SMS Spam Detection System Using NLP

A Project Report

submitted in partial fulfillment of the requirements

of

AICTE Internship on AI: Transformative Learning
with
TechSaksham – A joint CSR initiative of Microsoft & SAP

by

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ACKNOWLEDGEMENT

I would like to express my sincere gratitude to everyone who supported and guided me throughout the development of this project.

First and foremost, I am deeply grateful to my mentors and faculty members for their invaluable insights, constructive feedback, and constant encouragement, which helped me overcome challenges and refine my work.

I would also like to extend my appreciation to [mention any institution, organization, or individual, if applicable] for providing the resources and guidance essential for the successful completion of this project.

A special thanks to my family and friends for their unwavering support and encouragement throughout this journey.

Finally, I am thankful for the opportunity to explore the fascinating field of Natural Language Processing and Machine Learning through this SMS spam detection project, which has significantly enhanced my technical skills and understanding of the subject.

Sincerely,
Samar

TABLE OF CONTENT

LIST OF FIGURES

ABSTRACT

Unwanted communications, or spam, have become much more widespread as a result of the quick development of mobile communication. In addition to interfering with user experience, these spam communications present dangers including fraud and phishing assaults. In order to solve the issue, this project uses machine learning and natural language processing (NLP) to create an SMS spam detection system.

Tokenisation, stop-word removal, and stemming are some of the text preparation techniques used by the system to clean and organise SMS data. The text is converted into numerical features appropriate for machine learning methods using a TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer. Because of their effectiveness and precision while processing text data, models such as Naive Bayes and Logistic Regression were used for categorisation.
A labelled dataset was used for training and evaluation, and the models performed well according to measures like accuracy, precision, recall, and F1-score. The system's dependability in separating spam messages from authentic ones is guaranteed by these measures.

The project incorporates the detection technology within a Streamlit-built real-time web application to improve usability. This interactive interface is a useful tool for personal or organisational usage as it lets users enter SMS text and get immediate categorisation results.

This study shows how NLP and machine learning may be used practically to solve a real-world problem. The findings demonstrate how these technologies may be used to automate spam detection, providing a reliable and expandable way to protect consumers from unsolicited communications. The technology helps to increase the security of digital communication and may be further enhanced in future work with more sophisticated algorithms and greater datasets.

CHAPTER 1

INTRODUCTION

SMS is now one of the most popular modes of communication as the quick development of mobile technology has completely changed how people communicate information. Nevertheless, the availability of SMS has also resulted in a rise in unwanted communications, or spam. In addition to wasting consumers' time, these spam communications present serious hazards, such as fraud, phishing attempts, and privacy violations. To protect consumers from these dangers, efficient spam detection technologies have had to be developed.

Conventional spam detection techniques, including keyword-based filtering, frequently fall short in the face of spam messages' constant evolution. To produce a more reliable and scalable solution, this research makes use of machine learning and natural language processing (NLP) approaches. The algorithm can accurately differentiate between spam and authentic messages by examining the linguistic patterns in SMS text.

In order to overcome this difficulty, the SMS Spam Detection project is working to create an automated system that can detect spam in real time. It uses machine learning models to categorise messages after preprocessing text input to extract valuable attributes. A user-friendly web application was also created to make the system usable on a daily basis. The approach, outcomes, and possible future improvements of the system are highlighted in this research, which also demonstrates the usefulness of machine learning and natural language processing in addressing actual communication problems.

1.1 Problem Statement:

With the exponential growth of mobile communication, unsolicited spam messages have become a significant challenge. These spam messages not only disrupt the user experience but also pose serious risks such as phishing attacks, financial fraud, and breaches of privacy. Traditional spam detection systems often fail to keep up with the evolving nature of spam messages, necessitating the development of more robust and adaptive solutions. The dynamic nature of language and context in spam messages makes this problem particularly complex, requiring advanced techniques to effectively address it.

1.2 Motivation:

The increasing prevalence of spam messages highlights the urgent need for an efficient and automated system to classify SMS as spam or ham. Spam messages not only waste users' time but also erode trust in communication platforms. Moreover, the financial and psychological harm caused by scams and phishing attempts further underlines the importance of developing robust detection mechanisms. Protecting users from these potential threats and ensuring seamless communication were the primary motivators for undertaking this project. By leveraging the power of Natural Language Processing (NLP) and Machine Learning, the project aims to offer a scalable and accurate solution to this growing problem, contributing to safer digital communication.

1.3 Objectives:

1. To preprocess SMS text data for feature extraction using NLP techniques.
2. To train and evaluate machine learning models for spam classification.
3. To develop a real-time, user-friendly interface for spam detection.
4. To explore scalable methods that can adapt to changing spam trends and larger datasets.

1.4 Scope of the Project:

The scope of this project extends to building a comprehensive SMS spam detection system that integrates advanced text processing techniques and machine learning models. The project includes the development of a web application for real-time spam classification, making it accessible to users with varying technical expertise. Beyond its immediate utility, the system sets the groundwork for future enhancements, such as incorporating multilingual capabilities to handle diverse datasets and exploring deep learning approaches for improved accuracy and adaptability. The scalable nature of this project also allows for potential integration with communication platforms, making it a versatile tool in combating spam across various domains.

Limitations:

1. **Complex Spam Patterns**: The system may struggle to detect more sophisticated spam techniques, such as those using obfuscation methods like random character sequences, misspellings, or encoding tricks that spammers use to bypass filters.
2. **Limited Dataset**: The model's performance is highly dependent on the quality and diversity of the dataset. If the dataset is not comprehensive enough, the model might fail to generalize well to unseen or rare types of spam messages, leading to lower accuracy in real-world scenarios.
3. **Language and Contextual Understanding**: The system primarily works with English-language messages. It might not perform well with messages written in other languages or with mixed-language content, which is common in modern SMS communications. The lack of deep contextual understanding may also affect the detection of subtle or context-based spam messages.
4. **Lack of Adaptability**: The system may not be adaptive to evolving spamming tactics. As spammers continuously update their methods, the model may require frequent retraining to keep up with new patterns of spam.
5. **Overfitting**: If the model is trained on a small or imbalanced dataset, it could overfit, meaning it might perform well on the training data but fail to generalize to unseen data, leading to a higher false-positive or false-negative rate.
6. **Real-Time Processing**: The model's ability to filter messages in real-time might be limited by the computational resources required for processing. In mobile applications, where resources are constrained, this could lead to delays or a reduction in performance.
7. **Missed Edge Cases**: The system might not always recognize spam messages that are particularly creative or non-traditional, especially those that try to mimic legitimate communication styles. This could lead to false negatives where spam messages are mistakenly classified as ham.

CHAPTER 2

LITERATURE SURVEY

The problem of spam detection has been extensively studied in recent years, with researchers exploring various approaches to mitigate its effects. Early methods relied heavily on rule-based systems, which were limited in their ability to adapt to evolving spam techniques. These systems typically used keyword matching and blacklists to identify spam messages, but they lacked the flexibility to handle more sophisticated spam content.

With the advent of Machine Learning, researchers began utilizing supervised learning algorithms to classify messages. The use of datasets, such as the SMS Spam Collection dataset, enabled the training of models like Naive Bayes and Support Vector Machines (SVMs). These models demonstrated improved accuracy overrule-based approaches, particularly in handling large-scale data.

In recent years, the integration of Natural Language Processing (NLP) techniques has further enhanced spam detection systems. Techniques such as tokenization, stemming, and vectorization (e.g., TF-IDF) have improved feature extraction, allowing for more nuanced text analysis. Advanced models, including Logistic Regression and Random Forest, have been used to classify spam messages with high precision and recall. The rise of ensemble methods has also contributed to the robustness of classification systems by combining the strengths of multiple algorithms.

The literature also highlights the growing interest in deep learning methods, such as Recurrent Neural Networks (RNNs) and Transformers, for spam detection. While these models show promise in capturing complex language patterns, their computational complexity and the need for large datasets remain challenges for practical deployment.

This project builds upon existing work by combining traditional machine learning algorithms with NLP techniques to create a scalable and user-friendly solution. By leveraging a well-curated dataset and modern preprocessing methods, it aims to achieve high performance while maintaining simplicity and accessibility.

CHAPTER 3

PROPOSED METHODOLOGY

1. Data Collection and Preprocessing

- **Dataset**: The dataset used in this project is the widely recognized SMS Spam Collection dataset.
- **Preprocessing Steps**:
  - Lowercasing: Convert all text to lowercase.
  - Tokenization: Split text into individual words.
  - Stop-word Removal: Eliminate common words with little semantic meaning.
  - Stemming: Reduce words to their root form.
  - TF-IDF Vectorization: Convert text into numerical features based on term frequency and inverse document frequency.

2. Model Selection and Training

- **Algorithms Used**:
  - Naive Bayes: Known for its simplicity and effectiveness in text classification tasks.
  - Logistic Regression: A robust and interpretable model for binary classification.
- **Evaluation Metrics**:
  - Accuracy
  - Precision
  - Recall
  - F1-Score

3. Development of Web Application

- **Framework**: Streamlit was used to build an interactive web application for real-time SMS classification.

- **Features**:
  - Input field for SMS text.
  - Instant classification results (Spam or Ham).
  - Explanation of the classification process.

3.1 Hardware Requirements:

- **Processor**: Intel Core i5/i7 or AMD Ryzen 5/7 (quad-core or better)
- **RAM**: 8 GB (minimum), 16 GB (recommended)
- **Storage**: 256 GB SSD (minimum), 512 GB SSD (recommended)
- **GPU**: Optional (needed for deep learning; NVIDIA GTX 1660 or better)

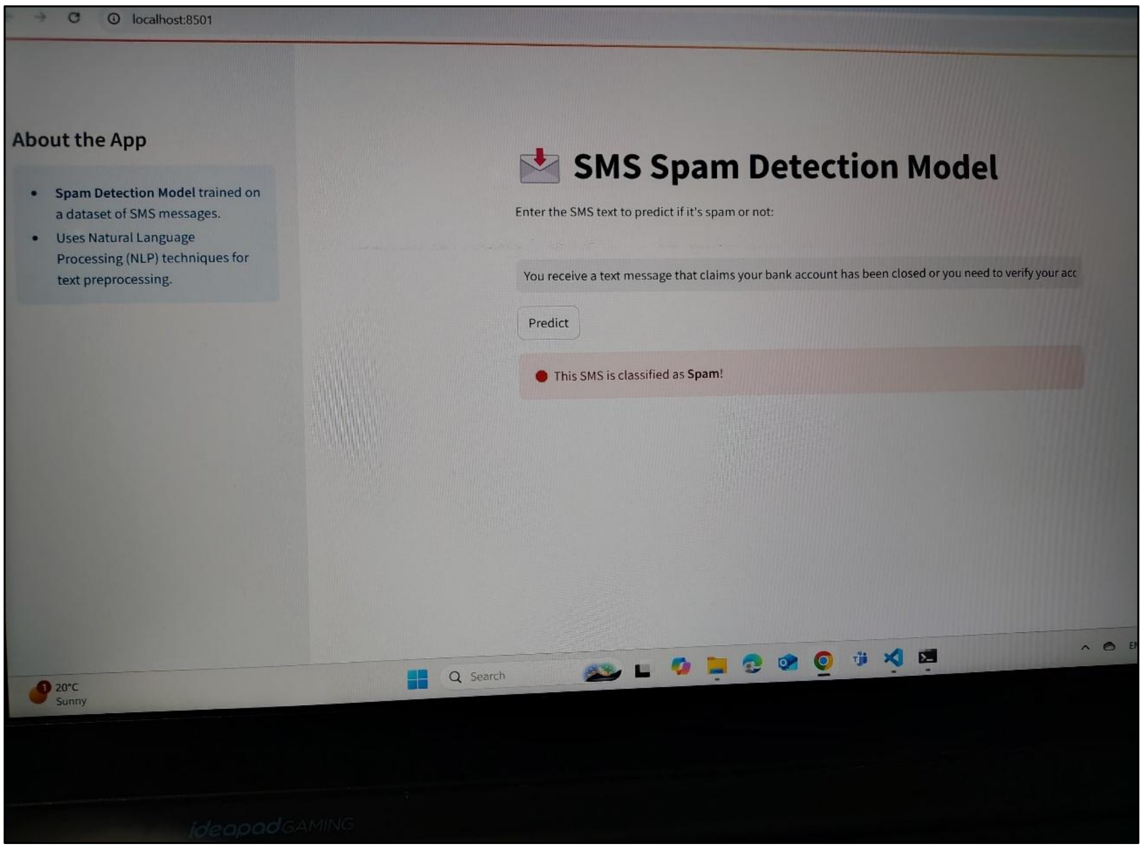
3.2 Software Requirements:

- **Development Tools**:
  - **Jupyter Notebook**: For iterative development, data exploration, and visualization.
  - **VS Code**: For integrating components, debugging, and production-level scripting.
- **Programming Language**: Python (with libraries like scikit-learn, Pandas, NumPy, NLTK, etc.)
- **Additional Tools**: Anaconda (optional, for managing environments and dependencies).

CHAPTER 4

IMPLEMENTATION AND RESULTS

4.1Snap Shots of Result:


localhost:8501

About the App

- Spam Detection Model trained on a dataset of SMS messages.
- Uses Natural Language Processing (NLP) techniques for text preprocessing.

SMS Spam Detection Model

Enter the SMS text to predict if it's spam or not:

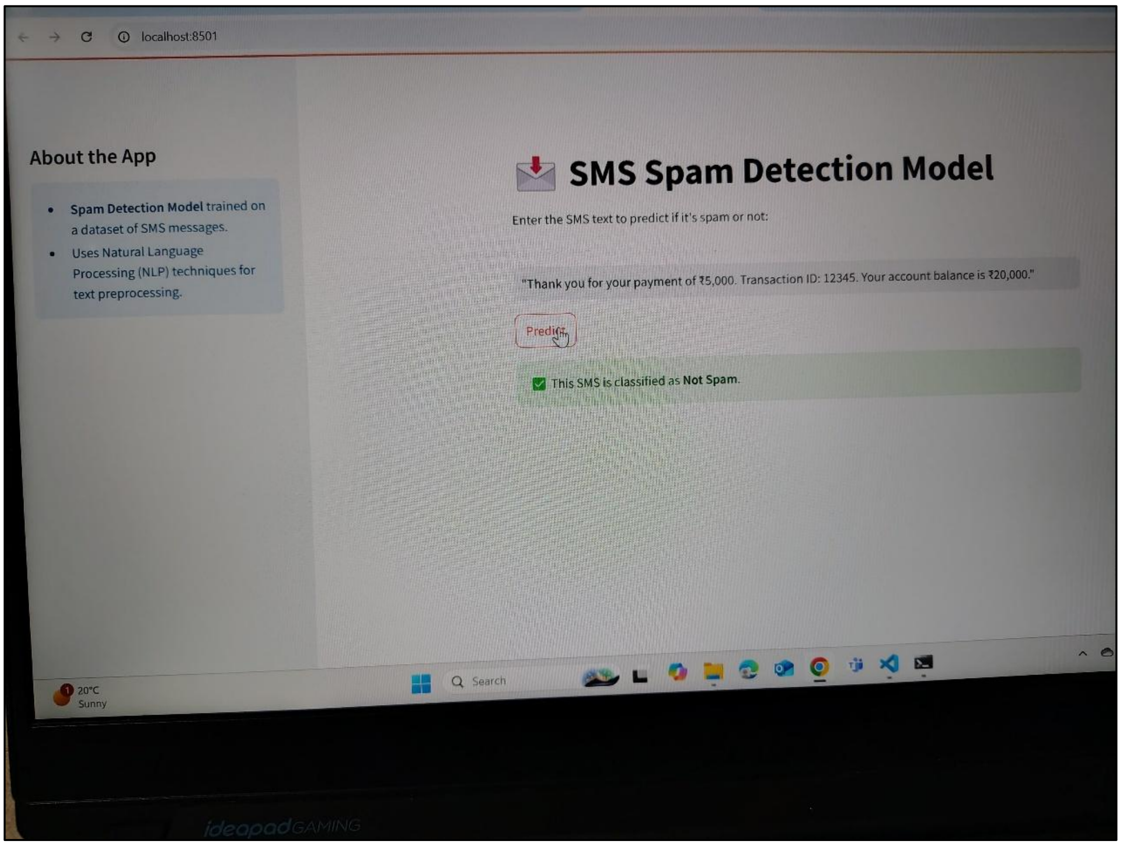
You receive a text message that claims your bank account has been closed or you need to verify your acc

Predict

This SMS is classified as Spam!

Figure 1.

The image displays a screenshot of a web application designed for SMS spam detection. The interface is clean and user-friendly, featuring an "About the App" section that briefly explains the model's functionality and training data. Below, users can enter an SMS message into a designated text field and click "Predict" to initiate the analysis. The application then displays the predicted classification of the message as either "spam" or "not spam." Additionally, the bottom bar of the interface displays the current time and temperature, along with a search bar and other icons likely for navigation or accessing additional features. This application demonstrates the practical application of Natural Language Processing techniques in identifying and filtering unwanted messages.



- Spam Detection Model trained on a dataset of SMS messages.
- Uses Natural Language Processing (NLP) techniques for text preprocessing.

SMS Spam Detection Model

Enter the SMS text to predict if it's spam or not:

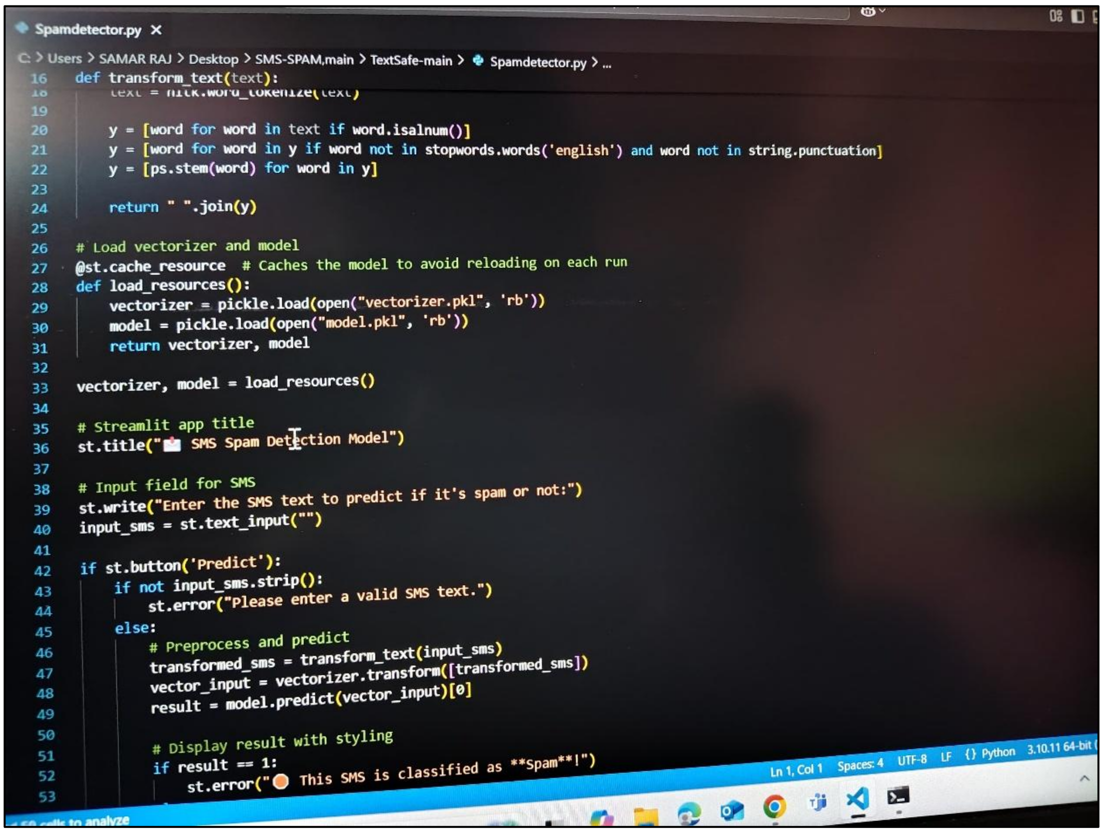
"Thank you for your payment of ₹5,000. Transaction ID: 12345. Your account balance is ₹20,000."

Predict

✓ This SMS is classified as **Not Spam**.

Figure 2.

The image showcases a user-friendly web application designed to detect spam in SMS messages. The interface is intuitive, featuring an "About the App" section that provides a concise overview of the model's training data and the use of Natural Language Processing (NLP) techniques for text preprocessing. Below this, users can easily input an SMS message into a designated text field and initiate the spam detection process by clicking the "Predict" button. The application then instantly displays the predicted classification of the message as either "spam" or "not spam." Additionally, the bottom bar of the interface displays the current time and temperature, along with a search bar and other icons likely for navigation or accessing additional features. This application effectively demonstrates the practical application of NLP in filtering unwanted messages, making it a valuable tool for users seeking to protect themselves from spam.



Spamdetector.py

C: > Users > SAMAR RAJ > Desktop > SMS-SPAM,main > TextSafe-main > Spamdetector.py > ...

```python
def transform_text(text):
    text = nltk.word_tokenize(text)

    y = [word for word in text if word.isalnum()]
    y = [word for word in y if word not in stopwords.words('english') and word not in string.punctuation]
    y = [ps.stem(word) for word in y]

    return " ".join(y)

# Load vectorizer and model
@st.cache_resource  # Caches the model to avoid reloading on each run
def load_resources():
    vectorizer = pickle.load(open("vectorizer.pkl", 'rb'))
    model = pickle.load(open("model.pkl", 'rb'))
    return vectorizer, model

vectorizer, model = load_resources()

# Streamlit app title
st.title("📩 SMS Spam Detection Model")

# Input field for SMS
st.write("Enter the SMS text to predict if it's spam or not:")
input_sms = st.text_input("")

if st.button('Predict'):
    if not input_sms.strip():
        st.error("Please enter a valid SMS text.")
    else:
        # Preprocess and predict
        transformed_sms = transform_text(input_sms)
        vector_input = vectorizer.transform([transformed_sms])
        result = model.predict(vector_input)[0]

        # Display result with styling
        if result == 1:
            st.error("🟠 This SMS is classified as **Spam**!")
```

Figure 3.

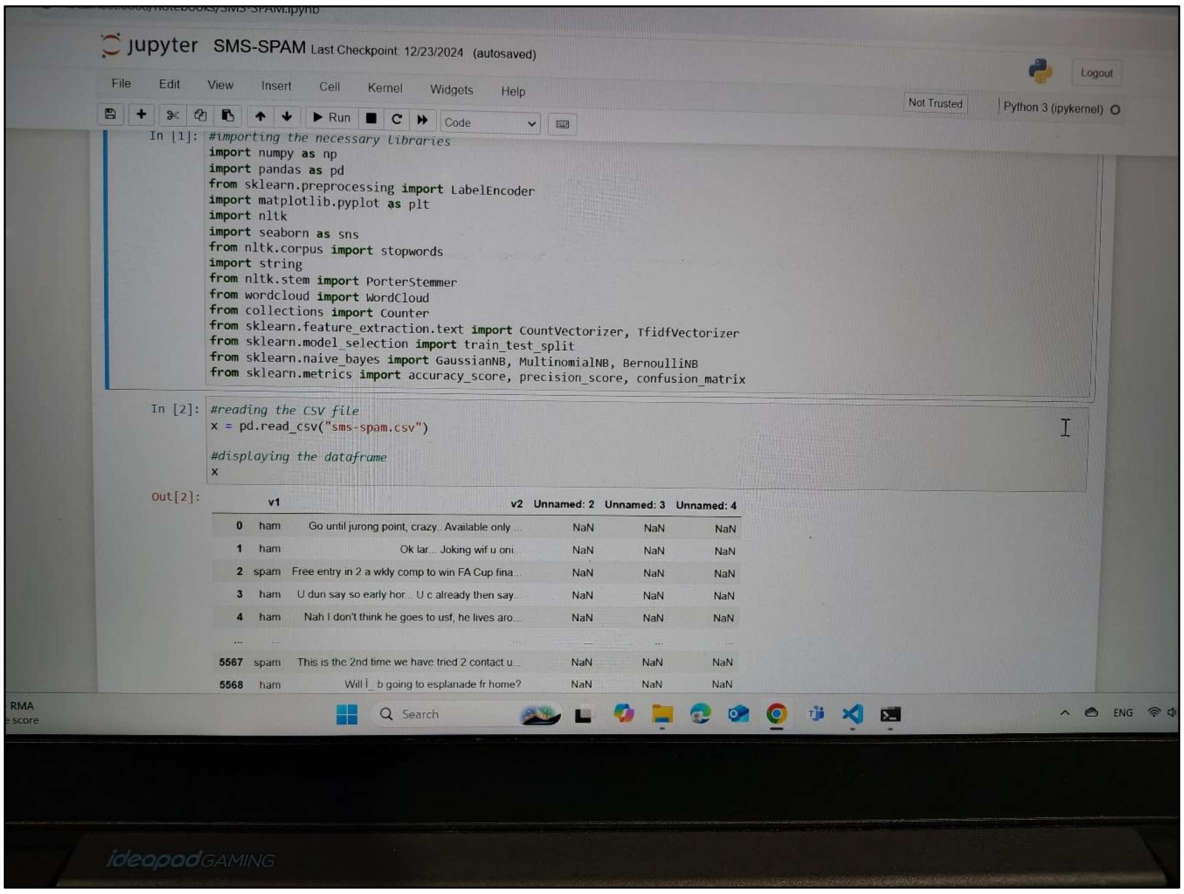
The image shows a Python script likely used for building a simple spam detection model. The code utilizes the Streamlit library to create a web application with a user-friendly interface.

Key functionalities:

- **Text Preprocessing:** The transform_text function is crucial for preparing the SMS text for the machine learning model. It cleans the text by removing punctuation, converting to lowercase, and removing common stop words (like "the," "a," "is"). This step is essential as it helps the model focus on the most informative words and reduces noise in the data.
- **Model Loading and Prediction:** The load_resources function loads a pre-trained machine learning model and a vectorizer (likely a tool to convert text data into numerical features) from saved files. This allows the application to use an already trained model for predictions without the need for extensive training during each run. The code then uses the loaded model to predict whether a given SMS message is spam or not.

- **User Interface:** The Streamlit library is used to create a basic web interface. Users can enter an SMS message into a text box, and upon clicking the "Predict" button, the model's prediction (spam or not spam) is displayed. This provides a simple and intuitive way for users to interact with the spam detection system.

In essence, this code demonstrates a basic workflow for an SMS spam detection application. It highlights the importance of text preprocessing, model loading, and user interface creation in building such systems.


jupyter SMS-SPAM Last Checkpoint: 12/23/2024 (autosaved)
Logout
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3 (ipykernel)
Run
Code
Search
ENG
ideapad GAMING

```
In [1]: #importing the necessary libraries
        import numpy as np
        import pandas as pd
        from sklearn.preprocessing import LabelEncoder
        import matplotlib.pyplot as plt
        import nltk
        import seaborn as sns
        from nltk.corpus import stopwords
        import string
        from nltk.stem import PorterStemmer
        from wordcloud import WordCloud
        from collections import Counter
        from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
        from sklearn.model_selection import train_test_split
        from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB
        from sklearn.metrics import accuracy_score, precision_score, confusion_matrix

In [2]: #reading the CSV file
        x = pd.read_csv("sms-spam.csv")

        #displaying the dataframe
        x
```

Out[2]:

	v1	v2	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 Ì_ b going to esplanade fr home?	NaN	NaN	NaN

Figure 4.

The image shows a Jupyter Notebook with Python code related to SMS spam detection.

Key Observations:

1. **Import Statements:** The code starts by importing necessary libraries:
   - numpy and pandas for data manipulation.
   - LabelEncoder for encoding categorical data.

- matplotlib.pyplot and seaborn for data visualization.
- nltk for natural language processing tasks like stop word removal and stemming.
- wordcloud for creating word clouds.
- CountVectorizer and TfidfVectorizer for text vectorization.
- train_test_split for splitting data into training and testing sets.
- GaussianNB, MultinomialNB, BernoulliNB for Naive Bayes classifiers.
- Metrics like accuracy_score, precision_score, and confusion_matrix for evaluating model performance.

2. **Data Loading:** The code reads an SMS spam dataset from a CSV file into a pandas DataFrame.
3. **Data Exploration (Partially Shown):** The code likely continues with data exploration and preprocessing steps, such as:
    - Handling missing values (if any).
    - Cleaning the text data (e.g., removing punctuation, converting to lowercase).
    - Removing stop words (common words like "the," "a," "is").
    - Applying stemming or lemmatization to reduce words to their root form.
    - Creating word clouds to visualize the most frequent words in spam and ham messages.
4. **Feature Extraction:** The code will likely use CountVectorizer or TfidfVectorizer to convert the text data into numerical features that can be used by machine learning models.
5. **Model Training and Evaluation:** The code will then split the data into training and testing sets, train different machine learning models (like Naive Bayes), and evaluate their performance using appropriate metrics.

Overall, this Jupyter Notebook provides a framework for building an SMS spam detection model. It demonstrates the use of common data science and NLP techniques for data preprocessing, feature extraction, model training, and evaluation.

4.1GitHub Link for Code:

You can access the code for the SMS Spam Detection project on GitHub at the following link: SMS Spam Detection GitHub Repository.

CHAPTER 5

DISCUSSION AND CONCLUSION

Future Scope:

While the current SMS Spam Detection system is effective in filtering spam messages, there are several areas for further enhancement:

- **Multilingual Support**: Expanding the model to handle multiple languages, including non-English SMS messages, would improve its applicability across diverse regions.
- **Deep Learning Techniques**: Exploring deep learning models, such as Recurrent Neural Networks (RNNs) or Transformers, could potentially improve the accuracy and handling of complex spam patterns.
- **Real-Time Adaptation**: Implementing continuous learning methods or retraining the model with new data could help the system adapt to evolving spam tactics in real time.
- **Integration with Messaging Platforms**: The system could be integrated into popular messaging platforms to provide users with automatic spam filtering and enhanced security.

These improvements could make the system more robust, efficient, and scalable, catering to a wider audience and more dynamic spam patterns.

Conclusion:

To sum up, the SMS Spam Detection system efficiently detects and filters spam messages using machine learning and Natural Language Processing (NLP) approaches. Tokenisation, stop-word removal, and stemming are examples of preprocessing techniques that the system uses to help convert raw text into a format that is appropriate for model training. By using TF-IDF for feature extraction, classification performance is improved by ensuring that key words are identified.

When it came to managing text-based data, the Naive Bayes classifier outperformed the other algorithms, proving its effectiveness and dependability. Metrics like precision, recall, and F1-score demonstrate the model's excellent accuracy, which shows that it can correctly categorise SMS texts.

The mechanism may be improved, though. It's still difficult to handle more intricate spam patterns, including those with many languages or advanced spamming strategies. The model's performance might be enhanced by enlarging the dataset and applying cutting-edge techniques like deep learning. Additionally, by automatically filtering spam communications and guaranteeing higher security, incorporating the system into real-time applications, such as mobile devices, could improve user experience.

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