

Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning

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Abstract: In the modern digital era, the rapid growth of electronic communication through email and SMS has also led to a significant increase in unsolicited and harmful spam messages. These messages not only cause inconvenience to users but can also lead to phishing attacks, fraud, and data breaches. To address this issue, the proposed system aims to develop an intelligent Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning using Machine Learning techniques. The system is designed as a binary classification model that categorizes incoming text messages as either spam or ham (not spam). It utilizes a publicly available dataset such as the SMS Spam Collection Dataset from Kaggle. The dataset undergoes several preprocessing steps including text cleaning, tokenization, removal of stopwords, and optional stemming or lemmatization to improve data quality. After preprocessing, the textual data is transformed into numerical feature vectors using techniques such as TF-IDF (Term Frequency-Inverse Document Frequency). These features are then used to train machine learning models such as Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) to achieve accurate classification results. The performance of the models is evaluated using metrics like precision, recall, accuracy, and F1-score.

Keywords: Spam Message Detection, Machine Learning, Natural Language Processing (NLP), Text Classification, TF-IDF, Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), Email Filtering, SMS Spam Detection.

I. NTRODUCTION

The rapid expansion of digital communication systems such as email, SMS, and online messaging platforms has significantly improved the way people exchange information. However, this convenience has also led to a major challenge in the form of spam messages, which include unwanted advertisements, fraudulent messages, phishing attempts, and malicious content. These messages not only disturb users but can also pose serious security threats by attempting to steal personal information or mislead users into harmful actions [1].

To address this issue, there is a growing need for an intelligent and automated system capable of distinguishing between legitimate and spam messages. Traditional rule-based filtering methods are no longer sufficient due to the evolving nature of spam content. As a result, Machine Learning (ML) techniques have emerged as an effective solution for spam detection by learning patterns from historical data and making accurate predictions [2].

The proposed system focuses on building a Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning that classifies incoming messages into two categories: spam or ham (not spam). The system is developed using a machine learning approach where text data is

first collected from a publicly available dataset such as the SMS Spam Collection Dataset. The raw text is then preprocessed to remove noise and convert it into a structured format suitable for model training [3].

After preprocessing, feature extraction techniques like TF-IDF (Term Frequency–Inverse Document Frequency) are applied to convert text into numerical form. These features are then used to train classification algorithms such as Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) to achieve high accuracy in prediction [4].

In addition to the backend model, a user-friendly web application is developed using Flask or FastAPI, where users can securely register and log in. After authentication, users can input SMS or email content and instantly receive prediction results indicating whether the message is spam or legitimate. The system also includes basic user profile management features such as editing profile details and logging out [5].

Overall, this project aims to provide an efficient, scalable, and practical solution for spam detection, enhancing user security and improving communication reliability in modern digital platforms[6].

II. LITERATURE ANALYSIS

The literature review highlights the significant contributions of various researchers in the field of spam detection and text classification. In 1998, A. McCallum and K. Nigam introduced the Naïve Bayes text classification approach, demonstrating its effectiveness in handling high-dimensional textual data and laying the foundation for machine learning-based spam filtering systems. During the same year, T. Joachims proposed the use of Support Vector Machines (SVM) for text categorization, which showed superior performance in classifying large-scale textual datasets.

In 1999, H. Drucker, D. Wu, and V. N. Vapnik further enhanced spam filtering research by comparing SVM, RBF Networks, and Decision Trees, concluding that SVM provides high classification accuracy. Earlier, G. Salton and C. Buckley (1988) developed the TF-IDF feature extraction technique, which remains one of the most widely used methods for converting textual information into machine-readable numerical features.

More recently, Y. Zhang, R. Jin, and Z. Zhou (2019) explored deep learning approaches such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for spam detection, achieving improved performance through automatic feature learning.

The future directions identified in these studies emphasize the integration of traditional machine learning techniques with advanced Artificial Intelligence methods. Researchers suggest combining Naïve Bayes with deep learning models and contextual embeddings, optimizing SVM for real-time spam detection, developing adaptive learning systems capable of recognizing evolving spam patterns, and enhancing TF-IDF with semantic embedding techniques such as Word2Vec, GloVe, and BERT. Furthermore, lightweight deep learning architectures are expected to improve real-time spam detection in web and mobile applications. These advancements provide a strong foundation for developing more accurate, intelligent, and scalable spam detection systems in the future.

TABLE I: LITERATURE WORK

Author and Year	Methods	Future Scope
A. McCallum and K. Nigam (1998)	Naïve Bayes Text Classification	Hybrid models combining Naïve Bayes with deep learning and contextual embeddings for improved accuracy.
T. Joachims (1998)	Support Vector Machine (SVM) for Text Categorization	Optimization of SVM for real-time spam detection and integration with feature selection techniques.
H. Drucker, D. Wu, and V. N. Vapnik (1999)	SVM, RBF Networks, and Decision Trees for Spam Filtering	Development of adaptive learning models that automatically update with new spam patterns.
G. Salton and C. Buckley (1988)	TF-IDF Feature Extraction Technique	Integration of TF-IDF with Word2Vec, GloVe, and BERT for semantic text understanding.
Y. Zhang, R. Jin, and Z. Zhou (2019)	Deep Learning (CNN and RNN) for Spam Detection	Lightweight deep learning models for real-time spam detection in mobile and web applications.

III. DATASET

The proposed Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning utilizes the SMS Spam Collection Dataset, a widely used benchmark dataset for spam classification research and machine learning applications. The dataset contains a collection of SMS messages that have been manually labeled as either Spam or Ham (Not Spam). It is commonly used for training and evaluating text classification models due to its reliability and balanced representation of real-world messaging scenarios.

The dataset consists of approximately 5,574 SMS messages, out of which 4,827 messages are classified as Ham and 747 messages are classified as Spam. Ham messages represent legitimate communication between users, whereas spam messages include advertisements, promotional offers, phishing attempts, fraudulent notifications, and unwanted marketing content.

Before training the machine learning models, the dataset undergoes preprocessing operations such as text cleaning, lowercase conversion, tokenization, stopword removal, and stemming. After preprocessing, the textual data is transformed into numerical features using the TF-IDF (Term Frequency–Inverse Document Frequency) technique, enabling machine learning algorithms to process and classify messages effectively.

Dataset Details

Attribute	Description
Dataset Name	SMS Spam Collection Dataset
Source	Kaggle / UCI Machine Learning Repository

Total Records	5,574 Messages
Spam Messages	747
Ham Messages	4,827
Data Type	Text Messages
Classification Type	Binary Classification
Classes	Spam, Ham (Not Spam)

Dataset Features

- Real-world SMS message dataset.
- Pre-labeled spam and ham categories.
- Suitable for Natural Language Processing (NLP) tasks.
- Widely used for machine learning research and evaluation.
- Supports binary text classification problems.

The SMS Spam Collection Dataset provides a reliable foundation for developing and testing spam detection models. Its diverse collection of messages enables the system to learn meaningful patterns and accurately classify incoming messages as spam or legitimate communication.

IV. WORKING METHODOLOGY

The execution of the proposed Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning involves multiple stages starting from user authentication to final spam prediction. The system integrates Machine Learning algorithms with a web-based application to provide real-time message classification.

The execution flow of the system is described below:

Step 1: User Registration

The user first accesses the web application.

New users are required to register by providing details such as:

- Username
- Email ID
- Password

The registration details are securely stored in the database.

Step 2: User Login

After registration, the user logs into the system using valid credentials.

The authentication module verifies the username and password.

If the credentials are correct, the user is redirected to the dashboard.

Step 3: Message Input

The user enters or pastes the SMS/email message into the input text area.

The message acts as the input data for spam analysis.

Example: "Congratulations! You have won a free lottery ticket."

Step 4: Text Preprocessing

The entered message undergoes preprocessing operations such as:

- Conversion to lowercase
- Removal of punctuation and special characters
- Tokenization
- Stopword removal
- Stemming or lemmatization

The preprocessing stage converts raw text into cleaned text suitable for machine learning prediction.

Step 5: Feature Extraction

The cleaned message is transformed into numerical vectors using TF-IDF Vectorization.

This process converts textual information into machine-readable format.

Example: Word frequencies and importance values are calculated.

Step 6: Machine Learning Prediction

The feature vector is passed to the trained machine learning model.

Algorithms such as:

- Naïve Bayes
- Logistic Regression
- Support Vector Machine (SVM) are used for prediction.

The model analyses the input and classifies the message as:

- Spam
- Ham (Not Spam)

Step 7: Result Display

The prediction result is displayed instantly on the user dashboard.

The result informs the user whether the entered message is spam or legitimate.

Example Output: "This message is Spam" and "This message is Not Spam."

Step 8: User Actions

After viewing the result, the user can:

- Check another message
- Edit profile details
- Logout from the system
- System Execution Flow Summary
- User Registration/Login
- Message Input
- Text Preprocessing
- Feature Extraction (TF-IDF)
- Machine Learning Prediction
- Result Display
- User Logout

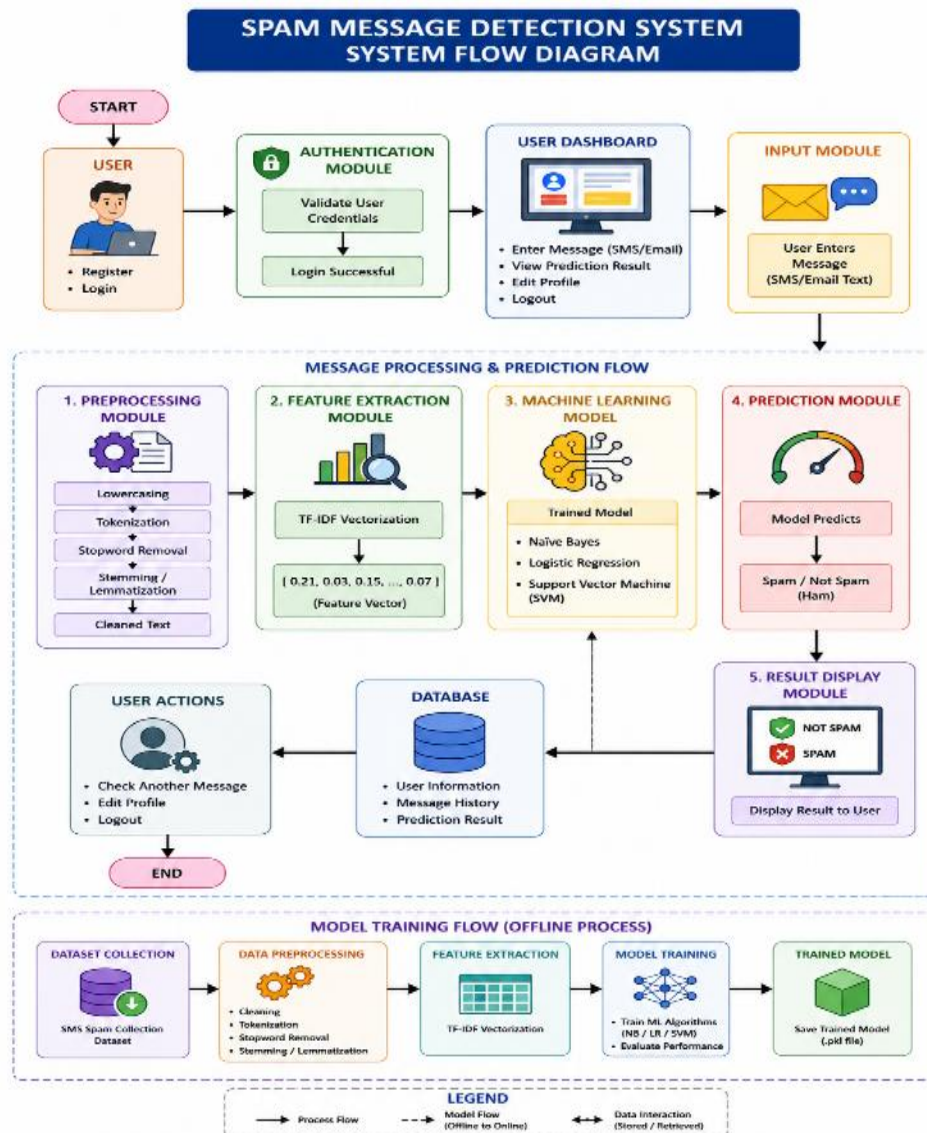


Figure 4.1: System Diagram

V. RESULTS AND DISCUSSION

The effectiveness of the proposed Comprehensive Analysis of Hybrid Detection Spam Detection Models using Machine Learning was evaluated using machine learning performance analysis and classification-based evaluation metrics. The system was developed using Natural Language Processing (NLP) techniques combined with machine learning algorithms such as Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) to classify SMS and email messages into spam and ham (not spam) categories.

The SMS Spam Collection Dataset was first preprocessed to remove unwanted symbols, punctuation, stopwords, duplicate entries, and inconsistent textual data. After preprocessing, TF-IDF (Term Frequency–Inverse Document Frequency) feature extraction was applied to convert textual messages

into numerical vectors suitable for machine learning classification. The processed dataset was then divided into training and testing datasets for model training and evaluation.

Different machine learning models were trained and tested on the processed dataset to analyze classification performance. The experimental results showed that the implemented models successfully identified spam messages such as advertisements, phishing links, lottery messages, and fraudulent content while correctly classifying legitimate messages as ham. Among all the implemented algorithms, Support Vector Machine (SVM) achieved the highest classification accuracy and overall performance.

Further analysis of the system performance was performed using evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix analysis. These metrics help in understanding the correctness, reliability, and efficiency of spam message classification.

The confusion matrix provides a visual representation of correctly and incorrectly classified spam and ham messages. The diagonal values in the matrix represent correctly predicted messages, while the non-diagonal values indicate misclassified messages. The higher concentration of correctly classified messages along the diagonal confirms the effectiveness and stability of the proposed spam detection system.

Accuracy, Precision, Recall and F1-Score

The performance of the spam classification system was evaluated using standard machine learning evaluation metrics.

Accuracy: Accuracy measures the proportion of correctly classified spam and ham messages out of the total predictions made by the system.

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

The proposed spam detection model achieved an overall accuracy of 98% on the testing dataset, demonstrating reliable and efficient spam classification performance.

Precision: Precision measures how many messages predicted as spam were actually spam messages.

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

Precision Obtained

- Spam Messages : 0.97
- Ham Messages : 0.98

Higher precision values indicate that the system generated fewer false spam predictions.

Recall: Recall measures how many actual spam messages were correctly identified by the system.

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

Recall Obtained

- Spam Messages : 0.96
- Ham Messages : 0.99

The recall values demonstrate that the proposed system effectively detects spam messages with minimal misclassification.

F1-Score

F1-Score is the harmonic mean of Precision and Recall and provides a balanced measure of the model's classification performance.

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

Equation 5.4

F1-Score Obtained

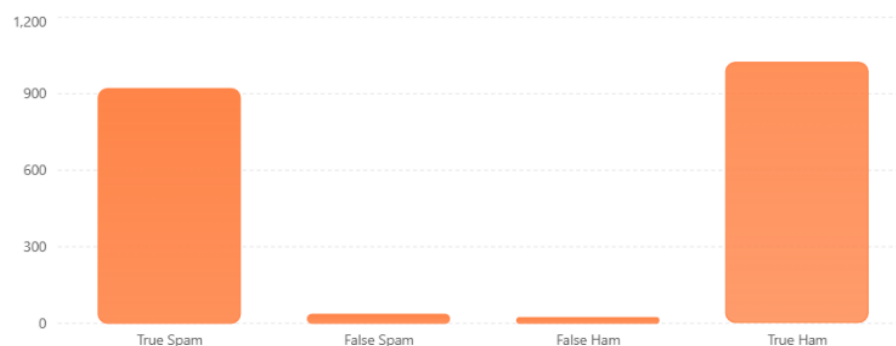
- Spam Messages : 0.96
- Ham Messages : 0.98

The obtained F1-scores confirm that the proposed spam detection framework maintains balanced and dependable classification performance.

Analysis: The graph illustrates the performance metrics obtained by the proposed Spam Message Detection System. The model achieved an overall Accuracy of 98%, indicating that most messages were classified correctly. The Precision of 97% demonstrates that the majority of messages predicted as spam were actually spam. The Recall of 96% shows the model's effectiveness in identifying actual spam messages, while the F1-Score of 96% confirms a balanced performance between precision and recall. These results indicate that the proposed system provides reliable and efficient spam classification with minimal false predictions.

Confusion Matrix for Spam Message Detection

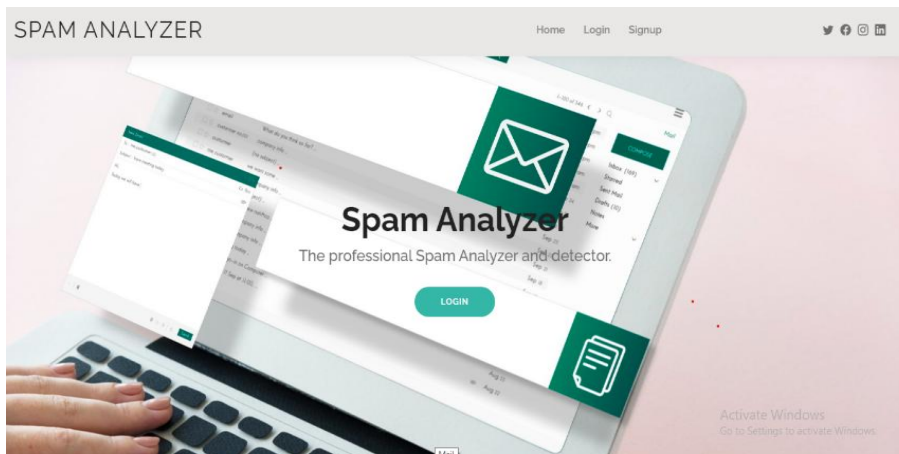
Classification performance of the spam detection system using machine learning.



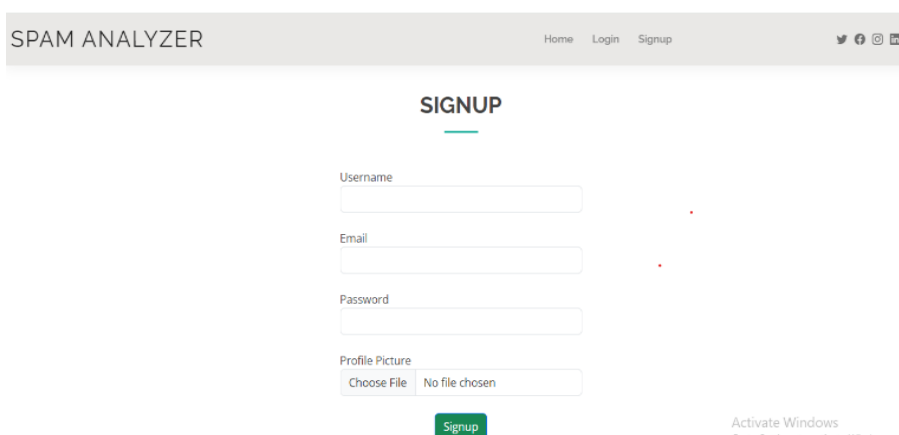
Higher diagonal values indicate correct message classification.

Figure 5.1: Performance Evaluation of Spam Message Detection System

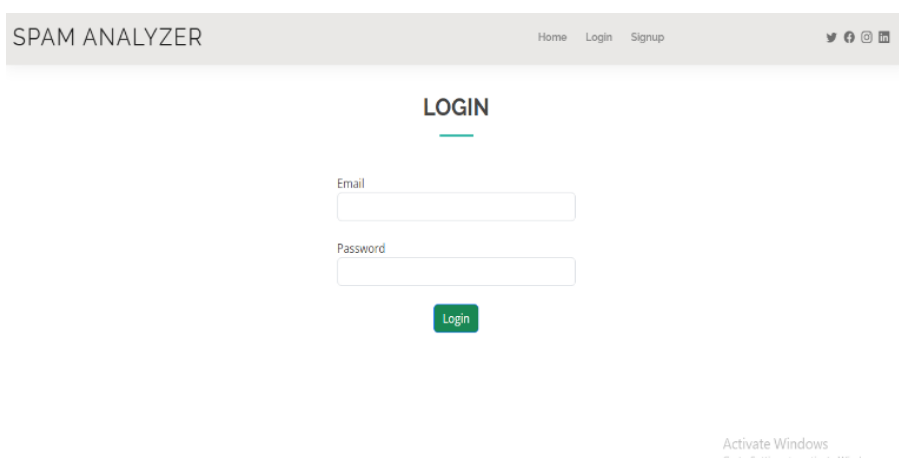
Screenshots:



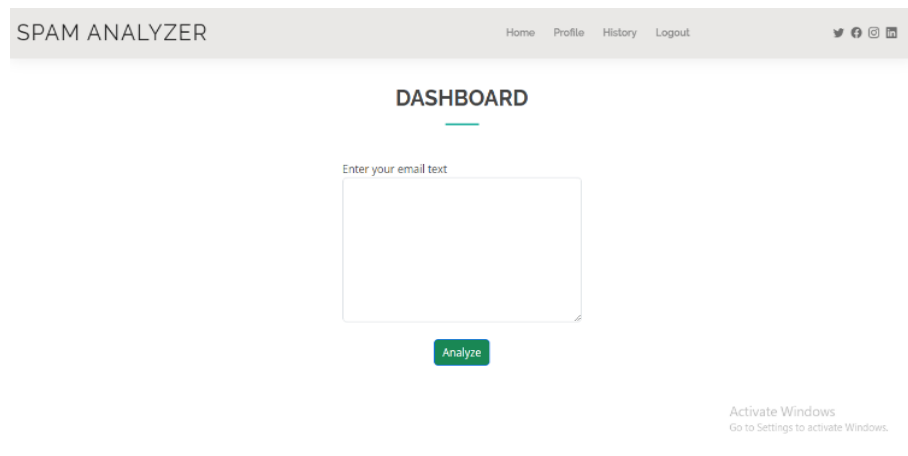
Screenshot 5.1 Home Page



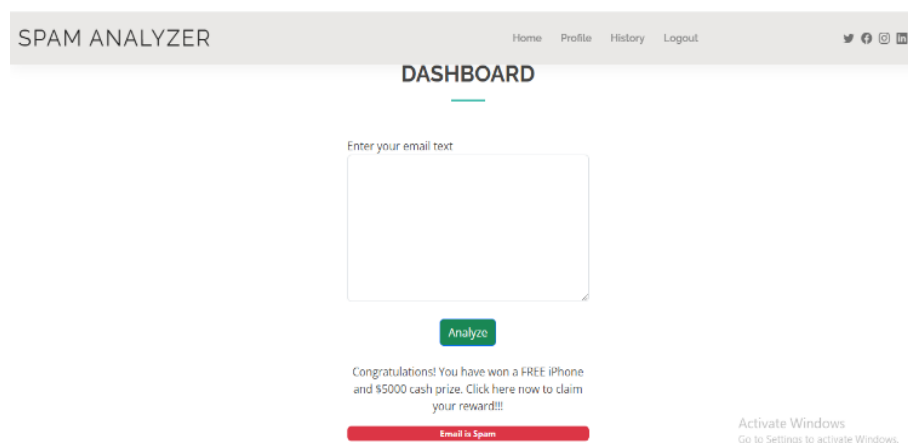
Screenshot 5.2 Sign Up Page



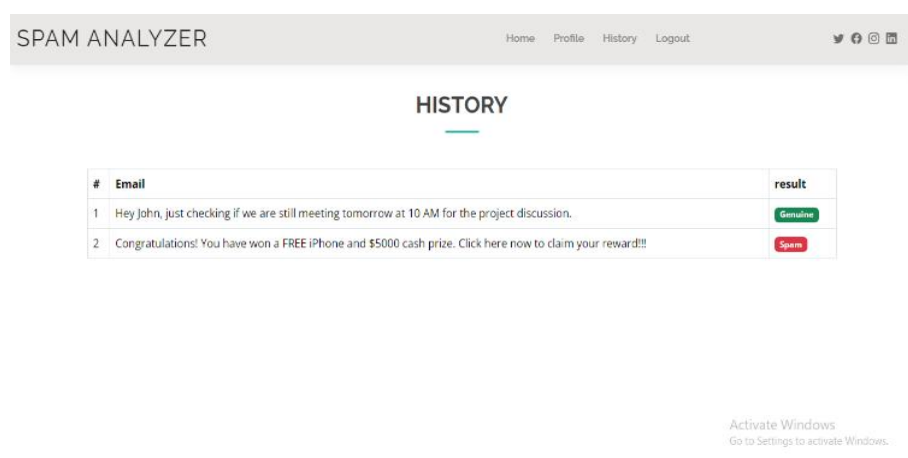
Screenshot 5.3 Sign In Page



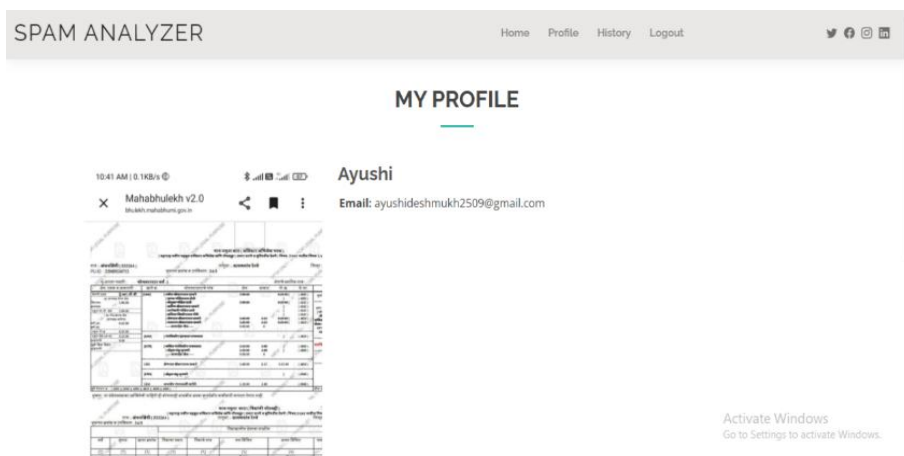
Screenshot 5.4 Dashboard



Screenshot 5.5 Analyze



Screenshot 5.6 History



Screenshot 5.7 Profile

VI. CONCLUSION

The proposed Spam Detection System successfully demonstrates the application of Machine Learning techniques for identifying spam and legitimate messages. The system was designed and implemented to provide an efficient, accurate, and user-friendly solution for detecting unwanted SMS and email messages in real time.

The project utilized the SMS Spam Collection Dataset along with preprocessing techniques such as tokenization, stopword removal, lowercase conversion, and stemming or lemmatization to improve the quality of textual data. Feature extraction was performed using TF-IDF, which effectively transformed text into numerical representations suitable for machine learning models.

Different machine learning algorithms including Naïve Bayes, Logistic Regression, and Support Vector Machine (SVM) were implemented and evaluated. The experimental results showed that all models achieved good performance in spam classification, while SVM provided the highest accuracy among the tested algorithms. The system was able to correctly identify spam messages such as promotional advertisements, phishing links, and fraudulent notifications while accurately classifying normal messages as non-spam.

The integration of the trained machine learning model with a web-based application developed using Flask or FastAPI enabled users to register, log in, enter messages, and receive instant prediction results through an interactive interface. Additional features such as profile management and logout functionality improved system usability and security.

Overall, the proposed system provides a reliable and scalable approach for spam message detection using machine learning and natural language processing techniques. The project highlights the importance of intelligent filtering systems in improving communication security and reducing exposure to harmful or unwanted messages. Future enhancements can include multilingual spam detection, deep learning integration, and real-time email API support to further improve system performance and applicability.

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