: 0.9650 - loss: 0.4367 - val_accuracy: 0.9630 - val_loss: 0.3837

Epoch 7/100

8/8 0s 8ms/step - accuracy: 0.9773 - loss: 0.3637 - val_accuracy: 1.0000 - val_loss: 0.3054

Epoch 8/100

8/8 0s 7ms/step - accuracy: 0.9666 - loss: 0.2992 - val_accuracy: 1.0000 - val_loss: 0.2439

Epoch 9/100

8/8 0s 6ms/step - accuracy: 0.9743 - loss: 0.2461 - val_accuracy: 1.0000 - val_loss: 0.1975

Epoch 10/100

8/8 0s 7ms/step - accuracy: 0.9853 - loss: 0.2089 - val_accuracy: 1.0000 - val_loss: 0.1628

Epoch 11/100

8/8 0s 9ms/step - accuracy: 0.9673 - loss: 0.1791 - val_accuracy: 1.0000 - val_loss: 0.1372

Epoch 12/100

8/8 0s 7ms/step - accuracy: 0.9832 - loss: 0.1367 - val_accuracy: 1.0000 - val_loss: 0.1164

Epoch 13/100

8/8 0s 9ms/step - accuracy: 0.9832 - loss: 0.1240 - val_accuracy: 1.0000 - val_loss: 0.1004

Epoch 14/100

8/8 0s 9ms/step - accuracy: 0.9802 - loss: 0.1082 - val_accuracy: 1.0000 - val_loss: 0.0871

Epoch 15/100

8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.1046 - val_accuracy: 1.0000 - val_loss: 0.0765

Epoch 16/100

8/8 0s 7ms/step - accuracy: 0.9947 - loss: 0.1041 - val_accuracy: 1.0000 - val_loss: 0.0688

Epoch 17/100

8/8 0s 7ms/step - accuracy: 0.9961 - loss: 0.0603 - val_accuracy: 1.0000 - val_loss: 0.0618

Epoch 18/100

8/8 0s 6ms/step - accuracy: 0.9947 - loss: 0.0550 - val_accuracy: 1.0000 - val_loss: 0.0553

Epoch 19/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0685 - val_accuracy: 1.0000 - val_loss: 0.0504

Epoch 20/100

8/8 0s 7ms/step - accuracy: 0.9929 - loss: 0.0459 - val_accuracy: 1.0000 - val_loss: 0.0458

Epoch 21/100

8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.0424 - val_accuracy: 1.0000 - val_loss: 0.0418

Epoch 22/100

8/8 0s 6ms/step - accuracy: 0.9906 - loss: 0.0525 - val_accuracy: 1.0000 - val_loss: 0.0394

Epoch 23/100

8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.0385 - val_accuracy: 1.0000 - val_loss: 0.0366

Epoch 24/100

8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0373 - val_accuracy: 1.0000 - val_loss: 0.0342

Epoch 25/100

8/8 0s 7ms/step - accuracy: 0.9763 - loss: 0.0555 - val_accuracy: 1.0000 - val_loss: 0.0323

Epoch 26/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0347 - val_accuracy: 1.0000 - val_loss: 0.0317

Epoch 27/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0212 - val_accuracy: 1.0000 - val_loss: 0.0309

Epoch 28/100

8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.0266 - val_accuracy: 1.0000 - val_loss: 0.0292

Epoch 29/100

8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0228 - val_accuracy: 1.0000 - val_loss: 0.0272

Epoch 30/100

8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.0218 - val_accuracy: 1.0000 - val_loss: 0.0261

Epoch 31/100

8/8 0s 9ms/step - accuracy: 0.9906 - loss: 0.0279 - val_accuracy: 1.0000 - val_loss: 0.0248

Epoch 32/100

8/8 0s 12ms/step - accuracy: 0.9871 - loss: 0.0357 - val_accuracy: 1.0000 - val_loss: 0.0229

Epoch 33/100

8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0198 - val_accuracy: 1.0000 - val_loss: 0.0221

Epoch 34/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0154 - val_accuracy: 1.0000 - val_loss: 0.0219

Epoch 35/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0126 - val_accuracy: 1.0000 - val_loss: 0.0220

Epoch 36/100

8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0140 - val_accuracy: 1.0000 - val_loss: 0.0217

Epoch 37/100

8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0222 - val_accuracy: 1.0000 - val_loss: 0.0215

Epoch 38/100

8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0128 - val_accuracy: 1.0000 - val_loss: 0.0210

Epoch 39/100

Epoch 85/100
8/8 0s 10ms/step - accuracy: 1.0000 - loss: 0.0020 - val_accuracy: 1.0000 - val_loss: 0.0122
Epoch 86/100
8/8 0s 12ms/step - accuracy: 1.0000 - loss: 0.0036 - val_accuracy: 1.0000 - val_loss: 0.0119
Epoch 87/100
8/8 0s 12ms/step - accuracy: 1.0000 - loss: 0.0079 - val_accuracy: 1.0000 - val_loss: 0.0113
Epoch 88/100
8/8 0s 13ms/step - accuracy: 1.0000 - loss: 0.0021 - val_accuracy: 1.0000 - val_loss: 0.0110
Epoch 89/100
8/8 0s 12ms/step - accuracy: 1.0000 - loss: 0.0013 - val_accuracy: 1.0000 - val_loss: 0.0109
Epoch 90/100
8/8 0s 11ms/step - accuracy: 1.0000 - loss: 0.0018 - val_accuracy: 1.0000 - val_loss: 0.0110
Epoch 91/100
8/8 0s 15ms/step - accuracy: 1.0000 - loss: 0.0028 - val_accuracy: 1.0000 - val_loss: 0.0113
Epoch 92/100
8/8 0s 10ms/step - accuracy: 1.0000 - loss: 0.0019 - val_accuracy: 1.0000 - val_loss: 0.0113
Epoch 93/100
8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0020 - val_accuracy: 1.0000 - val_loss: 0.0111
Epoch 94/100
8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0019 - val_accuracy: 1.0000 - val_loss: 0.0110
Epoch 95/100
8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0029 - val_accuracy: 1.0000 - val_loss: 0.0113
Epoch 96/100
8/8 0s 9ms/step - accuracy: 1.0000 - loss: 0.0011 - val_accuracy: 1.0000 - val_loss: 0.0115
Epoch 97/100
8/8 0s 7ms/step - accuracy: 1.0000 - loss: 0.0018 - val_accuracy: 1.0000 - val_loss: 0.0113
Epoch 98/100
8/8 0s 10ms/step - accuracy: 1.0000 - loss: 0.0027 - val_accuracy: 1.0000 - val_loss: 0.0110
Epoch 99/100
8/8 0s 8ms/step - accuracy: 1.0000 - loss: 0.0018 - val_accuracy: 1.0000 - val_loss: 0.0107
Epoch 100/100
8/8 0s 6ms/step - accuracy: 1.0000 - loss: 0.0022 - val_accuracy: 1.0000 - val_loss: 0.0109
Baseline Test Accuracy: 1.0000

--- Experiment 2: Deeper Network ---

Epoch 1/100
8/8 2s 36ms/step - accuracy: 0.3915 - loss: 1.0672 - val_accuracy: 0.8148 - val_loss: 0.8059
Epoch 2/100
8/8 0s 9ms/step - accuracy: 0.7289 - loss: 0.7895 - val_accuracy: 1.0000 - val_loss: 0.6198
Epoch 3/100
8/8 0s 9ms/step - accuracy: 0.7992 - loss: 0.6695 - val_accuracy: 1.0000 - val_loss: 0.4507
Epoch 4/100
8/8 0s 11ms/step - accuracy: 0.8608 - loss: 0.5231 - val_accuracy: 1.0000 - val_loss: 0.3117
Epoch 5/100
8/8 0s 10ms/step - accuracy: 0.9315 - loss: 0.4197 - val_accuracy: 1.0000 - val_loss: 0.2017
Epoch 6/100
8/8 0s 10ms/step - accuracy: 0.9277 - loss: 0.2765 - val_accuracy: 1.0000 - val_loss: 0.1343
Epoch 7/100
8/8 0s 9ms/step - accuracy: 0.9529 - loss: 0.1965 - val_accuracy: 1.0000 - val_loss: 0.0960
Epoch 8/100
8/8 0s 7ms/step - accuracy: 0.9676 - loss: 0.1743 - val_accuracy: 1.0000 - val_loss: 0.0725
Epoch 9/100
8/8 0s 9ms/step - accuracy: 0.9738 - loss: 0.1356 - val_accuracy: 1.0000 - val_loss: 0.0543
Epoch 10/100
8/8 0s 9ms/step - accuracy: 0.9802 - loss: 0.0920 - val_accuracy: 1.0000 - val_loss: 0.0430
Deeper Network Test Accuracy: 0.8148

--- Experiment 3: Lighter Network ---

Epoch 1/100
8/8 1s 35ms/step - accuracy: 0.2123 - loss: 1.7183 - val_accuracy: 0.0370 - val_loss: 1.5579
Epoch 2/100
8/8 0s 6ms/step - accuracy: 0.2246 - loss: 1.8354 - val_accuracy: 0.1111 - val_loss: 1.3539
Epoch 3/100
8/8 0s 7ms/step - accuracy: 0.2991 - loss: 1.3862 - val_accuracy: 0.2593 - val_loss: 1.1993
Epoch 4/100
8/8 0s 9ms/step - accuracy: 0.3631 - loss: 1.3060 - val_accuracy: 0.3333 - val_loss: 1.0865
Epoch 5/100
8/8 0s 7ms/step - accuracy: 0.3649 - loss: 1.2096 - val_accuracy: 0.4444 - val_loss: 0.9993
Epoch 6/100
8/8 0s 9ms/step - accuracy: 0.4890 - loss: 1.0203 - val_accuracy: 0.4444 - val_loss: 0.9319
Epoch 7/100
8/8 0s 9ms/step - accuracy: 0.6368 - loss: 0.9329 - val_accuracy: 0.5185 - val_loss: 0.8744
Epoch 8/100
8/8 0s 7ms/step - accuracy: 0.5233 - loss: 0.9812 - val_accuracy: 0.5926 - val_loss: 0.8306
Epoch 9/100
8/8 0s 8ms/step - accuracy: 0.6223 - loss: 0.8652 - val_accuracy: 0.6296 - val_loss: 0.7916
Epoch 10/100
8/8 0s 7ms/step - accuracy: 0.6204 - loss: 0.8301 - val_accuracy: 0.7037 - val_loss: 0.7572
Lighter Network Test Accuracy: 0.1111

--- Comparison of Models ---

Baseline Model Accuracy: 1.0000
Deeper Network Accuracy: 0.8148
Lighter Network Accuracy: 0.1111
1/1 0s 61ms/step

--- Classification Report for Baseline Model ---

precision	recall	f1-score	support
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0	1.00	1.00	1.00
			9

1	1.00	1.00	1.00	10
2	1.00	1.00	1.00	8
accuracy		1.00	27	
macro avg	1.00	1.00	1.00	27
weighted avg	1.00	1.00	1.00	27

Confusion Matrix:

```
[[ 9  0  0]
 [ 0 10  0]
 [ 0  0  8]]
```