Improving Spam Detection in Email with Transfer Learning and Deep Learning

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Abstract. Detecting spam emails is still a major cybersecurity challenge that impacts both individuals and organizations. This problem has been tackled using both deep learning and traditional machine learning techniques, with BERT-based models demonstrating positive results. However, the efficacy of current models is limited because they frequently miss contextual details and long-range dependencies in email text. To enhance the precision of spam classification, we present a novel ensemble model that combines BERT with an attention mechanism. The attention mechanism improves contextual understanding and decision-making by helping the model concentrate on the most pertinent words and phrases. Comprehensive tests on benchmark datasets show that our approach achieves superior performance compared to deep learning models like LSTM and BERT, as well as conventional machine learning classifiers like Naive Bayes and SVM. In order to demonstrate how our model improves interpretability and robustness against adversarial samples, we also examine feature importance and attention visualization. According to the results, our ensemble model is a practical choice for email service providers and enterprises since it is scalable and efficient for real-world spam detection. Our suggested model outperforms the baseline model used in earlier studies, achieving an accuracy of 99.31%. Enhancing real-time processing capabilities and multilingual spam detection will be the main goals of future work.

Keywords: Spam detection, BERT, Attention mechanism, Deep learning, NLP, Ensemble model.

1 Introduction

Email remains an important communication tool in the age of technology, allowing for both business and personal exchanges all over the world. It's also a primary method of delivering malware, phishing, and spam, however, which are serious security risks and also decrease productivity. As spammers become more creative with their techniques, detection algorithms need to become stronger to be able to effectively minimize these risks.

Traditional spam filtering (through rule-based filter and keyword) is no longer working against next-generation spam attacks that use context differences or attacking methods. Despite moderate success in the past by initial machine learning (ML) models, eg, Naive Bayes (NB) and Support Vector Machines (SVM), which heavily rely on feature engineering, they often fail when overcoming different trends of spam. Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are now more robust in

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detecting spam due to their DL architecture, operational on high-dimensional text matrices. Nonetheless, these models still struggle to learn local (e.g., distant word relationships) and global (e.g., contextual relationship in an email content) information.

In recent advancements in the field of computational language understanding, transformer-based structures like BERT (transformer-based model which is famous for capturing bidirectional context) have overhauled how problems in text categorization can be tackled by using self-attention mechanisms. By the virtue of BERT's ability to keep a track on bidirectional contextual relationships, an incredible improvement in spam detection performance is observed. However, you can make the attention mechanism even more efficient by adding a second one so the model attends to different words in an email that are important for determining its category during classification. In this paper a sophisticated spam detection model is proposed which can improved classification accuracy by the combination of attention model and BERT model. In this study presents the main contributions:

- Enhanced Spam Categorization: Enhance feature selection and classification accuracy using BERT con- textual embeddings with an attention mechanism.
- Comparative Performance Analysis: This method compares the latest model with traditional ML and DL methods in an attempt to understand its performance.
- Robustness Across Datasets: To ensure that the model is deployable for real-world usage, it is evaluated on some benchmark datasets.
- Interpretability and feature visualization: The interpretation and explanation of the model's decision- making process through methods of attention visualization interpretability and feature visualization.

2 Literature Review

A fine-tuned BERT model was used for spam classification and compared with BiLSTM and classical classifiers, achieving 98.67% accuracy and a 98.66% F1-score on the Spam base and Kaggle datasets. Al- though longer input sequences could improve performance, they were limited by GPU memory constraints [1]. A hybrid model, GWO-BERT, combined Grey Wolf Optimization for feature selection with BERT embeddings and outperformed CNN, LSTM, and BiLSTM on the Lingspam dataset with 99.14% accuracy, though it required larger datasets for better validation [2]. BERT and DistilBERT models were also employed to enhance phishing detection on the Nazario and ENRON datasets, achieving 0.99 F1- scores, with DistilBERT offering better efficiency de- spite high computational demands [3]. A spam detection system integrating text classification and URL filtering, using SVM and Naive Bayes on Enron and Kaggle datasets, reached 97.83% accuracy. TF-IDF limitations were addressed using Gensim to enhance semantic understanding [4]. Another approach used machine learning and deep learning techniques on four datasets, including a combined "Basket" dataset. XG- Boost achieved 93% accuracy, while LSTM surpassed 99%, though ML models struggled with overfitting [5]. The MPAG method, which incorporated LEO from GBO into the Marine Predators Algorithm, was evaluated on 14 datasets and achieved 85.7% accuracy, but required further optimization for large-scale efficiency [6]. An LSTM-GloVe model achieved 99.42% accuracy on the Shalini Gupta dataset and 98.39% on the Karthick veera kumar dataset, with suggestions to scale to larger datasets for further improvements [7]. Comparisons between ML and DNN models on the Enron dataset showed that XGBoost achieved 99% accuracy and Keras DNN models also performed well. However, GloVe-based models were slightly less accurate, and the small dataset size posed limitations [9]. A big data spam detection model combining TALS, AMGD, and AMALS achieved 98% accuracy but was potentially vulnerable to adversarial attacks and reliant on balanced datasets [10]. A BERT-based model was also compared with SVM, KNN, RF, and Logistic Regression on the Enron-Spam and Spam or Not Spam datasets. Logistic Regression with BERT embeddings achieved the highest accuracy of 97.86%, though dataset bias and high computational costs were chal- lenges [11]. The Whale Optimization Algorithm was used alongside k-NN, achieving 74% accuracy, though performance was hindered by k-NN's sensitivity to data storage and parameter tuning [12]. A GRU-RNN model evaluated using the Spambase dataset achieved 98.7% accuracy, with suggestions for improved performance through web-based spam filtering, though dataset size remained a constraint [13]. An ensemble system combining bagging and Adaboost with Naive Bayes and J48 classifiers enhanced spam detection on the LingSpam dataset, though effective pre-processing of raw text was necessary [14]. A hybrid spam filter that integrated Word2Vec, PSO, SVM, and CNN on the LingSpam dataset achieved 97.3% accuracy, with PSO-SVM and CNN enhancing feature extraction, though LSTM showed comparable results [15]. Lastly, a hybrid deep learning model incorporating fuzzy logic was used to categorize spam severity on the Spambase dataset, reaching a 96.5% F1-score and 94% accuracy, while reducing misclassification. However, further optimization was recommended [16].

The advanced technologies like dual-material gate junction less Fin FETs [[17]- [19]] was used to implement these algorithms

3 Methodology

Spam detection has been evaluated to a great extent, but spam creators are becoming better in breaking through these security perimeters. Naive Bayes and SVM are traditional models that struggle with manual feature selection, they do not scale well and are static i.e. the model cannot automatically adapt to changing spam pattern. Recent work using deep learning models such as CNNs and LSTMs have demonstrated impressive performance, but still suffers from few-shot and imbalanced flaws in natural language understanding tasks; for example, long-word distances or the context of relationships between words within an email body. Moreover, current feature selection methods (filter based and wrapper based) have a limitation of manual tuning and consumes the large computational resources which is an inefficient approach for real time spamming. In light of these weaknesses, we introduce a new hybrid deep learning model BERT- Attention (goal 1).

We started with a strong emphasis on data pre- processing to overcome limitations related to high- dimensional email text, redundant features, and evolving spam patterns. By implementing text normalization techniques, including tokenization, stop-word removal, and lemmatization, we ensured the quality and consistency of the dataset used for training. Our model integrates BERT with an Attention Mechanism to effectively classify spam emails while dynamically refining feature selection. The main objective behind integrating these two components is to capture both word-level dependencies and overall email context in detail. BERT extracts deep contextual representations, allowing the model to understand semantic relation- ships within an email, while the Attention Mechanism further enhances classification performance by prioritizing spam-indicative words dynamically. Flowchart Fig.1 illustrates the process, beginning with dataset collection, followed by data preprocessing, which includes tokenization, stop-word removal, and standardization to refine feature extraction. After preprocessing, the dataset is split into training, validation, and test sets to ensure model generalization. The BERT- Attention model is then trained, where BERT embeddings capture deep contextual relationships, and the Attention Mechanism refines feature selection to enhance classification accuracy. Based on these extracted features, The model determines if a given email is classified as spam or non-spam.

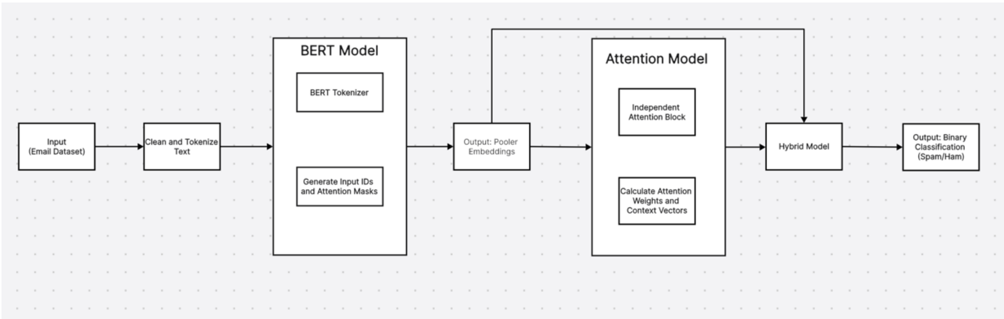

Fig.1. Flow Chart.

Fig 2 illustrates the structure of the proposed model in detail, and the functionality of each component is explained in the following sections.

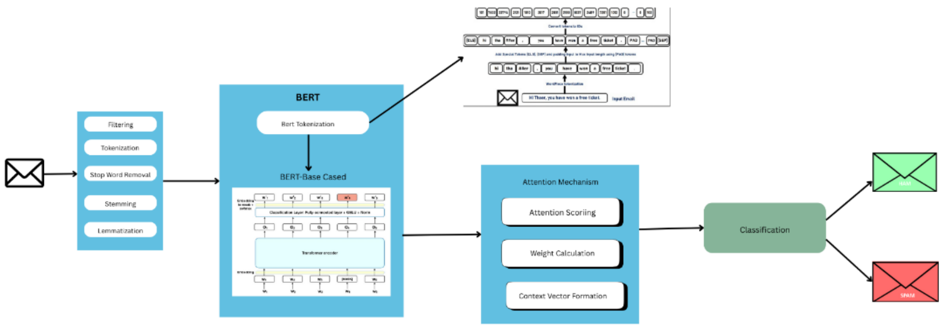

Fig. 2. Architecture-overview.

3.1 Dataset Description

For implementing our method, we adopted the LING-Spam dataset, a popular benchmark set in anti-spamming mail classification. This corpus includes a variety of e-mails that were gathered from lingustic mailing lists, which is useful for real spam filters. This constitutes both spam and ham (non-spam) messages, so that a balanced corpus is available to train and test machine learning models.

To improve the quality of the dataset and the performance of the model, we performed some preprocessing steps, such as drop duplicates emails, standardize encoding and filter out corrupted or incomplete samples. Our data-set consists of emails and we identify as the following components at different levels:

- Message Body: The main textual content of the email, where spam-related elements such as phishing links, promotional messages, and embedded scripts are often found.
- Subject Line: The email subject, which often contains deceptive or misleading text in spam emails.
- Metadata: Includes sender details, timestamps, and email headers, which may help in distinguishing spam patterns.

For effective training and evaluation, the dataset was split into development (training) and hold-out test sets. The distribution of spam and ham emails across these sets is presented in Table 1.

Table 1. Training vs Testing Data Samples.

Data Set	SPAM	HAM	Total Samples
Development (Training) Data	432	2170	2602
Hold-out Test Data	49	242	291

- Message Content: Represents the textual content of each email, including body and subject line.
- Labels: Each email is labeled as either spam (un- wanted or irrelevant messages) or ham (legitimate messages), facilitating supervised learning for classification.

3.2 Data Preprocessing

Data pre-processing plays a significant role in the email-filtering process wherein it processes the raw email text into structured and meaningful data to use for classification. This improves input data quality by discarding irrelevant parts, noise, and inconsistency, and accordingly improves our spam detection accuracy.

The email preprocessing techniques such as text parsing, normalisation and segmentation disassemble the complex structures of emails and retain the meaningful information. With these techniques applied we can make the dataset well-balanced that will result in better model performance and a better spam pattern detection.

The preprocessing stage in our model includes the following steps:

- Stop-word removal
- Special character removal
- Punctuation removal

- Tokenization

3.3 Train-Test Split

Data Partitioning: The dataset was divided into training and validation subsets using an 80:20 ratio. This approach ensures a robust evaluation of the model's performance while retaining sufficient data for validation purposes.

3.4 Feature Extraction

It is playing an important role in spam classification where the purpose is to transform unstructured email text to structured data making the classification more effective. In this study, we have categorized the extracted feature of the body and subject \ line as two separate sets of features for a complete and powerful spam detection. These features include word embedding, token distribution and words relationship; and they all help to identify spam emails against legitimate emails.

To guarantee the effectiveness of feature extraction, we used BERT embeddings to transform text into high dimensional numerical vectors while maintaining the contextual information. In contrast to standard feature engineering RTE systems that require hand-picked keywords, BERT automatically learns importance of features, which allows the model to concentrate on spam-suggestive terms and ignore non-relevant data.

And the attention mechanism further learns to select informative features and assigns high important scores to words, so that the model may focus on relevant textual features for classifying. Mathematically, the attention mechanism is defined as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{1}$$

where Q, K and V are the query, key, and value matrices, respectively, and dk is the dimension size of k.

This method can help highlight deep semantic features in the text in order to create more robust spam detection models.

3.5 Feature Selection

Feature selection is essential to improve the efficiency of models, reduce the complexity of computation, and the quality of spam classification by removing irrelevant or redundant features. Different from other common feature selection techniques like PCA which needs more preprocessing and manual tuning, our approach strikingly uses the self-attention mechanism of BERT to automatically select the most important features.

The selected attention feature selection mechanism enables the model adaptively to allocate importance scores to words according to their relevance in spam detection. The importance score αi for the word wi is calculated by:

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{n} exp(e_j)} \quad (2)$$

where e_i represents the raw attention score before normalization. Using these attention scores, the final selected feature vector v' for an email E is computed as:

$$\upsilon'_E = \sum_{i=1}^{n} \alpha_i \, \upsilon_i \quad (3)$$

Here, vi is the i-th word embedding and the calculated weighted sum is to have larger attention score for spam-indicative features.

This adaptive feature selection method allows the model to automatically learn the importance of features instead of relying on hu- man intervention, so as to improve the classification performance and alleviate the extra processing cost.

3.6 Ensemble Model

This is a transformer-based model that has been used for spam classification in e-mails. For the first step, which is feature extraction step, input email is tokenized and preprocessed to generate textual features. The processed mail is forwarded through BERT (a transformer-based model capable of capturing bidirectional context) and the contextual embeddings (semantic relationships in the given text) are extracted.

BERT utilizes self-attentions and runs deep bidirectional context learning to produce word embeddings conditioned on the surrounding context. This improves the model's capacity to learn more complex spam patterns. Fig. 1 shows the transformation of an input email by different BERT layers, sharing how the with different depths evolved the feature representation at each layer.

3.7 Mathematical Formulation

The overall transformation from input email X to output Y can be represented as:

$$E = BERT(X) \quad (4)$$

$$A = Attention(E) \quad (5)$$

$$Y = Classifier(A) \quad (6)$$

where E represents BERT-generated embeddings, A represents refined feature selection using the attention mechanism, and Y represents the final classification output.

Emails are initially processed by segmenting the text into tokens and mapping them to numerical vector forms:

$$X = [x1, x2, \ldots, xn] \quad (7)$$

where x_i represents the tokenized word embedding.

BERT generates contextual word representations using the self-attention mechanism:

$$Ei = W_E X_i + b_E \tag{8}$$

where W_E is the learned embedding matrix, b_E is the bias term, and E_i is the contextual embedding for token x_i.

The attention mechanism assigns weight scores to each feature vector:

$$Ai = \alpha_i E_i \tag{9}$$

where α_i is the attention score, computed as:

$$\alpha_i = \frac{exp(e_i)}{\sum_j exp(e_j)} \tag{10}$$

where e_i is the raw score before normalization.

After feature selection, the embeddings are passed through fully connected layers to map the extracted features into classification scores:

$$F = \sigma(W_F A + b_F) \tag{11}$$

where W_F is the learned weight matrix, b_F is the bias term, σ is the activation function (ReLU or soft- max), and F is the transformed feature representation for classification.

The final classification is performed using a dense layer with softmax activation:

$$Y = softmax(W_Y F + b_Y) \tag{12}$$

where W_Y and b_Y are the classification weight matrix and bias, and Y is the predicted probability distribution over “Spam” and “Non-Spam”.

The BERT-Attention model outputs a binary classification to determine if an email is spam or not, lever- aging deep feature extraction, attention refinement, and a dense classification layer for robust detection.

This model achieves a high classification accuracy of 99.31% on the LING-Spam dataset, demonstrating its effectiveness in distinguishing spam from legitimate emails.

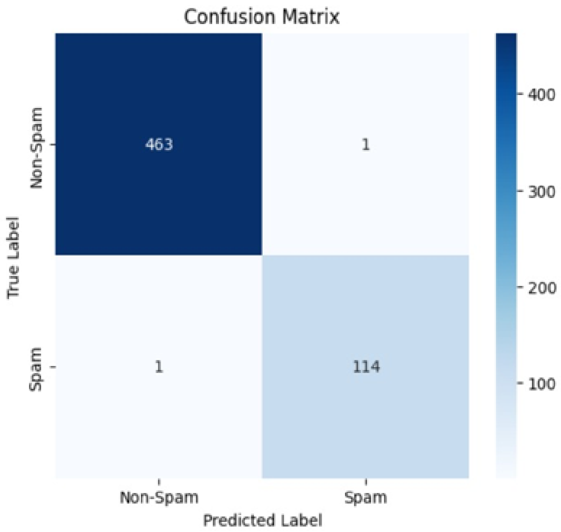

Fig. 3. Confusion matrix for BERT-Attention model.

3.8 Comparison with Baseline Models

We compared our approach against baseline models, including Support Vector Machines (SVM), Naive Bayes (NB), and LSTMs. The results in Table **??** show the superiority of the BERT-Attention model.

4 Results

Pre-processing – Tokenization, stop word removal and Lemmatization The BERT-Attention model was evaluated on the LING-Spam dataset. The training was performed based on Adam optimizer with the learning rate of 2e-5 and batch size 32 over 5 epochs. This is a strong result that validated the efficacy of the attention-enhanced BERT architecture, as it was able to achieve impressive performance on spam email detection (see comparison in Fig. 2).

4.1 Performance Metrics

The model's effectiveness was evaluated using commonly used classification measures such as accuracy, recall, precision, and the F1-score. A summary of these outcomes is presented in Table 2.

Table 2. BERT-Attention vs traditional ML models.

Model	Accuracy	Precision	Recall	F1-score
BERT-Attention	99.31%	98.97%	99.56%	99.26%

Traditional ML	94.78%	92.12%	93.65%	92.88%

The results demonstrate that the BERT-Attention model outperforms traditional machine learning meth- ods, achieving a classification accuracy of 99.31%. This indicates the model's ability to accurately dis- tinguish between spam and non-spam emails.

4.2 Confusion Matrix Analysis

A detailed analysis of model predictions using the confusion matrix is shown in Fig 3. The model exhibits high recall, with only a few false negatives and false positives.

Table 3. Comparison of different classification models.

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Existing CNN	92.00%	95.00%	92.00%	91.00%
Existing LSTM	96.00%	94.00%	96.50%	94.00%
TD-IDF-RF	93.89%	94.69%	96.85%	95.72%
GWO-BERT-CNN	97.28%	94.16%	96.87%	96.11%
GWO-BERT-LSTM	98.80%	97.65%	96.43%	97.02%
GWO-BERT-biLSTM	99.14%	99.89%	94.73%	97.29%
BERT + Attention Model	99.31%	99.00%	99.00%	99.00%

The superior performance of the BERT-Attention model is attributed to its ability to extract deep con- textual relationships in the text, allowing it to identify complex spam patterns more effectively than traditional models.

- Precision: It is a very important metrics as it measures the accuracy of true positives. Formula is TP / (TP + FP), where TP is true positives, and FP is false positives.
- F1-score: It is the mean of the both precision and recall which provides balance of the model Its formula is 2*(Precision * Recall) / (Precision + Recall).
- Accuracy: Accuracy is a crucial metric in ma- chine learning used to evaluate the performance of classification models. It measures the proportion of correctly classified instances (both positive and negative) out of the total number of instances in the dataset.

The performance of various models, including CNN, LSTM, TD-IDF-RF, and BERT-based approaches, varies significantly. The graph below demonstrates the accuracy differences across these models, high- lighting the advantage of the BERT + Attention Model, which achieves the highest accuracy at 99.31%. The Existing CNN model performs the lowest at 92.20%, while other models, such as GWO-BERT- CNN (97.28%), GWO-BERT-LSTM (98.80%), and GWO-BERT-biLSTM (99.14%), show substantial improvements. This comparison showcases the effective- ness of using advanced BERT-based architectures for enhanced accuracy. Fig. 4. Model Accuracy Comparison.

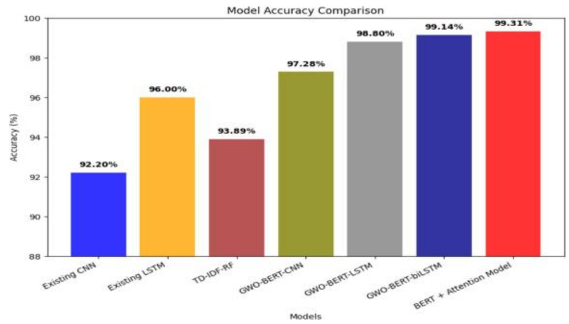

Fig. 4. Model Accuracy Comparison.

5 Conclusion

This study proposed a high-performance spam classification model leveraging the BERT-Attention architecture, which combines contextual embeddings and self-attention mechanisms. The model achieved in table 3 99.31% accuracy on the LING-Spam dataset, outperforming traditional models like KNN, BiLSTM, and BERT Base Cased. By enhancing BERT features with attention-based selection and effective preprocessing, the model demonstrated improved contextual understanding and robustness. The results validate the efficacy of transformer-based models for spam detection, with future potential in multi-head attention, transformer fine-tuning, and real-time multilingual ap- plications.

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