Data Analytics Project: Phishing Website Classification using Machine Learning.

Course: Data Analytics and (Data Driven Decision)

Objective: Apply descriptive and predictive analytics to classify websites as legitimate, suspicious, or phishy using the UCI Website Phishing dataset.

1. Dataset Description

This dataset is designed for the classification task of identifying whether a given website is legitimate potentially phishing or Suspecious. It contains a total of 1,353 website instances, each characterized by 9 numerical features and a binary target variable indicating the classification `Result`.

- Format: ARFF
- 1353 instances (websites)
- 9 features + 1 target (`Result`)
- Classes:
  - `-1` : Phishing
  - `0` : Suspicious
  - `1` : Legitimate

In [1]:
```
import arff
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
```

1.1 Loading and Previewing the DataSet

In [3]:
```
# Loading the arff datafile
with open('PhishingData.arff', 'r') as f:
    dataset = arff.load(f)

# converting the dataset to dataframe
df = pd.DataFrame(dataset['data'], columns=[attr[0] for attr in dataset['attributes']])

# preview the first 5 rows
display(df.head())
```

	SFH	popUpWidnow	SSLfinal_State	Request_URL	URL_of_Anchor	web_traffic	URL_Length	age_of_domain	having_IP_Address	Result
0	1	-1	1	-1	-1	1	1	1	0	0
1	-1	-1	-1	-1	-1	0	1	1	1	1
2	1	-1	0	0	-1	0	-1	1	0	1
3	1	0	1	-1	-1	0	1	1	0	0
4	-1	-1	1	-1	0	0	-1	1	0	1

1.2 checking the shape of the dataset

In [5]:
```
# checking the shape of the dataset
display("Dataset shape", df.shape)
```

```
'Dataset shape'
(1353, 10)
```

In [6]:
```
#column names and datatypes
print("\nColumn data type:")
print(df.dtypes)
```

```
Column data type:
SFH                 object
popUpWidnow         object
SSLfinal_State      object
Request_URL         object
URL_of_Anchor       object
web_traffic         object
URL_Length          object
age_of_domain       object
having_IP_Address   object
Result              object
dtype: object
```

In [7]:
```
#summary statistics
print("\nSummary Statistics:")
display(df.describe())
```

```
Summary Statistics:
```

	SFH	popUpWidnow	SSLfinal_State	Request_URL	URL_of_Anchor	web_traffic	URL_Length	age_of_domain	having_IP_Address	Re
count	1353	1353	1353	1353	1353	1353	1353	1353	1353	1
unique	3	3	3	3	3	3	3	2	2	
top	1	0	1	-1	-1	0	0	1	0	
freq	767	639	751	617	610	473	563	825	1198	

In [8]:
```
#checking class distribution in the target variable
print("\nTarget class distribution:")
print(df['Result']. value_counts())
```

```
Target class distribution:
Result
-1    702
1     548
0     103
Name: count, dtype: int64
```

1.3 Dataset Summary

- Shape: `1353 rows` x `10 coulmns`
- Target columns: (`Result`)
- Unique target values: `-1` , `0` , `1` .

This means that the dataset is likely Multi-class classification, where:

- `-1` = Phishy (or malicious)
- `0` = Suspicious or neutral
- `1` = Legitimate.

2 Data cleaing

Checking for missing values, Duplicates or any data type issues

In [11]:
```
#checking for missing values
print("Missing values per column")
print(df.isnull().sum())
```

```
Missing values per column
SFH                 0
popUpWidnow         0
SSLfinal_State      0
Request_URL         0
URL_of_Anchor       0
web_traffic         0
URL_Length          0
age_of_domain       0
having_IP_Address   0
Result              0
dtype: int64
```

In [12]:
```
#checking for duplicates
print("\nNumber of duplicate rows:", df.duplicated().sum())
```

```
Number of duplicate rows: 629
```

2.1 Data cleaning summary

- `No missing values` : There is no need to fill or drop rows due to missing data.
- `629 duplicate rows` : That is approximately 46% of the dataset!

We decided to keep duplicates becasue:

- Each row is a valid, independent observation, even if values match.
- The dataset behavior-based phishing indicators, it's possible that,Some websites exhibit identical behavior and hence should not be dropped.

In [14]:
```
#Keep the Original Dataset shape
print ("We keep the Original shape of the Dataset:", df.shape)
```

```
We keep the Original shape of the Dataset: (1353, 10)
```

3 Exploratory Data Analysis (EDA)

- Understanding the data visually and statistically, Identify trends. patterns, and feature relationships. Get insights into the Result class distribution.

3.1 Basic analysis

In [17]:
```
# Ensuring that all the values are numeric
df = df.apply(pd.to_numeric)

#getting baic statistic for all features
basic_stats =df.describe()
display(basic_stats)
```

	SFH	popUpWidnow	SSLfinal_State	Request_URL	URL_of_Anchor	web_traffic	URL_Length	age_of_domain	having_IP_Addre
count	1353.000000	1353.000000	1353.000000	1353.000000	1353.000000	1353.000000	1353.000000	1353.000000	1353.0000
mean	0.237990	-0.258684	0.327421	-0.223208	-0.025129	0.000000	-0.053215	0.219512	0.1145
std	0.916389	0.679072	0.822193	0.799682	0.936262	0.806776	0.762552	0.975970	0.3186
min	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	0.0000
25%	-1.000000	-1.000000	0.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	0.0000
50%	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.0000
75%	1.000000	0.000000	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	0.0000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0000

3.2 standard deviation analysis

In [19]:
```
print("Standard deviation per feature:\n")
print(df.std())
```

```
Standard deviation per feature:

SFH                 0.916389
popUpWidnow         0.679072
SSLfinal_State      0.822193
Request_URL         0.799682
URL_of_Anchor       0.936262
web_traffic         0.806776
URL_Length          0.762552
age_of_domain       0.975970
having_IP_Address   0.318608
Result              0.954773
dtype: float64
```

Basic Statistical Analysis

We performed basic statistical analysis using `df.describe()`. This provided insights into the distribution of each feature including mean, min, max, and standard deviatio##

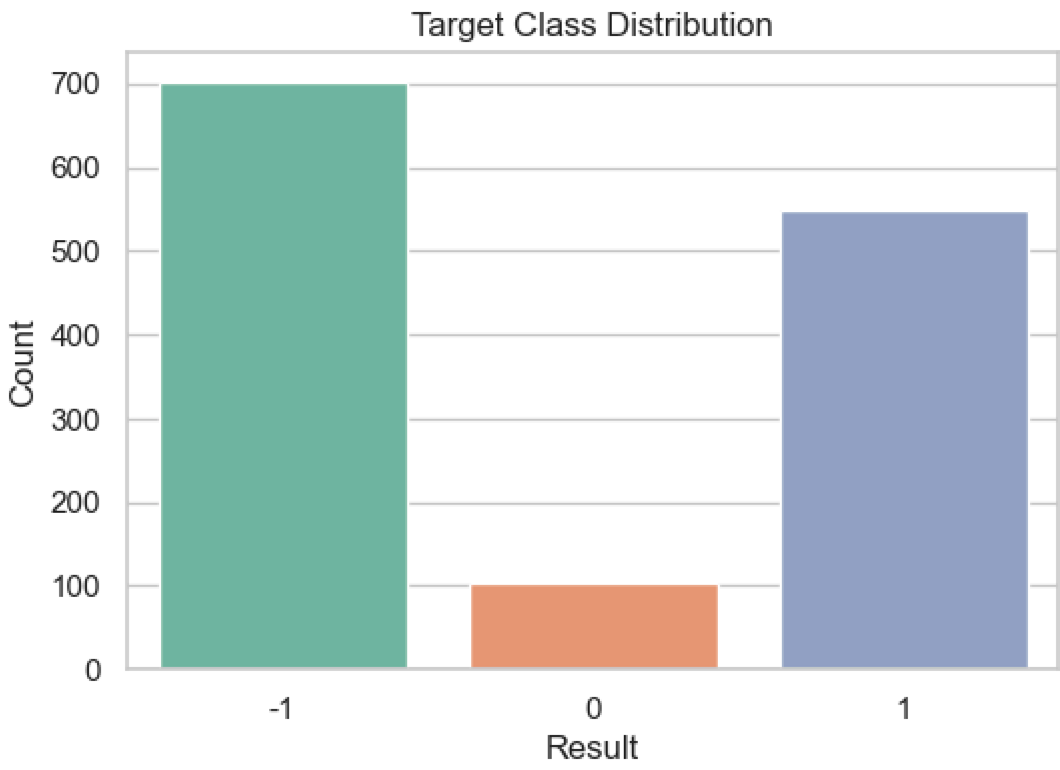
Standard Deviation Analysis

The standard deviation tells us how much the values for each feature vary from the mean. A higher standard deviation indicates greater variability across websites, while a lower standard deviation suggests uniform behavior for that feature.

In [21]:
```
#set seaborn style
# Set Seaborn style
sns.set(style='whitegrid')

# 1. Target class distribution
plt.figure(figsize=(6,4))
sns.countplot(x='Result', data=df, palette='Set2')
```

```
plt.title('Target Class Distribution')
plt.xlabel('Result')
plt.ylabel('Count')
plt.show()
```



3.1 class distribution Analysis

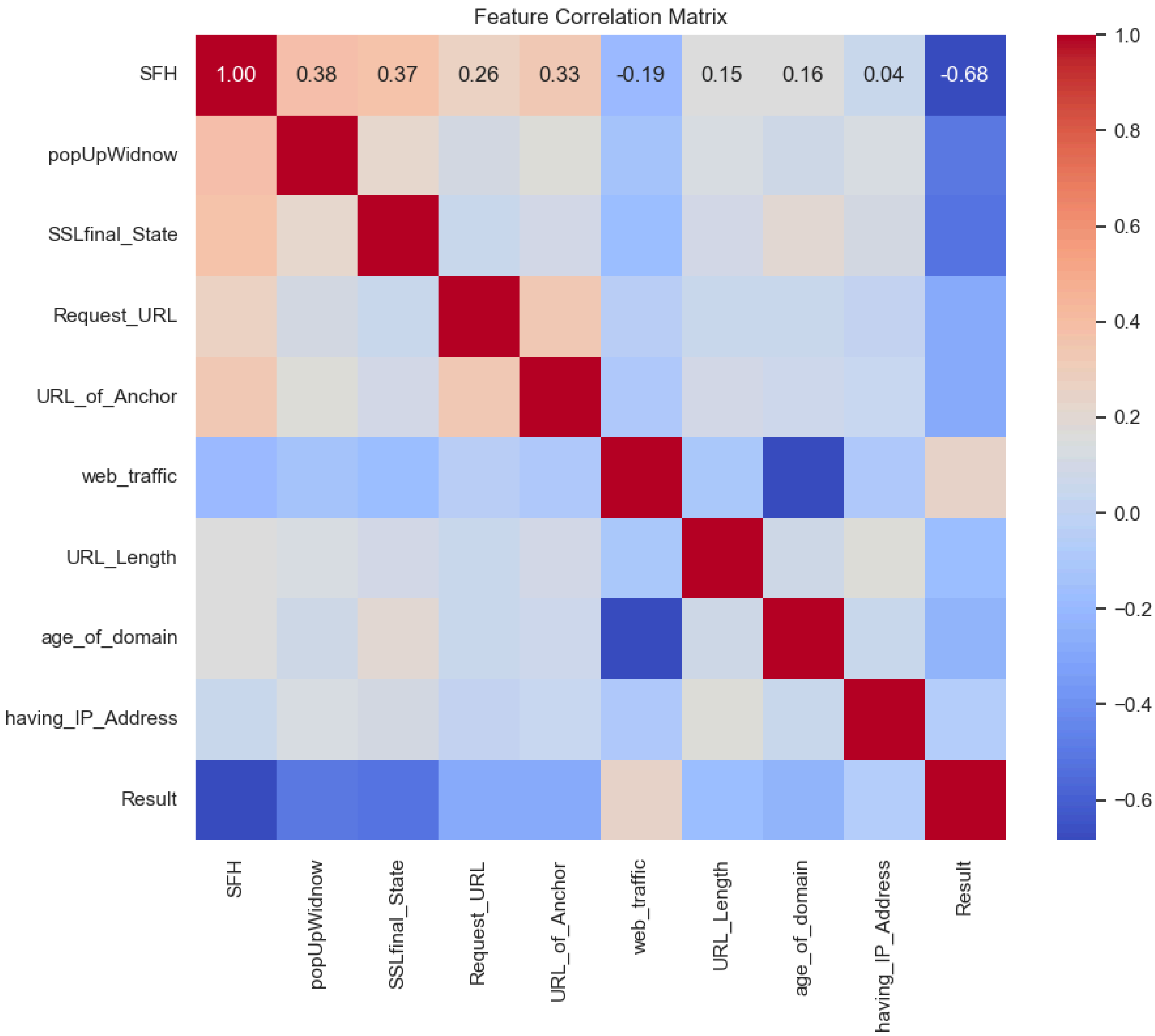
- `-1 = Phishing` with `700 count` is the `Majority class` .
- `1 = Legitimate` with `550 count` is the `Close Second` .
- `0 = Suspicious` with `100 count` is the `Minor Class(rare cases)` .

This is slightly `imbalanced dataset` , especially for class `0` .

3.4 Correlation Matrix

Most features are weakly correlated, meaning they provide independent information, which is useful for machine learning models

In [33]:
```
# 2. Heatmap to visualize correlation between features
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Feature Correlation Matrix')
plt.show()
```



3.5 PCA

In the case of our `Dataset` , `PCA` is best use for visualization only, not as a requirement before modelling, because the features are already informative and interpretable. The features like(`SFH` , `SSLfinal_State` , etc.) are:

- `Discrete, categorical-like values (-1, 0, 1)`
- `Already engineered by experts to reflect phishing behaviors`

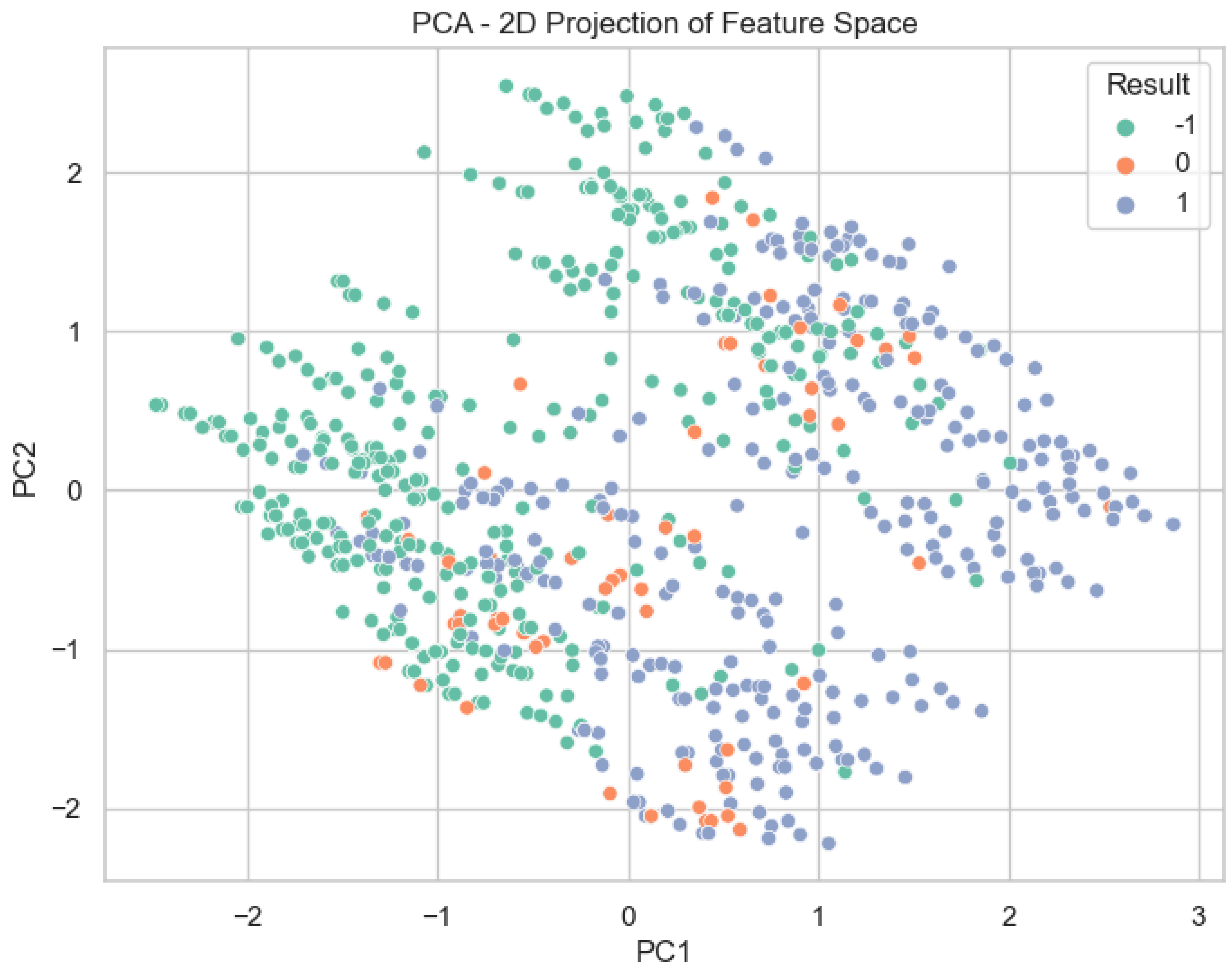
These features have clear meanings and are already effective as inputs.

In [38]:
```
# Prepare data
X = df.drop('Result', axis=1)
y = df['Result']

# Apply PCA to reduce to 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Create a DataFrame with PCA results
pca_df = pd.DataFrame(data=X_pca, columns=['PC1', 'PC2'])
pca_df['Result'] = y.values

# Plot
plt.figure(figsize=(8,6))
sns.scatterplot(data=pca_df, x='PC1', y='PC2', hue='Result', palette='Set2')
plt.title("PCA - 2D Projection of Feature Space")
plt.grid(True)
plt.show()
```

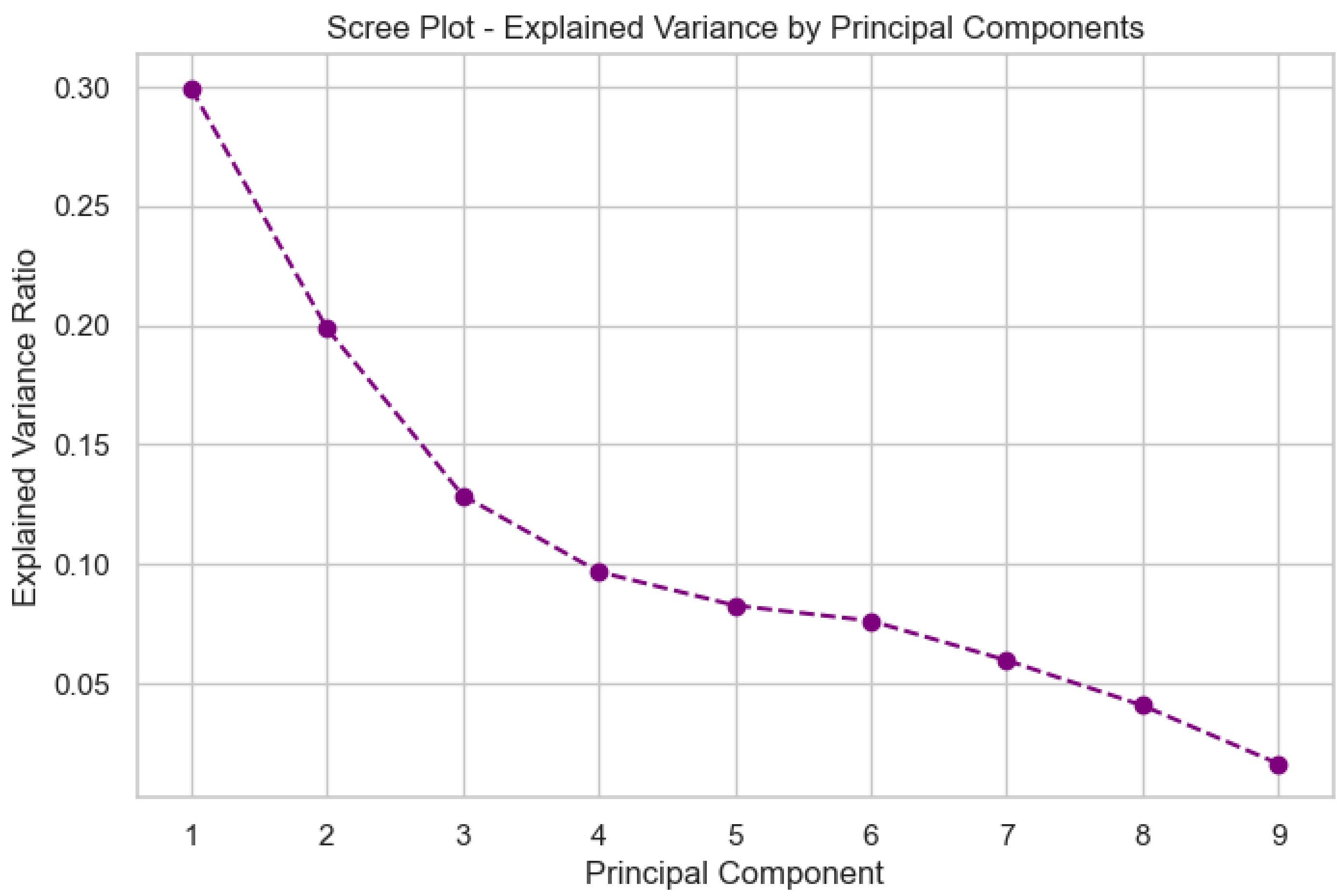


3.6 scree plot

In [41]:
```
# Prepare feature matrix (excluding the target)
X = df.drop('Result', axis=1)

# Apply PCA without limiting the number of components
pca = PCA()
pca.fit(X)

# Plot the explained variance for each principal component
plt.figure(figsize=(8, 5))
plt.plot(
    range(1, len(pca.explained_variance_ratio_) + 1),
    pca.explained_variance_ratio_,
    marker='o',
    linestyle='--',
    color='purple'
)
plt.title('Scree Plot - Explained Variance by Principal Components')
plt.xlabel('Principal Component')
plt.ylabel('Explained Variance Ratio')
plt.xticks(range(1, X.shape[1] + 1))
plt.grid(True)
plt.show()
```



4 Supervised ML model

Base on our dataset: We are working on a `Suppervised Learning Task`

- Data are lebeled: the `Result` column (values `-1`, `0`, `1`)
- Labels are already known in advance.

The `goal` is to use the labeled data to train a model to predict `Results` based on the feafures.

Main Analysis

- split the data into training and testing sets
- train a model
- evalute how well it performs.

4.1 Data splitting

- x = Features(everything except Results)
- y = Target (Result column)

In [47]:
```
# Features and Target
X = df.drop('Result', axis=1)
y = df['Result']

# Splitting the dataset (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42) #We use stratify=y to ensure all 3 classes are proportionally represente

# Check the shape of the splits
print("Training set:", X_train.shape)
print("Testing set:", X_test.shape)
```

```
Training set: (1082, 9)
Testing set: (271, 9)
```

4.2 Training the Decision Tree

In [50]:
```
# Initialize and train the classifier
clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict on test data
y_pred = clf.predict(X_test)
```

4.3 Evaluateing the model

In [53]:
```
# Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Confusion Matrix:
[[128   3   9]
 [  4  13   4]
 [ 10   2  98]]

Classification Report:
              precision    recall  f1-score   support

          -1       0.90      0.91      0.91       140
           0       0.72      0.62      0.67        21
           1       0.88      0.89      0.89       110

    accuracy                           0.88       271
   macro avg       0.84      0.81      0.82       271
weighted avg       0.88      0.88      0.88       271
```

Try with random forest

In [56]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Initialize and train the Random Forest classifier
rf_clf = RandomForestClassifier(random_state=42)
```

```
rf_clf.fit(X_train, y_train)

# Predict on test data
rf_pred = rf_clf.predict(X_test)

# Evaluation
print("Confusion Matrix:")
print(confusion_matrix(y_test, rf_pred))

print("\nClassification Report:")
print(classification_report(y_test, rf_pred))
```

```
Confusion Matrix:
[[126   2  12]
 [  5  12   4]
 [  8   2 100]]

Classification Report:
              precision    recall  f1-score   support

          -1       0.91      0.90      0.90       140
           0       0.75      0.57      0.65        21
           1       0.86      0.91      0.88       110

    accuracy                           0.88       271
   macro avg       0.84      0.79      0.81       271
weighted avg       0.88      0.88      0.88       271
```

Model Comparison – Decision Tree vs Random Forest

Both the Decision Tree and Random Forest classifiers achieved an overall accuracy of 88%, showing that each model is effective at detecting phishing websites. However, a deeper look at the precision, recall, and F1-scores reveals some key differences in performance.

Decision Tree:

- Slightly better recall and F1-score for the suspicious class (0).
- Strong performance across phishing (-1) and legitimate (1) classes.

Random Forest:

- Slightly higher precision on the suspicious class (0), but lower recall compared to Decision Tree.
- More stable across classes due to being an ensemble of multiple trees.
- Less prone to overfitting and generally more robust, especially on unseen data.

SUMMARY FOR THE LEARNING MODEL

Why We Used Supervised Learning.

We chose supervised learning because our problem involved predicting known classes, i.e. phishing (-1), suspicious (0), and legitimate (1) based on labeled historical data.

Reasons.

- The dataset includes a target variable (Result), which clearly labels each website.
- Our goal was to learn patterns from these labeled examples to predict future website behavior.
- Models like Decision Trees and Random Forests are well-suited for this kind of task.

Why we did not used Unsupervised Learning.

- Unsupervised learning is used when there's no labeled output for example, clustering websites based on similar behaviors without knowing if they're phishing or not.
- It's useful for exploration, but it won't give exact classifications like "this is a phishing site.

Final Thought: Because we had clear labels and a well-defined classification task, supervised learning was the most appropriate and effective choice for detecting phishing websites.

Conclusions

Descriptive analytics We began by exploring the dataset using descriptive analytics. This helped us to:

- Understand the distribution of the classes (phishing `-1`, suspicious `0`, legitimate `1`)
- Analyze the most common behaviors of websites, such as the use of SSL certificates, IP addresses, form handler etc.
- Revealed class imbalanced, with more legitimate and phishy sites.
- Generate summary statistics and visualizations (e.g., bar charts, correlation heatmaps).

Therefore; Descriptive analytics gave us the insight we needed to understand the dataset, detect patterns, and make informed decisions about how to clean the data and what models to use.

Predictive analytics

Predictive analytics enabled us to build models that could automatically classify websites. We, therefore; applied:

- Decision Tree and Random Forest models, both achieving an accuracy of 88%. Using both the models achieved reasonable classification performance.
- Feature importance analysis, which revealed that certain website characteristics (e.g., SSL use, URL structure) are strong predictors of phishing behavior.
- Feature importance analysis highlights which website characteristics are most predictive.
- Improvements: Try more models (Logistics regression,hyperparameter tuning, SVM), hyperparameter tuning, and cross-validation.