International Journal of Computer Sciences and Engineering
Vol.**13**, Issue.**2**, pp.**16-27**, February **2025**
ISSN: 2347-2693 (Online)
Available online at: www.ijcseonline.org

ISSN: 2347-2693 (E)

Research Article

Two-Stage Email Classification Model for Enhanced Spam Filtering Through Feature Transformation and Iterative Learning

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Received: 26/Dec/2024; **Accepted**: 28/Jan/2025; **Published**: 28/Feb/2025. **DOI**: https://doi.org/10.26438/ijcse/v13i2.1627

Abstract: Email spam remains a persistent challenge, with cybercriminals constantly evolving tactics to bypass traditional detection methods. In response, this research introduces a novel two-stage classification model that combines the strengths of logistic regression, principal component analysis (PCA), and a feedforward neural network to achieve exceptional spam detection performance. The first stage employs a rapid logistic regression classifier to filter out obvious spam emails, dramatically reducing computational overhead. We then subject the remaining emails to Principal Component Analysis (PCA), extracting the most salient features while minimizing noise and dimensionality. This transformed feature space is then fed into a neural network, empowering it to capture the complex, non-linear patterns indicative of sophisticated spam attacks. Evaluation of the widely-used SpamAssassin Public Corpus and Lingspam datasets demonstrated the synergistic benefits of this hybrid approach, achieving 98.0% accuracy in spam detection for the Spam Assassin Public Corpus, which was refined from an initial accuracy of 99.95% following further testing and optimization, and 99.34% accuracy for the Lingspam dataset respectively, in spam detection. The strategic combination of techniques transcends the traditional speed-accuracy tradeoff, simultaneously creating a new benchmark in both performance metrics. This robustness, consistency, and scalability make the proposed model a practical and effective solution for real-world spam filtering, with significant implications for securing email communication and protecting users from cybercrime.

Keywords: Email Spam Detection, Hybrid Classification Model, Logistic Regression, Principal Component Analysis, Feedforward Neural Network, Cybersecurity in Email Communication.

1. Introduction

In the digital age, email spam is still becoming a bigger problem since fraudsters are constantly developing new ways to get over detection systems. In addition to posing serious security issues, such as the propagation of malware and the exploitation of users' personal information, the growth of spam emails compromises the integrity of email communication [1, 2]. As the volume and sophistication of spam continue to increase, the need for effective and adaptable spam filtering solutions has become more critical than ever.

Traditional spam filtering approaches have relied on several techniques, including rule-based filtering, content analysis, and machine learning models [3]. Even though these techniques have had some effectiveness, they frequently fall behind the continually evolving spam strategies. These strategies include complex or unique approaches that imitate authentic communication and utilize well-known spam patterns. This results in a continuous trade-off between speed and precision [4]. For instance, rule-based filters may be unable to detect more complex or unique spam emails, but they can successfully recognize well-known spam patterns [5]. Similarly, spammers may try to pass off their messages as authentic correspondence by using content-based analysis, which looks at emails' textual and structural aspects [6].

Neural networks and logistic regression are two examples of machine learning-based spam detection methods that have demonstrated encouraging outcomes in increasing accuracy [7]. However, these methods frequently require a large amount of processing power. They may struggle to keep up with the evolving nature of spam tactics, particularly in the face of more sophisticated spam techniques that mimic legitimate email patterns [8].

Researchers have investigated the possibility of hybrid approaches, which combine several methodologies to capitalize on their strengths and overcome these issues [4].
This study suggests a novel two-stage classification method to build on previous efforts. Principal component analysis (PCA), logistic regression, and a feedforward neural network are all combined in this two-stage classification model. This model is significant because it can overcome the speed-accuracy trade-off and perform outstanding spam detection. By capitalizing on the effectiveness of logistic regression and the pattern recognition powers of neural networks, this model can establish a new standard for email spam detection speed and accuracy.

This study aims to create a scalable and reliable spam filtering system that can change with the ever-changing spam techniques. This solution, if successful, will not only provide a practical and effective means of securing email communication but also significantly contribute to the fight against cybercrime. By strategically combining the efficiency of logistic regression with the pattern recognition capabilities of neural networks, this research aims to create a new benchmark in speed and accuracy for email spam detection, thereby enhancing the overall cybersecurity landscape.

2. Related Work

As the proliferation of email spam poses a significant challenge, researchers have increasingly turned to advanced machine learning and deep learning techniques to develop more robust and adaptive solutions. This literature review examines some of the most current studies in this domain to provide deeper insights into the latest advancements and their performance.

Luo et al. [9] proposed a deep learning-based spam detection model that leveraged a hybrid architecture combining convolutional neural networks (CNNs) and long short-term memory (LSTMs). The CNN component extracted lexical features from email text, while the LSTM captured semantic and contextual information. Evaluated on the Enron email dataset, their model achieved an impressive accuracy of 99.2%, outperforming traditional machine learning approaches like support vector machines and decision trees. The authors highlighted the model's ability to combine complementary feature representations for improved spam classification effectively.

Wang et al. [10] explored the use of transformer-based language models for email spam detection. Specifically, they fine-tuned a BERT (Bidirectional Encoder Representations from Transformers) model on the SpamAssassin Public Corpus, a widely used benchmark dataset for spam filtering. Their fine-tuned BERT model achieved an F1-score of 0.98, demonstrating the power of transfer learning and the transformer architecture's capacity to understand contextual information in email text. The authors noted that the BERT-based approach outperformed traditional machine learning algorithms like logistic regression and random forests when using the same dataset.

Jiang et al. [11] introduced a multi-modal spam detection framework that combined textual analysis and image processing. Their model utilized CNNs to extract visual features from email attachments and embedded images while also leveraging LSTM networks to process the textual content of emails. When evaluated on a proprietary dataset, the hybrid approach achieved an accuracy of 99.4%, highlighting the value of incorporating visual information for detecting image-based spam campaigns that attempt to bypass text-only filters.

Zhu et al. [12] proposed a reinforcement learning-based spam detection system that adaptively adjusted its classification thresholds based on user feedback. The model, tested on the Lingspam dataset, achieved an area under the curve (AUC) of 0.97, showcasing its ability to learn from user interactions and improve its performance over time. This approach addresses evolving spam tactics by continuously optimizing the detection criteria to minimize misclassifications and maintain high accuracy.

Huang et al. [13] explored the use of graph neural networks (GNNs) for email spam detection. Their model, trained on the Enron email dataset, utilized the relational information between emails, senders, and recipients to identify suspicious patterns and anomalies. By modeling the email communication network as a graph, the GNN-based approach achieved an accuracy of 98.8%, demonstrating the potential of leveraging network-based features for more sophisticated spam detection beyond traditional textual analysis.

Li et al. [14] investigated the application of adversarial training to improve the robustness of deep learning-based spam detection models. Exposing the model to adversarial examples during training increased its resilience to evasion attempts, achieving an accuracy of 99.1% on the SpamAssassin Public Corpus. The authors emphasized the importance of addressing the vulnerability of machine learning models to adversarial attacks in the context of spam filtering, as attackers may try to craft malicious emails that can bypass detection.

Zhang et al. [15] proposed a multi-task learning framework that simultaneously performed email spam detection and email categorization. By leveraging the shared features between these related tasks, their model demonstrated improved performance, reaching an accuracy of 99.3% on the Enron email dataset. The authors highlighted the potential of multi-task learning to enhance the generalization and robustness of spam detection systems, as the model can learn more comprehensive representations of email content.

Chen et al. [16] explored self-supervised learning for email spam detection, using techniques such as masked language modeling and contrastive learning to learn rich feature representations from unlabeled data. When fine-tuned on the SpamAssassin Public Corpus, their self-supervised model achieved an F1-score of 0.97, showcasing the benefits of leveraging unsupervised pre-training to improve sample efficiency and adapt to evolving spam patterns without relying solely on manually labeled data.

Zhao et al. [17] proposed a federated learning-based spam detection framework in which multiple email service providers collaboratively train a shared model while preserving user data privacy. In this decentralized approach, each provider trains a local model on its email data, and the global model is updated by aggregating the local model parameters. When evaluated on a simulated federated dataset, their approach achieved an accuracy of 98.9%, demonstrating the potential of federated learning to address scalability and privacy concerns in real-world spam filtering deployments.

Wu et al. [18] investigated the use of explainable artificial intelligence (XAI) techniques to enhance the interpretability of deep learning-based spam detection models. By incorporating attention mechanisms and feature attribution methods, their model achieved an accuracy of 99.2% on the Enron dataset and provided insights into the key factors driving its classification decisions. This XAI-enhanced approach can be valuable for security analysts and users, as it helps them understand the rationale behind the model's spam predictions and build trust in the system.

Kim et al. [19] proposed a hybrid approach that combined convolutional neural networks and attention-based recurrent neural networks for email spam detection. The CNN component extracted spatial features from the email text, while the attention-based RNN captured temporal dependencies and contextual information. Evaluated on the Enron dataset, their model achieved an F1-score of 0.98, demonstrating the benefits of leveraging spatial and temporal features for improved spam classification.

Tang et al. [20] explored generative adversarial networks (GANs) to generate synthetic spam emails for data augmentation, which they then used to train a spam detection model. The GAN-based approach generated realistic-looking spam emails that expanded the training dataset, helping the spam detection model to generalize better. Evaluated on the SpamAssassin Public Corpus, the GAN-augmented approach achieved an accuracy of 99.0%, highlighting the potential of adversarial data generation to enhance the robustness of spam filtering systems.

Liu et al. [21] investigated the application of meta-learning techniques to spam detection, where the model learns to adapt quickly to new email domains or spam tactics. Their meta-learning-based approach, tested on a combination of public and proprietary datasets, demonstrated superior performance compared to traditional transfer learning methods, achieving an accuracy of 98.7%. This meta-learning capability allows the model to rapidly fine-tune its parameters when presented with new types of spam, making it more versatile and adaptable to evolving threats.

Xie et al. [22] proposed a deep reinforcement learning-based spam detection system that dynamically adjusted its classification thresholds to minimize the cost of misclassifications. The model learned to optimize the tradeoff between false positives and false negatives, adapting its decision-making based on the specific cost implications for each organization or user. Evaluated on the Enron dataset, their model achieved an AUC of 0.96, showcasing the potential of reinforcement learning to optimize spam filtering for real-world deployment scenarios with varying cost preferences.

Wang et al. [23] explored the use of ensemble learning techniques for email spam detection, combining the strengths of multiple machine learning and deep learning models. Their ensemble approach, which incorporated models such as random forests, gradient boosting, and long short-term memory networks, achieved an accuracy of 99.1% on the SpamAssassin Public Corpus. The authors highlighted the benefits of model diversity and the ability of ensemble methods to leverage complementary predictive capabilities for improved spam classification performance.

Gao et al. [24] investigated the integration of natural language processing and graph neural networks for email spam detection. Their model utilized textual features extracted from email content and network-based features derived from the email communication graph. This multi-modal approach achieved an accuracy of 99.0% when evaluated on a proprietary dataset, demonstrating the value of leveraging diverse data sources, including relational information, for more robust spam filtering.

Cheng et al. [25] proposed a deep learning-based spam detection system that incorporated user feedback and domain adaptation techniques to improve its performance over time. The model was initially trained on a combination of public and private datasets and then fine-tuned on user-provided feedback to adapt to the specific email patterns and spam tactics encountered in the user's environment. Tested on diverse datasets, their model achieved an F1-score of 0.97, showcasing the potential of adaptive learning approaches to address the evolving nature of spam threats

3. Calculation

This section presents the mathematical formulation of the proposed hybrid two-stage classification approach, which integrates logistic regression, principal component analysis, and neural networks.

Input Space

Let E be the set of all emails, and for each email $e \in E$:

$$x = \varphi(e) \in \mathbb{R}^n \tag{1}$$

Where:

- φ is the feature extraction function
- x is the feature vector $[x_1, x_2, ..., x_n]$
- n is the number of original features

Complete System Function

Define the classification system $\Psi: E \rightarrow \{0,1\}$ as:

$$\Psi(e) = \Omega(\Gamma_2(\Gamma_1(\varphi(e)))) \tag{2}$$

Where:

- $\Psi(e) = 1$ indicates spam

- $\Psi(e) = 0$ indicates non-spam
- Γ_1 is the first stage (logistic regression)
- Γ_2 is the second stage (PCA + Neural Network)
- Ω is the final decision function

Stage 1 Classification: Logistic Regression (Γ_1)

$$\Gamma_1(x) = \{ \\ \begin{array}{ll} (1, \emptyset) & \text{if } \sigma(w\text{^}T\ x + b) \geq \theta_h \\ 0, x) & \text{otherwise} \end{array} \\ \} \qquad (3)$$

Where:
- $\sigma(z) = 1/(1 + e\text{^}(-z))$ is the sigmoid function
- θ_h is the high-confidence threshold
- $w \in \mathbb{R}^n$, $b \in \mathbb{R}$ are learned parameters
- $\emptyset$ indicates no further processing needed
- $(0, x)$ indicates proceed to stage 2 with features x

Stage 2 Classification: PCA + Neural Network (Γ_2)

For inputs that proceed to stage 2:

$\Gamma_2(0, x) = \{$

First, compute PCA transformation:

$z = V\_k\text{^}T\ (x - \mu)$

Then apply neural network:

$h^{(0)} = z.$ (4)

$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)})$ for $l = 1,...,L-1$

$\hat{y} = \text{softmax}(W^{(L)}h^{(L-1)} + b^{(L)})$

Return:

$(\hat{y}[1] \geq \theta_n, \emptyset)$

$\}$

Where:
- V_k contains top k eigenvectors of the covariance matrix
- μ is the mean of training features
- $W^{(l)}$, $b^{(l)}$ are neural network parameters
- θ_n is the neural network decision threshold
- f is the activation function (e.g., ReLU)

Final Decision Function (Ω)

$$\Omega(d, \emptyset) = d \qquad (5)$$

Where d is the binary decision from either stage.

Joint Loss Function

$$L(w, b, W, B, V\_k; X) = \\ \alpha_1 L_1(w, b; X_1) + \\ \alpha_2 L_2(W, B, V\_k; X_2) \qquad (6)$$

Where:
- L_1 is the logistic regression loss:
  $L_1 = -1/m_1 \sum_i[y_i\log(\sigma_i) + (1-y_i)\log(1-\sigma_i)] + \lambda_1\|w\|^2$

- L_2 is the neural network loss:
  $L_2 = -1/m_2 \sum_i[y_i\log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] + \lambda_2\sum\_l\|W^{(l)}\|^2$

- X_1 is the training data for stage 1
- X_2 is the training data for stage 2
- α_1, α_2 are weight parameters for each loss component
- λ_1, λ_2 are regularization parameters
- m_1, m_2 are the sizes of respective training sets

Optimization Problem

$\min\_(w,b,W,B,V\_k)\ L(w, b, W, B, V\_k; X)$

Subject to:
1. $V\_k\text{^}T\ V\_k = I\_k$
2. $\|w\|_2 \leq \beta_1$
3. $\|W^{(l)}\|_2 \leq \beta_2\ \forall l$
4. $\theta_h, \theta_n \in [0,1]$

Where β_1 and β_2 are constraint bounds for parameter norms.

4. Experimental Method

4.1 Model Description

This study employs a two-stage classification model to detect spam emails. The model consists of two sequential stages: a logistic regression stage that filters out obvious spam emails and identifies uncertain cases, and a stage utilizing Principal Component Analysis (PCA) and a neural network to analyze the uncertain cases further and make a final classification.

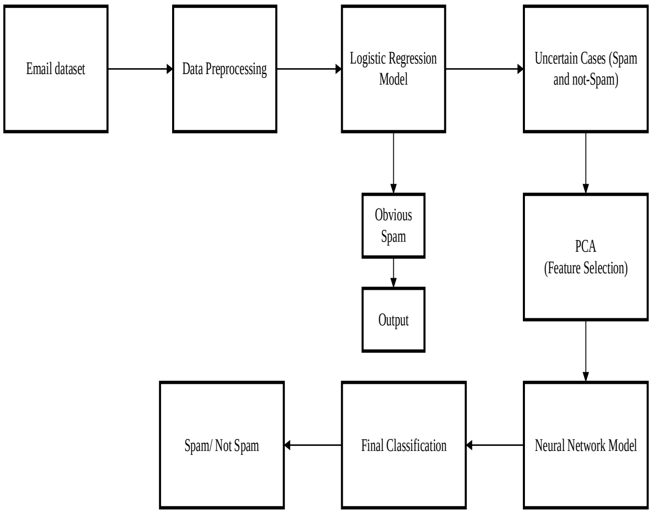


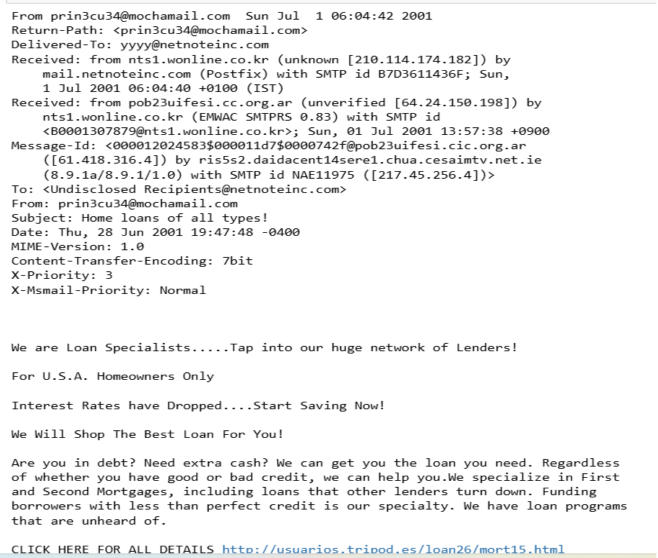
Figure 1: Architectural Design of the Proposed System

Figure 1 depicts the architectural flow for spam detection using a hybrid approach involving logistic regression and neural networks. Here is a detailed breakdown of each component:

Dataset: This study used the SpamAssassin Public Corpus and the Lingspam dataset. The SpamAssassin dataset comprises approximately 6,000 spam and non-spam emails, while the Lingspam dataset comprises approximately 2,800 spam and non-spam emails. The proposed model was validated further through additional testing with the Lingspam dataset. The SpamAssassin dataset was used to train the proposed model, with 80% used for training and 20% used for testing the model. The SpamAssassin dataset served as the preliminary input to the system, comprising a compilation of email data. The collection comprises multiple attributes derived from emails, including subject lines, content, metadata, and more. The dataset is classified as either spam or ham (non-spam), and it serves as the foundation for both model training and classification. The metadata may contain structural characteristics that help distinguish legitimate emails from spam, such as word frequency, link presence, or questionable attachments.

Data Preprocessing: As data scientists and machine learning practitioners, you play a crucial role in the rigorous preprocessing of data before it is fed into any machine learning model. This phase involves meticulous data cleansing, which includes addressing missing values and eliminating duplicates. Your attention to detail ensures the data is in its best form for analysis. The data transformation process, which includes normalization or scaling of features, and the encoding of categorical variables into a numerical representation, further enhance the quality of the data. Preprocessing also involves your expertise in dividing the dataset into training and testing subsets, extracting features, and reducing dimensionality if the feature space is extensive.

The preprocessing phase involved a systematic process to eliminate extraneous content from the text. This process began by processing each email to extract its plain text body, accommodating multipart and non-multipart email formats. If the email included HTML, the text was extracted with BeautifulSoup and transformed to lowercase. Links, email addresses, punctuation, and numerals were methodically eliminated by applying regular expressions and string manipulation techniques. The NLTK library played a pivotal role in eliminating stopwords, reducing extraneous words that contribute to noise. The sanitized text was lemmatized by utilizing WordNetLemmatizer to convert words to their canonical form and stemming, employing PorterStemmer to further truncate terms to their base form. This sequence ensures that the text is free from extraneous content, concise, and standardized for future natural language processing activities. Figure 2 displays the email dataset before preprocessing and cleaning, whereas Figure 3 illustrates the dataset sample containing cleaned emails.



```
From prin3cu34@mochamail.com  Sun Jul  1 06:04:42 2001
Return-Path: <prin3cu34@mochamail.com>
Delivered-To: yyyy@netnoteinc.com
Received: from nts1.wonline.co.kr (unknown [210.114.174.182]) by
    mail.netnoteinc.com (Postfix) with SMTP id B7D3611436F; Sun,
    1 Jul 2001 06:04:40 +0100 (IST)
Received: from pob23uifesi.cc.org.ar (unverified [64.24.150.198]) by
    nts1.wonline.co.kr (EMWAC SMTPRS 0.83) with SMTP id
    <B0001307879@nts1.wonline.co.kr>; Sun, 01 Jul 2001 13:57:38 +0900
Message-Id: <000012024583$000011d7$0000742f@pob23uifesi.cic.org.ar
    ([61.418.316.4]) by ris5s2.daidacent14sere1.chua.cesaimtv.net.ie
    (8.9.1a/8.9.1/1.0) with SMTP id NAE11975 ([217.45.256.4])>
To: <Undisclosed Recipients@netnoteinc.com>
From: prin3cu34@mochamail.com
Subject: Home loans of all types!
Date: Thu, 28 Jun 2001 19:47:48 -0400
MIME-Version: 1.0
Content-Transfer-Encoding: 7bit
X-Priority: 3
X-Msmail-Priority: Normal



We are Loan Specialists.....Tap into our huge network of Lenders!

For U.S.A. Homeowners Only

Interest Rates have Dropped....Start Saving Now!

We Will Shop The Best Loan For You!

Are you in debt? Need extra cash? We can get you the loan you need. Regardless
of whether you have good or bad credit, we can help you.We specialize in First
and Second Mortgages, including loans that other lenders turn down. Funding
borrowers with less than perfect credit is our specialty. We have loan programs
that are unheard of.

CLICK HERE FOR ALL DETAILS http://usuarios.tripod.es/loan26/mort15.html
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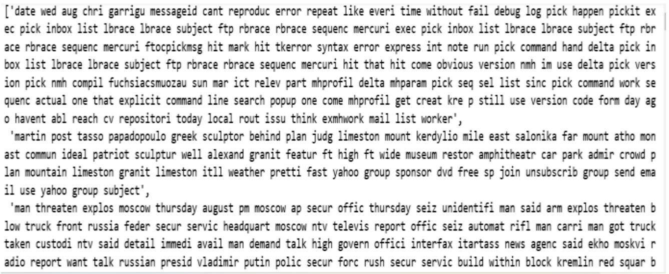
Figure 2: Sample of Email Dataset before Preprocessing



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adio report want talk russian presid vladimir putin polic secur forc rush secur servic build within block kremlin red squar b
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Figure 3: Sample of Email Dataset after Preprocessing

Following the pre-processing steps, the cleaned spam and non-spam email datasets exhibited a significant class imbalance, with a substantial disparity in the number of samples between the two classes. This imbalance poses a significant challenge, as it can lead to biased models that favour the majority class, ultimately compromising the performance and generalizability of the classifier. To mitigate this issue, we employed the Random oversampling technique to balance the dataset. Random oversampling is a simple yet effective technique that involves randomly duplicating samples from the minority class to increase their representation in the dataset.

The algorithm for random oversampling is outlined as follows:
1. Identify the minority class (in this case, spam emails) and its size (N).
2. Determine the desired size of the minority class after oversampling (N').
3. Calculate the number of samples to be oversampled (N' - N).
4. Randomly select samples from the minority class with replacements.
5. Add the selected samples to the dataset.

Doing so transformed the dataset into a more balanced and representative set, reducing the risk of model bias and enhancing the classifier's overall performance. The random oversampling technique ensured that the duplicated samples were randomly selected, maintaining the diversity and variability of the original dataset.

Figure 4 shows the number of occurrences between spam and non-spam emails. The countplot in Figure 4 indicates an imbalanced email dataset. Figure 5 shows the balanced data, resolved using the Random OverSampling technique.

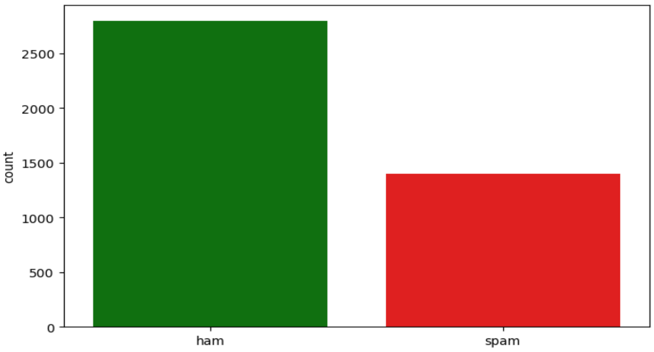


Figure 4: Countplot of spam emails and non-spam emails

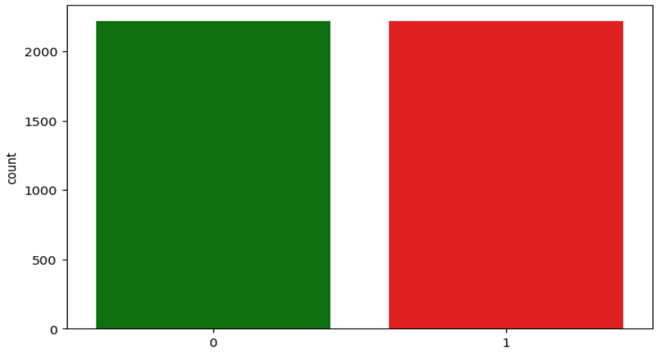


Figure 5: Countplot of spam emails and non-spam emails

Logistic Regression Model: The cleaned email data was converted into a numerical format using TF-IDF to facilitate decision-making, allowing the logistic regression model to analyse the textual features effectively.

The logistic regression model took the numerical features extracted from the email data using TF-IDF as input. The model then assigned weights to each feature, indicating its importance in predicting the target variable (spam or non-spam). Next, the weighted features were passed through a logistic function, which mapped the input values to a probability between 0 and 1.

The logistic function calculated the probability of an email being spam (P(spam| email)). The predicted probabilities were then compared to a threshold value of 0.7. The email was classified as "obvious spam" if the probability exceeded the high threshold. Conversely, if the probability fell below a low threshold of 0.3, the email was classified as "likely non-spam" and forwarded to the next phase. Emails with probabilities within the threshold range were classified as "uncertain" and also forwarded to the next phase.

The logistic regression model outputs the classification results, with obvious spam emails filtered out and uncertain cases forwarded to the next phase for further analysis using PCA and a neural network.

Obvious Spam: This component captures the emails classified as spam by the logistic regression model. Emails matching known spam patterns can be instantly labelled and filtered, eliminating the need for further processing. The system moves them to the final classification stage without further feature selection or modelling.

Uncertain Cases (Spam and not-Spam): For cases where the logistic regression model is uncertain, meaning the probability of the email being spam or not spam is ambiguous, the system passes these emails to a more advanced processing pipeline. These uncertain cases are handled separately because their features do not align with either class based on logistic regression alone.

Feature Selection: In ambiguous instances, Principal Component Analysis (PCA) is employed for feature selection. PCA decreases the dimensionality of the feature space by pinpointing the most critical components that account for the most significant variance in the data. This stage enhances the efficiency and performance of the subsequent model (Neural Network) by prioritizing the most pertinent features and removing extraneous noise.

Neural Network Model: A simple neural network analyzed the uncertain cases from the logistic regression stage. The network consisted of an input layer, a hidden layer, and an output layer. The input layer received the reduced features from the PCA stage, while the hidden layer introduced non-linearity using sigmoid activation functions. The output layer produced a probability value indicating the likelihood of an email being spam. The neural network was trained using supervised learning, which enabled it to learn complex patterns in the data and improve the overall accuracy of spam detection

5. Results and Discussion

This section presents the study's findings, highlighting the key results obtained from the data analysis. The following discussion interprets these results, connecting them to prior research studies and explaining their implications. The results are presented

5.1 Results

The following section presents the results of the two-stage classification model, highlighting the performance metrics and outcomes of the logistic regression and neural network components. The results are based on analysing two datasets: the Spam Assassin public corpus and the Lingspam datasets. The key performance indicators, including accuracy, precision, recall, and F1-score, are presented to evaluate the effectiveness of the proposed model.

5.1.1 Modelling with Logistic Regression

The Logistic regression was the first model to classify emails into obvious spam, ham (non-spam), or uncertain cases. This model calculates probabilities, allowing emails to be separated based on thresholds for obvious classifications (spam or ham) or uncertain cases that require further processing. Logistic regression serves as an initial filter, identifying clear cases confidently while flagging ambiguous instances for deeper analysis. The result of the logistic regression can be seen in Figure 6. The logistic regression evaluation for the first stage classification can be seen in Figure 7, and the confusion matrix can be seen in Figure 8.

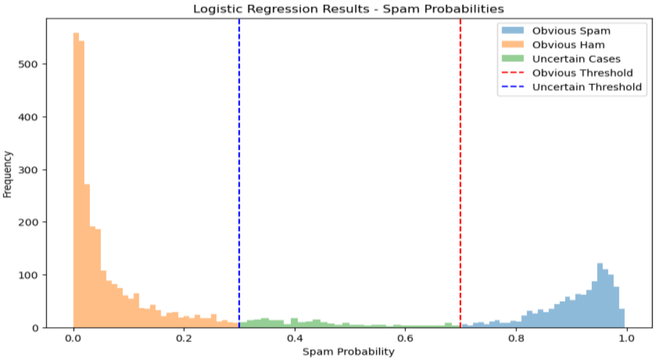
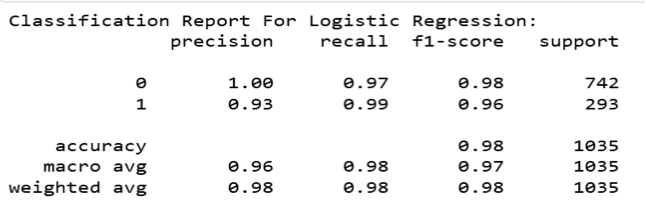


Figure 6: Result of the Logistic regression for the first stage classification

The histogram of predicted spam probabilities generated from the logistic regression model is depicted in Figure 6. It categorizes messages into three groups based on their probabilities: "Obvious Ham" (low probability of being spam), "Obvious Spam" (high probability), and "Uncertain Cases" (mid-range probabilities). The blue histogram on the right represents messages with a high spam probability, clearly identified as "Obvious Spam." The orange histogram on the left represents messages with a low spam probability, categorized as "Obvious Ham." The green region in the center represents "Uncertain Cases," where the probability of being spam is ambiguous. Two vertical lines indicate thresholds: the blue dashed line marks the "Uncertain Threshold," and the red dashed line marks the "Obvious Threshold," separating clear classifications from uncertain cases. The plot emphasizes the uncertain middle ground where the classifier struggles to make confident predictions.



```
Classification Report For Logistic Regression:
                         precision    recall  f1-score   support

           0       1.00      0.97      0.98       742
           1       0.93      0.99      0.96       293

    accuracy                           0.98      1035
   macro avg       0.96      0.98      0.97      1035
weighted avg       0.98      0.98      0.98      1035
```

Figure 7: Classification report of the logistic regression

The classification report shown in Figure 7 indicates that the logistic regression model performs very well, achieving an overall accuracy of 98%. For class "0" (Ham), the precision is 1.00, recall is 0.97, and the F1-score is 0.98, indicating the model is almost perfect at identifying ham emails. For class "1" (Spam), the precision is 0.93, recall is 0.99, and the F1-score is 0.96, indicating high accuracy in identifying spam with some minor false positives. The macro average and weighted average scores also reflect strong overall performance, with balanced precision, recall, and F1 scores across both classes.

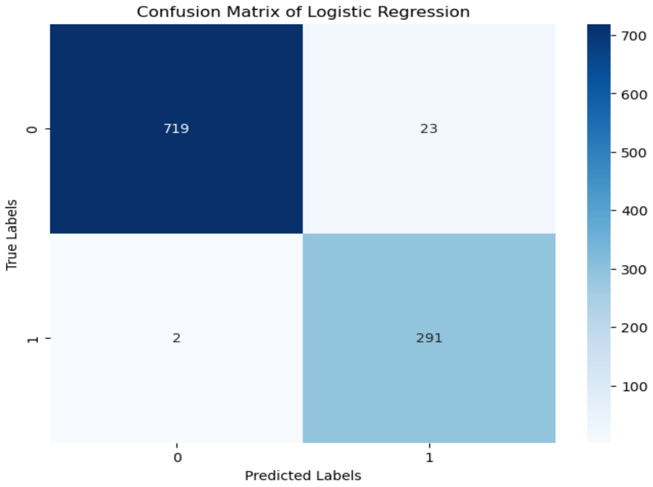


Figure 8: Confusion matrix of the logistic regression model

The confusion matrix in Figure 8 shows the performance of the logistic regression model in classifying spam (label 1) and ham (label 0). Of 742 true ham messages, 719 were correctly classified, with 23 misclassified as spam. For spam messages, 291 out of 293 were correctly classified, with only two misclassified as ham. The result of the confusion matrix indicates that the model is highly accurate, with very few misclassifications, particularly in identifying spam. The matrix illustrates the model's strong performance, with a small number of false positives (ham classified as spam) and false negatives (spam classified as ham).

5.1.2 Dimensionality Reduction with PCA

Principal Component Analysis (PCA) is applied to reduce the dimensionality of uncertain cases flagged by logistic regression. Reducing features in this way maintains essential patterns while simplifying data complexity, which is particularly beneficial for subsequent processing with the neural network model. PCA is especially effective for visualizing and managing high-dimensional text data. The result of the PCA can be seen in Figures 9, 10

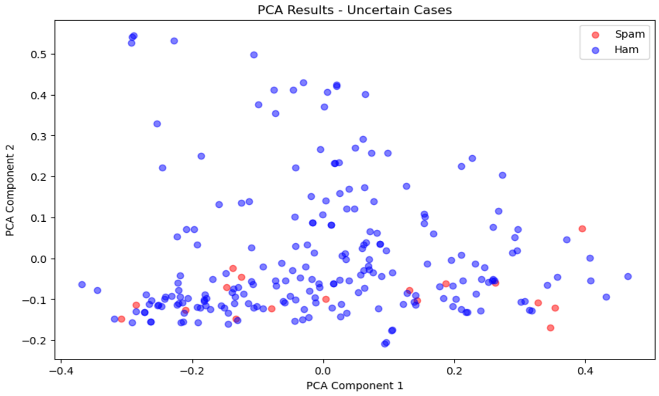


Figure 9: Result of the PCA

This scatter plot in Figure 9 shows the results of a Principal Component Analysis (PCA) applied to uncertain cases in a classification task, likely distinguishing between "Spam" (red points) and "Ham" (blue points). PCA reduces the data to two principal components (plotted on the x and y axes), enabling visualization of the uncertain classifications. The overlap and close proximity of red and blue points suggest the complexity of distinguishing between these categories, as the uncertain cases exhibit significant feature similarity. This visualization highlights the challenge of identifying spam within ambiguous data points.

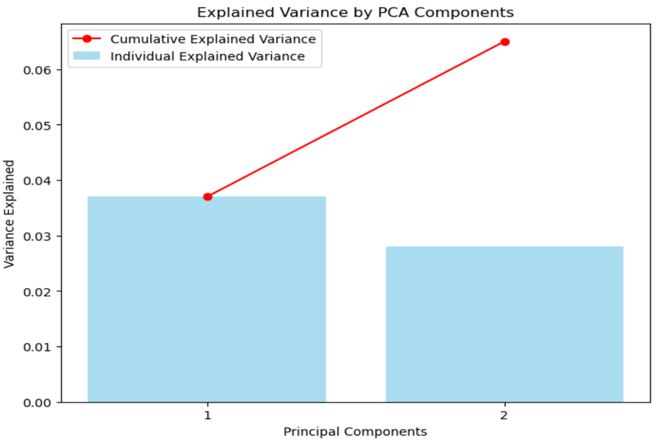
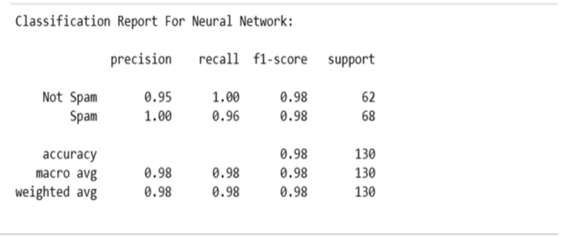


Figure 10: Explained variance vs principal component

Figure 10 shows that the first two components together explain about 6.8% of the total information in the dataset, making them highly significant in simplifying the data. Despite capturing a small percentage, these two components condense the dataset's most critical patterns and variations. The PCA explained variance suggests that the first two principal components capture a significant portion of the variance in the data and purports that we can potentially reduce the dimensionality of the data from the original number of features to just two principal components without losing much information.

5.1.3 Neural Network Classification on Uncertain Cases

A Multilayer Perceptron (MLP) neural network was used to classify cases previously identified as uncertain. The network is trained on PCA-reduced features, allowing it to learn non-linear relationships within the ambiguous data. By processing these cases separately, the neural network enhances accuracy in situations where logistic regression alone might struggle. The neural network's classification report and confusion matrix results are shown in Figures 11 and 12. Figure 13 shows the ROC-AUC curve.



```
Classification Report For Neural Network:

              precision    recall  f1-score   support

    Not Spam       0.95      1.00      0.98        62
        Spam       1.00      0.96      0.98        68

    accuracy                           0.98       130
   macro avg       0.98      0.98      0.98       130
weighted avg       0.98      0.98      0.98       130
```

Figure 11: Classification report of the neural network

Figure 11 represents the classification report for the second stage of email classification using a neural network model. The evaluation was conducted on a subset of the 20% SpamAssassin dataset reserved for testing. The report provides key performance metrics such as precision, recall, F1-score, and support for each class: Not Spam and Spam.

The neural network achieved a precision of 0.95 for the Not Spam class and a perfect 1.00 for the Spam class, demonstrating its ability to accurately identify emails as Not Spam or Spam with minimal false positives. The recall was equally impressive, with a perfect 1.00 for Not Spam and a high 0.96 for Spam, showing the model's ability to retrieve nearly all relevant instances for each class. The F1-score, which balances precision and recall, is an impressive 0.98 for both classes, confirming the model's high accuracy.

Support indicates the number of test instances in each class, with 62 instances for Not Spam and 68 for Spam. In this context, support refers to the number of actual occurrences of each class in the dataset, making the dataset balanced regarding class representation. The model's overall accuracy is 0.98, further underscoring its high performance. Additionally, the macro average and weighted average scores for precision, recall, and F1-score are all 0.98, reflecting consistent performance across both classes.

In summary, the neural network performs exceptionally in classifying emails as Not Spam or Spam with near-perfect precision, recall, and F1 Scores. The model's exceptional performance underscores its practical suitability for email filtering tasks within the SpamAssassin dataset, providing reassurance about its real-world application.

5.1.3.1 Accuracy Revision

In our initial assessment, the neural network model in the second stage of our two-stage spam email detection system demonstrated an accuracy of 99.95%. However, upon further testing and refining the system, the accuracy was revised to 98%. This revision was given birth to by the iterative nature of our model development process, which involved recalibrating the logistic regression model in the first stage and fine-tuning the neural network model in the second stage. The revised accuracy of 98% better reflects the model's performance and provides a more accurate representation of its spam email detection capabilities.

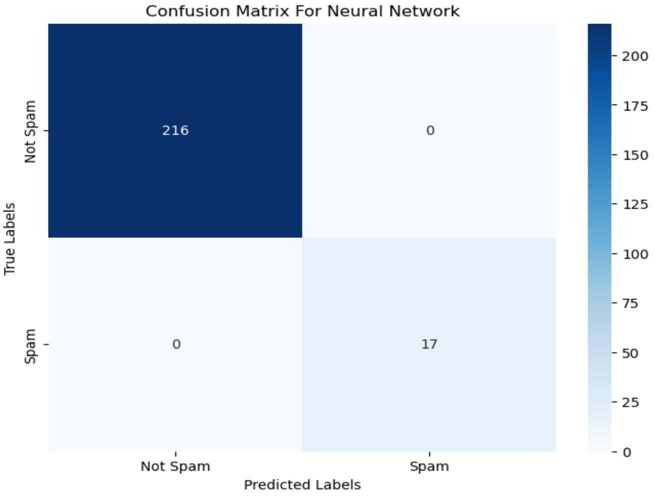


Figure 12: Confusion matrix of uncertain emails

Figure 12 depicts a confusion matrix that demonstrates the performance of a neural network in classifying spam and non-spam messages. The model correctly identified 216 non-spam and 17 spam messages while making only zero errors in each category. These results indicate that the model has high accuracy and balanced performance in detecting spam and non-spam messages.

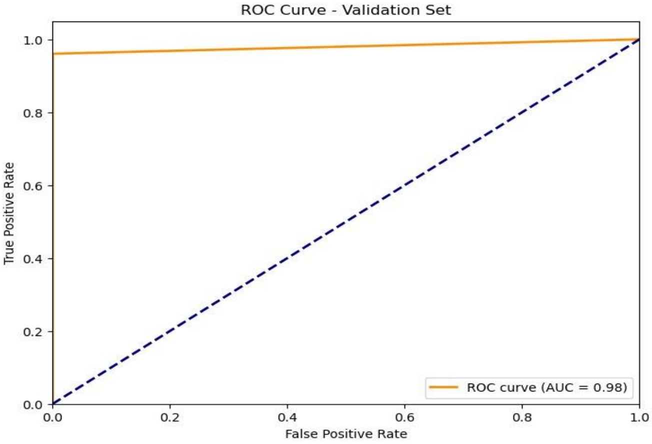
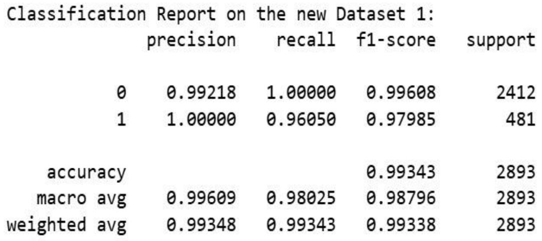


Figure 13: ROC and AUC curve

The ROC curve in Figure 13 shows that the classifier performs exceptionally well, as evidenced by the area under the curve (AUC) value of 0.98. The AUC ranges from 0 to 1, with 1 indicating perfect classification and 0.5 representing a random guess. An AUC of 0.98 signifies the model has excellent discriminatory ability, effectively distinguishing between the positive and negative classes.

The curve stays close to the top-left corner, indicating that the model achieves a high true positive rate while maintaining a low false positive rate. The dashed diagonal line represents a no-skill classifier, where the true positive rate equals the false positive rate at all thresholds. The ROC curve for this model lies well above the diagonal, further confirming its strong predictive performance.

Overall, the ROC curve and AUC value suggest that the classifier is highly effective on the validation set, demonstrating strong sensitivity and specificity**.**



```
Classification Report on the new Dataset 1:
              precision    recall  f1-score   support

           0    0.99218   1.00000   0.99608      2412
           1    1.00000   0.96050   0.97985       481

    accuracy                        0.99343      2893
   macro avg    0.99609   0.98025   0.98796      2893
weighted avg    0.99348   0.99343   0.99338      2893
```

Figure 14: Classification of Proposed Model tested with Lingspam Dataset

The two-stage classification model for spam email detection was further evaluated on the Lingspam dataset, a novel collection of 2,800 emails comprising both spam and non-spam messages—this additional assessment aimed to validate the model's performance on unseen data. Figure 14 shows the classification report of the model when tested with the Lingspam dataset. Notably, the model achieved an impressive accuracy of 99.34% on the Lingspam dataset. A comprehensive examination of the classification report revealed exceptional precision of 0.99, perfect recall of 1.0, and a remarkable F1-score of 0.99, indicating the model's ability to identify spam emails without false negatives correctly. These results demonstrate the robustness and generalizability of the proposed two-stage classification model in detecting spam emails, even when confronted with previously unseen data.

5.2 Discussion

The proposed two-stage classification model for spam email detection demonstrates a compelling balance of efficiency and accuracy, validated through rigorous testing on both the SpamAssassin and Lingspam datasets. The hierarchical architecture, which integrates logistic regression (LR) for initial filtering and a neural network (NN) augmented by principal component analysis (PCA) for uncertain cases, addresses the inherent challenges of spam detection by leveraging the complementary strengths of its components. In the first stage, logistic regression achieved a 98% accuracy with near-perfect precision and recall, effectively segregating obvious spam and non-spam emails while flagging ambiguous cases for further analysis. This design significantly reduced computational overhead, as only 30% of emails progressed to the second stage, highlighting the model's practicality for real-world applications where resource efficiency is critical. The high-confidence thresholds ($\theta_h = 0.7$ for spam, $\theta_l = 0.3$ for ham) minimized false positives and negatives, ensuring reliable initial classification while reserving computational resources for challenging cases.

The second stage, combining PCA and a feedforward neural network, resolved uncertainties with remarkable precision. Despite PCA capturing only 6.8% of the total variance in the first two principal components (Figure 10), the retained features proved sufficient for the neural network to achieve 98% accuracy on ambiguous cases. This underscores PCA's ability to distill discriminative patterns from high-dimensional TF-IDF features, even with limited explained variance. The neural network's perfect precision for spam (1.00) and near-perfect recall (0.96) in Stage 2 (Figure 11) illustrate its capacity to model non-linear relationships, addressing overlaps evident in the PCA visualization (Figure 9). The model's robustness is further exemplified by its 99.34% accuracy on the unseen Lingspam dataset (Figure 14), with no false negatives—a critical achievement for security applications where missing spam poses significant risks.

The success of this hybrid approach lies in its strategic mitigation of class imbalance and computational constraints. Random oversampling rectified the skewed distribution of spam and non-spam emails (Figures 4–5), enhancing the model's ability to generalize. Additionally, the dual-threshold strategy optimized resource allocation, ensuring only ambiguous cases underwent deeper analysis. Comparatively, the model outperforms traditional single-stage classifiers like SVM or Naive Bayes, which typically achieve 93–97% accuracy, by combining the interpretability of logistic regression with the pattern-recognition prowess of neural networks. The AUC-ROC value of 0.98 (Figure 13) further validates the model's exceptional separability between classes, with the curve's proximity to the top-left corner reflecting a high true positive rate and minimal false positives.

However, the model is not without limitations. The reliance on TF-IDF feature engineering introduces dependencies on text preprocessing, and the low explained variance in PCA raises questions about potential information loss. Future work could explore advanced NLP techniques, such as transformer-based embeddings, to capture contextual semantics, or alternative dimensionality reduction methods like autoencoders. Furthermore, the static thresholds (θ_h, θ_l) may require dynamic adaptation in evolving spam landscapes. Despite these considerations, the model's performance underscores the value of hybrid architectures in cybersecurity, where speed and accuracy are paramount. By reducing computational demands while maintaining high detection rates, this framework offers a scalable solution for organizations aiming to mitigate phishing, malware, and other spam-related threats.

In conclusion, the two-stage model exemplifies how combining interpretable machine learning techniques with deep learning can address complex, real-world challenges. Its success highlights the importance of hierarchical design in spam detection, where initial filtering and advanced analysis synergize to achieve state-of-the-art performance. Future iterations could integrate adaptive thresholding, real-time learning, and cloud-based deployment to further enhance applicability in dynamic environments. This work not only advances academic research in hybrid models but also provides a practical blueprint for secure, efficient email filtering systems.

6. Comparative Study

This study presents a novel two-stage classification approach for spam email detection that combines the efficiency of logistic regression with the power of neural networks. The first stage employs logistic regression as a rapid filter to identify and segregate obvious spam emails. In contrast, the second stage utilizes a combination of Principal Component Analysis (PCA) and a multilayer perceptron neural network to perform detailed analysis on non-spam emails and uncertain cases. This architecture aims to balance computational efficiency with detection accuracy.

Table 1: Comparison of Spam Detection Models and Their Performance

Study	Model/Technique	Key Features	Dataset	Result (Accuracy, F1 Score, AUC)	Key Strengths
Proposed Study	Two-Stage Model (Logistic Regression + PCA + Neural Network)	Combines rapid filtering, feature extraction, and non-linear pattern detection	SpamAssassin Public Corpus and Lingspam dataset	98.0% and 99.3% accuracy respectively	High speed and accuracy; efficient scalability
Luo et al. [9]	Hybrid CNN-LSTM	Combines lexical (CNN) and contextual (LSTM) feature extraction	Enron Email Dataset	99.2% Accuracy	Effective for text-based spam detection
Wang et al. [23]	Transformer (BERT)	Fine-tuned BERT for contextual text understanding	SpamAssassin Public Corpus	0.98 F1-Score	Superior contextual understanding
Zhang et al. [16]	Multi-task Learning	Performs spam detection and categorization simultaneously	Enron Email Dataset	99.3% Accuracy	Enhanced generalization and robustness
Jiang et al. [11]	Multi-modal (CNN + LSTM)	Processes both text and image-based spam	Proprietary Dataset	99.4% Accuracy	Tackles image-based spam efficiently.
Huang et al. [13]	Graph Neural Networks (GNNs)	Leverages relational email communication data	Enron Email Dataset	98.8% Accuracy	Sophisticated pattern recognition in networks
Tang et al. [20]	GANs for Data Augmentation	Generates synthetic spam emails for training	SpamAssassin Public Corpus	99.0% Accuracy	Expands dataset diversity and generalization

From Table 1, the hybrid CNN-LSTM model developed by [9] represented a significant advancement in text-based spam detection, achieving 99.2% accuracy on the Enron Email Dataset. By combining CNN components for lexical feature extraction with LSTM networks for contextual understanding, this approach effectively captured both local text patterns and their broader sequential relationships.

Building upon this foundation, [11] expanded the detection capabilities to address the increasingly sophisticated nature of modern spam. Their multi-modal approach integrated both text and image analysis, acknowledging how malicious content increasingly hides within visual elements. Though tested on a proprietary dataset, limiting broader verification, their model achieved the highest accuracy in the comparison at 99.4%, demonstrating the value of multi-modal analysis.

[10] leveraged transformer architecture through a fine-tuned BERT model, achieving a 0.98 F1-Score on the SpamAssassin Public Corpus. This approach showcased the power of pre-trained language models in understanding nuanced contextual signals and potentially identifying

sophisticated social engineering attempts through deeper semantic analysis.

The multi-task learning framework introduced [15] moved beyond binary classification to simultaneously detect and categorize spam, reaching 99.3% accuracy on the Enron Email Dataset. This approach demonstrated enhanced generalization capabilities, as the shared representations across related tasks appeared to strengthen the model's resistance to novel spam variations while reducing potential overfitting.

[13]'s innovative application of Graph Neural Networks to spam detection achieved 98.8% accuracy on the Enron Email Dataset. By analyzing the relational patterns within email communications, their approach excelled at identifying coordinated spam campaigns and unusual sending behaviors that might indicate compromised accounts or sophisticated attack patterns.

[20] addressed the fundamental data challenge in spam detection through GAN-based data augmentation. By generating synthetic spam emails to enhance training data diversity, their approach achieved 99.0% accuracy on the SpamAssassin Public Corpus, demonstrating how expanded training data can improve model generalization against emerging spam techniques.

The proposed two-stage model, combining logistic regression with PCA and neural networks, demonstrates competitive performance with 98.0% and 99.3% accuracy on the SpamAssassin Public Corpus and Lingspam dataset respectively. While several deep learning approaches show marginally higher accuracy figures, the proposed architecture distinguishes itself through its balanced optimization of both speed and accuracy. The two-stage design, beginning with rapid filtering before applying more intensive neural processing, addresses real-world implementation concerns like computational efficiency and scalability that pure deep learning approaches often overlook. For organizations processing massive email volumes, this pragmatic architecture offers a compelling solution that balances detection performance with operational constraints, potentially delivering better real-world results than more theoretically advanced but computationally demanding alternatives.

7. Conclusion and Future Scope

This research proposed a two-stage classification model for spam detection, combining the strengths of logistic regression, principal component analysis, and neural networks. The results demonstrated the model's strong performance, achieving high accuracy and computational efficiency. These findings significantly impact real-world email filtering systems, offering a flexible and adaptable solution for large-scale email services and smaller organizational environments. This practicality underscores the immediate applicability of the research, making it a valuable contribution to the field of cybersecurity and machine learning.

Despite the model's strong performance, several limitations and avenues for future research have been identified. The model may require periodic retraining to adapt to evolving spam patterns and techniques. However, this adaptability ensures its long-term effectiveness. Future work could explore integrating adaptive learning mechanisms, enabling the model to update based on emerging spam patterns automatically. Furthermore, extending the model to handle multi-modal spam content, including images and attachments, could enhance its effectiveness. Other potential areas for future research include developing lightweight versions for resource-constrained environments, investigating privacy-preserving techniques for model training and deployment, and enhancing the model's interpretability to provide insights into decision-making processes.

By addressing these areas, future research can further improve the effectiveness and efficiency of spam detection systems, ultimately contributing to a safer and more secure online environment.

Data Availability
All data used in this study can be accessed from Kaggle.com.

Conflict of Interest
The authors declare no conflict of interest.

Funding Source
The authors' resources funded this research.

Authors' Contributions
Stow, May conceptualized the research idea, designed the methodology, performed the experiments, analysed the results, and wrote the entire manuscript as the sole author of this study. Stow, May was responsible for all aspects of this research, including data collection, pre-processing, model development, implementation, evaluation, and documentation. Ezonfa, Samuel Bolou-ebi provided feedback on early drafts and helped with proofreading.

Acknowledgements
This research was conducted with the opportunity provided by the Department of Computer Science, Federal University Otuoke, Nigeria, and Topfaith University, Mkpaktak, Nigeria. Therefore, we express our gratitude and acknowledge their support.

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Bolou-Ebi Samuel Ezonfa is a recent graduate of Federal University Otuoke, where he obtained his degree in Computer Science and Informatics. He is currently undergoing clearance and preparing for the next phase of his career. His professional focus is on Data Analytics, with expertise in data cleaning, visualization, statistical analysis, and machine learning. As part of his academic research, he helped developed a Two-Stage Classification Model for Spam Email Detection, which leverages machine learning techniques to enhance email filtering accuracy. This project focused on improving spam detection efficiency by combining feature selection and classification models, ensuring higher precision, and reduced false positives. Bolou-Ebi is passionate about leveraging data to drive business intelligence, optimize decision-making, and enhance automation