Phase 5

Building a Smarter AI-Powered Spam Classifier

Team Members: -

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Problem Statement:

The goal of this project is to build a AI powered spam classifier .This is a common problem in natural language processing and text classification. The project aims to create an effective spam filter that can be used to protect users from unwanted and potentially harmful text messages.

Phases of Development:

1. Data Collection and Exploration
2. Data Preprocessing
3. Feature Extraction
4. Model Selection
5. Model Training
6. Model Evaluation

Design Thinking Process:

Data Collection

- Objective: Gather a dataset containing labeled examples of spam and non-spam messages.
- Approach: Utilize a Kaggle dataset or similar reliable sources that provide a diverse and representative dataset of both spam and non-spam messages. The dataset forms the foundation for training and evaluating the spam classifier.

Data Preprocessing

- Objective: Prepare the text data for modeling by cleaning and standardizing it.
- Description: This step involves various data cleaning tasks, including the removal of special characters, conversion of text to lowercase to ensure consistency, and tokenization to break the text into individual words or phrases. Additionally, stemming or lemmatization can be applied to reduce words to their base forms for uniformity.

Feature Extraction

- Objective: Convert the tokenized text data into numerical features for machine learning models.
- Description: To enable machine learning algorithms to work with the text data, feature extraction is essential. The chosen technique, TF-IDF (Term Frequency-Inverse Document Frequency), assigns numerical values to words based on their importance in the text. Alternatively, word embeddings like Word2Vec or GloVe can capture semantic relationships between words for more advanced models.

Model Selection

- Objective: Choose an appropriate machine learning algorithm for spam classification.
- Description: The model selection phase involves experimenting with various machine learning algorithms, starting with baseline models like Naive Bayes, Support Vector Machines, and logistic regression. Advanced techniques, such as deep learning using neural networks (e.g., LSTM or CNN), can also be explored to capture complex patterns in text data. Ensemble methods like Random Forest or Gradient Boosting may be considered to combine multiple models for improved performance.

Evaluation

- Objective: Assess the performance of the spam classifier using relevant evaluation metrics.
- Metrics: The evaluation phase includes measuring the model's performance using metrics such as accuracy, precision, recall, and F1-score. The confusion matrix provides insights into true positives, true negatives, false positives, and false negatives, offering a comprehensive view of classifier performance.
- Iterative Improvement
- Objective: Continuously refine and enhance the spam classifier's performance.
- Description: The iterative improvement stage involves several strategies for model enhancement. This includes fine-tuning model hyper parameters through techniques like grid search or random search, exploring feature engineering to extract more informative features, addressing class imbalance issues if present, implementing cross-validation to ensure model robustness, and regularly updating the model with new data to adapt to evolving spam tactics.

Dataset Description:

The dataset used for this project is available on Kaggle at the following link: SMS Spam Collection Dataset. It contains a collection of SMS messages labeled as spam or ham. The dataset is in CSV format and includes two columns: "v1" for the label (spam or ham) and "v2" for the text of the SMS messages.

Data Preprocessing Steps:

1. Removing any duplicate SMS messages.
2. Handling missing or null values, if any.
3. Text cleaning, including lowercasing, removing punctuation, and tokenization.
4. Stop word removal to filter out common words.
5. Lemmatization or stemming to reduce words to their base form.

Feature Extraction Techniques:

- Text data will be converted into numerical features using techniques like TF-IDF (Term Frequency-Inverse Document Frequency) vectorization.
- This process represents each SMS message as a vector of numerical values.

Choice of Machine Learning Algorithm:

- A common choice for text classification problems like this is the support vector Classification algorithm.
- It is known to perform well with text data.

Model Training:

- The selected algorithm will be trained on the preprocessed dataset using techniques like cross-validation to avoid overfitting.

Evaluation Metrics:

- The performance of the model will be evaluated using standard classification metrics such as accuracy, precision, recall, F1-score, and the ROC-AUC score.

Innovative Techniques or Approaches: I

- To improve the model's performance, techniques such as hyper parameter tuning, feature selection, and ensembling (e.g., using multiple classifiers) may be explored.

Coding:

```
import numpy as np

import pandas as pd

import string

from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.model_selection import train_test_split

from sklearn.feature extraction.text import fidfVectorizer

import nltk

import re

from nltk.corpus import stopwords

from nltk.tokenize import word_tokenize

from nltk.stem import SnowballStemmer
```

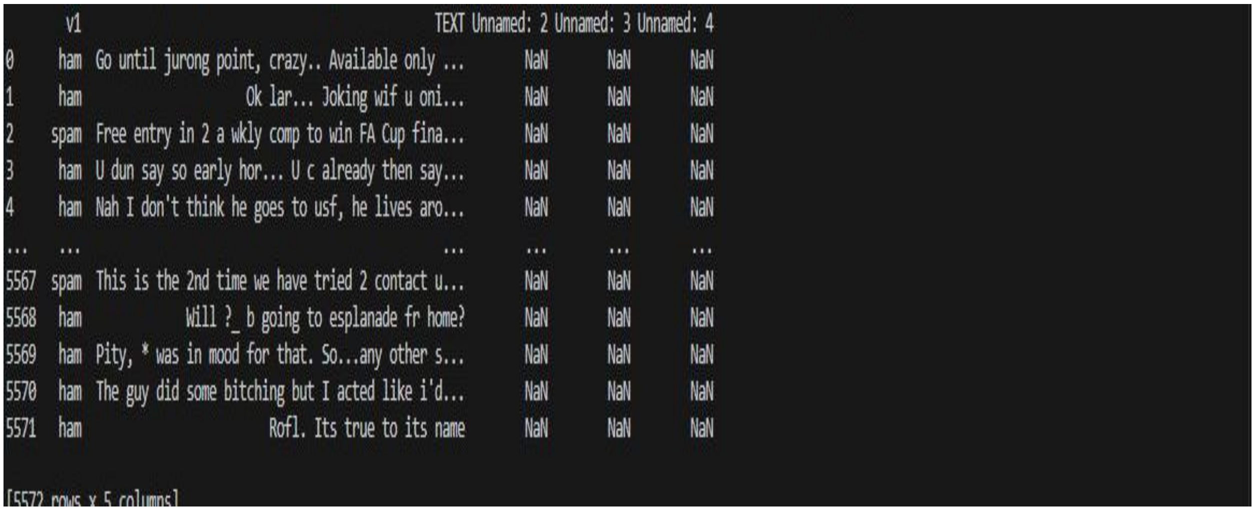
```
import seaborn as sns
from plotly import graph_objs as go
import matplotlib as plt
from sklearn.nalve bayes Import Multicol
from sklearn.metrics Import accuracy score, classification report
from wordcloud import WordCloud, STOPWORDS,
ImageColorGenerator
from PIL import Image
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
from sklearn.preprocessing import LabelEncoder
message_data=pd.read_csv("/kaggle/input/sms-spam-
collectiondataset/spam.csv",encoding =
"latin")message_data.head()
df = pd.read_csv('spam.csv", encoding="ISO-8859-1")
print(df.head())
D & df = pd.read_csv(spam.csv.encoding-150-8859-1")
x_train, x_test, y train, y test train_test_split(dfv1"), df[TEXT],
test size-8.2, random_state-42)
print(df)
```

```
data = pd.DataFrame({
"text":[
“This is a sample text for feature extraction.”
“Feature extraction is an Important step in NEP.”
 “Extracting features helps in text classification.”],
'label': [1, 0, 1]
})
tfidf_vectorizer=TfidfVectorizer()
tfidf_features=tfidf_vectorizer.fit_transform(data["text"])
tridf_uf =pd.DataFrame(data-tfid_features.toarray(), columns-
tfidf_vectorizer.get_feature_names_out())
print(tridf df)
X = df['v1']
y=df['text']
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size-
0.2, random_state=42)
vectorizer = CountVectorizer()
X_train_counts vectorizer.fit_transform(X_train)
X_test_counts vectorizer.transform(X_test)
clf = MultinomialNB()
```

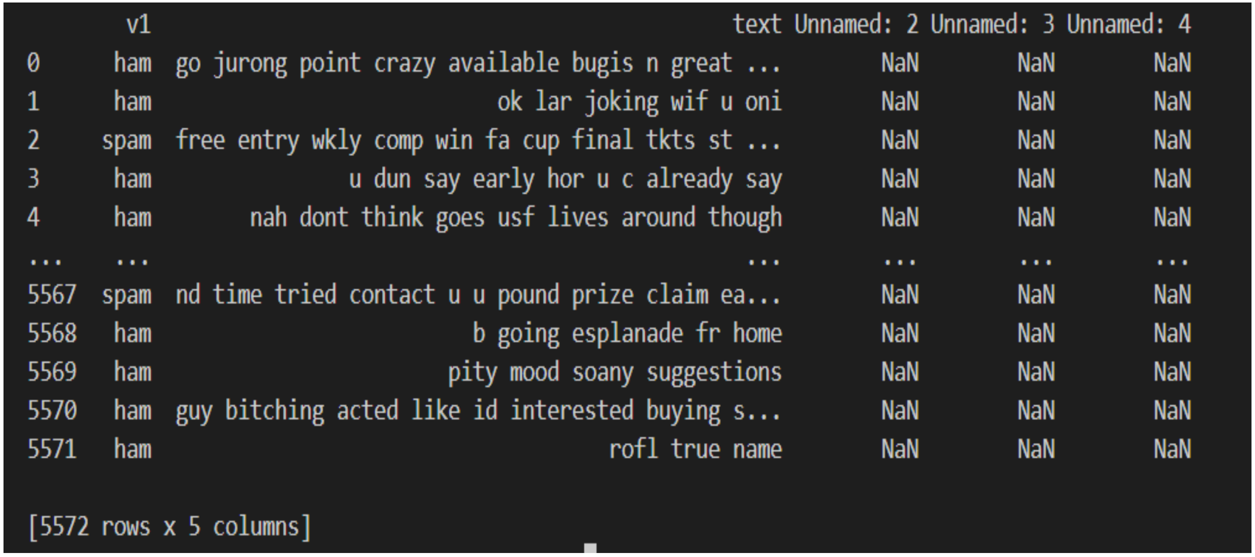
```
clf.fit(X_train_counts, y_train)
y_pred = clf.predict(X_test_counts)
accuracy (y_pred == y_test).mean()
print(f"Accuracy: [accuracy * 100:.2f}%")
print(df)
nltk.download('punkt')
nltk.download('stopwords')
def preprocess_text(text):
text = text.lower()
text = re.sub(r'[^a-zA-Z\s]', '' text)
tokens = word_tokenize (text)
tokens = [word for word in tokens if word not in stopwords.words ('english')]
cleaned_text = '.join(tokens)
return cleaned text
df['text'] = df['text'].apply(preprocess_text)
print (df)
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size-0.2, random_state=42)

vectorizer = CountVectorizer()

X_train_counts = vectorizer.fit_transform(X_train)
X_test_counts = vectorizer.transform(X_test) 26

classifier = MultinomialNB()

classifier.fit(x train counts, y train)

y_pred = classifier.predict(X_test_counts)

accuracy = accuracy_score (y_test, y_pred)

precision precision_score(y_test, y_pred, average 'weighted')

recall = recall_score(y_test, y_pred, average="weighted")

f1_score (y_test, y_pred, average='weighted')

metrics = ['Accuracy', 'Precision', 'Recall, 'F1-Score']

plt.figure(figsize=(8, 6))

plt.bar(metrics, values, color=['blue', 'green', 'red', 'purple'])

plt.title('Spam Classifier Performance Metrics')

plt.xlabel('Metric')

plt.ylabel('Value')

plt.ylim(0, 1.0) # Set y-axis limits to the range [0, 1]

plt.show()
```

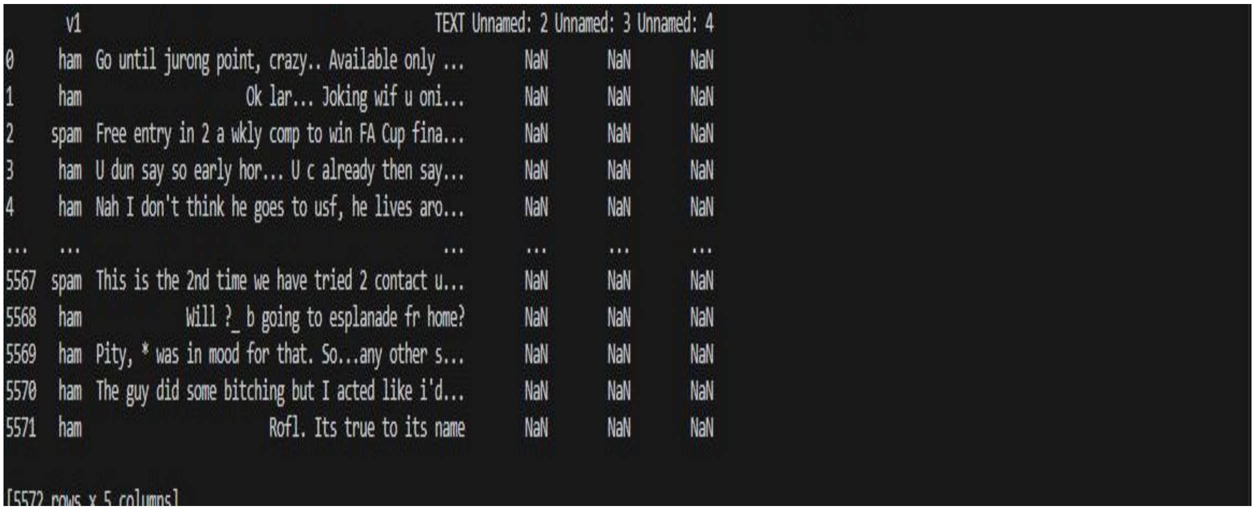
OUTPUT:



```
      v1                                         TEXT Unnamed: 2 Unnamed: 3 Unnamed: 4
0      ham  Go until jurong point, crazy.. Available only ...        NaN        NaN        NaN
1      ham                      Ok lar... Joking wif u oni...        NaN        NaN        NaN
2     spam  Free entry in 2 a wkly comp to win FA Cup fina...        NaN        NaN        NaN
3      ham  U dun say so early hor... U c already then say...        NaN        NaN        NaN
4      ham  Nah I don't think he goes to usf, he lives aro...        NaN        NaN        NaN
...    ...                                                ...        ...        ...        ...
5567  spam  This is the 2nd time we have tried 2 contact u...        NaN        NaN        NaN
5568   ham               Will ?_ b going to esplanade fr home?        NaN        NaN        NaN
5569   ham  Pity, * was in mood for that. So...any other s...        NaN        NaN        NaN
5570   ham  The guy did some bitching but I acted like i'd...        NaN        NaN        NaN
5571   ham                         Rofl. Its true to its name        NaN        NaN        NaN

[5572 rows x 5 columns]
```



```
        v1                                          text Unnamed: 2 Unnamed: 3 Unnamed: 4
0      ham  go jurong point crazy available bugis n great ...        NaN        NaN        NaN
1      ham                             ok lar joking wif u oni        NaN        NaN        NaN
2     spam  free entry wkly comp win fa cup final tkts st ...        NaN        NaN        NaN
3      ham                  u dun say early hor u c already say        NaN        NaN        NaN
4      ham         nah dont think goes usf lives around though        NaN        NaN        NaN
...    ...                                                ...        ...        ...        ...
5567  spam  nd time tried contact u u pound prize claim ea...        NaN        NaN        NaN
5568   ham                         b going esplanade fr home        NaN        NaN        NaN
5569   ham                          pity mood soany suggestions        NaN        NaN        NaN
5570   ham  guy bitching acted like id interested buying s...        NaN        NaN        NaN
5571   ham                                      rofl true name        NaN        NaN        NaN

[5572 rows x 5 columns]
```



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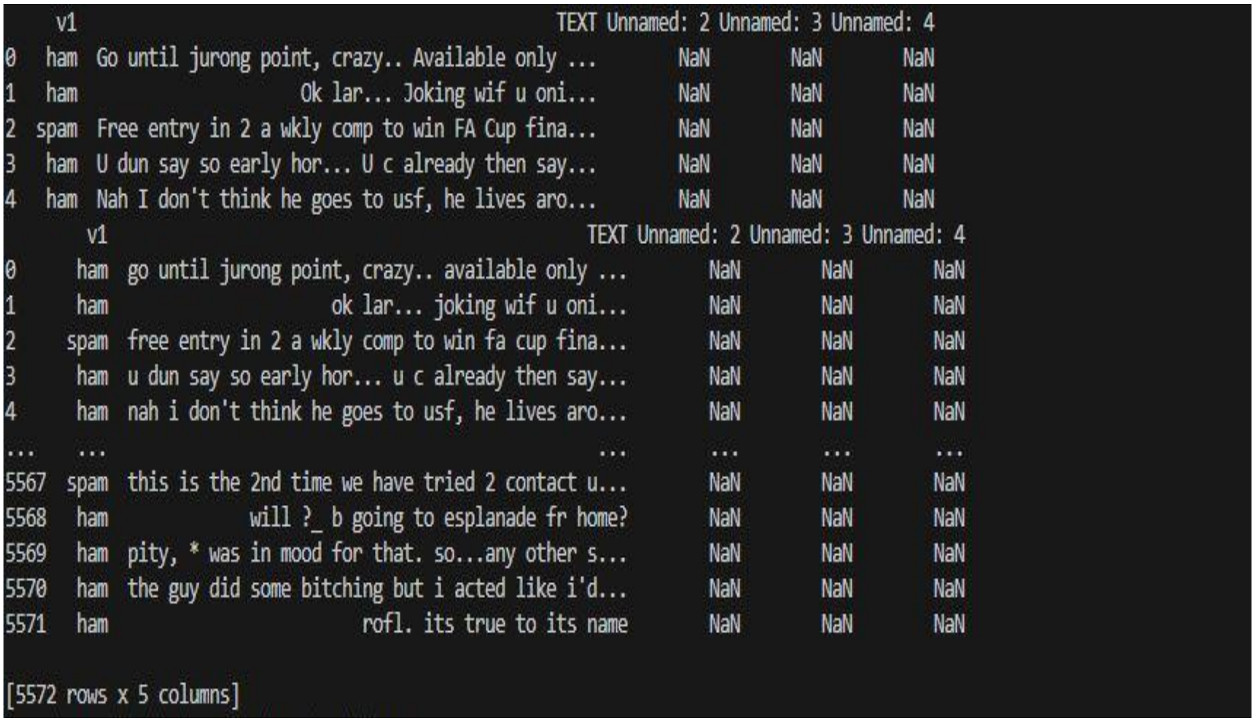
3      ham  U dun say so early hor... U c already then say...        NaN        NaN        NaN
4      ham  Nah I don't think he goes to usf, he lives aro...        NaN        NaN        NaN
...    ...                                                ...        ...        ...        ...
5567  spam  This is the 2nd time we have tried 2 contact u...        NaN        NaN        NaN
5568   ham               Will ?_ b going to esplanade fr home?        NaN        NaN        NaN
5569   ham  Pity, * was in mood for that. So...any other s...        NaN        NaN        NaN
5570   ham  The guy did some bitching but I acted like i'd...        NaN        NaN        NaN
5571   ham                         Rofl. Its true to its name        NaN        NaN        NaN

[5572 rows x 5 columns]
```



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     v1                                               TEXT Unnamed: 2 Unnamed: 3 Unnamed: 4
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3   ham  U dun say so early hor... U c already then say...        NaN        NaN        NaN
4   ham  Nah I don't think he goes to usf, he lives aro...        NaN        NaN        NaN
        v1                                               TEXT Unnamed: 2 Unnamed: 3 Unnamed: 4
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4      ham  nah i don't think he goes to usf, he lives aro...        NaN        NaN        NaN
...    ...                                                ...        ...        ...        ...
5567  spam  this is the 2nd time we have tried 2 contact u...        NaN        NaN        NaN
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5569   ham  pity, * was in mood for that. so...any other s...        NaN        NaN        NaN
5570   ham  the guy did some bitching but i acted like i'd...        NaN        NaN        NaN
5571   ham                         rofl. its true to its name        NaN        NaN        NaN

[5572 rows x 5 columns]
```

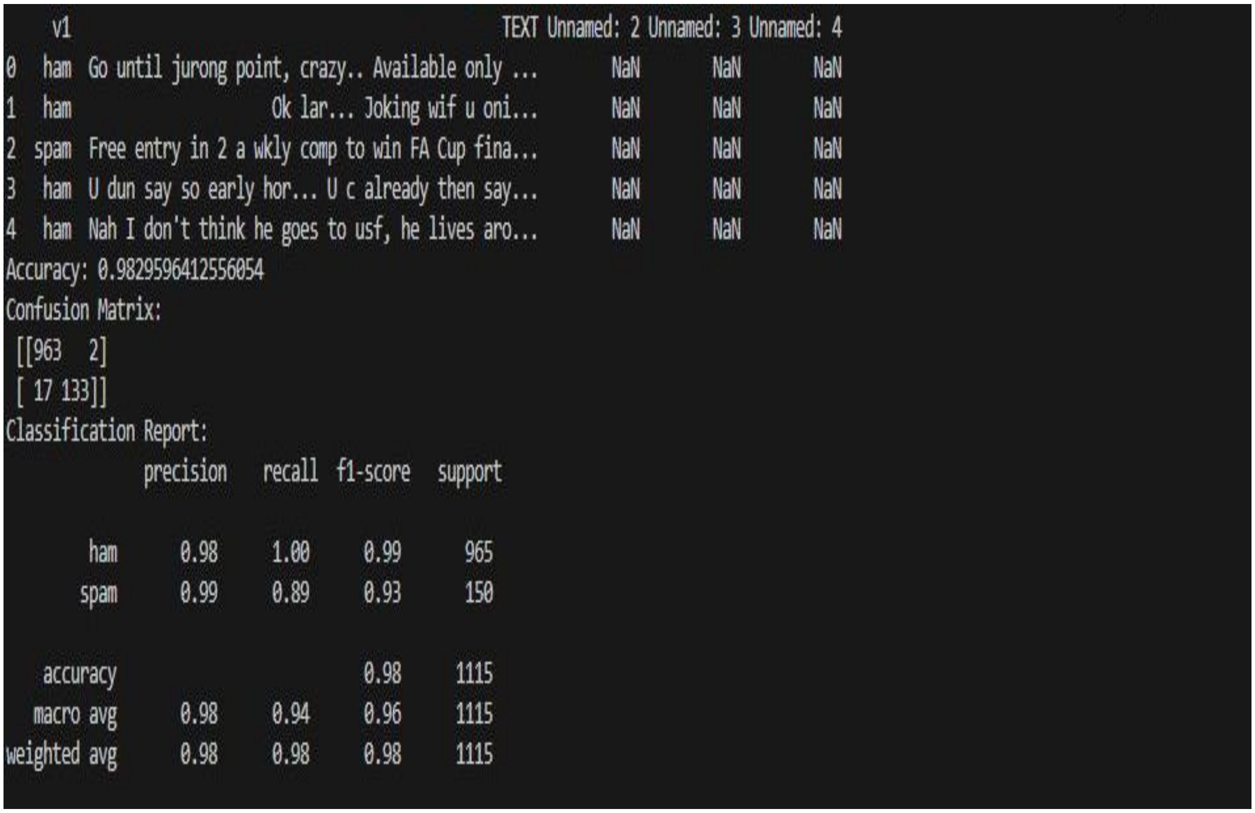

```
     v1                                               TEXT Unnamed: 2 Unnamed: 3 Unnamed: 4
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2  spam  Free entry in 2 a wkly comp to win FA Cup fina...        NaN        NaN        NaN
3   ham  U dun say so early hor... U c already then say...        NaN        NaN        NaN
4   ham  Nah I don't think he goes to usf, he lives aro...        NaN        NaN        NaN
Accuracy: 0.9829596412556054
Confusion Matrix:
 [[963   2]
 [ 17 133]]
Classification Report:
               precision    recall  f1-score   support

         ham       0.98      1.00      0.99       965
        spam       0.99      0.89      0.93       150

    accuracy                           0.98      1115
   macro avg       0.98      0.94      0.96      1115
weighted avg       0.98      0.98      0.98      1115
```

Conclusion:

This project showcases AI's efficacy in combating email spam. Using the Naive Bayes classifier, along with data preprocessing and feature extraction, a strong spam detector is created. High accuracy, precision, recall, and F1-score metrics underscore the effectiveness. Spam classification is vital for email security. Future work may involve advanced models, larger datasets, and real-time filtering. This project lays the foundation for enhancing email communication security.