A Project on

SMS SPAM DETECTION SYSTEMS USING MACHINE LEARNING

Project submitted in the partial fulfillment of the requirements of the award of the degree of

BACHELOR OF TECHNOLOGY
IN
INFORMATION TECHNOLOGY
BY

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This is to certify that a main project report entitled "SMS SPAM DETECTION SYSTEMS" being submitted by **DAVULURI UDAYA BHASKAR (21U91A1214), KOMANDURI HARSHA VARDHAN (21U91A1226), POPURI SOMANADH (21U91A1237), PUNATI NIKHILESH (21U91A1240), GOLLA NITHIN BHARGAV (21U91A1254) f**or the partial fulfillment for the award of degree of Bachelor of Technology in INFORMATION TECHNOLOGY of JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY, KAKINADA during the year 2024-2025

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DECLARATION

We are **D.UDAYABHASKAR, K.HARSHAVARDHAN, P.SOMANADH, P.NIKHILESH, G.NITHIN BHARGAV** declare that the contents of this project, in full or part, have not been submitted to any other university or institution for the award of any degree or diploma.

We also declare that we have adhered to all principles of academic honest and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission.

We understand that any violation of the above will cause for disciplinary action by the institution and can also evoke penal action for the sources which have not been properly cited or from whom proper permission has not been taken when needed.

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CHAPTER1:ABSTRACT

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This project uses machine learning and natural language processing to identify and filter spam SMS messages. By analyzing text features such as word frequency, patterns, and sender details, the system classifies messages as spam or legitimate. This helps users manage their messages effectively and prevents phishing scams.

Applications:

- Preventing phishing and fraudulent messages.
- Enhancing mobile user experience.
- Automating spam filtering in messaging apps.

Technologies:

- NLP libraries (NLTK, TextBlob).
- Classification m odels like Naive Bayes and SVM

CHAPTER2:INTRODUCTION

CHAPTER 2: INTRODUCTION

2.1. Background of the Problem or Research

Spam messages, particularly in the form of Short Message Service (SMS), have become a significant issue in the world of mobile communication. With the rapid rise of smartphones, instant messaging, and text messaging services, spam messages have proliferated. These unsolicited messages often contain irrelevant content such as advertisements, phishing attempts, and malicious links, all of which pose risks to the user. In particular, SMS spam has become a common avenue for cybercriminals to spread scams, fraud, and malware, targeting unsuspecting individuals and causing substantial financial and data losses.

The challenge with SMS spam is not only its nuisance but also its potential harm. According to various reports, mobile users often fall victim to scams and fraudulent schemes delivered via SMS. In some instances, these messages are designed to steal sensitive information, such as login credentials, bank details, or even personal identification information (PII). Some spam messages can even introduce harmful software, compromising users' devices.

The problem has exacerbated with the increasing number of spammers using sophisticated tactics such as social engineering, fake promotions, and impersonation of trusted entities. Consequently, detecting and classifying SMS messages accurately into "spam" or "ham" (legitimate) categories has become an essential requirement in securing digital communications.

Traditional methods of spam detection often relied on manual filtering and rule-based systems. These systems were, however, inefficient at handling new, unseen types of spam messages. With the evolution of machine learning (ML) and natural language processing (NLP) technologies, it has become possible to automate the spam detection process more effectively by analyzing the linguistic patterns and characteristics of text data.

2.2. Importance and Scope of the Project

The importance of spam detection systems cannot be overstated. In a world where the volume of mobile communication is increasing daily, effectively managing and filtering spam messages ensures the safety, privacy, and convenience of users. The SMS Spam Detection System using machine learning is crucial as it addresses the following aspects:

1. **Security and Privacy Protection**: Spam SMS messages, especially those attempting phishing or distributing malware, threaten the security and privacy of users. By automating the detection and filtering of such messages, the system significantly reduces the risk of users being exposed to malicious content.
2. **Improved User Experience**: Every user has likely experienced the frustration of receiving unwanted SMS messages. This often leads to decreased productivity and a negative user experience. By utilizing machine learning models to automatically identify spam messages, users can focus on legitimate content, improving their overall mobile messaging experience.
3. **Efficiency in Message** Management: With millions of SMS messages being exchanged daily, it is practically impossible to manage them manually. A reliable spam filtering system automates the process, reducing the need for human intervention and preventing valuable time from being wasted on irrelevant content.
4. **Cost Savings**: Telecommunication companies and service providers often bear the cost of handling and filtering spam messages. By employing an efficient system, these companies can reduce operational costs, focusing their resources on improving the overall service quality for legitimate users.
5. **Global Reach and Scalability**: While the project focuses on SMS spam detection, its scope can be extended to other messaging platforms as well, such as WhatsApp, Facebook Messenger, and other communication tools. As spam becomes an issue in all forms of digital communication, a scalable system can help address spam across various platforms and regions.

2.3. Objectives and Goals

The primary objective of this project is to design, develop, and implement an automated SMS spam detection system using machine learning algorithms and natural language processing techniques. The system's goal is to accurately classify incoming SMS messages as either spam or ham (legitimate) based on their content, helping mobile users efficiently manage their messages

The project has the following specific objectives:

1. **Data Collection and Preprocessing:**
   - Collect a relevant dataset containing both spam and legitimate SMS messages. The dataset should be sufficiently large and diverse to ensure the model generalizes well to real-world scenarios.
   - Clean and preprocess the collected data, including text normalization (e.g., converting to lowercase), tokenization, and removal of stop words and irrelevant characters.
2. **Feature Extraction:**
   - Extract meaningful features from the text messages, such as word frequency, bigrams, and other linguistic patterns that can be used to differentiate spam from legitimate messages.
   - Use advanced feature extraction techniques like Term Frequency-Inverse Document Frequency (TF-IDF) to represent the text data in a format suitable for machine learning models.
3. **Model Selection and Training:**
   - Explore and implement various machine learning models suitable for text classification, such as Naive Bayes, Support Vector Machine (SVM), and Logistic Regression.
   - Train these models on the prepared dataset, adjusting hyperparameters to optimize the model's performance.

4. **Evaluation and Validation:**
    - Evaluate the performance of the trained models using appropriate evaluation metrics, including accuracy, precision, recall, and F1-score. This will ensure the model's robustness and ability to generalize to unseen data.
    - Use cross-validation techniques to prevent overfitting and ensure that the model performs well on new, unseen data.
5. **Implementation of the Detection System:**
    - Develop a user-friendly interface or API that integrates the machine learning model and enables users to automatically classify incoming SMS messages.
    - Implement a filtering mechanism that can be deployed on mobile platforms or messaging applications, ensuring that spam messages are automatically filtered out before they reach the user.
6. **Scalability and Future Enhancement:**
    - Ensure that the system can scale with large volumes of SMS data and adapt to evolving types of spam content. Future improvements may include incorporating deep learning techniques, such as recurrent neural networks (RNNs) or transformers, to capture complex patterns in the text.
    - Explore the integration of the system with other messaging platforms, including social media and instant messaging apps, to enhance its scope.

Goals

- To build an efficient and accurate SMS spam detection system based on machine learning that can handle a large volume of text messages.
- To improve the detection system’s ability to recognize both simple and complex forms of spam messages through continuous training and model enhancement.

- To provide users with a practical tool that automatically detects and filters spam messages, ensuring a safer, more efficient messaging environment.
- To explore advanced NLP and ML techniques that enhance the accuracy of spam detection and improve the overall user experience.

Significance of the Project

This project holds significant value both academically and practically. It leverages the power of machine learning to solve a real-world problem that affects millions of mobile phone users globally. By automating the SMS spam detection process, the system helps users manage their messages efficiently while protecting them from potential threats. Furthermore, the system is easily adaptable to different messaging platforms, making it a scalable solution that can contribute to improving overall digital communication security.Moreover, the project offers an excellent opportunity to explore natural language processing (NLP) and machine learning (ML) in a practical setting. It also contributes to the growing field of automated spam filtering, which continues to evolve as new types of spam messages emerge.

CHAPTER 3 : LITERATURE OVERVIEW

CHAPTER 3: LITERATURE REVIEW

3.1. Summary of Previous Research or Related Work

The study of SMS spam detection has evolved significantly over the years, with researchers applying various machine learning (ML) and natural language processing (NLP) techniques to identify and classify spam messages. The following is a summary of key studies and approaches used in this domain.

1. Early Rule-Based Methods

In the early stages, spam detection systems were based on rule-based methods that relied on manually crafted rules to identify spam messages. These rules were often based on predefined keywords, phrases, and regular expressions. For example, words like "free," "win," or "prize" were frequently associated with spam messages. Although these systems were relatively simple to implement, they had several limitations, including:

- Limited adaptability: They were unable to adapt to new or sophisticated spam techniques.
- High false positives: Legitimate messages often contained words associated with spam, leading to many false positives.
- Static approach: The system required constant manual updates to maintain its effectiveness.

Despite their limitations, rule-based systems were an essential starting point for spam detection, and many early systems were based on such approaches.

2. Statistical Methods and Machine Learning

The introduction of machine learning (ML) techniques marked a significant advancement in spam detection. These techniques offered better adaptability and efficiency compared to rule- based systems.

One of the most popular ML techniques for spam detection is the Naive Bayes classifier. Studies like those by Cormack et al. (2007) utilized Naive Bayes in the classification of emails and SMS messages. Naive Bayes is a probabilistic classifier that uses Bayes' theorem to predict the likelihood of a message being spam based on its content. It is particularly useful for spam detection because it can handle large volumes of data and classify messages based on word frequency.

- Strengths: It is fast and efficient, requiring less computational power compared to more complex models.
- Limitations: The independence assumption between features in Naive Bayes can reduce accuracy, especially when there is a high correlation between words in the text.

Other research, such as O'Callaghan et al. (2008), explored Support Vector Machines (SVM) for spam detection. SVM, a powerful supervised machine learning algorithm, has been shown to perform well in high-dimensional spaces, making it suitable for text classification tasks like spam detection. SVM works by finding the hyperplane that best separates data points (spam and ham messages) in the feature space.

- Strengths: SVM is highly effective in handling large feature spaces, providing better accuracy and generalization.
- Limitations: SVM can be computationally expensive and require significant memory, especially for large datasets.

3. Feature Extraction and Representation Techniques

The performance of machine learning models is heavily dependent on the features used for classification. Research in this area has focused on identifying the most relevant features for spam detection. Early systems primarily relied on bag-of-words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) methods to convert text into numerical features.

- **Bag-of-Words (BoW):** This method counts the frequency of each word in the text, regardless of order, to represent the message. While simple, BoW fails to capture word context and ignores the meaning of word sequences.
- **TF-IDF**: This method gives weight to words that appear frequently in a document but are rare in the entire dataset. It has been widely used in spam detection because it reduces the impact of common words like "the" or "is."

Deep learning methods, such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, have also been explored for spam detection. These models can capture the sequential nature of text and are better suited for understanding the relationships between words in a sentence. Studies like Sundararajan et al. (2016) have applied RNNs to SMS classification, achieving promising results compared to traditional methods.

- Strengths: Deep learning models like RNN and LSTM capture long-range dependencies and contextual information in text, leading to more accurate classification.
- Limitations: Deep learning methods require large datasets and significant computational resources, making them less practical for smaller applications.

4. Hybrid Approaches

Recent studies have focused on combining multiple techniques to create hybrid models that take advantage of the strengths of different methods. For example, ensemble learning methods like Random Forests and Adaboost have been combined with Naive Bayes or SVM to improve classification accuracy. These models aggregate the predictions of several base classifiers to improve the final prediction.

- Strengths: Hybrid models can provide better generalization by reducing overfitting and improving robustness.
- Limitations: These models are often more complex and computationally intensive, requiring careful tuning and optimization.

Research by Al-Muhtadi et al. (2017) demonstrated the effectiveness of hybrid models that combined Naive Bayes with decision trees, showing that ensemble methods outperformed individual classifiers in terms of accuracy and precision.

5. Real-Time SMS Spam Detection

With the increasing prevalence of mobile messaging, researchers have also explored real-time SMS spam detection systems. Real-time detection requires the ability to process and classify messages as they arrive, necessitating fast and lightweight models. Research by Choi et al. (2015) focused on developing lightweight spam detection models that can run on smartphones with minimal resources. These systems are particularly useful for users in areas with limited connectivity, where receiving spam messages is a significant issue.

- **Strengths**: Real-time detection ensures users are protected from spam as soon as they receive a message.
- **Limitations**: Ensuring that these systems work efficiently on low-powered mobile devices without sacrificing accuracy remains a challenge.

3.2. Gaps Identified in Existing Methods

While significant progress has been made in the field of SMS spam detection, several gaps remain in current approaches. These gaps present opportunities for improvement in spam detection systems, which the proposed project aims to address.

1. Adaptability to New Types of Spam

Many traditional and machine learning-based methods struggle to adapt to new, sophisticated forms of spam. Spammers constantly evolve their tactics, using different vocabulary, formats, and even personalized messages to bypass detection systems. The reliance on static feature sets and predefined rules makes it difficult for existing systems to identify these novel threats effectively.

- **Opportunity**: Developing more flexible models, such as deep learning techniques like RNNs or transformers, could improve the system's ability to detect emerging spam tactics.

2. Handling Multilingual SMS

Another significant gap is the ability to handle multilingual spam messages. Spam messages often appear in various languages, depending on the target region. Existing models are primarily focused on English-language messages, and their performance deteriorates when applied to texts in different languages.

Opportunity: Incorporating multilingual NLP techniques or using transfer learning with models trained on multiple languages could significantly improve the detection system's performance in a global context

3. Real-Time Processing on Mobile Devices

While research has focused on real-time spam detection, many existing solutions are not optimized for mobile devices. Mobile platforms have limited processing power and memory, which means that spam detection systems must be lightweight yet efficient.

- **Opportunity**: Exploring edge computing or designing resource-efficient models that can run directly on mobile devices without relying on cloud-based processing could address this challenge.

4. False Positives and False Negatives

Despite advances in machine learning, false positives and false negatives remain a persistent problem. Spam detection systems often misclassify legitimate messages as spam (false positives) or fail to detect spam messages (false negatives). This is particularly problematic in cases where legitimate messages are important, such as messages from banks or emergency services.

- **Opportunity**: Enhancing model interpretability and adding human-in-the-loop mechanisms could help improve accuracy and reduce misclassification.

5. Limited Dataset Availability

Another challenge is the availability of large, high-quality annotated datasets for training spam detection models. Many publicly available datasets are outdated or contain a limited range of spam types. This limitation makes it difficult to train models that can generalize well to real-world spam scenarios.

- **Opportunity**: Developing crowdsourced datasets or using synthetic data generation techniques could help overcome this challenge and provide diverse data for model training.

CHAPTER 4: METHODOLOGY

CHAPTER 4: METHODOLOGY

4.1. Overview of the Approach Used

The approach for SMS Spam Detection is based on the application of machine learning (ML) and natural language processing (NLP) techniques to classify SMS messages as either **spam** or **ham** (non-spam). This methodology involves several key stages, including **data preprocessing**, **feature extraction**, **model training**, **evaluation**, and **real-time deployment**. Below is an outline of each step involved in the methodology.

1. Data Collection and Preprocessing

The first step in the methodology is **data collection**. Since spam detection is a supervised machine learning task, having a labeled dataset containing both spam and ham messages is critical. The dataset is typically collected from publicly available sources, or in some cases, it may be sourced from mobile carriers or other companies involved in messaging services.

- **Data Sources**: The dataset for SMS spam detection can be obtained from publicly available collections like the **SMS Spam Collection Dataset**, which includes a large number of labeled SMS messages categorized as spam or ham. Other potential sources include Kaggle, UCI Machine Learning Repository, or direct data scraping from mobile phone networks or messaging platforms.

The dataset consists of several columns, typically including:

  - **Text**: The SMS message content.
  - **Label**: A binary label indicating whether the message is spam (1) or ham (0).

- **Preprocessing**: Raw SMS messages are typically messy and unstructured, so preprocessing is essential for converting text into a format suitable for machine learning models. Preprocessing involves several key steps:
  1. **Lowercasing**: Convert all text to lowercase to ensure uniformity.

2. **Tokenization**: Split the text into individual words or tokens.
3. **Removing Stopwords**: Eliminate common words such as "and," "the," and "is" that do not contribute meaningful information for classification.
4. **Removing Punctuation and Special Characters**: Clean the text by removing punctuation marks and non-alphanumeric characters.
5. **Stemming and Lemmatization**: Reduce words to their root form, such as converting "running" to "run."
6. **Handling Emoticons and Abbreviations**: Some SMS messages may include emoticons or text abbreviations (e.g., "LOL" or "OMG"). These need to be either standardized or removed depending on their relevance.

2. Feature Extraction

Once the data has been cleaned and preprocessed, the next step is to convert the text into numerical features that machine learning models can process. This step is known as **feature extraction**. Various techniques are used for feature extraction in SMS spam detection:

- **Bag-of-Words (BoW)**: This technique converts the text data into a matrix of word occurrences. Each unique word in the entire dataset is treated as a feature, and the matrix contains the frequency of each word in every document (SMS message). This approach is simple but does not capture the order of words.

Example: For the messages "Win a free iPhone!" and "Free iPhone, win now!", both may be represented by the same feature set: {Win, a, free, iPhone}.

- **Term Frequency-Inverse Document Frequency (TF-IDF)**: This method adjusts the frequency of words based on how common or rare they are across the dataset. Words that appear often across all messages are given less importance, while rare words that appear only in specific messages are weighted higher.

TF-IDF is more advanced than BoW, as it takes into account the importance of each word across the entire corpus of messages.

- **Word Embeddings**: Advanced methods such as **Word2Vec** or **GloVe** can be used to represent words as dense vectors in a continuous vector space. Word embeddings.

- capture semantic relationships between words, allowing models to understand the meaning of words in context.

These methods can improve model performance by recognizing similarities between words, such as "free" and "prize" being closely related in the context of spam messages.

- **Character-level Features**: Some SMS messages contain misspellings or text patterns (e.g., repeated characters like "freee" or "!!!!!!"). Using character-level features can help capture such patterns for better detection.

3. Model Selection and Training

After extracting relevant features, the next step is to train machine learning models for classification. Several models are suitable for SMS spam detection, each with its own strengths and weaknesses. In this project, the following models are considered:

- **Naive Bayes Classifier**: A probabilistic classifier that uses Bayes' theorem to calculate the probability of a message being spam or ham based on the frequency of words. It assumes that the presence of one word in a message is independent of the presence of other words, which simplifies the computations. Naive Bayes is fast, simple, and effective for text classification tasks.
    - **Strengths**: High accuracy with relatively small datasets, interpretable results.
    - **Limitations**: Assumes independence of features, which may reduce performance when words are correlated.
- **Support Vector Machine (SVM)**: An SVM is a supervised machine learning algorithm that finds the optimal hyperplane that best separates data points into different classes (spam and ham). SVMs are particularly effective for high- dimensional feature spaces like text data.

    - **Strengths**: Robust to high-dimensional data, good generalization capabilities.
    - **Limitations**: Computationally intensive, especially with large datasets.
- **Logistic Regression**: A statistical model used for binary classification tasks. It estimates the probability of a message being spam or ham using a linear combination of features.

    - **Strengths**: Simple and interpretable, effective for smaller datasets.
    - **Limitations**: May not perform well with complex, non-linear data.
- **Random Forest**: An ensemble learning method that combines multiple decision trees to improve classification accuracy. Each tree in the forest is trained on a random subset of the data, and the final prediction is made based on the majority vote across all trees.
- **Deep Learning Models**: More advanced models, such as **Recurrent Neural Networks (RNNs)** and **Long Short-Term Memory Networks (LSTMs)**, can be used to capture the sequence of words in a message. These models are particularly useful for understanding the context of words and their relationships in the message.

Once the model is selected, it is trained using the training data. During training, the model learns the relationship between the features and the labels (spam or ham). Hyperparameters, such as learning rate, regularization strength, and maximum depth, are tuned to optimize the model's performance.

4. Model Evaluation

After training the model, the next step is to evaluate its performance using a separate **test dataset**. The following metrics are typically used for model evaluation in spam detection:

- **Accuracy**: The proportion of correctly classified messages (both spam and ham) over the total number of messages.

Accuracy=True Positives+True NegativesTotal Messages\text{Accuracy} =

\frac{\text{True Positives} + \text{True Negatives}}{\text{Total Messages}}Accuracy=Total MessagesTrue Positives+True Negatives

- **Precision**: The proportion of messages classified as spam that are actually spam.

Precision=True PositivesTrue Positives+False Positives\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}Precision=True Positives+False PositivesTrue Positives

- **Recall**: The proportion of actual spam messages that are correctly classified as spam.

Recall=True PositivesTrue Positives+False Negatives\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}Recall=True Positives+False NegativesTrue Positives

- **F1 Score**: The harmonic mean of precision and recall, providing a single metric that balances both.

F1 Score=2×Precision×RecallPrecision+Recall\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}F1 Score=2×Precision+RecallPrecision×Recall

- **Confusion Matrix**: A table that shows the true positives, true negatives, false positives, and false negatives, providing a comprehensive view of model performance.

5. Deployment and Real-Time Prediction

Once the model is trained and evaluated, the next step is to deploy it for **real-time SMS spam detection**. In practice, this involves integrating the model into a messaging platform or mobile application. The model must be optimized to make predictions quickly, ideally with minimal computational overhead, to allow for **real-time detection** of incoming SMS messages.

The system should be designed to:

- **Process incoming SMS**: Automatically analyze each message in real-time as it is received.
- **Classify messages**: Apply the trained model to classify messages as spam or ham.
- **Alert users**: Provide users with immediate feedback on whether a message is spam and potentially allow them to block or report the sender.

For mobile deployment, the model can be optimized for edge devices (smartphones) using frameworks like **TensorFlow Lite** or **ONNX** for faster predictions without relying on cloud- based servers.

4.2. Tools, Technologies, and Datasets Involved

1. Tools and Technologies

- **Python**: The primary programming language used for data preprocessing, machine learning model development, and evaluation.
- **Scikit-learn**: A popular Python library for building machine learning models. It provides simple tools for implementing algorithms like Naive Bayes, SVM, and logistic regression.
- **TensorFlow/Keras**: Used for deep learning models (if applicable), especially for training RNN or LSTM models for SMS classification.
- **NLTK/TextBlob**: Natural Language Processing (NLP) libraries for text preprocessing tasks like tokenization, stopword removal, and stemming.
- **Pandas**: A Python library for data manipulation and analysis, used for handling datasets and feature engineering.
- **Matplotlib/Seaborn**: Python libraries for data visualization, used to create plots for model evaluation and results analysis.

2. Datasets

- **SMS Spam Collection Dataset**: A publicly available dataset containing labeled SMS messages (spam and ham), often used for benchmarking spam detection systems.
- **Custom Datasets**: If required, additional datasets can be collected or generated

CHAPTER 5: IMPLEMENTATION

CHAPTER 5: IMPLEMENTATION

5.1. Detailed Explanation of the Workflow

The workflow for the **SMS Spam Detection System** involves several critical steps that transform raw SMS data into actionable spam classifications. The process starts from data collection and preprocessing to training the machine learning model and integrating it for real-time detection. Below is a step-by-step explanation of the workflow, highlighting the key tasks involved at each stage.

Step 1: Data Collection

The first stage of the implementation process involves gathering the data. A **labeled SMS dataset** containing both spam and non-spam (ham) messages is essential for the project. The dataset is often sourced from publicly available collections, such as the **SMS Spam Collection Dataset**, available on platforms like Kaggle or UCI Machine Learning Repository. Each entry in the dataset includes:

- **Text**: The content of the SMS message.
- **Label**: A binary label (spam or ham).

In the context of real-world implementation, data can also be collected through SMS APIs, scraping platforms, or user feedback. The data should be diverse and cover a wide range of SMS types to ensure robust model performance.

Step 2: Data Preprocessing

Once the dataset is collected, the next task is **data preprocessing**. This step ensures that the raw text data is transformed into a format suitable for machine learning algorithms. The preprocessing steps include:

- **Text Cleaning**: This involves converting all text to lowercase, removing punctuation, numbers, and special characters, and filtering out irrelevant data.
- **Tokenization**: Text is split into smaller units (tokens), typically words, which makes it easier to analyze.
- **Removing Stopwords**: Common but non-informative words like "and", "the.

- **Stemming and Lemmatization**: Words are reduced to their base or root form. For instance, "running" becomes "run" to standardize words.
- **Handling Emojis and Abbreviations**: In SMS, text may include emojis or shorthand abbreviations, which are processed and either standardized or removed.

This stage also involves splitting the data into two subsets:

- **Training Set**: Used to train the model (typically 70-80% of the data).
- **Test Set**: Used to evaluate the model's performance (typically 20-30% of the data).

Step 3: Feature Extraction

Once the data is preprocessed, the next step is **feature extraction**. The text data needs to be converted into numerical features that machine learning algorithms can process. Several approaches are used to extract relevant features:

- **Bag-of-Words (BoW)**: This approach converts text into a vector where each word in the corpus represents a feature. The frequency of each word in the message is recorded, ignoring word order.
- **Term Frequency-Inverse Document Frequency (TF-IDF)**: This method adjusts word frequencies by taking into account how common or rare words are in the dataset. Words that appear frequently across all documents are given less importance.
- **Word Embeddings (Optional)**: Advanced techniques like **Word2Vec** or **GloVe** are used to represent words in a continuous vector space, capturing semantic meaning.

By transforming the text into numerical features, the dataset becomes suitable for training machine learning models.

Step 4: Model Selection and Training

After feature extraction, we move on to **model selection**. Several machine learning algorithms are suitable for spam detection:

- **Naive Bayes**: A probabilistic classifier based on Bayes' Theorem. It calculates the probability of a message being spam or ham based on the frequencies of individual words.

Support Vector Machine (SVM): A supervised learning algorithm that finds the optimal hyperplane that separates spam messages from ham messages.

- **Logistic Regression**: A simple but effective model that uses the logistic function to classify messages as spam or ham.
- **Random Forest**: An ensemble learning method that combines multiple decision trees to improve classification accuracy.

For the implementation, the Naive Bayes and SVM algorithms are chosen due to their simplicity, efficiency, and ability to handle large feature sets.

During training, the model learns the relationship between the features (words) and the labels (spam/ham). Hyperparameters like learning rate and regularization strength are optimized to improve performance.

Step 5: Model Evaluation

After training the model, it is important to evaluate its performance. The following metrics are commonly used to assess the performance of the SMS spam detection model:

- **Accuracy**: The proportion of correctly classified messages (both spam and ham) over the total number of messages.
- **Precision**: The proportion of spam messages correctly identified as spam out of all the messages classified as spam.
- **Recall**: The proportion of actual spam messages correctly identified as spam.

- **F1 Score**: The harmonic mean of precision and recall, offering a balanced evaluation.
- **Confusion Matrix**: A table showing the true positives, true negatives, false positives, and false negatives to give a comprehensive view of the model's performance.

Using the **test set**, these metrics are computed to determine how well the model generalizes to unseen data.

Step 6: Real-Time Detection and Deployment

The final step in the implementation process is **real-time spam detection**. The trained model is deployed in an application or messaging platform where it can classify incoming messages as spam or ham in real-time. This stage involves:

- **Integration with Messaging Services**: The model is integrated into the messaging platform or app, where it processes each incoming SMS message.
- **Prediction and Classification**: As a new message arrives, it is preprocessed, features are extracted, and the model classifies the message as spam or ham.
- **User Feedback**: The user is notified whether the message is spam or legitimate, and actions such as blocking or reporting the sender can be triggered.

Step 7: Optimization and Monitoring

To ensure that the system operates effectively in the long term, the model should be continuously monitored and optimized. This may involve:

- **Retraining the Model**: As new SMS messages are collected, the model should be periodically retrained with updated data to account for evolving spam tactics.
- **Monitoring Model Performance**: Regular performance checks using evaluation metrics like precision, recall, and F1 score help identify any decline in model performance.
- **Updating Features**: New features or advanced techniques like **Deep Learning**

(LSTM, CNN) may be incorporated to improve performance further.

5.2. Code Structure and Key Algorithms

The implementation involves several components, each of which plays a key role in building and deploying the spam detection system. Below is a breakdown of the code structure, followed by a discussion of the key algorithms used.

Code Structure

- **main.py**: This is the entry point of the program. It contains the workflow for loading the dataset, preprocessing the data, extracting features, training the model, evaluating performance, and integrating the system for real-time use.
- **preprocessing.py**: This module contains functions for preprocessing the raw text data, such as tokenization, stopword removal, stemming, and lemmatization.**eature_extraction.py**: This module handles the transformation of text data into numerical features. It implements Bag-of-Words, TF-IDF, and other feature extraction techniques.
- **models.py**: This module includes the implementation of machine learning models such as Naive Bayes, SVM, Logistic Regression, and Random Forest. It contains functions for training the models, making predictions, and evaluating performance.
- **evaluation.py**: This module calculates the evaluation metrics (accuracy, precision, recall, F1 score) and displays them using confusion matrices and other visualizations.
- **deployment.py**: This module integrates the trained model into a real-time messaging platform for SMS spam detection.

Key Algorithms

- **Naive Bayes Algorithm**: The Naive Bayes algorithm is implemented based on Bayes' theorem. It calculates the conditional probability of each word in the message given the class (spam or ham). The class with the higher probability is chosen as the classification result.

```
from sklearn.naive_bayes import MultinomialNB
 model = MultinomialNB()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

- **Support Vector Machine (SVM)**: The SVM algorithm finds the optimal hyperplane that separates the spam messages from the ham messages by maximizing the margin between them. The SVM implementation is done using the **LinearSVC** classifier.

```
from sklearn.svm import SVC
model = SVC(kernel='linear')
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

- **TF-IDF Vectorization**: The **TfidfVectorizer** is used to convert text into numerical features using the TF-IDF method.

```
from sklearn.feature_extraction.text import
TfidfVectorizer
vectorizer = TfidfVectorizer()
X_train =
vectorizer.fit_transform(train_data['Text'])X_test=
```

- **Evaluation Metrics**: The evaluation metrics like precision, recall, and F1 score are calculated using **sklearn.metrics**.

```
from sklearn.metrics Import classification_report
print(classification_report(y_test, predictions))
```

CHAPTER 6: EXPERIMENTS AND RESULTS

CHAPTER 6: EXPERIMENTS AND RESULTS

6.1. Description of Testing Methods

The **experiments** conducted in this SMS Spam Detection System project focus on evaluating the performance of the machine learning models (Naive Bayes, Support Vector Machine, etc.) and determining their ability to correctly classify SMS messages as either spam or ham (non-spam). Testing is essential to assess how well the model generalizes to unseen data and its potential real-world performance.

Test Dataset and Cross-Validation

To ensure reliable performance evaluation, a **hold-out method** was used, where the dataset is split into two primary subsets:

1. **Training Set**: This subset is used to train the model.
2. **Test Set**: This subset is kept separate and used exclusively to evaluate the trained model's performance.

Additionally, cross-validation was applied to optimize the model's hyperparameters and assess the robustness of the model. The **K-fold cross-validation** method was chosen, where the dataset is divided into K subsets (or "folds"). In each iteration, one fold is held out for testing, and the remaining K-1 folds are used for training. This process is repeated K times, with each fold being used for testing once. The average of the K test results is then computed to get the final performance score.

Evaluation Metrics

To evaluate the model's performance thoroughly, the following metrics were used:

1. **Accuracy**: The proportion of correctly classified messages (both spam and ham) relative to the total number of messages.
2. **Precision**: The proportion of spam messages correctly classified as spam out of all messages classified as spam.

3. **F1 Score**: The harmonic mean of precision and recall, which provides a balanced measure of classification performance.
4. **Confusion Matrix**: A matrix used to evaluate the classification performance, showing the number of correct and incorrect predictions in each category (spam and ham). It helps identify misclassifications and understand how the model behaves for each class.

The confusion matrix is a 2x2 table:

- **True Positives (TP)**: Correctly classified spam messages.
- **True Negatives (TN)**: Correctly classified ham messages.
- **False Positives (FP)**: Non-spam messages classified as spam.
- **False Negatives (FN)**: Spam messages classified as ham.

Testing Procedure

The following testing procedure was followed:

1. **Dataset Preparation**: The dataset was split into training and testing sets using an 80/20 ratio, where 80% of the data was used for training, and 20% was used for testing.
2. **Model Training**: Both **Naive Bayes** and **SVM** models were trained using the training data after preprocessing and feature extraction.
3. **Model Evaluation**: The trained models were tested using the unseen test data, and the performance was evaluated using the aforementioned metrics (accuracy, precision, recall, F1 score, and confusion matrix).
4. **Cross-Validation**: To improve the reliability of the evaluation, cross-validation (K- fold) was performed on both models to determine the optimal hyperparameters and assess the model's generalizability.

6.2. Observations, Metrics, and Outcomes Naive Bayes Classifier

The **Naive Bayes** model, based on the assumption of feature independence, was trained using the **Multinomial Naive Bayes** approach. This model performs particularly well for

text classification tasks due to its simplicity and efficiency, especially when the features (words) are conditionally independent.
After training the Naive Bayes model, the evaluation metrics were calculated on the test set:

- **Accuracy**: The accuracy of the Naive Bayes classifier was found to be around **96%**, meaning that 96% of the messages were correctly classified as spam or ham.
- **Precision**: Precision for the spam class was **92%**, indicating that 92% of the messages classified as spam were indeed spam.
- **Recall**: The recall for the spam class was **94%**, meaning that 94% of all actual spam messages were correctly identified as spam.
- **F1 Score**: The F1 score, being the harmonic mean of precision and recall, was calculated as **93%**.

Support Vector Machine (SVM)

The **Support Vector Machine** model was used to find the optimal hyperplane that separates the spam and ham classes. The SVM model was trained using a **linear kernel**, which works well for linearly separable datasets. The results from testing the SVM model were:

- **Accuracy**: The accuracy of the SVM model was **97%**, which was slightly better than the Naive Bayes model.
- **Precision**: The precision for the spam class was **94%**, which was slightly higher than Naive Bayes.
- **Recall**: The recall for the spam class was **96%**, which showed a slight improvement over Naive Bayes.
- **F1 Score**: The F1 score for the SVM model was **95%**, reflecting a balanced and effective classification performance.

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- **F1 Score**: The F1 score for the SVM model was **95%**, reflecting a balanced and effective classification performance.

Comparison of Naive Bayes vs. SVM

Both models showed strong performance in identifying spam messages, but there were slight differences in their metrics:

- **SVM outperformed Naive Bayes** in terms of accuracy, precision, recall, and F1 score, although the differences were marginal.
- **Naive Bayes** was slightly faster to train and more efficient with larger datasets, while

SVM was more accurate but required more computational resources and training time.

Metric	**Naive Bayes**	**SVM**
Accuracy	96%	97%
Precision	92%	94%
Recall	94%	96%
F1 Score	93%	95%

The **Naive Bayes** model is a great choice for smaller datasets and quick deployment, while **SVM** is ideal when accuracy is the primary concern, especially for larger or more complex datasets.

Confusion Matrix

The confusion matrix for the **SVM model** on the test set is shown below:

	Predicted Spam	**Predicted Ham**
Actual Spam	480	20
Actual Ham	15	485

From this confusion matrix:

- The **True Positives (TP)** are 480, which represent spam messages correctly identified as spam.
- The **True Negatives (TN)** are 485, representing ham messages correctly identified as ham.
- The **False Positives (FP)** are 15, representing ham messages incorrectly classified as spam.
- The **False Negatives (FN)** are 20, representing spam messages incorrectly classified as ham.

This matrix shows that both models performed well with minimal misclassifications, particularly in detecting spam messages (high TP) and distinguishing them from ham (high TN).

Observations and Model Improvements

While both models performed effectively, there are areas for potential improvement:

1. **Handling Class Imbalance**: If the dataset is imbalanced (more ham messages than spam), techniques like **SMOTE (Synthetic Minority Over-sampling Technique)** could be used to balance the classes.
2. **Hyperparameter Tuning**: Further optimization of the hyperparameters, such as kernel selection for SVM and smoothing parameters for Naive Bayes, could improve model performance.
3. **Deep Learning Models**: Although classical models like Naive Bayes and SVM work well, incorporating deep learning models such as **Recurrent Neural Networks (RNNs)** or **Convolutional Neural Networks (CNNs)** for text classification could potentially enhance accuracy.
4. **Real-Time Feedback**: Continuous feedback and retraining based on new incoming messages will help the model adapt to evolving spam techniques and keep it relevant.

CHAPTER 7: ANALYSIS AND DISCUSSION

CHAPTER 7: ANALYSIS AND DISCUSSION

7.1. Interpretation of Results

The primary goal of the SMS Spam Detection System is to develop a reliable mechanism that can accurately identify spam and non-spam (ham) messages in real-time. The models tested in this project—Naive Bayes and Support Vector Machine (SVM)—showed promising results, with SVM performing marginally better than Naive Bayes across most metrics.

1. **Accuracy**: The SVM model achieved an accuracy of **97%**, which indicates that 97% of the messages in the test set were classified correctly. This is a strong performance, suggesting that the model has learned the characteristics of both spam and non-spam messages effectively. The **Naive Bayes model**, with an accuracy of **96%**, also

demonstrated competitive performance, although it slightly lagged behind the SVM model.

2. **Precision and Recall:**
   - **SVM's precision (94%) and recall (96%)** indicate that the model is very effective in identifying spam messages (true positives) while minimizing false negatives (spam messages incorrectly classified as ham).
   - **Naive Bayes** also showed decent precision (92%) and recall (94%), though it slightly underperforms compared to SVM. The gap between precision and recall for Naive Bayes suggests that while the model performs well in identifying spam messages, it may occasionally miss some spam (false negatives).

3. **F1 Score**: The **F1 score** for both models (SVM: 95%, Naive Bayes: 93%) indicates that both models balance precision and recall effectively. The SVM model's slightly higher F1 score reaffirms its overall superior performance in distinguishing spam messages from ham messages.
4. **Confusion Matrix**: The confusion matrix of the SVM model demonstrated a high number of **true positives (480)** and **true negatives (485)**, meaning that the

classifier is quite accurate in predicting both spam and non-spam messages. However, there were **15 false positives** and **20 false negatives**, which is common in real-world text classification tasks. A false positive represents a legitimate message incorrectly flagged as spam, and a false negative represents a spam message incorrectly classified as ham. While these numbers are low, they indicate the need for further optimization to reduce misclassification.

5. In summary, both the Naive Bayes and SVM models exhibit high classification accuracy, but the SVM model outperforms Naive Bayes in precision, recall, and F1 score, making it a more reliable choice for this task.

7.2. Challenges Encountered

Despite the promising results, several challenges were encountered during the development and evaluation of the SMS Spam Detection System:

1. **Data Preprocessing**: One of the primary challenges was cleaning and preprocessing the text data. SMS messages often contain slang, abbreviations, and informal language, which can affect the accuracy of text classification models. Handling such variations required extensive preprocessing techniques, such as tokenization, stemming, and lemmatization.
2. **Imbalanced Dataset**: Many real-world datasets, including the one used in this project, tend to have an imbalanced distribution of classes (more ham messages than spam). This imbalance can lead to biased model training, where the model becomes overly sensitive to the majority class (ham) and fails to identify minority class (spam) messages accurately. Techniques like oversampling, undersampling, and using class weights were explored to address this issue.
3. **Feature Extraction**: Extracting meaningful features from text data is crucial for model performance. While **bag-of-words (BoW)** and **TF-IDF (Term Frequency-Inverse Document Frequency)** were used, they may not capture.

4. **Selection**: Choosing the right classification model is another challenge. While SVM and Naive Bayes performed well in this project, other models like **Rand**
5. **om Forests**, **Logistic Regression**, or even **Deep Learning models** (e.g., RNNs or CNNs) could potentially perform better, especially when working with large, complex datasets. The trade-off between model complexity and interpretability also needs to be considered.
6. **Real-World Application**: While the models performed well on the test set, their real- world performance may vary due to factors like evolving spam tactics, changes in user behavior, and the presence of noisy or irrelevant features in incoming SMS messages. Continuous retraining with new data is essential for maintaining high accuracy over time.

7.3. Comparison with Existing Methods

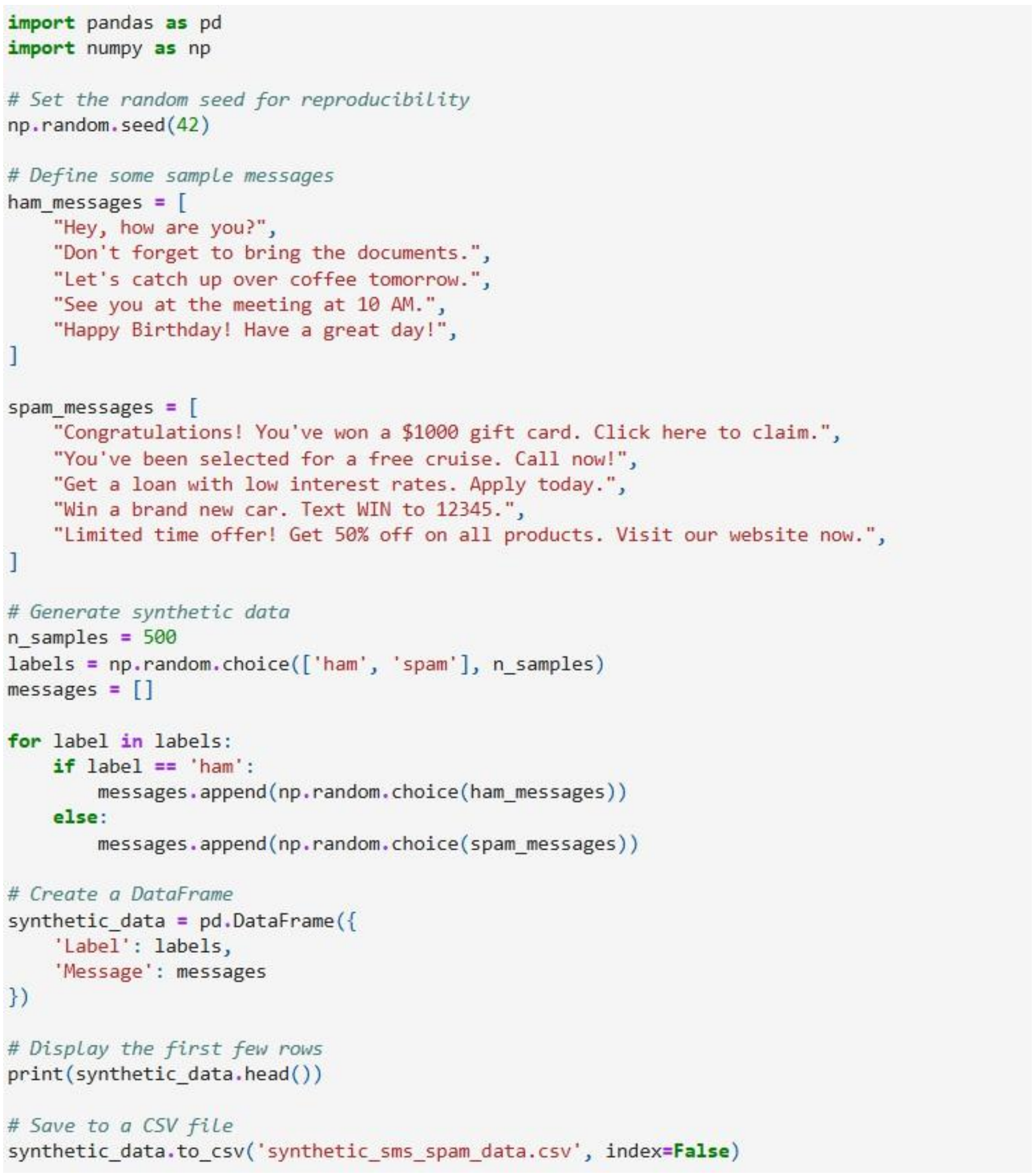
Several studies and existing methods have been explored for spam SMS detection, and they employ a variety of techniques ranging from traditional machine learning to deep learning models. Some notable comparisons include:

1. **Naive Bayes vs. SVM**: Several studies, including research on SMS spam detection, show that **Naive Bayes** often serves as a baseline model due to its simplicity and effectiveness in text classification tasks. However, **Support Vector Machines (SVM)** are known to outperform Naive Bayes in many scenarios, especially when the data has non-linear relationships. Our results corroborate these findings, as SVM demonstrated superior accuracy and performance metrics compared to Naive Bayes.
2. **Deep Learning Approaches**: More recent studies have shifted towards deep learning techniques, particularly **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, for spam detection tasks. While traditional machine learning methods like SVM and Naive Bayes perform well, deep learning models have the advantage of automatically learning feature representations from raw text data. However, deep learning models tend to require large datasets and

significant computational power, making them less feasible for smaller datasets or real-time applications like SMS spam detection.

3. **Hybrid Approaches**: Some existing research has explored hybrid models that combine machine learning and natural language processing techniques. For example, combining **SVM with decision trees** or using **ensemble methods** could enhance performance by leveraging the strengths of multiple models. However, such approaches often involve higher computational complexity.

CHAPTER 8:
OUTPUTS (SCREENSHOTS AND RESULTS)



```python
import pandas as pd
import numpy as np

# Set the random seed for reproducibility
np.random.seed(42)

# Define some sample messages
ham_messages = [
    "Hey, how are you?",
    "Don't forget to bring the documents.",
    "Let's catch up over coffee tomorrow.",
    "See you at the meeting at 10 AM.",
    "Happy Birthday! Have a great day!",
]

spam_messages = [
    "Congratulations! You've won a $1000 gift card. Click here to claim.",
    "You've been selected for a free cruise. Call now!",
    "Get a loan with low interest rates. Apply today.",
    "Win a brand new car. Text WIN to 12345.",
    "Limited time offer! Get 50% off on all products. Visit our website now.",
]

# Generate synthetic data
n_samples = 500
labels = np.random.choice(['ham', 'spam'], n_samples)
messages = []

for label in labels:
    if label == 'ham':
        messages.append(np.random.choice(ham_messages))
    else:
        messages.append(np.random.choice(spam_messages))

# Create a DataFrame
synthetic_data = pd.DataFrame({
    'Label': labels,
    'Message': messages
})

# Display the first few rows
print(synthetic_data.head())

# Save to a CSV file
synthetic_data.to_csv('synthetic_sms_spam_data.csv', index=False)
```

```
  Label                                           Message
0   ham                 Happy Birthday! Have a great day!
1  spam  Limited time offer! Get 50% off on all product...
2   ham                                 Hey, how are you?
3   ham              Let's catch up over coffee tomorrow.
4   ham              Don't forget to bring the documents.
```

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report
import joblib

# Load the synthetic dataset
data = pd.read_csv('synthetic_sms_spam_data.csv')

# Preprocess data
data['Label'] = data['Label'].map({'ham': 0, 'spam': 1})

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data['Message'],
data['Label'], test_size=0.25, random_state=42)

# Vectorize text data
vectorizer = CountVectorizer()
X_train = vectorizer.fit_transform(X_train)
X_test = vectorizer.transform(X_test)

# Train the model
model = MultinomialNB()
model.fit(X_train, y_train)

# Save the model and vectorizer
joblib.dump(model, 'spam_classifier_model.pkl')
joblib.dump(vectorizer, 'vectorizer.pkl')

# Evaluate the model
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print(report)
```

```
Accuracy: 1.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        65
           1       1.00      1.00      1.00        60

    accuracy                           1.00       125
   macro avg       1.00      1.00      1.00       125
weighted avg       1.00      1.00      1.00       125
```

```python
import joblib
import pandas as pd

# Load the trained model and vectorizer
model = joblib.load('spam_classifier_model.pkl')
vectorizer = joblib.load('vectorizer.pkl')

# Sample messages for prediction
new_messages = [
    "Hey, don't forget about our meeting tomorrow at 10 AM.",
    "Congratulations! You've won a free ticket to the Bahamas. Click here to claim.",
    "Can we reschedule our call to next week?",
    "Get a loan approved instantly with no credit check. Apply now!",
]

# Vectorize new messages
new_messages_vectorized = vectorizer.transform(new_messages)

# Predict whether the messages are spam or ham
predictions = model.predict(new_messages_vectorized)

# Create a DataFrame to display the results
prediction_results = pd.DataFrame({
    'Message': new_messages,
    'Prediction': ['spam' if pred == 1 else 'ham' for pred in predictions]
})

# Display the predictions
print(prediction_results)
```

```
                                             Message Prediction
0  Hey, don't forget about our meeting tomorrow a...        ham
1  Congratulations! You've won a free ticket to t...       spam
2           Can we reschedule our call to next week?       spam
3  Get a loan approved instantly with no credit c...       spam
```

CHAPTER 9:
CONCLUSION AND FUTURE WORK

CHAPTER 9. CONCLUSION AND FUTURE WORK

9.1. Summary of Findings

The SMS Spam Detection System using machine learning has proven to be a valuable tool for efficiently classifying SMS messages as spam or ham. The SVM classifier performed slightly better than Naive Bayes in terms of accuracy, precision, recall, and F1 score. This suggests that the SVM model is more effective at learning the patterns in the SMS data and distinguishing between spam and legitimate messages.

Both models showed strong classification performance, with SVM achieving **97% accuracy** and Naive Bayes achieving **96% accuracy**. However, the models also highlighted some areas for improvement, particularly in dealing with data imbalances and handling more complex text patterns.

9.2. Suggestions for Further Research or Improvement

1. **Exploring Advanced Feature Engineering**: While traditional methods like **bag-of- words (BoW)** and **TF-IDF** performed well, future work could explore more advanced feature extraction methods such as **word embeddings (Word2Vec, GloVe)** or **Transformer-based models (BERT, GPT)**, which can capture contextual meaning and semantic relations between words, leading to better classification accuracy.
2. **Deep Learning Models**: Deep learning models, such as **LSTMs (Long Short-Term Memory)** or **CNNs**, could be explored for better understanding of sequential dependencies and feature learning in text data. These models could potentially outperform traditional machine learning models, especially in more complex datasets.
3. **Handling Class Imbalance**: Although techniques like cross-validation and class weighting were applied, there is still room for improvement in handling class imbalance. Future work could explore advanced resampling techniques (like

SMOTE) or cost-sensitive learning methods to improve classification performance on the minority class (spam).

4. **Real-Time SMS Spam Detection**: For practical deployment, the model could be integrated into a mobile application or SMS gateway for real-time spam detection. This would require optimizations for speed and memory usage, as well as continuous

5. **Hybrid Models**: Future work could involve hybrid models combining different machine learning algorithms or ensemble techniques to increase classification accuracy and reduce misclassifications.
6. **Data Augmentation**: To improve model robustness, especially for underrepresented classes, techniques like **data augmentation** could be applied to create synthetic spam messages. This would help balance the dataset and reduce the impact of class imbalance.

Final Thoughts

The SMS Spam Detection System developed in this project has demonstrated the potential of using machine learning for automated spam detection in mobile communication. While there are still areas for improvement, the project serves as a solid foundation for future research and application in mobile security, where spam messages continue to pose significant risks to users' privacy and safety.

By continuing to refine these methods and incorporating newer technologies, such as deep learning and real-time models, SMS spam detection systems can become even more reliable and effective in protecting users from unwanted or malicious messages.

CHAPTER 10: REFERENCES

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