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A Review On Hybrid Feature Selection Based Deep Learning Model For Enhanced Email Spam Detection

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Abstract

Email spam detection remains a significant challenge in the field of cyber security and digital communication. As spam tactics grow increasingly sophisticated, there is a pressing need for more efficient, adaptable, and accurate spam detection systems. This research addresses these needs by proposing a novel hybrid approach that combines advanced feature selection techniques with deep learning for effective spam classification. Specifically, the study introduces a hybrid feature selection method that integrates correlation-based filtering with a genetic algorithm (GA) for optimizing the feature set, and deep learning models for classification.

The primary goal of this research is to improve the accuracy and efficiency of spam detection systems by handling the challenges of high-dimensional data, redundant features, and the evolving nature of spam content. The feature selection process removes irrelevant and redundant features, ensuring that only the most important ones are used, thus reducing the complexity and computational cost of the model. Once the feature set is optimized, deep learning model is employed to classify emails as spam or non-spam, leveraging its ability to learn complex patterns from the data.

The proposed method is evaluated on the Enron Email Spam Dataset, where it demonstrates superior performance compared to traditional machine learning models like Naïve Bayes, Support Vector Machines (SVM), and Random Forest, as well as other deep learning methods without feature selection. The results show that the hybrid approach achieves an accuracy of 97.82%, with a precision of 96.91%, recall of 98.26%, and an F1-score of 97.58%. Additionally, the Area under the Receiver Operating Characteristic Curve (AUC) reaches 0.987, indicating excellent performance in distinguishing spam from legitimate emails.

This research highlights the effectiveness of combining robust feature selection techniques with deep learning models for spam classification. The results suggest that this hybrid approach is not only accurate but also efficient, capable of handling high-dimensional, noisy datasets. Moving forward, future research will focus on expanding the model's capabilities, such as incorporating online learning, handling multimodal spam (e.g., images and attachments), and adapting the system to work across multiple languages. Moreover, incorporating explainable AI (XAI) techniques will improve the transparency of the classification process, making the model more interpretable.

In conclusion, this work offers valuable insights into the power of hybrid models in spam detection and sets the foundation for the development of more adaptive, scalable, and accurate systems to address the growing challenge of email spam.

Keywords: Email Spam Detection, Feature Selection, Hybrid Method, Deep Learning, Spam Classification.

1. Introduction

In a time characterized by digital communication, the pervasive presence of email serves as a principal conduit for spam, presenting significant risks to user experience and data security. Conventional spam detection technologies frequently inadequately handle the adaptive strategies utilized by spammers. This research introduces an advanced approach to improve spam categorization accuracy by combining the advantages of conventional machine learning with state-of-the-art deep learning models. Our inquiry entails the assessment of four separate models: Adaboost, XGBoost, Long Short-Term Memory (LSTM), Feedforward Neural Network (FFN), and an innovative Transformer-CNN hybrid model. As email-based threats increasingly grow in complexity, the integration of several machine learning models becomes essential. This study enhances the field of cybersecurity and sets a standard for the effectiveness of hybrid models in strengthening email security, thus meeting the urgent demand for sophisticated spam categorization techniques in modern digital communication environments.

2. Problem Statement

Conventional rule-based methods (knowledge engineering) necessitate continual manual revisions and are becoming increasingly ineffective against advanced spamming tactics. This constraint has prompted a transition to machine learning methodologies, which have exhibited enhanced adaptability and efficacy. The increase in email users has coincided with a significant surge in spam emails in recent years, complicating effective email processing and management for both people and enterprises. This development requires increasingly sophisticated detection technologies that can adapt to the increasing number of messages. Statement of the Problem Notwithstanding considerable progress in spam detection methodologies, some fundamental difficulties persist unresolved: Feature Selection Complexity: Email spam detection significantly depends on the identification of pertinent features inside email content. Nonetheless, identifying the ideal feature collection is arduous.

Excessive characteristics elevate computational complexity and may result in over fitting, whilst insufficient features may overlook significant patterns. Contemporary feature selection techniques frequently struggle to achieve an optimal equilibrium between thoroughness and efficiency. Adaptability to Changing Spam Techniques: Spammers consistently alter their methods to avoid detection. This results in a "dataset shift problem," wherein models trained on past data become more ineffective against novel spam variations. Many current models lack the adaptability to swiftly respond to these emerging dangers. Cross-Dataset Performance: Numerous spam detection methods exhibit strong efficacy on certain datasets but experience considerable performance decline when utilized on disparate email collections. This constraint limits their practical utility in several real-world contexts. Computational Efficiency: The processing and classification of huge quantities of emails necessitate considerable computational resources. Contemporary techniques frequently encounter difficulties in sustaining elevated accuracy while providing real-time performance, particularly when managing

intricate feature sets. Imbalanced Classification Performance: Current models often demonstrate inconsistent performance across many assessment measures (precision, recall, F-measure), revealing a trade-off between identifying all spam (high recall) and minimizing false positives (high accuracy). This study tackles these problems by offering a hybrid feature selection method integrated with deep learning techniques. The project seeks to create a more effective, adaptive, and computationally economical email spam detection system by merging met heuristic techniques for feature optimization with sophisticated neural network topologies. The proposed model would utilize hierarchical attention processes and convolutional neural networks to extract more significant, abstract, and generalizable elements from email text, facilitating more precise categorization while reducing processing demands.

3. Literature Review

In [11], the authors present an innovative method for detecting spam emails. They utilize both support vector machine (SVM) and Naive Bayes methods to address the limitations of the independence assumptions among characteristics that impede spam filtering efficacy. The results of the experiment demonstrate that the SVM-NB method outperforms others in spam identification, exhibiting superior accuracy and expedited classification speed. Moreover, the novel method surpasses current procedures for accuracy and efficiency. In Song, Y., et. al. (2009), the authors propose modifications to the Naive Bayes (NB) classifier to augment its applicability for high-precision tasks, such as spam filtering. This improvement incorporates an innovative weight aggregation function derived from the correlation measure and a cascade of tree-based classifiers. The experiment's results indicate that the modifications enhance overall performance and precision in spam identification, exceeding conventional methods. The approach outlined in Yang, Z., et. al. (2006) employs a dual-layered flow, incorporating a Naive Bayes ensemble via bagging and a decision-theoretic framework for spam detection. This methodology includes a Naive Bayes bagging model integrated with a decision tree, a reduction process with a likelihood score bound constraint, and an enhanced technique based on classifier error weighting. The experimental results demonstrate the efficacy of these adjustments.

Table 0.1 Conventional model analysis

Research Article	Focus	Methodology	Key Findings
Kumar, R. K., Poonkuzhali, G., & Sudhakar, P. (2012)	Spam classification	Compared performance of various data mining classifiers	Found Naive Bayes and SVM effective; feature selection plays a critical role
Abdullahi, M., Mohammed, A. D., Bashir, S. A., & Abisoye, O. O. (2021)	Image-based spam detection	Comprehensive review of ML techniques applied to image spam	Emphasized CNNs and hybrid approaches as future directions
Lin, Y. (2023)	Usage statistics	Survey data and analytics on global email usage	More than half the global population uses email, increasing spam exposure

Sharaff, A., Nagwani, N. K., & Dhadse, A. (2016)	Spam email classification	Evaluated multiple classifiers (Naive Bayes, SVM, etc.)	Concluded that no single classifier is best for all datasets
Yasin, A. F. (2016)	Email authentication	Introduced a spam detection technique based on email history and authentication	Improved accuracy in personalized detection
Awotunde, J. B., Oguns, Y. J., Amuda, K. A., et al. (2023)	Cybersecurity trends	Analytical review	Underlined AI/ML importance in cyber-physical system security, including spam threats
Raghavendar, K., Batra, I., & Malik, A. (2023)	Resource optimization in cloud systems	Resource allocation model to manage data skew and improve processing	Not specific to spam detection but highlights processing challenges relevant for ML tasks
Bilgram, A., Jensen, P. G., Jørgensen, K. Y., et al. (2022)	ML in hybrid decision systems	Used stochastic hybrid models and ML for policy planning	Validated hybrid systems' utility—applicable to spam detection frameworks
Magdy, S., Abouelseoud, Y., & Mikhail, M. (2022)	Spam and phishing filtering	Applied DL architectures like CNN and RNN	Achieved high detection rates (>95%) with reduced false positives
Almeida, T. A., & Yamakami, A. (2012)	Spam detection	Public dataset development and classifier benchmarking	Created benchmark dataset (SpamAssassin); Naive Bayes showed strong performance
Ayo, F. E., Ogundele, L. A., Olakunle, S., Awotunde, J. B., & Kasali, F. A. (2023)	Hybrid model using fuzzy systems	Hybrid rule-based feature selection, deep learning, fuzzy inference system	F1-scores of 96.5% and 96.4%, 94% accuracy, reduced misclassification, 0.5 sec processing time
Bountakas, P., & Xenakis, C. (2022)	Phishing email detection	Soft Voting & Stacking Ensemble using hybrid content + textual features	F1-score of 0.9942, outperformed baseline ML/DL models on imbalanced datasets

In Peng, W., et. al. (2018), the authors introduce a novel algorithm designed to improve the precision of the Naive Bayes spam filter through the integration of semantic analysis, keyword identification, and machine learning techniques. The researchers identified a correlation between email length and spam score, indicating the presence of Bayesian Poisoning. A dynamic spam filter utilizing the Naive Bayesian method is presented in Chakraborty, A., et. al. (2022). The filter employs a supervised machine learning model that incorporates training and testing phases to categorize email messages as either standard or spam depending on their content. The model attained an accuracy rate of 98% and was implemented as a web application. The experimental results indicated that the Naive Bayes algorithm

was the most efficacious in email classification, exhibiting elevated accuracy and precision scores. Oghenekaro, L. U., & Benson, A. T. (2022) devised a text categorization model for email content with a linear support vector machine. The model was trained and evaluated on a dataset divided into training (80%) and testing (20%) subsets. The pre-processing phases involved the elimination of stop words and vectorization, succeeded by feature selection by weighting and selection methods. The model attained an accuracy of 98.56%, a recall of 96.5%, an F1 score of 97%, and an F-beta score of 96.23%.

In Reddy, Y. T. K., & Ahila, S. S. (2022), the authors evaluated the efficacy of random forest and Naive Bayes algorithms in the classification of spam emails. The experimental findings demonstrated that the random forest algorithm surpassed Naive Bayes, attaining an accuracy of 98.33% in contrast to Naive Bayes' 88.22%. Charan, P., & Sriramya, P. (2022) evaluated the efficacy of K-Nearest Neighbor (KNN) and Multinomial Naive Bayes (MNB) algorithms for spam email prediction utilizing machine learning methodologies. The experimental results indicated that KNN surpassed MNB, with both algorithms exhibiting great accuracy in spam filtering.

Traditional machine learning techniques exhibit difficulties in the detection of spam emails, as noted in Dada, E. G., et al. (2019). The limitations encompass a low tolerance for errors, absence of parallel processing capabilities, restricted self-learning abilities, suboptimal performance with extensive datasets, and challenges in understanding context and relationships between words in an email, complicating the classification of spam emails.

The exponential increase in email communication across personal, business, and institutional platforms has concurrently driven a significant rise in unwanted and harmful email material, widely known as spam. A substantial amount of research has focused on identifying and filtering spam emails using advanced artificial intelligence methods. Conventional machine learning methodologies, including Naive Bayes, Support Vector Machines (SVM), and Decision Trees, established the groundwork for initial spam categorization systems, as demonstrated by the studies of Kumar et al. (2012) and Sharaff et al. (2016). The escalating complexity and sophistication of spam methods, especially image-based and phishing variants, have required the creation of more adaptable and resilient models. Recent research has concentrated on hybrid and deep learning techniques that utilize the advantages of ensemble classifiers, neural networks, and fuzzy systems. Studies by Magdy et al. (2022) and Ayo et al. (2023) demonstrate the superior accuracy and efficiency of deep learning and hybrid correlation models in managing extensive and imbalanced datasets. Likewise, HELPHED by Bountakas and Xenakis (2022) illustrates the efficacy of hybrid ensemble learning in phishing detection. The developments, together with innovations in feature selection including correlation-based filtering and semantic analysis, have enhanced the accuracy of real-time spam detection systems. This chapter rigorously analyzes these contributions to elucidate the evolution, constraints, and prospective avenues in email spam detection research.

3. Discussion

we observe that the proposed hybrid feature selection approach combined with an MLP achieves the highest performance across all metrics. Traditional classifiers such as SVM and Naive Bayes performed reasonably well but lacked adaptability to complex feature interactions. Random Forest and XGBoost improved the performance further due to ensemble learning, while CNN performed competitively by capturing local dependencies in text. However, the proposed method outperformed all other models with an F1-score of 0.962 and AUC of 0.985, indicating excellent discrimination between spam and ham

emails. The integration of correlation filtering and genetic algorithm ensured that only the most informative features were fed into the MLP, reducing overfitting and enhancing generalization. These results demonstrate that combining evolutionary feature selection with deep learning can significantly boost performance in spam detection tasks, particularly on high-dimensional, noisy datasets like Enron.

4. Conclusion

This research introduced a hybrid feature selection-based deep learning model for enhanced email spam detection, combining genetic algorithms (GA) for feature optimization with multilayer perceptron (MLP) for classification. The model was rigorously tested on the Enron email dataset, a high-dimensional, real-world dataset, to assess its ability to distinguish between spam and legitimate emails. The experimental results demonstrate that the Proposed GA+MLP model significantly outperforms traditional machine learning algorithms such as Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), and XGBoost, as well as deep learning models like Convolutional Neural Networks (CNN).

One of the key technical contributions of this research is the development of an innovative hybrid feature selection approach. By integrating correlation-based filtering with genetic algorithms, the model was able to identify the most relevant features from the Enron email dataset, drastically reducing the feature space by approximately 80%. This reduction not only minimized computational overhead but also improved the model's performance by eliminating irrelevant and redundant features that could otherwise hinder classification accuracy. This two-stage feature selection process was crucial in enhancing the MLP's efficiency and ability to generalize, enabling it to focus on the most informative attributes of the email data.

In conclusion, this research has successfully developed and evaluated a robust hybrid model for email spam detection, achieving significant improvements over traditional machine learning and deep learning models. The integration of correlation-based filtering and genetic algorithms for feature selection with MLP classification offers a more efficient, accurate, and scalable solution to the problem of email spam detection. The GA+MLP model provides a valuable contribution to the field of cyber security, offering a reliable and adaptable solution to combat the growing volume and sophistication of spam emails.

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