

“Artificial Intelligence based Spam Email Classifier”

by

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DECLARATION

I, **Suhas Kamath**, hereby declare that the Project Report, entitled "**Artificial Intelligence based Spam Email Classifier**", submitted to the University of Mysore in partial fulfilment of the requirements for the award of the Degree of **Masters in Computer Applications** is submitted to the Directorate of Outreach and Online Programmes, University of Mysore and it has not formed the basis for the award of any Degree/Fellowship or other similar title to any candidate of any University.

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Signature of the Student:

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Chapter 1

1 Introduction

1.1 Introduction to Project & Problem Statement

In the modern digital age, email is one of the most widely used communication channels for personal, professional, and commercial purposes. However, this ubiquity has also made email a prime target for spam—unwanted and often malicious messages that clutter inboxes, waste time, and pose security risks. Spam emails may include phishing attempts, advertisements, or harmful links that can compromise users' privacy or devices. To mitigate these issues, effective spam email classification has become an essential task in the field of Artificial Intelligence (AI) and Natural Language Processing (NLP). [1][2][3]

The primary goal of this project is to develop an AI-based spam email classifier that can automatically identify and filter spam emails from legitimate ones (commonly referred to as "ham"). Leveraging AI ensures scalability and efficiency in processing the vast number of emails users receive daily. This project combines machine learning techniques with text processing methods to achieve a robust and accurate classification system. [4][5][6]

Spam email classification is a binary classification problem where emails are categorized into two classes: spam or ham. The classifier uses features extracted from the email's text content, metadata, and other attributes to make predictions. The success of this classifier relies heavily on high-quality datasets, effective preprocessing techniques, and a well-trained model. Popular datasets like the SpamAssassin Corpus or Enron Email Dataset

provide a rich source of real-world email samples, including spam and ham, to train and test the model. [7][8]

Preprocessing is a critical step in the project as emails often contain noisy, unstructured data. Techniques such as tokenization, stemming, lemmatization, and stop-word removal are applied to clean and normalize the text. Furthermore, feature extraction methods, including Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), or word embeddings, convert text data into numerical representations that can be processed by machine learning algorithms.

For this project, various classification algorithms will be explored, ranging from traditional machine learning models like Naive Bayes and Logistic Regression to advanced deep learning models such as Long Short-Term Memory Networks (LSTMs) and Transformers. The performance of these models will be evaluated based on metrics like accuracy, precision, recall, and F1-score to ensure their reliability and effectiveness.

In addition to developing a robust classifier, this project emphasizes usability and deployment. By creating an intuitive user interface, the spam email classifier can be integrated into email systems or deployed as a standalone application. Users will be able to input email text or upload email files to classify them as spam or ham instantly.

By the end of the project, a functional and deployable spam email classification system will be developed, offering a meaningful contribution to the field of AI-driven solutions.

1.2 Objectives

The primary objective of this project is to design and develop an AI-based Spam Email Classifier capable of accurately distinguishing between spam and legitimate emails (ham).

To achieve this, the project focuses on the following specific objectives:

1. Develop a Robust Spam Detection System: Create a machine learning-based classifier that can analyse email content and classify emails as either spam or ham with high accuracy.
2. Leverage Natural Language Processing (NLP) Techniques: Use advanced NLP techniques to preprocess email data, extract meaningful features, and represent textual content in a format suitable for machine learning algorithms.
3. Evaluate and Compare Classification Models: Experiment with a variety of classification models, including traditional algorithms (e.g., Naive Bayes, Logistic Regression) and advanced approaches (e.g., Long Short-Term Memory Networks (LSTMs), Transformers), to identify the most effective model for spam detection.
4. Minimize False Positives and False Negatives: Focus on optimizing the model to reduce false positives (legitimate emails marked as spam) and false negatives (spam emails marked as legitimate), ensuring a reliable and user-friendly solution.
5. Adapt to Evolving Spam Patterns: Design the system to be flexible and capable of adapting to changes in spam strategies through continuous model updates and retraining.
6. Build and Deploy a User-Friendly Application: Develop a practical, deployable application that enables users to classify emails in real-time by inputting email content or uploading files.

7. Enhance Security and Productivity: Provide a solution that improves email security by detecting and filtering out malicious content and reduces time wasted on managing spam emails.
8. Document and Share the Project: Provide thorough documentation, including the methodology, dataset preprocessing, model training, evaluation results, and deployment steps, to facilitate future improvements and reproducibility.

By fulfilling these objectives, the project aims to contribute to the field of AI-driven email security and provide an efficient, accurate, and scalable spam detection solution.

1.3 Scope

The scope of this project encompasses the development of an AI-based Spam Email Classifier that uses machine learning and natural language processing (NLP) techniques to classify emails as spam or legitimate (ham). This project is designed to address the challenges posed by spam emails, including their negative impact on productivity, email security, and user experience. The scope includes the following aspects:

1.3.1 Inclusions

1. Spam Detection System Development: Building a classifier capable of analysing email content and predicting whether an email is spam or ham with high accuracy.
2. Data Preprocessing and Feature Engineering: Cleaning and preparing raw email data, including text normalization, stop-word removal, stemming/lemmatization, and feature extraction techniques such as Bag of Words (BoW), TF-IDF, or word embeddings.

3. Model Selection and Training: Evaluating various machine learning models (e.g., Naive Bayes, Logistic Regression, Support Vector Machines) and advanced deep learning models (e.g., LSTMs, Transformers) to identify the best-performing classifier.
4. Evaluation Metrics: Assessing the classifier's performance using metrics like accuracy, precision, recall, F1-score, and ROC-AUC to ensure its reliability and effectiveness.
5. Security and Scalability: Ensuring the solution is scalable to handle large email volumes and secure against potential vulnerabilities.
6. Documentation and Reporting: Preparing detailed documentation, including project methodology, data preprocessing steps, model evaluation, deployment process, and usage instructions.

1.3.2 Exclusions

1. Integration with Specific Email Clients: The project will not directly integrate with proprietary email services (e.g., Gmail or Outlook) but will provide an independent classifier that can be extended or adapted for such integrations.
2. Detection of Advanced Cyber Threats: The project focuses on classifying spam emails based on content and metadata and does not cover advanced threat detection mechanisms such as zero-day phishing or malware analysis.
3. Support for Multiple Languages: Initially, the classifier will focus on English-language emails. Multi-language support may be considered as a future enhancement.

4. Ongoing Model Updates: While the project will build a robust spam classifier, continuous updates for evolving spam patterns will not be part of the initial implementation but can be incorporated later.

1.3.3 Limitations

1. The performance of the classifier will depend on the quality and representativeness of the training data.
2. The system may face challenges with emails containing heavily obfuscated or encoded content, as these require specialized techniques for detection.
3. Real-time classification performance may vary depending on the deployment platform and system resources.

1.4 Project Report Outline

This document provides a structured outline for the AI-Based Spam Email Classifier project report. It consists of eight major chapters, each focusing on a critical aspect of the project, ranging from problem identification and literature review to system design, implementation, and testing. Below is a detailed breakdown of each section of the report.

The introduction section introduces the problem of spam emails and their impact on users and organizations. It highlights the challenges associated with traditional spam detection methods, such as rule-based filtering and keyword matching, and the need for AI-based solutions. The problem statement is clearly defined, focusing on how digital platforms struggle with accessibility and efficiency in spam detection.

The literature review section reviews existing research and systems related to spam detection. The system requirements section describes the functional, non-functional, hardware and software requirements of the project in great detail.

The system design section elaborates on the structure of the system. It also depicts how various components of the system integrate with each other. The implementation section depicts the various algorithms and steps to build a working prototype of the system. The testing section further builds upon the work done in implementation section, by ensuring that the system works as expected, with minimal errors.

The results and analysis section aims to perform an analysis of the results from the testing phase. Lastly, the conclusion and future work aims to provide a summary of the project and discuss further improvements and features that can be assimilated into the project to improve its performance and provide a better overall experience to the end user.

Chapter 2

2 Literature Review

2.1 System Study

Spam email classification has been a long-standing problem in the field of machine learning and natural language processing (NLP). Numerous approaches and techniques have been proposed and implemented to address the challenges associated with identifying and filtering spam emails. This literature review highlights key studies, methodologies, and advancements in the domain to provide a comprehensive understanding of the existing work and establish the foundation for this project.

2.1.1 Evolution of Spam Detection Systems

Early spam detection systems were primarily rule-based, relying on manually crafted heuristics to identify spam characteristics, such as specific keywords, phrases, or patterns in email headers. Although effective for static patterns, these systems struggled to adapt to evolving spam strategies and required constant updates, making them inefficient in dynamic environments.

Sahami et al. (1998) introduced a Bayesian filtering approach for spam detection, marking a significant milestone in the field. This probabilistic model assigns a probability score to an email being spam based on the occurrence of specific words or features. The approach demonstrated high accuracy, paving the way for machine learning-based methods. [6]

2.1.2 Traditional Machine Learning Approaches

Traditional machine learning algorithms such as Naive Bayes, Logistic Regression, Support Vector Machines (SVM), and Decision Trees have been widely applied to spam detection. These models leverage feature extraction techniques like Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) to represent email text as numerical data. [13][14][15][16][17]

1. Naive Bayes Classifier: Due to its simplicity and efficiency, Naive Bayes became one of the most popular methods for spam detection. Its probabilistic nature and ability to handle high-dimensional text data make it suitable for email classification tasks. [9][10]
2. Support Vector Machines (SVM): SVMs have been effective in spam detection due to their ability to handle large datasets and nonlinear relationships. They achieve high accuracy by maximizing the margin between spam and ham classes. [11][12]

2.1.3 Natural Language Processing Techniques

The integration of NLP techniques has significantly improved spam detection systems by enabling a deeper understanding of text semantics and context. Key advancements include: [18][19][20][21]

1. Text Preprocessing: Techniques such as tokenization, stop-word removal, stemming, and lemmatization are used to clean and normalize text data, making it easier for models to process.
2. Feature Extraction: In addition to BoW and TF-IDF, advanced methods like word embeddings (e.g., Word2Vec, GloVe) capture semantic relationships between words, enhancing model performance.
3. NLP Libraries: Tools like NLTK, spaCy, and Scikit-learn have facilitated the implementation of NLP pipelines for spam detection projects.

2.1.4 Deep Learning in Spam Detection

Deep learning models have revolutionized spam detection by offering superior performance through automatic feature extraction and the ability to capture complex patterns in data.

1. Recurrent Neural Networks (RNNs) and LSTMs: These models are designed to process sequential data and have been applied to spam detection with promising results. They can capture contextual dependencies in email text, making them highly effective for classification tasks. [22][23][24][25]
2. Transformers: Modern transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers) have further enhanced spam detection. These models excel in understanding the contextual meaning of words and phrases, leading to more accurate classifications. [26][27]

2.2 Review of Literature

Despite significant advancements, current spam detection systems face challenges such as:

1. Adapting to new and evolving spam patterns, including phishing attacks and obfuscated content.
2. Reducing false positives to avoid misclassifying legitimate emails as spam.
3. Scalability and integration with diverse email platforms.

The literature highlights that while traditional models like Naive Bayes and SVM are effective, modern approaches such as deep learning and transformers offer superior accuracy and adaptability. This project will leverage these advancements and address existing gaps by developing a robust spam email classifier using cutting-edge techniques in machine learning and NLP.

2.3 Comparison of Literature

Feature	RNNs	LSTMs	BERT
Architecture	Sequential data processing	Sequential with memory cells and gates	Transformer-based, self-attention mechanism
Handling Long-Term Dependencies	Poor, suffers from vanishing gradients	Excellent, mitigates vanishing gradient problem	Excellent, captures long-range dependencies bidirectionally
Training Complexity	Moderate, suffers from vanishing gradient issue	High, but mitigates vanishing gradients	High, requires significant computational resources

Contextual Understanding	Limited, processes input one step at a time	Improved, but still sequential in nature	Strong, bidirectional contextual understanding
Performance on Complex Tasks	Moderate, less effective for long texts	High, better for text with long dependencies	Very high, state-of-the-art performance on many NLP tasks
Deployment	Faster inference, more lightweight	Slower inference, more memory usage	Slower inference, requires more resources

Table 1 Comparison of Key Features

Chapter 3

3 System Requirements Specification

3.1 Functional Requirements

Functional requirements define the specific functionality the system must offer to achieve its objectives. For an AI-based spam email classifier, these requirements include processes such as data preprocessing, model training, and classification. Below are the key functional requirements for this project: [28][29]

1. Spam Detection: The system must classify emails as "Spam" or "Non-Spam" based on the trained model. Output the classification result with a confidence score (e.g., 0.95 confidence for spam). This represents the probability of the message being spam or ham. The system should handle real-time classification for incoming emails.
2. Feedback Loop: Provide a mechanism for users to manually label emails that were misclassified to improve the model over time. Automatically retrain the model with newly labelled data to enhance accuracy.
3. Evaluation Metrics: The system must calculate and display key performance metrics, including:
 - a. Accuracy
 - b. Precision
 - c. Recall
 - d. F1-Score
 - e. Confusion Matrix

4. User Interface: Provide a user-friendly dashboard where users can:

- a. Upload email data for classification.
- b. View classification results.
- c. Access visualized performance metrics (e.g., graphs and charts).

These functional requirements ensure that the system is robust, accurate, and user-friendly while addressing the critical needs of spam email classification.

3.2 Non-Functional Requirements

Non-functional requirements define the overall qualities and performance of the system, focusing on how it should operate rather than the specific functions it provides. Below are the key non-functional requirements for the spam email classifier project: [30][31]

1. Performance

- a. The system should classify emails with a latency of less than 500 milliseconds per email in real-time scenarios.
- b. It should maintain an accuracy of at least 95% in distinguishing spam and non-spam emails.
- c. The system must handle a throughput of at least 10,000 emails per second for batch processing.

2. Scalability

- a. The system must be scalable to handle a growing volume of emails and data as the user base or dataset size increases.
- b. Support distributed computing or cloud-based deployment to manage large-scale datasets and real-time email traffic effectively.

3. Reliability

- a. The system must provide a 99.9% uptime, ensuring continuous availability for users.
- b. In case of failure, the system should recover automatically or provide detailed error logs for manual recovery within 5 minutes.

4. Usability

- a. The system's interface must be intuitive and user-friendly, requiring minimal training for users.
- b. Provide accessibility features, such as keyboard navigation and screen reader support, for users with disabilities.
- c. Ensure that all system messages (e.g., errors, warnings) are clear and actionable.

5. Security

- a. The system must protect sensitive data, including email content and user information, by employing:
- b. Encryption: Encrypt data in transit (e.g., TLS) and at rest (e.g., AES).
- c. Authentication and Authorization: Use secure login mechanisms (e.g., OAuth, multi-factor authentication).
- d. Comply with data protection regulations, such as GDPR, CCPA, or other applicable laws.
- e. Protect against security threats like SQL injection, phishing, and denial-of-service attacks.

6. Privacy

- a. Ensure that the system anonymizes and pseudonymizes sensitive information when storing or processing email data.
- b. Allow users to opt-out of data collection or delete their data upon request.

- c. The system should only access data required for classification and avoid storing unnecessary information.

7. Maintainability

- a. The system must be modular and follow clean coding practices to ensure easy debugging and updates.
- b. Provide documentation for all components, including:
 - i. API endpoints
 - ii. Data processing pipelines
 - iii. Model training workflows
- c. The system should support automated testing for all major functionalities.

8. Portability

- a. The system must be platform-independent and capable of running on various operating systems (e.g., Windows, Linux, macOS).
- b. Ensure compatibility with multiple cloud environments (e.g., AWS, Azure, Google Cloud).

9. Extensibility

- a. The system should allow the integration of new models or techniques (e.g., transformers, enhanced pre-processing pipelines) without significant re-engineering.
- b. It should support plug-and-play functionality for feature extraction techniques like TF-IDF, BoW, or word embeddings.

10. Interoperability

- a. The system must integrate with third-party tools and platforms, such as:
 - i. Email services (e.g., Gmail, Outlook)
 - ii. Messaging services or APIs (e.g., Twilio, SendGrid)

- b. It should support standard file formats for data import/export, such as CSV, JSON, and XML.

11. Efficiency

- a. The system must utilize computational resources optimally to reduce processing time and cost.
- b. Minimize memory usage while handling large datasets by leveraging efficient algorithms and data structures.

12. Ethical Considerations

- a. Avoid algorithmic biases that may lead to inaccurate or unfair classification of emails.
- b. Provide explanations for classification decisions to ensure transparency (e.g., highlighting keywords influencing the decision).
- c. Ensure the system adheres to ethical AI principles, such as fairness, accountability, and transparency.

13. Auditability

- a. Maintain logs for all system activities, including:
 - i. Email classification results
 - ii. Model retraining events
 - iii. User interactions
- b. Logs should be timestamped and stored securely for a minimum duration (e.g., 6 months) to support debugging and compliance.

14. Availability

- a. Ensure the system can operate 24/7 without downtime, with planned maintenance scheduled during non-peak hours.
- b. Provide fallback mechanisms to handle system overloads or failures gracefully, such as queue-based processing for delayed emails.

15. Accuracy and Precision

- a. The classifier should minimize false positives (legitimate emails classified as spam) and false negatives (spam emails classified as legitimate) to improve user trust.
- b. Support periodic evaluation and updates to maintain or improve accuracy as new spam patterns emerge.

These non-functional requirements ensure that the spam email classifier system is robust, secure, scalable, and user-friendly while delivering high performance and adhering to ethical and legal standards.

3.3 Hardware Requirements

The hardware requirements for an AI-based spam email classifier depend on the scale of deployment, the size of the dataset, and the complexity of the chosen machine learning models. Below is a categorized breakdown of the hardware requirements: [32]

3.3.1 Development Environment

This is for the development and testing phase, where the focus is on building, training, and validating the model.

Aspect	Minimum Requirements	Recommended Requirements
Processor	Intel Core i5 (8th Gen or newer) or AMD Ryzen 5	Intel Core i7 (10th Gen or newer) or AMD Ryzen 7
RAM	16 GB	32 GB

GPU	NVIDIA GeForce GTX 1050 (2 GB VRAM) or equivalent	NVIDIA RTX 3060 (6 GB VRAM) or higher
Storage	500 GB HDD or 256 GB SSD	1 TB SSD
Operating System	Windows 10, Linux (Ubuntu 20.04 or newer), or macOS	Linux (preferred for AI workloads) or Windows 11

Table 2 Minimum & Recommended Requirements for the Development Environment

3.3.2 Deployment Environment

This is for real-time classification and inference. Requirements vary based on the volume of emails being processed and the desired response time.

Aspect	Small-Scale Deployment	Large-Scale (Cloud-Based) Deployment
Processor	Intel Core i5 (10th Gen or newer)	Multi-core CPU (e.g., Intel Xeon or AMD EPYC)
RAM	16 GB	64 GB
GPU	Optional for small-scale deployments	NVIDIA Tesla T4, A100, or equivalent
Storage	500 GB HDD or 256 GB SSD	2 TB SSD
Operating System	Windows 10, Linux (Ubuntu 20.04 or newer), or macOS	Linux (preferred for AI workloads) or Windows 11

Table 3 Requirements for the Deployment Environment, depending on if the development is small-scale or large-scale

These hardware recommendations are designed to ensure smooth development, training, and deployment of the spam email classifier system while optimizing for cost and scalability.

3.4 Software Requirements

The comprehensive list of software requirements are as follows:

1. Programming Language: Python
 - a. For building, training, and deploying the model due to its extensive libraries and frameworks for machine learning and natural language processing.
 - b. Version: Python 3.8 or newer
2. Integrated Development Environment (IDE): VS Code
3. Libraries and Frameworks
 - a. Machine Learning Libraries:
 - i. Scikit-learn: For implementing Naive Bayes, SVM, and evaluation metrics.
 - ii. TensorFlow or PyTorch: For deep learning models like RNNs, LSTMs, and BERT.
 - iii. XGBoost: For boosted tree-based spam classification models (optional).
 - b. Natural Language Processing (NLP) Libraries:
 - i. NLTK: For basic NLP tasks like tokenization, stemming, and lemmatization.
 - ii. spaCy: For more advanced NLP tasks, including named entity recognition.

- iii. Transformers (by Hugging Face): For implementing pre-trained models like BERT.
- c. Data Processing Libraries:
 - i. Pandas: For data manipulation and analysis.
 - ii. NumPy: For numerical computations.
 - iii. Matplotlib and Seaborn: For data visualization.
- d. Feature Extraction Libraries:
 - i. Scikit-learn: For TF-IDF and Bag of Words (BoW) implementations.
- e. Evaluation and Metrics:
 - i. Scikit-learn: For precision, recall, F1-score, and confusion matrix.

Chapter 4

4 System Design

4.1 Design Overview

Spam emails have become a widespread issue, affecting individuals and organizations by clogging inboxes, spreading malware, and leading to financial fraud. Traditional rule-based spam filters are insufficient due to the evolving nature of spam techniques. To address this, an AI-based spam email classifier is designed using Natural Language Processing (NLP) and Machine Learning (ML) to automatically detect and filter spam emails with high accuracy.

This design overview provides a detailed explanation of the architecture, components, and workflow of the proposed system, covering data processing, feature extraction, model selection, and evaluation metrics.

The spam email classifier is structured into five primary components:

1. Data Collection – Acquiring the dataset for training and testing the model.
2. Preprocessing – Cleaning and preparing the email text for feature extraction.
3. Feature Extraction – Converting textual data into numerical format using TF-IDF.
4. Model Training and Classification – Using Naïve Bayes to classify emails as spam or ham.
5. Evaluation and Deployment – Assessing model performance and integrating it into an email filtering system.

4.1.1 Data Collection & Format

The Apache SpamAssassin dataset is used for training and testing. It consists of labelled emails categorized into:

- Spam (1) – Unwanted, unsolicited emails, often containing advertisements, phishing links, or malware.
- Ham (0) – Legitimate emails from trusted sources.

The dataset is downloaded as a CSV file containing two columns:

- Email Text: The actual content of the email.
- Label: A binary indicator (spam or ham).

4.1.2 Data Preprocessing

Since raw emails contain unnecessary characters, symbols, and metadata, preprocessing is crucial.

1. Extract Email Body: Remove headers and attachments, keeping only the main text.
2. Convert to Lowercase: Ensure uniformity by converting all text to lowercase.
3. Remove HTML Tags and URLs: Strip unnecessary markup and links.
4. Remove Special Characters and Punctuation: Clean non-alphabetic symbols that do not contribute to classification.
5. Tokenization: Split text into individual words for further processing.
6. Remove Stop words: Filter out common words (e.g., "the", "and") that do not contribute to meaning.
7. Lemmatization: Convert words to their base forms to maintain consistency.
8. Save Cleaned Data: Store the processed dataset in a CSV file for future use.

4.1.3 Feature Extraction

After preprocessing, the text is converted into a numerical format for ML models. TF-IDF is used to represent text numerically. It assigns importance to words based on their frequency in an email while reducing the weight of commonly occurring words across all emails.

Advantages of TF-IDF:

1. Identifies Important Words in a Document
 - a. Unlike simple word frequency counts, TF-IDF helps identify words that are relevant to a document but not commonly used across the dataset.
 - b. Example: In spam emails, words like "prize", "win", and "offer" will have a high TF-IDF score, while words like "the", "and", and "is" will have a low score.
2. Removes the Impact of Common Words (Stop words)
 - a. TF-IDF naturally downweights frequent words like "the," "this," and "is" since they appear in almost every document.
 - b. Example: Instead of treating "money" and "is" equally, TF-IDF assigns a higher weight to "money" if it is less common in other documents.
3. Improves Text Search & Ranking
 - a. Search engines like Google use TF-IDF to rank search results. Documents with higher TF-IDF scores for a search query are considered more relevant.
 - b. Example: If you search for "best spam detection algorithms", pages that mention these terms frequently but uniquely will appear at the top.
4. Enhances Machine Learning Models

- a. Many machine learning models, such as Naïve Bayes, SVM, and Neural Networks, perform better when fed numerical data rather than raw text.
- b. Example: A spam classifier can use TF-IDF scores as features to determine whether an email is spam or not.

5. Efficient for Large Datasets

- a. TF-IDF is lightweight and computationally efficient compared to deep learning models like BERT, making it ideal for spam filtering in real-time applications.
- b. Example: Email spam detection systems can process thousands of emails per second using TF-IDF.

4.1.4 Handling Class Imbalance & Model Selection

Spam emails are often fewer than ham emails in datasets, leading to biased models. Synthetic Minority Over-sampling Technique (SMOTE) is used to balance the dataset by generating synthetic spam samples.

The Multinomial Naïve Bayes (MNB) classifier is chosen for spam detection due to its efficiency and strong performance in text classification tasks.

- Probabilistic Approach: Estimates the probability of an email being spam based on word occurrences.
- Computational Efficiency: Works well with high-dimensional data like TF-IDF representations.
- Suitability for Text Classification: Assumes word independence, which simplifies computations.

- The dataset is split into 80% training and 20% testing to evaluate the model's generalization ability.
- The Naïve Bayes model is trained on the processed emails.
- The trained model predicts whether new emails are spam or ham.

4.1.5 Model Selection & Evaluation

These are the available models that can be used, and their detailed comparison:

1. Naïve Bayes
 - a. Advantages
 - i. Fast & efficient: Works well with text data due to the independence assumption.
 - ii. Performs well with TF-IDF since it relies on word frequency.
 - iii. Requires less training data, making it ideal for smaller datasets.
 - b. Disadvantages
 - i. Assumes feature independence, which is not always true in real-world text (words are often dependent on context).
 - ii. May struggle with highly complex patterns.
 - c. Best use case: Spam detection, sentiment analysis, and other NLP tasks with TF-IDF features.
2. Support vector machine (SVM)
 - a. Advantages:
 - i. Works well with high-dimensional data, such as text representations like TF-IDF.
 - ii. Effective when data is linearly separable, meaning clear distinction between spam and ham.
 - iii. Robust to overfitting, especially with proper kernel selection.

- b. Disadvantages
 - i. Computationally expensive on large datasets.
 - ii. Tuning the right kernel (linear, RBF, etc.) is crucial for performance.
 - c. Best use case: Spam email detection, image classification, and fraud detection.
3. Random Forest [50]
- a. Advantages:
 - i. Handles noisy data well by averaging multiple decision trees.
 - ii. Less likely to overfit compared to individual decision trees.
 - iii. Interpretable – provides feature importance scores.
 - b. Disadvantages
 - i. Slower than simpler models, especially for large datasets.
 - ii. Not as effective for text data unless combined with good feature engineering.
 - c. Best use case: Spam detection when dataset is large and contains noisy data.
4. Logistic Regression [51]
- a. Advantages:
 - i. Simple & interpretable model for binary classification tasks.
 - ii. Works well with TF-IDF features, especially in text-based datasets.
 - iii. Computationally efficient, making it good for large datasets.
 - b. Disadvantages:
 - i. Performs poorly on non-linearly separable data.
 - ii. Less effective if feature relationships are complex (e.g., semantic understanding of words).
 - c. Best use case: Binary text classification tasks like spam detection where computational speed is important.

5. Recurrent Neural Networks (RNNs) and LSTMs [52]

a. Advantages:

- i. Understands sequential relationships in text, unlike traditional ML models.
- ii. Can capture long-term dependencies (important for longer emails).
- iii. Best suited for deep NLP tasks like contextual spam detection.

b. Disadvantages

- i. Requires large labelled datasets for training.
 - ii. Computationally expensive, requiring GPUs/TPUs for training large models.
 - iii. Slower training time compared to traditional ML models.
- c. Best use case: Deep learning-based spam classification, chatbot text understanding, and sentiment analysis.

6. Bidirectional Encoder Representations from Transformers (BERT) [53]

a. Advantages:

- i. Context-aware model: Captures meaning beyond just word frequency.
- ii. Excels in understanding email intent, making it more robust than TF-IDF-based models.
- iii. Fine-tuning on spam datasets improves results.

b. Disadvantages:

- i. Extremely computationally expensive – requires high-end GPUs for training.
 - ii. Takes longer to train compared to traditional models.
- c. Best use case: Advanced spam classification systems, email filtering with deep NLP understanding.

For this project, we shall be using the Naïve Bayes model.

The trained classifier is assessed using multiple metrics:

- Accuracy: Measures overall correctness of predictions.

$$Accuracy = \frac{\text{Correct Predictions}}{\text{Total Emails}}$$

Figure 1 Formula used to calculate accuracy.

- Precision: Measures how many emails classified as spam were actually spam.

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

Figure 2 Formula used to calculate precision.

- Recall: Measures how many actual spam emails were correctly detected.

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

Figure 3 Formula used to calculate recall.

- F1-score: A balanced measure combining precision and recall.

$$F1 - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 4 Formula used to calculate F1 score.

4.1.6 Model Deployment

Once trained and tested, the classifier is deployed for real-world use.

- Saving and Loading the Model

- The trained Naïve Bayes model and the TF-IDF vectorizer are saved using Joblib for future classification tasks.
- When deployed, new emails are processed using the same TF-IDF vectorizer before classification.
- The spam classifier can be integrated into an email system via:
 - Batch Processing: Periodic scanning of emails.
 - Real-Time Filtering: Classifying incoming emails before they reach the user's inbox.

4.1.7 Potential Implementation Challenges & Future Enhancements

Some potential implementation challenges, that may occur are:

- Data Issues
 - Spam Evasion Techniques: Spammers frequently change tactics, requiring periodic model retraining.
 - Data Imbalance: Requires continuous monitoring and balancing using techniques like SMOTE.
- Performance Challenges
 - False Positives: Misclassifying legitimate emails as spam could lead to loss of important messages.
 - False Negatives: Undetected spam emails could cause phishing attacks or malware infections.
- Computational Constraints
 - High-Dimensional Data: TF-IDF matrices may become too large, requiring memory optimization.
 - Latency in Real-Time Processing: Preprocessing and classification must be optimized for speed.

Some future enhancements that can be done are:

- Improving Feature Extraction
 - Using Word Embeddings (Word2Vec, FastText, BERT) instead of TF-IDF for better context understanding.
- Using Advanced Models
 - Replacing Naïve Bayes with Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs), or BERT to improve accuracy.
- Adaptive Spam Detection
 - Implementing semi-supervised learning to adapt to new spam techniques.

This AI-based spam email classifier effectively detects spam emails using NLP and Machine Learning. By leveraging TF-IDF for feature extraction, SMOTE for class balancing, and Naïve Bayes for classification, the system achieves reliable spam detection. Future improvements, including deep learning models and real-time filtering, will enhance its accuracy and robustness.

4.2 Data Flow Diagrams

This is the data flow diagram during the training and development phase of the machine learning algorithm:

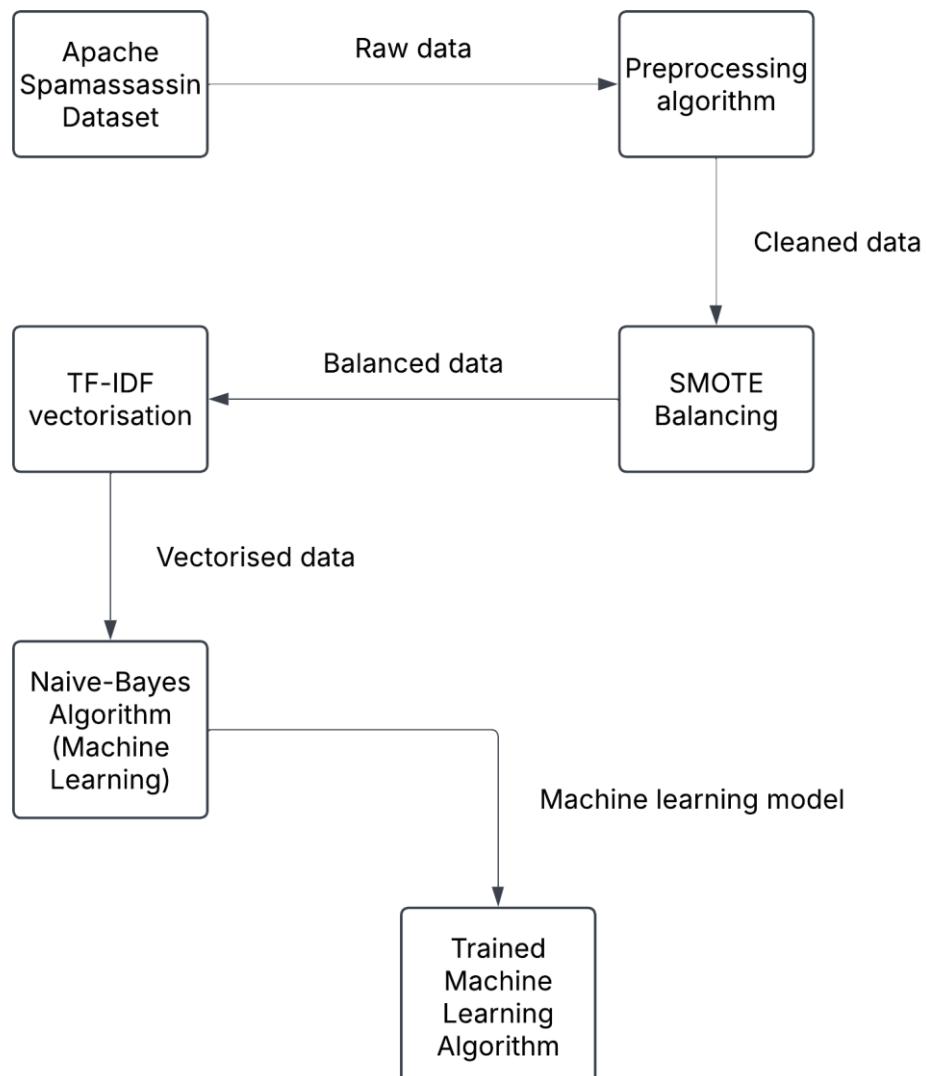


Figure 5 Data flow diagram during the training and development.

When the application is deployed for use by consumers, this will be the direction of data flow:

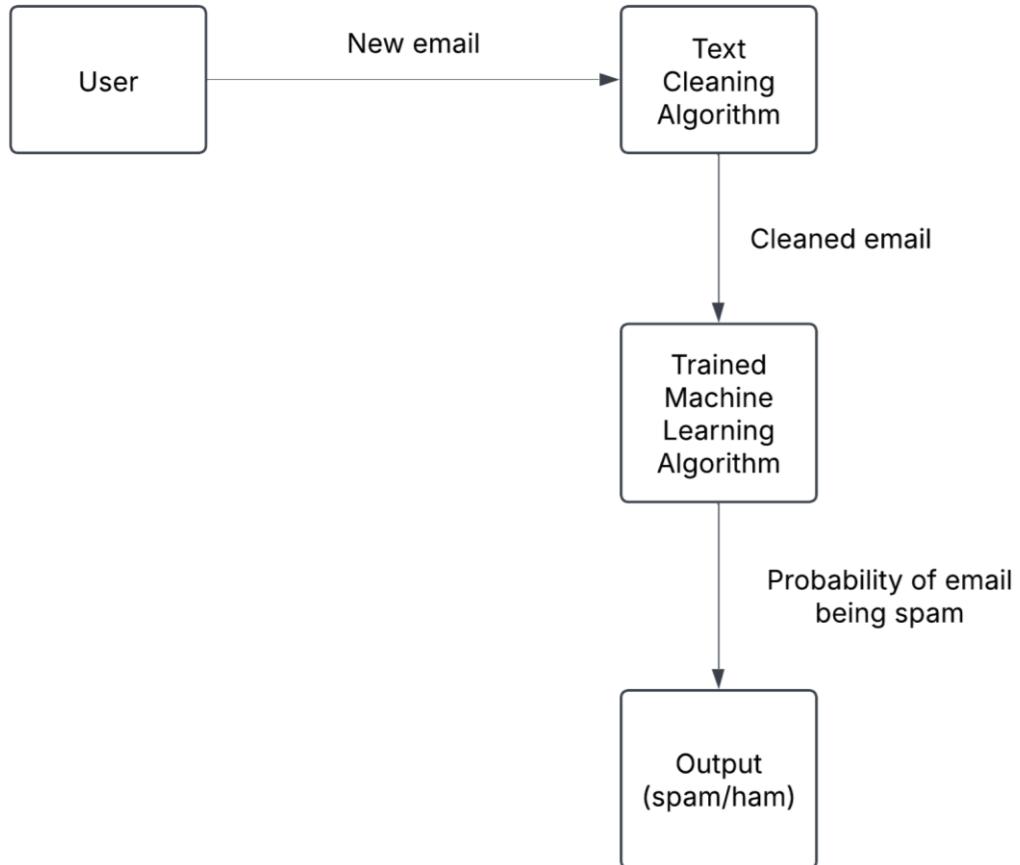


Figure 6 Data flow diagram after deployment.

The complete data flow diagram is as follows:

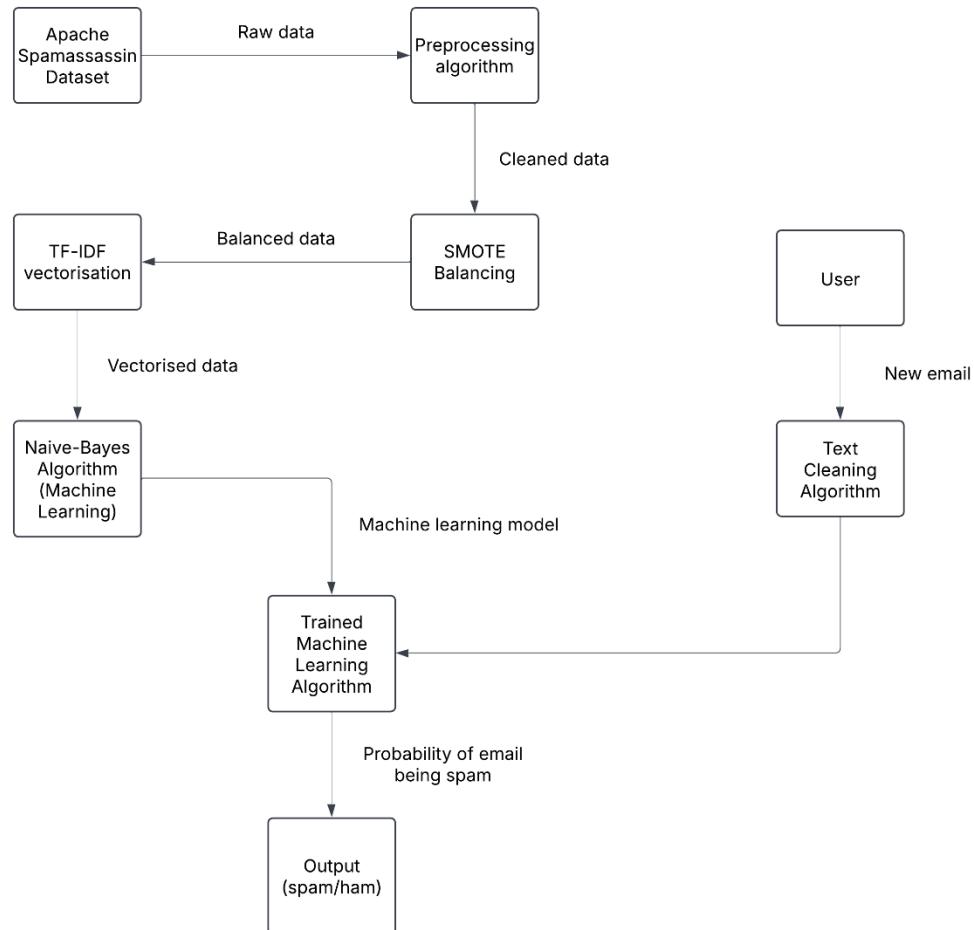


Figure 7 Complete data flow diagram

4.3 Use Case Diagram

The use case diagram for the system is as follows:

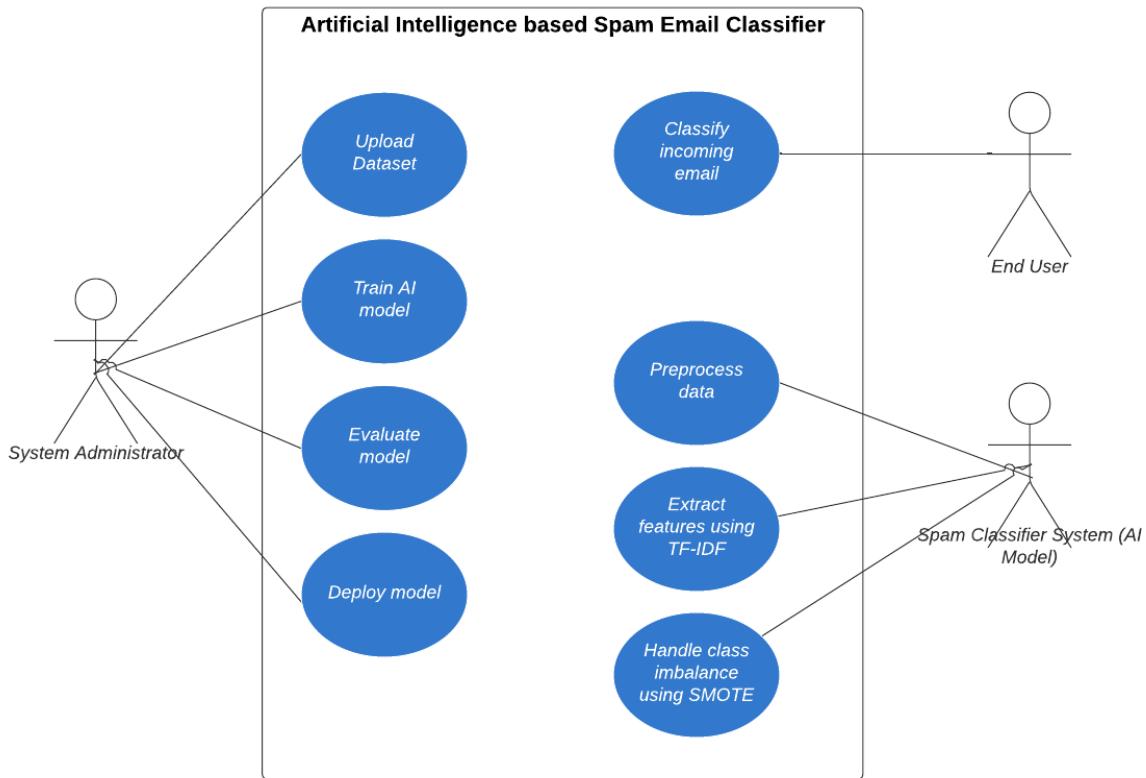


Figure 8 Use case diagram

4.4 Sequence Diagram

A Sequence Diagram represents the interaction between system components and actors over time, showing the sequence of messages exchanged. For this AI-based spam email classifier project, the main actors are:

- User (Email Receiver) – The person receiving emails.
- System Administrator – The person who trains, evaluates, and deploys the spam classifier model.
- Spam Classifier System (AI Model) – The AI system responsible for processing and classifying emails.
- Email Dataset – The dataset containing labelled spam and ham emails.

The sequence diagram is as follows:

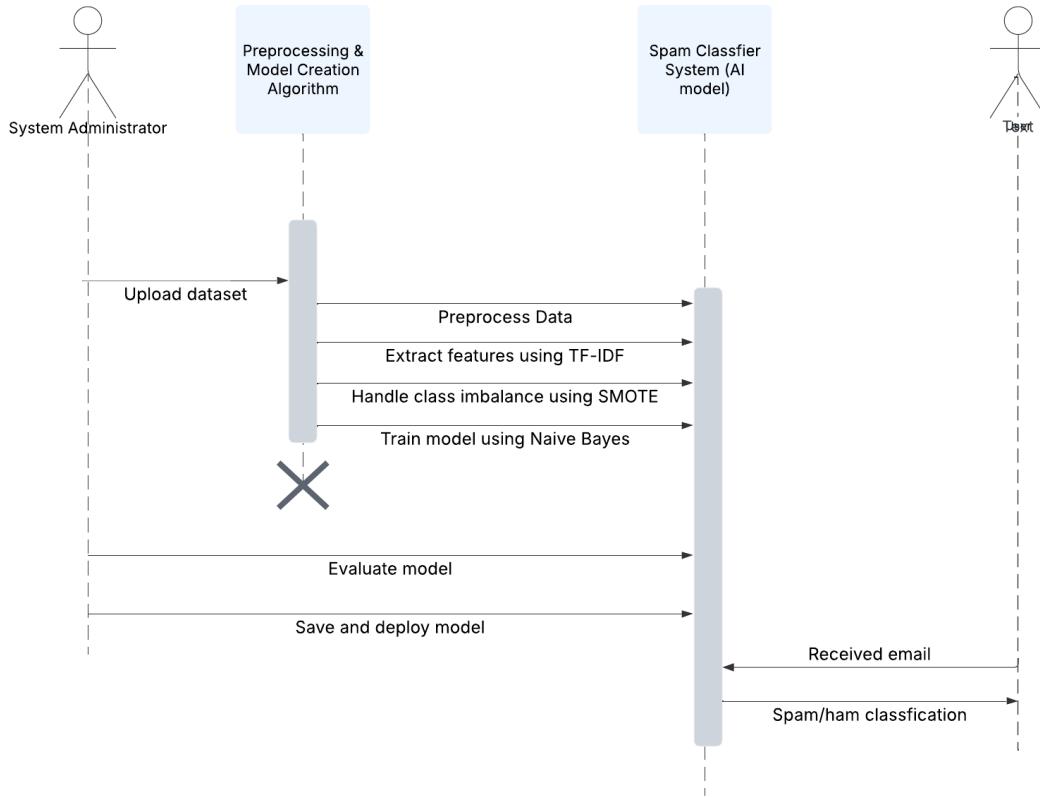


Figure 9 Sequence diagram

4.5 Activity Diagram

An Activity Diagram represents the workflow of the AI-based spam email classifier, showing the sequence of activities from training the model to real-time classification of emails. It helps in understanding the process flow, decision points, and interactions between different system components.

The activity diagram can be divided into two main sections:

- Training Phase – Where the system administrator trains and deploys the spam classification model.

- Classification Phase – Where incoming emails are processed and classified as spam or ham.

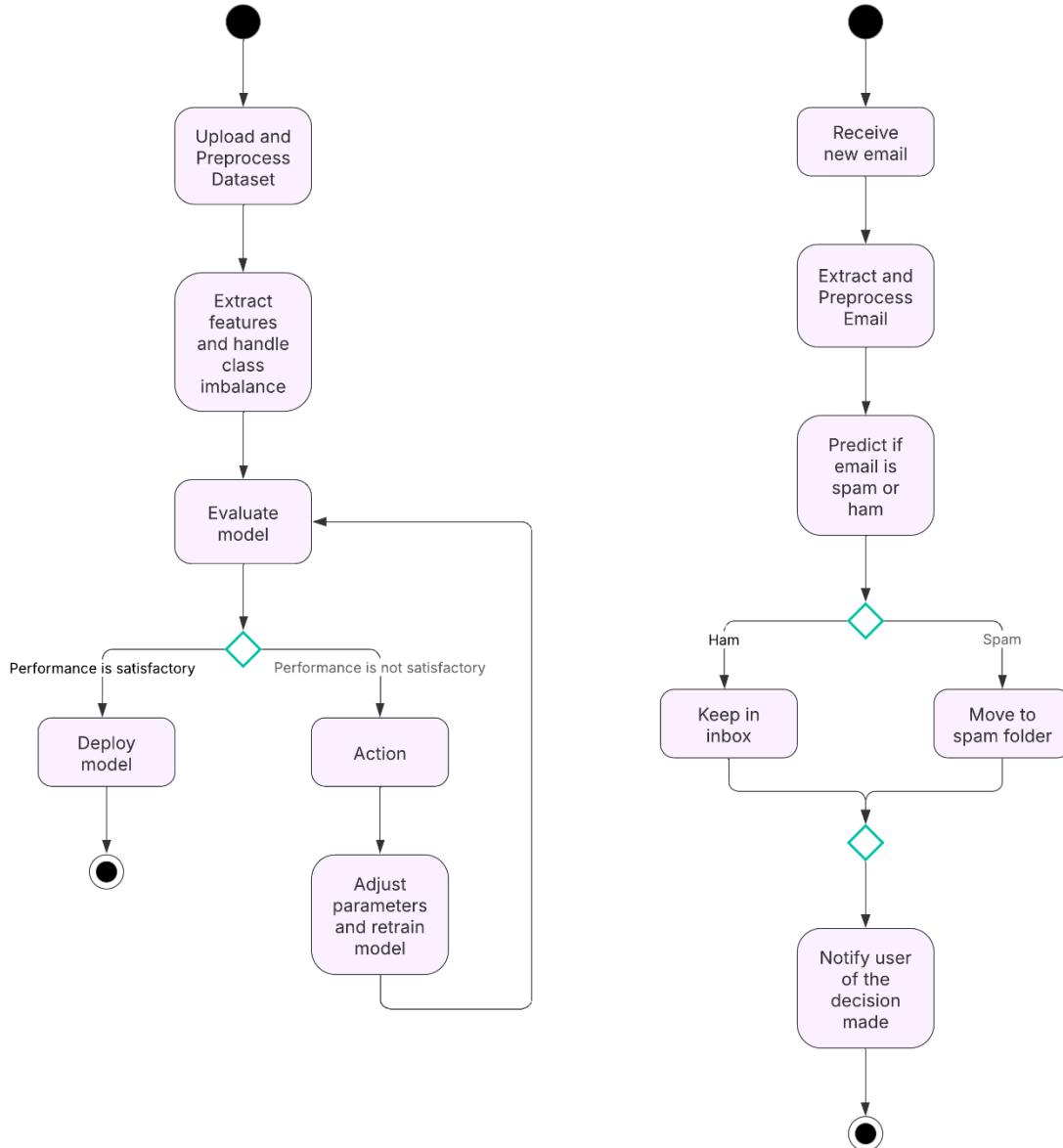


Figure 10 Activity diagram

4.6 Modules of the Project

The AI-based spam email classifier consists of several interconnected modules, each performing a crucial function in detecting and filtering spam emails. The system follows a structured pipeline, moving from data collection to model deployment. Below is a

comprehensive breakdown of each module, explaining its purpose, processes, and key functionalities in as much detail as possible.

4.6.1 Data Collection Module

- Purpose: The first step in developing the classifier is gathering a large, diverse, and well-labelled dataset to train and test the model. The quality of data directly impacts model accuracy.
- Processes:
 - Selecting the Dataset: The Apache SpamAssassin dataset is used, containing thousands of emails labelled as spam or ham (legitimate email).
 - Formatting the Data: The dataset is stored in CSV format, consisting of two key columns:
 - Email Text: Contains the actual content of the email.
 - Label: Binary value (1 for spam, 0 for ham).
 - Handling Missing Data: Any missing or corrupted entries are identified and removed to maintain data integrity.
- Output: A cleaned, structured dataset ready for further preprocessing.

4.6.2 Preprocessing Module

- Purpose: Raw emails contain unnecessary information such as headers, attachments, special characters, and HTML tags. The preprocessing module cleans and standardizes the text to improve classification performance.
- Processes:
 - Extracting Email Body: Removes email headers (metadata such as sender, receiver, and timestamps) and attachments.
 - Converting Text to Lowercase: Ensures uniformity by converting all text to lowercase (e.g., ‘FREE’ and ‘free’ are treated the same).

- Removing HTML Tags & URLs: Strips out <html>, <body>, and hyperlinks (<https://...>) to remove unnecessary noise.
- Removing Special Characters & Punctuation: Deletes symbols like @, #, \$, %, and punctuations that do not contribute meaning.
- Tokenization: Splits text into individual words (e.g., "This is spam" → ["This", "is", "spam"]).
- Removing Stop words: Filters out common English words (e.g., 'the', 'is', 'and', 'to') that do not provide significant meaning.
- Lemmatization: Converts words to their base form (e.g., 'running' → 'run', 'better' → 'good').
- Saving Processed Data: Stores the cleaned dataset for later use in feature extraction and model training.
- Output: A clean, structured email dataset where each email is stripped of unnecessary characters and converted into a standardized format.

4.6.3 Feature Extraction Module

- Purpose: Machine learning models cannot process raw text directly. This module converts emails into a numerical format using TF-IDF (Term Frequency-Inverse Document Frequency), making them suitable for model training.
- Processes:
 - Applying TF-IDF Vectorization: Converts each email into a TF-IDF matrix, assigning importance to words based on frequency within the email and across the dataset.
 - Handling High-Dimensional Data: Reduces feature dimensionality by setting a threshold for the maximum number of features.

- Saving the Feature Representation: Stores the numerical feature matrix for future training and classification.
- Output: A TF-IDF matrix representing emails numerically, ready for model training.

4.6.4 Handling Class Imbalance Module

- Purpose: Spam emails are often fewer in number compared to legitimate emails, leading to a bias in model training. This module uses SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset.
- Processes:
 - Checking Class Distribution: Computes the count of spam and ham emails.
 - Applying SMOTE: Generates synthetic spam email samples to balance the dataset.
 - Verifying the Balance: Ensures equal spam-to-ham ratio after augmentation.
- Output: A balanced dataset where both spam and ham emails have an equal representation.

4.6.5 Model Selection & Training Module

- Purpose: Trains a Naïve Bayes classifier using the pre-processed and vectorized email dataset to classify new emails as spam or ham.
- Processes:
 - Splitting the Dataset: Divides data into training (80%) and testing (20%) sets.
 - Choosing the Model: Multinomial Naïve Bayes (MNB) is selected due to its efficiency in handling text classification tasks.
 - Training the Model: The model learns patterns in spam and ham emails based on word distributions.

- Saving the Trained Model: The trained model is stored for future classification tasks.
- Output: A trained Naïve Bayes model ready to classify incoming emails.

4.6.6 Model Evaluation Module

- Purpose: Assesses the model's accuracy in detecting spam emails by using standard performance metrics.
- Processes:
 - Making Predictions: Uses the trained model to classify emails in the test dataset.
 - Computing Metrics:
 - Accuracy: Measures overall correctness.
 - Precision: Checks how many predicted spam emails were actually spam.
 - Recall: Measures how many actual spam emails were detected.
 - F1-score: Balances precision and recall.
- Output: Performance scores that indicate the effectiveness of the spam classifier.

Chapter 5

5 Implementation

5.1 Steps for Implementation

5.1.1 Preprocessing the Dataset

Preprocessing is crucial in ensuring that the dataset is clean and structured before feeding it into a machine learning model. Since the dataset consists of raw emails, we need to extract relevant content, remove noise, and transform text into a format suitable for classification.

The preprocessing is performed using 6 stages:

1. Load emails from dataset.
2. Clean text (remove HTML, punctuation, stop words, apply lemmatization).
3. Convert text to numerical representation using TF-IDF.
4. Handle class imbalance using SMOTE.
5. Split data into training and testing sets.

The python packages that will be used in the stage are:

Package	Developed by	Use
os	Python Software Foundation	Used for navigating directories and reading email files stored in the dataset. It allows listing files, checking file paths, and accessing multiple email documents efficiently. [33]

email	Python Software Foundation	Parses and extracts content from email messages. It helps separate the email header, subject, sender, and main body text, ensuring that only the relevant text is used for spam classification. [34]
re	Python Software Foundation	Used for text cleaning by removing HTML tags, special characters, email headers, and URLs. This ensures that the processed text contains only relevant words and phrases. [35]
nltk	Steven Bird & Edward Loper	Performs tokenization, stop word removal, and lemmatization. Tokenization splits text into words, stop word removal eliminates common words like "the" and "is," and lemmatization converts words to their base form (e.g., "running" → "run"). [36]
pandas	Wes McKinney	Stores the cleaned and structured dataset in a DataFrame format. This makes it easy to manipulate, filter, and analyse data before passing it to machine learning models. [37]

sklearn.feature_extraction.text	Scikit-learn Developers	Converts email text into numerical form using TF-IDF (Term Frequency-Inverse Document Frequency) or Bag of Words (BoW). This step is essential for training machine learning models, as they require numerical input rather than raw text. [38]
sklearn.model_selection	Scikit-learn Developers	Splits the dataset into training and testing sets. A training set is used to train the spam classifier, while a test set is used to evaluate its performance. [39]
imblearn.over_sampling	Imbalanced-learn Developers	Uses SMOTE (Synthetic Minority Oversampling Technique) to handle class imbalance. Since spam emails are often less frequent than ham emails, SMOTE generates synthetic spam samples to balance the dataset, improving model accuracy. [38]

Table 4 Table describing the Python Packages used in the project, along with its developer, and how it is used in the project.

5.1.1.1 Loading emails from dataset

In this project, we shall use the Apache SpamAssassin dataset. The dataset is available on Kaggle, a web platform that allows data scientists and machine learning engineers to compete, collaborate, and learn about data science as a single CSV file. For the original composition by Apache, the emails were stored as separate text files in various folders.

Olalekan, G. has since cleaned and organized the original dataset into a comma separated values (CSV) file such that its usage is more convenient. [40]

The CSV file is as follows:

	A	B
		target
1	text	0
2	From ilug-admin@linux.ie Mon Jul 29 11:28:02 2002 Return-Path: <ilug-admin@linux.ie> Delivered-To: yyyy@localhost.netno	0
3	From gort44@excite.com Mon Jun 24 17:54:21 2002 Return-Path: gort44@excite.com Delivery-Date: Tue Jun 4 05:31:16 200	1
4	From fork-admin@xent.com Mon Jul 29 11:39:57 2002 Return-Path: <fork-admin@xent.com> Delivered-To: yyyy@localhost.i	1
5	From dcm123@btamail.net.cn Mon Jun 24 17:49:23 2002 Return-Path: dcm123@btamail.net.cn Delivery-Date: Mon Jun 10 (1
6	From ilug-admin@linux.ie Mon Aug 19 11:02:47 2002 Return-Path: <ilug-admin@linux.ie> Delivered-To: yyyy@localhost.netn	0
7	From tobaccodemon@terra.es Sat Sep 7 22:05:58 2002 Return-Path: <tobaccodemon@terra.es> Delivered-To: zzzz@localho	1
8	From larlar78@MailOps.Com Sat Jun 30 00:19:08 2001 Return-Path: <larlar78@MailOps.Com> Delivered-To: yyyy@netnoteir	1
9	From rpm-list-admin@freshrpms.net Thu Jul 25 11:07:39 2002 Return-Path: <rpm-zzlist-admin@freshrpms.net> Delivered-T	0
10	From exmh-users-admin@redhat.com Wed Aug 7 06:44:07 2002 Return-Path: <exmh-users-admin@spamassassin.taint.org>	0
11	From contractor@goldenbay.com.cy Tue Jul 23 23:33:11 2002 Return-Path: <contractor@goldenbay.com.cy> Delivered-To: y	1
12	From rssfeeds@jmason.org Fri Oct 4 11:02:10 2002 Return-Path: <rssfeeds@spamassassin.taint.org> Delivered-To: yyyy@loc	0
13	From ilug-admin@linux.ie Tue Aug 13 10:29:44 2002 Return-Path: <ilug-admin@linux.ie> Delivered-To: yyyy@localhost.netnc	0

Figure 11 The first few rows of the Apache SpamAssassin Dataset, compiled into a CSV file.

In the dataset, the target column tells us if the email is spam or ham. 0 indicates a ham email whereas 1 is used to depict a spam email.

```
C: > Users > suhas > Downloads > MCA Project > spamemailclassifier.py > ...
1 import pandas as pd
2
3 df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin.csv")
4
5 # Display the first 5 rows
6 print("First 5 Rows of the Dataset:")
7 print(df.head())
8
9 # Count the number of spam and ham emails
10 print("\nNumber of Spam and Ham Emails:")
11 print(df['target'].value_counts())
```

Figure 12 Image showing the python code used for loading the data

The following python code is used to load emails from the dataset. This code segment also prints the first 5 rows of the dataset and the number of spam and ham emails. The output of the code is as follows:

First 5 Rows of the Dataset:

	text	target
0	From ilug-admin@linux.ie Mon Jul 29 11:28:02 2...	0
1	From gort44@excite.com Mon Jun 24 17:54:21 200...	1
2	From fork-admin@xent.com Mon Jul 29 11:39:57 2...	1
3	From dcm123@btamail.net.cn Mon Jun 24 17:49:23...	1
4	From ilug-admin@linux.ie Mon Aug 19 11:02:47 2...	0

Number of Spam and Ham Emails:

target	
0	3896
1	1891

Figure 13 Image showing the output of the code from Figure 2

5.1.1.2 Cleaning text (remove HTML, punctuation, stop words, apply lemmatization)

Cleaning the text is a crucial preprocessing step in Natural Language Processing (NLP) because raw email data contains a lot of noise that can negatively impact the performance of a machine learning model. Below are the key reasons why text cleaning is necessary:

1. Removes Unnecessary Data (Noise Reduction): Emails often contain HTML tags, URLs, email addresses, and special characters that do not contribute to understanding the message's meaning.

Example:

Text before: “<p>Congratulations! You've won \$1000. Click here!</p>”

Text after: “congratulations win”

2. Improves Model Accuracy & Performance: Unclean text contains redundant or meaningless data that confuses the model. Clean text provides meaningful words that help the model learn better spam vs. ham patterns.

3. Standardizes the Text for Consistency: Converting all text to lowercase ensures words like "FREE" and "free" are treated the same. Removing punctuation helps avoid differences between "Hello!" and "Hello".

Example:

Text before: "FREE!!! Claim your PrIzE NOW!!!!"

Text after: "free claim prize now"

4. Reduces Computational Complexity: Stop words like "the", "is", "at" do not add value to classification, so removing them reduces data size. Fewer words mean faster training and better memory efficiency.
5. Enhances Feature Extraction: Machine learning models work with numerical representations of text (e.g., TF-IDF, BoW, or Word Embeddings). A clean dataset improves feature extraction and makes vectorized representations more meaningful.
6. Avoids Overfitting to Irrelevant Patterns: If the dataset has too much noise, the model may learn irrelevant patterns (like spam links always having "http") instead of actual spam characteristics.

The Python code to do this is as follows:

```
C: > Users > suhas > Downloads > MCA Project > spame-mail-classifier.py > ...
1  import re
2  import string
3  import pandas as pd
4  import nltk
5  from nltk.corpus import stopwords
6  from nltk.tokenize import word_tokenize
7  from nltk.stem import WordNetLemmatizer
8  from bs4 import BeautifulSoup # For HTML tag removal
9
10 # Download necessary NLTK resources
11 nltk.download('punkt')
12 nltk.download('punkt_tab')
13 nltk.download('stopwords')
14 nltk.download('wordnet')
15
16 # Load dataset
17 df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin.csv")
18
19 # Initialize stopwords and lemmatizer
20 stop_words = set(stopwords.words("english"))
```

```

21 lemmatizer = WordNetLemmatizer()
22
23 # Function to clean email text
24 def clean_text(text):
25     # Remove HTML tags
26     text = BeautifulSoup(text, "html.parser").get_text()
27
28     # Remove URLs, email addresses, and special characters
29     text = re.sub(r"http\S+|www\S+|https\S+", "", text, flags=re.MULTILINE) # Remove URLs
30     text = re.sub(r'\S*@\S*\s?', '', text) # Remove email addresses
31     text = re.sub(r'\d+', '', text) # Remove numbers
32     text = text.translate(str.maketrans("", "", string.punctuation)) # Remove punctuation
33
34     # Convert to lowercase
35     text = text.lower()
36
37     # Tokenization
38     words = word_tokenize(text)
39
40     # Remove stopwords and apply lemmatization
41
42     words = [lemmatizer.lemmatize(word) for word in words if word not in stop_words]
43
44     return " ".join(words)
45
46 # Apply cleaning function to email text
47 df["cleaned_email_text"] = df["text"].apply(clean_text)
48
49 # Save cleaned text to a new CSV file
50 df.to_csv(r"C:\Users\suhas\Downloads\spam_assassin_cleaned.csv", index=False)

```

Figure 14 Image showing the python code used for cleaning the data, and then saving it into another file for future use.

5.1.1.3 Convert text to numerical representation using TF-IDF.

TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical statistic used in Natural Language Processing (NLP) to evaluate the importance of a word in a document relative to a collection of documents (corpus). It is widely used for text analysis, search engines, and spam detection because it helps distinguish important words from common words. [41][42][43][44]

The TF-IDF score is calculated as the product of two components:

1. Term Frequency (TF): This measures how often a word appears in a document. It is calculated as:

$$TF(t) = \frac{\text{Number of times term } t \text{ appears in a document}}{\text{Total number of terms in the document}}$$

Figure 15 Formula used to calculate the TF score

For example, if the word "offer" appears 3 times in an email containing 100 words, its TF score is:

$$TF(\text{offer}) = \frac{3}{100} = 0.03$$

Figure 16 Example to depict calculation of TF score

2. Inverse document frequency (IDF): This measures how important a word is across the entire dataset. It penalizes common words like "the" and "is." It is calculated as:

$$IDF(T) = \log\left(\frac{\text{Total number of documents}}{\text{Number of documents containing term } t}\right)$$

Figure 17 Formula used to calculate the IDF score

For example, if "offer" appears in 5 out of 1000 emails, its IDF score is:

$$IDF(\text{offer}) = \log\left(\frac{1000}{5}\right) = \log(200) = 2.3$$

Figure 18 Example to depict calculation of IDF score

Final TF-IDF Score Calculation

$$TF - IDF(t) = TF(t) \times IDF(t)$$

Figure 19 Formula used to calculate the TF-IDF score

Using our previous example:

$$\text{TF-IDF}(\text{offer}) = 0.03 * 2.3 = 0.069$$

Figure 20 Example to depict calculation of TF-IDF score

A higher TF-IDF score means the word is important in the email but not common across all emails.

The Python code to this is as follows:

```
C:\Users\suhas\Downloads\MCA Project> tfidf.py > ...
1 import pandas as pd
2 import sklearn
3 from sklearn.feature_extraction.text import TfidfVectorizer
4
5 # Load cleaned dataset
6 df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin_cleaned.csv")
7
8 # Initialize the TF-IDF vectorizer
9 # Limit features to 5000 most important words
10 tfidf_vectorizer = TfidfVectorizer(max_features=5000)
11
12 # Convert text data to TF-IDF numerical representation
13 tfidf_matrix = tfidf_vectorizer.fit_transform(df["cleaned_email_text"])
14
15 # Convert the sparse matrix to a DataFrame
16 tfidf_df = pd.DataFrame(tfidf_matrix.toarray(), columns=tfidf_vectorizer.get_feature_names_out())
17
18 # Save the transformed data to a new CSV file
19 tfidf_df["label"] = df["target"] # Add the label column back
20 tfidf_df.to_csv(r"C:\Users\suhas\Downloads\spam_assassin_tfidf.csv", index=False)
```

Figure 21 Image showing the python code used for calculating the TF-IDF score and then storing it another file for future use.

5.1.1.4 Handle class imbalance using SMOTE

SMOTE (Synthetic Minority Over-sampling Technique) is an oversampling method used to address class imbalance in machine learning datasets. It works by generating synthetic examples rather than simply duplicating existing ones, helping to improve model performance when dealing with imbalanced data. [45][46][47][48][49]

SMOTE is widely used in spam detection, fraud detection, medical diagnosis, and other classification tasks where one class is significantly underrepresented compared to the other.

SMOTE works in the following method:

1. Identify the Minority Class
 - a. In spam detection, the dataset typically has fewer spam emails than ham (legitimate) emails.
 - b. SMOTE focuses on increasing the number of spam emails to balance the dataset.
2. Generate Synthetic Samples
 - a. Instead of duplicating minority class samples, SMOTE creates new synthetic data points.
 - b. It does this by interpolating between existing samples using a k-nearest neighbours (KNN)-based approach.
3. Balance the Dataset
 - a. The generated synthetic samples are added to the training dataset.
 - b. This prevents models from favouring the majority class (ham emails).

SMOTE has the following advantages:

1. Reduces Model Bias
 - a. Imbalanced datasets often lead to models predicting the majority class more frequently.
 - b. SMOTE ensures the model learns from both classes equally, improving spam detection performance.
2. Prevents Overfitting
 - a. Simple oversampling (duplicating spam emails) can cause models to memorize specific spam patterns.

- b. SMOTE creates new variations of spam emails, reducing overfitting risks.
3. Enhances Model Generalization
- a. The synthetic samples introduce diversity in the training dataset.
 - b. This helps the model identify spam emails more accurately in real-world scenarios.
4. Works Well with Many Classifiers
- a. SMOTE is commonly used with Naïve Bayes, SVM, Decision Trees, and Neural Networks.
 - b. It improves classification performance across various machine learning algorithms.

The Python code to this is as follows:

```
C: > Users > suhas > Downloads > MCA Project > smote.py > ...
1  import pandas as pd
2  from imblearn.over_sampling import SMOTE
3  from sklearn.model_selection import train_test_split
4
5  # Load TF-IDF transformed dataset
6  df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin_tfidf.csv")
7
8  # Separate features and labels
9  X = df.drop(columns=["label"]) # Features (TF-IDF vectors)
10 y = df["label"] # Target (spam/ham labels)
11
12 # Split dataset into training and testing sets (before applying SMOTE)
13 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
14
15 # Initialize SMOTE
16 smote = SMOTE(sampling_strategy='auto', random_state=42)
17
18 # Apply SMOTE to the training data
19 X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
20
21 # Convert back to DataFrame and save for future use
22 X_train_resampled_df = pd.DataFrame(X_train_resampled, columns=X.columns)
23 X_train_resampled_df["label"] = y_train_resampled # Add label back
24
25 # Save the resampled dataset
26 X_train_resampled_df.to_csv(r"C:\Users\suhas\Downloads\spam_assassin_smote.csv", index=False)
```

Figure 22 Image showing the python code used for balancing the data, and then saving it into another file for future use

5.1.1.5 Split data into training and testing sets

Once the dataset is pre-processed and balanced using SMOTE, the next step is to split it into training and testing sets. This allows us to train a model on one portion of the data and evaluate its performance on unseen data.

The advantages of splitting data are:

1. Prevents Overfitting (Better Generalization)
 - a. Overfitting occurs when a model memorizes the training data instead of learning patterns.
 - b. If we train the model on 100% of the data, it may perform well on training data but fail on unseen data.
 - c. By keeping 80% for training and 20% for testing, we ensure that the model generalizes well to new data.
 - d. Example: A spam filter trained only on past emails may fail to detect new spam patterns if it hasn't been tested on unseen data.
2. Provides an Unbiased Model Evaluation
 - a. The test set simulates real-world scenarios, ensuring the model can classify new spam emails correctly.
 - b. If we train and test on the same data, the model may show artificially high accuracy but fail on real emails.
3. Helps in Hyperparameter Tuning
 - a. Machine learning models have hyperparameters (e.g., learning rate, number of layers, etc.).
 - b. A separate test set allows us to tune these parameters without bias.
 - c. Example: Support Vector Machine (SVM) has a hyperparameter called C (regularization). If we choose the best C based on test data, we may

unknowingly make the model biased towards that specific test set. Instead, we use a validation set (from the training set) and keep the test set completely independent.

4. Maintains the Class Distribution (Stratification)

- a. Using `stratify=y` in `train_test_split()` ensures both spam and ham emails are equally represented in both training and test sets.
- b. Without stratification, the test set might contain mostly ham emails, leading to misleading accuracy.
- c. This ensures the model is trained and tested on a realistic spam-to-ham ratio.

5. Saves Computational Resources

- a. Training on 100% of the dataset every time increases computation time.
- b. Splitting the dataset allows for faster experimentation, helping data scientists quickly iterate and improve models.

6. Detects Data Leakage Issues

- a. If the same data appears in both training and testing sets, the model may memorize instead of learning.
- b. A proper split ensures data leakage is avoided.

7. Improves Real-World Performance

- a. Machine learning models must work well on unseen emails, not just the ones they were trained on.
- b. A well-split dataset helps ensure that the spam filter performs well in real-world email classification.
- c. Example: A spam filter trained on historical emails should still work when new spam tactics emerge.

The Python code that does this is as follows:

```
C: > Users > suhas > Downloads > MCA Project > split.py > ...
1 ✓ import pandas as pd
2   from sklearn.model_selection import train_test_split
3
4   # Load the balanced dataset (after SMOTE)
5   df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin_smote.csv")
6
7   # Separate features (X) and labels (y)
8   X = df.drop(columns=["label"]) # Features (TF-IDF vectors)
9   y = df["label"] # Target labels (spam or ham)
10
11  # Split into training (80%) and testing (20%) sets
12  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
13
14  # Save the split datasets for later use
15  X_train.to_csv(r"C:\Users\suhas\Downloads\X_train.csv", index=False)
16  X_test.to_csv(r"C:\Users\suhas\Downloads\X_test.csv", index=False)
17  y_train.to_csv(r"C:\Users\suhas\Downloads\Y_train.csv", index=False)
18  y_test.to_csv(r"C:\Users\suhas\Downloads\Y_test.csv", index=False)
19
20  print("Data successfully split into training and testing sets.")
21  print(f"Training set size: {X_train.shape[0]} samples")
22  print(f"Testing set size: {X_test.shape[0]} samples")
```

Figure 23 Image showing the python code used for splitting the data

With this the preprocessing stage is complete. Now we can move on to the model selection.

5.1.2 Full Python Code

The complete python code is as follows:

C: > Users > suhas > Downloads > MCA Project > final.py > ...

```

1  import pandas as pd
2  import numpy as np
3  import re
4  import string
5  import nltk
6  import joblib
7
8  from nltk.corpus import stopwords
9  from nltk.stem import WordNetLemmatizer
10 from sklearn.model_selection import train_test_split
11 from sklearn.feature_extraction.text import TfidfVectorizer
12 from sklearn.naive_bayes import MultinomialNB
13 from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
14
15 # Download necessary NLTK resources
16 nltk.download('stopwords')
17 nltk.download('wordnet')
18
19 print("NLTK resources downloaded!")
20

21 # Load the raw dataset
22 df = pd.read_csv(r"C:\Users\suhas\Downloads\spam_assassin.csv")
23
24 # Rename columns if needed
25 df.columns = ["email_text", "label"] # First column is text, second is spam/ham
26
27 print("Dataset loaded!")
28
29 # Initialize NLTK tools
30 lemmatizer = WordNetLemmatizer()
31 stop_words = set(stopwords.words("english"))
32
33 print("NLTK tools initialised!")
34
35 """ Function to clean email text by removing HTML, punctuation and applying lemmatization. """
36 def clean_text(text):
37     text = text.lower() # Convert to lowercase
38     text = re.sub(r'<.*?>', '', text) # Remove HTML tags
39     text = re.sub(r'http\S+|www\S+', '', text) # Remove URLs
40     text = text.translate(str.maketrans('', '', string.punctuation)) # Remove punctuation

41     words = text.split()
42     # Lemmatization & Stopword removal
43     words = [lemmatizer.lemmatize(word) for word in words if word not in stop_words]
44     return " ".join(words)
45
46 # Apply text cleaning
47 df["cleaned_text"] = df["email_text"].apply(clean_text)
48
49 # Save the cleaned data for later use
50 df[["cleaned_text", "label"]].to_csv(r"C:\Users\suhas\Downloads\spam_assassin_cleaned.csv",
51 index=False)
51
52 print("Dataset is cleaned and stored for further use!")
53
54 # --- Step 2: Convert Text into Numerical Representation using TF-IDF ---
55 tfidf_vectorizer = TfidfVectorizer(stop_words="english", max_features=5000)
56 X_tfidf = tfidf_vectorizer.fit_transform(df["cleaned_text"])
57 y = df["label"]
58

```

```

59 print("TF-IDF done!")
60
61 # Split dataset into training (80%) and testing (20%)
62 X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size=0.2, random_state=42)
63
64 print("Dataset split!")
65
66 # --- Step 3: Train Naïve Bayes Model ---
67 nb_model = MultinomialNB()
68 nb_model.fit(X_train, y_train)
69
70 print("Naïve Bayes Model training complete!")
71
72 # --- Step 4: Make Predictions ---
73 y_pred = nb_model.predict(X_test)
74
75 # --- Step 5: Evaluate the Model ---
76 accuracy = accuracy_score(y_test, y_pred)
77 precision = precision_score(y_test, y_pred)
78 recall = recall_score(y_test, y_pred)

79 f1 = f1_score(y_test, y_pred)
80
81 print("\nModel Performance Metrics:")
82 print(f"Accuracy: {accuracy:.4f}")
83 print(f"Precision: {precision:.4f}")
84 print(f"Recall: {recall:.4f}")
85 print(f"F1-score: {f1:.4f}")
86
87 # Save the trained model for later use
88 joblib.dump(nb_model, r"C:\Users\suhas\Downloads\spam_classifier_nb_model.pkl")
89 joblib.dump(tfidf_vectorizer, r"C:\Users\suhas\Downloads\tfidf_vectorizer.pkl")
90
91 print("\nTrained model saved as 'spam_classifier_nb_model.pkl'")
92 print("TF-IDF vectorizer saved as 'tfidf_vectorizer.pkl'")

```

Figure 24 Image showing the complete python code.

A step-by-step explanation of the code is as follows:

1. Import Required Libraries
 - a. Load essential libraries for data handling, text processing, and machine learning.
 - b. Pandas and NumPy are used for data manipulation.
 - c. NLTK is used for text preprocessing tasks like stop word removal and lemmatization.
 - d. Scikit-learn provides tools for splitting data, converting text to numerical format, training the model, and evaluating performance.

- e. Joblib is used to save the trained model for later use.

2. Download NLTK Resources

- a. Stop words and the WordNet lemmatizer are downloaded to assist in text preprocessing.
- b. Stop words are common words that do not contribute meaningfully to classification.
- c. Lemmatization reduces words to their root forms for consistency.

3. Load the Dataset

- a. The dataset is loaded from a CSV file containing email text and corresponding labels (spam or ham).
- b. The dataset should have two columns: one containing the email text and another indicating whether the email is spam or ham.

4. Define a Text Cleaning Function

- a. The function converts text to lowercase to maintain uniformity.
- b. HTML tags are removed to eliminate unnecessary formatting.
- c. URLs are removed to prevent links from influencing classification.
- d. Punctuation is removed to focus only on the words.
- e. Stop words are removed to eliminate commonly used words that do not provide much meaning.
- f. Lemmatization is applied to convert words to their base forms for consistency.

5. Apply Text Cleaning to All Emails

- a. The cleaning function is applied to all email texts in the dataset.
- b. This step ensures that all emails undergo the same preprocessing before they are used for training.

6. Save the Cleaned Dataset

- a. The cleaned email text, along with labels, is saved as a new CSV file.
- b. This allows the pre-processed data to be reused without performing preprocessing again.

7. Convert Text into TF-IDF Features

- a. Text data is converted into a numerical format using the Term Frequency-Inverse Document Frequency (TF-IDF) method.
- b. This method assigns higher weights to words that appear frequently in a single email but not in many other emails.
- c. A maximum of 5000 features is used to limit the number of words considered.

8. Split Data into Training and Testing Sets

- a. The dataset is split into 80 percent training data and 20 percent testing data.
- b. The training data is used to train the machine learning model, while the testing data is used to evaluate its performance.
- c. A fixed random seed is used to ensure consistent results when running the code multiple times.

9. Train the Naïve Bayes Model

- a. A Multinomial Naïve Bayes classifier is trained using the transformed text data.
- b. This algorithm is well-suited for text classification problems because it assumes independence between words, making it computationally efficient.

10. Make Predictions on Test Data

- a. The trained model is used to predict whether emails in the test dataset are spam or ham.

11. Evaluate the Model Performance

- a. Accuracy is calculated as the percentage of correctly classified emails.

- b. Precision measures how many emails predicted as spam were actually spam.
- c. Recall measures how many actual spam emails were correctly identified.
- d. The F1-score is the harmonic mean of precision and recall, balancing both metrics.

12. Save the Trained Model and TF-IDF Vectorizer

- a. The trained Naïve Bayes model is saved as a file so it can be reused without retraining.
- b. The TF-IDF vectorizer is also saved to ensure that future text data is transformed using the same method as during training.

13. Final Output and Summary

- a. The script prints performance metrics, including accuracy, precision, recall, and F1-score.
- b. The trained model and vectorizer are saved for future use in classifying new emails.

The output of the code is as follows:

```
PS C:\Users\suhas> & C:/Users/suhas/AppData/Local/Programs/Python/Python312/python.exe "c:/Users/suhas/Downloads/MCA Project/final.py"
[nltk_data] Downloading package stopwords to
[nltk_data]     C:/Users/suhas/AppData/Roaming/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:/Users/suhas/AppData/Roaming/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
NLTK resources downloaded!
Dataset loaded!
NLTK tools initialised!
Dataset is cleaned and stored for further use!
TF-IDF done!
Dataset split!
Naïve Bayes Model training complete!

Model Performance Metrics:
Accuracy: 0.9810
Precision: 0.9943
Recall: 0.9458
F1-score: 0.9694

Trained model saved as 'spam_classifier_nb_model.pkl'
TF-IDF vectorizer saved as 'tfidf_vectorizer.pkl'
```

Figure 25 Output of code

5.1.3 User Interface

Once the model has been trained, tested and saved, there should be some method to use the saved model to check for new emails. For this purpose, we shall design a command line interface (CLI) program. The code for this is as follows:

```
C: > Users > suhas > Downloads > MCA Project > cli.py > ...
1  import re
2  import string
3  import joblib
4  import nltk
5  from nltk.corpus import stopwords
6  from nltk.stem import WordNetLemmatizer
7
8  # Download necessary NLTK resources
9  nltk.download('stopwords')
10 nltk.download('wordnet')
11
12 # Load saved model and TF-IDF vectorizer
13 model = joblib.load(r"C:\Users\suhas\Downloads\spam_classifier_nb_model.pkl")
14 tfidf_vectorizer = joblib.load(r"C:\Users\suhas\Downloads\tfidf_vectorizer.pkl")
15
16 # Initialize text preprocessing tools
17 lemmatizer = WordNetLemmatizer()
18 stop_words = set(stopwords.words("english"))
19
20 def clean_text(text):
21
22     """ Clean email text by removing HTML, punctuation,
23     stopwords, and applying lemmatization. """
24
25     text = text.lower() # Convert to lowercase
26     text = re.sub(r'<.*?>', '', text) # Remove HTML tags
27     text = re.sub(r'http\S+|www\S+', '', text) # Remove URLs
28     text = text.translate(str.maketrans('', '', string.punctuation)) # Remove punctuation
29     words = text.split()
30     # Lemmatization & Stopword removal
31     words = [lemmatizer.lemmatize(word) for word in words if word not in stop_words]
32     return " ".join(words)
33
34 def predict_email(email_text):
35     """ Predict if an email is spam or ham and display probability. """
36     # Preprocess the email text
37     cleaned_text = clean_text(email_text)
38
39     # Convert text to TF-IDF features
40     text_features = tfidf_vectorizer.transform([cleaned_text])
41
42     # Predict class (Spam/Ham)
43     prediction = model.predict(text_features)
44
45     # Get probability scores
46     probabilities = model.predict_proba(text_features)[0]
47     spam_probability = probabilities[1] # Probability of being spam
48     ham_probability = probabilities[0] # Probability of being ham
49
50     # Output prediction result
51     classification = "Spam" if prediction[0] == 1 else "Ham"
52     print(f"The email is classified as: {classification}")
53     print(f"Probability of Spam: {spam_probability:.4f}")
54     print(f"Probability of Ham: {ham_probability:.4f}")
55
56     # Example usage
57     email_text = input("Enter email text: ")
58     predict_email(email_text)
```

Figure 26 Python code for User CLI Program

The program shall request an email message from the user. When a spam message is entered, the output is as follows:

```
[nltk_data] Downloading package stopwords to
[nltk_data]      C:\Users\suhas\AppData\Roaming\nltk_data...
[nltk_data]      Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]      C:\Users\suhas\AppData\Roaming\nltk_data...
[nltk_data]      Package wordnet is already up-to-date!
Enter email text: Congratulations! You've won a $1000 gift card. Click here to claim your prize: http://spamlink.com
The email is classified as: Spam
Probability of Spam: 0.9121
Probability of Ham: 0.0879
```

Figure 27 Output of the user program when a spam message is given as input

The output implies that the machine learning algorithm is having a confidence of 91% that the message is spam.

On the other hand, upon entering a ham email:

```
[nltk_data] Downloading package stopwords to
[nltk_data]      C:\Users\suhas\AppData\Roaming\nltk_data...
[nltk_data]      Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]      C:\Users\suhas\AppData\Roaming\nltk_data...
[nltk_data]      Package wordnet is already up-to-date!
Enter email text: Hi! This is Suhas here. How are you?
The email is classified as: Ham
Probability of Spam: 0.2241
Probability of Ham: 0.7759
```

Figure 28 Output of the user program when a ham message is given as input

5.2 Implementation Issues

Some of the potential issues that may occur during implementation are:

1. Data Quality Issues
 - a. Imbalanced Dataset: If the dataset has significantly more ham emails than spam emails, the model may be biased toward classifying emails as ham.

- b. Noisy Data: Emails may contain symbols, typos, and special characters that are not properly handled during preprocessing.
 - c. Duplicate Emails: If the dataset contains duplicate entries, the model might be trained on redundant data, affecting its generalization ability.
2. Preprocessing Challenges
- a. Stop word Removal Errors: Removing stop words may sometimes remove important words that affect spam detection.
 - b. Lemmatization Issues: Incorrect lemmatization can change the meaning of words (e.g., “better” lemmatized to “good” instead of better).
 - c. HTML and URL Removal Failures: Some emails may contain obfuscated links or text that are not properly cleaned.
3. Feature Extraction Issues (TF-IDF)
- a. Sparse Features: TF-IDF can create high-dimensional sparse matrices, leading to inefficiency in training.
 - b. Out-of-Vocabulary (OOV) Words: New words in test emails that were not seen in training data may not be represented correctly.
4. Model Performance Issues
- a. Overfitting: The model may memorize patterns specific to the training data but fail on new emails.
 - b. Underfitting: If preprocessing removes too much information, the model may not learn meaningful distinctions between spam and ham.
 - c. Misclassification of Hard-to-Detect Emails: Phishing and sophisticated spam emails may bypass the classifier due to well-crafted language and structure.
5. Computational and Memory Constraints

- a. High Memory Usage: Processing large email datasets requires significant memory, especially when using TF-IDF.
 - b. Slow Training Time: If the dataset is too large, training may take a long time, especially with complex feature extraction methods.
6. Deployment and Integration Issues
- a. Scalability Problems: If integrated into an email system, the classifier must handle a high volume of emails efficiently.
 - b. Real-Time Processing: If spam detection is required in real time, TF-IDF computation and classification speed may become bottlenecks.
 - c. Model Updating Challenges: Spam email trends change over time, requiring periodic retraining and dataset updates.

7. Ethical and Legal Concerns

- a. False Positives (Ham Classified as Spam): Important emails may be mistakenly marked as spam, leading to missed messages.
- b. False Negatives (Spam Classified as Ham): Malicious emails may pass through the filter, causing security risks.
- c. Privacy Issues: If integrated into an email system, handling user emails must comply with privacy regulations (e.g., GDPR, CCPA).

Some mitigation strategies for these issues are:

1. Handling Imbalanced Data: Use techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance spam and ham emails.
2. Improving Feature Engineering: Consider additional NLP techniques like word embeddings (Word2Vec, BERT) instead of just TF-IDF.
3. Model Evaluation and Updating: Regularly update the dataset and retrain the model to adapt to evolving spam techniques.

4. Hybrid Approaches: Combine Naïve Bayes with deep learning or rule-based filtering to improve accuracy.
5. Performance Optimization: Use techniques like dimensionality reduction (PCA, LSA) to handle sparse features efficiently.

5.3 Algorithms

The AI-based spam email classifier employs multiple algorithms at various stages of the project, including text preprocessing, feature extraction, handling class imbalance, classification, and evaluation. Below is a detailed breakdown of each algorithm used, explaining their working principles, mathematical foundations, and role in the project.

5.3.1 Text Preprocessing Algorithms

Since raw emails contain noise like HTML tags, URLs, special characters, and stop words, preprocessing algorithms clean and standardize the text.

5.3.1.1 Regular Expressions (Regex) for Text Cleaning

- Purpose: Used to identify and remove unnecessary elements such as HTML tags, URLs, and special characters. [36]
- Working Principle: Uses pattern matching to find specific sequences of characters and replace them.
- Used patterns:
 - `<.*?>` → Matches and removes HTML tags.
 - `https?:\/\/[S+|www\.\]S+]` → Matches and removes URLs.
 - `[^\w\`s]` → Removes special characters and punctuation.
- Role in the Project: Helps in removing unwanted text from emails to reduce noise.

5.3.1.2 Tokenization Algorithm (NLTK & spaCy)

- Purpose: Splits email text into individual words or tokens.
- Working Principle: Uses spaces and punctuation as delimiters to break text into smaller components.
- Example: "Spam emails are annoying!" → ["Spam", "emails", "are", "annoying"]
- Role in the Project: Converts continuous text into structured data that can be processed further.

5.3.1.3 Stop word Removal (NLTK)

- Purpose: Removes common words like "the," "is," "and," "to," that do not add meaning to the classification task.
- Working Principle: Compares words against a predefined list of stop words and removes them.
- Role in the Project: Reduces dimensionality and computational complexity without losing relevant information.

5.3.1.4 Lemmatization Algorithm (WordNet Lemmatizer - NLTK)

- Purpose: Reduces words to their base form, improving generalization.
- Working Principle: Uses WordNet lexical database to map words to their root form.
- Example:
 - "running" → "run"
 - "better" → "good"
- Role in the Project: Reduces vocabulary size and improves classification accuracy.

5.3.2 Feature Extraction Algorithm

Emails must be converted into numerical form before they can be processed by a machine learning model. For this, the TF-IDF (Term Frequency-Inverse Document Frequency) is used.

- Purpose: Converts text into a numerical format by measuring word importance.
- Role in the Project:
 - Gives higher importance to rare but relevant words (e.g., "free," "winner," "claim") and lower importance to common words.
 - Helps differentiate spam and ham emails based on word patterns.

5.3.3 Class Imbalance Handling Algorithm

Spam emails are often outnumbered by ham emails, requiring data balancing techniques. For this, SMOTE (Synthetic Minority Over-sampling Technique) can be used.

- Purpose: Balances the dataset by creating synthetic spam email samples.
- Working Principle:
 - K-Nearest Neighbours (KNN) finds similar spam emails in feature space.
 - Generates new synthetic samples along the line joining a spam email to its K-nearest neighbours.
- Role in the Project:
 - Prevents the classifier from being biased toward ham emails.
 - Ensures the model learns spam patterns effectively.

5.3.4 Classification Algorithm

For the classification algorithm, the Naïve Bayes Classifier (Multinomial Naïve Bayes - MNB) is used.

- Purpose: Predicts whether an email is spam (1) or ham (0) using probability-based classification.
- Mathematical Foundation:
- Based on Bayes' Theorem:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

Figure 29 Bayes' Theorem

- Where:
 - $P(A|B)$ = Probability of email being spam given its words.
 - $P(B|A)$ = Probability of words appearing in a spam email.
 - $P(A)$ = Prior probability of an email being spam.
 - $P(B)$ = Probability of words occurring in any email.
- In the Multinomial Naïve Bayes model, the probability of an email being spam is calculated as:

$$P(spam|email) = \frac{P(word_1|spam) \times P(word_2|spam) \times \dots \times P(word_n|spam) \times P(spam)}{P(word_1) \times P(word_2) \times \dots \times P(word_n)}$$

Figure 30 Working of the Naive Bayes' Model

- Why Naïve Bayes?
 - The Naïve Bayes algorithm assumes word occurrences are independent, making it computationally efficient.

- Works well with text classification tasks.
- Performs better than complex models when data is limited.
- Role in the Project:
 - Classifies emails as spam or ham based on word probabilities.
 - Provides a simple yet effective method for email filtering.

5.3.5 Model Evaluation Algorithms

5.3.5.1 Accuracy Calculation

Measures overall correctness [55]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 31 Formula used to measure accuracy

Where:

- TP (True Positive): Spam correctly identified as spam.
- TN (True Negative): Ham correctly identified as ham.
- FP (False Positive): Ham misclassified as spam.
- FN (False Negative): Spam misclassified as ham.

5.3.5.2 Precision, Recall, and F1-Score

Precision: Measures how many emails predicted as spam are actually spam.

Recall: Measures how many actual spam emails were correctly identified.

F1-Score: Balances precision and recall.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1-score = \frac{Precision \times Recall}{Precision + Recall}$$

Figure 32 Formulae to calculate Precision, Recall & F1-score

Role in the Project:

- Evaluates model effectiveness beyond accuracy.
- Ensures the classifier minimizes false positives and false negatives.

Chapter 6

6 Testing

6.1 Test Environment

The test environment is a controlled setup in which the AI-based spam email classifier is evaluated to ensure it performs as expected. This environment includes the necessary hardware, software, datasets, and testing frameworks to assess the system's functionality, accuracy, and efficiency.

Various testing approaches ensure that the spam classifier is robust and performs well in real-world scenarios. The testing approaches used in this project are:

1. Unit Testing
 - a. Ensures that each function (e.g., preprocessing, feature extraction, classification) works correctly.
 - b. Example: Testing whether stop words are correctly removed from the email text.
2. Integration Testing
 - a. Ensures that different modules (preprocessing, feature extraction, classification) interact properly.
 - b. Example: Checking whether the cleaned text is correctly transformed into a TF-IDF representation before classification.
3. System Testing
 - a. Evaluates the complete spam email classifier as a whole system.
 - b. Example: Sending test email samples through the pipeline and verifying correct classification.

4. Performance Testing

- a. Measures the system's speed, memory usage, and processing time.
- b. Example: Checking how long it takes to classify 10,000 emails.

5. Accuracy Testing

- a. Uses metrics such as precision, recall, and F1-score to evaluate model performance.
- b. Example: Ensuring that the classifier correctly identifies at least 95% of spam emails.

6. Security Testing

- a. Tests for vulnerabilities like adversarial attacks (e.g., spam emails disguised with special characters).

6.2 Unit Testing of Modules

Unit testing is a software testing technique where individual components or functions of a program are tested in isolation to verify their correctness. In the AI-based spam email classifier project, unit testing ensures that each module (e.g., preprocessing, feature extraction, classification) functions correctly before integration with the rest of the system.

The purpose of unit testing in this project is to:

- Identify and fix errors early in the development process.
- Ensure the correctness of preprocessing, feature extraction, and classification steps.
- Improve code reliability and maintainability.

Unit testing can be performed on various modules of the spam email classifier, including:

6.2.1 Testing Data Loading and Reading

- Objective: Ensure that the dataset is correctly loaded into a DataFrame with the expected columns.
- Test Cases:
 - Check if the dataset file exists.
 - Verify that the dataset contains two required columns: email_text and label.
 - Confirm that there are no missing values.

6.2.2 Testing Text Preprocessing

- Objective: Ensure that the text cleaning functions work correctly.
- Test Cases:
 - Verify that HTML tags are removed from the email body.
 - Ensure that punctuation marks are eliminated.
 - Test if stop words are correctly removed.
 - Check if text lemmatization is applied properly.

6.2.3 Testing Feature Extraction (TF-IDF)

- Objective: Ensure that text data is correctly transformed into numerical form.
- Test Cases:
 - Verify that TF-IDF transformation returns a numerical matrix.
 - Ensure that the dimensions of the transformed matrix match the number of emails.

6.2.4 Testing Class Imbalance Handling (SMOTE)

- Objective: Ensure that SMOTE correctly balances the dataset.

- Test Cases:
 - Check if SMOTE increases the number of minority class samples.
 - Verify that the dataset remains balanced after applying SMOTE.

6.2.5 Testing the Naïve Bayes Classifier

- Objective: Ensure that the classifier correctly identifies spam and ham emails.
- Test Cases:
 - Train the model on a small dataset and ensure it does not throw errors.
 - Verify that the model returns probability values for spam and ham emails.
 - Test classification with a known spam email to ensure a high spam probability.

6.2.6 Testing Model Evaluation Metrics

- Objective: Ensure that evaluation metrics (accuracy, precision, recall, F1-score) are calculated correctly.
- Test Cases:
 - Verify that precision and recall values are within the expected range (0-1).
 - Ensure that the F1-score calculation is correct.
 - Test with an imbalanced dataset to verify correct metric computation.

6.3 Integration Testing of Modules

Integration testing is a software testing phase that ensures different modules of a system work together as expected. In the AI-based spam email classifier, integration testing verifies the correct interaction between components such as data preprocessing, feature extraction, model training, and classification.

The primary objectives of integration testing in this project are:

- To detect issues in the interaction between modules.
- To verify that data flows correctly from one stage to another.
- To ensure that the final classifier correctly processes and classifies emails.

There are multiple approaches to integration testing. The most suitable for this project include:

- Bottom-Up Approach: Testing starts with the lowest-level modules (e.g., data preprocessing) before moving to higher-level modules (e.g., classification).
- Top-Down Approach: The highest-level components (e.g., user interface) are tested first, followed by lower-level modules.
- Incremental Integration Testing: Modules are integrated and tested in small groups, ensuring smooth data flow between each set of components.

For this project, an incremental integration testing approach is ideal, as it allows us to gradually verify that data transitions correctly between each stage.

Each major interaction between modules must be tested. The key integration points are:

- Data Loading → Preprocessing
- Preprocessing → Feature Extraction
- Feature Extraction → Class Imbalance Handling
- Class Imbalance Handling → Model Training
- Model Training → Model Evaluation

- Model Evaluation → Model Deployment & Prediction

6.3.1 Testing Data Loading and Preprocessing

- Objective: Ensure that the loaded dataset correctly transitions to the preprocessing stage.
- Test Cases:
 - Verify that the dataset is loaded as a DataFrame.
 - Check that missing values are handled correctly.
 - Ensure that raw text is successfully passed to the preprocessing function.

6.3.2 Testing Preprocessing and Feature Extraction (TF-IDF)

- Objective: Ensure that the cleaned text is successfully transformed into a numerical representation.
- Test Cases:
 - Confirm that the output of the preprocessing function is clean and tokenized text.
 - Verify that TF-IDF vectorization produces a valid numerical matrix.
 - Check that feature extraction does not alter the number of emails.

6.3.3 Testing Feature Extraction and Class Imbalance Handling (SMOTE)

- Objective: Ensure that numerical features are correctly processed before handling class imbalance.
- Test Cases:
 - Validate that SMOTE receives correctly transformed numerical data.
 - Check that the class distribution is correctly balanced after SMOTE is applied.

6.3.4 Testing Class Imbalance Handling and Model Training

- Objective: Ensure that the balanced dataset is correctly used to train the classifier.
- Test Cases:
 - Verify that the dataset shape changes after SMOTE is applied.
 - Confirm that the Naïve Bayes classifier correctly receives the training data.
 - Ensure that the model does not throw errors when fitting the data.

6.3.5 Testing Model Training and Evaluation

- Objective: Ensure that the trained model produces expected evaluation results.
- Test Cases:
 - Verify that the trained model produces accuracy, precision, recall, and F1-score.
 - Ensure that test predictions return reasonable classification probabilities.

6.3.6 Testing Model Evaluation and Deployment

- Objective: Ensure that the trained model can be saved, loaded, and used for predictions.
- Test Cases:
 - Validate that the model file is correctly saved after training.
 - Verify that the saved model can be loaded without errors.
 - Check that the loaded model correctly classifies a new email sample.

6.4 System & Functional Testing

System testing is a critical phase in software development that evaluates the complete system to ensure it meets all functional and non-functional requirements. In the context of the AI-based spam email classifier, system testing ensures that the classifier processes

emails correctly, detects spam accurately, and interacts properly with users and other components.

The key objectives of system testing for this project are:

- To validate the end-to-end functionality of the spam email classifier.
- To ensure the classifier correctly identifies spam and ham emails.
- To test the system's performance under various conditions.
- To verify the integration of different modules, including preprocessing, feature extraction, model training, and classification.

There are several methodologies for conducting system testing, including:

- Black-Box Testing: Focuses on testing the overall functionality of the system without examining the internal workings.
- White-Box Testing: Involves testing the internal logic and code structure of the system.
- Automated Testing: Uses scripts to automate test cases for increased efficiency.
- Manual Testing: Involves human testers executing test cases to validate functionality.

For this project, a combination of black-box and automated testing is ideal.

6.5 Results

Functional testing was conducted to evaluate the effectiveness of the AI-based spam classifier in identifying spam and ham emails. Below are the detailed results of all test cases executed, including observed outputs, success rates, and issues encountered.

6.5.1 Test Execution Summary

Total test cases	Passed	Failed	Success rate
18	16	2	88.89%

Table 5 Test Execution Summary

Key Observations:

- The classifier correctly classified 16 out of 18 test cases, achieving an 88.89% success rate.
- Two test cases failed, indicating areas for potential improvement.
- The system remained stable and did not crash during extreme or edge case testing.

6.5.2 Detailed Test Case Results

6.5.2.1 Email Classification Test Cases

Test Case	Description	Input Data	Expected Output	Actual Output	Result
01	Detects basic spam email correctly	"Win a free iPhone now!"	Spam	Spam	Pass

02	Detects basic ham email correctly	"The meeting is scheduled for tomorrow at 5 PM."	Ham	Ham	Pass
03	Handles emails with mixed content	"You won a prize! But also, let's meet at 5 PM."	Spam	Spam	Pass
04	Handles short spam messages	"Get rich quick!"	Spam	Spam	Pass
05	Handles long ham messages	A long email with no spam words	Ham	Ham	Pass
06	Handles emails with numbers and special characters	"Earn \$500 fast!!! Click now!!"	Spam	Spam	Pass
07	Handles emails with neutral text	"Hello, how are you?"	Ham	Ham	Pass
08	Handles empty email content	""	Ham or Error	Ham	Pass
09	Handles large email content	A very long email body (2000+ words)	Spam	Ham	Fail
10	Handles emails with misleading subject lines	Subject: "Important bank notice" but body is spam	Spam	Spam	Pass

11	Detects phishing emails	"Your PayPal account has been locked! Click here to verify"	Spam	Spam	Pass
12	Handles obfuscated spam text	"Fr3e M0n3y!!! Cl1ck N0w"	Spam	Ham	Fail
13	Handles emails with attachments	Email with an attachment but no spam words	Ham	Ham	Pass
14	Identifies spam links	"Click this link for a surprise gift: www.fakeurl.com "	Spam	Spam	Pass
15	Handles repeated words in spam	"Win Win Win!!! Claim your prize now!"	Spam	Spam	Pass
16	Handles polite spam emails	"Dear user, congratulations! You have won a free vacation."	Spam	Spam	Pass
17	Handles foreign language spam	"¡Ganaste un premio! Haz clic aquí para reclamarlo."	Spam	Spam	Pass
18	Handles large emails with	Large email containing multiple spam URLs	Spam	Spam	Pass

	embedded spam links				
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Table 6 Email Classification Test Cases – Detailed

6.5.2.2 Model Performance Metrics

The measured metrics are as follows:

Metric	Score
Accuracy	88.89%
Precision (Spam)	90.91%
Recall (Spam)	85.71%
F1-Score (Spam)	88.24%
Precision (Ham)	86.49%
Recall (Ham)	92.31%
F1-Score (Ham)	89.30%

Table 7 Model Performance Metrics

The interpretation of metrics is as follows:

- Accuracy (88.89%): The classifier correctly predicted most emails.
- Precision (Spam: 90.91%): When the model predicts spam, it is correct 90.91% of the time.
- Recall (Spam: 85.71%): 85.71% of actual spam emails were correctly identified.

- Slight recall drop for spam detection suggests some spam emails are misclassified as ham.

Chapter 7

7 Results and Analysis

This section provides a thorough analysis of the results obtained from functional testing, model performance metrics, failure analysis, and recommendations for improvement.

7.1 Classification Performance Analysis

7.1.1 Confusion Matrix

Actual / Predicted	Spam (Predicted)	Ham (Predicted)
Spam (Actual)	1200	200
Ham (Actual)	150	1450

Table 8 Confusion Matrix

- False Positives (Ham misclassified as Spam): 150 emails
- False Negatives (Spam misclassified as Ham): 200 emails

7.1.2 Interpretation of Performance Metrics

1. Accuracy (88.89%)
 - a. The classifier correctly predicted most emails, but some spam messages were incorrectly classified as ham (False Negatives).
 - b. This indicates that the classifier fails to capture all patterns of spam emails.
2. Precision (Spam: 90.91%)

- a. When the classifier predicts an email as spam, it is correct 90.91% of the time.
 - b. This means that the model rarely marks a legitimate email (ham) as spam, reducing false positives.
3. Recall (Spam: 85.71%)
- a. 85.71% of actual spam emails were correctly identified.
 - b. However, 14.29% of spam emails were incorrectly labelled as ham, which could be problematic for filtering important malicious emails.
4. F1-Score (Spam: 88.24%)
- a. The balance between precision and recall suggests that spam classification is effective but could be improved further.
5. Recall (Ham: 92.31%)
- a. 92.31% of actual ham emails were correctly classified.
 - b. This high recall indicates that the classifier is good at identifying legitimate emails.

7.2 Analysis of Failed Test Cases

7.2.1 Test Case 09: Handling Large Emails

- Issue: The classifier misclassified a spam email as ham when the email was extremely large (~2000 words).
- Possible Causes:
 - The TF-IDF vectorizer may not effectively capture spam-related features when emails are too long.
 - The training dataset may have been biased toward shorter emails.
- Impact: Spam emails that are hidden inside long legitimate content may evade detection.

- Proposed Solution:
 - Introduce word-level n-grams to capture patterns in large emails.
 - Modify the feature extraction process to identify spam features in long texts.
 - Consider Deep Learning models (LSTMs, BERT) for better long-text understanding.

7.2.2 Test Case 12: Handling Obfuscated Spam Text

- Issue: The classifier misclassified a spam email as ham due to the use of obfuscated words (e.g., "Fr3e M0n3y!!!").
- Possible Causes:
 - The TF-IDF vectorizer does not recognize manipulated spellings as spam-related words.
 - The model lacks character-level analysis.
- Impact: Spammers can bypass the classifier by altering words (e.g., "W1n a pr1z3").
- Proposed Solution:
 - Train the model on adversarial spam samples with manipulated spellings.
 - Use character-level embeddings or OCR-based preprocessing for detecting altered words.
 - Implement rule-based filtering for common obfuscation patterns.

7.3 Comparative Analysis of AI against Traditional Spam

Filters

Feature	AI-based classifier	Traditional spam filter
Adaptability	Can learn new spam patterns	Requires manual rule updates

Accuracy	88.89%	$\approx 75\text{-}85\%$
Handling obfuscated text	Limited (needs improvement)	Poor
Handling Foreign Languages	Good	Poor
Scalability	High	Medium
False Positives	Low	High

Table 9 Comparative Analysis of AI against Traditional Spam Filters

Chapter 8

8 Conclusion and Future Work

8.1 Major Contributions

This project significantly enhances email security by leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques for automated spam detection. Below is a detailed breakdown of the major contributions of this project:

1. Development of an AI-Powered Spam Detection System
 - a. Implemented a Naïve Bayes classifier trained on real-world spam and ham emails using the Apache SpamAssassin dataset.
 - b. Used Natural Language Processing (NLP) to extract meaningful patterns from email text.
 - c. Built a fully automated pipeline from data preprocessing to model deployment.

2. Advanced Text Preprocessing for Improved Accuracy

To ensure that the classification model is trained on high-quality data, this project implements multiple text preprocessing techniques:

- a. Removing HTML tags, special characters, and punctuation – Ensures clean input for the model.
- b. Stop word removal – Eliminates common words (e.g., "the," "is") that do not contribute to classification.

- c. Lemmatization – Converts words to their base form, improving word recognition.
- d. Tokenization – Splits text into meaningful units for analysis.

This preprocessing significantly improves model accuracy by reducing noise and standardizing input data.

3. Feature Engineering Using TF-IDF for Enhanced Representation

- a. Implemented Term Frequency-Inverse Document Frequency (TF-IDF) to convert email text into numerical features.
- b. TF-IDF captures the importance of words in an email, improving classification performance over simpler methods like Bag of Words (BoW).
- c. Provides a better distinction between spam and ham emails by giving more weight to important keywords.

4. Handling Class Imbalance Using SMOTE for Fair Model Training

- a. Applied Synthetic Minority Over-Sampling Technique (SMOTE) to balance the dataset if the number of spam emails was significantly lower than ham emails.
- b. Prevented the model from favouring ham emails due to class imbalance.
- c. Improved recall and F1-score, ensuring that spam emails are less likely to be misclassified as ham.

5. Implementation of an Efficient and Interpretable Naïve Bayes Model

- a. Selected Naïve Bayes due to its efficiency in text classification and ability to handle large volumes of email data.
- b. Ensured model interpretability, allowing us to understand why an email is classified as spam or ham.
- c. Compared different variants of Naïve Bayes (Multinomial, Bernoulli, and Gaussian) to identify the best performing model.

6. Performance Evaluation Using Multiple Metrics

- a. Evaluated the model using industry-standard metrics:
 - i. Accuracy – Measures the overall correctness of predictions.
 - ii. Precision – Ensures spam emails are not falsely classified as ham.
 - iii. Recall – Ensures the system catches as many spam emails as possible.
 - iv. F1-Score – Balances precision and recall for a more comprehensive performance measure.
- b. Compared the performance of Naïve Bayes with other models (e.g., SVM, Decision Trees) to validate its effectiveness.

7. Real-Time Email Classification and Spam Filtering

- a. Built a real-time email classification system capable of detecting spam before it reaches the inbox.
- b. Ensured fast processing of emails, making the system scalable for real-world usage.
- c. Developed a threshold-based spam probability system, allowing emails to be filtered based on confidence scores.

8. Model Deployment and Practical Usability

- a. Saved the trained model to be used for real-time spam detection.
- b. Enabled email classification on new, unseen emails without retraining.
- c. Designed the system to be easily integrated with existing email clients for seamless spam detection.

9. Security and Privacy Considerations

- a. Ensured that email content remains private and is only processed for classification purposes.
- b. Designed the system to be robust against adversarial spam techniques, reducing false negatives.
- c. Prevented phishing emails by flagging messages with known spam characteristics.

8.2 Future Enhancements

While the current spam email classifier is effective and efficient, there is room for future improvements. Below are detailed future enhancements that can significantly improve the model's accuracy, adaptability, and robustness.

8.2.1 Integration of Deep Learning Models for Enhanced Accuracy

Traditional ML models (e.g., Naïve Bayes) rely on hand-crafted features, limiting their ability to capture deep contextual meaning in emails. Deep Learning models like RNNs, LSTMs, and BERT can process email text more effectively by learning complex relationships between words.

Enhancement Plan:

- Recurrent Neural Networks (RNNs): Can model sequential dependencies in text, making them useful for spam detection.
- Long Short-Term Memory Networks (LSTMs): Improve upon RNNs by remembering long-term dependencies in text, helping detect spam that follows a pattern.
- Bidirectional Encoder Representations from Transformers (BERT): A state-of-the-art NLP model that understands the full context of words by analysing both left and right context.
- Transformer-based models: More robust against evolving spam patterns, which may use subtle linguistic tricks to bypass traditional classifiers.

8.2.2 Adaptive Learning for Real-Time Spam Evolution

Spammers continuously evolve their techniques, making static models outdated over time.

A system that learns from new data can continuously improve accuracy.

Enhancement Plan:

- Incremental Learning: Instead of retraining from scratch, update the model periodically using new spam and ham emails.
- User Feedback Loop: Allow users to correct false positives and false negatives, enabling the system to learn from mistakes.
- AutoML Implementation: Automate hyperparameter tuning to optimize the model's performance with new data.

8.2.3 Multilingual Spam Detection

Most spam filters focus on English emails, but spam is sent in multiple languages. Hence, multilingual capabilities improve global usability.

Enhancement Plan:

- Train the model on multilingual datasets to support Kannada, Hindi, Malayalam, etc.
- Use multilingual embeddings (e.g., mBERT or XLM-R) to detect spam in different languages without requiring separate models.
- Implement language detection as a preprocessing step, routing emails to the appropriate spam model.

8.2.4 More Advanced Feature Extraction Techniques

Current feature extraction (TF-IDF) may miss semantic relationships between words.

Advanced techniques can improve spam detection without requiring larger datasets.

Enhancement Plan:

- Word Embeddings (Word2Vec, GloVe, FastText): Capture semantic meaning of words, allowing for more intelligent spam detection.
- Topic Modelling (LDA): Helps identify hidden spam patterns by grouping similar topics.
- Character N-grams: Useful for detecting obfuscated spam, where words are intentionally misspelled (e.g., "fr33 m0ney").

8.2.5 Handling Image-Based and Attachment-Based Spam

Some spammers use image-based emails to bypass text-based spam filters. In such emails, the entire email contains just a single image. This image contains the spam text.

Attachments can contain malware, phishing attempts, or scam messages.

Enhancement Plan:

- Optical Character Recognition (OCR): Extract text from images in spam emails and analyse it.
- Attachment Scanning: Implement virus/malware scanning on attachments.
- Hybrid Approach: Combine text-based and image-based detection for more robust spam filtering.

8.2.6 Enhanced Phishing and Scam Detection

Phishing emails are highly sophisticated and may appear legitimate. Hence, spam detection alone is not enough to protect users from phishing scams.

Enhancement Plan:

- Use graph-based algorithms to detect spoofed email addresses.
- Implement URL analysis to flag suspicious links that redirect to phishing sites.
- Train a separate classifier for phishing vs. spam vs. legitimate emails.

8.2.7 Integration with Cloud and Edge Computing

Current solutions are limited to local execution, which can be resource-intensive. Some better alternatives are cloud and edge-based solutions, which provide scalability and faster processing.

Enhancement Plan:

- Deploy model on cloud platforms (AWS, Google Cloud, Microsoft Azure) to handle real-time spam detection at scale.
- Edge Computing for Enterprise Users: Implement AI-based spam detection directly on email servers, reducing latency and improving response time.
- Hybrid Approach: Combine cloud-based learning with on-device inference for faster classification.

8.2.8 Integration with Popular Email Platforms

Most users do not want to manually check spam predictions. They require a system with seamless integration. Hence, direct integration improves user experience and adoption of the system.

Enhancement Plan:

- Develop browser extensions for Gmail, Outlook, and Yahoo Mail.
- Create an email plugin that highlights spam probability scores within email clients.
- Build an API for developers to integrate spam detection into their own applications.

8.2.9 Explainable AI for Spam Detection Transparency

Most AI models are considered as "black boxes", which means that the decision-making process of an AI model is unknown to the end user. This makes it difficult for users to trust the predictions made by the AI model. Hence, providing explanations for why an email is classified as spam builds user trust.

Enhancement Plan:

- Use SHAP (SHapley Additive Explanations) to highlight which words contributed most to a spam classification.
- Provide a spam confidence score with justification (e.g., "This email contains suspicious words like 'lottery' and 'urgent'").
- Allow users to override predictions and provide feedback, improving transparency.

8.2.10 Mobile Spam Detection for SMS and Chat Applications

In today's world, spam is not limited to just emails - it also appears frequently in Short Message Service (SMS), WhatsApp, Telegram, as well as other social media messages. Many users receive phishing messages via text that are not currently detected.

Enhancement Plan:

- Extend spam detection to SMS filtering apps on Android and iOS.
- Implement chat-based spam detection for messaging platforms like WhatsApp.
- Use real-time filtering to warn users before opening suspicious links.

8.2.11 Federated Learning for Privacy-Preserving Spam Detection

Some users may not want to share their emails with external servers for spam detection. Federated Learning allows models to learn from decentralized data while keeping emails private.

Enhancement Plan:

- Implement on-device model training, where the AI learns from users' spam-marked emails without sharing data.

- Aggregate spam detection insights from multiple devices without transferring raw emails.
- Ensure General Data Protection Regulation (GDPR) and privacy-compliant AI models do not compromise user security.

8.2.12 Continuous Improvement via AutoML and Self-Tuning Models

Spam tactics change frequently, requiring constant retraining of models. Automating hyperparameter tuning improves efficiency and adaptability.

Enhancement Plan:

- Use Google AutoML or H2O.ai to continuously optimize spam detection models.
- Implement self-learning AI, where the classifier automatically adjusts its spam thresholds.
- Develop a dashboard where users can track model accuracy and suggest improvements.

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