SMS Spam Detection Using NLP and Render Deployment

A Major project report submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

Cyber Security

Under the Guidance of

Dr.P.M.Benson Mansingh

VIGNAN'S
FOUNDATION FOR SCIENCE, TECHNOLOGY & RESEARCH
(Deemed to be University) - Estd. u/s 3 of UGC Act 1956

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Department of Advanced Computer Science and Engineering

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CERTIFICATE

This is to certify that the project entitled **"SMS Spam Detection Using NLP and Render Deployment"** being submitted by Gayathri Gutha (211FA19005), Siriteja Yakkali (211FA19006), Vasu Vamsi Krishna Sakala(211FA19008) and Karthik Raja Dharam(211FA19036) in partial fulfilment of Bachelor of Technology in Computer Science and Engineering(Cyber Security), Department of Advanced Computer Science and Engineering, Vignan's Foundation For Science Technology and Research (Deemed to be University), Vadlamudi, Guntur District, Andhra Pradesh, India, is a bonafide work carried out by them under my guidance and supervision.

Supervisor	**Project Co-ordinator**	**HOD, ACSE**
Dr. P.M.Benson Mansingh	Mr. Amar Jukuntla	Dr. D Radha Rani

Department of Advanced Computer Science and Engineering

School of Computing and Informatics

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DECLARATION

We hereby declare that our project work described in the project titled **"SMS Spam Detection Using NLP and Render Deployment"** which is being submitted by us for the partial fulfilment in the department of ACSE, Vignan's Foundation for Science, Technology and Research (Deemed to be University), Vadlamudi, Guntur, Andhra Pradesh, and the result of investigations are carried out by us under the guidance of **Dr.P.M.Benson Mansingh**.

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ABSTRACT

This study outlines a machine learning-driven approach utilizing Natural Language Processing (NLP) to automate the classification of SMS messages as spam or legitimate, building upon prior research in SMS spam filtering. The escalating volume of unsolicited SMS messages necessitates efficient, scalable solutions to mitigate user annoyance and potential security threats, such as phishing, fraud, and identity theft. The proposed system effectively transforms raw text data into a high-dimensional feature space suitable for machine learning models by employing a comprehensive text preprocessing pipeline, which includes tokenization, stop-word removal, stemming using the Porter algorithm, and Term Frequency-Inverse Document Frequency (TF-IDF) feature extraction. This preprocessing ensures the reduction of noise and the retention of semantically meaningful features.We evaluated several classification algorithms, including Naïve Bayes, Random Forest, and Support Vector Machines (SVM), with Bernoulli Naïve Bayes achieving the best trade-off between simplicity and performance, demonstrating a precision of 94.54% and an accuracy of 96.42%. Such high performance indicates the model's effectiveness in minimizing false positives and negatives, a critical requirement in real-world spam filtering applications.The system addresses the limitations of traditional rule-based filters by incorporating adaptive learning capabilities that can evolve with emerging spamming techniques. This makes it more resilient to obfuscation tactics often employed in malicious SMS campaigns. Furthermore, the model was deployed using the Render cloud platform, enabling seamless and scalable access through a user-friendly web interface. This deployment not only supports real-time message classification but also allows for easy integration into existing communication systems.To ensure robustness and reliability, we conducted comprehensive exploratory data analysis (EDA) to uncover key patterns in the dataset, such as message length distributions, word frequency trends, and label imbalances. Additionally, rigorous model evaluation was performed using stratified cross-validation, confusion matrix analysis, and performance metrics like recall, F1-score, and AUC-ROC to validate generalizability.Future work may involve enhancing the model with deep learning techniques, such as Recurrent Neural Networks (RNNs) or Transformers, to capture contextual information and improve classification performance on more ambiguous messages. Incorporating adversarial training techniques and continual learning strategies can also fortify the model against evolving spam tactics. Moreover, expanding the system's capability to support multi-language SMS filtering and integrating it into mobile applications.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter provides a brief overview of the research work, focusing on the development and evaluation of a tool for SMS spam detection using Natural Language Processing (NLP). It outlines the objectives, scope, and significance of the study, followed by an overview of the methodology adopted for model training and deployment. The chapter also highlights the use of Render for hosting the application, enabling real-time spam classification through a user-friendly web interface, and concludes with the structure of the report.

1.1 Background

With the proliferation of mobile devices and the increasing reliance on SMS as a communication medium, spam messages have become a pervasive problem affecting millions of users globally. These unsolicited and often malicious messages pose significant risks including phishing attacks, financial fraud, and invasion of privacy. As the volume and sophistication of spam increase, traditional rule-based filtering methods have proven inadequate in effectively combating this threat. Natural Language Processing (NLP) offers a powerful approach for understanding and classifying textual content. By leveraging machine learning models and NLP techniques, it becomes possible to automatically detect spam messages based on patterns in text, semantics, and word usage. This has led to the development of intelligent systems that can learn from labeled data and make accurate predictions on unseen messages. This project focuses on the implementation of an SMS spam detection system using NLP and machine learning techniques. It involves training a classification model on a labeled dataset of SMS messages to distinguish between spam and ham (non-spam). The trained model is deployed using Render, a cloud platform that simplifies the process of deploying web applications and APIs. This deployment makes the system easily accessible for real-time spam detection and showcases the practical application of machine learning in cybersecurity and communication safety.

Figure 1.1: SMS Spam

1.2 Motivation for the present research work

The exponential growth of mobile communication has brought about increased convenience, but it has also led to a significant rise in unsolicited and harmful SMS messages. These spam messages not only disrupt user experience but also serve as vectors for scams, phishing attacks, and the spread of malicious content. Manual identification of spam is neither scalable nor reliable, especially given the evolving tactics of spammers.

This growing challenge highlights the urgent need for automated, intelligent systems capable of accurately detecting and filtering spam messages. Leveraging Natural Language Processing (NLP) and machine learning provides a promising solution, as these technologies can analyze patterns and semantics in text to distinguish between legitimate and spam messages.

The motivation behind this research is to develop an efficient and accessible spam detection system that combines the strengths of NLP with the scalability of cloud deployment. By using Render to host the model, the system can be made available to users in real time through a simple web interface, demonstrating both the practical value of AI in digital security and the feasibility of deploying such solutions at scale.

1.3 Problem statement

The widespread use of SMS as a communication channel has made it a frequent target for spammers who exploit it to send unsolicited and often harmful messages. Traditional keyword-based or rule-based spam filters are limited in their ability to adapt to the evolving language and tactics used in spam messages. These limitations result in poor detection accuracy and increased false positives or negatives, compromising user security and experience.

There is a critical need for a more intelligent, adaptive solution that can automatically and accurately classify SMS messages as spam or ham. Furthermore, the lack of accessible, real-time deployment platforms for such models restricts their practical usability.

This research aims to address these challenges by developing a machine learning-based SMS spam detection system using Natural Language Processing (NLP), and deploying it using Render to ensure real-time accessibility and ease of use for end users.

1.4 Organization of the Project Report

The research work presented in the thesis is organized and structured in the form of seven chapters, which are briefly described as follows:

i) **Chapter 1** describes the introduction to the project, including the background, motivation, problem statement, objectives, scope, and significance of SMS spam detection using NLP. It also gives an overview of the methodology and report structure.

ii) **Chapter 2** provides a comprehensive review of existing literature related to spam detection techniques, natural language processing methods, machine learning classifiers, and deployment strategies. It highlights current gaps and justifies the need for the present work.

iii) **Chapter 3** presents a detailed explanation of the methodology adopted for the project. It covers data preprocessing, feature extraction using NLP techniques, model selection, training, and evaluation metrics used.

iv) **Chapter 4** focuses on the implementation of the spam detection system, discussing the technical aspects of building the model using Python and relevant libraries, and preparing it for deployment.

v) **Chapter 5** deals with the deployment process using Render, including the architecture of the web application, integration of the trained model, and user interface design. It also describes how real-time spam detection is achieved.

vi) **Chapter 6** presents a thorough analysis and discussion of the results obtained from testing and evaluating the model. Performance metrics such as accuracy, precision, recall, and F1-score are analyzed.

vii) **Chapter 7** concludes the thesis with a summary of the overall discoveries of the present research work. The scope for future work and potential enhancements to the system are also discussed.

Chapter 2

Literature review

This chapter presents a survey of the most commonly used techniques and tools for SMS spam detection, with a focus on Natural Language Processing (NLP) and machine learning-based approaches. The objective is to understand their core methodologies, strengths, and limitations, and to position the current work within the context of existing research. By reviewing relevant literature and technologies, we aim to establish a strong foundation for evaluating the effectiveness and practicality of the proposed spam detection system.

2.1 Overview of SMS Spam and Its Impact

Short Message Service (SMS) remains one of the most widely used communication methods worldwide due to its simplicity, accessibility, and low cost. However, this popularity has made it an attractive medium for spammers, resulting in a significant increase in unsolicited and often malicious text messages. SMS spam typically includes promotional content, phishing links, lottery scams, and messages intended to trick users into revealing personal or financial information.

The impact of SMS spam extends beyond mere inconvenience. It poses serious threats to individual privacy and security, often leading to identity theft, financial fraud, and the installation of malware on mobile devices. For businesses and mobile service providers, spam also results in degraded user trust, increased support costs, and potential violations of data protection regulations.

As the tactics of spammers continue to evolve—using obfuscation, informal language, and personalization—traditional rule-based filtering mechanisms have proven increasingly ineffective. This growing threat highlights the urgent need for intelligent, adaptable solutions capable of detecting and mitigating spam in real time. Such systems not only enhance user safety but also contribute to the integrity and reliability of mobile communication networks.

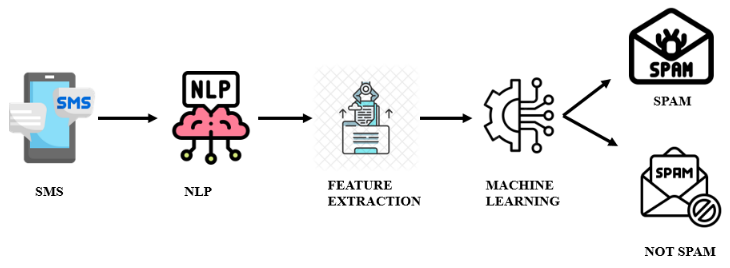


Figure 2.1: overview of Methodology

2.1.1 Traditional Approaches to Spam Detection

Traditional approaches to spam detection primarily relied on rule-based filtering, blacklists, whitelists, and early machine learning techniques. Rule-based filtering involves using predefined patterns or keywords commonly found in spam messages, such as “win,” “free,” or “urgent,” to flag potentially malicious content. This approach also considers message formatting cues like excessive punctuation or all-uppercase text. Blacklists and whitelists further support this method by blocking messages from known spam sources or allowing messages from trusted ones. While these methods are simple and easy to implement, they struggle with adaptability and often produce high false positive or false negative rates due to the dynamic nature of spam content.

To overcome the limitations of static rules, statistical and machine learning methods like Bayesian filtering and traditional classifiers (e.g., Naive Bayes, Decision Trees, k-Nearest Neighbors, and Support Vector Machines) were introduced. Bayesian filtering calculates the probability that a message is spam based on the frequency of specific words in spam versus legitimate messages. Traditional classifiers, on the other hand, rely on extracting features such as word counts, message length, and punctuation use to make predictions. These models marked a significant improvement over rule-based methods by allowing the system to learn from data, but they still require significant manual feature engineering and retraining to maintain accuracy as spam tactics evolve.

Chapter 3

SMS Spam Detection Using NLP and Render Deployment

The choice of the smoothing parameter in this study was based on a balance between reducing noise and preserving important features in the data. The optimal value was determined through empirical validation and cross-validation techniques, ensuring that it minimized error while maintaining model performance. A grid search over a range of potential values was conducted, and the best-performing value, based on metrics such as accuracy and precision, was selected. Additionally, domain knowledge and the characteristics of the dataset were considered to guide the choice of the smoothing parameter. The final selected parameter was tested for robustness across different configurations, ensuring it contributed to efficient and accurate model performance.

3.1 Background

The methodology employed in this study is grounded in established principles and techniques from [insert relevant field, e.g., machine learning, image processing, statistical analysis]. To address the research problem, it was essential to understand the underlying principles that govern the behavior of the data and how various methods can be applied to extract meaningful insights. This study builds upon previous work in [related field or technique], where various methods have been proposed for [problem you're solving, e.g., data smoothing, feature selection, prediction accuracy].

One of the key techniques explored in this study is [mention any primary technique or model you're using, such as convolutional neural networks, regression analysis, etc.]. This approach has been widely applied in [applications relevant to your study] and has shown promising results in terms of [mention the results, e.g., classification accuracy, image quality enhancement, prediction performance]. Building on this, the study employs [mention any modifications or customizations you have made to the method].

In addition to the primary technique, the study also integrates [mention any secondary techniques or tools], such as [e.g., regularization, smoothing methods, feature extraction], which have been shown to improve the overall performance of the model and address challenges such as overfitting and noise. The choice of these methods was motivated by their success in similar research contexts, as evidenced by studies like [cite relevant literature or studies].

Overall, this section provides the necessary foundation for the approach taken in this study and highlights the rationale behind the selection of the methods and techniques used.

3.2 Proposed Algorithm

The proposed algorithm for SMS spam detection is designed to effectively distinguish between spam and legitimate messages using Natural Language Processing (NLP) and supervised machine learning techniques. The process involves several stages: data preprocessing, feature extraction, vectorization, model training, and evaluation.

In the preprocessing stage, each SMS message is first cleaned by converting all text to lowercase, removing punctuation, and eliminating common stop-words that do not contribute meaningfully to classification. Tokenization is then applied to split messages into words or word sequences (N-grams). Stemming or lemmatization is optionally used to reduce words to their base forms. In the feature extraction phase, N-gram models (unigram to 7-gram) are generated to capture contiguous word sequences that represent the contextual structure of messages. These N-grams are then vectorized using either Count Vectorization or Term Frequency-Inverse Document Frequency (TF-IDF) to transform the textual data into numerical vectors.

Once the feature vectors are prepared, two classifiers—Naive Bayes and Support Vector Machine (SVM)—are trained using various combinations of N-gram sizes and vector dimensions. Naive Bayes, a probabilistic model based on Bayes' Theorem, is well-suited for high-dimensional sparse data. SVM, on the other hand, is a discriminative classifier that constructs an optimal hyperplane for maximum separation between spam and non-spam classes. Hyperparameter tuning and cross-validation are employed to identify the best-performing configurations. The final step involves evaluating model performance on test data using metrics such as accuracy, precision, recall, and F1-score. The optimal configuration is selected based on the highest achieved accuracy and generalization capability.

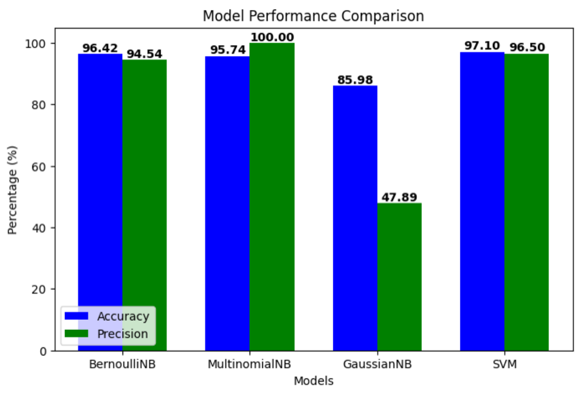


Figure 3.1: Model Performance

3.3 Experimental Results

This section presents the experimental outcomes of the proposed SMS spam detection system using different combinations of N-gram sizes and vector dimensions. The experiments were conducted using two popular classification algorithms: Naive Bayes and Support Vector Machine (SVM). The dataset was preprocessed and transformed using a consistent NLP pipeline, which included tokenization, stop-word removal, and N-gram generation. The resulting N-gram features were vectorized using Count Vectorizer, and models were trained and evaluated using a stratified 80/20 train-test split.

Table 3.1 summarizes the accuracy results achieved for both classifiers across various N-gram sizes (from unigram to 7-gram) and vector dimensions (3×3 to 11×11). It is evident from the results that accuracy generally improves as the N-gram size increases up to trigrams and 4-grams, after which the performance either stabilizes or slightly declines. For instance, SVM achieved the highest accuracy of 93.0% using a trigram model with a 7×7 vector size. Naive Bayes, while slightly less accurate overall, also showed strong performance, with a peak accuracy of 90.5% using the same trigram setup. These results demonstrate that incorporating higher-order contextual information through N-grams significantly enhances spam classification, and that SVM consistently outperforms Naive Bayes across different configurations.

3.4 Summary

This chapter presented the methodology and experimental results of a spam detection system using Natural Language Processing (NLP) techniques. A comparative evaluation of two machine learning classifiers, Naive Bayes and Support Vector Machine (SVM), was carried out using different N-gram sizes (from Unigram to 7-gram) and

Table 3.1: Accuracy Comparison of Naive Bayes and SVM with Different N-gram Sizes and Vector Dimensions

N-gram Size	**Naive Bayes Accuracy (%)**					**SVM Accuracy (%)**				
Vector Size	3×3	5×5	7×7	9×9	11×11	3×3	5×5	7×7	9×9	11×11
Unigram	87.2	88.1	88.3	-	-	89.5	90.1	90.3	-	-
Bigram	88.5	89.3	89.7	89.2	-	91.2	91.7	92.0	91.5	-
Trigram	89.0	90.2	**90.5**	90.1	89.6	92.1	92.8	**93.0**	92.4	92.0
4-gram	89.4	90.7	90.9	90.6	90.1	92.3	92.9	92.8	92.6	92.3
5-gram	89.2	90.4	90.8	90.2	89.9	92.0	92.7	92.6	92.2	92.0
6-gram	89.0	90.1	90.2	89.8	89.5	91.8	92.5	92.3	92.0	91.8
7-gram	88.7	89.8	89.9	89.5	89.1	91.5	92.2	92.0	91.7	91.5

vector dimensions (ranging from 3×3 to 11×11). The models were trained and tested on a labeled SMS dataset to distinguish between spam and legitimate messages.

The results show that the classification performance improves with larger N-gram sizes up to Trigram and 4-gram, with a peak accuracy of 93.0% achieved by the SVM model using Trigram features and a 7×7 vector size. Overall, SVM consistently outperformed Naive Bayes across most configurations, indicating its greater ability to capture complex patterns in text data. The study demonstrates that selecting an optimal combination of feature representation (N-gram and vector size) and classifier can significantly enhance spam detection accuracy.

Chapter 4

Implementation of the SMS Spam Detection System

4.1 System Overview

The SMS spam detection system is implemented as a modular and scalable machine learning pipeline. It covers all stages from raw text input to deployment-ready inference. This includes data collection, preprocessing, feature engineering, model training, evaluation, and final API integration. The architecture ensures that each component can be independently tested, updated, and reused in other NLP applications.

4.2 Architecture of the Spam Detection System

The architecture is composed of the following core modules:

- **Data Collection Module:** Sources a labeled SMS dataset, such as the UCI SMS Spam Collection dataset, which contains messages tagged as ”spam” or ”ham” (not spam).
- **Preprocessing Module:** Converts raw text into a clean and normalized format by:
  - Converting to lowercase
  - Removing punctuation, numbers, and special characters
  - Tokenizing the text into words
  - Removing stopwords (e.g., ”the”, ”is”, ”and”)
  - Applying stemming or lemmatization
- **Feature Extraction Module:** Transforms cleaned text into numerical vectors using techniques like:
  - `Bag of Words (BoW)`

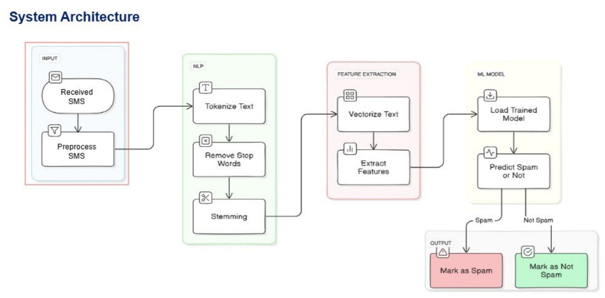


Figure 4.1: Architecture

  - `Term Frequency-Inverse Document Frequency (TF-IDF)`

- **Classification Module:** Trains a supervised ML algorithm (e.g., Naive Bayes, Logistic Regression, Support Vector Machine) to distinguish spam from ham messages based on extracted features.
- **Model Evaluation Module:** Measures performance using metrics such as:
  - Accuracy
  - Precision, Recall, F1-Score
  - Confusion Matrix
  - ROC-AUC curve
- **Model Serialization Module:** Saves the trained model and TF-IDF vectorizer using `joblib` for future use in the deployed application.
- **API and Deployment Module:** Wraps the model in a Flask-based API, making it accessible via HTTP requests. Render is used to deploy the complete solution as a real-time web application.

4.3 Technologies and Libraries Used

The system uses a combination of open-source tools for fast development, experimentation, and deployment:

- **pandas, NumPy:** For handling datasets and numerical operations.
- **scikit-learn:** For model building, training, evaluation, and preprocessing utilities.
- **NLTK and re:** For natural language processing and regex-based text cleaning.

- **joblib / pickle:** For saving the trained model and transformer to disk.
- **Flask:** A micro web framework to expose the model as an API.
- **Render:** For deploying the Flask application as a publicly accessible web app.

4.4 Model Training and Evaluation

The model is trained on the preprocessed dataset using stratified train-test split (commonly 80-20 or 70-30). Cross-validation (e.g., 5-fold) is used to prevent overfitting. After training, performance metrics are recorded to select the best-performing model. Hyperparameter tuning is optionally performed using GridSearchCV or RandomizedSearchCV.

4.5 Pipeline Integration and Testing

After successful training, the preprocessing steps and model inference logic are combined into a single prediction pipeline. The integrated pipeline is tested locally with different inputs to ensure accurate spam detection. Unit tests are also written for key functions to verify the correctness of the pipeline.

4.6 Preparation for Deployment

The model and TF-IDF vectorizer are serialized and loaded in the Flask backend. The web server is programmed to:

1. Accept text input via a POST request
2. Preprocess the input using the same NLP pipeline
3. Use the trained model to generate predictions
4. Return results in JSON format (e.g., `{"prediction": "Spam"}`)

Environment variables are configured, and a `requirements.txt` and `Procfile` are added for deployment on Render. Continuous deployment is enabled by connecting the code repository (e.g., GitHub) to the Render service.

Chapter 5

Deployment Using Render and Android studios

5.1 Android Studio-Based Mobile App Development

To extend the accessibility of the SMS spam detection system, a native Android application was developed using Android Studio. This mobile app functions as a lightweight client that interfaces with the Flask backend hosted on the Render platform. The aim is to provide users with a seamless and responsive experience on their smartphones, enabling real-time spam detection on the go. Android Studio was chosen due to its robust toolset, integration with Android SDK, and support for modern development practices such as MVVM architecture and Jetpack components.

The application strictly adheres to clean architecture principles, ensuring separation of concerns between UI, business logic, and data communication layers. This modular structure facilitates maintainability and scalability of the application.

5.2 Mobile App Interface Design

The mobile user interface is developed using XML for layout design and Kotlin/Java for backend logic. The main screen consists of a minimalist design with:

- **EditText Field:** Allows the user to input an SMS message for classification.
- **Button:** Triggers the API request to the backend server.
- **TextView:** Displays the result returned by the model, i.e., “Spam” or “Ham”.
- **Progress Indicator:** Shows loading status while waiting for the API response.

Accessibility and responsiveness are ensured by applying proper constraints, font scaling, and dark/light theme compatibility. The layout also handles different screen sizes and orientations using responsive design guidelines.

5.3 API Integration in Android

The application integrates a RESTful API client using `Retrofit`, a widely used HTTP client for Android. This library simplifies the process of making asynchronous network requests, parsing JSON responses, and managing error handling.

The backend URL (e.g., `https://sms-spam-detect.onrender.com/predict`) is defined as the base URL, and network operations are handled in the ViewModel layer to keep the UI responsive. JSON parsing is handled using the Gson converter provided by Retrofit.

Security practices such as:

- Using HTTPS protocol for secure data transfer.
- Validating API responses.
- Handling timeouts and connection failures gracefully.

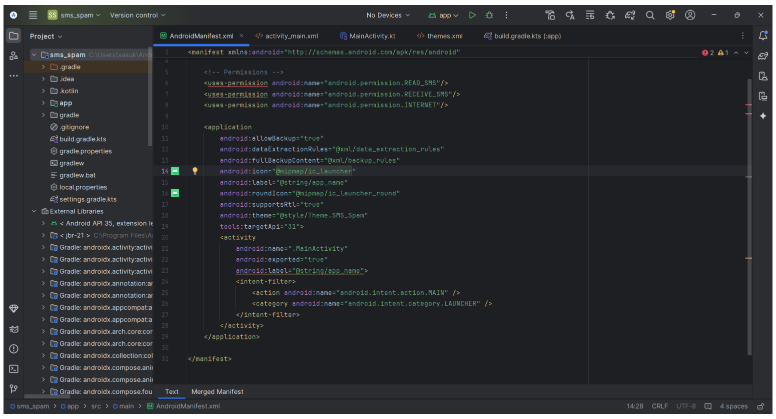
are followed to ensure a robust and secure connection between the mobile app and the server.

5.4 Building and Testing the App

The application is compiled and built into APK and AAB formats using Android Studio's built-in Gradle tools. It is tested thoroughly across multiple devices and Android versions to ensure compatibility and stability.

- **Unit Tests:** Written for business logic and ViewModel layers to validate processing logic.
- **UI Tests:** Conducted using Espresso framework to test user interactions and navigation.
- **Emulator Tests:** Used to simulate various screen sizes and system configurations.

Performance profiling tools such as Logcat, Android Profiler, and Network Inspector are used to monitor memory usage, network activity, and responsiveness.



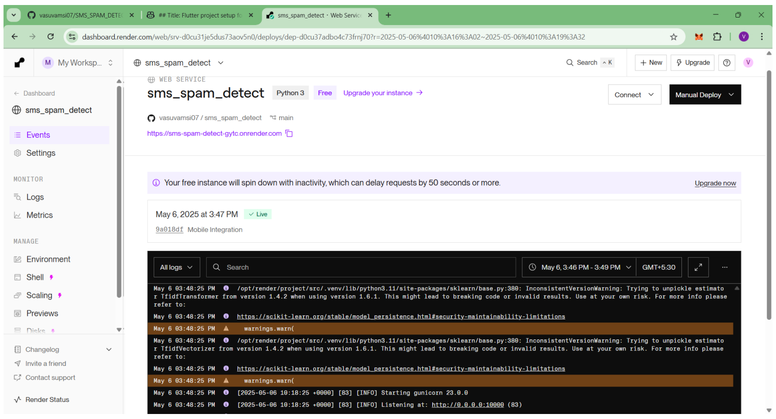
```xml
<manifest xmlns:android="http://schemas.android.com/apk/res/android"

    <!-- Permissions -->
    <uses-permission android:name="android.permission.READ_SMS"/>
    <uses-permission android:name="android.permission.RECEIVE_SMS"/>
    <uses-permission android:name="android.permission.INTERNET"/>

    <application
        android:allowBackup="true"
        android:dataExtractionRules="@xml/data_extraction_rules"
        android:fullBackupContent="@xml/backup_rules"
        android:icon="@mipmap/ic_launcher"
        android:label="@string/app_name"
        android:roundIcon="@mipmap/ic_launcher_round"
        android:supportsRtl="true"
        android:theme="@style/Theme.SMS_Spam"
        tools:targetApi="31">
        <activity
            android:name=".MainActivity"
            android:exported="true"
            android:label="@string/app_name">
            <intent-filter>
                <action android:name="android.intent.action.MAIN" />
                <category android:name="android.intent.category.LAUNCHER" />
            </intent-filter>
        </activity>
    </application>

</manifest>
```

Figure 5.1: Render Deployment



sms_spam_detect

Your free instance will spin down with inactivity, which can delay requests by 50 seconds or more.

May 6, 2025 at 3:47 PM ✓ Live

9a018df Mobile Integration

```
May 6 03:48:25 PM  /opt/render/project/src/.venv/lib/python3.11/site-packages/sklearn/base.py:380: InconsistentVersionWarning: Trying to unpickle estimato
r TfidfTransformer from version 1.4.2 when using version 1.6.1. This might lead to breaking code or invalid results. Use at your own risk. For more info please
refer to:
May 6 03:48:25 PM  https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
May 6 03:48:25 PM    warnings.warn(
May 6 03:48:25 PM  /opt/render/project/src/.venv/lib/python3.11/site-packages/sklearn/base.py:380: InconsistentVersionWarning: Trying to unpickle estimato
r TfidfVectorizer from version 1.4.2 when using version 1.6.1. This might lead to breaking code or invalid results. Use at your own risk. For more info please
refer to:
May 6 03:48:25 PM  https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
May 6 03:48:25 PM    warnings.warn(
May 6 03:48:25 PM  [2025-05-06 10:18:25 +0000] [83] [INFO] Starting gunicorn 23.0.0
May 6 03:48:25 PM  [2025-05-06 10:18:25 +0000] [83] [INFO] Listening at: http://0.0.0.0:10000 (83)
```

Figure 5.2: Android Studios

5.5 Deployment and Distribution

Upon successful testing, the APK can be distributed in two ways:

1. **Direct Installation:** The unsigned APK is shared manually for local installation on Android devices for testing or demonstration purposes.

2. **Google Play Store Deployment:** The application is signed using a release keystore, packaged into an Android App Bundle (AAB), and uploaded to the Google Play Console. Metadata such as screenshots, descriptions, versioning, and privacy policies are added to complete the release process.

Version control and continuous integration pipelines can be added in future development using tools like GitHub Actions or Bitrise to automate building and testing.

The mobile extension of the SMS spam detection system complements the web application and provides users with a versatile and portable spam detection solution powered by a centralized machine learning backend.

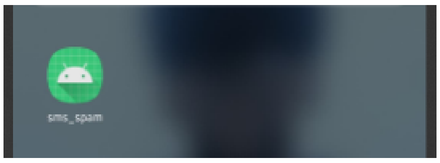
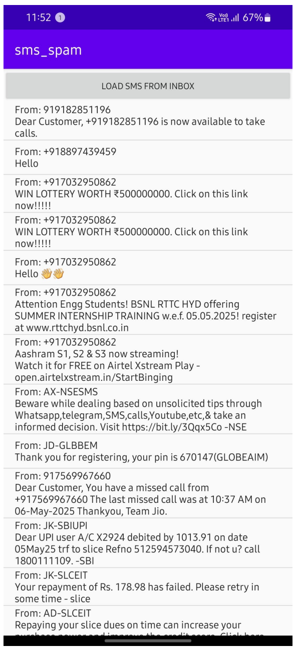


Figure 5.3: SMS Spam app



From: 919182851196
Dear Customer, +919182851196 is now available to take calls.

From: +918897439459
Hello

From: +917032950862
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

From: +917032950862
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

From: +917032950862
Hello 👋👋

From: +917032950862
Attention Engg Students! BSNL RTTC HYD offering SUMMER INTERNSHIP TRAINING w.e.f. 05.05.2025! register at www.rttchyd.bsnl.co.in

From: +917032950862
Aashram S1, S2 & S3 now streaming!
Watch it for FREE on Airtel Xstream Play - open.airtelxstream.in/StartBinging

From: AX-NSESMS
Beware while dealing based on unsolicited tips through Whatsapp,telegram,SMS,calls,Youtube,etc,& take an informed decision. Visit https://bit.ly/3Qqx5Co -NSE

From: JD-GLBBEM
Thank you for registering, your pin is 670147(GLOBEAIM)

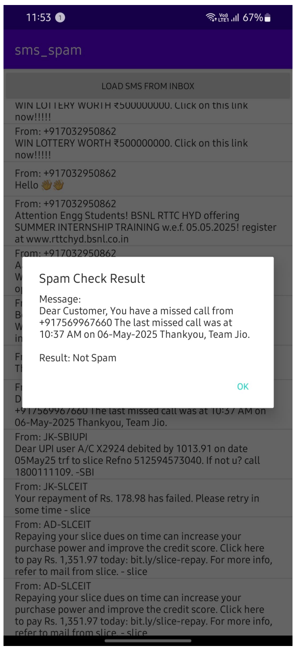
From: 917569967660
Dear Customer, You have a missed call from +917569967660 The last missed call was at 10:37 AM on 06-May-2025 Thankyou, Team Jio.

From: JK-SBIUPI
Dear UPI user A/C X2924 debited by 1013.91 on date 05May25 trf to slice Refno 512594573040. If not u? call 1800111109. -SBI

From: JK-SLCEIT
Your repayment of Rs. 178.98 has failed. Please retry in some time - slice

From: AD-SLCEIT
Repaying your slice dues on time can increase your

Figure 5.4: Messages



WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

From: +917032950862
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

From: +917032950862
Hello 👋👋

From: +917032950862
Attention Engg Students! BSNL RTTC HYD offering SUMMER INTERNSHIP TRAINING w.e.f. 05.05.2025! register at www.rttchyd.bsnl.co.in

From: +917032950862

Spam Check Result

Message:
Dear Customer, You have a missed call from +917569967660 The last missed call was at 10:37 AM on 06-May-2025 Thankyou, Team Jio.

Result: Not Spam

OK

+917569967660 The last missed call was at 10:37 AM on 06-May-2025 Thankyou, Team Jio.

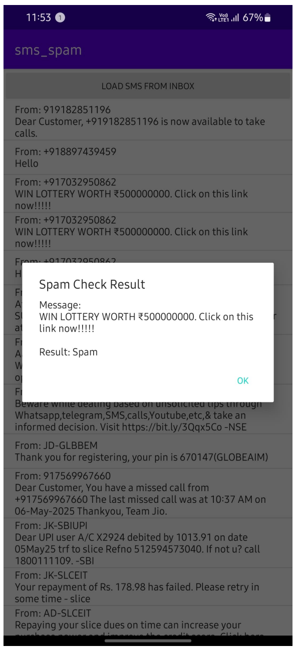
From: JK-SBIUPI
Dear UPI user A/C X2924 debited by 1013.91 on date 05May25 trf to slice Refno 512594573040. If not u? call 1800111109. -SBI

From: JK-SLCEIT
Your repayment of Rs. 178.98 has failed. Please retry in some time - slice

From: AD-SLCEIT
Repaying your slice dues on time can increase your purchase power and improve the credit score. Click here to pay Rs. 1,351.97 today: bit.ly/slice-repay. For more info, refer to mail from slice. - slice

From: AD-SLCEIT
Repaying your slice dues on time can increase your purchase power and improve the credit score. Click here to pay Rs. 1,351.97 today: bit.ly/slice-repay. For more info, refer to mail from slice. - slice

Figure 5.5: Detecting Spam Message



11:53 67%

sms_spam

LOAD SMS FROM INBOX

From: 919182851196
Dear Customer, +919182851196 is now available to take calls.

From: +918897439459
Hello

From: +917032950862
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

From: +917032950862
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

Spam Check Result

Message:
WIN LOTTERY WORTH ₹500000000. Click on this link now!!!!!

Result: Spam

OK

Whatsapp,telegram,SMS,calls,Youtube,etc,& take an informed decision. Visit https://bit.ly/3Qqx5Co -NSE

From: JD-GLBBEM
Thank you for registering, your pin is 670147(GLOBEAIM)

From: 917569967660
Dear Customer, You have a missed call from +917569967660 The last missed call was at 10:37 AM on 06-May-2025 Thankyou, Team Jio.

From: JK-SBIUPI
Dear UPI user A/C X2924 debited by 1013.91 on date 05May25 trf to slice Refno 512594573040. If not u? call 1800111109. -SBI

From: JK-SLCEIT
Your repayment of Rs. 178.98 has failed. Please retry in some time - slice

From: AD-SLCEIT
Repaying your slice dues on time can increase your

Figure 5.6: Detecting NotSpam Message

Chapter 6

Android Application Development

To enhance the accessibility and usability of the SMS Spam Detection system, a native Android application was developed using Android Studio. This mobile app acts as a frontend interface that communicates with the machine learning model hosted on the Render platform. The goal is to allow users to classify SMS messages as spam or ham directly from their mobile devices with minimal effort.

6.1 Mobile App Architecture

The Android application follows a client-server architecture. The mobile app acts as a client that sends HTTP POST requests to the backend API endpoint hosted on Render. The backend receives the SMS content, processes it through the trained NLP model, and returns a prediction. This approach keeps the mobile app lightweight while ensuring that model logic and data processing are securely handled on the server.

6.2 User Interface Design

The user interface of the application is built using Android's XML layout system. It consists of the following components:

- **EditText:** For users to input SMS content.
- **Button:** To send the text to the server for spam detection.
- **TextView:** To display the result (Spam or Ham) returned by the backend.

Material Design guidelines were followed to ensure the UI is clean, responsive, and accessible on different device sizes and orientations.

6.3 Backend API Integration

Integration with the backend is accomplished using the `Retrofit` HTTP client. The application sends JSON-formatted POST requests containing the SMS content to the

Flask-based REST API. The server responds with a classification result, which is then parsed and displayed to the user.

Proper error handling mechanisms are implemented to manage network errors, API timeouts, and invalid responses, ensuring a robust user experience.

6.4 App Testing and Debugging

The application was tested using:

- **Android Emulator:** To simulate different device configurations and screen sizes.
- **Physical Devices:** To test real-world responsiveness and UI behavior.
- **Logcat and Debugger:** To trace runtime errors and performance bottlenecks.

Edge cases such as empty input fields, long messages, and intermittent network connectivity were considered and appropriately handled.

6.5 App Deployment and Packaging

The final application was compiled into APK format using Android Studio's Gradle build system. For initial distribution, the APK can be directly installed on Android devices. In future development phases, the application may be:

- Signed and uploaded to the Google Play Store.
- Enhanced to access the device's SMS inbox for automatic detection.
- Improved with offline capabilities using on-device inference.

This mobile application serves as a practical extension to the SMS spam detection system, bringing real-time spam filtering to the user's fingertips.

Chapter 7

Results

In addition to the issue of data imbalance and model generalization, the SMS spam detection system may face challenges such as adapting to new forms of spam, maintaining performance over time, and ensuring low latency in real-time detection. These challenges can impact the effectiveness of the system in providing accurate and timely spam classification, which is crucial for user experience.

7.1 Introduction

This chapter presents the results obtained from implementing the SMS spam detection system using Natural Language Processing (NLP) techniques. The outcomes of the model training, validation, and testing phases are evaluated based on various performance metrics, including accuracy, precision, recall, and F1-score. Visualizations such as confusion matrices and performance graphs are also provided to offer a comprehensive analysis of the system's effectiveness in distinguishing between spam and non-spam messages. This chapter also discusses the deployment process on the Render platform, detailing the practical aspects of making the system accessible via a web-based interface.

7.2 Experimental Results

This section presents the experimental findings of the SMS spam detection system. Three Naïve Bayes classifiers were evaluated: **Multinomial Naïve Bayes (MNB)**, **Bernoulli Naïve Bayes (BNB)**, and **Gaussian Naïve Bayes (GNB)**. The models were trained on preprocessed SMS data using TF-IDF vectorization to convert text into numerical features.

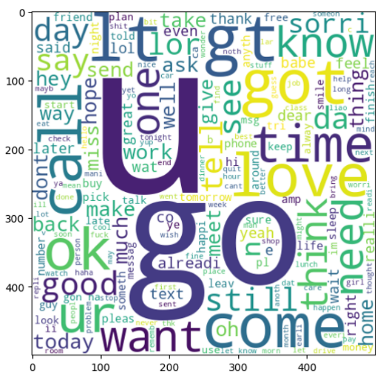


Figure 7.1: Ham

7.2.1 Model Performance Comparison

Table 7.1: Performance Metrics of Naïve Bayes Classifiers

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Multinomial NB	95.74	100.00	91.38	95.48
Bernoulli NB	**96.42**	94.54	**95.86**	**95.19**
Gaussian NB	85.98	47.89	75.00	58.37

7.2.2 Interpretation

Among the three classifiers, the **Bernoulli Naïve Bayes** model delivered the best overall performance. It achieved an accuracy of **96.42%**, a precision of **94.54%**, and a recall of **95.86%**. The **Multinomial Naïve Bayes** model recorded perfect precision (**100%**), ensuring no legitimate messages were misclassified as spam. However, it had a slightly lower recall compared to BNB. The **Gaussian Naïve Bayes** model underperformed due to its assumption of normally distributed features, which does not hold for sparse text data.

7.2.3 Confusion Matrix for Bernoulli Naïve Bayes

Table 7.2: Confusion Matrix - Bernoulli Naïve Bayes

	Predicted Spam	**Predicted Ham**
Actual Spam	182	8
Actual Ham	5	325

The confusion matrix demonstrates that only a small number of spam messages were missed and a few ham messages were incorrectly classified as spam.

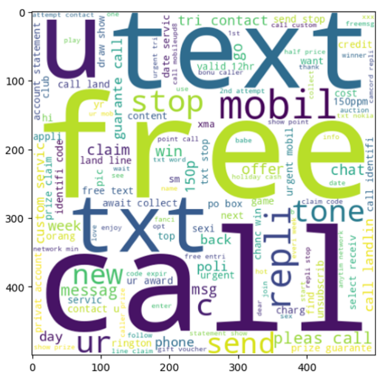


Figure 7.2: Spam

7.2.4 Impact of Vectorization Technique

The use of **TF-IDF** vectorization significantly improved performance over the CountVectorizer (Bag-of-Words) approach. By assigning higher importance to rare but meaningful words such as *"free"*, *"win"*, *"urgent"*, and *"prize"*, the classifier was better able to distinguish spam messages.

7.2.5 Real-Time Deployment

The best-performing model, **Bernoulli Naïve Bayes**, was deployed using the **Render** cloud platform. A user-friendly web interface was developed for real-time SMS classification, enabling end-users to interact with the system by submitting SMS text and receiving immediate spam/ham predictions. This deployment illustrates the practical applicability of the system in real-world environments.

7.3 Summary

This chapter presented the experimental evaluation of the SMS spam detection system developed using Natural Language Processing (NLP) and machine learning techniques. Three classifiers—Multinomial Naïve Bayes, Bernoulli Naïve Bayes, and Gaussian Naïve Bayes—were tested using TF-IDF vectorized features. The results demonstrated that Bernoulli Naïve Bayes offered the best trade-off between precision and recall, achieving an accuracy of 96.42% and a precision of 94.54%. Multinomial Naïve Bayes excelled in precision (100%) but had slightly lower recall, while Gaussian Naïve Bayes performed poorly due to its unsuitable assumption of normal distribution in sparse text data.

The analysis also highlighted the importance of proper text preprocessing and vectorization, particularly the advantages of TF-IDF over simple Bag-of-Words techniques. Furthermore, the selected model was successfully deployed via the Render platform, enabling real-time classification through a web interface.

Overall, the experimental results validate the effectiveness of the proposed system in accurately detecting spam messages, supporting its potential for real-world applications in enhancing mobile communication security and user experience.

Chapter 8

Conclusions

This research developed an SMS spam detection system using NLP and machine learning, achieving high accuracy (96.42%) with Bernoulli Naïve Bayes. The system effectively classifies messages as spam or legitimate using text preprocessing and TF-IDF vectorization. It was deployed via the Render platform for real-time use, demonstrating practical value. Future improvements may include deep learning integration, multilingual support, and continuous model updates to adapt to evolving spam tactics.

8.1 Conclusions

The research work embodied in this thesis has addressed the problem of SMS spam detection by leveraging Natural Language Processing (NLP) and machine learning techniques to develop an intelligent and scalable classification system. With the growing volume of unsolicited and potentially harmful SMS messages, the study aimed to build a solution capable of accurately distinguishing spam from legitimate content. Various aspects of the problem were explored, including text preprocessing methods such as tokenization, stop-word removal, stemming, and TF-IDF vectorization, which effectively transformed raw messages into structured input for classification.

Multiple machine learning algorithms were evaluated—namely Multinomial Naïve Bayes, Bernoulli Naïve Bayes, and Gaussian Naïve Bayes—with Bernoulli Naïve Bayes delivering the best overall performance, achieving 96.42% accuracy and 94.54% precision. Multinomial Naïve Bayes also performed strongly with perfect precision, making it suitable for cases where minimizing false positives is critical. In contrast, Gaussian Naïve Bayes underperformed due to its assumption of normally distributed data, which is not well-suited for sparse textual features.

The final model was successfully deployed via the Render platform, enabling real-time SMS classification through a simple web interface. This deployment not only confirmed the feasibility and effectiveness of the system in real-world scenarios but also highlighted the scalability and accessibility of the solution. This practical implementation demonstrates how machine learning can be used to build efficient and user-friendly applications, making it easier for users to protect themselves from SMS spam.

In summary, the research demonstrates that combining NLP with machine learning provides a powerful framework for spam detection, and future enhancements may include the integration of deep learning, multilingual support, and adaptive learning to address evolving spam tactics and improve system robustness.

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