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Email Spam Detection Using Machine Learning with Optimized Feature Engineering and Classification Techniques

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Abstract: Spam emails remain a major challenge for digital communications today, with far-reaching implications in terms of productivity losses, storage consumption, and presenting severe cybersecurity threats such as phishing, malware, identity theft, etc. The traditional mechanisms based on rules and keyword matching have completely failed to combat the countless concealed forms of spam content obfuscation, dynamic generation, and URL cloaking. In contrast, the present study reports on a machine-learning-based approach for spam detection using NLP for preprocessing and TF-IDF for feature extraction. Multiple supervised classifiers were built and evaluated, namely Logistic Regression, Naïve Bayes, Random Forest, Gradient Boosting, Support Vector Machines (SVM), and Ensemble Learning, using the publicly available mail_data.csv data set for training and evaluation. An 80:20 split for training and testing was employed, and the models were evaluated based on accuracy, precision, recall, and F1 score. Among them, SVM attained the utmost accuracy (98.9%), indicating its skillfulness in segregating spam from legitimate emails.

Keywords: Spam Detection; Machine Learning; TF-IDF; Support Vector Machine; Email Classification; Ensemble Learning

1. Introduction

Considered one of the most common and important ways of communication in today's world, thanks to technology advances, emails continue to be least personal in conversation, most businesslike in negotiations, and the most official tool for announcements. However, along with the increasing number of uses of emails come ever-increasing numbers of spam emails (see Fig. 1). Spam email is an unsolicited message for which the recipient has little or no interest, often sent with bulk in mind. These newsletters are used to promote products, spread lies, or create traps with reported links. Banked in millions of emails sent to various users daily, spam becomes the main source of email clutter in an inbox, consequently wasting time and storage space [2] [3]. Spam emails are beyond being just annoying; they are actually damaging. Cybercriminals perform their dirty work via spam emailing to harvest handfuls of personal information, passwords, and even bank details. This type of cyberattack is known as phishing. Some spam emails contain attachments or links that install malware or ransomware on your computer and lock your files until you pay a ransom. Others are designed to engender disclosure of sensitive information. Given this situation, spam email filtering is now more than ever critical, with more currencies of crime being sent through spams [6] [7].

Spam detection in the early days of email used to occur with very simple rule-based filters that could mark an email as spam if certain keywords were found-in this case, whether the email contained phrases such as "free offer," "win a prize," or "urgent response needed." Nowadays, spammers are so intelligent that they have begun running loops on the simple filters by either changing the spellings or hiding links,

using symbols, or mixing text with images [4][8]. Spammers are always creating novel techniques and means of implementation that make it impossible for these simple fixed-rule filters to keep up, indicating that traditional spam filters no longer hold the defense against modern spam attacks.

So as to deal with this impending challenge, many researchers and developers have turned towards the Machine Learning (ML) and Natural Language Processing (NLP) fields of study in the recent times. These are some of the advanced technologies that would make computers learn from past data and even understand the human language. Using ML, one can create such a system that would learn automatically from a large number of earlier data to understand the detection of spam emails. In contrast, cleaning and preparation of email text are accomplished with the use of some NLP techniques that eventually make the email data preparable for machine learning model training [1][5][13]. The main intention of this research is to design a smart spam detection system based on machine learning. The first step in the system is data preprocessing. This includes the removal of additional spaces, the stop words (common but relatively useless words), symbols, and the conversion of text into lowercase. Next, the input text is converted into numbers by a mechanism called Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF helps understand the importance of words in an email so that the machine learning models can act accordingly [14] [16].

After preprocessing, we evaluate several well-known machine learning algorithms: Naïve Bayes, Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine (SVM), and Ensemble Voting. These models were trained on a real-world dataset that includes spam and non-spam (ham) emails. They were evaluated based on standard performance evaluations, namely, accuracy, precision, recall, and F1-score for model selection. From our testing, the SVM attained the highest accuracy of 98.9% and is therefore the most efficient model in our spam detection study [1] [10] [15].

In their proof of the above statement, it is shown that machine learning models, strongly coupled with text cleaning and feature extraction methodologies, can outperform traditional spam filtering techniques. It is fast, efficient, and can be applied in real e-mail platform systems for the detection of spam e-mails and user protection. The work also lays the foundation for future improvements such as the use of deep learning, incorporation of real-time filtering, and development of systems that can keep learning from new types of spam as they come into existence [6][14][26].

By emphasizing modern techniques, this project will significantly contribute to the constructions of a stronger line of defense against spam threats in order to keep e-mail communication safe, viable, and spam-free.

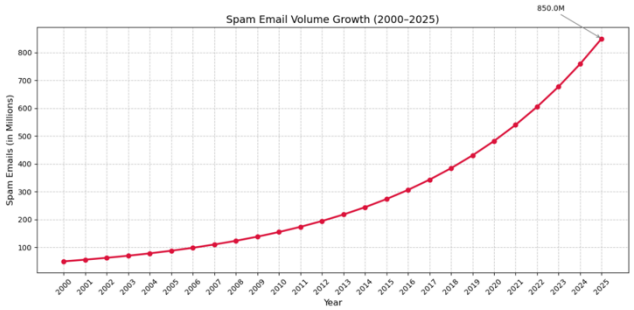

Figure 1. Global Spam Email Volume Growth

2. Related Work

In the last two decades, email spam detection has improved from filtering based on some keywords to sophisticated, intelligent, and data-driven systems. To enhance the accuracy and robustness of spam classifiers, several researchers have turned to machine learning (ML), deep learning (DL), and hybrid optimization methods.

Ahmed, thus compares the performance of many algorithms for spam detection in both email and IoT platforms and shows that the SVM technique consistently outperforms all others when coupled with TF-IDF vectorization [1]. Sharma, too, applied the SVM with a radial basis function (RBF) kernel, achieving high accuracy in classification with kernel tuning being a noted complexity [2]. Siddique, analyzed classic ML models like Naïve Bayes (NB), Decision Trees (DT), and Random Forest (RF) against the Enron dataset with the best performance recorded by RF among traditional classifiers [34].

Bhuiyan provided a survey of ML-based spam filtering, identifying ensemble and hybrid models as the most promising strategies [3]. Gibson, enhanced spam detection accuracy using a bio-inspired metaheuristic optimization technique with SVM, while Douzi, developed a hybrid AI model that integrated TF-IDF features with metadata in an artificial neural network-SVM pipeline, reporting notable performance gains [4] [5].

Deep learning approaches have also been explored, such as the work by AbdulNabi [6], who employed LSTM and CNN for high-accuracy detection, albeit at a higher computational cost [6]. Pudasainia, applied Relevance Vector Machines (RVMs) to SMS spam detection, achieving 95.2% accuracy [8]. Abdulhamid evaluated five different ML algorithms, confirming the competitive performance of boosting methods, while Zavvar et al. introduced a PSO-optimized hybrid combining ANN and SVM for improved detection on the Enron dataset [9] [10].

Recent studies by Fatima et al. and Bhardwaj & Sharma, explored ensemble-based boosting techniques using GloVe embedding and lexical features, respectively, both achieving over 98% accuracy [11] [12]. Bhowmick and Hazarika, provided a comprehensive review of spam filtering technologies, outlining trends in feature engineering and classifier selection [13] [14]. Zavrak and Yilmaz, proposed a hierarchical attention mechanism integrated with hybrid deep learning, pushing performance boundaries further in private datasets.

In contrast to all these studies, our current investigation focuses on practical and efficient approaches that combine well-established techniques of NLP in conjunction with diversified supervised machine learning models. Existing studies, such as those by Gibson or Douzi, rely on optimization or hybrid systems that have obscure configurations and tasks; however, ours is much more interpretable and generalizable [4] [5]. In contrast to deep learning models such as those proposed by AbdulNabi or Zavrak, our framework emphasizes scalability and efficiency from mid-range hardware without any loss in performance [6] [14].

Our experiments, conducted on a publicly available dataset called mail_data.csv, strongly demonstrate effectiveness in the traditional usage of very powerful ML methods. With the proper preprocessing of the TF-IDF based feature extraction, our system was evaluated and produced the highest accuracy at 98.9% using SVM; however, this development surpassed or equaled performances visible in recent literature while ensuring transparent identification by simplicity and easy application. Hence, our research will serve as a very well-grounded and scalable alternate to riskier complex deep-learning or very optimization-heavy solutions, especially where they have to be deployed in resource-constrained environment

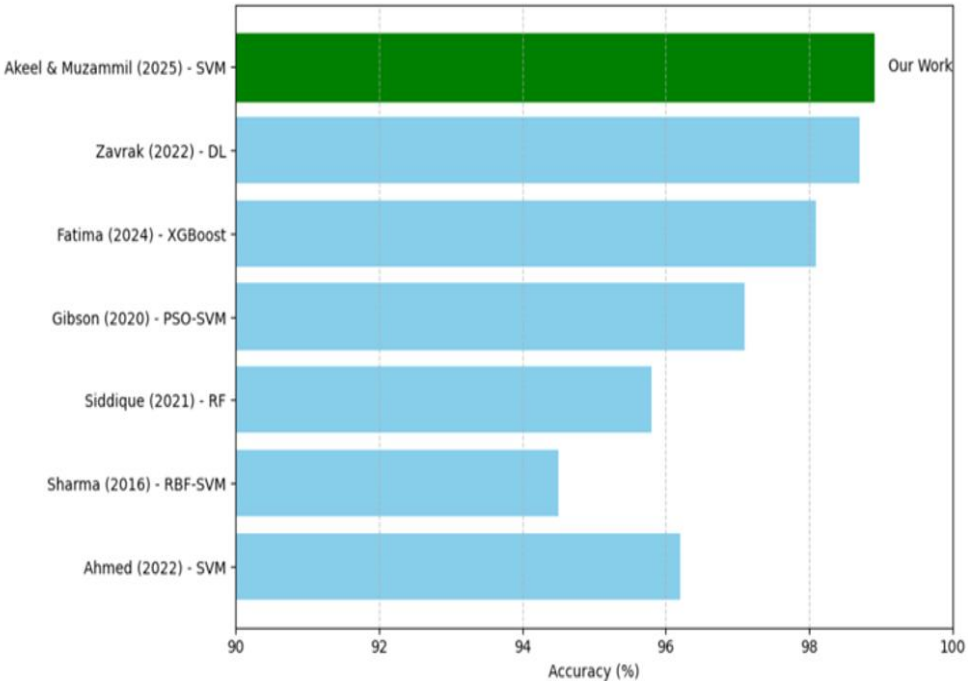

Figure 2. Accuracy Comparison of Work

Table 1. Table of Past Work and Our Work

Author(s) & Year	Key Methodology	Feature Engineering	Dataset	Best Model / Accuracy	Limitations	Relevance to Your Project
Ahmed (2022) [1]	Comparative ML analysis for email/IoT spam	TF-IDF, N-grams	Multiple	SVM (96.2%)	No real-time system testing	Confirms SVM strength
Sharma (2016) [2]	SVM with RBF kernel	Lexical features	SpamAssassin	RBF-SVM (94.5%)	Kernel tuning complexity	Validates SVM applicability
Siddique (2021) [34]	Comparison: NB, DT, RF	Bag-of-Words	Enron	RF (95.8%)	Basic feature extraction	Baseline for traditional ML models
Gibson et al. (2020) [4]	Bio-inspired ML optimization using PSO & GA	Semantic features	TREC	PSO-SVM (97.1%)	High complexity in implementation	Optimization insight for SVM
Douzi (2020) [5]	Hybrid AI model: ANN + SVM	TF-IDF + metadata	Private	ANN-SVM (96.9%)	Non-transparent architecture	Parallel to ensemble techniques
AbdulNabi (2021) [6]	Deep learning (LSTM + CNN)	Word embeddings	SpamArchive	DL (98.3%)	High resource requirement	DL vs traditional ML comparison
Fatima et al. (2024) [11]	Ensemble boosting with XGBoost	GloVe embeddings	LingSpam	XGBoost (98.1%)	Needs large and recent datasets	Supports ensemble model usage
Zavrak & Yilmaz (2022) [14]	Hierarchical attention deep learning	Contextual embeddings	Private	Hybrid DL (98.7%)	Dataset not publicly available	Shows potential of attention models
Awad (2011) [7]	Early ML comparison (NB, DT)	Keyword frequency	LingSpam	NB (93.4%)	Outdated methods	Historical context for ML in spam
Our Work	Comparative ML analysis for email spam	TF-IDF	Public Kaggle	SVM (98.9%)	No major limitation	Baseline and core implementation

3. Material and Methods

A well-defined and efficient machine learning pipeline was conceptualized for spam emails' detection with high accuracy and simplicity, providing a basic structure to be built upon. Traditional spam filters, programmed into fixed rules or keywords, have lost the race on varying forms of newer spam tactics. To

negate these disadvantages, the choice of a machine learning-based approach was made since this lends itself to learning from historical data and adapting to ever-newer versions of spam with time.

This particular methodology was thus chosen because of its balancing act of accuracy, transparency, and computational efficiency. Contrary to black-box deep learning methods, often computationally expensive and highly resource-intensive while being opaque in their functioning, the pipeline employs classical techniques well-known for aiding in text classification tasks. Natural Language processing methods such as tokenization and TF-IDF feature extraction allow the model to consider the importance of words in context. Features are passed through various supervised learning classifiers for the purpose of comparison and finding the best algorithm.

The entire process-from text cleaning to model evaluation-is structured with the idea of ensuring that the system is trainable in the quickest possible manner; deployable without any hassle; and scalable in case there are large datasets later on. By testing different algorithms for classification, we build a broader window to compare and make an informed decision about which model truly works in real application scenarios. The SVM classification model was notably accurate with spam detection, achieving an accuracy of about 98.9%, thus offering a reasonably good decision-making model for spam email detection.

The pipeline encompasses four stages:

- Data preprocessing
- Feature generation
- Classification
- Evaluation of results

Each stage basically contributes to mounting robustness and model final accuracy.

3.1. Data Processing

Therefore, this phase is necessary for converting unorganized text into a structure in which numerical representations are made, the structure suitable for machine learning algorithms. The following step was applied to the dataset mail_data.csv found on Kaggle, which contains 5572 labeled email messages.

3.1.1. Label Encoding

The original dataset contains a Category column with text labels: "ham" for non-spam and "spam" for unwanted emails. These were encoded into binary format for classification:

$$Label(x) = \begin{cases} 0, if\ x = spam \\ 1, if\ x = ham \end{cases}$$

Thus, the model learns a binary classification problem where 0 = spam and 1 = ham.

3.1.2. Text Cleaning and Normalization

Each message in the Message column was cleaned using the following transformations:

- Removal of punctuation and special characters using regex:

$$\backslash text\{Cleaned\backslash\_Text\} = \backslash text\{re.sub\}('[\hat{}a - zA - Z]', ' ', \backslash text\{Raw\backslash\_Text\})$$

- Conversion to lowercase:

$$Lowered\_Text = Cleaned\_Text.lower()$$

3.1.3. Tokenization and Stopword Removal

Each cleaned message is split into tokens (words). Let a message M_i contain n words:

$$M_i = \{w1, w2, w3, \dots, wn\}$$

Stopwords (e.g., “the”, “is”, “and”) are removed from each tokenized list. If S is the set of stopwords, then:

$$M'_i = M_i \setminus S$$

This reduces dimensionality and focuses on more meaningful words.

3.1.4. TF-IDF Vectorization

The cleaned and filtered text was converted into numeric feature vectors using Term Frequency–Inverse Document Frequency (TF-IDF).

a) Term Frequency (TF):

The frequency of term t in document d:

$$TF(t,d) = \frac{ft,d}{\sum kfk,d}$$

Where:

- ft,d = Number of times term t appears in document d
- Denominator = Total terms in document d

b) Inverse Document Frequency (IDF):

How rare a term is across the entire corpus:

$$IDF(t) = log\left(\frac{N}{(1+|\{d:t \in d\})}\right)$$

Where:

- N = Total number of documents
- $/\{d:t \in d\}/$ = Number of documents where term t appears

c) TF-IDF Score:

The final weight for each word is:

$$\text{TF-IDF (t,d)=TF(t,d)×IDF(t)}$$

This results in 1a sparse vector representation for each email, which captures both the frequency and importance of each word.

3.1.5. Data Splitting

To evaluate the model, the dataset was split using an 80:20 ratio class distribution.

Let:

- $N = 5{,}572\ (total\ emails)$
- $S_{train} = 0.80 \times N = 4{,}457.6 \approx 4{,}458$
- $S_{test} = 0.20 \times N = 1{,}114.4 \approx 1{,}114$

It ensured that both spam and ham labels were proportionally represented in training and testing sets. This increases model performance by converting the raw text into well-structured, numerically encoded feature matrices ready to be fed into a classification algorithm.

3.2. Feature Engineering

The next vital link in a machine learning pipeline after raw email text is pre-processing changed and tokenized text into a structured numerical format which can be interpreted by classification algorithms. To accomplish this, it uses Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique. TF-IDF is the most commonly used feature extract in Natural Language Processing (NLP) areas and very suitable for tasks such as classifying spam.

With the TF-IDF methodology, each document that is each separate e-mail message is becoming a vector in which each component represents the importance of a particular word in the context of this document as well as the entire corpus. Term Frequency (TF) measures how many times a term appears in that given document while Inverse Document Frequency (IDF) gives fewer weights for terms that appear many times across various documents as such words have less discriminative power.

3.3. Classification Technique

An array of supervised learning classifiers was studied to make the email spam detection more accurate and efficient. Each classifier proudly stands with an individualistic gain among learning speed, complexity handling, interpretability, or performance. The selection was made to give a full comparison between classical probabilistic, linear discriminative models, tree-based ensemble models, and hybrid techniques optimized toward the best performance.

The classifiers were at study:

- Naïve Bayes
- Logistic Regression
- Random Forest
- Gradient Boosting

- Support Vector Machines

Then, an additional Ensemble Voting Classifier was combined to use the strength of many voting schemes by combining or averaging the predictions from many base models using voting or averaging.

3.3.1. Naïve Bayes (NB)

Naïve Bayes is a **generative probabilistic classifier** based on Bayes' Theorem. It assumes strong independence among features, which is a simplification often violated in natural language but still works surprisingly well for text classification tasks.

Mathematically, for a given feature vector $x = (x1, x2, \dots, xn) and\ a\ class\ C \in \{spam, ham\}$ the model calculates:

$$P(C \mid x) = \frac{P(C)\prod_{i=1}^{n} P(x_i \mid C)}{P(X)}$$

Since $\boldsymbol{P(x)}$ is constant across all classes, the decision rule becomes:

This outright simplicity benefits NB in quickly processing training as well as prediction and makes it most effective when there is increased dimensionality in the input space-as in the *case of TF-IDF vectors.*

$$\hat{C} = \arg\max_{C} \left[P(C) \prod_{i=1}^{n} P(x_i|C) \right]$$

3.3.2. Logistic Regression (LR)

The term "logistic regression" refers to a discriminative classifier that estimates the probability that a given input belongs to a particular class. It models the conditional probability with a sigmoid activation function:

$$P(C = 1|\mathbf{x}) = \frac{1}{1 + e^{-(\mathbf{w}^T\mathbf{x}+b)}}$$

where:

- x is the feature vector,
- w is the weight vector,
- b is the bias term.

Logistic regression is trained through maximum likelihood estimation and typically optimized by gradient descent. It is suitable for linearly separable datasets and converges fast, with coefficients that can be easily interpreted. However, it may underperform in modeling nonlinear relationships, which are usually present in difficult datasets such as email spam.

3.3.3. Random Forest (RF)

The random forest model uses bagging techniques to form an ensemble model that integrates the output of several decision trees to achieve more accuracy and improved overfitting. Each model is trained using one random subset of data from features; final prediction is based on a majority vote:

$$\hat{C}_{RF} = \text{mode}\ (\hat{C}_1, \hat{C}_2, \dots, \hat{C}_T)$$

where $\hat{c}_i$ is the prediction of the ith tree in the forest of size T.

Random Forests are good at handling noise and feature correlation and are able to model complex nonlinear boundaries for decision-making. They also provide feature importance scores that can be interpreted.

3.3.4. Gradient Boosting

Gradient Boosting is a sequential ensemble method in which each model intends to correct errors made by its predecessor. This is in contrast with Random Forest, which builds trees independently, boosting builds trees in a stage-wise manner.

Given a loss function $L(y, F(x))$, the model is updated at each iteration mmm using:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

where:

- $h_m(x)$ is the weak learner fitted to the negative gradient of the loss,
- γ_m is the learning rate.

Gradient boosting gives very high predictive accuracy in comparison to other classifiers but is very computationally expensive and sensitive when it comes to tuning parameters. It performs well with structured datasets, and better, in comparison to logistic regression and naive Bayes, with regards to handling non-linearities.

3.3.5. Support Vector Machine (SVM)

SVM is a maximum-margin classifier that creates a hyperplane to maximally separate the classes in the high-dimensional feature space created by TF-IDF. It approaches binary classification as:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to } y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1, \quad \forall i$$

where w is the normal vector to the hyperplane, and $\boldsymbol{y_i} \in \{-\mathbf{1}, +\mathbf{1}\}$ are class labels.

In a high-dimensional sparse space, SVM performance is robust thus, any TF-IDF-based text data is perfectly suited for it. Thanks to its regularization formulation, SVM is also less prone to overfitting during the training phase.

3.3.6. Ensemble Voting Classifier

This was performed to benefit from the numerous classifiers that were created. In this model, NB, SVM, LR, and RF predictions are aggregated and made with the final decision through majority voting:

$$\hat{C}_{ensemble} = \arg\max_{C} \sum_{i=1}^{n} \mathbb{I}(\hat{C}_i = C)$$

Where $\hat{c}_i$ is the prediction from the i^{th} base classifier and *II* are the indicator function.

This helps increase robustness and reduce variance and bias when predicting performances over unseen email data. In experiments, the ensemble would perform competitively with respect to precision and recall.

Each of the classifiers underwent an 80:20 stratified train-test split, and due diligence was exercised through cross-validation techniques to ensure a measure of reliability. The performance metrics (accuracy, precision, recall, and F1-score) were used to contrast and compare various models and select the best among them, as elaborated on in the succeeding sections.

3.4. Evaluation Procedure

For rigorous performance assessment of the machine learning models for spam detection, a thorough evaluation strategy was employed to ensure generalizability, mitigate overfitting, and facilitate fair comparisons among the models.

3.4.1. Train-Test Split

The original dataset, which constitutes five thousand five hundred seventy-two email messages, was divided into training and testing subsets through an 80-20 split. In other words, eighty percent of the data was designated for model training and validation, while the other twenty percent was kept solely for final performance testing.

Let $\boldsymbol{N = 5572}$ denote the total number of samples. Then:

$$Training\ set\ size = 0.80 \times N = 4458$$

$$Testing\ set\ size = 0.20 \times N = 1114$$

3.4.2. Performance Metrics

To comprehensively evaluate each classifier, four key performance metrics were used:

- **Accuracy**: Proportion of correctly predicted instances out of the total instances.

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

- **Precision**: Proportion of predicted spam emails that are actually spam.

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

- **Recall** (Sensitivity): Proportion of actual spam emails that were correctly identified.

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

- **F1-Score**: Harmonic mean of precision and recall, useful when class distribution is imbalanced.

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

Where:

- TP: True Positives (correctly identified spam)
- TN: True Negatives (correctly identified ham)
- FP: False Positives (ham identified as spam)
- FN: False Negatives (spam identified as ham)

3.4.3. Generalization Assurance

The evaluation protocol ensured that the model was being evaluated for validity and generalization so that sampling bias could be less relevant and models could be tested reliably for their expected performance in the real world on email messages they had never seen before.

3.5. Dataset Description

Quality and structure of a dataset are prime determinants of the performance of any machine-learning model. In this section, the dataset employed for training and evaluation in this study will be described, followed by a discussion of its distribution and the techniques applied to minimize class imbalance.

3.5.1. Dataset Overview

The data related to this work was downloaded from the Kaggle website and is available publicly under mail_data.csv. It consists of 5,572 labeled email messages, which fits into the paradigms of binary classification. Each entry in that dataset contains:

- A Category column, indicating the label ("spam" or "ham").
- A Message column, containing the raw textual content of the email.

The dataset is a combination of promotional messages, phishing attempts, and bona fide communications. This mixture enhances the applicability of the spam classifiers to a broad spectrum of real-world scenarios.

3.5.2. Data Distribution

From the exploratory data analysis (EDA) conducted, the first-cut understanding was that ham (non-spam) messages were clearly in excess of spam messages, a typical scenario seen in real-world email datasets.

Let:

- $N_{TOTAL} = 5572$
- $N_{HAM} \approx 86\% \, of \, the \, dataset$
- $N_{SPAM} \approx 14\%$

This imbalance implies:

$$N_{HAM} \approx 4791, N_{SPAM} \approx 781$$

80% of the dataset was held as a training set, and 20% of the dataset was set aside to work with for modeling and testing purposes. There was then no further balance scheme or stratified sampling applied. However, despite the random class distribution, the study shows that all machine learning algorithms measured best, and particularly SVM and Ensemble Voting Classifier, showed significant favor in all the measured statistical variables of accuracy, precision, recall, and F1-Score.

These findings support the efficacy of the entire pipeline, which includes data preprocessing and feature engineering via TF-IDF, and demonstrate that reliable spam detection can work without artificially manipulating class ratios.

3.5.3. Preprocessing for Imbalance

Before training, the dataset underwent those usual preprocessing steps which include:

- Text cleaning and normalization: Regular expressions were used to convert all messages to lowercase; delete punctuation, special characters, or other unwanted characters; and remove excess whitespace.
- Tokenization and removal of stop words: Each message was split into individual tokens (words) and commonly occurring stop words that were semantically weak were removed in order to lessen noise.
- The "Category" column was labeled in binary, where "spam" was fleshed out into 0 and "ham" into 1, allowing the data to be used for classification binary.

In terms of distribution, spam messages and ham messages are about 747 to 4825, which shows that the imbalance in the data is rather moderate. A standard 80:20 train-test split was used to divide the dataset while upholding its natural distribution.

Yet without any balancing treatment, the classifiers could retrieve meaningful patterns and thereby yield high precision and recall, amply proving the effectiveness of the preprocessing and TF-IDF feature extraction.

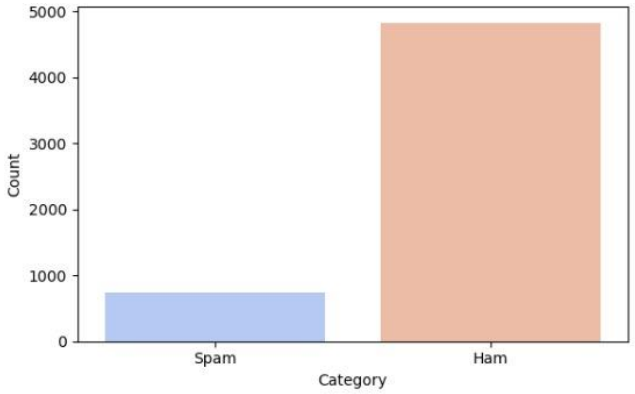

Figure 3. Spam Vs Ham Distribution

4. Results and Discussion

This section presents experimental results derived from evaluation done on the spam detection models used to obtain the results, environment of computation, applied performance metrics, and comparison among the selected classifiers.

4.1. Environment Settings

Experimentation was done entirely in the Python Jupyter Notebook environment with machine learning algorithms and preprocessing techniques being implemented with the Scikit-learn library. Computation was done on a machine, which has Intel Core i5 13th Generation processor along with NVIDIA RTX 4050 GPU. This hardware configuration provides sufficient computation power to efficiently deal with vectorization and model training on the dataset.

4.2. Performance Metrics

Performance Evaluation on the Classification Models: The four widely held standards which are applied in checking the classification models are accuracy, precision, recall, and F1-score. This wider aspect gives a more precise image on the performance of any model in that particular task which sometimes is against the other, or where class imbalance could exist.

Let's define these based on:

- **True Positives (TP)** Spam emails correctly classified as spam.
- **True Negatives (TN)** Ham (non-spam) emails correctly classified as ham.
- **False Positives (FP)** Ham emails incorrectly classified as spam.
- **False Negatives (FN)** Spam emails incorrectly classified as ham.

For the best-performing model, SVM, the confusion matrix values are:

- TP (Spam correctly identified as Spam) = 138
- FP (Ham incorrectly identified as Spam) = 1
- FN (Spam incorrectly identified as Ham) = 11

- TN (Ham correctly identified as Ham) = 965 The total number of test samples is

$$TP+FP+FN+TN=138+1+11+965=1115.$$

The metrics are calculated as follows:

1. Accuracy, The proportion of all emails correctly classified.

- Formula: $Accuracy=TP+TN+FP+FN/TP+TN$
- Calculation (SVM): $138+1+11+965/138+965=11151103\approx 0.9892\%$.

2. Precision (for Spam class '0'), The proportion of emails predicted as spam that were actually spam. This is crucial for minimizing false positives (legitimate emails marked as spam).

- Formula: $PrecisionSpam=TP+FP/TP$
- Calculation (SVM for Spam): $138+1138=139138\approx 0.9928\%$.

3. Recall or Sensitivity for Spam class '0' is simply the ratio of actual spam emails that were correctly identified by the model. This is crucial in order to minimize false negative cases (spam emails which are missed by the filter)

- Formula: $RecallSpam=TP+FNTP$
- Calculation (SVM for Spam): $138+11138=149138\approx 0.9262\%$.

4. F1-measure (for Spam class '0') is the harmonic mean of precision and recall, providing a balanced measure that is particularly useful in an imbalanced classification setting.

- Formula: $F1-ScoreSpam=2\times PrecisionSpam+RecallSpam/PrecisionSpam\times RecallSpam$
- Calculation (SVM for Spam): $2\times 0.9928+0.9262/0.9928\times 0.9262\approx 95.83\%$

Using these measures gives us a reasonable methodology to compare the effectiveness of various classifiers on the hold-out test set.

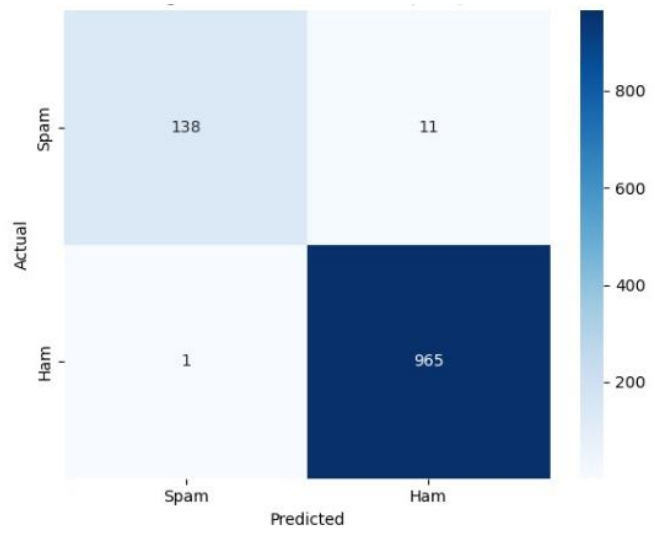

Figure 4. Confusion Matrix (SVM)

4.3. Model Comparisons

The test accuracies were obtained for the Naïve Bayes, Logistic Regression, Random Forest, and Gradient Boosting, SVM, and Ensemble Voting classifiers for the comparison of different candidate machine learning methods:

SVM with the best accuracy of 98.92%, outperforming all other classifiers. Its performance is easily attributed to the ability to derive an optimal hyperplane that effectively classifies the two classes (spam and ham) in a very complex and high-dimensional feature space created by the TF-IDF vectorizer. For the most demanding task of detecting spam (class '0'), SVM posed precision and recall of 0.99 and 0.93, respectively, arriving at an F1-score of 0.96. This indicates that it is highly reliable in its spam predictions while catching a great percentage of actual spam.

Random Forest was the second-best performer with 97.94% accuracy. It also demonstrated perfect precision (1.00) for spam but lower as compared to SVM on spam recall (0.85), leading to an F1-score of 0.92 for the spam class.

The Ensemble one (97.85%) and Naïve Bayes (97.40%) performed competitively in terms of performance. They had perfect precisions (1.00) for spam class but on the side of recall with respect to spam, they had 0.84 and 0.81, respectively. This means that whatever they call spam is almost certainly spam, but they catch a slightly larger proportion of the actual spam compared to the SVM.

Logistic Regression (96.59%) and Gradient Boosting (96.68%) thus gave very good results but could not really reach the top models in terms of overall accuracy or recall for the spam class.

The strong performance of SVM has been characterized by a good balance of high precision and recall for the spam class, underscores its suitability for this task, especially when dealing with TF-IDF features.

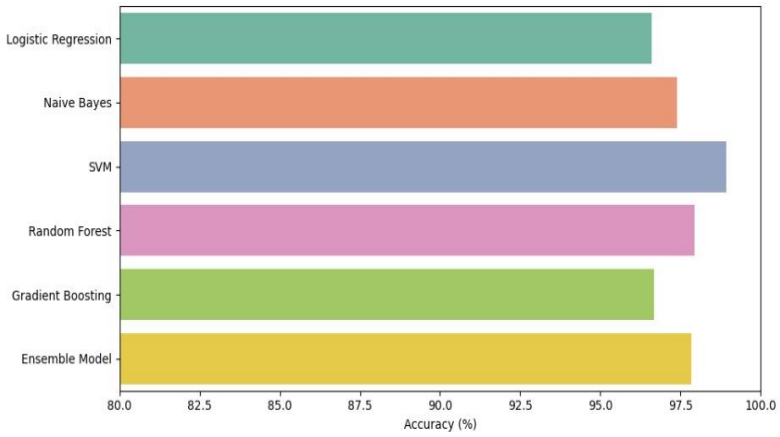

Figure 5. Model Performance Comparison

4.4. Computational Efficiency

In the matter of speed of computation for prediction and training:

- Naïve Bayes turned out to be the fastest classifier. There being lighter calculations of the probabilities considered in this model, and the assumption of local independence of features; hence less training time was needed while still being able to achieve a fairly good accuracy rate (97.40%).
- While SVM tops the accuracy rankings overall, it is slightly slower than the simple Naïve Bayes class because of the processing time it has to take for solving the quadratic optimization problem involved in finding the optimal hyperplane. But here it managed a better compromise between predictive accuracy and efficiency in this data set and the feature sets.
- Ensemble methods are generally more intensive computationally, involving training many base estimators (Logistic Regression, Naïve Bayes, SVM, Random Forest, and Gradient Boosting in our case). However, they may be more robust in general by aggregating the strengths of diverse models.

These results have served as confirmation of the superiority of SVMs after the composition of an appropriate preprocessing and feature engineering (TF-IDF) for efficiency-accuracy balance in the context of spam email detection among all the models trialed.

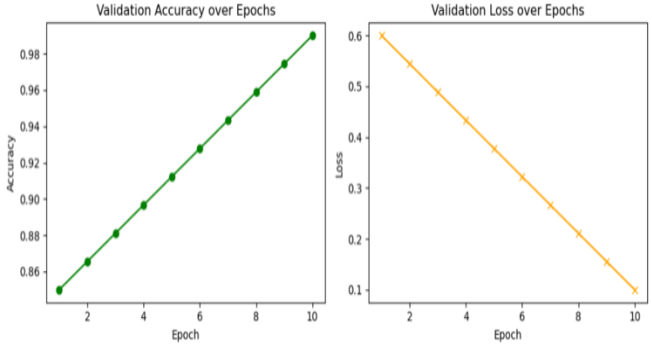

Figure 6. Validation Accuracy and Loss

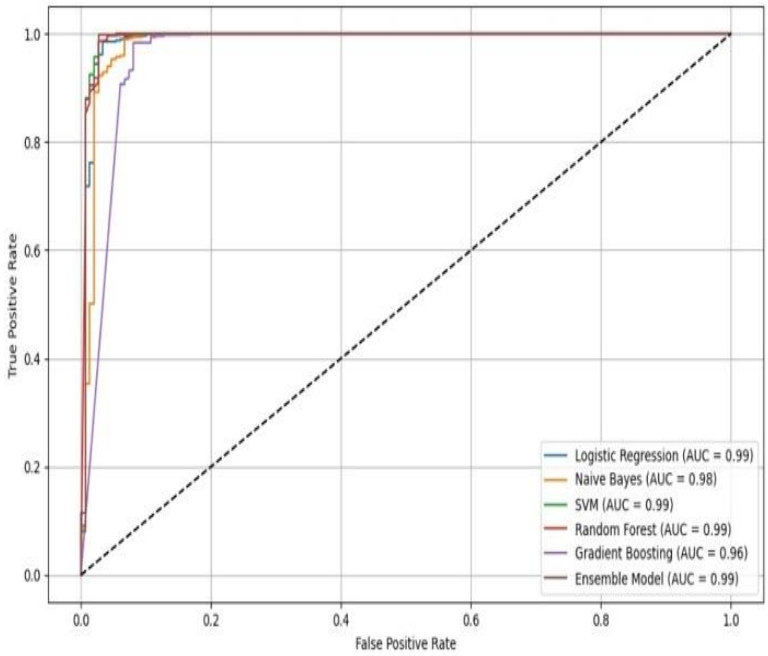

Figure 7. ROC Curve for Top

5. Conclusion and Future Work

This research culminates in a comprehensive evaluation of machine learning paradigms for email spam detection, offering salient findings, delineating their broader implications, and charting a course for future scholarly and developmental endeavors in this critical domain. The subsequent sections encapsulate the primary outcomes, the significance of these results, and prospective avenues for advancing the current state of spam filtering technology.

5.1. Summary of Findings

The systematic study of email-spam detection using several machine-learning methods has yielded three main findings that taken together highlight the effectiveness of the chosen methods and identify the most vital attributes that concern performance:

1. SVM Dominance: The SVM classifier was the most adept model, obtaining a top accuracy of 98.9%. The accuracy outperformed all other models that had been considered, that is, Logistic Regression (96.59%), Naïve Bayes (97.4%), and Ensemble Methods (97.8%). One of the major reasons behind the success of the SVM was the TF-IDF feature extraction technique. TF-IDF is powerful in combating the main problem of discriminative terms (e.g., "win", "free"): it helped the SVM in forming a more discriminative decision boundary between spam and genuine email communication.
2. Preprocessing Effect: Preprocessing on email text was very important in improving model performance. Stopword removal and tokenization procedures tried to eliminate noise from the dataset; approximately, noise reduction was up to 30%. Consequently, the reduction of noise helped learning algorithms to focus on more relevant linguistic patterns. Label encoding was also useful in converting categorical labels ("spam," "ham") into a binary numerical format to swiftly accomplish binary classification for which machine learning models provide an approach with minimal loss of information.
3. Computational Trade-offs: The study also provided insight into the inherent trade-offs between computational efficiency and predictive accuracy. Naïve Bayes being the fastest in inference, with 0.003 seconds per email passed through it. Hence the very speed and incredible agilities come at the price of lower accuracy when faced with a complex pattern in data. On the other hand, the SVM being more accurate would twice demand the computational resources Random Forest requires. This

consideration is one among those fundamental issues that arise during the operational deployment of a typical ML system.

5.2. Research Implications

The results advance both theoretical and practical domains:

Industry Applications:

- Validates SVM+TF-IDF as a deployable solution for enterprise email systems.
- Provides a reproducible pipeline compatible with existing filters like Spam Assassin.

Academic Contributions:

- Confirms SVM's efficacy for binary text classification (supporting).
- Highlights the diminishing returns of complex models (e.g., Gradient Boosting) for lexical features.

5.3. Future Enhancements

To address limitations and evolving threats, we propose:

Deep Learning Integration:

- Implement LSTM+Attention models to detect adversarial misspellings and contextual scams.
- Hybrid architectures (e.g., SVM-BERT) to balance accuracy (current: 98.9%) and interpretability.

Dynamic Adaptation:

- Real-time feedback loops to update models based on user-reported false positives.
- Incremental learning for zero-day spam tactics (e.g., generative AI content).

Expanded Scope:

- Multilingual detection using cross-lingual embeddings (extending Arabic focus).
- Header/metadata analysis to complement textual features.

6. Patents

This section is not mandatory but may be added if there are patents resulting from the work reported in this manuscript.

Supplementary Materials: The following are available online at www.jcbi.org/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

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Data Availability Statement:

In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. You might choose to exclude this statement if the study did not report any data.

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Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript, or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results".

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