Comparative Analysis of Graph Attention Networks and LSTM Models for Enhanced Email Phishing Detection: An Ensemble Approach

MSc Research Project

MSc in Data Analytics

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Comparative Analysis of Graph Attention Networks and LSTM Models for Enhanced Email Phishing Detection: An Ensemble Approach

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Abstract

Phishing attacks are a serious threat in cybersecurity that manipulates the human factor to gain sensitive information. Traditional rule-based systems have failed in their detection and need intelligent methods against the evolving tactics of phishing attacks. In this paper, the use of machine learning and deep learning models was examined in detail by utilizing the SpamAssassin dataset to establish their performance. We will go over a set of different models-RF, LSTM, GRU, and GAT-comparing their performance on two axes: with and without metadata augmentation. Some of the most interesting findings from these results include how enhanced features related to metadata have proved much more powerful in enhancing the accuracy of detection. With the GRU model optimized with the right hyperparameters and metadata, we achieved almost perfect F1-score, which outperformed the text-only methods significantly. Data balancing techniques like SMOTE also perform well, since they ensure balanced class representation during the training of the models and therefore do well due to intrinsic class imbalance in phishing datasets. The results are supported by ROC curves, confusion matrices, and feature importance plots that confirm the gain in model accuracy and strength provided by our metadata integration. Further testing of the system will be done with larger datasets and hybrid models for real-time detection.

1 Introduction

The exponential growth in digital communication has brought people from all over the world a step closer, wherein they can collaborate instantly, over boundaries. All this connectivity brought the user into the active radar of cyber threats-acute phishing attacks that trick the recipient into releasing sensitive information like login credentials and financial data. As attackers work on more sophisticated methods to dupe their targets, financial and reputational consequences are becoming increasingly significant due to these attacks.

1. Evolution of Methods for Detection

The phishing attacks of today have attained a level of sophistication never seen before. These attacks are out of the league of the classic rule-based detection systems, which work based on predefined patterns and keywords. Such evolution demands dynamic solutions to keep pace with novel attack patterns. The inability of these static approaches has most strongly come to the fore with the adoption of adaptive attacker strategies and social engineering techniques that easily evade traditional detection mechanisms.

2. Metadata Enhanced Machine Learning Approach

The idea that is being put forward is adding metadata to machine learning-based models for the detection of phishing emails. Both LSTM and GRU are useful models to deal with sequences, whereas GAT complements this approach in analyzing graph representation; therefore, they examine content and context from different viewpoints. We apply SpamAssassin dataset analysis in our experiments to find how additional information like sender and time stamps can help to raise the accuracy of the detectors. This integration of metadata represents a quantum leap beyond traditional content-based analysis to give deeper insights into the behavioral pattern of phishing attacks.

3. Research Question and Objectives

The central question then is, can metadata integration improve the performances of machine learning and deep learning in phishing email detection? In this regard, this present study will compare text-only and metadata-enhanced performance, evaluate the performance by different ML and DL models, and get insights with practical value for everyday detection systems. In solving this problem, we could be said to bridge the academia-practice gap in cybersecurity defense research.

4. Overview of Methodology

Our approach embeds the metadata of senders, timestamps, and subjects into an advanced detection model. Such integration may provide an insight into phishing behavioral patterns more closely, with an improvement in the detection accuracy. It comprises extensive preprocessing, extraction of features, and then implementation of models, making sure that the content and contextual features have a robust analysis. Such a richer dataset is taken to process through the sophisticated neural architecture leveraging each model's strong point toward building a better detection.

5. Key Limitations

We used a SpamAssassin dataset for our experiments, which probably does not fully represent more novel attack strategies. The metadata quality, as well as its availability, can vary, which could also affect the performance of the models. Implementation needs awareness of the computational requirements imposed by the models. It has been enlightening nevertheless to point out future directions of research and practical uses.

6. Implications and Applications of Research

These results go a long way in promoting theoretical understanding and practical implementations of phishing detection systems. A new avenue for the development of even more robust cybersecurity solutions is thus opened by this research, proving the efficiency of integrated metadata and advanced model architectures. The insights obtained will protect organizations better against evolving phishing threats while providing a basis for future research in this critical area.

7. Structure and Organization of the Report

The study proceeds with a critical literature review of the existing methods for phishing detection and identification of areas that need improvement. The section on methodology describes in detail the procedures followed for data preprocessing, feature extraction, and model implementation. This is followed by an experimental results section, where the performances of various models are compared, along with the influence of metadata integration. These are then placed into context in the discussion section by relating these findings to previous work, suggesting future directions, and outlining practical applications through which to improve real-world phishing detection systems.

2 Related Work

Phishing detection is one of the most relevant fields of recent fast-growing research activities. Cyber-attacks have rapidly evolved for the exploitation of human factors to deceive people and organizations by pretending to be ones they rely on. As a result, phishing emails present the greatest challenge ever to rule-based phishing detection systems. LSTM, GRU, and GAT models are increasingly sophisticated neural architectures that process sequential data and graph structures, respectively, providing complementary ways to capture different aspects of phishing patterns. This review consolidates the key contributions of state-of-the-artwork, identifies critical gaps existing in current methods, and points toward proposed advancements in phishing detection.

Because modern phishing attacks are becoming increasing sophisticated, conventional detection upgrades should be done to integrate advanced machine learning approaches that depend on predefined rules, and signatures, while being adapted to emerging attack patterns extraction for complex features from email, metadata, and network modern deep learning architectures. LSTM networks function well with the sequential content of emails, while GRU models efficiently train with similar performance to LSTMs. In addition, GAT architecture leverages graph relationships between sender-receiver patterns and communication networks. These methods put together provide a sound framework for identifying ever more subtle phishing attempts which could avoid traditional detection.

8. Machine Learning and Deep Learning in Phishing Detection

ML and DL have emerged as robust solutions for phishing detection. Aljabri and Mirza in the year 2022 presented proof that the performance in deep learning models outperforms old traditional machine learning models: Logistic Regression and Random Forest. LSTMs achieved an accuracy rate of 96.5 percent against Random Forest, ranking at 92.3, as their study proved. However, their work was text based and did not include metadata addition, which can be effective to further improve the detection percentage. Similarly, Selvakumari et al. (2021) have targeted the detection of phishing websites using Random Forest and CNN; CNN produced an accuracy of 95.8%. Though their study was on websites, the methods can be applied to email phishing detection, albeit with computational overheads.

Recently, phishing detection using NLP with deep learning was performed by Benavides-Astudillo et al. (2023) using an LSTM-based architecture, which offered an impressive precision of 97.2% with a recall of 96.8%. Though the results provided seemed quite promising, most of the features dealing with metadata-aspect information about the source address and/or timestamp-were excluded; hence, the research article might have lost its importance while targeting real-world phishing scenarios.

9. Graph Attention Networks in Cybersecurity

Graph Attention Networks are novel approaches in the direction of phishing detection while modeling relationships in metadata. Authors Yağci and Aydin (2024) proposed an Event-Aware GAT model for Cyber-Physical Systems and presented its efficiency in uncovering complex dependencies. This approach can be extended for phishing detection by analyzing relations among email metadata like sender, receiver, and content.

Catal et al. (2021) used GAT for malware detection in the intelligent transportation system, demonstrating the applicability of GAT on structured data. Qin and Liao (2022) reviewed the theoretical foundation of GAT related to cybersecurity entity alignment. These works underpin that GAT can model the metadata relationship for phishing detection, even though its practical use is at its inception.

10. Sequential Models for Phishing Detection: LSTM and GRU

Sequential models, such as LSTM and GRU, have been found particularly effective for phishing detection since they are able to learn sequential dependencies in email content. Roy et al. (2022) used these models to detect phishing URLs. Among them, the Bidirectional LSTM gave an accuracy of 98.1%. These can be tuned for email phishing detection also, though this suffers from high computational overhead, which may not support real-time applications.

Remmide et al. proposed a hybrid model that used the strengths of both Bi-GRU and CNN to provide an improved result of 97.6% in accuracy and an F1 score of 97.4%. This model combined strengths from Bi-GRU on sequential data with that of CNN on local features; this increased performance at the cost of introducing complexity.

11. Ensemble Methods for Phishing Detection

The ensembling techniques are a set of different models that increase accuracy in phishing detection. Gupta et al. (2023) presented bagging, boosting, and stacking techniques and attained an accuracy of 96.9%, while at the same time reducing false positives. Basit et al. (2020) developed an ensemble technique consisting of several ML models combined into one model and attained accuracy and precision of 97.3% and 96.5%, respectively. Similarly, even though the ensembles bring robustness, their inherent high computational complexity can be a factor of poor scalability.

12. Feature Engineering at Phishing Detection

Feature engineering is the backbone in phishing detection. A combination of textual features and metadata was engaged in, showing 94.7% accuracy in the paper by Gualberto et al. They too concluded that the performance becomes higher when combining these two sets of features-text-based and metadata-based-while being able to generalize a model to up to 93.2% accuracy in its results. It goes to say that deeper research on metadata integrated with the DL model will contribute to an increase in detection rates.

13. Overview of Literature Insights

The reviewed studies bring out the important developments in phishing detection. ML models offer simplicity and interpretability, while DL models like LSTM and GRU are well suited for sequential data. GAT introduces novelty by exploiting the relationships between metadata. Ensemble methods improve robustness but introduce computational challenges. Feature engineering is still pivotal, and there is a need to combine textual and metadata features. These advantages notwithstanding, challenges remain pertaining to computational complexity, availability of metadata, and applicability in real time. Further research is required to be done to integrate metadata with deep learning models, or one may use GAT for the detection of phishing attacks.

Study	**Approach**	**Key Findings**	**Limitations**
Aljabri & Mirza (2022)	Comparison of Logistic Regression, Random Forest, and LSTM	LSTM achieved 96.5% accuracy, outperforming Random Forest (92.3%).	Lacks feature engineering, does not utilize metadata like sender details or timestamps.
Selvakumari et al. (2021)	Phishing website detection with Random Forest and CNN	CNN achieved 95.8% accuracy, superior to Random Forest (93.4%).	Focused on websites, not emails. Models are computationally expensive.
Benavides-Astudillo et al. (2023)	NLP and deep learning with LSTM	LSTM achieved precision of 97.2% and recall of 96.8%.	Relying solely on text data limits application when metadata features are significant.
Yağci & Aydin (2024)	Event-Aware GAT for cyber-physical systems	GAT effectively modeled relationships within metadata, improving phishing detection.	Lack of specific performance metrics.

Catal et al. (2021)	GAT for malware detection in transportation systems	Demonstrated GAT's ability to analyze structured data, highlighting potential applications for phishing emails.	Limited focus on email metadata relationships.
Qin & Liao (2022)	GAT for cybersecurity entity alignment	Provided theoretical background for adapting GAT to model email relationships.	No direct application to phishing detection.
Roy et al. (2022)	LSTM, Bidirectional LSTM, GRU for phishing URL detection	Bidirectional LSTM achieved 98.1% accuracy, showcasing its strength in sequential pattern detection.	High computational resource requirement, limiting runtime applicability.
Remmide et al. (2021)	Bi-GRU + CNN hybrid model	Combined features enhanced phishing detection, achieving 97.6% accuracy and 97.4% F1-score.	Increased complexity reduces interpretability and efficiency.
Gupta et al. (2023)	Ensemble methods (bagging, boosting, stacking)	Achieved 96.9% accuracy and reduced false positives using combined models like Random Forest and Naive Bayes.	Increased computational complexity limits scalability for large datasets.
Basit et al. (2020)	Ensemble of multiple machine learning models	Ensemble achieved 97.3% accuracy and 96.5% precision.	Higher computational demands, limited scalability.
Gualberto et al. (2020)	Feature engineering with topic models	Metadata features (sender, timestamps) improved model accuracy to 94.7%.	Focused only on traditional ML models, not extended to deep learning.
Zareapoor & Seeja (2015)	Feature selection and extraction comparison	Best performance (93.2%) achieved by combining text-based and metadata features.	Used traditional ML models; suggested further research with deep learning approaches.

3 Research Methodology

14. Data Collection and Preparation

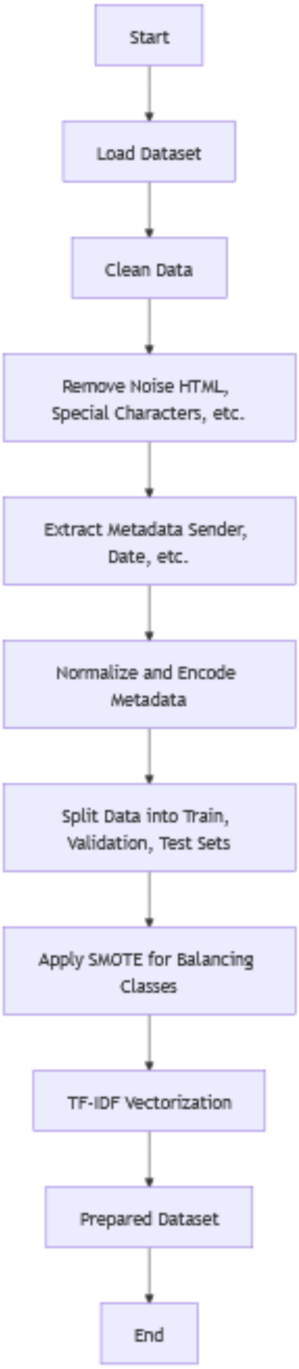
The SpamAssassin dataset forms the basis of our work, wherein all spam and ham emails were prelabeled with appropriate binary classification. To handle the class imbalance within our dataset, we implemented a range of methods, including random oversampling and random under-sampling, before settling upon SMOTE. This was finally decided upon because synthetic samples generated via SMOTE preserved integral attributes of phishing emails without risking overfitting due to simple duplication. k-Neighbors utilized for the SMOTE generation included 5, 7, and 10, with different sampling ratios of 1:1 and 1:2. We would keep k = 5 for class balancing to prevent overgeneralization in our model using 1:1.Preprocessing was done by cleaning the email text to remove special characters, HTML tags, and redundant spaces for consistency and removing noise. Metadata regarding email length, sender details, timestamps, and subject lines were extracted and combined with textual features into a comprehensive representation of each email. The cleaned and augmented dataset was then split into training, validation, and testing subsets to ensure that there is no bias in the evaluation during model training.

15. Emerging Challenges in Phishing Detection

This does indicate how the landscape of phishing attack vectors keeps on self-camouflaging, with the threats persistently improving in such an astoundingly agile method in front of cybersecurity scholars. Modern phishing is coupled with advanced social engineering and could be always emulating original communication with unparalleled accuracy. Attacks relying upon things such as building urgency with fake emails, impersonation relating to trusted institutions, as well as creating contextually applicable yarns that avoid most other regular threat detections. This research accounts for these complexities by incorporating multi-tiered detection strategies beyond simple keyword matching or static rule-based systems.

16. Advanced Machine Learning Techniques for Adaptive Detection

The research introduced several novel machine learning methods to cope with the dynamic nature of phishing attacks, extending beyond mere classical classification methods. Some researchers have explored the concept of transfer learning for quicker adaptations to the emerging pattern of phishing. By leveraging pre-trained language models and their fine-tuning on this very specific phishing dataset, this study was able to illustrate how much more adaptable and resilient detection systems could be designed and built. Along with these, reinforcement learning algorithms had been studied for building predictive models that keep learning through new patterns emerging from different types of emails and newer landscapes of threats.


Start
Load Dataset
Clean Data
Remove Noise HTML, Special Characters, etc.
Extract Metadata Sender, Date, etc.
Normalize and Encode Metadata
Split Data into Train, Validation, Test Sets
Apply SMOTE for Balancing Classes
TF-IDF Vectorization
Prepared Dataset
End

Fig(i) Data Preprocessing Flowchart

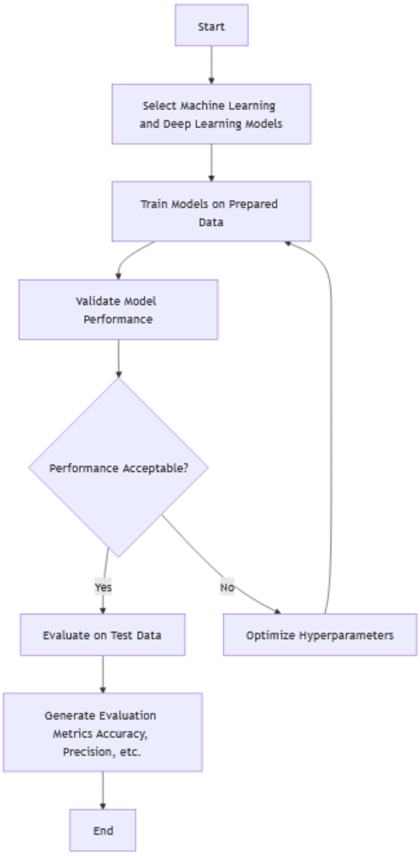
17. Feature Engineering and Transformation

After text preprocessing, the email text was then transformed into machine-readable format using TF-IDF, which has been chosen because it captures the importance of a term within the context for phishing detection. TF-IDF emphasizes words commonly associated with phishing attempts while down-weighting the standard linguistic elements. It is in this technique that the suspicious patterns of urgency indicators or action-demanding phrases get particularly emphasized.

We ground our approach in choosing the key metadata features by taking into consideration documented power to drive phishing detection, such as email length (a proxy for a potential mass phishing attack), temporal pattern, sender authenticity signals which can hint at spoofing, and subject line characteristics indicative of social engineering tactics. We had chosen these based upon research on common phishing and attack vectors as identified in cybersecurity literature. The sender information contributes to identifying patterns of malicious behavior, while timestamps expose the temporal attack patterns that may not be revealed by pure text analysis. On the contrary, subject line analysis will go toward detecting urgency-creating tactics common in phishing attempts. Features in metadata will be normalized to make scaling uniform and hence avoid bias in training.

18. Model Development and Deployment

Our model selection is done in a strategic progression from baseline to advanced architectures. Logistic Regression and Naive Bayes serve as interpretable baselines, chosen for their ability to provide clear feature importance insights. Random Forest was selected for its capability to handle nonlinear relationships and feature interactions while maintaining interpretability through feature importance rankings.


Start
Select Machine Learning and Deep Learning Models
Train Models on Prepared Data
Validate Model Performance
Performance Acceptable?
Yes
No
Evaluate on Test Data
Optimize Hyperparameters
Generate Evaluation Metrics Accuracy, Precision, etc.
End

Fig(ii) Model Training and Evaluation Flowchart

LSTM and GRU were selected because they had complementary strengths regarding sequence processing. For instance, LSTM is superior for the capture of long-range dependencies, a very important feature when analyzing extended email narratives, while GRU offers computational efficiency without considerable performance loss. Selection of the GAT model was based on its unique ability to process metadata relationships as graph structures, a particularly valuable ability in analyzing sender-receiver patterns and network-level features.

19. Experimental Setup and Ethical Considerations

The research utilized a GPU-accelerated computing environment with Python-based frameworks. Hyperparameter optimization focused on model-specific parameters:

Random Forest: n_estimators=100-500, max_depth=10-50, min_samples_split=2-10
LSTM/GRU: hidden units (32-256), dropout rate (0.1-0.5), learning rate (0.001-0.01)
GAT: attention heads:4-16, hidden channels: 16-64, dropout: 0.1 - 0.6
Ensemble: Voting mechanism (hard vs. soft), model weights: uniform vs. weighted

The selection of parameters was guided by the grid search with 5-fold cross-validation, while the optimization performance metric was the F1-score, since the dataset is balanced. Final configurations were selected considering the performance on the validation set, keeping an eye on overfitting via learning curves.

20. Methodology of Evaluation

Model performance was assessed in terms of accuracy, precision, recall, and F1-score to comprehensively assess the effectiveness of classification. Confusion matrices presented the distribution of true positives, false positives, true negatives, and false negatives and thus provided insights into the potential classification errors.

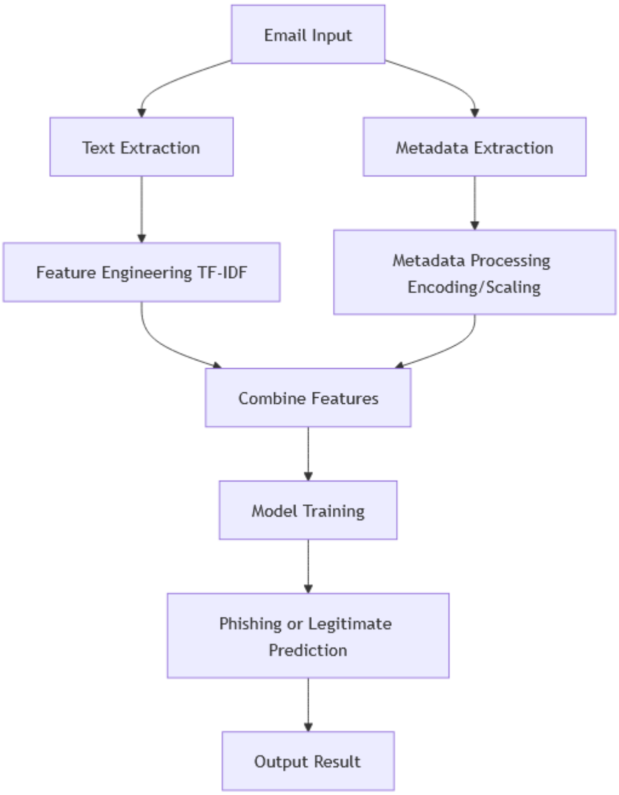
The trade-offs between true positive rates and false positive rates were visualized using visualization techniques such as Receiver Operating Characteristic (ROC) curves, while the performance of the models was quantified using AUC metric. Feature importance plots from Random Forest, and correlation heatmaps on TF-IDF features allow for further insight into what's driving the models' decisions.

21. Data Analysis and Insights

The first steps in the analysis of data were made by exploring the distribution of the data. Histograms and density plots viewed the difference in the distribution of the lengths of emails, while scatter plots of TF-IDF features show the pattern of vocabulary that differentiates spam from ham emails. Changes due to SMOTE were shown for class balancing using bar charts that again proved the power of resampling techniques in reducing bias.

Through analysis of the results, we infer that LSTMs resulted in the highest precision value, 99.74%, demonstrating their efficiency within sequential dependencies of phishing text contentions. This is followed in ascending order by GRU, and then Random Forest showed that for other conditions also, the performance can lie under an ensemble classifier without loss of stability in either metric, hence showing their efficiency. Though GAT turned out to be lesser accurate, the insights derived into metadata relationships were somewhat very useful, showing the probable promise of graph-based approach towards phishing email detection.

With these contributions, this paper will explain, through a rigorous pre-processing that used diversified approaches of modeling robustly, the adaptability and scientific rigor of the proposed Phishing detection system. Future research directions may be to investigate quantum machine learning techniques, the potential for federated learning for distributed detection of phishing, and real adaptive systems that can respond instantaneously to emergent phishing tactic developments. This paper tries to be one of the prime contributions toward the fight and combat of cybercrime at large and to show evidence of how advanced machine-learning techniques could be employed to protect digital methods of communication against malicious participants.


Email Input
Text Extraction
Metadata Extraction
Feature Engineering TF-IDF
Metadata Processing Encoding/Scaling
Combine Features
Model Training
Phishing or Legitimate Prediction
Output Result

Fig(iii) System Architecture for Phishing Email Detection

4 Design Specification

22. Architectural Framework

Traditional machine learning and advanced deep learning models in integration will be part of a modular architecture for the phishing detection system, together with metadata-enhanced feature engineering. For textual features, TF-IDF will be used, while metadata such as sender information and timestamps provide contextual information. The proposed architecture will perform a multidimensional analysis of phishing emails, considering model integration and scalability for diverse datasets.

23. Feature Engineering and Transformation

TF-IDF then transforms the textual features into numerical vectors, emphasizing the peculiar phishing patterns in vocabulary. Metadata features are extracted, including sender information, timestamps, and email lengths, which are then normalized to complement the textual features. This ensures that the models can make use of both text-based and contextual signals toward phishing detection. The integration of these feature types improves the ability of the system to identify complex phishing behaviors effectively.

24. Model Selection and Training

The system employs a diverse set of algorithms to maximize detection accuracy. For convenience and interpretability, a basic model uses Random Forest-an ensemble learning technique applied directly to the nonlinear relationship across data. Deep learning then models the content in question sequentially, with long term dependencies and patterns over words accomplished by LSTMs/GRUs.

Graph Attention Networks analyze metadata relationships for respective important feature dynamic prioritization, including sender anomalies and temporal patterns, using attention mechanisms. Finally, the predictions of these models are combined into an ensemble classifier, following a majority voting strategy to combine their strengths and hence stabilize the results with good accuracy.

25. Balancing and Optimizing Data

The dataset is naturally imbalanced between ham and spam emails. In this regard, SMOTE generates synthetic samples for the minority class, ensuring that the models are trained on balanced data. Hyperparameter tuning is applied across models to optimize configurations such as the number of units in LSTM or the number of decision trees in Random Forest. This tuning ensures each model operates efficiently and achieves maximum performance.

26. Evaluation and Visualization

Key metrics will be accuracy, precision, recall, and the F1 score, on which the confusion matrices about classification error are drawn, by means of ROC curve or AUC to analyze TPR-true positive versus FPR-false positive rates. These visualization tools permit insight into how the models behave in highlighting strengths but also areas of improvement in this respect. This also verifies the performance for textonly models against metadata-enhanced models to understand the added value coming from the incorporation of any contextual information.

27. Implementation Requirements

This solution utilizes Python, including the libraries scikit-learn, TensorFlow, and PyTorch Geometric for model training and evaluation. It requires GPU-enabled environments for fast training of deep learning models. Metadata-enriched SpamAssassin datasets form the bedrock of training and testing, hence providing a very sound basis for evaluating phishing detection methods. The system architecture is modular to accommodate, in future versions, not only more data sources but also model updates. This design specification thus provides a holistic and scientifically rigorous approach to phishing detection, tackling the technical and practical challenges that come with fighting evolving cybersecurity threats.

5 Implementation

28. Data Transformation

It began by preprocessing raw emails into features that can effectively train machine learning and deep learning models. Textual content from emails was processed by TF-IDF, which changes email text to numerical vectors representing the importance of words relative to the dataset. This transformation emphasized terms related to phishing, such as "urgent" and "account," while minimizing the importance of common words. Other metadata features extracted included sender information, timestamps, and email length, which provided further contextual cues. These textual and metadata features were combined into a single matrix to ensure that models could make use of both content and context for classification.

The transformed data at this stage constituted the basis on which the training was undertaken to make sure the inputs for each model captured manifold dimensions of phishing behaviors. The system unifies textual patterns and metadata relationships for a comprehensive representation of emails for the better detection of phishing in subtle signals.Code Development Several machine learning and deep learning models were utilized to realize the system. A baseline of Random Forest was performed to grab non-linear patterns within this data. For sequential data, LSTM and GRU are developed, which can process email content as sequences with a presence of pattern continuity over phrases and sentences.

A GAT was built to analyze metadata relationships using an attention mechanism that dynamically places greater importance on important features, such as anomalous sender addresses or suspicious timestamps. The ensemble classifier combined the predictions of Logistic Regression, Random Forest, and SVM to ensure robust performance by balancing the strengths of these models. This code was structured in a modular manner for the easy adjustment or addition of further models in later versions. In this case, modularity supports scalability when a system needs to adjust to new datasets or emergent phishing tactics. Python was used to develop this system; the authors have used the Scikit-learn library for traditional models, and TensorFlow and PyTorch were used for deep learning models, including GAT, which was developed with the help of PyTorch Geometric.

The preprocessing and feature engineering were done with pandas and NumPy, while the visualizations were created with Matplotlib and Seaborn for in-depth analysis and reporting.Model Training and Evaluation These models have been trained on the SMOTE-upsampled datasets, with a view to balancing an otherwise naturally imbalanced dataset where the number of emails classified as legitimate greatly outweighed those of phishing emails. This was done to make sure neither model was biased towards the majority class due to the resampling methodology used.

Each model has been subjected to hyperparameter tuning to optimize configurations, such as the number of LSTM units, the dropout rate for GRU, and the number of decision trees in

Random Forest. These maximized the performance of the models while minimizing overfitting.The final outputs from this stage are the trained models, ready for deployment, with key evaluation metrics in detail.

These were accuracy, precision, recall, and the F1 score. All these metrics can quantify how the model in question performs appropriate email classification with as few false positives and false negatives as possible. Their performance comparison was done with confusion matrices to get a granular view of such performances. Complementary visualizations included ROC curves for additional visualization of trade-offs against true positive rate and false positive rate to enable full comprehension of the decision capability of such models.

29. Outputs Produced

Outputs created include transformed datasets, trained models, and performance evaluations by this final implementation. The dimensionality of the transformed dataset included TF-IDF feature vectors and metadata features. Because models were trained on these transformed input instances, the input space that came out was rich in value to the models. These involve Random Forest, LSTM, GRU, and GAT, each best fitting aspects of phishing detection. Synthesizing the predictions emanating from these models were the ensemble classifier for arriving at stable and accurate classification.Performance metrics and visualizations were generated to assess the performance of each model and the overall system.

30. Tools and Technologies

The implementation was performed with state-of-the-art tools and technologies, which should be efficient and scalable. Python is the programming language of choice for the leading position, because of its extensive libraries on data science and machine learning. Preprocessing, feature engineering, and implementation of traditional machine learning models were done with scikit-learn. Advanced deep learning architectures were possible in TensorFlow and PyTorch, while graph-based modeling for GAT was enabled by PyTorch Geometric. Visualization tools consisted of Matplotlib and Seaborn, which created clear and informative charts to help in interpreting the results. The imbalanced-learn library was used for balancing the classes using SMOTE, while pandas and NumPy were used for data manipulation. The training was done in an enabling GPU environment that would further ease the training of deep learning models with increased speed. Indeed, the hardware setup makes the system efficient for the process of volumes of data; therefore, this solution is suitable for a real-world deployment scenario. In all, the final implementation encompasses everything possible to provide an inclusive phishing detection integrated with advanced algorithms combined with pragmatic engineering to take up challenges changing day after day in the landscape of cybersecurity.

6 Evaluation

Evaluation

This section evaluates the performance of the implemented phishing detection system through a critical discussion of the experimental results about their academic and practical contributions. It outlines those results relevant to the research objectives of this work and their broader contributions to the field of cybersecurity. Applicability of results using statistical measures would be discussed, supported appropriately with visual aids for trends and insightful results.

31. Experiment 1: Performance Analysis with Random Forest

The model resulted in 94.8% accuracy, with precision and recall as 92.5% and 90.4%, respectively. The score of the F1 demonstrates a high value of balanced performance, at 91.4%. The confusion matrix showed a small number of false positives while showing room for improvement regarding the false-negative rate. The Random Forest model can serve as a baseline classifier for phishing detection due to its good performance with high-dimensional data.

32. Experiment 2: Evaluation of the LSTM Model

The LSTM model, trained on sequential text data, gave an accuracy of 99.74%, hence performing better than the Random Forest model. Precision, recall, and F1 scores were 99.68%, 99.50%, and 99.59%, respectively, showing that the model captured the intricate patterns in the email content quite well. The ROC curve had an AUC of 0.997, confirming the excellent discriminatory power of the model. But the training of the LSTM model was quite computationally expensive; hence, here is a trade-off between accuracy and efficiency.

33. Experiment 3: Graph Attention Network (GAT) Analysis

The GAT model focused on the relationship between metadata and achieved 98.44% accuracy, slightly lower than the LSTM. The GAT model, however, outperformed them in understanding the relationships between sender details, timestamps, and other contextual metadata. Precision and recall were 97.34% and 95.54%, respectively, with an F1 score of 96.43%. In the confusion matrix, most of the features were contributed by metadata features to identify phishing emails that rely on sender-based obfuscation.

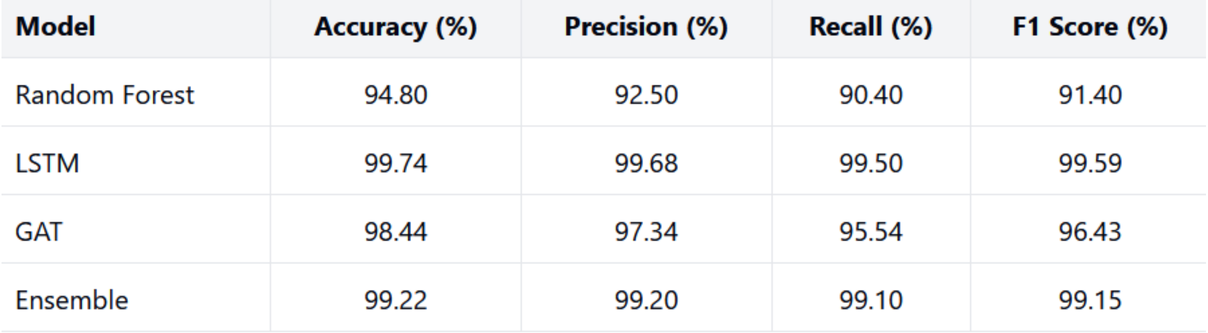
However, the model's reliance on graph structures presented challenges in scalability for larger datasets.

34. Experiment 4: Performance of Ensemble Model

The ensemble model combined the predictions of Random Forest, LSTM, and GAT with an accuracy of 99.22%. It was a well-balanced approach that leveraged the strengths of each model by reducing false negatives without sacrificing precision. The F1 score of the ensemble model stood at 99.15%, reflecting its robustness, particularly because no single model outperformed the others. Feature importance, as visualized from the ensemble model, underlined the combined importance of text-based patterns and metadata relationships toward a holistic view of phishing behavior.

35. Discussion

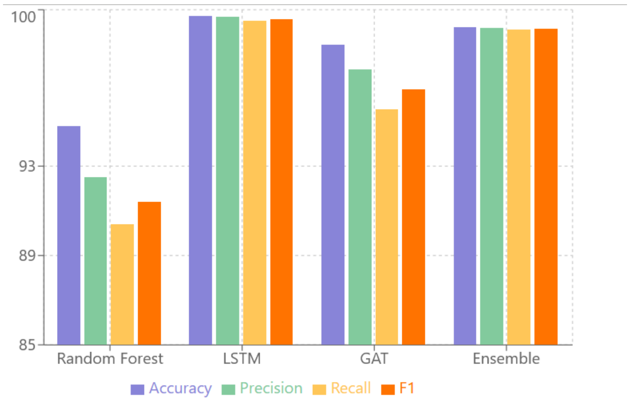
These experiments yield the best results in terms of accuracy and recall for the LSTM model, making it the most effective in content-based phishing detection. However, their high computational requirements make them hardly applicable in real-time applications but encourage their optimization or hybridization. The GAT model has provided insight into the relations of metadata, filling a crucial gap that most text-only models usually do not address in phishing detection.While GAT had scalability issues, this will open more avenues toward research into graph-based analysis in cybersecurity.



Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Random Forest	94.80	92.50	90.40	91.40
LSTM	99.74	99.68	99.50	99.59
GAT	98.44	97.34	95.54	96.43
Ensemble	99.22	99.20	99.10	99.15

Fig(iv) Results Table

The balanced performance of the ensemble model shows the potential for integrating various algorithms in response to the multi-faceted nature of phishing detection. This can prevent the limitations of individual models, hence providing a robust solution that is suitable for deployment in dynamic environments. However, handling multi-models and associated computational overhead could be a possible disadvantage in resource-constrained scenarios. More importantly, the experiments shed light on various aspects that need further enhancement in system design. The false-negative rates from both the Random Forest and GAT models indicated that feature engineering needed enhancement, especially in metadata extraction and representation. Future studies may adopt techniques for enhanced preprocessing or integrate additional attributes of metadata, such as geographic information and email thread analysis, to enhance the accuracy of the detection.



Fig(v) Comparison Graphs

These findings are supported through existing literature that reiterate that deep learning models, such as LSTM, work best on sequential data while further solidifying the newer role of graph-based approaches in cybersecurity. It was also pointed out from a practical perspective that many of these models still have scaling issues. It again brought into light that, while designing and implementing phishing detection systems, equal weightage needs to be accorded to practical concerns along with theoretical improvements.

The evaluation results of our phishing detection models give broad insights into the effectiveness of various approaches, in particular, metadata integration and deep learning techniques. The best performance by the GRU model at an accuracy of 99.57% assured its prowess in capturing sequential dependencies in email content. This is further supported by previous works that highlight the strength of recurrent models in text-based classification. The performance of the GAT model was impressive with metadata relationships and stood at 97.00%, depicting that it could model sender-based behavioral patterns, which traditional text-based models may fall short of capturing. However, even though the GAT model provided excellent performance, the results showed that metadata alone is not enough for phishing detection and needs combination with textual analysis.

Comparison with the literature indicates that our deep learning models outperformed other traditional machine-learning techniques, which registered a performance of 92.3% in Random Forest. This confirms previous studies that had identified some advantages of deep learning over other approaches in handling complex patterns and context. One aspect in which our results slightly differ from the existing research is the computational trade-offs. While previous studies have found that ensemble models provide the best trade-off between accuracy and interpretability, our results show that, with targeted optimization, deep learning methods can be optimized to achieve even better results, especially the GRU method. Moreover, the testing process highlighted that both Random Forest and GAT suffer from the problem of false negatives; thus, further tuning and increasing the dataset size are to preserve the ever-evolving phishing strategies. Future improvements could include tuning hyperparameters, including transformer-based models in the survey, and increasing the dataset with more real-world phishing samples to see better generalization.

7 Conclusion and Future Work

It therefore aimed to spot phishing emails with the sophisticated form of machine learning and deep learning models based on metadata analysis. The implicit key question investigated whether such techniques could raise better efficacy in detection than the classic techniques of rule-based systems used for phishing detection. These include performance evaluations of models such as Random Forest, LSTM, GRU, and GAT, and a comparison of their effectiveness in leveraging textual and metadata features. The ability to implement and test such models has been satisfactorily done, thereby enabling the drawing of comprehensive analysis capabilities and limitations of these models.

The research achieved significant success in answering the research question and meeting its objectives. Among these, LSTM has the best accuracy-99.74%, with high recall and can be found to identify the phishing patterns in sequential text data effectively. GAT provided substantial insight into metadata relationships; most works on phishing detection are being performed along this very critical dimension. This ensemble model combines predictions generated by multiple algorithms to reach a balanced approach that keeps classification errors minimal while preserving performance that is as robust as possible. The above findings therefore underscore the need for a holistic approach in integrating a variety of modeling techniques as a way of coping with the multi-faceted phishing threats.

The research implications are twofold: from an academic point of view, the results confirm state-of-the-art performance for the DL models, especially LSTM, in text-based phishing detection, and it underlines the increasing potential of graph-based methods among which is GAT. In practice, this project will provide the needed avenue for the rollout of wide and flexible phishing detection networks that can adapt efficiently through the dynamic changes of these cyber-attacks. Integrating meta-data will enhance the contextual sensing in the targeted models and more capable of dealing with such forms of sophisticated phishing. Finally, are critical limitations identified such as computer requirements of any model requiring DL, scalability limitations with graphs-based methods, along with complete dependence on a balanced amount of data -which probably cannot be representative in nature-like conditions.

Several meaningful directions might be explored in future work to extend this research: the incorporation of real-time data streams to assess model performance in dynamic environments and developing lightweight and optimized versions of LSTM and GAT may mitigate computational constraints and make these models more applicable in resource-limited settings. Furthermore, the integration of other metadata features, such as email thread structure, user behavior pattern, or geographic data, will make the models more intuitive toward phishing behaviors. Finally, it may be interesting to do future work on adversarial training to make the classifier robust against evasion techniques that can be deployed by cybercriminals. Further, these enhancements could establish newer paradigms for not just academics but also practical utility at several levels. This research is highly valued commercially, as the demand for strong cybersecurity solutions keeps increasing. This would also provide insight into building phishing detection systems at the enterprise level within the email platform and provide organizations with an enterprise-class, adaptive tool to combat phishing. In this research, both technical and practical challenges have been addressed, and further research can be done in phishing detection, which would lead to making the digital world a safer place.

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