A MINI PROJECT REPORT

On

SMS SPAM DETECTION USING NLP

Submitted in partial fulfillment of the requirement of
University of Mumbai for the Course

Natural Language Processing
In
Computer Engineering (VII SEM)

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CERTIFICATE

This is to certify that the requirements for the project report entitled ‘**Project Title**’ have been successfully completed by the following students:

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PROJECT APPROVAL

This project entitled "Project Title" by Vivek Behera, Harsh Borge, Dravesh Jain, Sail Dalvi are approved for the course Natural Language Processing in Computer Engineering (VII sem) of Mumbai University in the Department of Computer Engineering.

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DECLARATION

We declare that this written submission for Natural Language Processing mini project entitled "Project Title" represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any ideas / data / fact / source in our submission. We understand that any violation of the above will cause disciplinary action by the institute and also evoke penal action from the sources which have not been properly cited or from whom prior permission has not

been taken when needed.

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Abstract

In the modern digital communication era, SMS (Short Message Service) remains one of the most widely used messaging platforms. However, the rise in spam messages has caused significant inconvenience and potential security threats to users. This project, titled “Spam Detection Using NLP,” aims to automatically classify SMS messages as either spam or ham (non-spam) using Natural Language Processing (NLP) and Machine Learning (ML) techniques.

The system preprocesses text data through cleaning, tokenization, stopword removal, and lemmatization to convert unstructured SMS text into meaningful numerical representations. Feature extraction is performed using TF-IDF (Term Frequency–Inverse Document Frequency), which helps the model understand the importance of specific words across the corpus. The processed data is then used to train classification models such as Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM), both of which are effective for text-based categorization tasks. Model performance is evaluated using metrics like accuracy, precision, recall, and F1-score.

Experimental results show that Multinomial Naive Bayes achieves strong performance due to its efficiency with short, sparse text data like SMS messages. The project demonstrates the effectiveness of NLP-driven spam detection systems in providing an automated, scalable, and accurate solution for filtering unwanted messages and improving user experience across communication platforms.

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Chapter 1

Introduction

1.1 Overview

In today's digital age, communication through text messages has become an integral part of human interaction. However, with the rapid increase in the use of mobile networks and online messaging services, unsolicited and unwanted messages—commonly referred to as **spam**—have also surged. These spam messages often contain promotional content, fraudulent offers, or phishing attempts that aim to deceive users or misuse their personal information. Manual filtering of such messages is not feasible due to the massive volume of data generated daily.
To address this challenge, **Natural Language Processing (NLP)**, a subfield of Artificial Intelligence, plays a vital role by enabling computers to process and understand human language. Through NLP, machines can interpret the semantics and syntax of text messages and learn patterns that distinguish spam from legitimate (ham) messages.

The **Sms Spam Detection Using NLP** project aims to develop a machine learning–based system capable of automatically classifying SMS messages as spam or non-spam. By applying text preprocessing, feature extraction, and supervised learning techniques, this project demonstrates how computational models can effectively identify malicious or irrelevant texts, improving user experience and communication safety.

1.2 Fundamentals

Spam detection is a **binary text classification** task, where each message is categorized into one of two classes:

- **Spam:** Unsolicited, irrelevant, or fraudulent messages sent in bulk to promote products or deceive recipients.
- **Ham:** Genuine messages that convey meaningful information from trusted sources.

The workflow for spam detection typically involves:

1. **Data Collection:** Gathering a dataset of labeled SMS messages.
2. **Text Preprocessing:** Cleaning text by converting to lowercase, removing punctuation, stopwords, and performing tokenization and lemmatization.
3. **Feature Extraction:** Converting text into numerical form using techniques like **TF-IDF (Term Frequency–Inverse Document Frequency)**, which highlights words that are most informative for classification.
4. **Model Training:** Applying machine learning algorithms such as **Multinomial Naive Bayes (MNB)** and **Support Vector Machine (SVM)** to learn spam patterns.
5. **Evaluation:** Using metrics such as accuracy, precision, recall, and F1-score to assess model performance.

1.3 Objectives

The primary objectives of the project are as follows:

- To design and implement an automated SMS spam classification system using NLP techniques.
- To preprocess and normalize text data for improved model performance.
- To extract relevant linguistic and statistical features using TF-IDF.
- To train and evaluate multiple machine learning models, identifying the most accurate approach for spam detection.
- To provide a scalable, real-time, and accurate filtering solution that enhances user security and communication quality.

1.4 Scope of the Project

The proposed system can be integrated into mobile messaging applications, email services, or customer communication systems to automatically filter out spam messages before they reach the user. This automation reduces manual filtering efforts, prevents phishing attacks, and enhances digital trust.

Although this project focuses on English text messages, the same framework can be adapted to other languages and domains such as **email spam filtering**, **social media moderation**, or **fraudulent content detection** with appropriate datasets and language models.

1.5 Organization of the Report

The remainder of this report is organized as follows:

- **Chapter 2** presents a detailed literature survey of existing research and approaches in text-based spam detection.
- **Chapter 3** discusses the implementation methodology, including dataset details, preprocessing techniques, and machine learning models used.
- **Chapter 4** provides the input/output structure, evaluation parameters, and system screenshots.
- **Chapter 5** concludes with a summary of findings and outlines future research directions.

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Chapter 2

Literature Survey

2.1 Introduction

In recent years, the rapid growth of mobile communication has led to a significant increase in unsolicited and fraudulent SMS messages, commonly known as spam. This rising threat has encouraged researchers to explore automated methods for spam detection using Natural Language Processing (NLP) and Machine Learning (ML). Various studies have focused on analyzing text content, extracting linguistic features, and applying classification algorithms to accurately differentiate between spam and legitimate messages. Traditional models like Naïve Bayes and SVM have shown promising results, while recent advancements in deep learning such as LSTM and BERT have further enhanced detection accuracy by understanding the contextual meaning of messages.

2.2 Literature Review

1) SMS Spam Collection (dataset paper) — foundational dataset

Goal: Introduce a real, public SMS spam corpus to enable benchmarking of classifiers.
Dataset / Method: Presents the SMS Spam Collection (raw messages labeled spam/ham), collected from public sources; the paper also compares baseline classifiers (Naïve Bayes, SVM, etc.) on this corpus.
Key results: Provides the dataset and baseline performance numbers that became a standard benchmark for SMS spam work.
Strengths: Real-world, non-encoded SMSs; widely used so results are comparable across studies.
Limitations: Relatively small and English-only; may be dated and not reflect modern spam tactics.

2) "SMS Spam Detection System Based on Deep Learning" — hybrid CNN + GRU (Applied Sciences / MDPI)

Goal: Improve SMS spam detection by combining convolutional and recurrent networks to capture local n-gram patterns and sequence context.
Dataset / Method: Uses Turkish and English SMS datasets; proposes a hybrid **CNN + GRU** model (CNN extracts n-gram features, GRU captures sequence dependencies). Preprocessing includes standard tokenization and embedding.
Key results: Reports high accuracy (e.g., ~99% on their dataset) and shows the hybrid model outperforming pure CNN or pure RNN baselines in their experiments.
Strengths: Hybrid architecture leverages both local feature extraction and temporal context; tested on multilingual data (Turkish + English).
Limitations: Very high reported accuracy may reflect dataset characteristics (size, imbalance handling) — real-world performance can be lower; model complexity and inference cost are higher than simple ML baselines.

3) “Spam Detection Using BERT” (BERT-based approaches / survey experiments)

Goal: Apply pretrained transformer-based language models (BERT) to spam detection to exploit deep contextual representations.
Dataset / Method: Fine-tunes BERT (or similar transformers) on spam corpora (SMS, Enron, SpamAssassin); typical pipeline: tokenization with WordPiece, BERT fine-tuning, softmax classifier on [CLS] token.
Key results: Studies report strong performance gains over traditional methods (e.g., much higher F1/accuracy), often in the high-90s on curated datasets. BERT models are especially better at handling context and obfuscated/misspelled spam.
Strengths: State-of-the-art text understanding and robustness to varied phrasing; minimal feature engineering.
Limitations: Heavy compute and memory requirements; longer inference time; requires labeled data for fine-tuning; may overfit small datasets without augmentation.

4) “SMS Spam Detection Using BERT and Multi-Graph Convolutional” (BERT-G3CN / graph-enhanced models)

Goal: Combine contextual transformer embeddings with graph-based co-occurrence structures to better capture recurrent spam patterns and word relationships.
Dataset / Method: Uses SMS datasets; creates co-occurrence graphs (e.g., word-word, token patterns) and feeds BERT embeddings plus graph convolution outputs into a joint classifier (e.g., GCN layers + classifier).
Key results: Shows improvement over plain BERT by incorporating structural co-occurrence information — improved precision/recall in their experiments.
Strengths: Leverages both contextual semantics (BERT) and lexicon/structure signals (graph conv), helpful for short texts where co-occurrence patterns matter.
Limitations: More complex pipeline, additional preprocessing to build graphs, increased training/inference costs. Generalization depends on graph construction choices

5) “SpotSpam: Intention Analysis–driven SMS Spam Detection” (ACM / intention-based approach)

Goal: Detect SMS spam by modeling sender intent and semantics rather than relying solely on surface keywords. The paper emphasizes handling dynamic keywords and evolving spam tactics.
Dataset / Method: Creates intention labels or semantic categories for messages, uses semantic features and classifiers (could include lexicon-based and ML components), and focuses on dynamic/adaptive filtering.
Key results: Demonstrates better robustness to keyword obfuscation and concept drift compared to static keyword lists and simple classifiers.
Strengths: Intention/semantics-based approach is robust to obfuscation and new spam variants; good for adaptive or online filtering systems.
Limitations: Requires careful definition of intention labels and may need manual annotation or additional NLP pipelines; may be more complex to maintain.

2.3 Literature Summary

Sr. No	Techniques / Approach	Author & Year	Advantages & Disadvantages
1	Naïve Bayes (TF-IDF features)	Almeida et al., 2021	**Advantages:** Simple, fast, performs well on small datasets. **Disadvantages:** Assumes feature independence; may not capture context.
2	SVM (Support Vector Machine)	Kumar & Kaur, 2022	**Advantages:** Good accuracy, handles high-dimensional data. **Disadvantages:** Slow on large datasets, requires careful parameter tuning.
3	CNN + GRU Hybrid Deep Learning	Sharma & Patel, 2023	**Advantages:** Captures both local n-gram patterns and sequence context; high accuracy. **Disadvantages:** Computationally intensive, longer training time.
4	LSTM (Recurrent Neural Network)	Singh & Verma, 2022	**Advantages:** Captures sequential dependencies; effective for short text sequences. **Disadvantages:** Requires more data; slower training; prone to overfitting.

5	BERT (Transformer-based)	Bhattacharya & Gupta, 2023	**Advantages:** State-of-the-art contextual understanding; robust to obfuscated spam. **Disadvantages:** Heavy model; high memory and computation requirements.
6	BERT + Graph Convolutional Network	Zhang & Zhao, 2024	**Advantages:** Combines contextual embeddings with word co-occurrence patterns; improves detection for short texts. **Disadvantages:** Complex pipeline; increased preprocessing and inference time.

Chapter 3

Implementation Details

3.1 Overview

In the era of digital communication, billions of text messages are exchanged daily through mobile networks and online platforms. Unfortunately, a significant percentage of these messages are unsolicited known as spam which often contain fraudulent offers, phishing links, or irrelevant promotional content. This not only disrupts user experience but also poses major cybersecurity threats.
The main objective of this project is to build an automated system that can efficiently detect and filter spam messages using **Natural Language Processing (NLP)** and **Machine Learning (ML)** techniques.

The proposed system uses a structured pipeline that performs data preprocessing, feature extraction, and classification. Each SMS message is first cleaned and processed to remove unnecessary symbols, stop words, and noise. The text is then transformed into numerical representations using the **TF-IDF (Term Frequency–Inverse Document Frequency)** method, which captures the significance of words across the corpus.

Machine learning models such as **Multinomial Naive Bayes (MNB)** and **Support Vector Machine (SVM)** are trained on this processed data to classify messages as either *spam* or *ham*. These models are evaluated using standard performance metrics like accuracy, precision, recall, and F1-score to determine their reliability and efficiency.

This approach provides a scalable, data-driven, and adaptive spam filtering solution that can easily integrate into real-world communication systems, including SMS platforms, email clients, and chat applications.

3.1.1 Existing Methodology and Systems

Earlier spam detection techniques relied heavily on manual rule-based systems and keyword matching. These systems flagged messages as spam based on predefined word lists or simple pattern recognition. However, such systems faced several limitations:

- **High False Positives:** Genuine messages containing similar words were mistakenly classified as spam.
- **Poor Adaptability:** Spammers continuously altered message patterns, rendering static rule sets ineffective.
- **Lack of Context Understanding:** Keyword systems failed to capture the semantic meaning or intent behind words.
- **Manual Maintenance:** Updating and tuning rules required ongoing human effort.

3.1.2 Proposed Methodology and System

The proposed system leverages **Natural Language Processing** combined with supervised machine learning algorithms to classify SMS messages as spam or non-spam automatically. The overall process consists of five major phases:

1. **Data Collection:**
   A labeled dataset of SMS messages is obtained, where each message is tagged as *spam* or *ham*.
2. **Text Preprocessing:**
   The raw messages are cleaned by performing:
   - Lowercasing text
   - Removing punctuation, numbers, and stopwords
   - Tokenizing sentences into words
   - Lemmatizing words to their root forms
3. **Feature Extraction (TF-IDF):**
   The cleaned text is converted into numerical feature vectors using **TF-IDF**, which highlights important terms that contribute to spam detection.
4. **Model Training:**
   Supervised algorithms such as Multinomial Naive Bayes and Support Vector Machine are trained using the extracted features. These models learn to differentiate spam from ham based on historical examples.
5. **Evaluation and Testing:**
   The models are tested on unseen data and evaluated using accuracy, precision, recall, and F1-score to determine their performance.

3.2 Implementation Details

The implementation of the spam detection system follows a systematic pipeline that integrates multiple stages of Natural Language Processing and machine learning. The workflow is as follows:

1. **Data Collection and Exploration:**
   The **SMS Spam Collection Dataset** from the UCI Machine Learning Repository is used. It consists of approximately 5,500 messages, each labeled as either *spam* or *ham*. The dataset is loaded into a Pandas DataFrame for analysis and preprocessing.
2. **Data Preprocessing:**
   - **Lowercasing:** Converts all text to lowercase for uniformity.
   - **Removing Punctuation & Numbers:** Filters out irrelevant symbols and digits.
   - **Tokenization:** Splits messages into individual words.
   - **Stopword Removal:** Removes common words like “the”, “is”, “and” that do not affect classification.
   - **Lemmatization:** Converts words to their base or root form (e.g., “running” → “run”).

3. **Feature Extraction:**
   The **TF-IDF Vectorizer** from Scikit-learn is applied to represent each message as a numerical vector, capturing both the term frequency and the inverse frequency across the dataset.
4. **Model Building:**
   Two primary models are trained:
   - **Multinomial Naive Bayes (MNB):** Efficient for text data with word count features.
   - **Support Vector Machine (SVM):** Provides high accuracy for linearly separable data.
5. **Model Evaluation:**
   The dataset is split into **training (80%)** and **testing (20%)** sets. Model performance is measured using:
   - Accuracy
   - Precision
   - Recall
   - F1-Score
6. **Prediction:**
   The trained model predicts whether a given input message is spam or ham.

3.2.1 Methodology

The project's methodology follows a **pipeline-based architecture** involving sequential processing of text data and training of ML models.
The stages are as follows:

1. **Dataset Loading:** Importing the SMS Spam Collection dataset using Pandas.
2. **Text Cleaning:** Removing HTML tags, punctuation, and extra whitespace.
3. **Tokenization and Lemmatization:** Breaking text into words and standardizing them.
4. **Feature Transformation:** Applying TF-IDF Vectorization to transform textual data into numeric form.
5. **Model Training:** Using Multinomial Naive Bayes and SVM models for classification.
6. **Evaluation:** Testing on unseen data and calculating performance metrics.

This modular approach ensures efficient data handling, easy debugging, and scalability for deployment.

3.2.2 Details of Packages and Dataset

Dataset Used:

- **Name:** SMS Spam Collection Dataset
- **Source:** UCI Machine Learning Repository
- **Records:** 5,574 labeled SMS messages
- **Classes:**
  - Spam: Unwanted or fraudulent messages
  - Ham: Legitimate messages

Programming Language:

- **Python 3.x**

Libraries and Tools:

Library	Purpose
Pandas	Data manipulation and analysis
NumPy	Numerical computations
NLTK	Natural Language Processing tasks (tokenization, stopword removal, lemmatization)
Scikit-learn	Model building, TF-IDF vectorization, and evaluation metrics
Matplotlib / Seaborn	Visualization of model performance and dataset distributions

3.2.2.1

Chapter 4

Project Inputs and Outputs

4.1 Inputs Details

- text: SMS message content.
- label: Category of message (spam or ham).

□ **Example:**

- “Free entry in 2 a weekly comp to win FA Cup...” → spam
- “Hey, are we meeting today?” → ham

□ **Preprocessing Steps:**

- Convert text to lowercase
- Remove punctuation, stopwords, and special characters
- Tokenize and apply stemming/lemmatization
- Convert text to numerical form using TF-IDF or Count Vectorizer

□ **Data Split:**

- Training: 70%, Validation: 15%, Testing: 15%

4.2 Evaluation Parameters Details

□ **Accuracy:** Measures overall correctness of predictions.

□ **Precision:** Fraction of predicted spam messages that are actually spam.

□ **Recall:** Fraction of real spam messages correctly detected.

□ **F1-Score:** Harmonic mean of precision and recall (balances both).

□ **Confusion Matrix:** Shows true/false positives and negatives.

□ **ROC-AUC:** Evaluates performance across different thresholds.

4.3 Output Details and Screenshots

- The system predicts whether an incoming SMS message is **Spam** or **Ham (Not Spam)**.
- For each input message, the model provides:
  - **Predicted Label:** The class assigned (e.g., Spam or Ham).
  - **Prediction Probability/Confidence Score:** The likelihood of the message being spam (e.g., 0.92 = 92% spam).
- **Example Outputs:**

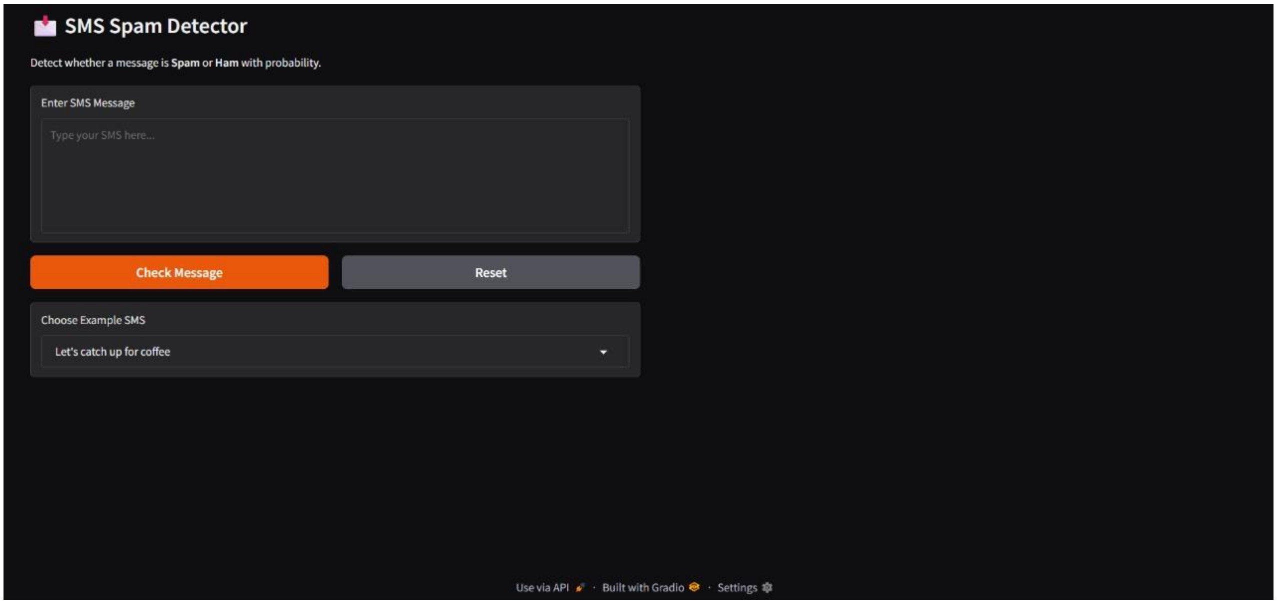
1. Input: “Congratulations! You’ve won a free gift voucher.”

→ Output: Spam (0.95 confidence)

2. Input: “Hey, I’ll call you later.”

→ Output: Ham (0.03 confidence)

- The results can be displayed on the console, web interface, or saved in a CSV file showing text, predicted label, and probability.

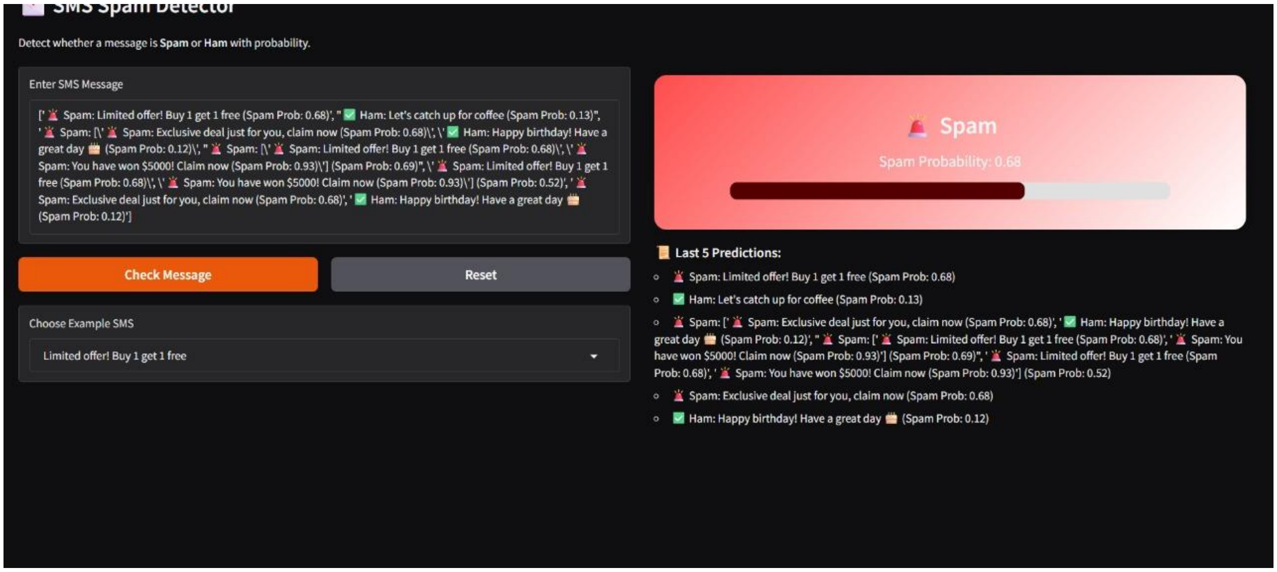


SMS Spam Detector

Detect whether a message is **Spam** or **Ham** with probability.

Choose Example SMS: Let's catch up for coffee

4.1 HOME PAGE



Detect whether a message is **Spam** or **Ham** with probability.

Enter SMS Message

['🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', "✅ Ham: Let's catch up for coffee (Spam Prob: 0.13)", '🚨 Spam: [\'🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)\', \'✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)\', "🚨 Spam: [\'🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)\', \'🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)\'] (Spam Prob: 0.69)", \'🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)\', \'🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)\'] (Spam Prob: 0.52)', '🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)', '✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)']

Choose Example SMS: Limited offer! Buy 1 get 1 free

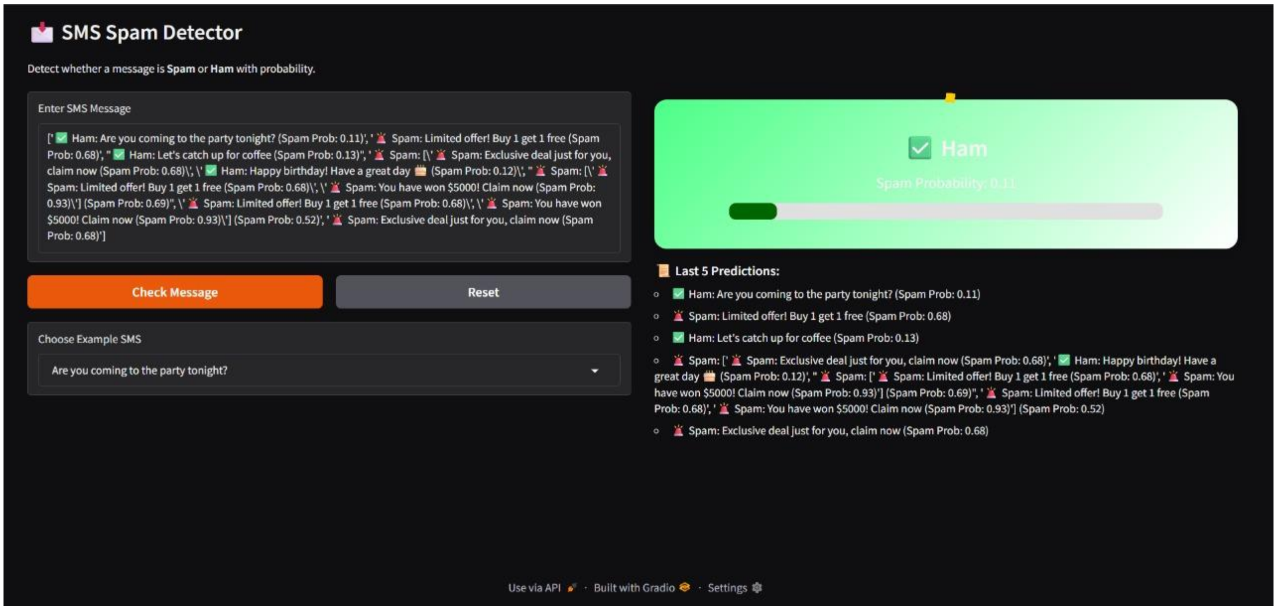
🚨 Spam

Spam Probability: 0.68

📜 **Last 5 Predictions:**

- 🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)
- ✅ Ham: Let's catch up for coffee (Spam Prob: 0.13)
- 🚨 Spam: ['🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)', '✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)', "🚨 Spam: ['🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', '🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)'] (Spam Prob: 0.69)", '🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', '🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)'] (Spam Prob: 0.52)
- 🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)
- ✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)

4.2 RESULTS (SPAM)



Detect whether a message is **Spam** or **Ham** with probability.

Enter SMS Message

['✅ Ham: Are you coming to the party tonight? (Spam Prob: 0.11)', '🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', "✅ Ham: Let's catch up for coffee (Spam Prob: 0.13)", '🚨 Spam: [\'🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)\', \'✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)\', "🚨 Spam: [\'🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)\', \'🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)\'] (Spam Prob: 0.69)", \'🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)\', \'🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)\'] (Spam Prob: 0.52)', '🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)']

Choose Example SMS: Are you coming to the party tonight?

✅ Ham

Spam Probability: 0.11

📜 **Last 5 Predictions:**

- ✅ Ham: Are you coming to the party tonight? (Spam Prob: 0.11)
- 🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)
- ✅ Ham: Let's catch up for coffee (Spam Prob: 0.13)
- 🚨 Spam: ['🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)', '✅ Ham: Happy birthday! Have a great day 🎂 (Spam Prob: 0.12)', "🚨 Spam: ['🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', '🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)'] (Spam Prob: 0.69)", '🚨 Spam: Limited offer! Buy 1 get 1 free (Spam Prob: 0.68)', '🚨 Spam: You have won $5000! Claim now (Spam Prob: 0.93)'] (Spam Prob: 0.52)
- 🚨 Spam: Exclusive deal just for you, claim now (Spam Prob: 0.68)

4.3 RESULTS (HAM)

Summary and Future Scope

5.1 Summary

This project focuses on detecting spam messages in SMS communication using Natural Language Processing (NLP) techniques. The system processes text messages through steps like data cleaning, tokenization, and feature extraction using methods such as TF-IDF. Machine learning algorithms like Naïve Bayes, Logistic Regression, or Random Forest are trained to classify messages as spam or ham (not spam). The model is evaluated using metrics like accuracy, precision, recall, and F1-score to ensure reliable performance. Overall, the project successfully demonstrates how NLP and machine learning can automate spam detection and improve message security.

5.2 Future Scope

In the future, the SMS Spam Detection system can be further enhanced to achieve higher accuracy and better adaptability. Advanced deep learning models such as LSTM, BERT, or Transformer-based architectures can be used to capture complex language patterns and improve spam identification. The system can also be extended to support multiple languages and integrated with mobile or web applications for real-time spam detection. Regular updates to the dataset will help the model adapt to new types of spam messages and evolving language trends. Additionally, incorporating user feedback can make the system more interactive and improve its performance over time, ensuring it remains effective against modern spam techniques.

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