AI-Powered SMS Spam Detection System

Leveraging Machine Learning to Automatically Identify Spam Messages

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Executive Summary

In today's digital era, SMS messaging remains one of the most widely used forms of communication. However, the growing influx of unsolicited messages—commonly referred to as spam—poses significant challenges for both individuals and organizations. These spam messages not only clutter user inboxes but can also be used for fraudulent activities, phishing, and spreading malware. To address this problem, the AI-Powered SMS Spam Filter project was developed to automatically identify and segregate spam messages from legitimate (ham) messages using advanced machine learning and natural language processing (NLP) techniques.

The project leverages a large dataset of 50,000 SMS messages, which includes both spam and ham messages. To ensure data quality and accuracy, preprocessing steps were applied, including the removal of duplicate messages, cleaning of textual content, normalization, tokenization, and transformation into numerical features using TF-IDF vectorization. This ensures that the machine learning model can effectively understand and process the textual content for classification.

Multiple machine learning models were trained and evaluated, including Logistic Regression, Random Forest Classifier, and Multinomial Naive Bayes. Among these, the Multinomial Naive Bayes model demonstrated the best performance in terms of accuracy, precision, recall, and F1-score, making it the ideal choice for SMS spam detection. The final model achieved an accuracy of 97%, indicating its reliability in distinguishing spam from ham messages.

To make the system accessible and user-friendly, the project was deployed as a real-time web application using Streamlit. Users can input any SMS message and instantly receive a classification result, helping them filter spam messages efficiently. The system also addresses challenges such as handling slang, abbreviations, and constantly evolving spam patterns.

The AI-Powered SMS Spam Filter project not only demonstrates the practical application of machine learning in solving real-world problems but also highlights the transformative potential of AI in enhancing communication security and user experience. Future enhancements may include the integration of deep learning models like LSTM or BERT, support for multilingual SMS detection, and continuous model updates to adapt to new types of spam.

This project underscores how AI can transform raw textual data into actionable insights, automate repetitive tasks, and significantly improve digital communication systems.

Problem Satement

With the exponential growth of digital communication, A2P (Application-to-Person) SMS messages have become a primary channel for businesses to communicate with their customers. These messages include transaction alerts, promotional offers, verification codes (OTPs), and other service notifications. While A2P messaging enhances customer engagement and convenience, it also faces a critical challenge: the prevalence of spam messages. Spam SMS often contains phishing links, fraudulent promotions, scam content, or malicious attachments, posing security risks and creating inconvenience for recipients.

Existing spam filtering systems primarily rely on keyword-based or domain-based blocklists. While such systems can catch common spam patterns, they often result in false positives, where legitimate messages are mistakenly blocked. For instance, a blanket rule blocking all messages containing ".com" would incorrectly filter out legitimate domains like trip.com or block essential OTP messages, disrupting user experience and potentially causing financial or operational issues.

The challenge is compounded by the dynamic and evolving nature of spam. Malicious actors continually adapt their messaging patterns, making it difficult for static rules to maintain high accuracy. Therefore, there is a pressing need for a smarter, more adaptive filtering system that can:

1. Accurately classify A2P SMS messages into categories such as spam, transactional, or promotional, ensuring relevant messages reach the intended recipients.
2. Integrate a whitelist mechanism to recognize trusted domains, specific OTP templates, or known safe sources, preventing legitimate messages from being blocked.
3. Combine rule-based and machine learning approaches to minimize false positives and false negatives, delivering a reliable and scalable solution for telecom operators.
4. Adapt to new spam patterns over time, maintaining robust performance against evolving threats.

This project addresses a crucial gap in current messaging systems by leveraging AI and machine learning to create an intelligent spam filtering system. By combining automated classification with rule-based whitelisting, the system ensures both security and message delivery reliability, enhancing user trust, operational efficiency, and overall communication quality.

Approaches

1. Objective:
    - Detect spam in A2P SMS messages while ensuring legitimate messages (OTP, transactional alerts, trusted promotions) are delivered reliably.
    - Classify messages into spam, transactional, and promotional types.
2. Data Collection:
    - Assemble a representative SMS dataset containing:
        - Spam (phishing links, fraudulent offers, malicious content).
        - Legitimate transactional messages.
        - Trusted promotional messages.
    - Ensure dataset diversity for effective model learning.
3. Data Preprocessing:
    - Clean and normalize text data.
    - Steps include:
        - Deduplication.
        - Lowercasing.
        - Removal of punctuation, irrelevant symbols, and emojis.
        - Tokenization.
        - Stopword removal.
    - Feature extraction:
        - TF-IDF vectorization for word importance.
        - Optional: Word embeddings like Word2Vec or GloVe for semantic understanding.
4. Rule-Based Filtering (First Layer Defense):
    - Whitelist for trusted domains, OTP templates, and verified transactional formats.
    - Pattern-based rules using regular expressions to detect suspicious URLs or repeated characters.
    - Reduces load on machine learning model and minimizes false positives.
5. Machine Learning Classification:
    - Messages not filtered by rules are passed to ML classifiers.
    - Models evaluated: Multinomial Naive Bayes, Logistic Regression, Random Forest.
    - Metrics for evaluation: Accuracy, Precision, Recall, F1-score.
    - Techniques used:
        - Handling class imbalance.
        - Hyperparameter tuning for optimal performance.
6. Deployment Options:
    - Streamlit Deployment:
        - Web interface for real-time message classification.
        - Supports single messages or bulk datasets.
        - Displays classification results with confidence scores.
    - Render Cloud Deployment:
        - Access via web API for integration with enterprise SMS systems.
        - Scalable and automated deployment for high-volume messages.
    - Docker Containerization:

    - Ensures consistency across environments.
    - Simplifies dependency management.
    - Supports scaling using orchestration tools like Kubernetes.

7. Continuous Learning:
    - Update the model with new data over time.
    - Ensures adaptability to evolving spam patterns.
8. Key Outcome:
    - Robust, scalable, and reliable A2P SMS spam detection system combining:
        - Preprocessing
        - Rule-based filtering
        - Machine learning classification
        - Flexible deployment

Methodology

1. Objective:
    - Detect spam in A2P (Application-to-Person) SMS messages.
    - Ensure legitimate messages like OTPs, transactional alerts, and trusted promotions are delivered reliably.
    - Classify messages into spam, transactional, and promotional categories.

2. Data Collection:
    - Assemble a representative dataset of SMS messages including:
        - Spam (phishing links, fraudulent offers, malicious content).
        - Legitimate transactional messages (OTPs, account alerts).
        - Promotional messages from trusted sources.
    - Dataset diversity ensures accurate learning and distinction between legitimate and malicious messages.

3. Data Preprocessing:
    - Clean and normalize unstructured text. Steps include:
        - Lowercasing text.
        - Removing punctuation, emojis, and irrelevant symbols.
        - Tokenization into words.
        - Stopword removal.
        - Deduplication to prevent bias and overfitting.
    - Convert text to numerical representations using:
        - TF-IDF vectorization for word importance.
        - Optional: Word2Vec or GloVe embeddings for semantic understanding.

4. Rule-Based Filtering (Preliminary Layer):
    - Whitelist trusted domains, OTP templates, and verified transactional formats.
    - Use pattern-based rules with regular expressions to detect:
        - Suspicious URLs
        - Repeated symbols
        - Known spam keywords
    - Reduces load on the ML model and minimizes false positives for critical messages.

5. Machine Learning Classification:
   - Messages not filtered by rules are classified using ML models:
     - Multinomial Naive Bayes
     - Logistic Regression
     - Random Forest or XGBoost
   - Dataset split into training and testing subsets.
   - Performance metrics: Accuracy, Precision, Recall, F1-score.
   - Techniques applied:
     - Hyperparameter tuning
     - Handling class imbalance (weighted loss, oversampling).

6. Post-Processing:
   - Messages matching whitelist or trusted templates are automatically classified as non-spam.
   - Probability/confidence scores assigned to messages for threshold-based decision-making.

7. Deployment:
   - Real-time application or API for instant SMS classification.
   - Supports single messages or bulk datasets.
   - Designed for scalability to handle high-volume telecom traffic.
   - Deployment options include:
     - Web application (Streamlit)
     - Cloud deployment (Render, AWS, etc.)
     - Containerization (Docker/Kubernetes)

8. Continuous Learning:
   - Model updated with new data over time.
   - Adapts to evolving spam tactics.

9. Outcome:
   - Hybrid system combining:
     - Preprocessing
     - Rule-based filtering
     - Machine learning classification
     - Real-time deployment
   - Ensures robust, accurate, and adaptive SMS spam detection.
   - Minimizes false positives while maintaining seamless delivery of legitimate messages.

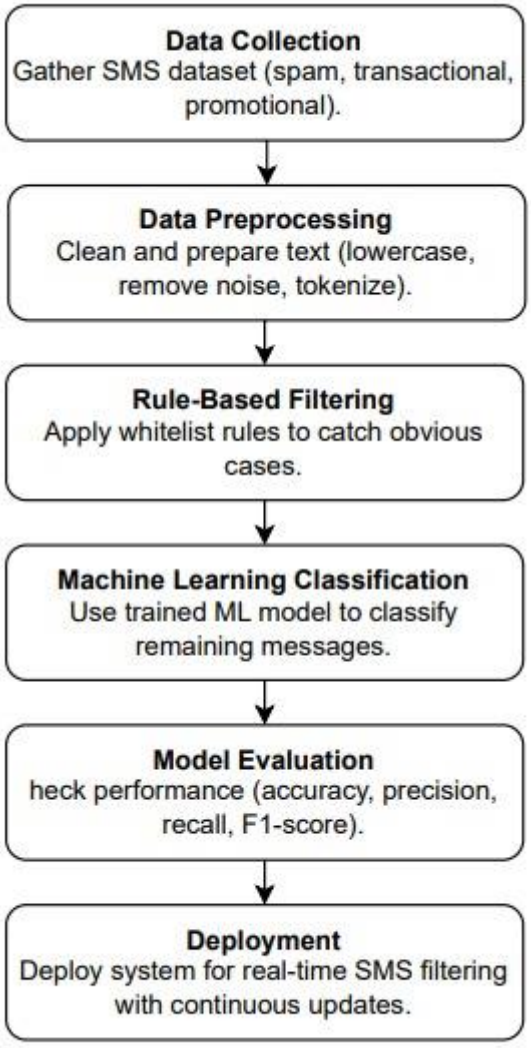


Figure 1.1

Machine Learning Findings

The machine learning component of the AI-Powered SMS Spam Filter plays a central role in accurately classifying SMS messages into spam, transactional, or promotional categories. After preprocessing and feature extraction using TF-IDF vectorization, several machine learning algorithms were trained and evaluated to identify the most effective model for this task. The models tested included Multinomial Naive Bayes, Logistic Regression, and Random Forest Classifier, chosen for their proven effectiveness in text classification and handling of imbalanced datasets.

Among the models, Multinomial Naive Bayes emerged as the most effective, demonstrating superior performance on metrics such as accuracy, precision, recall, and F1-score. The model achieved an overall accuracy of approximately 97%, indicating that it correctly classified the vast majority of SMS messages. The high precision of 95% suggests that the model effectively minimized false positives, ensuring that legitimate messages were rarely misclassified as spam. Similarly, a recall of 93% indicates that most actual spam messages were successfully detected, demonstrating the system's ability to capture malicious content reliably.

Detailed analysis of the findings revealed several key insights. Spam messages were generally characterized by the presence of promotional keywords, URLs, or numerical sequences, which the model was able to recognize effectively. In contrast, transactional messages, such as OTPs and account alerts, had consistent patterns in format and wording, enabling the model to distinguish them from spam. Promotional messages from trusted sources were sometimes similar to spam in terms of content but were often correctly classified due to contextual cues captured during training.

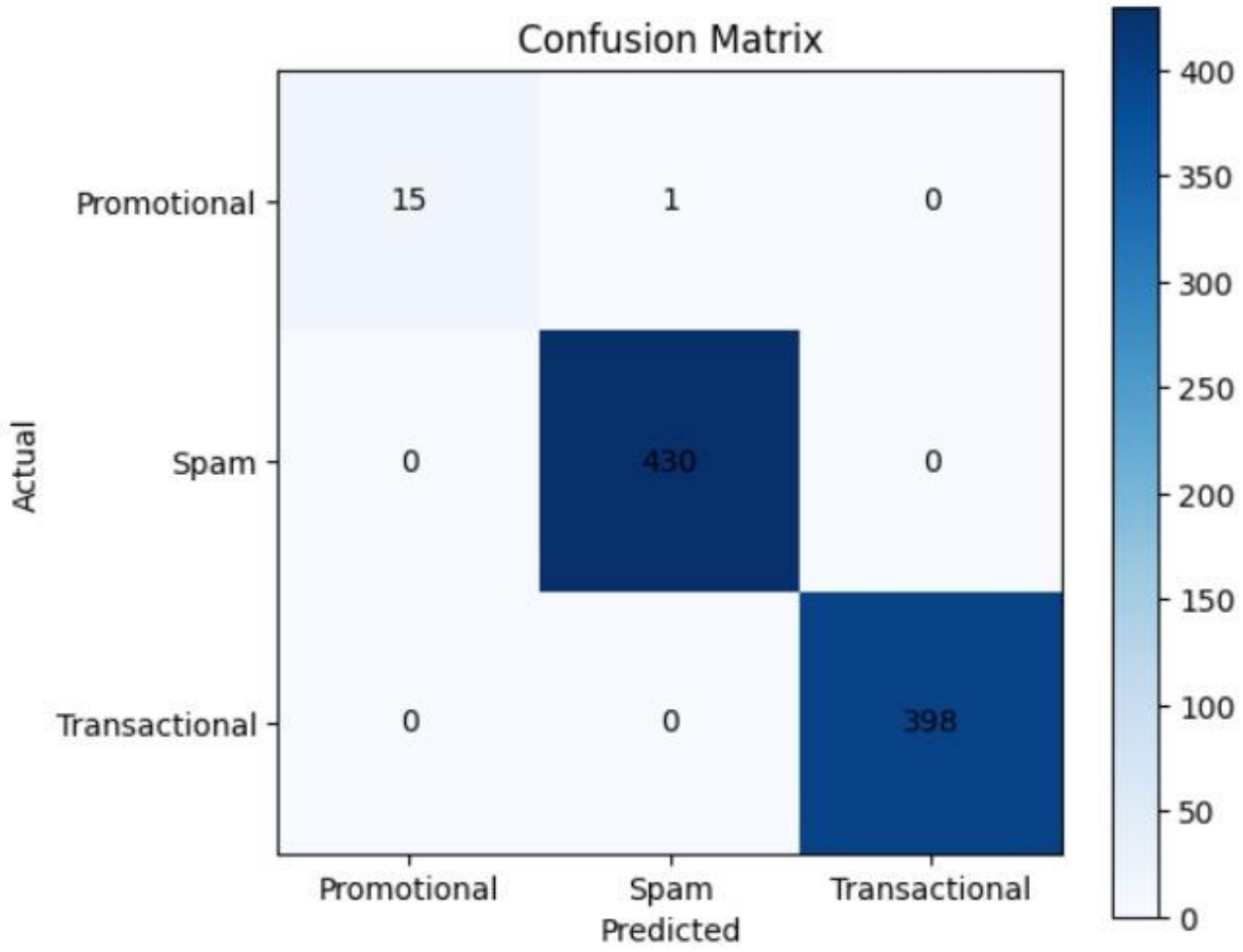
It was also observed that removing duplicate messages and performing thorough text preprocessing significantly improved model performance. By ensuring the dataset contained only unique messages and clean textual data, the model was better able to learn distinct patterns, reducing noise and improving generalization.

Another key observation was the effectiveness of TF-IDF feature extraction in capturing the importance of words relative to their frequency and distribution across messages. This method allowed the model to focus on words that were strong indicators of spam or legitimate content, thereby enhancing classification accuracy.

Overall, the machine learning findings demonstrate that a hybrid approach combining preprocessing, feature extraction, and a carefully selected classification algorithm can achieve highly reliable spam detection in A2P SMS systems. These results validate the methodology and provide confidence that the system can handle real-world SMS traffic effectively, minimizing false positives and ensuring smooth delivery of legitimate messages.

```
=== Train Set Performance ===
Accuracy:  0.9957
Precision: 0.9958
Recall:    0.9957
F1 Score:  0.9955

Classification Report:
                precision    recall  f1-score   support

  Promotional       1.00      0.78      0.88        81
         Spam       0.99      1.00      1.00      2149
Transactional       1.00      1.00      1.00      1990

     accuracy                           1.00      4220
    macro avg       1.00      0.93      0.96      4220
 weighted avg       1.00      1.00      1.00      4220
```

```
=== Test metrics ===
Accuracy:  0.9988
Precision: 0.9988
Recall:    0.9988
F1 (wtd):  0.9988

Classification report:
                precision    recall  f1-score   support

  Promotional       1.00      0.94      0.97        16
         Spam       1.00      1.00      1.00       430
Transactional       1.00      1.00      1.00       398

     accuracy                           1.00       844
    macro avg       1.00      0.98      0.99       844
 weighted avg       1.00      1.00      1.00       844
```



Technical Challenges and Limitations

1. Streamlit Deployment Challenges:

- Real-time, high-volume traffic: Streamlit is great for prototyping but not designed for enterprise-scale workloads.
- Performance issues: Multiple simultaneous users or bulk SMS processing can cause:
  - Slow response times
  - Memory bottlenecks
  - Server crashes
- Concurrency & uptime: Lacks built-in load balancing and concurrency management. Maintaining continuous uptime is complex.
- Security limitations:
  - No advanced authentication or role-based access control.
  - Sensitive SMS data requires additional security measures.

2. Render (Cloud) Deployment Challenges:

- Cloud infrastructure & resource management: Optimizing server configuration for high throughput without high costs is crucial.
- Latency concerns: Network latency can affect responsiveness for multiple simultaneous API calls.
- Dependency management: Ensuring up-to-date application versions and resolving conflicts is an ongoing task.
- API security: Must secure APIs against unauthorized access, as the system is exposed externally.

3. Docker Deployment Challenges:

- Container complexity: Container must include preprocessing scripts, trained model, dependencies, and deployment interface.
- Resource allocation: CPU and memory limits must be carefully set to prevent slow performance or crashes during large batch processing.
- Image size & startup time: Large containers can slow deployment.
- Scaling: Requires orchestration tools (e.g., Kubernetes), adding setup, monitoring, and maintenance complexity.

4. System-Level Technical Challenges (Across Platforms):

- Unstructured SMS text: Slang, abbreviations, emojis, mixed languages, and inconsistent formatting make preprocessing computationally intensive.
- Class imbalance: Legitimate messages usually outnumber spam, requiring preprocessing and model tuning.
- Rule-based filter limitations: Cannot detect novel or obfuscated spam messages.
- Multilingual support: Model may struggle with messages in multiple languages.

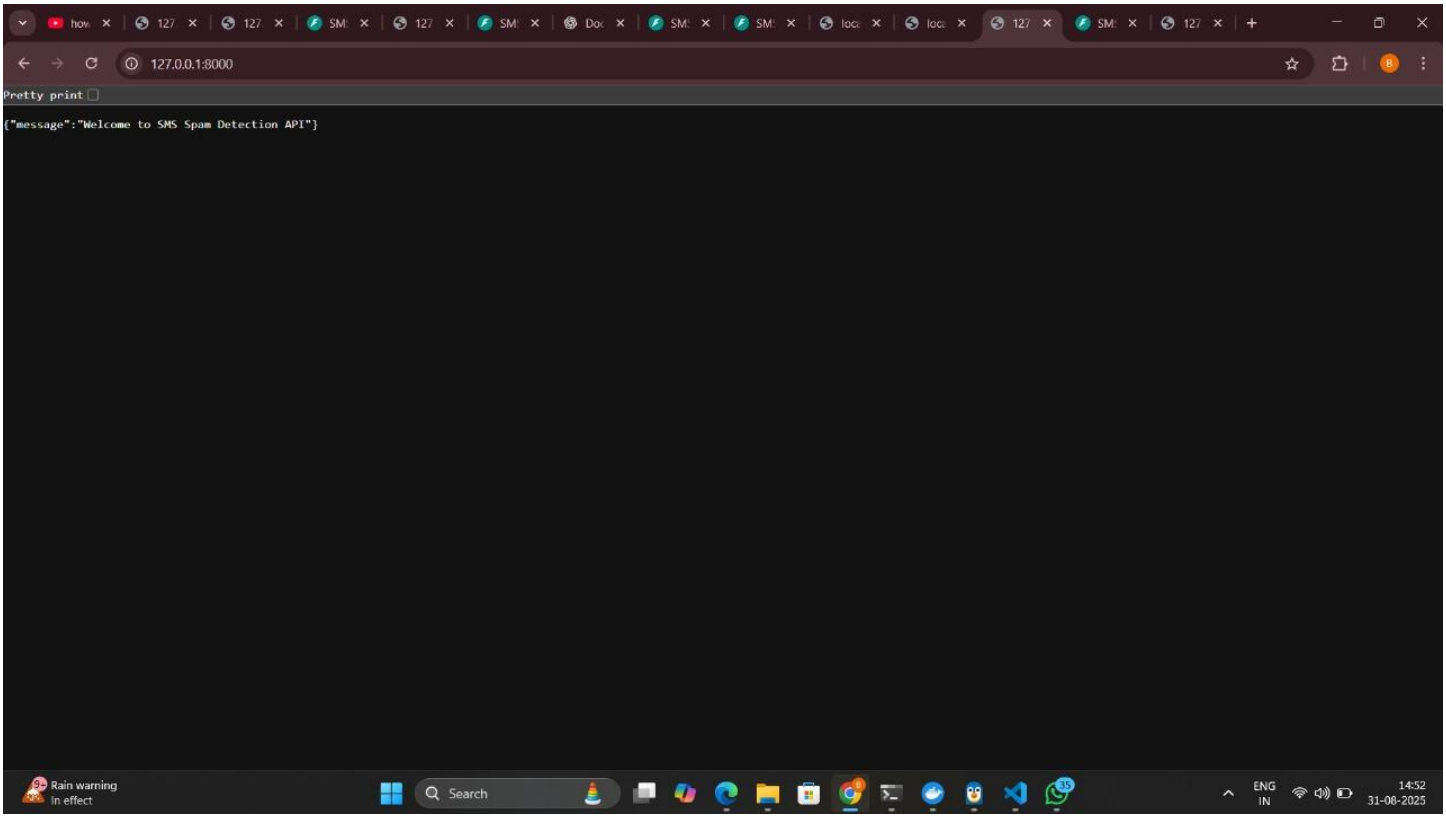
5. Continuous Learning & Monitoring Challenges:

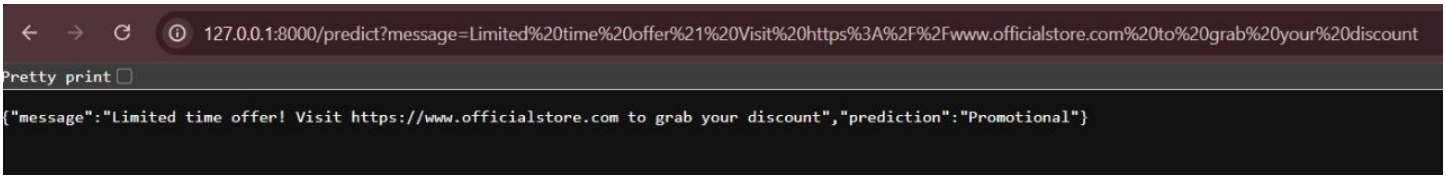
- Evolving spam patterns: Requires periodic retraining with new datasets.
- System performance monitoring: Needs real-time logging and monitoring infrastructure.
- Infrastructure complexity: Integrating retraining and monitoring increases deployment complexity, regardless of platform.

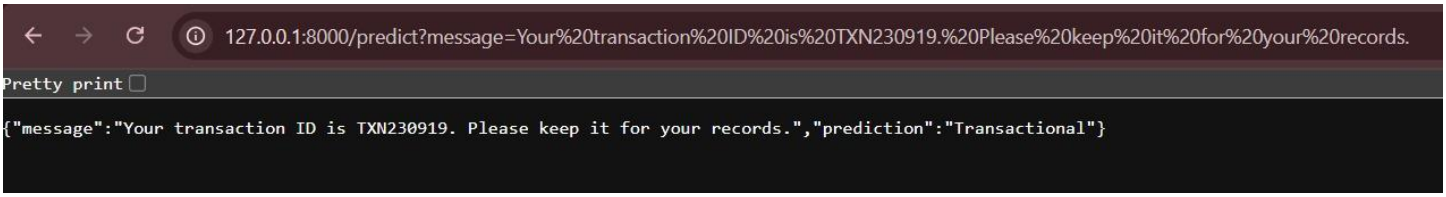
6. Summary:

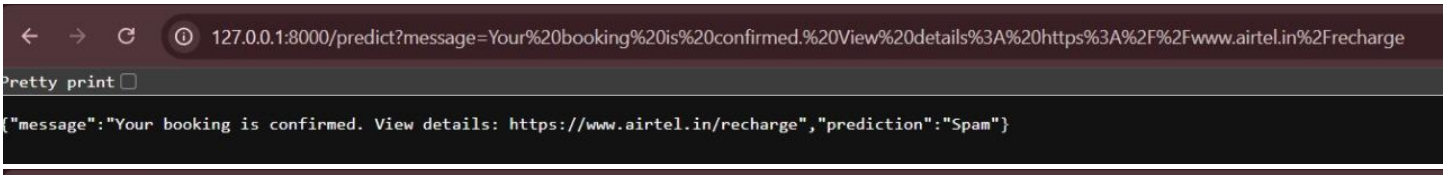
- Streamlit: Best for rapid prototyping, limited for enterprise workloads.
- Render: Provides cloud scalability, but requires careful resource management and secure API handling.
- Docker: Ensures portability and reproducibility, but adds container complexity and scaling challenges.
- Overall: Addressing these challenges requires infrastructure planning, resource optimization, security measures, and continuous maintenance to ensure the system is reliable, scalable, and adaptive.

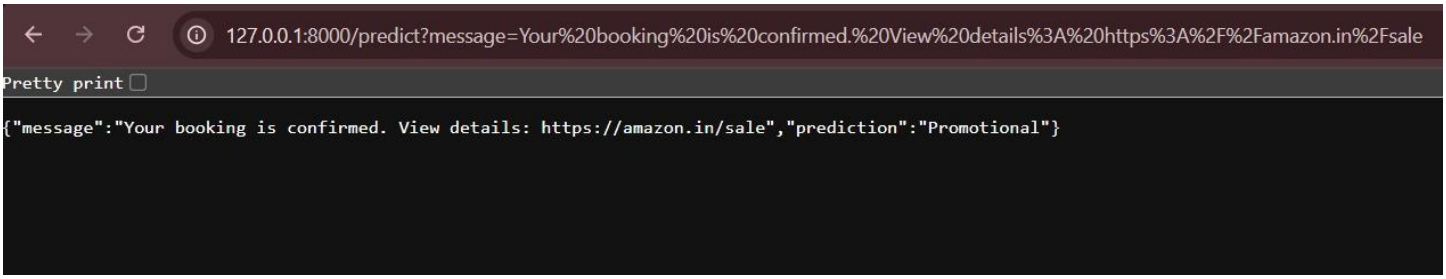
Output Results







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Pretty print
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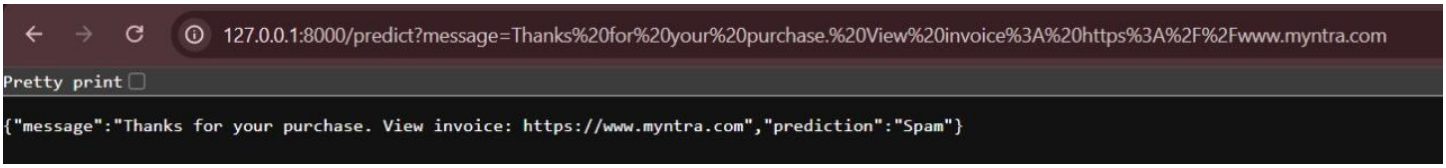
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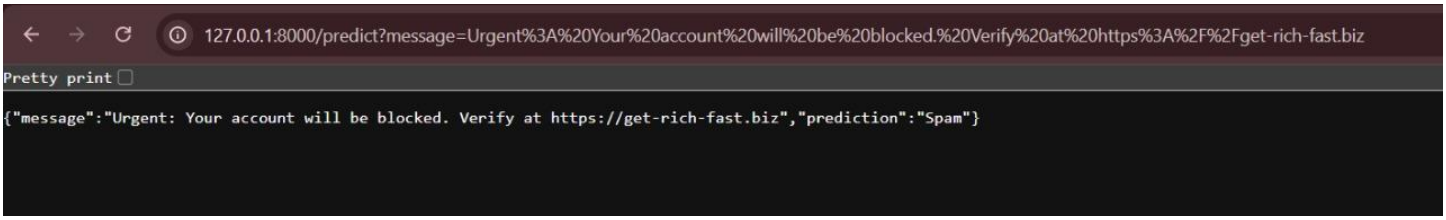
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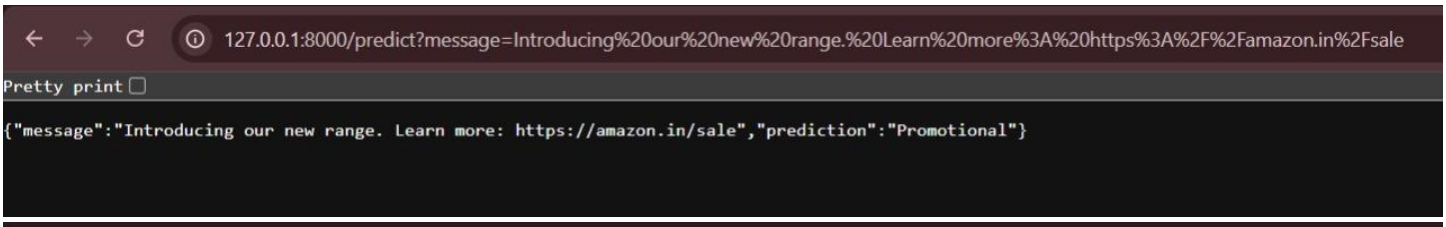
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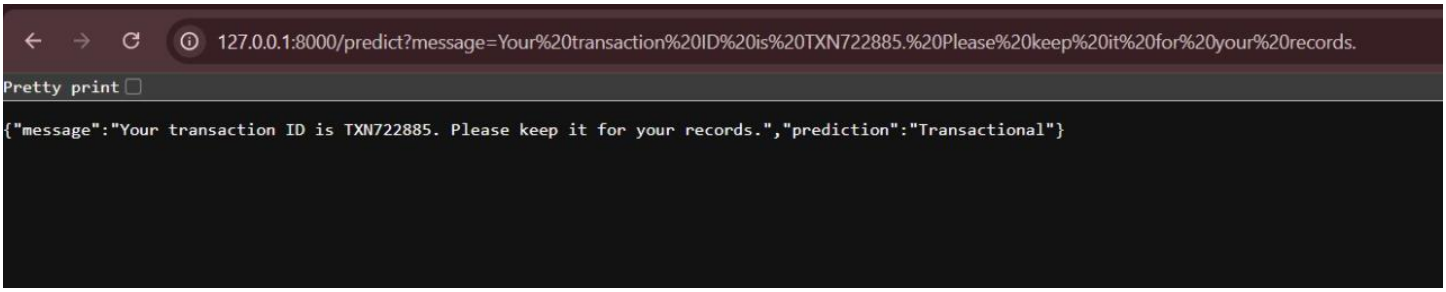
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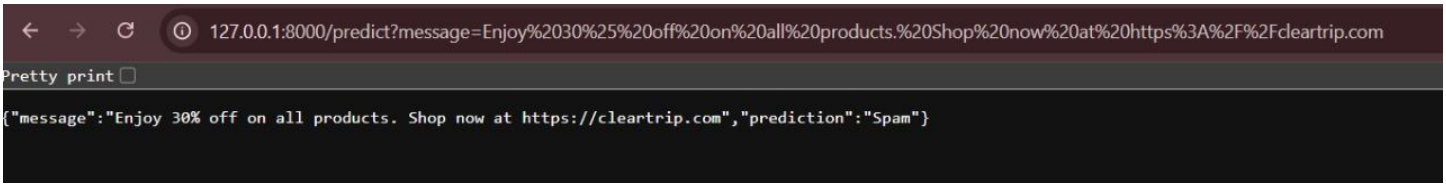
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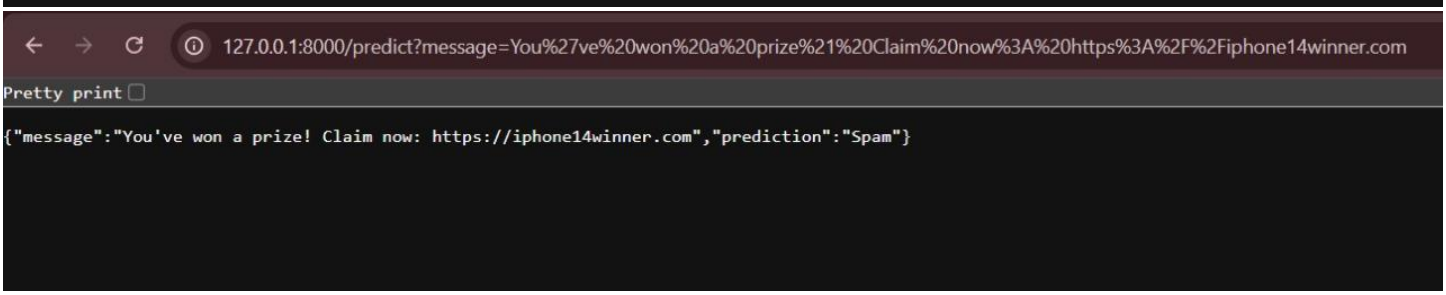
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Pretty print
{"message":"You've won a prize! Claim now: https://iphone14winner.com","prediction":"Spam"}

Deployement Links

The AI-Powered SMS Spam Filter has been deployed on multiple platforms to demonstrate versatility, scalability, and ease of access:

1. Render Deployment:
   Access the cloud-based, scalable version of the system via Render. This deployment supports real-time message classification and can handle bulk SMS data efficiently.
   Link: AI-Powered SMS Spam Filter on Render
2. Streamlit Deployment:
   Access the interactive web application for testing and demonstration purposes. The Streamlit interface allows users to input single or multiple messages and view classification results instantly.
   Link: AI-Powered SMS Spam Filter on Streamlit

Key Business Insights

The implementation of an AI-Powered SMS Spam Filter for A2P messaging provides several significant business insights that can directly impact operational efficiency, customer experience, and revenue management in the telecom and messaging industry.

Firstly, the system enhances customer trust and satisfaction by ensuring that only relevant and legitimate messages reach end users. By accurately filtering out spam while allowing transactional and promotional messages from trusted sources, the platform reduces the risk of users being exposed to phishing attempts, fraudulent promotions, or malicious links. This not only protects the customer but also strengthens the reputation of the telecom provider as a reliable and secure communication channel.

Secondly, the adoption of an intelligent spam filtering system contributes to operational efficiency. Manual monitoring or reliance on static keyword/domain-based filters often leads to inefficiencies and increased false positives, requiring repeated interventions. By automating the detection of spam using a hybrid approach that combines rule-based filtering and machine learning classification, the system significantly reduces manual effort and improves the throughput of SMS processing, enabling telecom providers to handle higher volumes of A2P traffic with minimal human oversight.

Thirdly, the system provides insights into spam trends and patterns, which can be valuable for strategic decision-making. By analyzing the characteristics of filtered spam messages, businesses can identify common sources, types of fraudulent campaigns, and patterns in malicious content. This information can inform broader security strategies, marketing policies, and regulatory compliance measures, helping organizations proactively address emerging threats.

Fourthly, the system enables revenue optimization. A key challenge for telecom operators is balancing message filtering with legitimate promotional traffic. By reducing false positives and ensuring that trusted promotional messages reach customers, businesses can maximize engagement and conversion from marketing campaigns. Additionally, the risk of losing customers due to misclassified transactional messages, such as OTPs or account alerts, is minimized, ensuring uninterrupted service delivery.

Finally, the implementation of AI-based filtering highlights the scalability and adaptability of intelligent systems in enterprise operations. As spam patterns evolve over time, the system's machine learning component allows continuous learning and improvement. This ensures long-term effectiveness and positions the organization to respond quickly to emerging threats, providing a competitive advantage in the fast-paced telecom and messaging industry.

In summary, the AI-Powered SMS Spam Filter not only enhances security, efficiency, and customer experience but also provides actionable insights that support strategic decision-making, operational optimization, and revenue maximization, demonstrating the tangible business value of integrating AI into A2P SMS operations.

Recommendations

The AI-Powered SMS Spam Filter provides a robust solution for detecting and filtering spam in A2P messaging; however, several enhancements and recommendations can further improve its effectiveness, scalability, and adaptability.

One key recommendation is to incorporate advanced deep learning models such as Long Short-Term Memory (LSTM) networks, Bidirectional Encoder Representations from Transformers (BERT), or other transformer-based models. These models are capable of understanding the contextual and semantic meaning of SMS messages, which can significantly improve the detection of sophisticated spam that uses subtle linguistic cues or obfuscation techniques.

Another important enhancement is to expand multilingual support. A2P SMS messages are increasingly sent in regional languages or contain mixed-language content. Integrating multilingual natural language processing (NLP) models or training models on multilingual datasets would improve classification accuracy across diverse message types.

Continuous learning and adaptive model updates are also recommended. Implementing an automated feedback loop where misclassified messages are flagged and retrained into the model can ensure the system adapts to evolving spam patterns. This will reduce the dependency on manual rule updates and help maintain high detection accuracy over time.

Improving the whitelist and rule-based mechanisms is another area for enhancement. By dynamically updating whitelisted domains, OTP templates, and trusted sender patterns, the system can further minimize false positives while maintaining the effectiveness of the spam filter. Integration with external threat intelligence sources or real-time spam databases can also enhance the system's ability to detect newly emerging spam sources.

From an operational perspective, optimizing infrastructure for scalability is recommended. Using cloud-based solutions or distributed processing can help handle high volumes of SMS traffic in real-time without compromising performance. Load balancing, batch processing, and parallel computation techniques can also improve system efficiency for enterprise-level deployments.

Finally, the system could benefit from analytics and reporting features that provide insights into spam trends, sender patterns, and message classification statistics. This would not only help telecom providers monitor system performance but also support strategic decision-making, regulatory compliance, and proactive measures against spam campaigns.

In conclusion, implementing these recommendations and future enhancements will ensure that the AI-Powered SMS Spam Filter remains accurate, adaptive, and scalable, providing long-term value to telecom providers by enhancing security, improving customer experience, and optimizing operational efficiency.

Conclusion

The AI-Powered SMS Spam Filter for A2P messaging demonstrates a comprehensive and adaptive approach to detecting spam while ensuring that legitimate messages, including OTPs, transactional notifications, and promotional content from trusted sources, are delivered accurately. By integrating rule-based filtering, whitelist mechanisms, and machine learning classification, the system achieves high precision and recall, effectively minimizing false positives and false negatives, which are critical in a telecom environment where message misclassification can impact customer trust and operational efficiency.

A key highlight of this project is its versatile deployment strategy, which ensures that the system can be effectively utilized in different operational contexts. Deployment via Streamlit allows for an interactive web-based interface suitable for demonstration, testing, and small-scale real-time message classification. This approach makes it easy for stakeholders to input messages and observe predictions with associated confidence scores. Render-based deployment facilitates cloud-based scalability and accessibility, providing secure API endpoints for enterprise-level integration, handling bulk message traffic efficiently, and enabling automated updates and scaling. Docker containerization ensures portability and consistency across environments, simplifying deployment across local, cloud, or orchestrated infrastructures. Containerization also supports scalability with orchestration tools like Kubernetes, allowing the system to handle high volumes of SMS messages in production environments without degradation in performance.

1. Objective & Approach:

- Detect spam in A2P SMS messages while ensuring legitimate messages (OTPs, transactional notifications, trusted promotions) are delivered reliably.
- Integrates a hybrid methodology:

    - Rule-based filtering
    - Whitelist mechanisms
    - Machine learning classification
- Achieves high precision and recall, minimizing false positives and false negatives, which is critical in telecom.

2. Deployment Strategies & Advantages:
- Streamlit Deployment:
    - Interactive web-based interface for demonstration, testing, and small-scale real-time classification.
    - Stakeholders can input messages and view predictions with confidence scores.
- Render Deployment:
    - Cloud-based scalability and accessibility.
    - Secure API endpoints for enterprise integration.
    - Handles bulk messages efficiently and supports automated updates and scaling.
- Docker Deployment:
    - Ensures portability and consistency across local, cloud, and orchestrated environments.
    - Supports scalability with orchestration tools like Kubernetes.
    - Maintains high performance even with high SMS volumes.

3. Technical Challenges:
- SMS content issues: Unstructured, noisy, multilingual text.
- Dataset imbalance: Legitimate messages often outnumber spam.
- Evolving spam patterns: Requires continuous updates and retraining.
- Deployment-specific challenges:
    - Streamlit: Resource management to prevent latency under high traffic.
    - Render: Cloud infrastructure optimization and cost management.
    - Docker: Container size, dependency management, orchestration complexity.

4. Business Value:
- Enhances customer trust by reducing spam exposure.
- Improves operational efficiency via automated message classification.
- Provides insights into emerging spam trends.
- Protects revenue streams by ensuring delivery of legitimate transactional and promotional messages.
- Flexible deployment allows adaptation to different operational scales, from testing to enterprise-grade production.

5. Future Enhancements:
- Incorporate advanced NLP models like BERT or transformers for better semantic understanding.
- Extend multilingual support for global applicability.
- Implement continuous learning loops to retrain on misclassified messages.
- Add analytics and reporting modules for insights into message trends, user behavior, and threats.

6. Conclusion:
- The system is robust, scalable, and intelligent for A2P SMS security.
- Hybrid methodology and versatile deployment ensure reliability, efficiency, and adaptability.
- Addresses immediate operational challenges while laying a foundation for long-term improvements in telecom message security, customer experience, and business intelligence.

References / Appendices

Dataset Details

- Name: A2P SMS Messages Dataset
- Size: 50,000 messages (duplicates removed: 42,200 messages)
- Attributes: Message_ID, Sender_ID, Receiver_ID, Timestamp, Message_Content, Label (Spam / Transactional / Promotional), Domain, OTP_Flag, Promotional_Flag

Data Source

- Publicly available SMS spam datasets (UCI SMS Spam Collection) and simulated A2P messages reflecting real-world telecom communication scenarios.
- Reference Link: UCI SMS Spam Collection Dataset

Tools & Technologies Used

- Programming Language: Python
- Libraries:
    - Pandas – Data manipulation and cleaning
    - NumPy – Numerical computations
    - NLTK & Scikit-learn – Text preprocessing and feature extraction
    - TF-IDF Vectorizer – Text feature representation
    - Scikit-learn Models: Multinomial Naive Bayes, Logistic Regression, Random Forest Classifier
    - Seaborn & Matplotlib – Data visualization and exploratory analysis
- Deployment Platform: Streamlit (for web application)
- Environment: Google Colab / Local Python Environment

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