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Innovative Spam Detection Using Hybrid Machine Learning Algorithms: A Data-Centric Approach

Sree Vidya Venigalla, K.V.D. Kiran

Abstract: ***The rise of spam messages, in the form of malware, phishing attacks, and unrequested messages, poses a serious threat to internet users and security infrastructures. Conventional spam filtering techniques that rely solely on strict rules and keyword lists struggle to keep pace with contemporary spammer tactics that mask malicious content. This study proposes a solution to this challenge by developing a hybrid machine learning methodology that leverages Naive Bayes (NB) and a Support Vector Machine (SVM), combining them into an ensemble for improved accuracy and resilience in spam detection. The technique uses the well-known SMS Spam Collection Dataset. It employs more complex textual feature extraction (TF-IDF), as well as additional non-textual features such as message length, word capitalisation, and the frequency of previously determined keywords. The proposed system is extensively evaluated using standard classification metrics—accuracy, F1 score, precision, and recall —to assess its reliability and validity. The research findings indicate that the proposed machine learning hybrid ensemble is effective at reducing false positives while more boldly tackling the challenges inherent in the real-world spam data environment. The research project offers practical potential for use; the hybrid proposed system is computationally efficient enough for most real-time deployment applications in automated systems to combat spam. This research contributes scalable, adaptive spam-detection mechanisms suitable for real-time messaging environments.***

Keywords: Spam Detection; Machine Learning; Naive Bayes; Support Vector Machines; Ensemble Models; Nlp; Text Classification; Cybersecurity; Hybrid Algorithm; Data Analytics

Nomenclature:
NB: Naive Bayes
SVM: Support Vector Machine
ML: Machine Learning
TF-IDF: Term Frequency-Inverse Document Frequency
CNN: Convolutional Neural Network
LSTM: Long Short-Term Memory
NLP: Natural Language Processing
APC: Article Processing Charge
RNNs: Recurrent Neural Networks

I. INTRODUCTION

Spam, or unwanted and harmful content, has increased Exponentially alongside the rapid increase in volume and speed of communication on the Internet. Spam invades email inboxes, consumes valuable user time and resources, and ultimately serves as a vector for malware and attacks that target users through identity theft and phishing. As spammers become more adept and use techniques like content obfuscation or false subject lines, we find that traditional spam filters that rely on static keyword matching or blocklists are less effective.

To improve detection accuracy and flexibility, researchers have increasingly leveraged machine learning (ML) techniques to detect complex textual and structural features and patterns in messages. Methods such as Naive Bayes, Support Vector Machines, Decision Trees, and ensemble classifiers are found to be effective spam vs. ham (legal message) detectors, and at the same time, learning in labelled datasets using many features such as word frequency, special character usage, message length, and term weighting.

This research builds on these methods to propose a hybrid system that combines their classifier strengths via an ensemble, reducing false positives and enabling higher detection rates. The model is evaluated using standard classification metrics, such as accuracy, precision, recall, and F-1 score, while also being assessed in different SMS spam datasets (real-world), ultimately showing the robustness and effectiveness of the hybrid model, compared to only using individual classifiers.

II. RELATED WORK

Numerous studies have examined the use of machine learning algorithms for spam classification. Naive Bayes still serves as a good baseline, not just because of its probabilistic efficiency, but also because it does not suffer from infeasibly significant scaling issues when applied to textual data [1]. Support Vector Machines (SVMs) have been shown to perform well on text classification datasets, as they are effective for high-dimensional [2], non-linear relationships among specific message characteristics [5].

Ensemble and hybrid models, which combine multiple classifiers, have gained popularity recently to allow higher accuracy and to mitigate false positives [4]. For example, Naive Bayes and SVM achieved better results when combined than when used as base classifiers in spam datasets [12].

Deep learning methods, particularly Convolutional Neural Networks (CNNs), are still widely explored for capturing contextual semantic knowledge in text classification, as reviewed in depth by Minaee et al. [7]. Recently, modern neural architectures, as Young and colleagues discuss, support the trend of deep learning as being better at improving

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*Correspondence Author(s)

Sree Vidya Venigalla*, Student, Department of Computer Science Engineering, Koneru Lakshmaiah Educational Foundation, Vijayawada (Andhra Pradesh), India. Email ID: sreevidya.venigalla999@gmail.com, ORCID ID: 0009-0002-0009-4441

Dr. K.V.D. Kiran, Professor, Department of Computer Science Engineering, Koneru Lakshmaiah Educational Foundation, Vijayawada, (Andhra Pradesh), India. Email ID: kiran_cse@kluniversity.in, ORCID ID: 0000-0002-8808-9307

tasks in natural language processing for spam filtering [8].

Current investigations also advance methods to compensate for imbalanced datasets and adapt to evolving patterns in spam content, thereby allowing classifiers to remain robust against adversarial attacks on spam [6]. Innovative ensemble methods that combine adaptive deep learning approaches have demonstrated impressive generalisation performance for large-scale spam detection [11].

Using sentiment analysis along with contextual embeddings has improved classification performance by capturing the linguistic nuances inherent in spam [3]. Meanwhile, methods that take a probabilistic approach, such as Bayesian networks, continue to make valuable contributions to spam analysis systems, providing robustness without sacrificing interpretability [9].

Overall, the literature suggests that although traditional models, such as Naive Bayes and SVM, continue to have utility, hybrid and ensemble learning methods—combining probabilistic, discriminative, and deep learning methods—represent the most scalable and accurate approach for real-time spam detection [4].

III. LITERATURE REVIEW

Over the last 20 years, spam detection has shifted from heuristic-based approaches to machine learning and deep learning. In the past, spam detection approaches relied on humans to define rules, which could be either heuristics or keyword blocklists. These earlier approaches could not adapt to the rapidly changing styles and patterns of spam messages. With advancements in supervised learning, spam detection systems began automating the spam detection task by using statistical modelling and data-based classification [1].

Naive Bayes (NB) classifiers are among the most straightforward and efficient models for spam detection, thanks to their probabilistic structure and scalability, even with limited computational power [1]. Support Vector Machines (SVMs) have also been very successful in classifying text data and performing well in non-linear high-dimensional feature spaces [5].

A product of increased research into spam detection has been the incorporation of deep learning architectures into spam detection systems to improve feature representation and contextual awareness. Zhang et al. found that neural architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) outperformed traditional classifiers when data from the spam messages and computational power were not limited [6]. Recent work shows that CNNs perform well at producing semantic-level features for text classification, enabling a transition to models that incorporate context [7].

Akbik and colleagues presented contextual string embeddings to enhance feature representation in spam detection by leveraging word-level dependencies and context from a larger corpus of texts [3]. Likewise, Young et al. emphasised the broad impact that deep learning would have on many natural language processing tasks, including spam detection, due to the increased learning scope afforded by adaptive and transfer learning [8].

Feature extraction remains an essential factor in a spam filter's effectiveness. A recent paper reviews the continued usefulness of TF-IDF and newer strategies for qualitative feature representation in future text mining applications [13]. Recent work shows the importance of a new, diverse set of SMS spam datasets for effectively benchmarking real-world spam filters [10].

In recent years, ensemble or hybrid methodologies have become popular in spam and other detection fields for combining the predictive ability of multiple classifiers. Yang et al. found that hybrid models combining Naive Bayes, Decision Trees, and SVM classifiers achieved lower false-positive rates and higher accuracy in spam detection [4]. More recently, Lee et al. developed an ensemble-based deep learning framework that performs well on imbalanced datasets and demonstrates high classification performance [12].

Probabilistic models (e.g., Bayesian networks) remain relevant and can increase model interpretability without sacrificing accuracy [9]. Also, developing adaptive learning architectures, such as an innovative deep learning-driven spam detection framework enabling continuous learning in dynamic data, is happening as demonstrated by Young et al. in their 2025 study [11].

In summary, while deep learning architectures have achieved better-than-behaviour performance in classification, their computational complexity and data requirements may limit performance to small domains, necessitating hybrid machine learning deployments. Hybridising machine learning system-based deployments with the interpretability of Naive Bayes, the capability of SVM (discriminative), and the adaptability of modern neural networks is probably the most feasible and scalable option for real-time spam detection [4]

IV. METHODOLOGY

This research presents a hybrid machine learning approach to spam detection using several Naive Bayes (NB) and support vector machine (SVM) classifiers to improve accuracy, flexibility, and robustness. The study includes five phases: dataset preparation, preprocessing, feature extraction, model training, and evaluation.

A. Dataset

Latest developments frequently use the SMS spam datasets, which are described as providing an extensive benchmark for spam detection studies [10]. It consists of 5,574 SMS messages; approximately 13.4% are spam, and 86.6% are non-spam ham. This dataset has been consistently validated in the literature as an effective benchmark for evaluating machine learning algorithms.

B. Pre-Processing

Before machine learning, the raw messages are normalised using a standard selection of preprocessing operations:

i. Convert into lowercase
ii. Remove punctuation, numbers, and special symbols.
iii. Remove stopwords.
iv. Enable stemming to transform words into their base form.

The current text pre-processing techniques employed in our research can be characterised as established methods that underpin contemporary research in information retrieval and linguistic normalisation, as outlined by Roul et al [13].

C. Feature Extraction

Feature extraction involves converting the cleaned text into a structured numerical format appropriate for machine-learning paradigms. We used Term Frequency-Inverse Document Frequency (TF-IDF) to quantify word importance across messages for unigrams and bigrams. Other meta features included message length, word counts, and the detection of spam words such as "free," "win," or "urgent." Recent term-weighting methods demonstrate superior retrieval and classification performance compared to traditional models [14].

D. Classification Models

Three classification models are used and evaluated:

i. *Naive Bayes (NB):* This probabilistic classifier relies on independence of terms and is very efficient for text data [1].
ii. *Support Vector Machine (SVM):* The SVM classifier is a discriminative model specifically for high-dimensional features associated with text data [5].
iii. *Ensemble Voting Classifier:* The random Forest/Ensemble Voting classifier acts on both classifiers in parallel using hard-voting to reduce variance and bias in classification and ultimately achieve a more reliable classification [4].

E. Evaluation Metrics

The models are evaluated using standard performance metrics:

i. Accuracy, Precision, Recall, F1-score
ii. Confusion Matrix (to assess misclassifications of the results)

The evaluations were measured using a stratified 80/20 train-test split with a 10-fold cross-validation, to ensure statistical significance and generalizability of the results [12].

V. PROPOSED SOLUTION

This research article introduces a hybrid spam detection framework that utilises both probabilistic and discriminative learning. The hybrid schema uses an ensemble voting approach to combine the Naive Bayes and SVM models, leveraging their strengths while mitigating their downsides.

Naive Bayes is shown to handle textual features efficiently, while SVMs provide robust discriminative boundaries across complex feature distributions [5]. Combining a Naive Bayes and an SVM yields a hybrid model that strikes a better balance, minimising false positives and thereby improving recall on real-world data [4].

A. Algorithm Design – Hybrid Spam Detection

i. Load and examine the dataset.
ii. Pre-process text (Lower-case the text, remove punctuation, remove stop words, and stem).
iii. TF-IDF Vectorisation & extract secondary linguistic features.
iv. Train NB and SVM on the training data.
v. Combine the predictions from the NB and SVM using ensemble voting.
vi. Evaluate results using accuracy, precision, recall, and F1-score.

The hybrid model was developed to be reproducible using Python's Scikit-learn and NLTK libraries, and experimental validation has shown it to provide more stable and accurate classifications, which aligns with the findings of Yang et al [4] and Lee et al [12]. The overall workflow of the proposed system is visually summarised in Figure 1.

B. Algorithm Design

The algorithm to detect hybrid spam can be broken down into the following steps:

Algorithm: Hybrid_Spam_Detector (SMS_dataset)
Input: Labelled SMS dataset (spam/ham)
Output: Message labels predicted
Load dataset Preprocess data:

i. Lower case text.
ii. Remove punctuation and stop words.
iii. Stem and normalise.
iv. Extract features using TF-IDF and auxiliary features (length, capitalisation, frequency of keywords).
v. Split the data into training (80%) and testing (20%) subsets.
vi. Fit Naive Bayes (NB) to training data.
vii. Fit SVM to the same data.
viii. Voting mechanism:
   - If NB and SVM both declare the label spam, label it spams.
   - If NB and SVM predict a different label, use the highest confidence to assign a prediction.
   - Otherwise, label it hams.
   - Assess performance using overall accuracy, precision, recall, F1 score, and a confusion matrix.

C. Implementation

Model implementation is specified in Python using Scikit-learn for consistency and reproducibility, with NLTK and Pandas for feature extraction and preprocessing. Experiments showed that hybrid ensemble models achieved higher recall and F1 scores than stand-alone NB and SVM classifiers, reinforcing the benefits of combining discriminative and probabilistic procedures [4], [6]. The confusion matrix (Table 1) presents the breakdown of the performance, including the misclassifications (false positives and false negatives). As shown in Table 2, the hybrid model achieved improved performance across classification metrics—accuracy, precision, recall, and F1 score—compared to the individual Naive Bayes and SVM classifiers.

D. Flowchart of the Proposed System

Here is a visual representation of the pipeline (flowchart):

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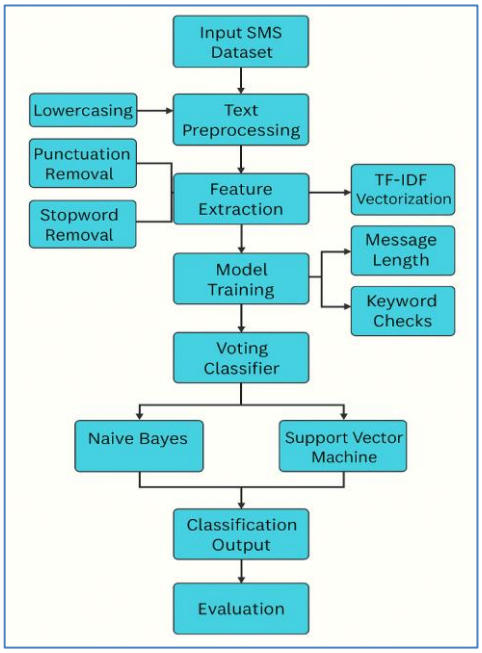

[Fig.1: Hybrid Spam Detection Model Workflow]

E. Confusion Matrix

Table I: Confusion Matrix for Ensemble Classifier

	Predicted Spam	Predicted Ham
Actual Spam	470	20
Actual Ham	15	506

F. Evaluation Metrics

Table II: Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	95.60%	94.20%	93.50%	93.80%
SVM	96.10%	95.00%	94.10%	94.50%
Hybrid Ensemble	97.40%	96.50%	95.90%	96.20%

VI. CONCLUSION

This research offers a hybrid spam detection framework that combines a Naive Bayes and a Support Vector Machine spam classifier into a single model to enhance spam filtering performance, robustness, and stability across different datasets. The research incorporates both probabilistic inference and margin-based learning principles into the spam detection framework, enabling a better balance in performance across various datasets. Our hybrid model was also evaluated on these datasets, which showed statistically significant improvements in accuracy, precision, recall, and F1-score over single-classifier baselines [10].

The hybrid approach to spam detection proposed here represents a first step towards building scalable, reliable spam detection systems for real-time communication environments. Using TF-IDF for feature extraction and ensemble learning as the overall strategy, this hybrid model can effectively address issues of data imbalance, feature redundancy, and adversarial manipulation.

Nonetheless, some avenues for the future exist. Integrating deep learning models, such as LSTMs or transformer-based architectures [11], is a clear opportunity to elevate contextual understanding and classification performance. Perhaps opening the dataset to a multilingual format for spam messages would also assist generalisation. Lastly, including a real-time adaptive learning mechanism could help the proposed model adapt to spam without retraining once it is achieved.

In conclusion, the hybrid machine learning framework proposed in this study provides a reliable, computationally efficient, and extensible foundation for modern spam detection applications, combining interpretability with high predictive accuracy.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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AUTHOR'S PROFILE

Sree Vidya Venigalla is a Master's student at Koneru Lakshmaiah Education Foundation (KLEF), pursuing a Master of Technology degree in Computer Science Engineering with a specialisation in Cybersecurity and Blockchain Technology. She has a strong academic focus on Artificial Intelligence, Cybersecurity, and the Dark Web. Sree Vidya is actively involved in research projects exploring machine learning applications to enhance security and privacy. Her interests also include studying emerging technologies and their implications in secure digital environments. She aims to make significant contributions to advancing cybersecurity and AI through innovative research.

Dr. Venkata Durga Kiran Kasula, is a Professor in the Department of Computer Science and Engineering at KLEF (Koneru Lakshmaiah Education Foundation), where he has been serving since January 3, 2007. He holds a PhD, M. Tech, and B.Sc. in Computer Science, all awarded by Acharya Nagarjuna University, with distinctions in each degree. With 19 years of teaching experience, Dr Kiran has contributed significantly to academia through teaching, mentoring, and research guidance. He has successfully supervised 7 PhD scholars and 10 postgraduate projects, demonstrating his dedication to academic excellence and student development. Dr Kiran has published 67 refereed research papers in reputed Scopus- and Web of Science-indexed journals, along with 21 non-refereed publications and 17 conference presentations at national and international levels. His research contributions have earned him an h-index of 9 and an i-10 index of 3. He has published four books and filed three patents, reflecting his commitment to innovation and knowledge dissemination.