Group 6

Title: Noise-Robust Speech Signal Processing: Enhancing Speech-to-Text Model Performance in Noisy Environments through Advanced Feature Engineering.

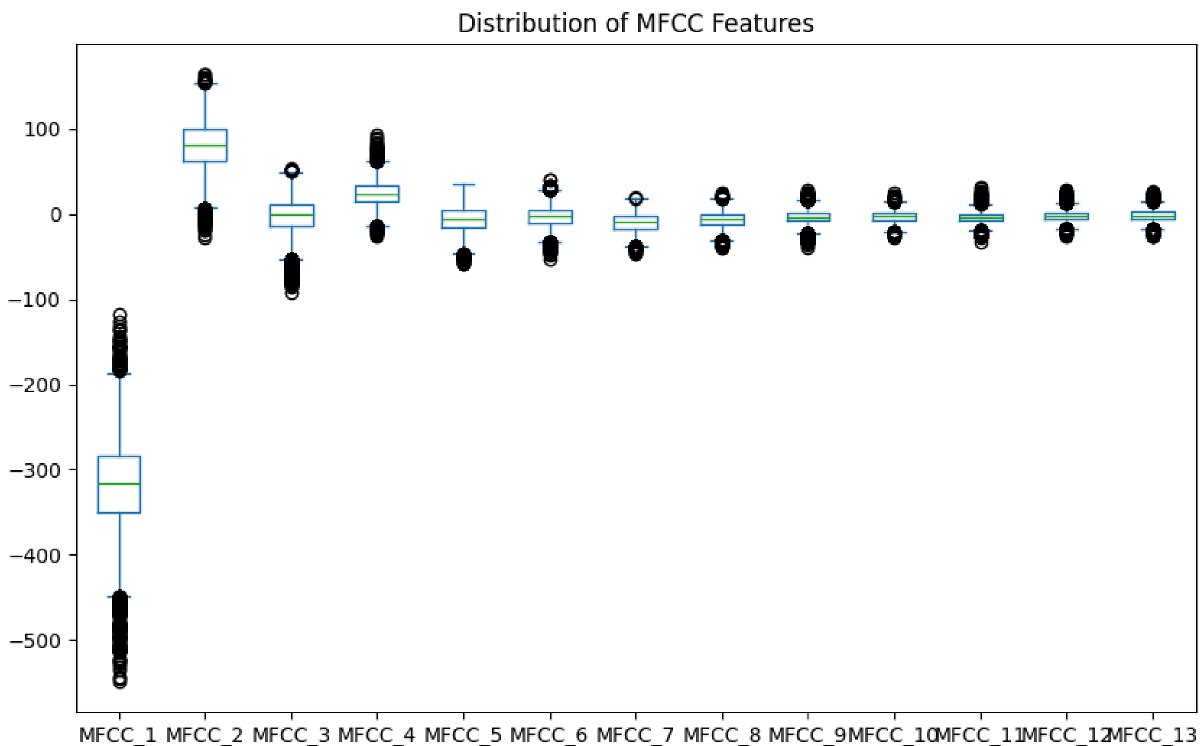
In [ ]:
```
import os
import glob
import librosa
import numpy as np
import pandas as pd

data_paths = [
    "F:/Project/LibriSpeech/Clean_data",  # Clean data path
    "F:/Project/LibriSpeech/Noisy_data"   # Noisy data path
]

def read_transcriptions(transcript_file):
    transcriptions = set()
    with open(transcript_file, 'r') as file:
        for line in file:
            parts = line.strip().split(" ", 1)
            if len(parts) == 2:
                file_name = parts[0]
                transcriptions.add(file_name)
    return transcriptions

# Extracting MFCC features
def extract_mfcc(audio_path):
    audio, sr = librosa.load(audio_path, sr=None)
    mfcc = librosa.feature.mfcc(y=audio, sr=sr, n_mfcc=19)
    return np.mean(mfcc, axis=1)

def extract_additional_features(audio_path):
    audio, sr = librosa.load(audio_path, sr=None)

    # Spectral Centroid
    spectral_centroid = librosa.feature.spectral_centroid(y=audio, sr=sr)
    spectral_centroid_mean = np.mean(spectral_centroid)

    # Spectral Rolloff
    spectral_rolloff = librosa.feature.spectral_rolloff(y=audio, sr=sr, roll
    spectral_rolloff_mean = np.mean(spectral_rolloff)

    # Spectral Bandwidth
    ral_bandwidth = librosa.feature.spectral_bandwidth(y=audio, sr=sr)
```

```
    spectral_bandwidth_mean = np.mean(spectral_bandwidth)

    # Spectral Flatness
    spectral_flatness = librosa.feature.spectral_flatness(y=audio)
    spectral_flatness_mean = np.mean(spectral_flatness)

    # Zero Crossing Rate
    zero_crossing_rate = librosa.feature.zero_crossing_rate(y=audio)
    zero_crossing_rate_mean = np.mean(zero_crossing_rate)

    # RMS Energy
    rms_energy = librosa.feature.rms(y=audio)
    rms_energy_mean = np.mean(rms_energy)

    return [spectral_centroid_mean, spectral_rolloff_mean, spectral_bandwidt

def process_audio_files_in_folder(folder_path, label, feature_data):
    for subfolder in os.listdir(folder_path):
        subfolder_path = os.path.join(folder_path, subfolder)
        if os.path.isdir(subfolder_path):
            print(f"Processing folder: {subfolder_path}")
            transcript_file = None
            for txt_file in glob.glob(os.path.join(subfolder_path, "*.trans.
                transcript_file = txt_file
                break

            if transcript_file:
                print(f"Transcript file found: {transcript_file}")
                transcriptions = read_transcriptions(transcript_file)

                for flac_file in glob.glob(os.path.join(subfolder_path, "*.f
                    file_name = os.path.splitext(os.path.basename(flac_file)

                    if file_name in transcriptions:
                        mfcc_features = extract_mfcc(flac_file)
                        additional_features = extract_additional_features(fl
                        feature_data.append([file_name] + list(mfcc_features
                    else:
                        print(f"No transcription found for FLAC file: {flac_
            else:
                print(f"No transcript file found in subfolder: {subfolder_pa

def process_data(data_paths):
    feature_data = []

    for data_path in data_paths:
        label = "clean" if "Clean_data" in data_path else "noisy"
        print(f"Processing {label} data in: {data_path}")
        for main_folder in os.listdir(data_path):
            main_folder_path = os.path.join(data_path, main_folder)
            if os.path.isdir(main_folder_path):
                process_audio_files_in_folder(main_folder_path, label, featu

    columns = ['File Name'] + [f'MFCC_{i+1}' for i in range(13)] + \
              ['Spectral_Centroid', 'Spectral_Rolloff', 'Spectral_Bandwidth'
               'Spectral_Flatness', 'Zero_Crossing_Rate', 'RMS_Energy', 'Lab
```

```
    df = pd.DataFrame(feature_data, columns=columns)

    df.to_csv("F:/Project/LibriSpeech/features_data_main.csv", index=False)
    print("Features saved to CSV file.")

process_data(data_paths)
```

In [ ]:

```
#Distribution of MFCC Features

import pandas as pd
import matplotlib.pyplot as plt

feature_df = pd.read_csv('features_data_main.csv')

mfcc_columns = [col for col in feature_df.columns if 'MFCC' in col]

feature_df[mfcc_columns].plot(kind='box', figsize=(10, 6), title='Distributi

plt.show()
```



In [ ]:

```
# Spectral features Distribution
spectral_features = ['Spectral_Centroid', 'Spectral_Rolloff', 'Spectral_Banc
feature_df[spectral_features].plot(kind='box', figsize=(10, 6), title='Spect
plt.show()
```

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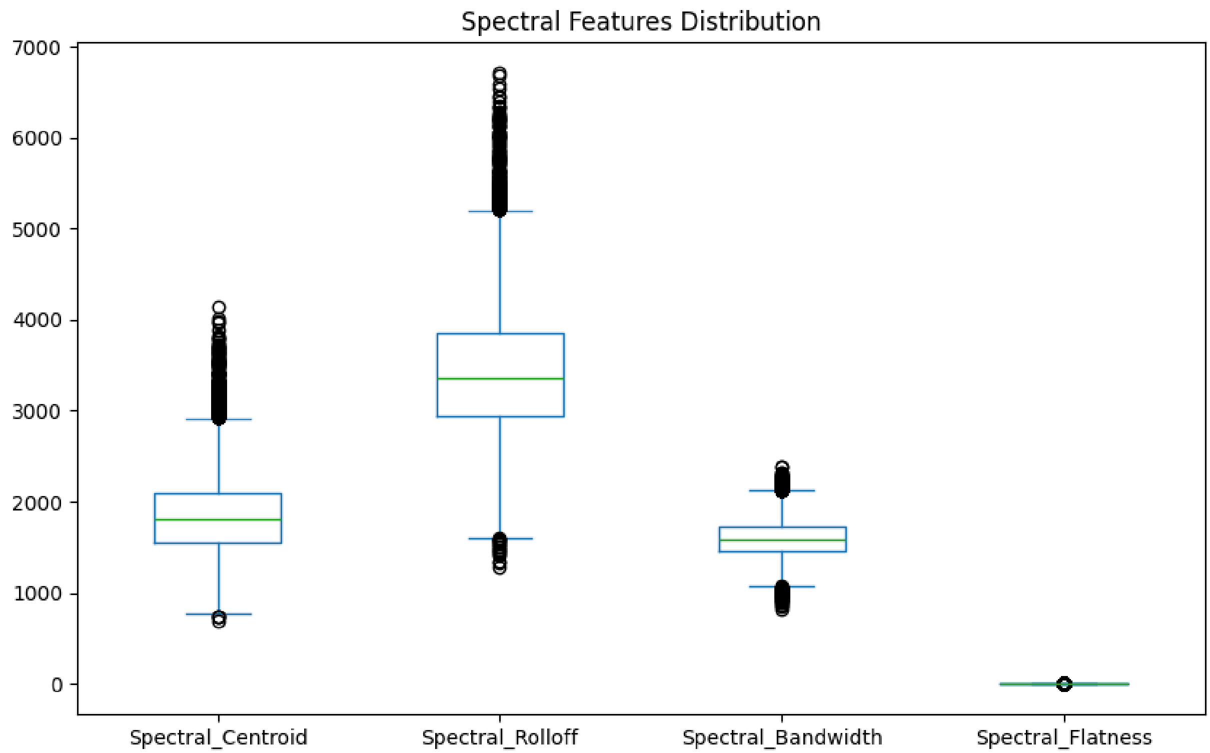

In [ ]:
```
# Correlation Heatmap of Features

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

numeric_features = feature_df.select_dtypes(include=['number', 'float64', 'i

corr_matrix = numeric_features.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=
plt.title('Correlation Heatmap of Features')
plt.show()
```

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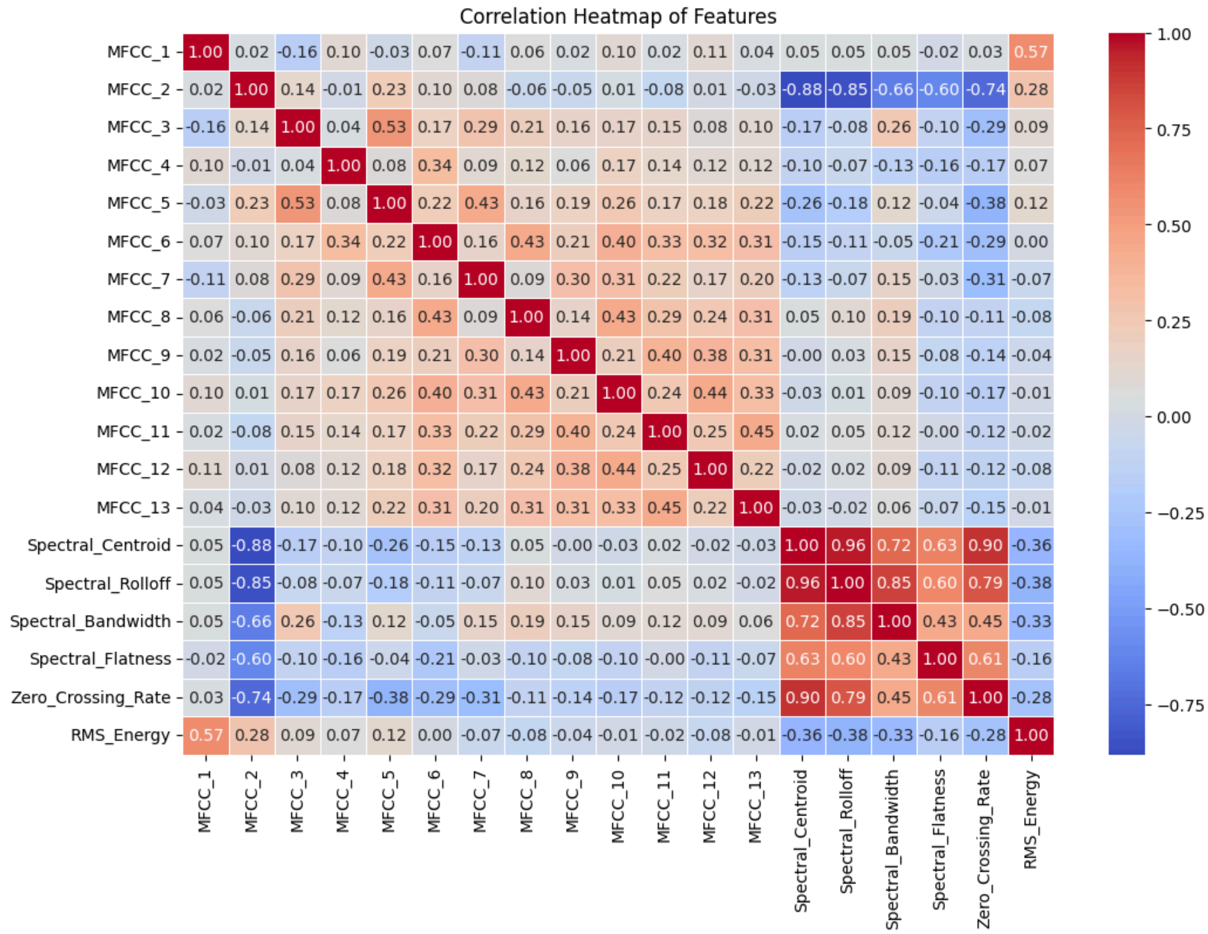
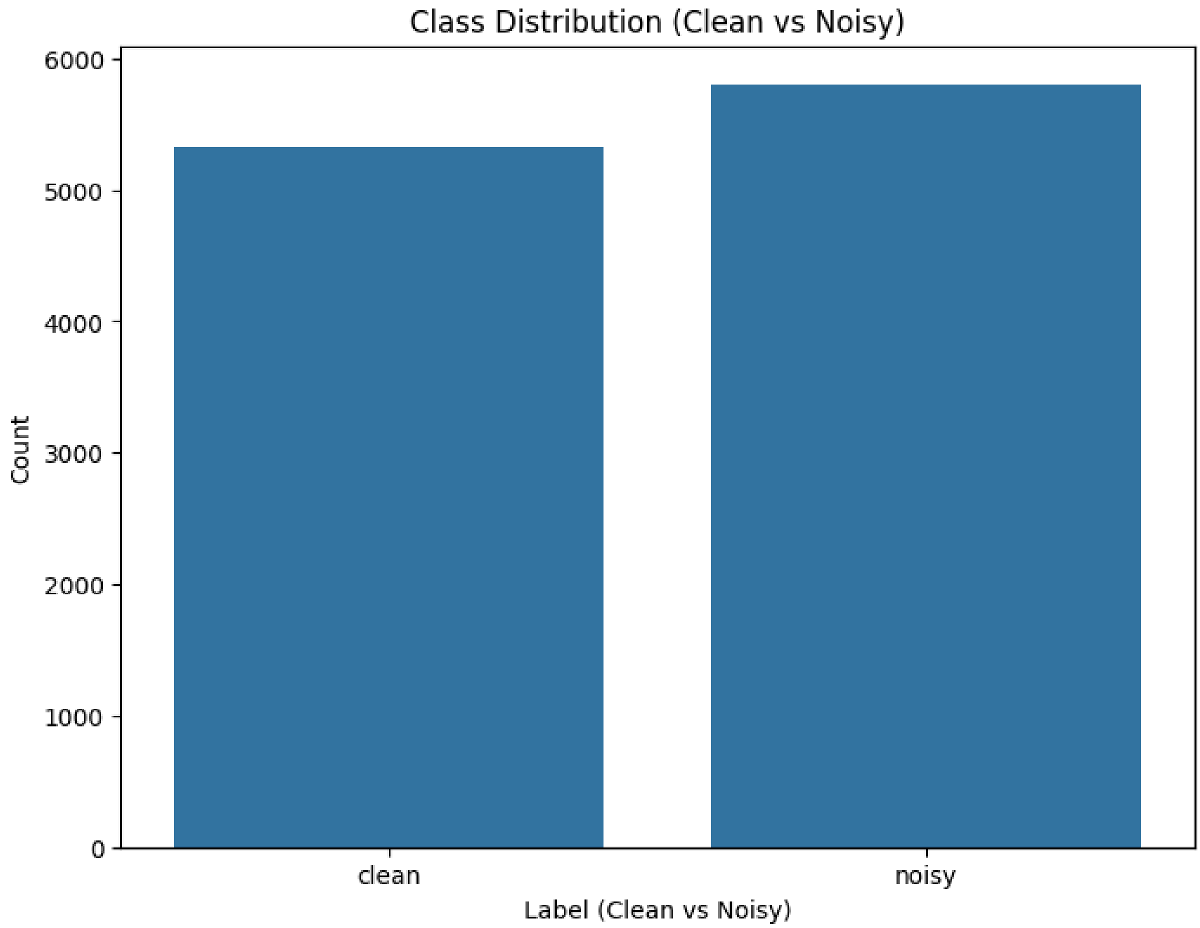


In [79]:

```
# Plotting class distribution
plt.figure(figsize=(8, 6))
sns.countplot(x='Label', data=feature_df)
plt.title('Class Distribution (Clean vs Noisy)')
plt.xlabel('Label (Clean vs Noisy)')
plt.ylabel('Count')
plt.show()
```



data preprocessing

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.utils import resample

# Extract features and labels
X = feature_df.drop(columns=['File Name', 'Label'])
y = feature_df['Label']

# Normalize/Standardizing the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0

print("\nClass distribution in the training set:")
print(y_train.value_counts())

if 'noisy' in y_train.value_counts().index and 'clean' in y_train.value_cour
    X_train_resampled, y_train_resampled = resample(X_train[y_train == 'nois
                                                    replace=True, n_samples=X
                                                    random_state=42)

    X_train_balanced = np.vstack((X_train[y_train == 'clean'], X_train_resam
```

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```
    y_train_balanced = np.hstack((y_train[y_train == 'clean'], y_train_resam
    print("\nResampling completed. Balanced class distribution in training s
    print(np.unique(y_train_balanced, return_counts=True))
else:
    print("Class distribution is already balanced in the training set.")
```

```
Class distribution in the training set:
Label
noisy    4642
clean    4258
Name: count, dtype: int64

Resampling completed. Balanced class distribution in training set:
(array(['clean', 'noisy'], dtype=object), array([4258, 4258], dtype=int64))
```

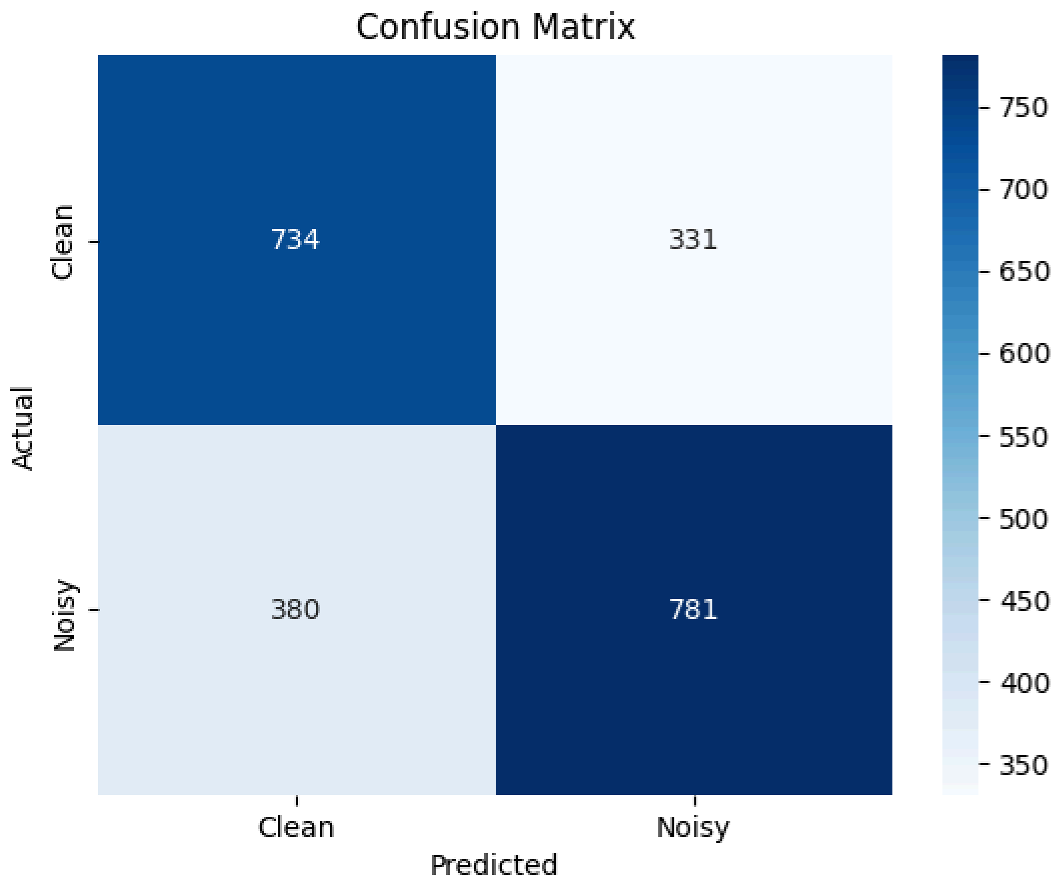
Baseline Model – SVM

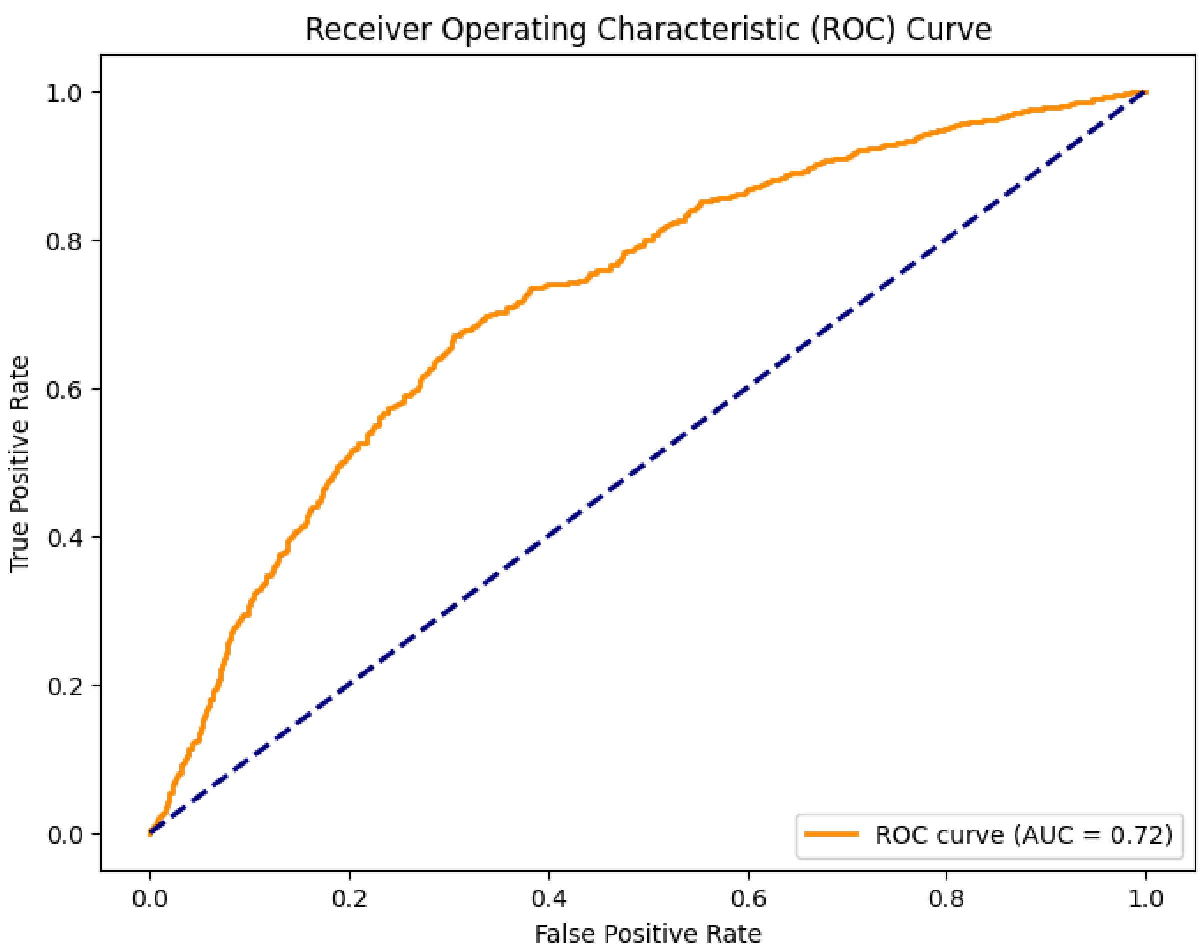
In [ ]:

```
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix, roc_cur
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
import seaborn as sns
import joblib

# Training SVM Model
svm_model = SVC(kernel='linear', class_weight='balanced', random_state=42)
svm_model.fit(X_train_balanced, y_train_balanced)

# Cross-validation using 5-folds
cv_scores = cross_val_score(svm_model, X_train_balanced, y_train_balanced, c

print("Cross-Validation Accuracy Scores: ", cv_scores)
print(f"Mean Accuracy: {cv_scores.mean():.4f}")
print(f"Standard Deviation: {cv_scores.std():.4f}")

y_pred = svm_model.predict(X_test)

print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='binary', pos_label='noi
recall = recall_score(y_test, y_pred, average='binary', pos_label='noisy')
f1 = f1_score(y_test, y_pred, average='binary', pos_label='noisy')

roc_auc = roc_auc_score(y_test, svm_model.decision_function(X_test))

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"ROC AUC: {roc_auc:.4f}")

conf_matrix = confusion_matrix(y_test, y_pred)
```

```
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Cl
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

fpr, tpr, thresholds = roc_curve(y_test, svm_model.decision_function(X_test)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_a
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

model_filename = 'svm_linear_model.pkl'
joblib.dump(svm_model, model_filename)
print(f"Model saved as {model_filename}")
```

```
Cross-Validation Accuracy Scores:  [0.66901408 0.67645332 0.69406929 0.68467
41  0.65590135]
Mean Accuracy: 0.6760
Standard Deviation: 0.0131
Classification Report:
               precision    recall  f1-score   support

       clean       0.66      0.69      0.67      1065
       noisy       0.70      0.67      0.69      1161

    accuracy                           0.68      2226
   macro avg       0.68      0.68      0.68      2226
weighted avg       0.68      0.68      0.68      2226

Confusion Matrix:
 [[734 331]
 [380 781]]
Accuracy: 0.6806
Precision: 0.7023
Recall: 0.6727
F1-Score: 0.6872
ROC AUC: 0.7217
```


Confusion Matrix
Actual
Clean
Noisy
734
331
380
781
Clean
Noisy
Predicted
750
700
650
600
550
500
450
400
350


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.72)
0.0
0.2
0.4
0.6
0.8
1.0

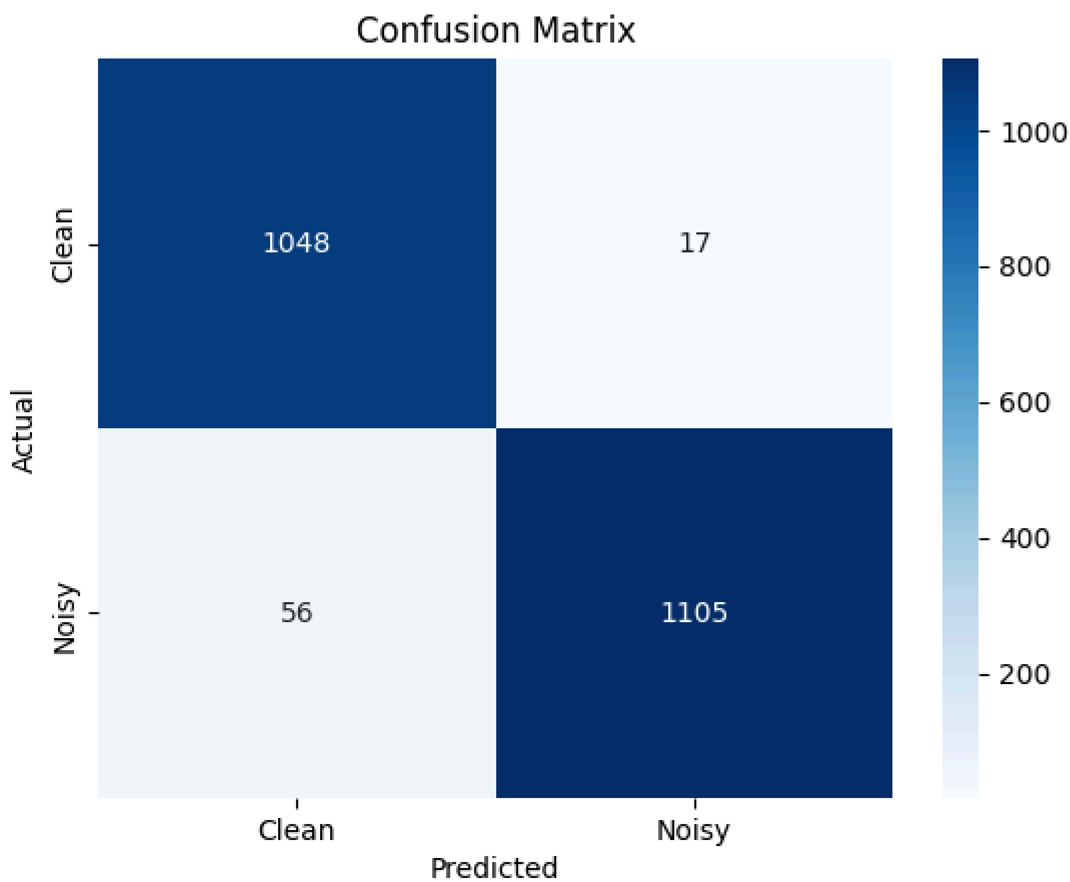
```
Model saved as svm_linear_model.pkl
```

Hyperparameter Tuning

In [ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf', 'poly'],
    'gamma': ['scale', 'auto']
}

grid_search = GridSearchCV(SVC(), param_grid, cv=5, scoring='accuracy')

grid_search.fit(X_train_balanced, y_train_balanced)

print("Best parameters found: ", grid_search.best_params_)

svm_best_model = grid_search.best_estimator_
cv_scores = grid_search.cv_results_['mean_test_score']

print("Cross-Validation Accuracy Scores: ", cv_scores)
print(f"Mean Accuracy: {cv_scores.mean():.4f}")
print(f"Standard Deviation: {cv_scores.std():.4f}")

y_pred_best = svm_best_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_best)
precision = precision_score(y_test, y_pred_best, average='binary', pos_label
recall = recall_score(y_test, y_pred_best, average='binary', pos_label='nois
f1 = f1_score(y_test, y_pred_best, average='binary', pos_label='noisy')

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")

roc_auc = roc_auc_score(y_test, svm_best_model.decision_function(X_test))
print(f"ROC AUC: {roc_auc:.4f}")

conf_matrix = confusion_matrix(y_test, y_pred_best)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Cl
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

fpr, tpr, thresholds = roc_curve(y_test, svm_best_model.decision_function(X_
plt.figure(figsize=(8, 6))
```

```python
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_a
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

import joblib
model_filename = 'svm_best_model.pkl'
joblib.dump(svm_best_model, model_filename)
print(f"Best Model saved as {model_filename}")
```

```
Best parameters found:  {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
Cross-Validation Accuracy Scores:  [0.67402616 0.81892973 0.77125585 0.67402
616 0.81810765 0.76867238
 0.67578755 0.93365553 0.87341635 0.67578755 0.93236377 0.8723596
 0.67637461 0.96688659 0.91181373 0.67637461 0.96676915 0.91087428]
Mean Accuracy: 0.8110
Standard Deviation: 0.1105
Accuracy: 0.9672
Precision: 0.9848
Recall: 0.9518
F1-Score: 0.9680
ROC AUC: 0.9931
```



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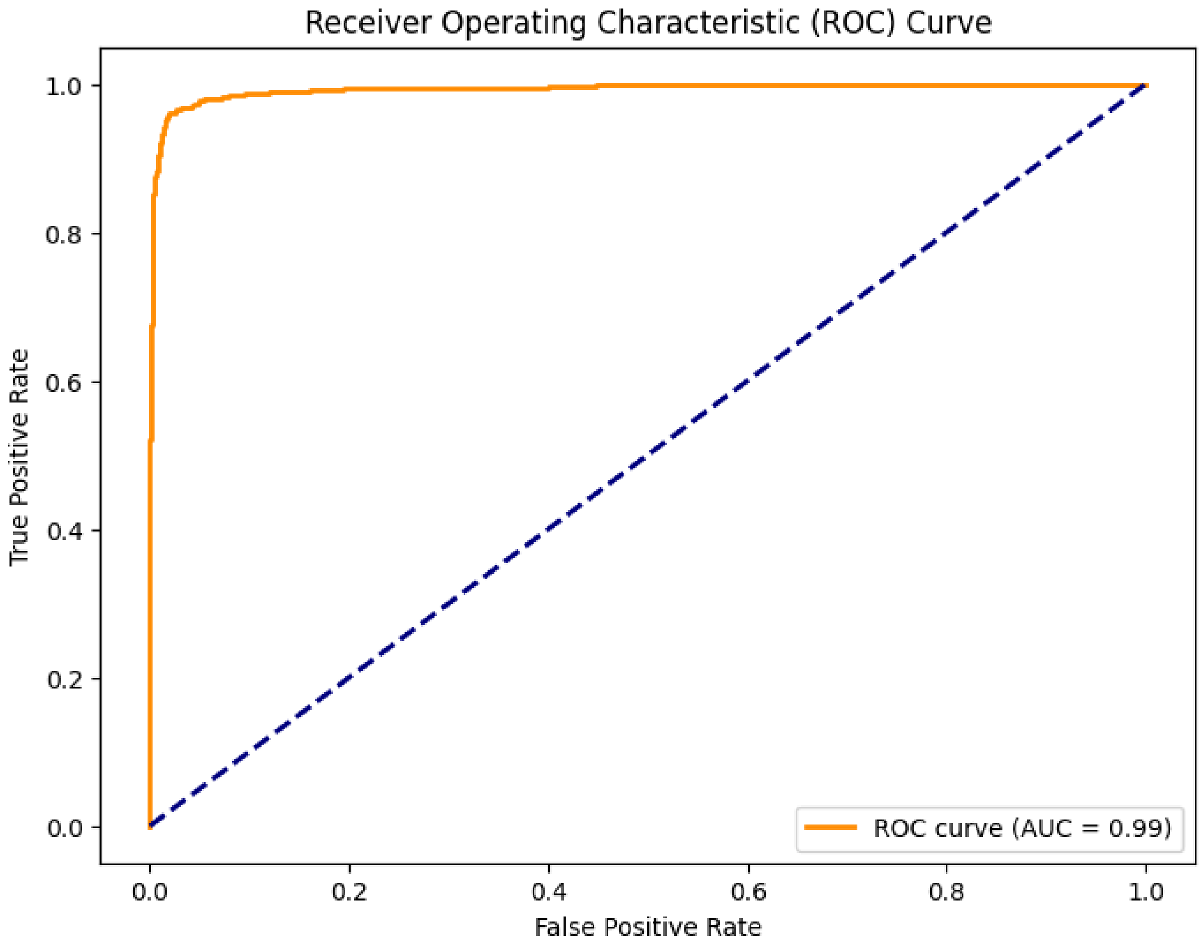


```
Best Model saved as svm_best_model.pkl
```

In [87]:

```
# Model Evaluation
print("Classification Report:\n", classification_report(y_test, y_pred_best)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_best))
```

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

       clean       0.95      0.98      0.97      1065
       noisy       0.98      0.95      0.97      1161

    accuracy                           0.97      2226
   macro avg       0.97      0.97      0.97      2226
weighted avg       0.97      0.97      0.97      2226

Confusion Matrix:
 [[1048   17]
 [  56 1105]]
```

Advanced Feature Engineering (RFE and PCA)

In [ ]:

```
from sklearn.decomposition import PCA
from sklearn.feature_selection import RFE
```

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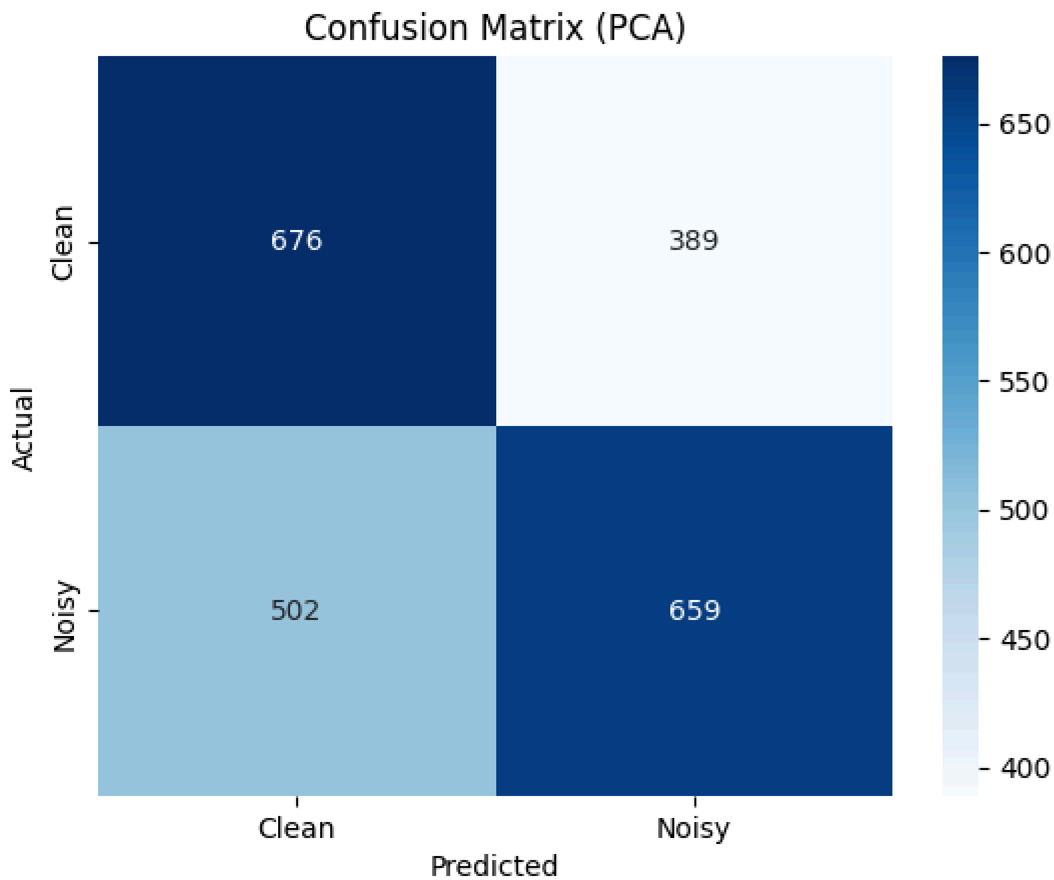
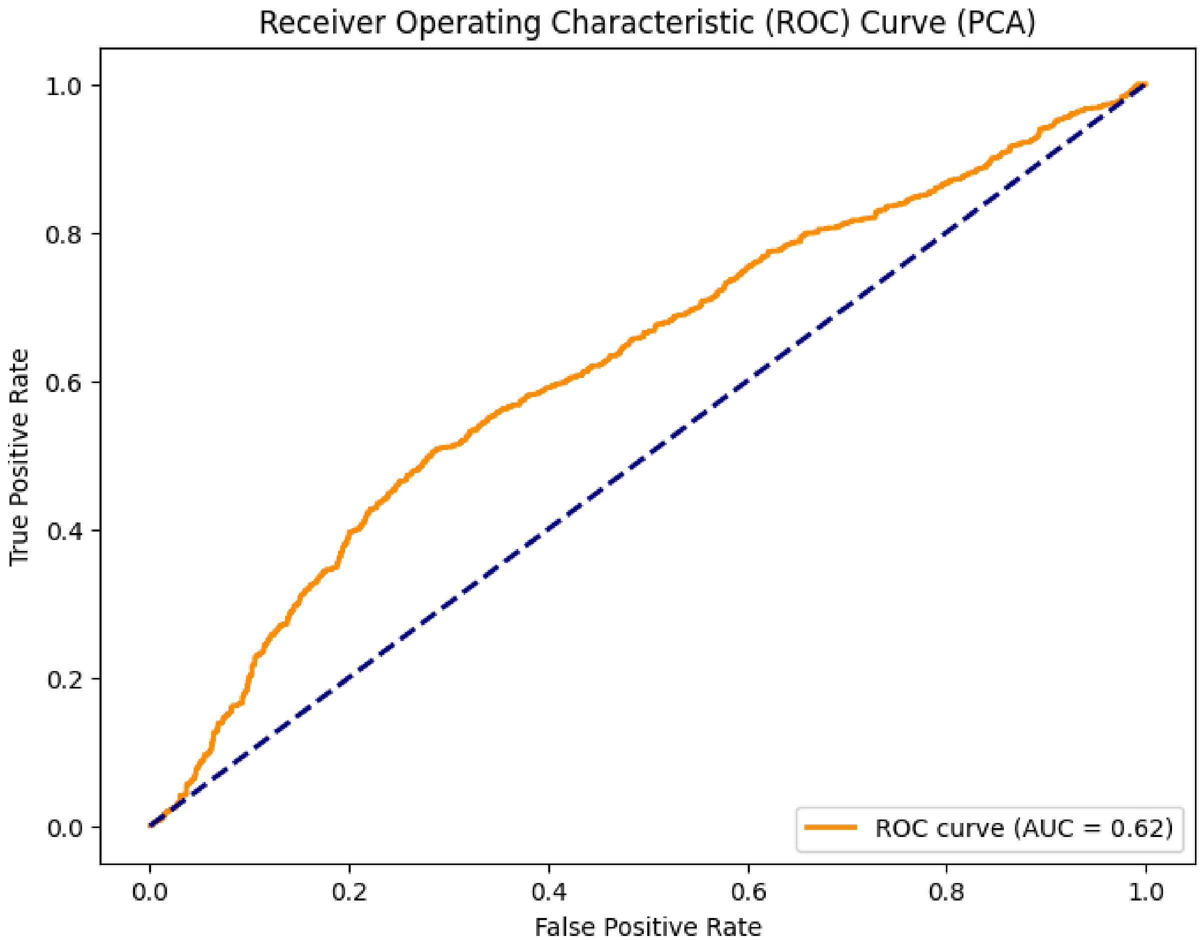
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score
import numpy as np

# PCA for Dimensionality Reduction
pca = PCA(n_components=10)
X_train_pca = pca.fit_transform(X_train_balanced)
X_test_pca = pca.transform(X_test)

# RFE for Feature Selection
svm_rfe = SVC(kernel='linear', random_state=42)
rfe = RFE(svm_rfe, n_features_to_select=10)
X_train_rfe = rfe.fit_transform(X_train_balanced, y_train_balanced)
X_test_rfe = rfe.transform(X_test)

# Train SVM with PCA features
svm_model_pca = SVC(kernel='linear', random_state=42)
svm_model_pca.fit(X_train_pca, y_train_balanced)
y_pred_pca = svm_model_pca.predict(X_test_pca)

# Classification Report for PCA
print("Classification Report with PCA:\n", classification_report(y_test, y_p

# Calculate Accuracy, Precision, Recall, F1-Score for PCA
accuracy_pca = accuracy_score(y_test, y_pred_pca)
precision_pca = precision_score(y_test, y_pred_pca, average='binary', pos_la
recall_pca = recall_score(y_test, y_pred_pca, average='binary', pos_label='r
f1_pca = f1_score(y_test, y_pred_pca, average='binary', pos_label='noisy')

# Metrics for PCA model
print(f"Accuracy (PCA): {accuracy_pca:.4f}")
print(f"Precision (PCA): {precision_pca:.4f}")
print(f"Recall (PCA): {recall_pca:.4f}")
print(f"F1-Score (PCA): {f1_pca:.4f}")

# ROC AUC for PCA
roc_auc_pca = roc_auc_score(y_test, svm_model_pca.decision_function(X_test_p
print(f"ROC AUC (PCA): {roc_auc_pca:.4f}")

# Confusion Matrix for PCA
conf_matrix_pca = confusion_matrix(y_test, y_pred_pca)
sns.heatmap(conf_matrix_pca, annot=True, fmt='d', cmap='Blues', xticklabels=
plt.title('Confusion Matrix (PCA)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# ROC Curve for PCA
fpr_pca, tpr_pca, thresholds_pca = roc_curve(y_test, svm_model_pca.decision_
plt.figure(figsize=(8, 6))
plt.plot(fpr_pca, tpr_pca, color='darkorange', lw=2, label=f'ROC curve (AUC
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve (PCA)')
plt.legend(loc='lower right')
plt.show()

# Cross-Validation for PCA
cv_scores_pca = cross_val_score(svm_model_pca, X_train_pca, y_train_balanced
print("Cross-Validation Accuracy Scores for PCA:", cv_scores_pca)
print(f"Mean Accuracy for PCA: {cv_scores_pca.mean():.4f}")
print(f"Standard Deviation for PCA: {cv_scores_pca.std():.4f}")

# Train SVM with RFE features
svm_model_rfe = SVC(kernel='linear', random_state=42)
svm_model_rfe.fit(X_train_rfe, y_train_balanced)
y_pred_rfe = svm_model_rfe.predict(X_test_rfe)

# Classification Report with RFE
print("Classification Report with RFE:\n", classification_report(y_test, y_p

# Calculate Accuracy, Precision, Recall, F1-Score for RFE
accuracy_rfe = accuracy_score(y_test, y_pred_rfe)
precision_rfe = precision_score(y_test, y_pred_rfe, average='binary', pos_la
recall_rfe = recall_score(y_test, y_pred_rfe, average='binary', pos_label='r
f1_rfe = f1_score(y_test, y_pred_rfe, average='binary', pos_label='noisy')

# Metrics for RFE model
print(f"Accuracy (RFE): {accuracy_rfe:.4f}")
print(f"Precision (RFE): {precision_rfe:.4f}")
print(f"Recall (RFE): {recall_rfe:.4f}")
print(f"F1-Score (RFE): {f1_rfe:.4f}")

# ROC AUC for RFE
roc_auc_rfe = roc_auc_score(y_test, svm_model_rfe.decision_function(X_test_r
print(f"ROC AUC (RFE): {roc_auc_rfe:.4f}")

# Confusion Matrix for RFE
conf_matrix_rfe = confusion_matrix(y_test, y_pred_rfe)
sns.heatmap(conf_matrix_rfe, annot=True, fmt='d', cmap='Blues', xticklabels=
plt.title('Confusion Matrix (RFE)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# ROC Curve for RFE
fpr_rfe, tpr_rfe, thresholds_rfe = roc_curve(y_test, svm_model_rfe.decision_
plt.figure(figsize=(8, 6))
plt.plot(fpr_rfe, tpr_rfe, color='darkorange', lw=2, label=f'ROC curve (AUC
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve (RFE)')
plt.legend(loc='lower right')
plt.show()

# Cross-Validation for RFE
cv_scores_rfe = cross_val_score(svm_model_rfe, X_train_rfe, y_train_balanced
```

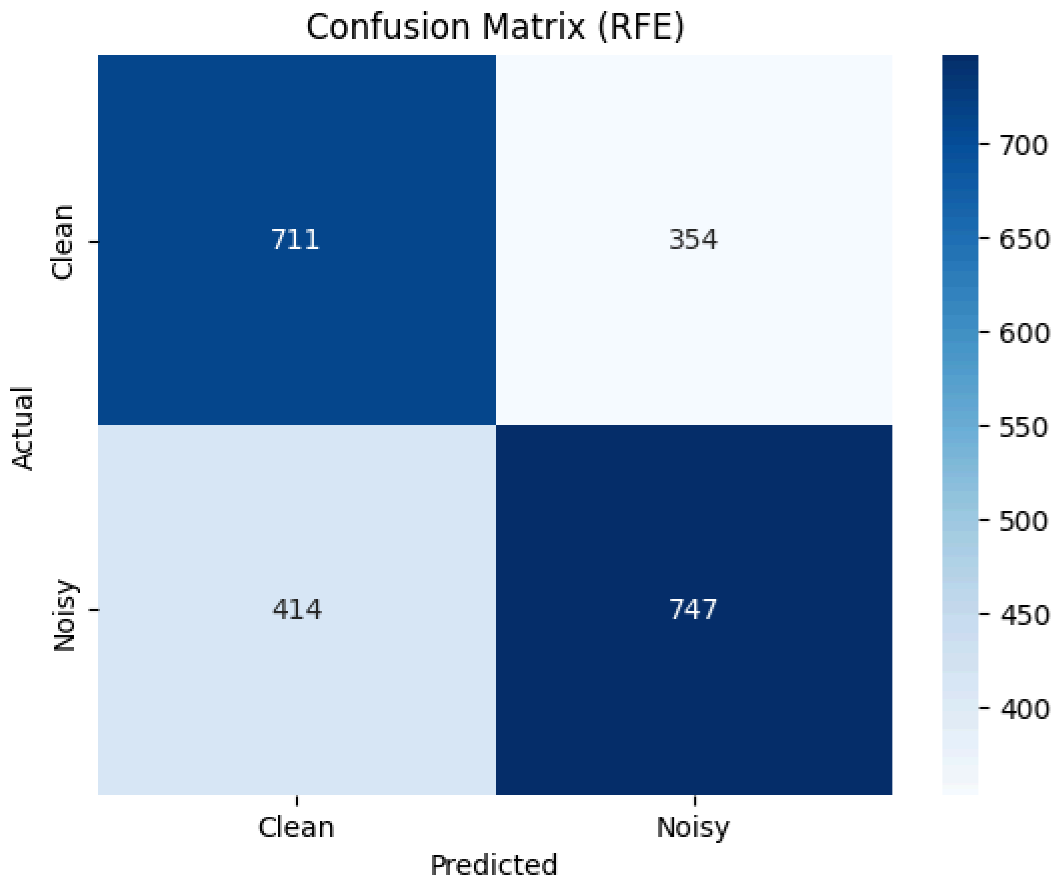
```python
print("Cross-Validation Accuracy Scores for RFE:", cv_scores_rfe)
print(f"Mean Accuracy for RFE: {cv_scores_rfe.mean():.4f}")
print(f"Standard Deviation for RFE: {cv_scores_rfe.std():.4f}")
```

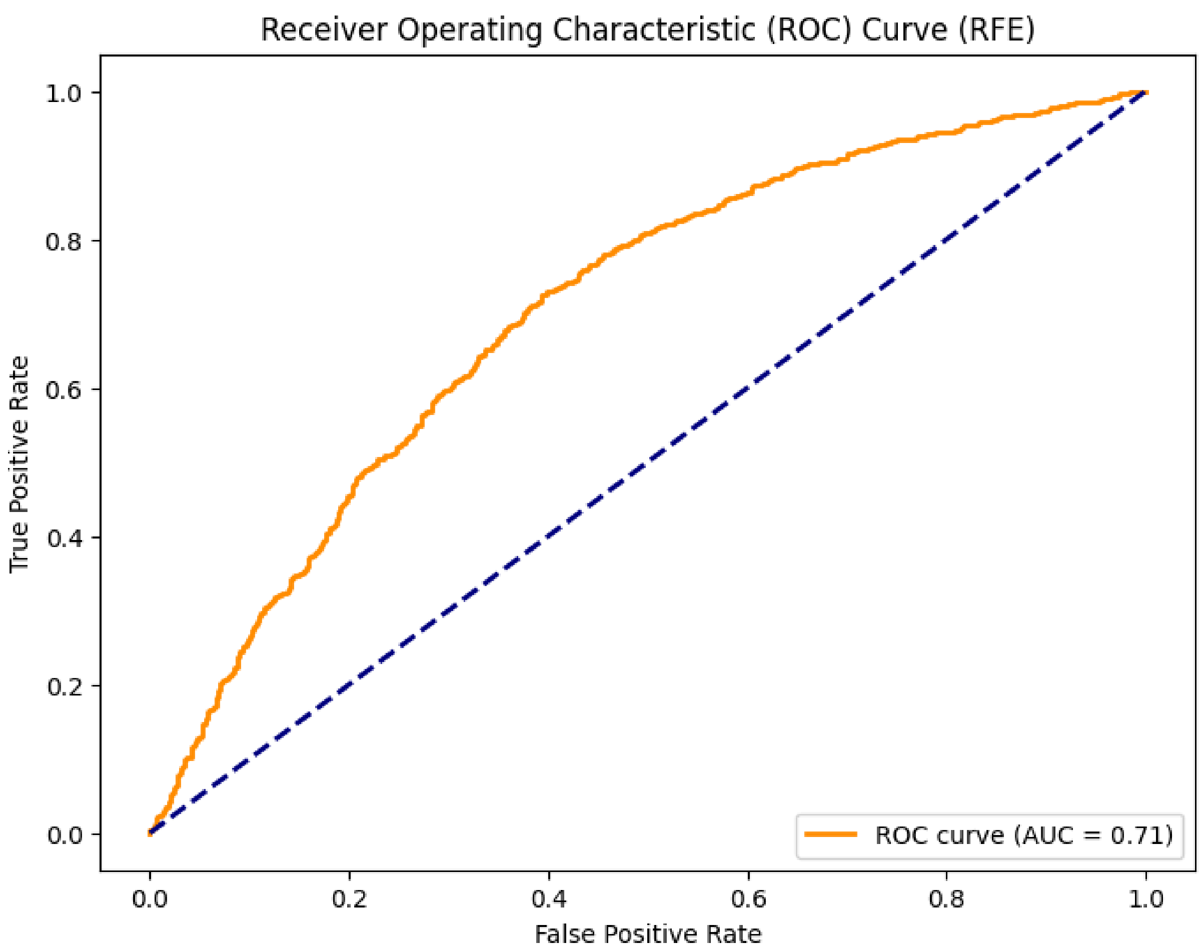
```
Classification Report with PCA:
              precision    recall  f1-score   support

       clean       0.57      0.63      0.60      1065
       noisy       0.63      0.57      0.60      1161

    accuracy                           0.60      2226
   macro avg       0.60      0.60      0.60      2226
weighted avg       0.60      0.60      0.60      2226

Accuracy (PCA): 0.5997
Precision (PCA): 0.6288
Recall (PCA): 0.5676
F1-Score (PCA): 0.5967
ROC AUC (PCA): 0.6220
```






```
Cross-Validation Accuracy Scores for PCA: [0.59683099 0.59953024 0.61421022
0.59541985 0.59130945]
Mean Accuracy for PCA: 0.5995
Standard Deviation for PCA: 0.0078
Classification Report with RFE:
               precision    recall  f1-score   support

       clean       0.63      0.67      0.65      1065
       noisy       0.68      0.64      0.66      1161

    accuracy                           0.65      2226
   macro avg       0.66      0.66      0.65      2226
weighted avg       0.66      0.65      0.66      2226

Accuracy (RFE): 0.6550
Precision (RFE): 0.6785
Recall (RFE): 0.6434
F1-Score (RFE): 0.6605
ROC AUC (RFE): 0.7056
```


Confusion Matrix (RFE)
Actual
Predicted
Clean
Noisy
Clean
Noisy
711
354
414
747
700
650
600
550
500
450
400


Receiver Operating Characteristic (ROC) Curve (RFE)
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.71)
0.0
0.2
0.4
0.6
0.8
1.0

```
Cross-Validation Accuracy Scores for RFE: [0.65551643 0.67410452 0.66294774
0.66529654 0.63358779]
Mean Accuracy for RFE: 0.6583
Standard Deviation for RFE: 0.0137
```

In [ ]:
```
import joblib

joblib.dump(svm_model_pca, 'svm_model_pca.pkl')
joblib.dump(pca, 'pca_transformer.pkl')
joblib.dump(svm_model_rfe, 'svm_model_rfe.pkl')
joblib.dump(rfe, 'rfe_transformer.pkl')
print("Models and transformers saved successfully!")
```

```
Models and transformers saved successfully!
```

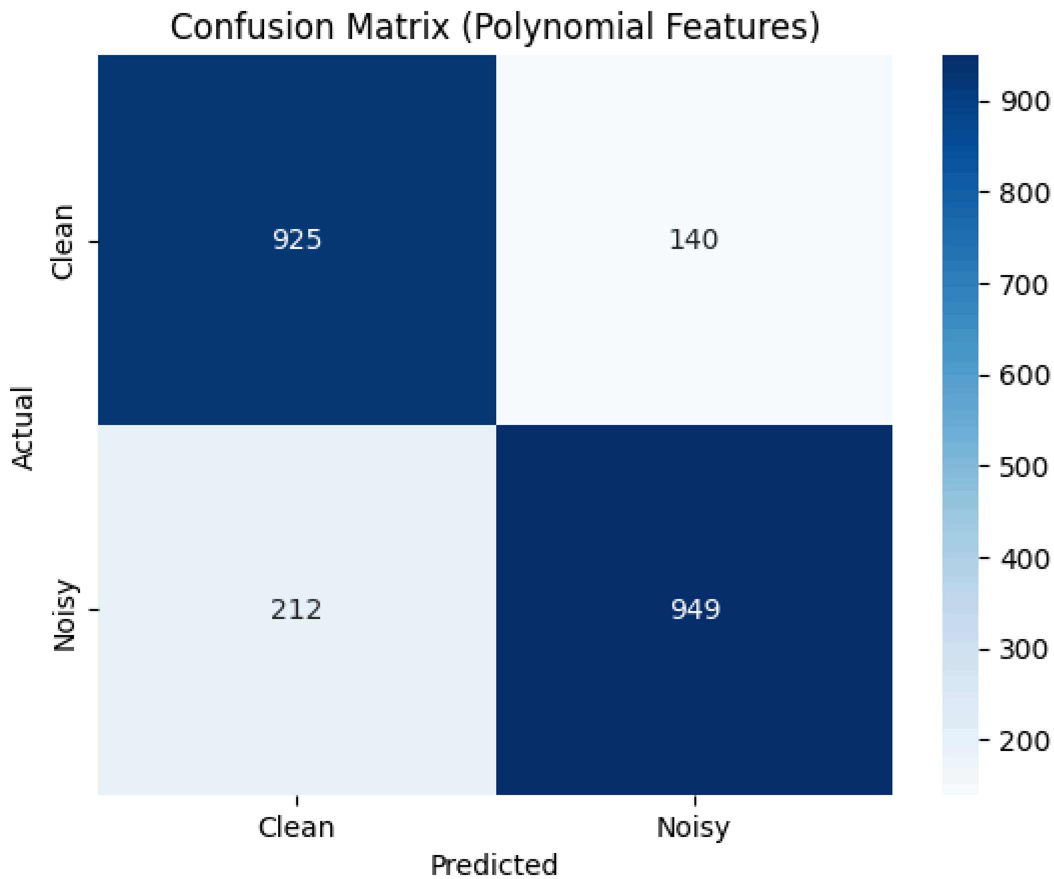
Polynomial Features

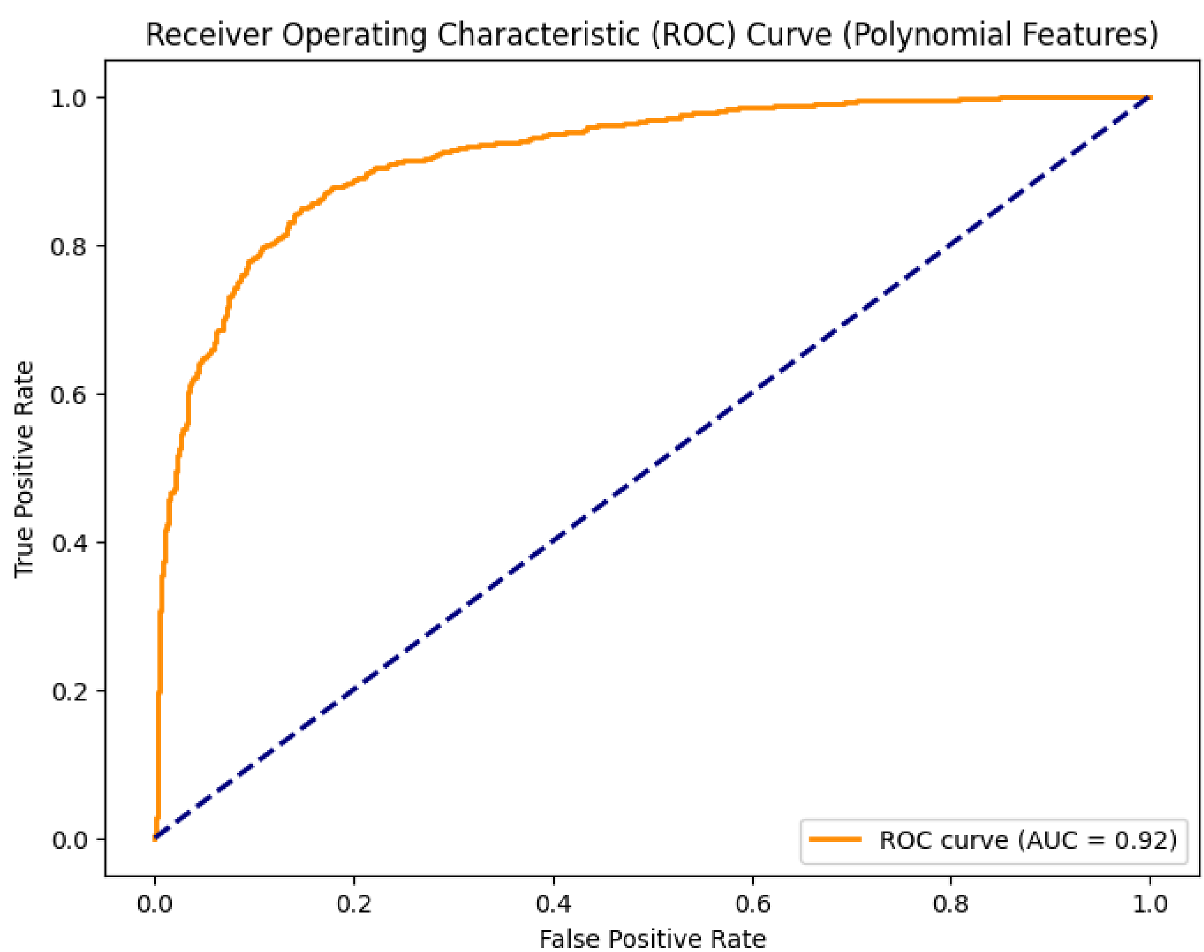
In [ ]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score
import numpy as np

# Adding polynomial features
poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train_balanced)

svm_poly_model = SVC(kernel='linear', random_state=42)
svm_poly_model.fit(X_train_poly, y_train_balanced)

y_pred_poly = svm_poly_model.predict(poly.transform(X_test))

print("SVM Model with Polynomial Features Classification Report:\n", classif

accuracy_poly = accuracy_score(y_test, y_pred_poly)
precision_poly = precision_score(y_test, y_pred_poly, average='binary', pos_
recall_poly = recall_score(y_test, y_pred_poly, average='binary', pos_label=
f1_poly = f1_score(y_test, y_pred_poly, average='binary', pos_label='noisy')

print(f"Accuracy (Polynomial): {accuracy_poly:.4f}")
print(f"Precision (Polynomial): {precision_poly:.4f}")
print(f"Recall (Polynomial): {recall_poly:.4f}")
print(f"F1-Score (Polynomial): {f1_poly:.4f}")

roc_auc_poly = roc_auc_score(y_test, svm_poly_model.decision_function(poly.t
print(f"ROC AUC (Polynomial): {roc_auc_poly:.4f}")

conf_matrix_poly = confusion_matrix(y_test, y_pred_poly)
sns.heatmap(conf_matrix_poly, annot=True, fmt='d', cmap='Blues', xticklabels
plt.title('Confusion Matrix (Polynomial Features)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Loading [MathJax]/extensions/Safe.js

```
plt.show()

fpr_poly, tpr_poly, thresholds_poly = roc_curve(y_test, svm_poly_model.decis
plt.figure(figsize=(8, 6))
plt.plot(fpr_poly, tpr_poly, color='darkorange', lw=2, label=f'ROC curve (AU
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve (Polynomial Feature
plt.legend(loc='lower right')
plt.show()

cv_scores_poly = cross_val_score(svm_poly_model, X_train_poly, y_train_balar
print("Cross-Validation Accuracy Scores for Polynomial Features:", cv_scores
print(f"Mean Accuracy for Polynomial Features: {cv_scores_poly.mean():.4f}")
print(f"Standard Deviation for Polynomial Features: {cv_scores_poly.std():.4
```

```
SVM Model with Polynomial Features Classification Report:
               precision    recall  f1-score   support

       clean       0.81      0.87      0.84      1065
       noisy       0.87      0.82      0.84      1161

    accuracy                           0.84      2226
   macro avg       0.84      0.84      0.84      2226
weighted avg       0.84      0.84      0.84      2226

Accuracy (Polynomial): 0.8419
Precision (Polynomial): 0.8714
Recall (Polynomial): 0.8174
F1-Score (Polynomial): 0.8436
ROC AUC (Polynomial): 0.9209
```


Confusion Matrix (Polynomial Features)
Actual
Clean
Noisy
925
140
212
949
900
800
700
600
500
400
300
200
Clean
Noisy
Predicted


Receiver Operating Characteristic (ROC) Curve (Polynomial Features)
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (AUC = 0.92)

```
Cross-Validation Accuracy Scores for Polynomial Features: [0.83861502 0.8608
3382 0.83910746 0.85731063 0.85613623]
Mean Accuracy for Polynomial Features: 0.8504
Standard Deviation for Polynomial Features: 0.0095
```

In [ ]:

```python
import joblib

joblib.dump(svm_poly_model, 'svm_poly_model.pkl')
joblib.dump(poly, 'polynomial_transformer.pkl')
print("SVM model and Polynomial Features transformer saved successfully!")
```

```
SVM model and Polynomial Features transformer saved successfully!
```