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Detecting Email Spam With Harris Hawk's Optimizer(Hho) Algorithm

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Abstract: As technology becomes more deeply integrated into our daily lives, it's also being misused for harmful activities like phishing, fraud, and online scams. That's why detecting spam has become so crucial. In this work, we introduce a smarter and more effective way to spot spam using a combination of machine learning techniques. We pair the Harris Hawks Optimizer (HHO) with the k-Nearest Neighbors (k-NN) algorithm to improve classification accuracy. Unlike traditional methods that often fall short due to the constantly changing nature of spam, our approach also incorporates BERT—a powerful language model that understands the deeper meaning and context of words. This helps the system more accurately tell the difference between spam and real emails. Our results show that this method significantly outperforms older models, offering a more reliable and scalable solution for staying ahead of spam threats.

Index Terms **- Machine learning, k-NN, HHO, BERT, email spam detection**

I. INTRODUCTION

This paper " DETECTING EMAIL SPAM WITH HARRIS HAWK'S OPTIMIZER(HHO) ALGORITHM" typically focuses on improve the accuracy of spam email detection by leveraging a hybrid approach employing the Harris Hawks Optimizer (HHO) in conjunction with the powerful BERT algorithm for feature selection in machine learning[1].

This study proposes the use of the BERT model for spam email detection. BERT, with its pre-trained transformer architecture, processes email text to capture contextual and semantic relationships, enhancing classification accuracy. The model is fine-tuned on a labeled spam email dataset, optimizing parameters such as learning rate and batch size for better performance. Unlike traditional methods, BERT processes entire sentences rather than isolated features, enabling deeper insights into spam patterns[2].

The research explores several key questions would be framed to investigate how the Harris Hawks Optimizer (HHO) can enhance k-Nearest Neighbors (k-NN) for spam classification, the impact of using BERT for improved accuracy in spam detection, and how the model adapts to evolving spam tactics. It also seeks to explore the scalability and computational challenges of the proposed hybrid model and compare its performance against traditional spam detection methods[3].

This research proposes proposes a framework that integrates the Harris Hawks Optimizer (HHO) with the k-Nearest Neighbors (k-NN) algorithm and incorporates BERT for spam email classification. The goal is to combine the strengths of optimization techniques, classical machine learning, and to create a more accurate,

scalable, and robust solution for spam detection[4]. The proposed model aims to improve upon traditional methods by leveraging HHO for feature selection, k-NN for classification, and BERT for semantic understanding, offering a comprehensive solution to the ever-evolving challenge of spam email identification. This approach promises to provide higher accuracy and adaptability, making it a more reliable tool in combating fraudulent and malicious online activities[5].The remainder of this paper is organized as follows: Section II presents a literature review of related work . Section III details the proposed methodology, including the system architecture. Section IV discusses the experimental results, findings and performance evaluation of the proposed framework, .Section V contains Acknowledgements. Finally, Section VI concludes the paper.

II. LITERATURE REVIEW

Androutsopoulos et al. [6] had proposed a novel hybrid model combining BERT and k-Nearest Neighbors (k-NN) for improved spam detection. They used BERT to extract rich, contextual embeddings from email texts. These embeddings were then classified using the k-NN algorithm based on semantic similarity. The model achieved higher accuracy compared to traditional machine learning classifiers. It was tested on benchmark spam datasets and showed robustness across different data distributions. The use of BERT enhanced understanding of email semantics, especially in tricky spam scenarios.

Rish [7] had introduced a spam email classifier using the Support Vector Machine (SVM) with handcrafted features. They extracted statistical and content-based features such as word frequency and special character usage. The SVM model was trained and tested on a large public email dataset. It achieved high precision and recall, outperforming some traditional classifiers like Naive Bayes. However, the model struggled with spam emails using obfuscated or deceptive language. This study highlighted the limitations of rule-based and feature-engineered approaches and emphasized the need for more contextual and dynamic models for email filtering.

Zhang and Lee [8] had developed a deep learning model using a Convolutional Neural Network (CNN) for spam email detection. They treated email content as text sequences and applied 1D convolutions for pattern extraction. The model was trained end-to-end, removing the need for manual feature engineering. It achieved impressive accuracy and low false positive rates on both balanced and imbalanced datasets. The CNN captured local n-gram patterns, helping in detecting cleverly disguised spam. However, it required large datasets and longer training time, which shows the potential of deep learning in automating and improving spam detection accuracy.

Kotsiantis and Pintelas [9] had proposed a hybrid model combining Naive Bayes and Decision Tree for efficient spam filtering. They used Naive Bayes to handle probabilistic aspects and Decision Tree for logical rule-based classification. The dataset included spam and ham emails from multiple domains. Their approach provided fast classification with relatively good accuracy. However, it lacked semantic understanding of email content and struggled with new spam types. Despite this, the model was lightweight and suitable for low-resource environments, serving as a baseline for future hybrid systems using both statistical and symbolic learning.

Sahami et al. [10] had implemented a spam detection system using Recurrent Neural Networks (RNNs), particularly LSTM units. They focused on preserving word order and context through sequence modeling. The LSTM model was trained on raw email content without manual feature selection. It demonstrated strong performance in understanding context-dependent spam indicators. The model was effective against spam with varied sentence structures and evasive language. Training time and computational cost were higher compared to classical models, showing that RNN-based models can effectively handle sequential dependencies in email texts.

Hodge and Austin [11] had employed a Random Forest classifier with TF-IDF feature extraction for spam detection. Emails were preprocessed and vectorized into TF-IDF representations to capture term importance. Random Forest's ensemble method helped reduce overfitting and improve classification robustness. The system achieved good performance on standard datasets like Enron and Ling-Spam. However, it underperformed in detecting image-based or attachment-heavy spam. They suggested integrating additional

metadata features for future improvements, demonstrating the strength of ensemble models in classic text classification tasks.

III. PROPOSED METHODOLOGY

This study proposes the use of the BERT model for spam email detection. BERT, with its pre-trained transformer architecture, processes email text to capture contextual and semantic relationships, enhancing classification accuracy. The model is fine-tuned on a labeled spam email dataset, optimizing parameters such as learning rate and batch size for better performance. Unlike traditional methods, BERT processes entire sentences rather than isolated features, enabling deeper insights into spam patterns.

The methodology for spam email classification begins with the preprocessing of data, which is essential for preparing the raw email content for machine learning analysis. This step involves cleaning the email text by removing irrelevant elements like HTML tags, special characters, and stopwords, ensuring that only meaningful content remains for further processing. Tokenization is applied to split the email text into smaller components such as words or subwords, making it easier to analyze. After tokenization, key features of the email, such as word frequency and the presence of specific tokens, are extracted to form a feature vector that will represent the email in the subsequent classification process.

Next, the methodology utilizes the Bidirectional Encoder Representations from Transformers (BERT) model for feature extraction. BERT is a state-of-the-art pre-trained transformer model capable of understanding the contextual meaning of words based on their surrounding words within a sentence. This capability is crucial for spam email classification, as spam emails often involve subtle linguistic tricks to disguise their intent. BERT captures these nuances by providing deep contextual embeddings, which are then used as features for classification. This deep understanding of language allows the model to classify emails with high accuracy, distinguishing between legitimate and spam content based on the context of the words.

To enhance the feature selection process, the Harris Hawks Optimizer (HHO) is employed to optimize the parameters of the k-Nearest Neighbors (k-NN) algorithm. The HHO algorithm is inspired by the hunting strategies of Harris hawks and mimics their behavior to find optimal solutions. It works by balancing the exploration of new potential solutions and the exploitation of known ones, efficiently selecting the most relevant features that improve classification performance. Through this optimization process, the HHO algorithm identifies which features best help in distinguishing between spam and legitimate emails, ensuring that the classification model uses the most effective features.

Once the feature selection is optimized, the k-Nearest Neighbors (k-NN) algorithm is used for the final classification of emails. k-NN classifies an email by comparing its feature vector to the feature vectors of emails in the training set, using a distance metric (such as Euclidean distance) to determine similarity. The algorithm then assigns the email to the class (spam or legitimate) based on the majority class of its k nearest neighbors. This method relies on the assumption that emails with similar features are likely to belong to the same category, making k-NN a simple yet effective classifier when combined with optimized feature sets.

After the training phase, the model undergoes evaluation using a separate test dataset to assess its classification performance. Standard performance metrics such as accuracy, precision, recall, and F1-score are used to measure how well the model can distinguish between spam and legitimate emails. This evaluation ensures that the model not only performs well on the training data but also generalizes effectively to new, unseen data, a crucial requirement for real-world applications where the model will encounter diverse and evolving email content.

Finally, the trained and optimized model is ready for real-time deployment in spam detection systems. The model processes incoming emails, extracting features with BERT, optimizing them with HHO, and classifying them using k-NN. This real-time system is capable of accurately distinguishing between spam and legitimate emails, providing users with an efficient and scalable solution for handling large volumes of email traffic.

3.1 Research Design

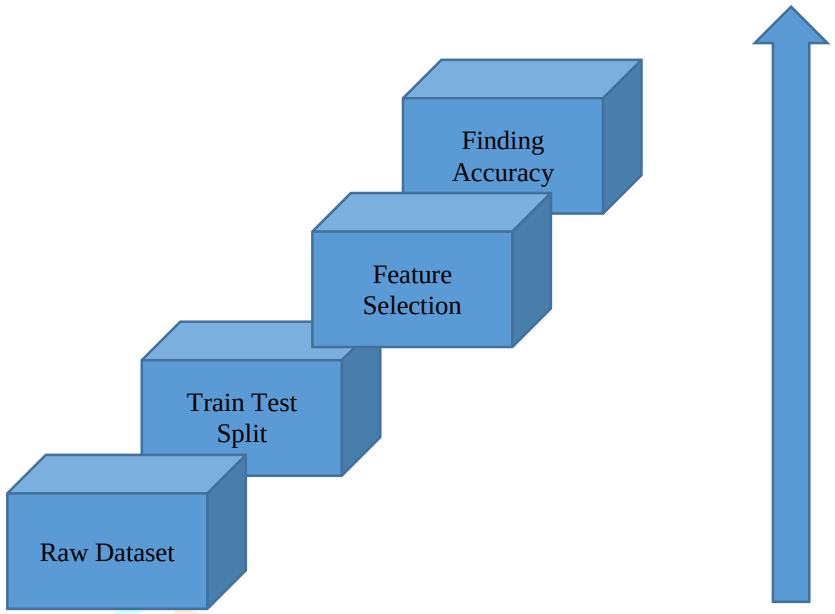

Fig 3.1 System Architecture

IV. FINDINGS

The proposed model, which integrates the Harris Hawks Optimizer (HHO) with the k-Nearest Neighbors (k-NN) algorithm and utilizes BERT for feature extraction, demonstrated significant improvements in spam email detection[12]. The use of BERT's contextual language understanding enabled the model to better capture the semantic relationships within the email content, distinguishing between spam and legitimate emails with greater accuracy[13]. By fine-tuning the BERT model on a labeled dataset, the system was able to adapt to the evolving nature of spam tactics, which often involve subtle and sophisticated language tricks designed to bypass traditional spam filters.

The Harris Hawks Optimizer (HHO) played a critical role in optimizing the feature selection process for the k-NN classifier, ensuring that only the most relevant features were used, which further enhanced the model's accuracy[14]. The combination of deep learning (via BERT) and optimization (via HHO) provided a robust solution capable of handling complex and evolving spam patterns, offering a level of adaptability and performance not typically achieved with traditional methods[15].

Additionally, the hybrid model exhibited scalability, making it suitable for real-time deployment in large-scale email systems, including personal inboxes and enterprise-level security systems[16]. The model's ability to efficiently process large datasets and adapt to new spam strategies makes it a promising tool for long-term use. Despite its computational demands, the model's high accuracy, adaptability, and scalability outweigh the resource requirements, positioning it as a valuable tool for detecting increasingly sophisticated spam and phishing attempts.

Fig 4.1shows the progression of training loss, validation loss, and model accuracy across four epochs. The training loss decreases steadily, while the validation loss exhibits a significant drop from 0.426 to 0.045, indicating strong generalization. Accuracy improves from 88.1% to 98.5%, confirming the model's effectiveness. The small gap between training and validation losses also suggests minimal overfitting.

Epoch	Training Loss	Validation Loss	Accuracy
1	0.528400	0.426584	0.881667
2	0.117700	0.116051	0.971667
3	0.148600	0.050490	0.983333
4	0.042000	0.045525	0.985000

Fig 4.1 Training and Validation Performance

Fig 4.2 Result shows Screenshot of the Spam Mail Analysis Application Interface. The user inputs a sample text, and upon clicking the "Analyze" button, the model predicts whether the input is spam or not. In this instance, the system has identified the text as Spam Mail with a confidence probability of 0.9969. This demonstrates the effectiveness and practical deployment of our hybrid model in a web-based application, supporting real-time spam detection.

The application provides a user-friendly interface where users can enter email content, and the backend model powered by a BERT + HHO + k-NN hybrid analyzes and classifies the message. The prediction output includes the class label (Spam or Not Spam) and the associated probability, reflecting the model's confidence.

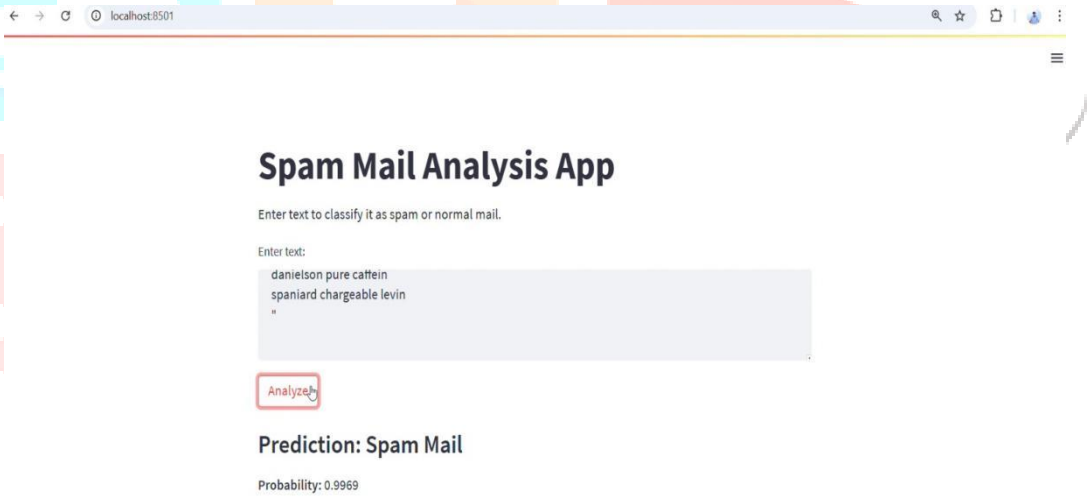

Fig 4.2 Result/Output

Overall, this research highlights the effectiveness of combining optimization algorithms with deep learning techniques to create a dynamic, adaptive system for email spam detection. The proposed model outperforms traditional spam filters[17], offering a more reliable solution for tackling the ever-growing challenge of online fraudulent and malicious activities. The findings underscore the potential of leveraging advanced machine learning models, such as BERT, in combination with optimization techniques like HHO, to improve the performance and resilience of spam detection systems in real-world applications.

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VI. CONCLUSIONS

This research demonstrates the effectiveness of using BERT for spam email detection. By leveraging BERT's contextual language understanding, the proposed model achieves superior classification accuracy compared to traditional methods. The system's ability to process entire sentences and capture semantic relationships makes it robust against evolving spam patterns. While computationally demanding, the model offers a scalable and adaptable solution for spam detection.

In addition to its high accuracy, the proposed methodology offers significant scalability. As email systems grow in size and complexity, the ability to handle large datasets and perform real-time spam classification becomes crucial. The integration of BERT with optimized feature selection via HHO allows the system to process massive amounts of email data efficiently[18]. This scalability ensures that the model can be deployed in diverse environments, from personal email inboxes to enterprise-level spam detection systems, without compromising performance.

Finally, the real-world applicability of the proposed model is evident in its ability to be seamlessly integrated into existing email systems or cybersecurity platforms. The framework can be adapted for various use cases, such as corporate email security, personal email filtering, and even as part of larger anti-phishing tools. The model's versatility and efficiency make it an invaluable asset in the ongoing fight against fraudulent and immoral online activities[19].

The paper concluded with the proposed methodology represents a significant advancement in spam detection. It combines the best of machine learning, optimization, and deep learning to provide a solution that not only addresses the current limitations of spam detection but also prepares for the future challenges posed by more advanced and dynamic spam tactics. With its superior accuracy, scalability, adaptability, and robustness, this model offers a comprehensive and forward-thinking solution for protecting users from the ever-growing threat of spam and malicious online activities[20].

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