Binary Classification on Raisin Dataset

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Abstract

This project focuses on using machine learning and deep learning techniques to classify two types of raisins, Kecimen and Besni, based on their physical attributes.
Models such as K-Nearest Neighbors (KNN), Random Forest, and Long Short-Term Memory (LSTM) were applied to the Raisin dataset.
Comprehensive preprocessing steps, including data cleaning and scaling, were employed to optimize model performance.
Evaluation metrics such as accuracy, precision, recall, F1-score, and ROC AUC were used to compare models, with Random Forest achieving the best overall results.

Introduction

Classification is a fundamental task in data science and machine learning, with applications across various industries,
including agriculture, healthcare, and e-commerce. In this project, the Raisin dataset, containing detailed physical attributes
of two raisin types, was utilized to develop predictive models. The primary objective was to determine the type of raisin with high accuracy,
leveraging the power of machine learning and deep learning methods.
This report details the steps taken to preprocess the data, build and evaluate models, and derive insights from the analysis.

About the Dataset

The Raisin dataset, obtained from a public repository, consists of 900 samples with 8 features, including 'Area',
'MajorAxisLength', 'MinorAxisLength', 'Eccentricity', 'ConvexArea', 'Extent', and 'Perimeter'.
The target variable 'Class' represents the raisin type: Kecimen (encoded as 0) or Besni (encoded as 1).
The features are numerical and describe the physical characteristics of raisins, making the dataset suitable for binary classification tasks.

Preprocessing Steps

Effective preprocessing is critical for achieving optimal performance in machine learning models.
The preprocessing steps applied to the Raisin dataset included the following:
1.Data Cleaning:Duplicate entries were removed, and the dataset was checked for missing values, ensuring data integrity.
2. Encoding: The target variable 'Class' was encoded into binary values (0 for Kecimen and 1 for Besni).
3. Feature Scaling: A StandardScaler was used to standardize numerical features, improving model performance by ensuring uniform feature distributions.
4. Feature Selection: Correlation analysis was performed to identify the top features: 'MajorAxisLength', 'Perimeter', 'Area', 'ConvexArea', and 'Eccentricity'.
5. Data Splitting: The dataset was divided into 75% training and 25% testing subsets to evaluate model performance effectively.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) provided insights into feature distributions and relationships within the dataset.
Histograms and scatter plots revealed the distribution of features, while correlation heatmaps highlighted relationships between features and the target variable.
Key findings included strong correlations of 'MajorAxisLength' and 'Perimeter' with the target variable, validating their inclusion in model training.

Machine Learning Models

Three models were implemented to classify the raisin types:
1. K-Nearest Neighbors (KNN): This algorithm classifies samples based on their proximity to neighboring data points.
It performed well but showed sensitivity to outliers.
2. Random Forest (RF): An ensemble learning method combining multiple decision trees, it outperformed other models by capturing complex patterns.
3. Long Short-Term Memory (LSTM):A type of recurrent neural network, LSTM leveraged sequential data patterns but required more data and computational power for optimal results.

Metrics and Results

Model performance was evaluated using metrics such as accuracy, precision, recall, F1-

score, and ROC AUC.
Random Forest consistently achieved the highest scores, demonstrating its ability to handle feature correlations and data variability.
While KNN provided interpretable results, its sensitivity to noise affected its performance.
LSTM showed potential but underperformed due to the dataset size.

Comparison of Models

The comparison of model performance highlighted the strengths and weaknesses of each approach:
- **Random Forest: Best-performing model with high accuracy and balanced precision-recall metrics**.
-KNN: Simple and interpretable but sensitive to outliers and high-dimensional data.
- LSTM: Demonstrated potential but required larger datasets and computational resources.

Conclusion and Future Work

This project successfully demonstrated the application of machine learning and deep learning models for binary classification of raisin types.
Random Forest emerged as the top-performing algorithm, leveraging its ensemble learning capabilities.
Future work could focus on expanding the dataset and exploring additional deep learning architectures to improve classification performance further.

Screen shots:

Binary Classification on Raisin Dataset

In this project, we aim to build a binary classification system to predict the target class of a dataset using machine learning (ML) and deep learning (DL) techniques. The classification models will be optimized through random search hyperparameter tuning and evaluated using 10-fold cross-validation to ensure robust performance. The results will include detailed evaluation metrics and visualizations (e.g., ROC curves) for model comparison.

Install All Necessary Packages

[1]:
```
!pip install pandas
!pip install numpy
!pip install matplotlib
!pip install seaborn
!pip install scikit-learn
!pip install tensorflow
!pip install keras-models
!pip install scikeras
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (2.2.2)
Requirement already satisfied: numpy>=1.22.4 in /usr/local/lib/python3.10/dist-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
```

Import all packages & librabries

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, StratifiedKFold, RandomizedSearchCV
from sklearn.metrics import (
    confusion_matrix, accuracy_score, precision_score, recall_score, f1_score,
    roc_auc_score, log_loss, matthews_corrcoef, roc_curve, auc
)
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM
from tensorflow.keras.optimizers import Adam
from scikeras.wrappers import KerasClassifier, KerasRegressor
from tensorflow.keras.utils import to_categorical
```

Load Dataset

Dataset link - https://www.kaggle.com/datasets/nimapourmoradi/raisin-binary-classification

In [3]:
```
# Load Dataset
data = pd.read_csv("raisin_dataset.csv")
data.head()
```

Out[3]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
0	87524	442.246011	253.291155	0.819738	90546	0.758651	1184.040	Kecimen
1	75166	406.690687	243.032436	0.801805	78789	0.684130	1121.786	Kecimen
2	90856	442.267048	266.328318	0.798354	93717	0.637613	1208.575	Kecimen
3	45928	286.540559	208.760042	0.684989	47336	0.699599	844.162	Kecimen
4	79408	352.190770	290.827533	0.564011	81463	0.792772	1073.251	Kecimen

Basic Information of Dataset

In [4]:
```
# Display Shape and Info
print("Dataset Shape:", data.shape)
print("\nDataset Info:")
print(data.info())
```

```
Dataset Shape: (900, 8)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             900 non-null    int64  
 1   MajorAxisLength  900 non-null    float64
 2   MinorAxisLength  900 non-null    float64
 3   Eccentricity     900 non-null    float64
 4   ConvexArea       900 non-null    int64  
 5   Extent           900 non-null    float64
 6   Perimeter        900 non-null    float64
 7   Class            900 non-null    object 
dtypes: float64(5), int64(2), object(1)
memory usage: 56.4+ KB
None
```

EDA

Remove null values & duplicate values

In [5]:
```
# Basic EDA
print("\nNull Values:\n", data.isnull().sum())
data.drop_duplicates(inplace=True)
print("\nAfter Removing Duplicates - Shape:", data.shape)
```

```
Null Values:
 Area               0
MajorAxisLength    0
MinorAxisLength    0
Eccentricity       0
ConvexArea         0
Extent             0
```

In [5]:
```python
# Basic EDA
print("\nNull Values:\n", data.isnull().sum())
data.drop_duplicates(inplace=True)
print("\nAfter Removing Duplicates - Shape:", data.shape)
```

```
Null Values:
 Area              0
MajorAxisLength    0
MinorAxisLength    0
Eccentricity       0
ConvexArea         0
Extent             0
Perimeter          0
Class              0
dtype: int64

After Removing Duplicates - Shape: (900, 8)
```

Describe Dataset

In [6]:
```python
# Describe Dataset
print("\nDataset Description:")
data.describe()
```

```
Dataset Description:
```

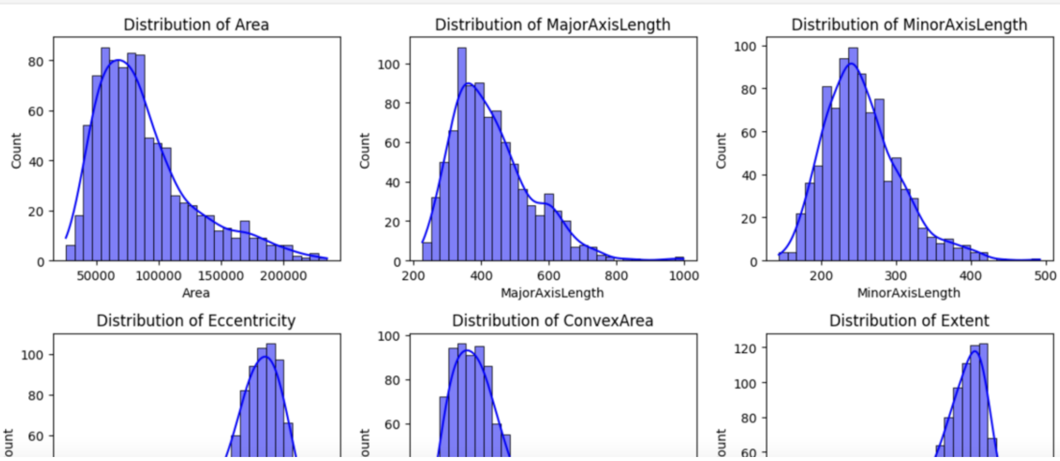
Out[6]:

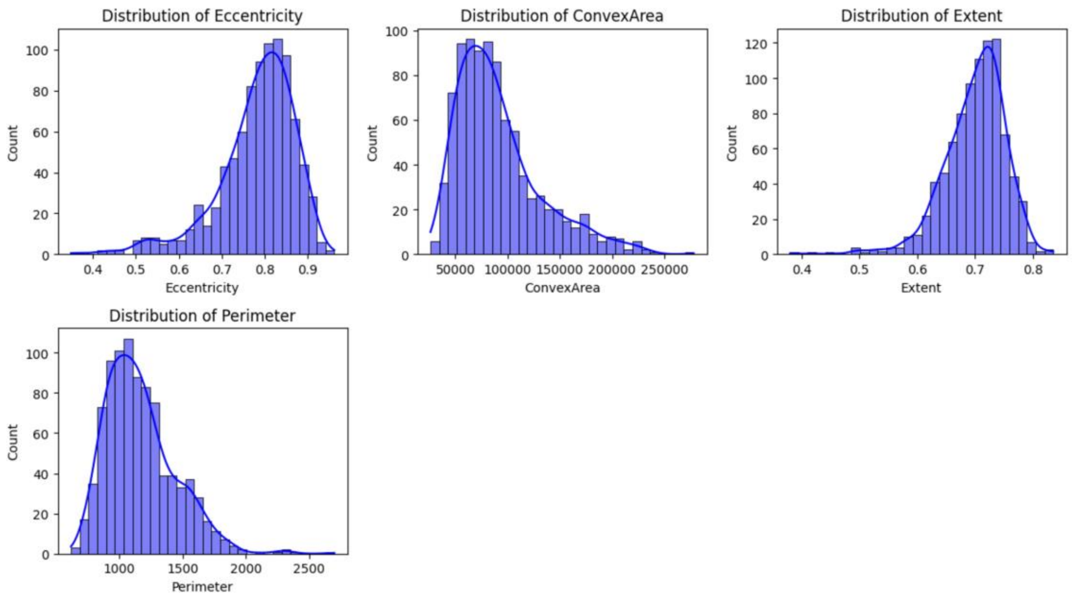
	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
count	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000
mean	87804.127778	430.929950	254.488133	0.781542	91186.090000	0.699508	1165.906636
std	39002.111390	116.035121	49.988902	0.090318	40769.290132	0.053468	273.764315
min	25387.000000	225.629541	143.710872	0.348730	26139.000000	0.379856	619.074000
25%	59348.000000	345.442898	219.111126	0.741766	61513.250000	0.670869	966.410750
50%	78902.000000	407.803951	247.848409	0.798846	81651.000000	0.707367	1119.509000
75%	105028.250000	494.187014	279.888575	0.842571	108375.750000	0.734991	1308.389750
max	235047.000000	997.291941	492.275279	0.962124	278217.000000	0.835455	2697.753000

Histogram

Shows the distribution of each feature across the dataset.

[7]:
```python
# Histograms for Feature Distribution
plt.figure(figsize=(12, 10))
for i, column in enumerate(data.columns[:-1], start=1):  # Exclude Outcome
    plt.subplot(3, 3, i)
    sns.histplot(data[column], kde=True, color='blue', bins=30)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```





Count Plot - Target Class Distribution

Displays the frequency distribution of each class, providing insight into class imbalance.

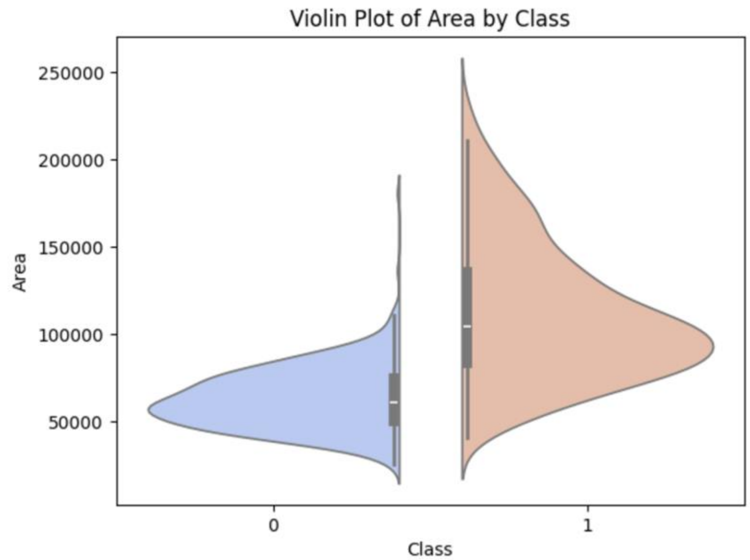
In [8]:
```
# Check class distribution
sns.countplot(x='Class', data=data)
plt.title("Target Class Distribution")
plt.show()

# Encode the target column ('Class')
data['Class'] = data['Class'].map({'Kecimen': 0, 'Besni': 1})
```

Violin Plot

Combines box plots with kernel density estimation, providing more insight into the data distribution.

In [9]:
```python
import warnings
warnings.filterwarnings('ignore')
```

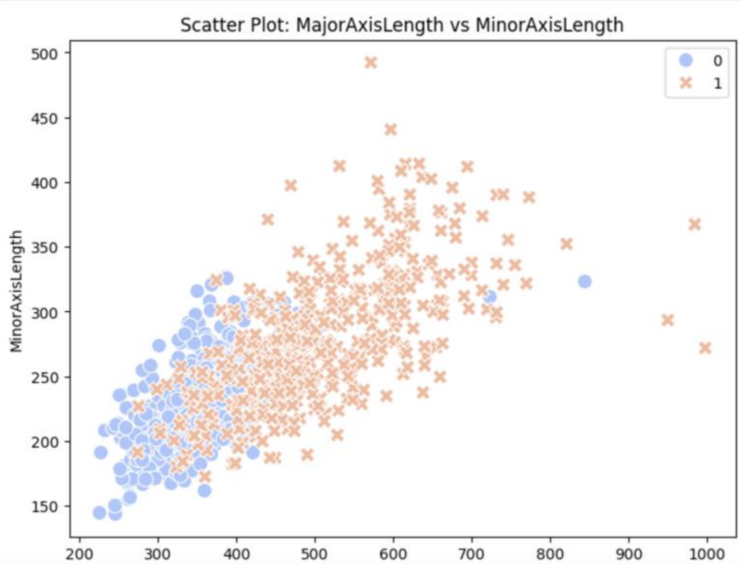
In [10]:
```python
for column in data.columns[:-1]:
    sns.violinplot(data=data, x="Class", y=column, palette="coolwarm", split=True)
    plt.title(f"Violin Plot of {column} by Class")
    plt.show()
```



Scatter Plot

Examines relationships between two key features, categorized by the class.

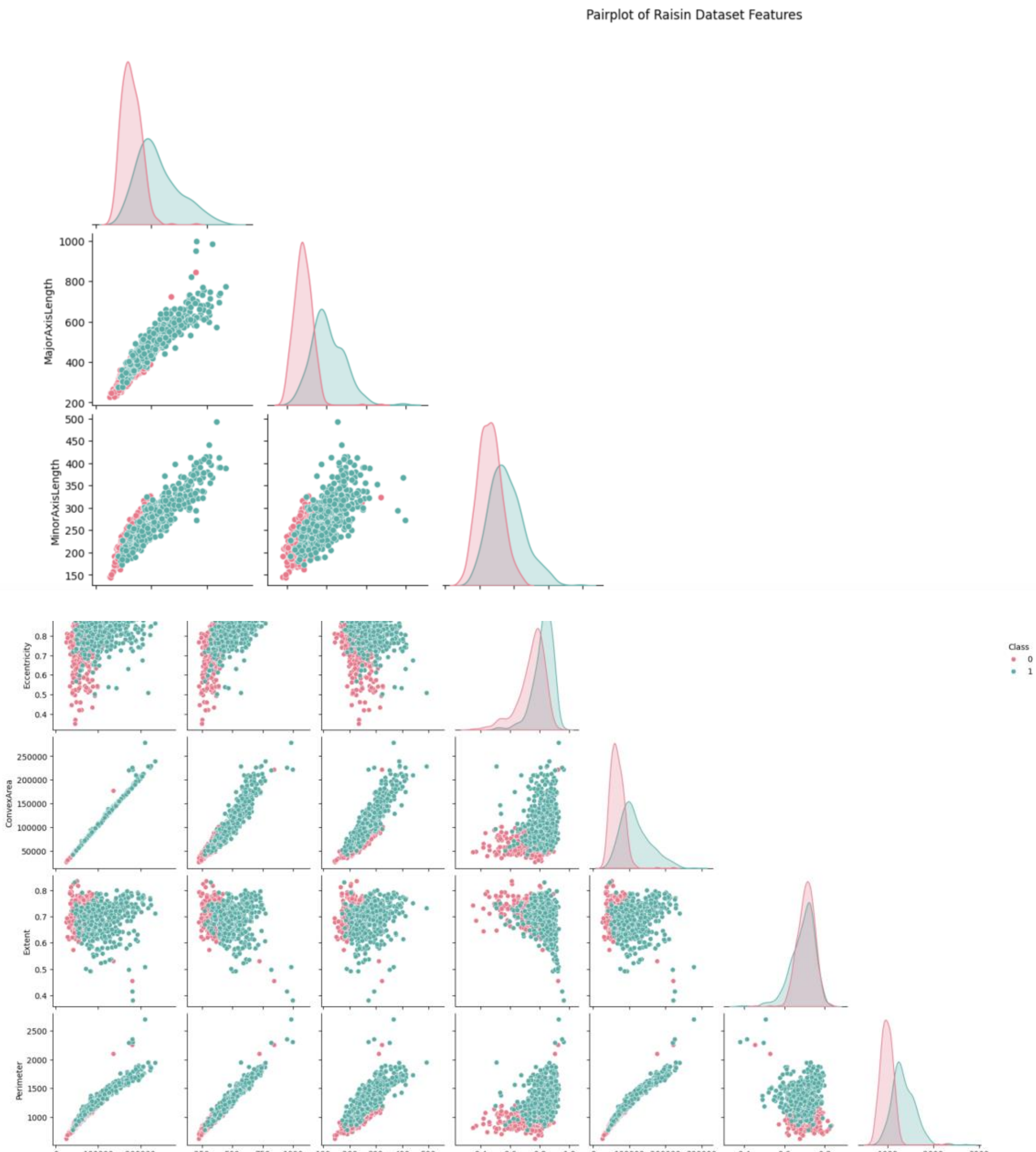
In [11]:
```python
plt.figure(figsize=(8, 6))
sns.scatterplot(data=data, x="MajorAxisLength", y="MinorAxisLength", hue="Class", style="Class", palette="coolwarm", s=100)
plt.title("Scatter Plot: MajorAxisLength vs MinorAxisLength")
plt.xlabel("MajorAxisLength")
plt.ylabel("MinorAxisLength")
plt.legend()
plt.show()
```



Pairplot

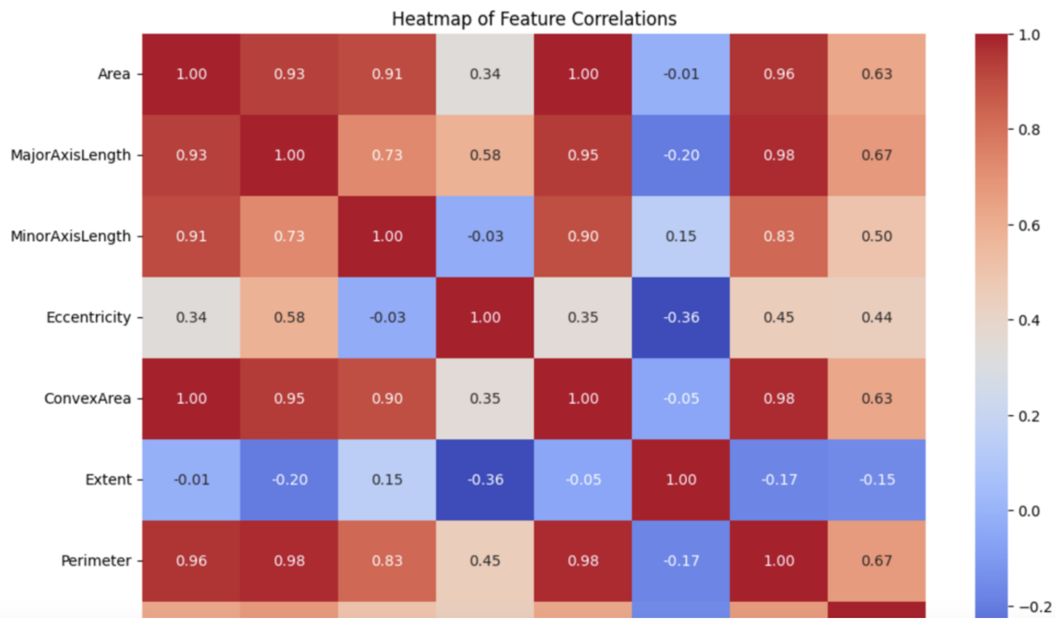
In [12]:

```python
# Pairplot for feature relationships with respect to the target
sns.pairplot(data, hue="Class", diag_kind='kde',  corner=True, palette='husl')
plt.suptitle("Pairplot of Raisin Dataset Features", y=1.02)
plt.show()
```



Heatmap to find correlation between features

In [13]:
```
# Heatmap for Feature Correlations
plt.figure(figsize=(12, 8))
sns.heatmap(data.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Heatmap of Feature Correlations")
plt.show()
```



Finding best features to train model

In [14]:
```
# Select Top 6 Features Based on Correlation
correlation = data.corr()
top_features = correlation['Class'].abs().sort_values(ascending=False).index[1:7]
print("Selected Top Features for Prediction:", list(top_features))

# Prepare Data
X = data[top_features]
y = data['Class']
```

```
Selected Top Features for Prediction: ['MajorAxisLength', 'Perimeter', 'Area', 'ConvexArea', 'MinorAxisLength', 'Eccentricity']
```

Standardization & Normalization

In [15]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

In [16]:
```
# Normalize data if algorithms require it
from sklearn.preprocessing import MinMaxScaler
normalizer = MinMaxScaler()
X = normalizer.fit_transform(X)
```

Spliting Dataset into Train & Test

Training Data - 75% & Testing Data - 25%

In [17]:
```
# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, stratify=y, random_state=42)
```

Machine Learning Models - Random Forest & KNN

1. Train two machine learning models:

- K-Nearest Neighbors (KNN).
- Random Forest (RF).

1. Use RandomizedSearchCV for hyperparameter optimization.
2. Perform 10-fold cross-validation and evaluate metrics across all folds.

Machine Learning Models - Random Forest & KNN

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- K-Nearest Neighbors (KNN).
- Random Forest (RF).

1. Use RandomizedSearchCV for hyperparameter optimization.
2. Perform 10-fold cross-validation and evaluate metrics across all folds.

Random Search - Hyperparameters Tuning

In [18]:
```python
def knn_random_search(X, y):
    knn = KNeighborsClassifier()
    param_dist = {
        "n_neighbors": range(1, 10),
        "weights": ["uniform", "distance"]
    }
    search = RandomizedSearchCV(knn, param_distributions=param_dist, n_iter=20, cv=5, scoring='roc_auc', random_state=42)
    search.fit(X, y)
    return search.best_estimator_, search.best_params_
```

In [19]:
```python
def rf_random_search(X, y):
    rf = RandomForestClassifier(random_state=42)
    param_dist = {
        "n_estimators": [10, 50, 100, 200],
        "max_depth": [None, 10, 20, 30],
        "min_samples_split": [2, 5, 10],
        "min_samples_leaf": [1, 2, 4]
    }
    search = RandomizedSearchCV(rf, param_distributions=param_dist, n_iter=20, cv=5, scoring='roc_auc', random_state=42)
    search.fit(X, y)
    return search.best_estimator_, search.best_params_
```

Best Hyperparameters - KNN

In [20]:
```python
# Random Search and Evaluation for KNN
print("Tuning KNN...")
knn_model, knn_params = knn_random_search(X_train, y_train)
print("Best KNN Params:", knn_params)
```

print("Best KNN Params:", knn_params)

```
Tuning KNN...
Best KNN Params: {'weights': 'uniform', 'n_neighbors': 9}
```

Best Hyperparameters - Random Forest

In [21]:
```python
# Random Search and Evaluation for Random Forest
print("\nTuning Random Forest...")
rf_model, rf_params = rf_random_search(X_train, y_train)
print("Best Random Forest Params:", rf_params)
```

```
Tuning Random Forest...
Best Random Forest Params: {'n_estimators': 100, 'min_samples_split': 5, 'min_samples_leaf': 4, 'max_depth': 10}
```

Helper Function to print all metrics

In [25]:
```python
def compute_metrics(y_true, y_pred, y_proba):
    cm = confusion_matrix(y_true, y_pred)

    tp, fn = cm[0][0], cm[0][1]
    fp, tn = cm[1][0], cm[1][1]
    tpr = tp / (tp + fn)
    tnr = tn / (tn + fp)
    fpr = fp / (tn + fp)
    fnr = fn / (tp + fn)
    precision = tp / (tp + fp)
    f1 = 2 * tp / (2 * tp + fp + fn)
    accuracy = (tp + tn) / (tp + fp + fn + tn)
    error_rate = (fp + fn) / (tp + fp + fn + tn)
    bacc = (tpr + tnr) / 2
    tss = tpr - fpr
    hss = 2 * (tp * tn - fp * fn) / ((tp + fn) * (fn + tn) + (tp + fp) * (fp + tn))
    recall = tp / tp + fn

    roc = roc_auc_score(y_true, y_proba)

    return {
        "tp": tp, "tn": tn, "fp": fp, "fn": fn,
        "tpr": tpr, "tnr": tnr, "fpr": fpr, "fnr": fnr,
        "Accuracy": accuracy, "Precision": precision, "Error Rate": error_rate,
        "Recall": recall, "F1 Score": f1,
        "bacc": bacc, "tss": tss, "hss": hss, "roc": roc
    }
```

```
    roc = roc_auc_score(y_true, y_proba)

    return {
        "tp": tp, "tn": tn, "fp": fp, "fn": fn,
        "tpr": tpr, "tnr": tnr, "fpr": fpr, "fnr": fnr,
        "Accuracy": accuracy, "Precision": precision, "Error Rate": error_rate,
        "Recall": recall, "F1 Score": f1,
        "bacc": bacc, "tss": tss, "hss": hss, "roc": roc
    }
```

Helper Function to train model

In [26]:
```
def evaluate_ml_model(model, X, y):
    skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
    all_metrics = []
    X = np.array(X)
    y = np.array(y)

    for fold, (train_idx, test_idx) in enumerate(skf.split(X, y), 1):
        X_train, X_val = X[train_idx], X[test_idx]
        y_train, y_val = y[train_idx], y[test_idx]

        model.fit(X_train, y_train)
        y_pred = model.predict(X_val)
        y_proba = model.predict_proba(X_val)[:, 1]

        metrics = compute_metrics(y_val, y_pred, y_proba)
        metrics["Fold"] = fold
        all_metrics.append(metrics)
        print(f"Fold {fold} Metrics:")
        for metric, value in metrics.items():
            print(f"{metric}: {value}")
        print('#'*30+'\n')

    return pd.DataFrame(all_metrics)
```

Training RandomForest Model

In [27]:
```
rf_metrics = evaluate_ml_model(rf_model, X_train, y_train)
```

```
Fold 1 Metrics:
tp: 26
tn: 28
fp: 6
```

Training RandomForest Model

```
In [27]: rf_metrics = evaluate_ml_model(rf_model, X_train, y_train)
```

```
Fold 1 Metrics:
tp: 26
tn: 28
fp: 6
fn: 8
tpr: 0.7647058823529411
tnr: 0.8235294117647058
fpr: 0.17647058823529413
fnr: 0.23529411764705882
Accuracy: 0.7941176470588235
Precision: 0.8125
Error Rate: 0.20588235294117646
Recall: 9.0
F1 Score: 0.7878787878787878
bacc: 0.7941176470588235
tss: 0.588235294117647
hss: 0.5882352941176471
roc: 0.9238754325259515
Fold: 1
##############################

Fold 2 Metrics:
tp: 28
tn: 31
fp: 3
fn: 6
tpr: 0.8235294117647058
tnr: 0.9117647058823529
fpr: 0.08823529411764706
fnr: 0.17647058823529413
Accuracy: 0.8676470588235294
Precision: 0.9032258064516129
Error Rate: 0.1323529411764706
Recall: 7.0
F1 Score: 0.8615384615384616
bacc: 0.8676470588235294
tss: 0.7352941176470588
hss: 0.7352941176470589
roc: 0.9385813148788927
Fold: 2
```

Training KNN Model

In [28]:
```
knn_metrics = evaluate_ml_model(knn_model, X_train, y_train)
```

```
Fold 1 Metrics:
tp: 27
tn: 28
fp: 6
fn: 7
tpr: 0.7941176470588235
tnr: 0.8235294117647058
fpr: 0.17647058823529413
fnr: 0.20588235294117646
Accuracy: 0.8088235294117647
Precision: 0.8181818181818182
Error Rate: 0.19117647058823528
Recall: 8.0
F1 Score: 0.8059701492537313
bacc: 0.8088235294117647
tss: 0.6176470588235293
hss: 0.6176470588235294
roc: 0.9052768166089966
Fold: 1
##############################

Fold 2 Metrics:
tp: 29
tn: 30
fp: 4
fn: 5
tpr: 0.8529411764705882
tnr: 0.8823529411764706
fpr: 0.11764705882352941
fnr: 0.14705882352941177
Accuracy: 0.8676470588235294
Precision: 0.8787878787878788
Error Rate: 0.1323529411764706
Recall: 6.0
F1 Score: 0.8656716417910447
```

DL Model - LSTM

Train a deep learning model using LSTM:

- Sequential LSTM architecture for handling sequential or structured data.
- Use random search to optimize batch size and epochs.
- Perform 10-fold cross-validation to evaluate performance.

Helper Functions

In [29]:

```
def build_lstm(input_shape):
    model = Sequential()
    model.add(LSTM(32, input_shape=input_shape))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

In [30]:

```
def lstm_random_search(X, y):
    lstm = KerasClassifier(build_fn=lambda: build_lstm((X.shape[1], 1)), verbose=0)
    param_dist = {
        "batch_size": [16, 32, 64],
        "epochs": [10, 20, 30]
    }
    search = RandomizedSearchCV(lstm, param_distributions=param_dist, n_iter=10, cv=3, scoring='roc_auc', random_state=42)
    search.fit(X, y)
    return search.best_estimator_, search.best_params_
```

In [31]:

```
def evaluate_lstm_model(X, y):
    skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
    all_metrics = []
    X = np.array(X)
    y = np.array(y)

    for fold, (train_idx, test_idx) in enumerate(skf.split(X, y), 1):
        X_train, X_val = np.expand_dims(X[train_idx], axis=2), np.expand_dims(X[test_idx], axis=2)
        y_train, y_val = y[train_idx], y[test_idx]

        model = build_lstm((X_train.shape[1], 1))
        model.fit(X_train, y_train, epochs=10, batch_size=32, verbose=0)
        y_proba = model.predict(X_val).ravel()
        y_pred = (y_proba > 0.5).astype(int)
```

In [33]:
```python
# Random Search and Evaluation for LSTM
print("\nTuning LSTM...")
lstm_model, lstm_params = lstm_random_search(np.expand_dims(X_train, axis=2), y_train)
print("Best LSTM Params:", lstm_params)
```

```
Tuning LSTM...
WARNING:tensorflow:5 out of the last 24 calls to <function TensorFlowTrainer.make_predict_function.<locals
function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating
fferent shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function ou
rue option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide
api_docs/python/tf/function for  more details.
WARNING:tensorflow:5 out of the last 17 calls to <function TensorFlowTrainer.make_predict_function.<locals
function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating
fferent shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function ou
rue option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide
api_docs/python/tf/function for  more details.
Best LSTM Params: {'epochs': 30, 'batch_size': 16}
```

Model Training

In [34]:
```python
lstm_metrics = evaluate_lstm_model(X_train, y_train)
```

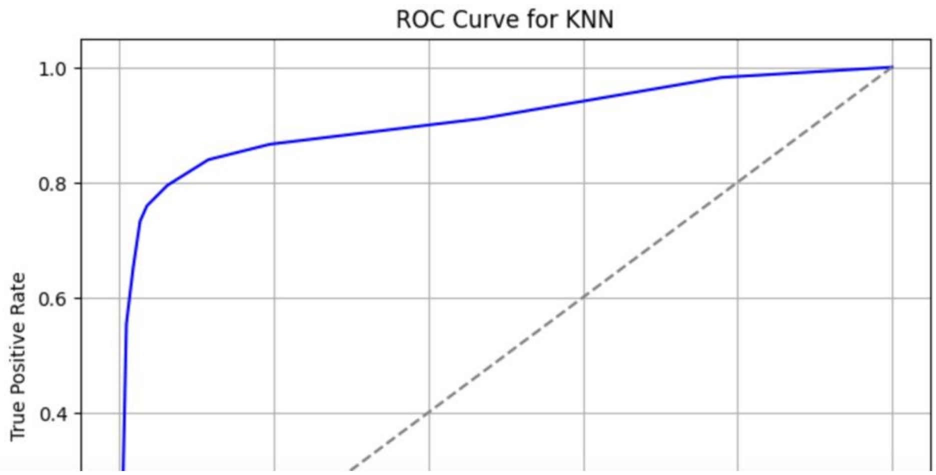
```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
Fold 1 Metrics:
tp: 28
tn: 28
fp: 6
fn: 6
tpr: 0.8235294117647058
tnr: 0.8235294117647058
fpr: 0.17647058823529413
fnr: 0.17647058823529413
Accuracy: 0.8235294117647058
Precision: 0.8235294117647058
Error Rate: 0.17647058823529413
Recall: 7.0
F1 Score: 0.8235294117647058
bacc: 0.8235294117647058
tss: 0.6470588235294117
hss: 0.6470588235294118
roc: 0.8979238754325258
Fold: 1
##############################
```

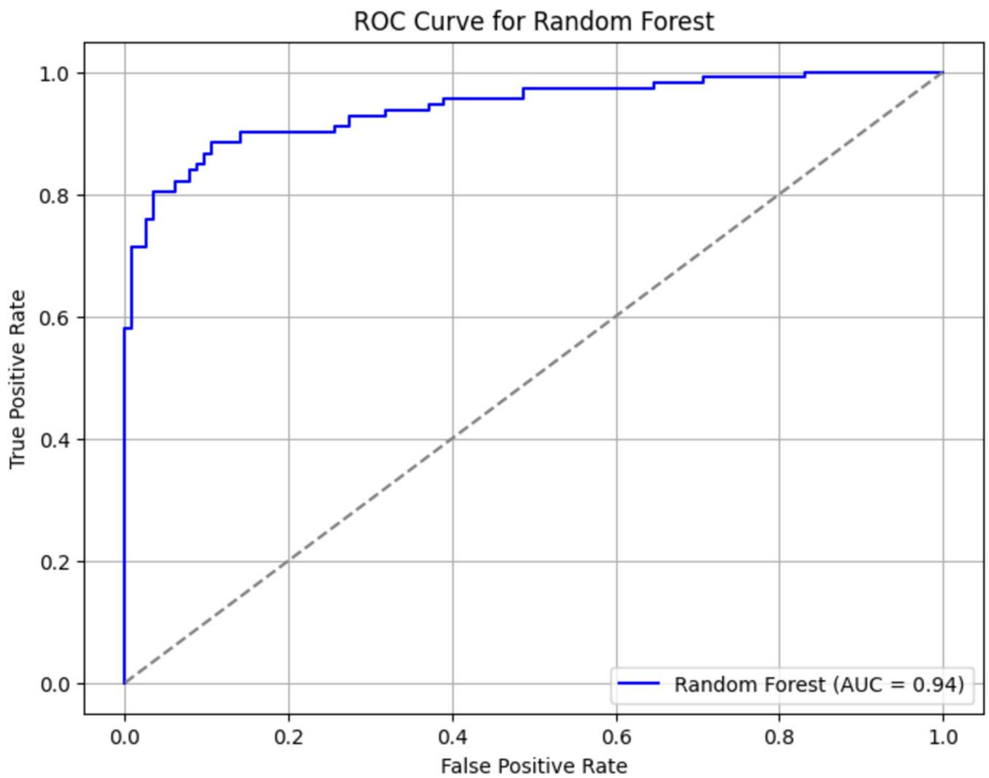
ROC Curve

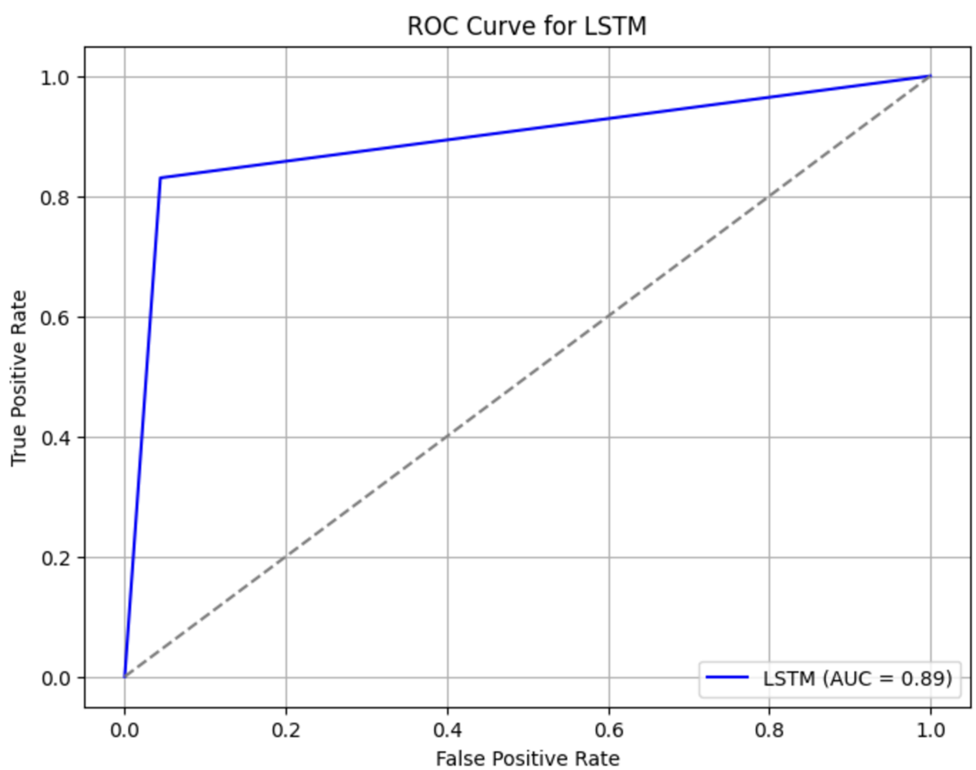
In [35]:
```
def plot_roc_curve(model_name, y_test, y_proba):
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='blue', label=f"{model_name} (AUC = {roc_auc:.2f})")
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
    plt.title(f"ROC Curve for {model_name}")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc="lower right")
    plt.grid()
    plt.show()
```

In [36]:
```
# Plot ROC Curves
print("\nPlotting ROC Curves...")
plot_roc_curve("KNN", y_test, knn_model.predict_proba(X_test)[:, 1])
plot_roc_curve("Random Forest", y_test, rf_model.predict_proba(X_test)[:, 1])
plot_roc_curve("LSTM", y_test, lstm_model.predict(np.expand_dims(X_test, axis=2)).ravel())
```

```
Plotting ROC Curves...
```




ROC Curve for Random Forest
True Positive Rate
False Positive Rate
Random Forest (AUC = 0.94)


ROC Curve for LSTM
True Positive Rate
False Positive Rate
LSTM (AUC = 0.89)

Models Comparision

Compare the performance of KNN, Random Forest, and LSTM models using the metrics from the 10th fold.

In [37]:
```
rf_metrics['Model'] = 'Random Forest'
knn_metrics['Model'] = 'KNN'
lstm_metrics['Model'] = 'LSTM'
all_metrics = pd.concat([rf_metrics, knn_metrics, lstm_metrics], ignore_index=True)
```

In [38]:
```
all_metrics = all_metrics[all_metrics['Fold']==10]
all_metrics.set_index('Model', inplace=True)
all_metrics.T
```

Out[38]:

Model	Random Forest	KNN	LSTM
tp	27.000000	28.000000	29.000000
tn	28.000000	26.000000	24.000000
fp	6.000000	8.000000	10.000000
fn	6.000000	5.000000	4.000000
tpr	0.818182	0.848485	0.878788
tnr	0.823529	0.764706	0.705882
fpr	0.176471	0.235294	0.294118
fnr	0.181818	0.151515	0.121212
Accuracy	0.820896	0.805970	0.791045
Precision	0.818182	0.777778	0.743590
Error Rate	0.179104	0.194030	0.208955
Recall	7.000000	6.000000	5.000000
F1 Score	0.818182	0.811594	0.805556
bacc	0.820856	0.806595	0.792335
tss	0.641711	0.613191	0.584670
hss	0.641711	0.612372	0.583111
roc	0.899733	0.887255	0.879679
Fold	10.000000	10.000000	10.000000