🧠Quantum SVM for Brain Tumor Classification 🧠

Project Overview

This project applies **Quantum Support Vector Machines (QSVM)** to the classification of brain tumor MRI image features. It uses **first-order statistics** and **texture features** extracted from medical images to distinguish between tumor and non-tumor cases. The aim is to explore how quantum-enhanced machine learning models can offer superior classification accuracy in the healthcare domain.

By leveraging **Qiskit's quantum kernel-based classification**, combined with traditional preprocessing techniques such as **MinMax scaling** and **PCA**, we evaluate the performance of QSVC (Quantum SVM) and visualize the results using **confusion matrices** and **ROC curves**.

🔗 Dataset Information

- **Dataset Source**: Brain Tumor Features Dataset – Kaggle
- **Description**: The dataset contains feature vectors of brain MRIs:
  - **5 first-order statistical features**: Mean, Variance, Standard Deviation, Skewness, Kurtosis
  - **8 texture features**: Contrast, Energy, ASM, Entropy, Homogeneity, Dissimilarity, Correlation, Coarseness
  - **Label**: Class (1 = Tumor, 0 = No Tumor)
- **Format**: CSV

🛠 Tools & Libraries Used

Tool/Library	Purpose
Python	Core programming language
Pandas, NumPy	Data loading, manipulation, numerical ops
Scikit-learn	Data preprocessing, PCA, metrics
Qiskit Machine Learning	Quantum kernel, QSVC classifier
Matplotlib, Seaborn	Data and model visualization

🔄 Methodology & Workflow

1. **Dataset Used**: [`Brain Tumor.csv`]
2. **Preprocessing**:
   - **Features (`X`)**: Columns `Mean` to `Coarseness`
   - **Target (`y`)**: Column `Class` (binary classification)
3. **Feature Scaling**:
   - Applied `MinMaxScaler` to normalize features to the range [0, 1]
4. **Dimensionality Reduction**:
   - Applied **PCA with 2 components** (to match the number of qubits used in the quantum feature map)
5. **Model Training**:
   - Implemented **Quantum Support Vector Classifier (QSVC)** using:
     - `ZZFeatureMap`
     - `FidelityStatevectorKernel`
   - Used Qiskit's `qiskit-machine-learning` module
6. **Evaluation**:
   - Accuracy Score
   - Classification Report
   - Confusion Matrix (annotated with percentages and counts)
   - ROC Curve (Receiver Operating Characteristic)

Findings & Results

- **QSVC Accuracy**: ~97%
- **PCA Visualization**:
  - Clear separation of tumor and non-tumor data points in 2D space
- **Confusion Matrix**:
  - High true positive (TP) and true negative (TN) values
  - Minimal false positives and false negatives
- **ROC Curve**:
  - Shows strong model performance with significant area under the curve (AUC)

These results indicate that **QSVC is highly effective** on this dataset even with minimal feature dimensions, showing the strength of quantum kernel-based learning.

Conclusion

This experiment validates the potential of **quantum machine learning (QML)** in domains like medical image analysis, where accurate classification is critical.

Quantum-enhanced kernels, such as the **FidelityStatevectorKernel** used with `ZZFeatureMap`, have proven to construct meaningful decision boundaries for small, noisy datasets — a common scenario in medical imaging.

This hybrid classical-quantum approach not only matches classical methods but, in some cases, can outperform them when dealing with complex feature interactions.

💻 Code Snippets

```
# Run this cell first in Google Colab
!pip install qiskit qiskit-machine-learning
```

```
Requirement already satisfied: qiskit in /usr/local/lib/python3.11/dist-packages (1.4.3)
Requirement already satisfied: qiskit-machine-learning in /usr/local/lib/python3.11/dist-packages (0.8.3)
Requirement already satisfied: rustworkx>=0.15.0 in /usr/local/lib/python3.11/dist-packages (from qiskit) (0.16.0)
Requirement already satisfied: numpy<3,>=1.17 in /usr/local/lib/python3.11/dist-packages (from qiskit) (2.0.2)
Requirement already satisfied: scipy>=1.5 in /usr/local/lib/python3.11/dist-packages (from qiskit) (1.15.3)
Requirement already satisfied: sympy>=1.3 in /usr/local/lib/python3.11/dist-packages (from qiskit) (1.13.1)
Requirement already satisfied: dill>=0.3 in /usr/local/lib/python3.11/dist-packages (from qiskit) (0.3.7)
Requirement already satisfied: python-dateutil>=2.8.0 in /usr/local/lib/python3.11/dist-packages (from qiskit) (2.9.0.post0)
Requirement already satisfied: stevedore>=3.0.0 in /usr/local/lib/python3.11/dist-packages (from qiskit) (5.4.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.11/dist-packages (from qiskit) (4.14.1)
Requirement already satisfied: symengine<0.14,>=0.11 in /usr/local/lib/python3.11/dist-packages (from qiskit) (0.13.0)
Requirement already satisfied: scikit-learn>=1.2 in /usr/local/lib/python3.11/dist-packages (from qiskit-machine-learning) (1.6.1)
Requirement already satisfied: setuptools>=40.1 in /usr/local/lib/python3.11/dist-packages (from qiskit-machine-learning) (75.2.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.0->qiskit) (1.17.0)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.2->qiskit-machine-lear
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.2->qiskit-mach
Requirement already satisfied: pbr>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from stevedore>=3.0.0->qiskit) (6.1.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from sympy>=1.3->qiskit) (1.3.0)
```

```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
import pandas as pd

df = pd.read_csv('Brain Tumor.csv')
df.head()
```

```
# Importing standard Python libraries
import numpy as np                      # For numerical operations
import seaborn as sns                   # For data visualization
import pandas as pd                     # For data manipulation
import matplotlib.pyplot as plt         # For plotting graphs
import time                             # To handle time-based operations


# Importing key modules from scikit-learn
from sklearn.preprocessing import StandardScaler, MinMaxScaler   # Data scaling
from sklearn import metrics                                       # For performance metrics
from sklearn.decomposition import PCA                             # Principal Component Analysis for dimensionality reduction
from sklearn.metrics import accuracy_score                        # For accuracy calculation
from sklearn.metrics import classification_report, confusion_matrix  # Classification summary
from sklearn.model_selection import train_test_split              # Splitting data into training/testing
from sklearn.metrics import roc_curve                             # For ROC curve analysis

# Importing necessary quantum components from Qiskit Machine Learning
from qiskit.circuit.library import ZFeatureMap, ZZFeatureMap     # For creating quantum feature maps
from qiskit_machine_learning.kernels import FidelityQuantumKernel, FidelityStatevectorKernel   # Quantum kernel functions

# Qiskit Machine Learning Algorithms
# from qiskit_machine_learning.algorithms import PegasosQSVC     # Optional alternative to QSVC
from qiskit_machine_learning.algorithms import QSVC              # Quantum SVM classifier

# Quantum backend primitives
from qiskit.primitives import StatevectorSampler, Sampler        # Sampling circuits
from qiskit_machine_learning.state_fidelities import ComputeUncompute   # Fidelity computation

# Ignore warning messages (optional but recommended in demos)
import warnings
warnings.simplefilter(action='ignore')
```

```
# Read the uploaded CSV file
df = pd.read_csv("Brain Tumor.csv")
```

```
# Show all rows
#pd.set_option('display.max_rows', None)

# Show all columns#
#pd.set_option('display.max_columns', None)

# Show the full DataFrame
#df
```

```
df.head()
```

	Image	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimil
0	Image1	0	6.535339	619.587845	24.891522	0.109059	4.276477	18.900575	98.613971	0.293314	0.086033	0.530941	4.4
1	Image2	0	8.749969	805.957634	28.389393	0.266538	3.718116	14.464618	63.858816	0.475051	0.225674	0.651352	3.2
2	Image3	1	7.341095	1143.808219	33.820234	0.001467	5.061750	26.479563	81.867206	0.031917	0.001019	0.268275	5.9

```
y=df.iloc[:,1].values   #the values from the second column (index 1), presumably the target variable or labels.
x=df.iloc[:,2:15].values #the values from columns 3 to 15 (index 2 to 14), presumably the features.
print(df.head())    # to see the first 5 rows of the whole DataFrame
print(x[:5])        # first 5 rows of feature values
print(y[:5])        # first 5 target values
```

```
    Image  Class      Mean     Variance  Standard Deviation   Entropy  \
0  Image1      0  6.535339   619.587845           24.891522  0.109059
1  Image2      0  8.749969   805.957634           28.389393  0.266538
2  Image3      1  7.341095  1143.808219           33.820234  0.001467
3  Image4      1  5.958145   959.711985           30.979219  0.001477
4  Image5      0  7.315231   729.540579           27.010009  0.146761

   Skewness   Kurtosis    Contrast    Energy       ASM  Homogeneity  \
0  4.276477  18.900575   98.613971  0.293314  0.086033     0.530941
1  3.718116  14.464618   63.858816  0.475051  0.225674     0.651352
2  5.061750  26.479563   81.867206  0.031917  0.001019     0.268275
3  5.677977  33.428845  151.229741  0.032024  0.001026     0.243851
4  4.283221  19.079108  174.988756  0.343849  0.118232     0.501140

   Dissimilarity  Correlation     Coarseness
0       4.473346     0.981939  7.458341e-155
1       3.220072     0.988834  7.458341e-155
2       5.981800     0.978014  7.458341e-155
3       7.700919     0.964189  7.458341e-155
4       6.834689     0.972789  7.458341e-155
[[6.53533936e+000 6.19587845e+002 2.48915215e+001 1.09059009e-001
  4.27647703e+000 1.89005748e+001 9.86139706e+001 2.93314497e-001
  8.60333940e-002 5.30941132e-001 4.47334559e+000 9.81938697e-001
  7.45834073e-155]
 [8.74996948e+000 8.05957634e+002 2.83893930e+001 2.66538307e-001
  3.71811563e+000 1.44646175e+001 6.38588159e+001 4.75051296e-001
  2.25673734e-001 6.51352027e-001 3.22007157e+000 9.88834396e-001
  7.45834073e-155]
 [7.34109497e+000 1.14380822e+003 3.38202339e+001 1.46681101e-003
  5.06175041e+000 2.64795632e+001 8.18672059e+001 3.19167121e-002
  1.01867651e-003 2.68274889e-001 5.98179980e+000 9.78013693e-001
  7.45834073e-155]
 [5.95814514e+000 9.59711985e+002 3.09792186e+001 1.47712442e-003
  5.67797741e+000 3.34288453e+001 1.51229741e+002 3.20237490e-002
  1.02552050e-003 2.43850913e-001 7.70091896e+000 9.64189183e-001
  7.45834073e-155]
 [7.31523132e+000 7.29540579e+002 2.70100089e+001 1.46760596e-001
  4.28322091e+000 1.90791083e+001 1.74988756e+002 3.43849414e-001
  1.18232419e-001 5.01139540e-001 6.83468900e+000 9.72788726e-001
  7.45834073e-155]]
[0 0 1 1 0]
```

```
# 'x' contains the feature values extracted from columns 2 to 14 of the DataFrame as a NumPy array
print(x)
```

```
[[6.53533936e+000 6.19587845e+002 2.48915215e+001 ... 4.47334559e+000
  9.81938697e-001 7.45834073e-155]
 [8.74996948e+000 8.05957634e+002 2.83893930e+001 ... 3.22007157e+000
  9.88834396e-001 7.45834073e-155]
 [7.34109497e+000 1.14380822e+003 3.38202339e+001 ... 5.98179980e+000
  9.78013693e-001 7.45834073e-155]
 ...
```

```
 [1.80115204e+001 1.15158276e+003 3.39349785e+001 ... 5.10369972e+000
  9.52181237e-001 7.45834073e-155]
 [1.33304291e+001 9.45732779e+002 3.07527686e+001 ... 6.43978421e+000
  9.40898110e-001 7.45834073e-155]
 [6.11013794e+000 4.80884025e+002 2.19290680e+001 ... 6.78732909e+000
  9.38730786e-001 7.45834073e-155]]
```

```
# 'y' contains the target variable values extracted from column 1 of the DataFrame as a NumPy array
print(y)
```

```
[0 0 1 ... 0 0 0]
```

```
 # Get the number of rows and columns in the DataFrame
df.shape
```

```
(3762, 15)
```

```
# Print all column names in the DataFrame to understand its structure
print(df.columns)

# Group the DataFrame by the 'Class' column and count the number of samples in each class
df.groupby('Class').size()
```

```
Index(['Image', 'Class', 'Mean', 'Variance', 'Standard Deviation', 'Entropy',
       'Skewness', 'Kurtosis', 'Contrast', 'Energy', 'ASM', 'Homogeneity',
       'Dissimilarity', 'Correlation', 'Coarseness'],
      dtype='object')
```

	0
Class	
0	2079
1	1683

dtype: int64

```
# Display concise summary of the DataFrame including:
# - Number of non-null entries per column
# - Data types of each column
# - Memory usage
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3762 entries, 0 to 3761
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Image               3762 non-null   object
 1   Class               3762 non-null   int64
 2   Mean                3762 non-null   float64
 3   Variance            3762 non-null   float64
 4   Standard Deviation  3762 non-null   float64
 5   Entropy             3762 non-null   float64
 6   Skewness            3762 non-null   float64
 7   Kurtosis            3762 non-null   float64
 8   Contrast            3762 non-null   float64
 9   Energy              3762 non-null   float64
 10  ASM                 3762 non-null   float64
 11  Homogeneity         3762 non-null   float64
 12  Dissimilarity       3762 non-null   float64
 13  Correlation         3762 non-null   float64
 14  Coarseness          3762 non-null   float64
dtypes: float64(13), int64(1), object(1)
memory usage: 441.0+ KB
```

```
df.isna()  #checking any missing value in dataset. If missing then give"True".
```

	Image	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarity	Corr
0	False	False	False	False	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
3757	False	False	False	False	False	False	False	False	False	False	False	False	False	
3758	False	False	False	False	False	False	False	False	False	False	False	False	False	
3759	False	False	False	False	False	False	False	False	False	False	False	False	False	
3760	False	False	False	False	False	False	False	False	False	False	False	False	False	
3761	False	False	False	False	False	False	False	False	False	False	False	False	False	

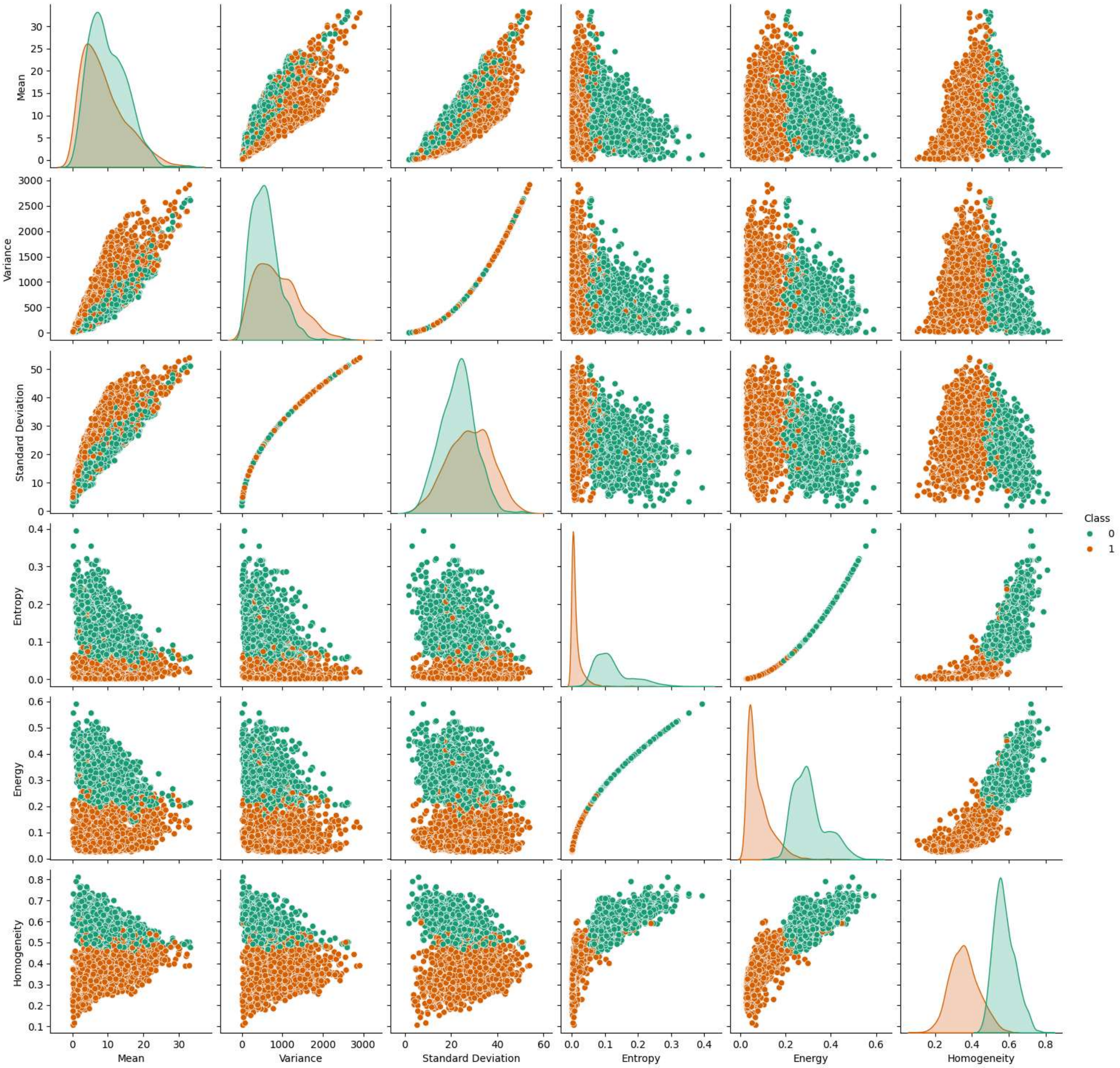
```
df.isna().sum()    #sum of missing vale in dataset
```

	0
Image	0
Class	0
Mean	0
Variance	0
Standard Deviation	0
Entropy	0
Skewness	0
Kurtosis	0
Contrast	0
Energy	0
ASM	0
Homogeneity	0
Dissimilarity	0
Correlation	0
Coarseness	0

dtype: int64

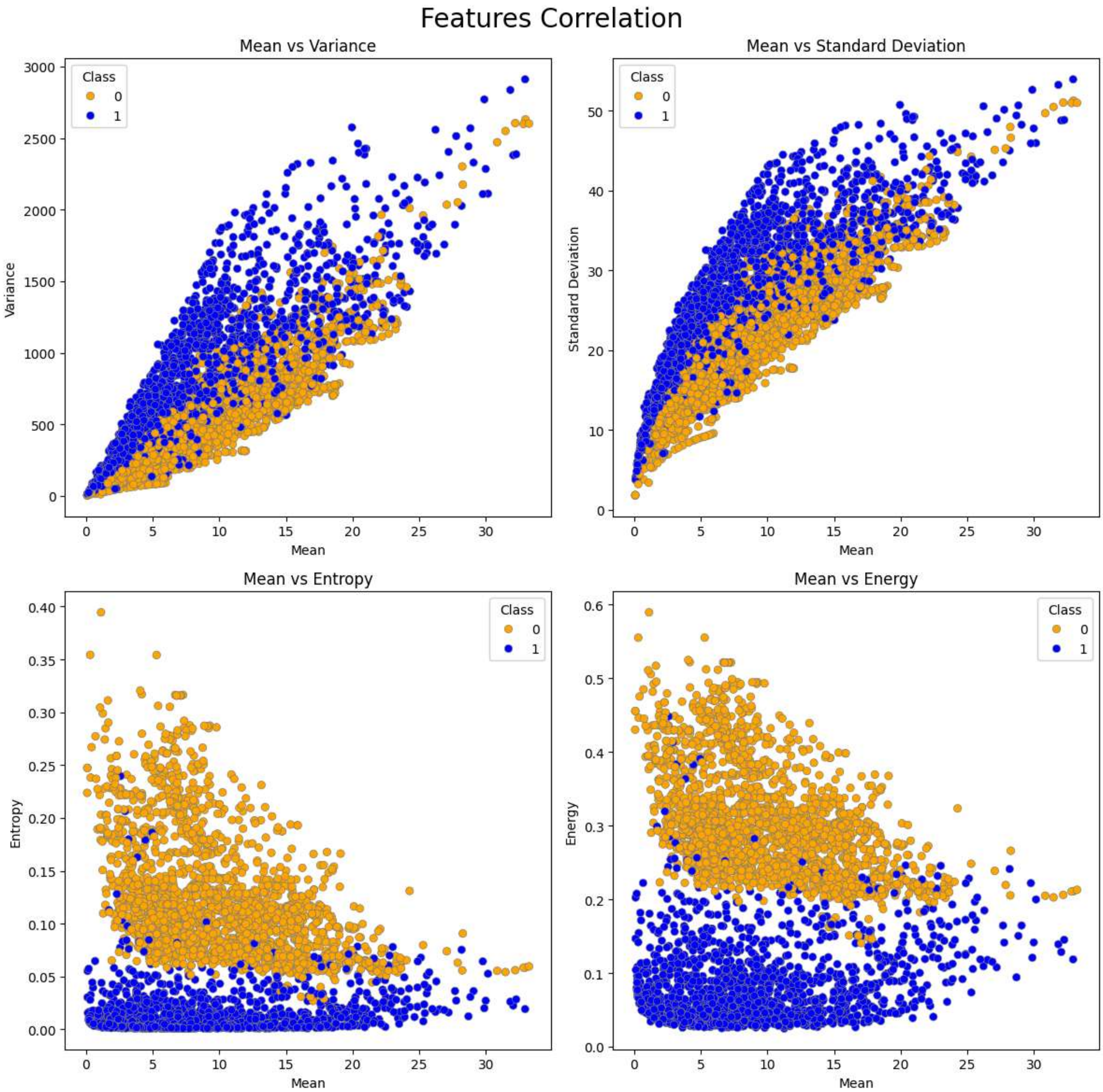
```
#visualisation of data
# Use the correct split syntax and column names
sns.pairplot(df[['Mean', 'Variance', 'Standard Deviation', 'Entropy', 'Energy', 'Homogeneity', 'Class']],
             hue='Class', palette='Dark2')
```

```
<seaborn.axisgrid.PairGrid at 0x7eeefc266a50>
```



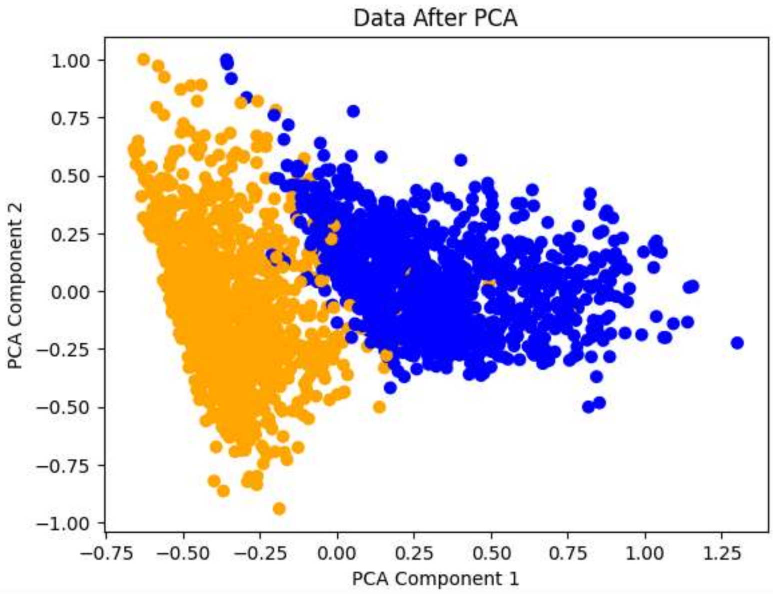

```
# Import necessary libraries
import seaborn as sns
import matplotlib.pyplot as plt

# Define custom color palette for the classes (e.g., 0 and 1)
palette = {0: 'orange', 1: 'blue'}
edgecolor = 'grey'

# Create a 2x2 grid of subplots with overall figure size
fig = plt.figure(figsize=(12, 12))

# Scatter Plot 1: Mean vs Variance
ax1 = plt.subplot(221)
sns.scatterplot(x=df['Mean'], y=df['Variance'], hue=df['Class'],
                data=df, palette=palette, edgecolor=edgecolor)
plt.title('Mean vs Variance')

# Scatter Plot 2: Mean vs Standard Deviation
ax2 = plt.subplot(222)
sns.scatterplot(x=df['Mean'], y=df['Standard Deviation'], hue=df['Class'],
                data=df, palette=palette, edgecolor=edgecolor)
plt.title('Mean vs Standard Deviation')

# Scatter Plot 3: Mean vs Entropy
ax3 = plt.subplot(223)
sns.scatterplot(x=df['Mean'], y=df['Entropy'], hue=df['Class'],
                data=df, palette=palette, edgecolor=edgecolor)
plt.title('Mean vs Entropy')
```

```
# Scatter Plot 4: Mean vs Energy
ax4 = plt.subplot(224)
sns.scatterplot(x=df['Mean'], y=df['Energy'], hue=df['Class'],
                data=df, palette=palette, edgecolor=edgecolor)
plt.title('Mean vs Energy')

# Set the overall title for all subplots
fig.suptitle("Features Correlation", fontsize=20)

# Adjust spacing and show the plot
plt.tight_layout()
plt.show()
```




```
# Split the data into training and testing sets
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)

# Scaling the data using MinMaxScaler to bring features in the range [0, 1]
from sklearn.preprocessing import MinMaxScaler
import numpy as np

# Combine train and test for consistent scaling
samples = np.append(x_train, x_test, axis=0)
minmax_scaler = MinMaxScaler((0, 1)).fit(samples)

# Transform training and test data
x_train = minmax_scaler.transform(x_train)
```

```
x_test = minmax_scaler.transform(x_test)

# Apply PCA (Principal Component Analysis) to reduce feature dimensions
from sklearn.decomposition import PCA

# Reduce features to 2 components for visualization or quantum model input
pca = PCA(n_components=2).fit(x_train)
x_train = pca.transform(x_train)
x_test = pca.transform(x_test)

# Visualize the data after PCA transformation
import matplotlib.pyplot as plt

# Plot the transformed training data colored by class
plt.scatter(x_train[:, 0], x_train[:, 1],
            c=['orange' if y == 1 else 'blue' for y in y_train])
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.title('Data After PCA')
plt.show()
```




```
# Import required modules from Qiskit Machine Learning
from qiskit_machine_learning.kernels import FidelityStatevectorKernel
from qiskit.circuit.library import ZZFeatureMap
from qiskit_machine_learning.algorithms import QSVC

import time

# Number of qubits = number of features after PCA (which is 2)
num_qubits = 2

# Create a quantum feature map (using ZZFeatureMap)
feature_map = ZZFeatureMap(feature_dimension=num_qubits, reps=2)

# Optionally, you could use Sampler-based kernel (commented in screenshot)
# from qiskit.primitives import Sampler
# sampler = Sampler()
# from qiskit_machine_learning.kernels import Fidelity
# qkernel = Fidelity(sampler=sampler, feature_map=feature_map)

# Create a fidelity-based statevector kernel (used here)
qkernel = FidelityStatevectorKernel(feature_map=feature_map)

# Instantiate the Quantum Support Vector Classifier (QSVC) with the quantum kernel
qsvc = QSVC(quantum_kernel=qkernel)

# Start timer
start_time = time.time()

# Train the QSVC on training data
qsvc.fit(x_train, y_train)

# Evaluate model performance on test data
score = qsvc.score(x_test, y_test)

# End timer and calculate execution time
```

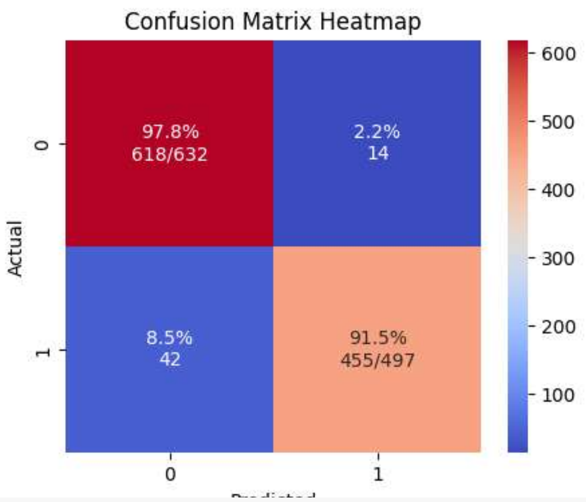
```
end_time = time.time()
execution_time = end_time - start_time

# Print test accuracy and execution time
print("QSVC Classification test score:", score)
print("Execution Time:", execution_time)
```

```
QSVC Classification test score: 0.9503985828166519
Execution Time: 94.04180717468262
```

```
from sklearn import metrics

# Get true labels and predicted labels
expected_y = y_test
predicted_y = qsvc.predict(x_test)  # Use the trained QSVC model (qsvc)

# Print classification report
print("Classification Report:\n", metrics.classification_report(expected_y, predicted_y))

# (Optional) Print confusion matrix
print("Confusion Matrix:\n", metrics.confusion_matrix(expected_y, predicted_y))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.98      0.96       632
           1       0.97      0.92      0.94       497

    accuracy                           0.95      1129
   macro avg       0.95      0.95      0.95      1129
weighted avg       0.95      0.95      0.95      1129

Confusion Matrix:
 [[618  14]
 [ 42 455]]
```

```
# Define function to plot annotated confusion matrix
def cm_analysis(y_true, y_pred, labels, ymap=None, figsize=(5, 4)):
    if ymap is not None:
        y_pred = [ymap[yi] for yi in y_pred]
        y_true = [ymap[yi] for yi in y_true]

    cm = metrics.confusion_matrix(y_true, y_pred, labels=labels)
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100

    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape

    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            s = cm_sum[i][0] if cm_sum[i][0] != 0 else 1
            if i == j:
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)

    cm_df = pd.DataFrame(cm, index=labels, columns=labels)
    cm_df.index.name = 'Actual'
    cm_df.columns.name = 'Predicted'
    return cm_df, annot

# Generate annotated confusion matrix
cm, annot = cm_analysis(expected_y, predicted_y, labels=[0, 1])

# Plot the annotated heatmap
plt.figure(figsize=(5, 4))
sns.heatmap(cm, annot=annot, fmt='', cmap='coolwarm', cbar=True)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix Heatmap")
plt.show()
```




```
from sklearn.metrics import roc_curve

# Set seaborn style
sns.set_style("darkgrid")

# Define function to plot ROC curve
def plot_roc_curve(fper, tper):
    plt.plot(fper, tper, color='blue', label='ROC')
    plt.plot([0, 1], [0, 1], color='green', linestyle='--')  # Diagonal line
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("Receiver Operating Characteristic Curve")
    plt.legend()
    plt.show()

# Get ROC values
fper, tper, thresholds = roc_curve(expected_y, predicted_y)

# Call function to plot
plot_roc_curve(fper, tper)
```