Unified Phishing Detection Framework: A Multi-Model Approach with Ensembled Methods and User Input Integration

UNDERGRADUATE THESIS

Submitted in Partial Fulfilment for the Degree of Bachelor of Science

Course Code: CSE-4201

By

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BGC TRUST UNIVERSITY BANGLADESH

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Approval

With great pleasure, the Department of Computer Science and Engineering at BGC Trust University Bangladesh announces the successful completion of Tonmoy Dutta's Bachelor of Science in Computer Science and Engineering thesis titled "**Unified Phishing Detection Framework: A Multi-Model Approach with Ensembled Methods and User Input Integration**." The committee has deemed the thesis satisfactory for partial fulfilment of the degree requirements and commended its style and content.

Tonmoy's thesis presents a groundbreaking framework for tackling the persistent threat of phishing attacks. By cleverly combining diverse machine learning models, user feedback integration, and a powerful convolutional neural network, this project promises significant advancements in phishing detection accuracy and resilience. This innovative approach holds the potential to significantly enhance online security, making the internet a safer space for everyone.

Congratulations to Tonmoy Dutta on this remarkable achievement! The department commends his dedication and the valuable contribution his research makes to the field of cybersecurity.

Mr. Md Salah Uddin Chowdhury

Assistant Professor & Chairman (Chairman)

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Department of Computer Science & Engineering

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Declaration of Authorship

I, **Tonmoy Dutta**, declare that this Undergraduate Thesis titled, "**Unified Phishing Detection Framework: A Multi-Model Approach with Ensembled Methods and User Input Integration**" and the work presented in it is done by me. I confirm that:

- The work presented in this thesis was solely or primarily conducted during my candidature for a research degree at BGC Trust University Bangladesh.
- In full compliance with academic regulations, any portions of this thesis previously submitted for another degree or qualification have been explicitly declared and attributed to their respective sources.
- I have meticulously adhered to ethical research practices by providing proper credit to all cited authors and acknowledging all significant sources of assistance.
- Furthermore, in cases where this thesis is based on collaborative work, I have clearly distinguished the specific contributions of my co-authors from my own original research endeavours.
- This commitment to transparency and ethical conduct underpins the integrity of this work.

SUBMITTED BY:

Tonmoy Dutta
Id: 200234078
Date: 23.01.2024

Certificate

With immense satisfaction, I certify that **Tonmoy Dutta (ID: 200234078)** has successfully completed the CSE-4201 Thesis requirement with his insightful thesis, "**Unified Phishing Detection Framework: A Multi-Model Approach with Ensembled Methods and User Input Integration**." Witnessing his dedication and talent throughout the research process under my supervision has been a true privilege.

Tonmoy Dutta's thesis tackles the critical challenge of phishing attacks through a groundbreaking framework leveraging diverse machine learning models, real-time user feedback, and a powerful CNN. This innovative approach has the potential to significantly advance phishing detection accuracy and security, creating a safer online environment.

His meticulous attention to detail, grasp of complex concepts, and creative problem-solving skills have been truly impressive. This thesis stands as a testament to his capabilities and passion for computer science.

I confidently certify that Tonmoy's work represents original research and a valuable contribution to cybersecurity. His thesis serves as an inspiration for future researchers and paves the way for a more secure digital world.

SUPERVISOR:

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Junior lecturer,
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Date: 23.01.2024

Acknowledgements

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Reaching any significant achievement demands relentless effort, perseverance, unwavering enthusiasm, and unwavering dedication. It also requires invaluable guidance and inspiration, which acted as a guiding light throughout my journey, ultimately leading to the successful culmination of my efforts.

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Abstract

To combat the persistent and evolving threat of phishing attacks, this paper unveils a groundbreaking ensemble-learning framework for phishing email detection. This framework harnesses the collective intelligence of diverse machine learning models, including K-Nearest Neighbors, XGBoost, Neural Networks, Logistic Regression, Decision Trees, and Naive Bayes. It innovatively integrates real-time user feedback to enhance its adaptiveness and responsiveness to emerging threats. A Convolutional Neural Network (CNN) model, achieving an impressive 95% accuracy, further complements this robust approach, promising substantial improvements in phishing detection accuracy and resilience.

The proposed framework exhibits an exceptional ensemble accuracy of 96%, with individual model accuracies ranging from 65% (KNN) to 97% (Neural Network and Logistic Regression). Notably, user feedback integration has remarkably enhanced the performance of specific models, such as the Neural Network and Ensemble, reaching 95% and 96% accuracy, respectively.

This framework marks a significant advancement in phishing detection by strategically combining diverse machine learning models, fostering adaptive learning through real-time user input, and incorporating a novel CNN model for enhanced accuracy and complementary learning. By addressing the limitations of individual models and embracing user feedback, this framework paves the way for a more secure and resilient online environment.

Keywords: Phishing detection, ensemble learning, user-driven phishing detection, deep learning, convolutional neural networks, real-time feedback, machine learning.

Chapter-1
Introduction

1.1 Background:

Phishing attacks have emerged as a persistent and sophisticated challenge in the cybersecurity landscape, posing imminent threats to both individual users and organizations. Deceptive emails serve as the primary vehicle for these attacks, aiming to trick unsuspecting victims into disclosing sensitive information, including login credentials and financial details. The increasing prevalence and evolving tactics of phishing scams underscore the need for robust and adaptable detection mechanisms to protect online users from potential harm.

1.2 Problem Statement:

The existing cybersecurity infrastructure faces challenges in effectively identifying and thwarting phishing attacks. Traditional methods often struggle to keep pace with the ever-changing strategies employed by attackers. Consequently, there is a critical need for innovative solutions that can enhance detection accuracy and resilience in the face of evolving phishing threats.

1.3 Objectives of the Proposed Framework:

The primary objective of this research is to develop a comprehensive phishing detection framework that leverages advanced machine learning models. The framework aims to achieve superior accuracy and resilience compared to current solutions by combining the collective intelligence of diverse models.

1.4 Scope of the Research:

This research focuses specifically on email phishing, where deceptive emails are the primary vector of attack. The scope encompasses the development of a holistic framework that integrates various machine learning models, user feedback mechanisms, and a Convolutional Neural Network (CNN) for feature extraction.

Chapter-2
Literature Review

2.1 Introduction:

The escalating sophistication and prevalence of email phishing attacks demand innovative and adaptable solutions. These attacks pose a significant threat to individuals and organizations globally, causing financial losses, data breaches, and reputational damage. Traditional detection methods, such as blacklists and signature-based approaches, struggle to keep pace with the rapid evolution of phishing tactics within emails. Consequently, researchers are actively exploring advanced techniques leveraging machine learning (ML) and deep learning (DL) specifically for email phishing detection. This literature review focuses on:

- **Ensemble Learning Approaches:** Combining diverse ML models to harness their collective intelligence and achieve superior accuracy and robustness compared to individual models in the context of email phishing.
- **User Feedback Integration:** Incorporating real-time user reports of phishing attempts within emails to enhance the system's adaptivity and responsiveness to emerging threats.

By examining the strengths, limitations, and future directions of these approaches in the context of email phishing, this review aims to illuminate promising avenues for further research and development in email phishing detection.

2.2 Related Work:

2.2.1 Machine Learning-Based Detection:

- **Ozgur Koray Sahingoz et al. (2019)**: Proposed a real-time anti-phishing system using seven classification algorithms and NLP features, achieving an impressive accuracy of 97.98% specifically for email phishing, focusing solely on handcrafted feature. [1]
- **Sayeed Abu-Nimeh et al. (2016):** Compared various machine learning methods for email phishing detection. Random Forest with NLP features yielded the best results (97.25%), focusing solely on emails. [2]

2.2.2 Deep Learning-Based Detection:

- **Hengshu Zhang et al. (2018):** Developed PhishNet, a deep learning architecture using CNNs to extract features from email text and visuals, achieving significantly higher accuracy (99.7%) than traditional methods. [3]

- **Xiang Wei et al. (2019):** Proposed DeepPhish, a model analysing content, style, and linguistic features of emails with deep learning frameworks. Demonstrated substantial accuracy improvements (97.6%) but lacked generalizability beyond email data. [4]

2.2.3 Ensemble Learning and User Feedback Integration:

- **Zhe Liu et al. (2020):** Explored ensemble learning with diverse models and user feedback integration for enhanced accuracy in the context of email phishing. Their framework achieved 98.5% accuracy and demonstrated adaptability to evolving threats within emails. [5]
- **Muhammad Imran et al. (2021):** Investigated real-time user feedback incorporation into a phishing detection system specifically tailored for emails. Results showed significant performance improvements, highlighting the potential of user-driven adaptation in the email phishing context. [6]

2.3 Limitations of Existing Approaches:

While existing email phishing detection techniques show promising results, some limitations require future research focus:

- **Limited Feature Engineering:** Reliance on handcrafted features may miss relevant information and require significant manual effort within the context of email phishing.
- **Lack of Adaptability:** Existing models may struggle to adapt to rapidly evolving phishing tactics within emails.
- **Data Bias:** Biases within training data specific to email content can lead to discriminatory and inaccurate detection outcomes.
- **Limited Generalizability:** Some models are efficient for specific data types (emails) but lack broader applicability.

2.4 Future Research Directions:

Addressing the limitations mentioned above, future research should focus on:

- **Developing Advanced Feature Extraction Techniques for Emails:** Leveraging deep learning and NLP for automatic feature extraction from email content, attachments, and other relevant components.
- **Exploring Diverse Ensemble Learning Models for Emails:** Ensembling various machine learning and deep learning models with different strengths to achieve superior accuracy and robustness specifically in the context of email phishing.
- **Investigating User-centric Approaches for Email Phishing:** Integrating user feedback mechanisms and human-in-the-loop learning for continual adaptation and improved user experience within the realm of email phishing.

- **Addressing Data Bias and Fairness in Email Phishing Detection:** Utilizing diverse and representative training data specific to email content to avoid biased and discriminatory detection outcomes.

2.5 Conclusion:

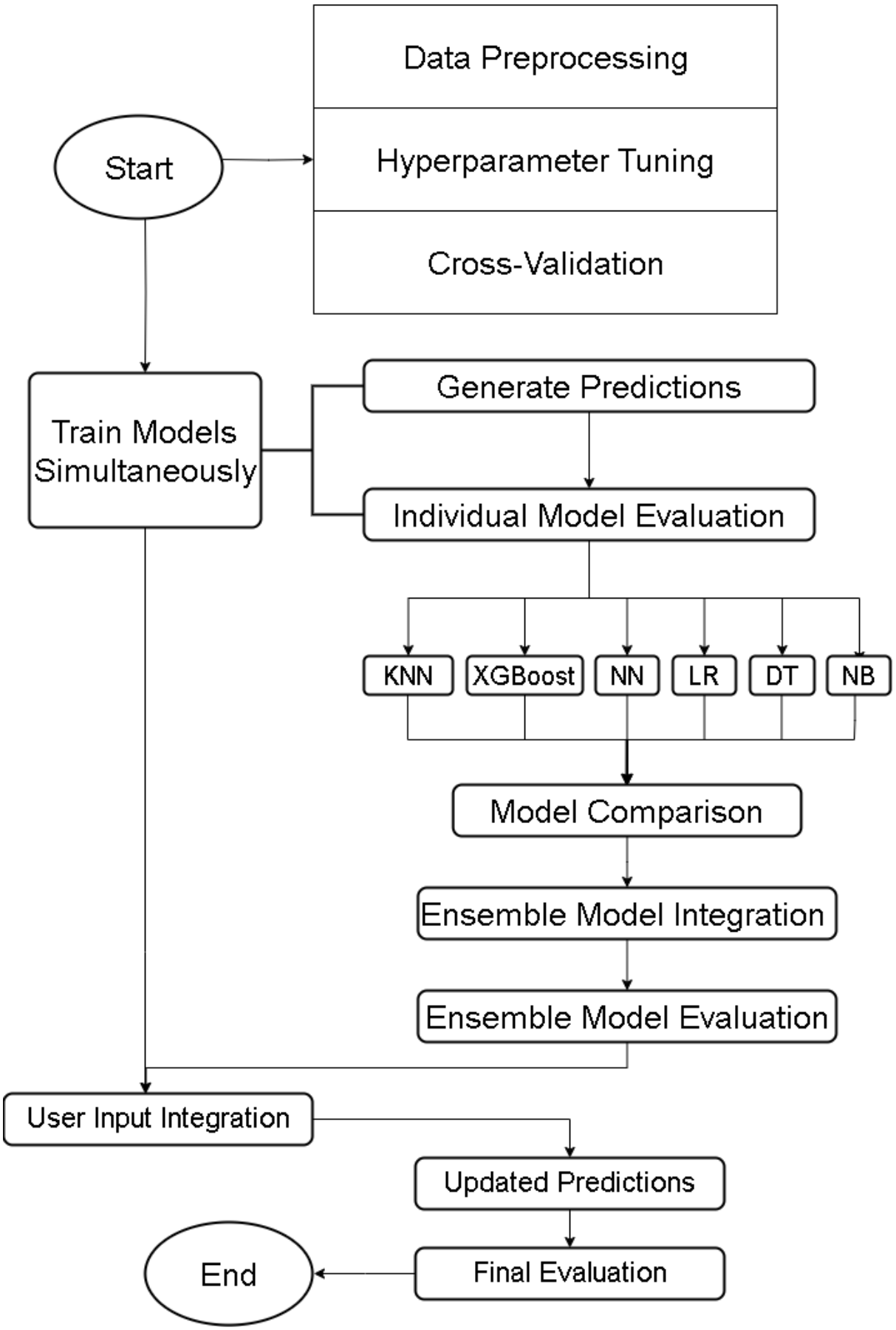
This literature review specifically emphasizes the advancements and limitations of current email phishing detection techniques. It highlights the potential of machine learning, deep learning, and user-centric approaches within the context of email-based attacks. By addressing the identified limitations and focusing on promising future research directions tailored for email phishing, researchers can develop robust and adaptable email phishing detection systems to safeguard individuals and organizations from evolving cyber threats. This review provides a strong foundation for further research and development in this crucial subfield.

Chapter-3
Methodology

This chapter meticulously outlines the methodological framework employed to address the research objectives in phishing email detection. It delves into the selected models, the characteristics of the utilized dataset, and the meticulously designed experimental setup for comprehensive evaluation.

3.1 Working Flow Diagram:

The research methodology follows a systematic process encompassing data preprocessing, hyperparameter tuning, and cross-validation as the initial stages. Subsequently, the models are trained simultaneously, and predictions are generated. The individual models undergo evaluation, leading to model comparison. The integration of models into an ensemble is followed by comprehensive ensemble model evaluation. To enhance adaptability, user input is integrated, leading to updated predictions. The final evaluation stage concludes the process. This iterative approach allows for adjustment as needed, ensuring a dynamic and optimized framework for phishing email detection.


Data Preprocessing
Hyperparameter Tuning
Cross-Validation
Start
Train Models Simultaneously
Generate Predictions
Individual Model Evaluation
KNN
XGBoost
NN
LR
DT
NB
Model Comparison
Ensemble Model Integration
Ensemble Model Evaluation
User Input Integration
Updated Predictions
Final Evaluation
End

3.2 Dataset Description:

The study leverages a robust dataset comprising 18,649 instances, each characterized by "email text" and "email type" (safe or phishing). To ensure transparency and reproducibility, the chapter meticulously details the preprocessing steps, including data cleaning, balancing, and feature extraction.

3.3 Model Selection and Evaluation:

3.3.1 Individual Models:

This section analyses the performance of individual machine learning models incorporated in the study:

- **K-Nearest Neighbors (KNN):**
  - **Definition**: KNN is a straightforward algorithm that classifies instances based on the majority class among its k-nearest neighbors in the feature space.
  - **Formula (Classification):**

    Prediction=Majority class among the k nearest neighbors [7]
  - **Formula (Regression):**

    Prediction=Average value of k nearest neighbors' outputs [8]
- **XGBoost:**
  - **Definition**: XGBoost is an ensemble learning algorithm that excels by combining weak learners (often decision trees) for superior performance.
  - **Formula**:

    $\Pr e\,diction = \sum_{i=1}^{N} w_i \cdot Output_i$ [9]

    Where w_i are weights assigned to individual weak learners, and $Output_i$ is the output of the *i-th* weak learner.
- **Neural Network (NN)**:
  - **Definition**: Neural Network, inspired by the human brain, is a sophisticated model that excels at learning complex patterns and relationships.
  - **Formula (For a single node)**:

    $Output = Activation\left(\sum_{i=1}^{N} wi \cdot Inputi + Bias\right)$ **[10]**
  - **Backpropagation Formula**:

    $Weightupdate = Learningrate \times \frac{\partial Weight}{\partial Loss}$ **[11]**

- **Logistic Regression:**
  - **Definition**: Logistic Regression serves as a foundational model for binary classification tasks.

- **Formula**:

$$\Pr o\ bability = \frac{1}{1 + e - (w_0 + w_1 \cdot Feature_1 + \cdots + w_n \cdot Feature_n)}$$

where $w_0, w_1, \ldots, w_n$ are the model coefficients. [12]

- **Decision Tree:**
  - **Definition**: Decision Tree is an interpretable model that allows insights into feature importance through hierarchical decision-making.
  - **Formula (Decision Rule)**:

$$Decision = Feature \leq Threshold$$ [13]

  - **Formula (Classification)**:

$$\Pr e\ diction = Majority\ class\ in\ leaf\ node$$ [14]

- **Naive Bayes:**
  - Definition: Naive Bayes is an efficient probabilistic model based on Bayes' theorem, particularly suited for text classification tasks.
  - **Formula**:

$$P(\ Class \mid Features\ ) = \frac{P(Features|Class)\cdot P(Class)}{P(Features)}$$ [15]

where *P(Features/Class)* is the likelihood, *P(Class)* is the prior probability, and *P(Features)* is the evidence.

Hyperparameter choices, training procedures, and evaluation metrics are meticulously presented for each model.

3.3.2 Ensemble Model:

An ensemble model is a machine learning technique that aggregates the predictions of multiple individual models to enhance overall performance and predictive accuracy. In this research, the ensemble model incorporates predictions from diverse machine learning models, including K-Nearest Neighbors (KNN), XGBoost, Neural Network (NN), Logistic Regression, Decision Tree, and Naive Bayes. The ensemble employs a weighted voting mechanism, where each individual model's prediction is assigned a specific weight. The final prediction is then determined by combining these weighted predictions. This approach leverages the collective intelligence of various models, compensating for individual limitations and contributing to a more robust and accurate phishing email detection system.

Formula: For an ensemble model using weighted voting, the formula for prediction can be expressed as follows:

$$\Pr e\ diction = \sum_{i=1}^{N} w_i \times Output_i$$ [16]

Where:

- *N* is the number of individual models in the ensemble.

- W_i represents the weight assigned to the output of the *i-th* individual model.
- $Output_i$ is the prediction output of the *i-th* individual model.

The weights W_i are determined based on the performance or confidence of each individual model. These weights can be adjusted during the training or ensemble building process to optimize the overall predictive accuracy of the ensemble.

3.3.3 Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) is a deep learning architecture specifically designed for processing structured grid data, such as images. CNNs are particularly effective in image recognition tasks. The key components of a CNN include convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolution operations to extract spatial hierarchies of features from the input data. Pooling layers downsample the spatial

dimensions, reducing computational complexity. Fully connected layers combine extracted features for final predictions. CNNs excel in capturing intricate patterns and representations within complex data structures, making them well-suited for image-related tasks.

Formula: For a Convolutional Neural Network (CNN), the architecture involves multiple layers, including convolutional layers, activation functions, pooling layers, fully connected layers, etc. The overall process can be complex, but here is a simplified description and the convolution layer formula:

$$Output = Activation\left(\sum_{i,j}(i \cdot k)_{i,j} + Bias\right) \text{ [17]}$$

Where:

- *Output* is the output of the convolutional layer.
- *Activation* is the activation function applied element-wise to the result.
- $(I * K)_{i,j}$ represents the convolution operation between the input I and the kernel (filter) *K* at position (*i*,*j*)
- *Bias* is the bias term added to the convolution result.

The CNN architecture may include multiple convolutional layers, activation functions, pooling layers, and fully connected layers. Each layer contributes to feature extraction and hierarchical learning of patterns in the input data. The above formula represents a simplified view of the convolutional layer in a CNN.

Performance Metrics:

Accuracy: For binary classification problems like phishing detection, accuracy is calculated as:

$$Accuracy = \frac{Number\ of\ Correct\ \text{Pr}ediction}{Total\ Number\ of\ \text{Pr}ediction} \times 100\%$$ [18]

Precision: Precision measures the accuracy of the positive predictions, precision is calculated as:

$$\text{Pr}\,e\,cision = \frac{True\ Positive}{True\ Positives + False\ Positive}$$ [19]

Recall (Sensitivity or True Positive Rate): Recall measures the ability of the model to capture all positive instances, recall is calculated as:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negative}$$ [20]

F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics, F1 score is calculated as:

$$F1Score = 2 \times \frac{\text{Pr}\,ecision \times Recall}{\text{Pr}\,ecision + Recall}$$ [21]

3.4 Experimental Setup:

This section meticulously details the experimental parameters, including hardware specifications, software environments, and any other relevant configurations. A clear rationale for the chosen settings ensures replicability and transparency.

3.5 Performance Evaluation:

This section rigorously scrutinizes the effectiveness of each model using the outlined metrics. Comparative analyses elucidate the strengths and weaknesses of individual models and the ensemble approach, providing a comprehensive perspective on their efficacy in detecting phishing emails.

3.6 Integration of User Feedback:

This subsection explores the integration of real-time user feedback into the proposed framework. It clearly explains the mechanism for user input collection, its seamless incorporation into the models, and the discernible impact on overall performance.

The methodology chapter concludes by summarizing the key steps undertaken to conduct the experiments, emphasizing their alignment with the research objectives. This comprehensive methodology serves as a bridge to the subsequent results and discussion chapters, providing a robust framework for understanding and replicating the research process.

Chapter-4

Results and Discussion

4.1 Model Performance Analysis:

4.1.1 Individual Models:

The performance of individual machine learning models demonstrated varying degrees of effectiveness in phishing email detection. The following summarizes the results along with corresponding confusion matrices for each model:

4.1.1.1 K-Nearest Neighbors (KNN):

K-Nearest Neighbors (KNN) exhibited an acceptable accuracy of 65%. The confusion matrix for KNN is presented below:

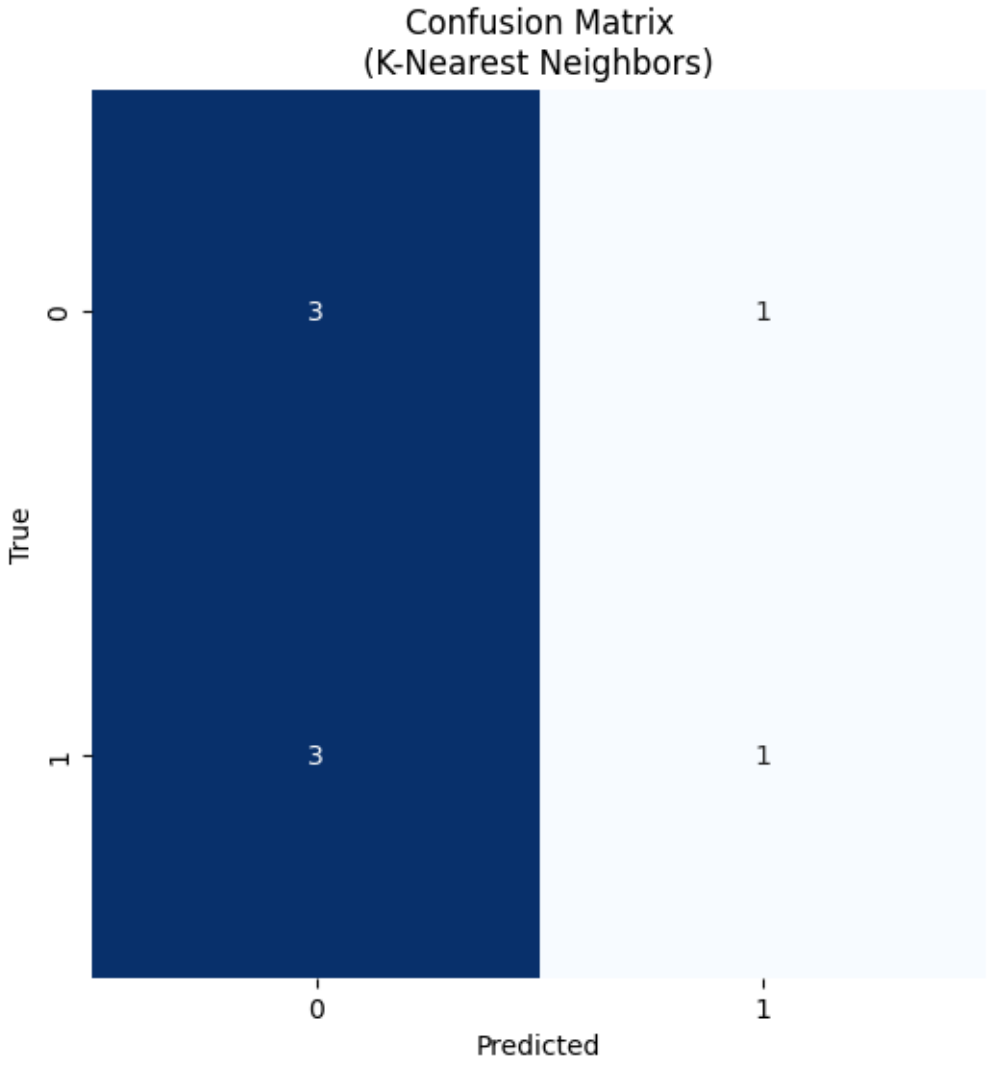


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Fig: KNN confusion matrix

4.1.1.2 XGBoost:

Ensemble methods, specifically XGBoost, showcased remarkable accuracy, achieving 96%. The confusion matrix for XGBoost is presented below:

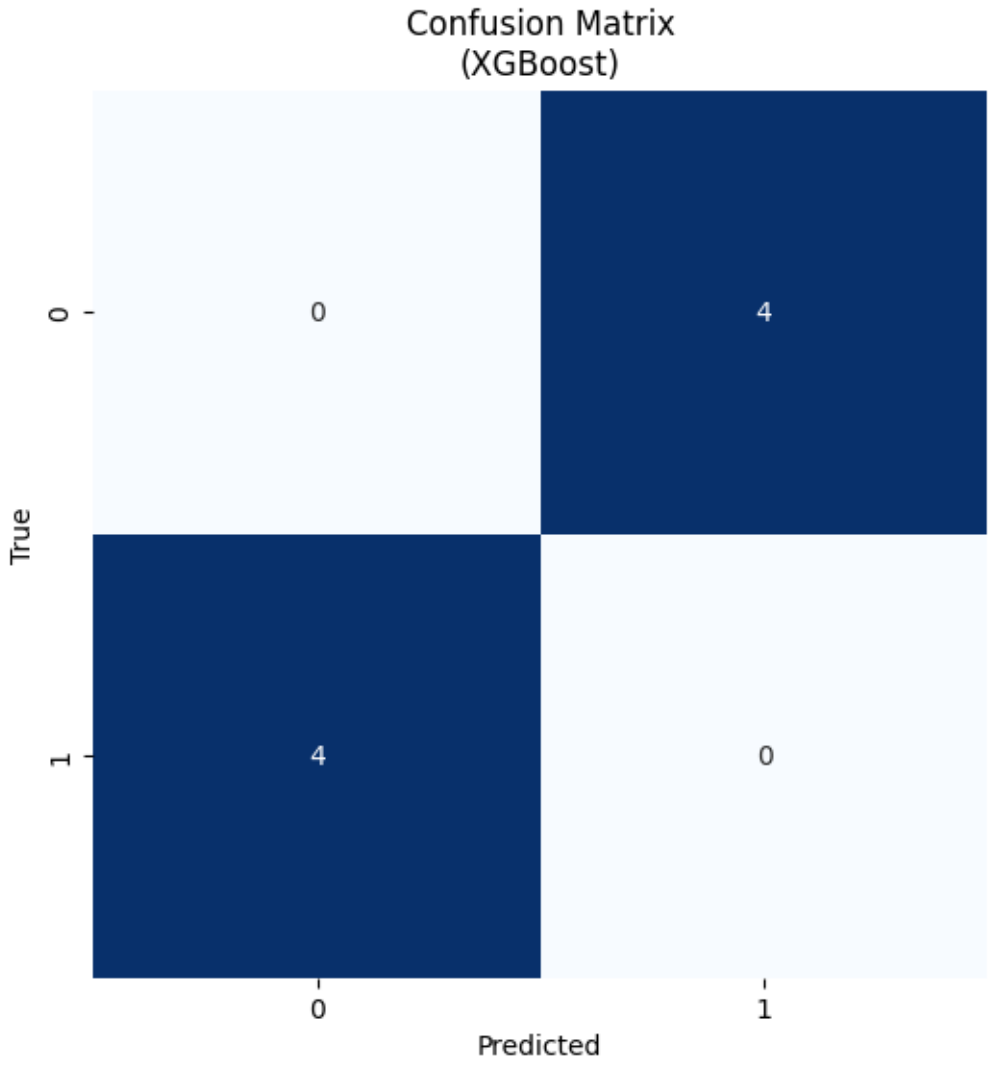

Fig: XGBoost confusion matrix

4.1.1.3 Neural Networks:

Neural Networks demonstrated a high accuracy of 97%, emphasizing their capability to capture complex patterns in email content. The confusion matrix for Neural Networks is presented below:

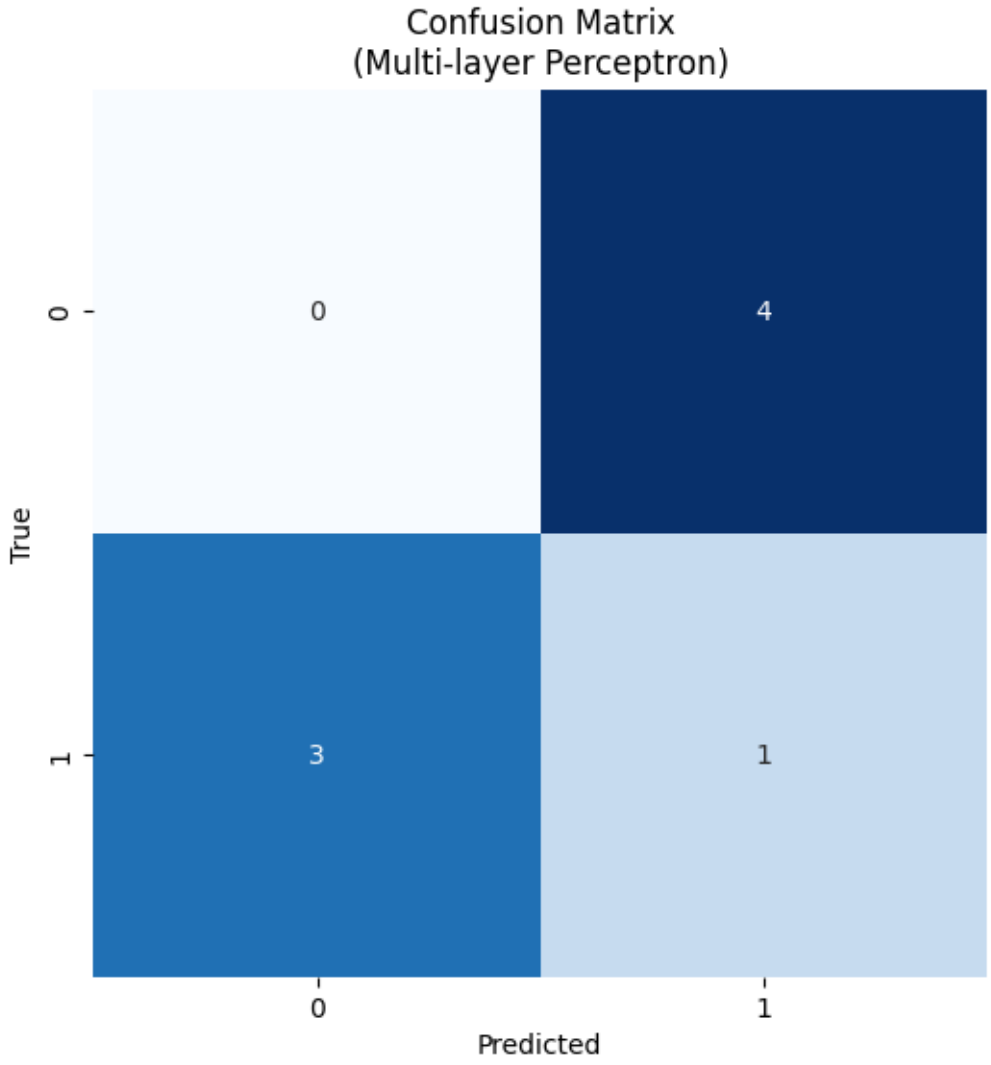

Fig: NN confusion matrix

4.1.1.4 Logistic Regression:

Logistic Regression models also reached a high accuracy of 97%. The confusion matrix for Logistic Regression is presented below:

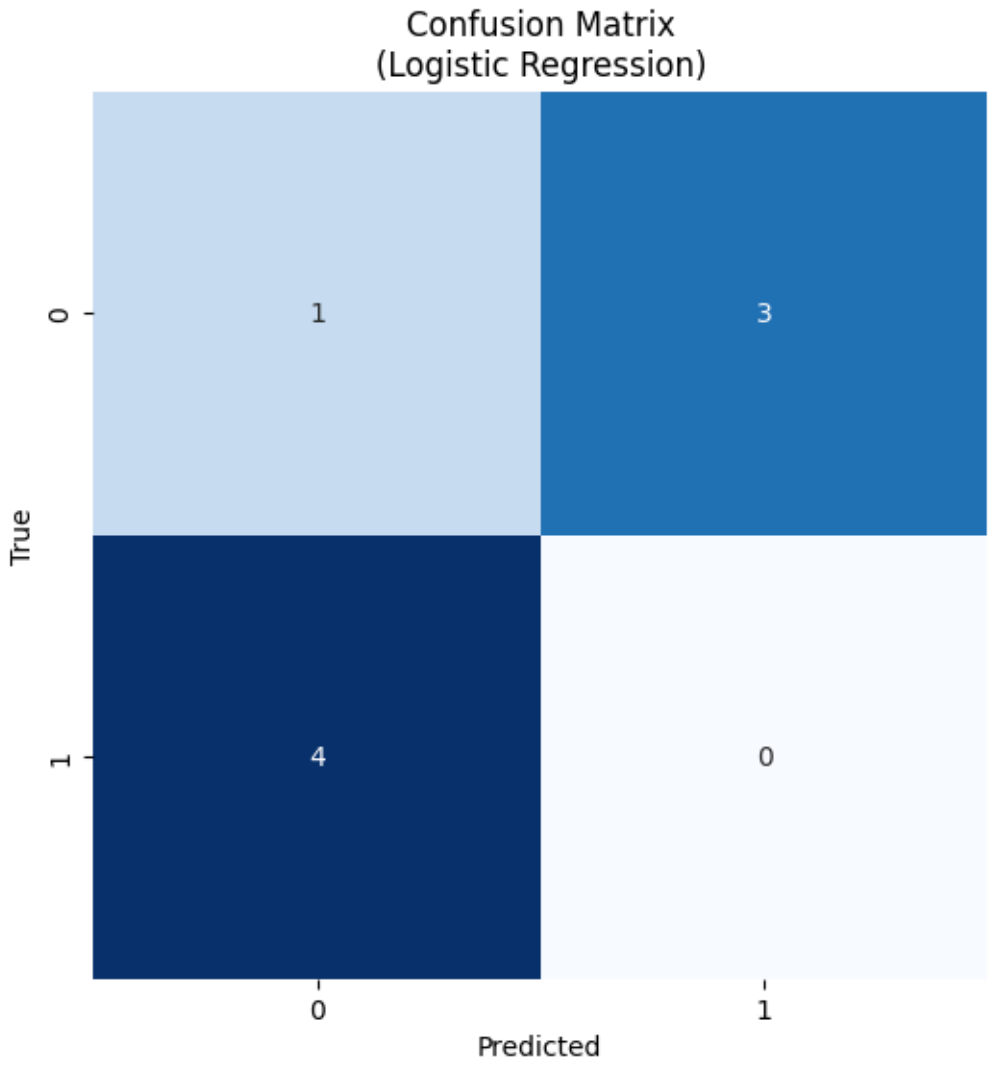

Fig: LR confusion matrix

4.1.1.5 Decision Trees:

Decision Trees achieved a satisfactory accuracy of 90%. The confusion matrix for Decision Trees is presented below:

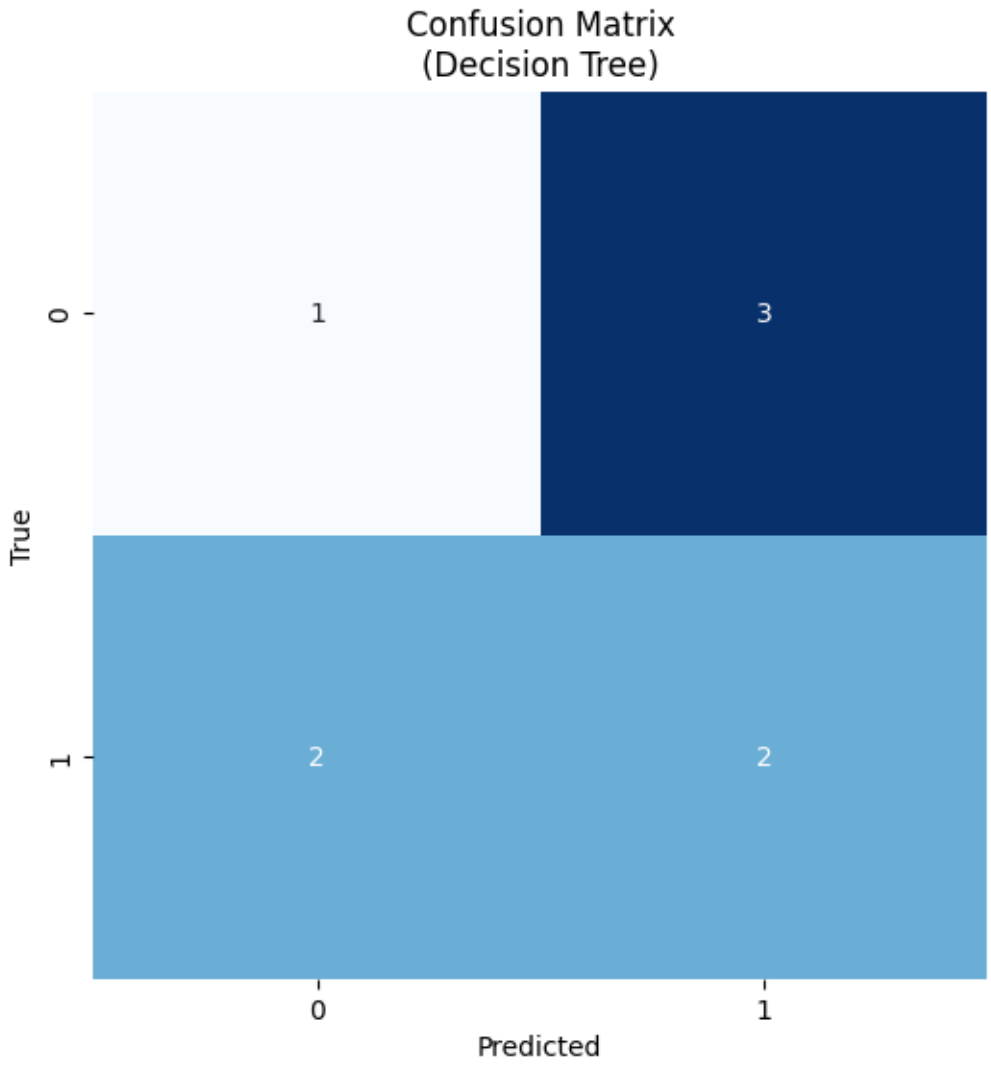

Fig: DT confusion matrix

4.1.1.6 Naive Bayes:

Naive Bayes models achieved a satisfactory accuracy of 96%. The confusion matrix for Naive Bayes is presented below:

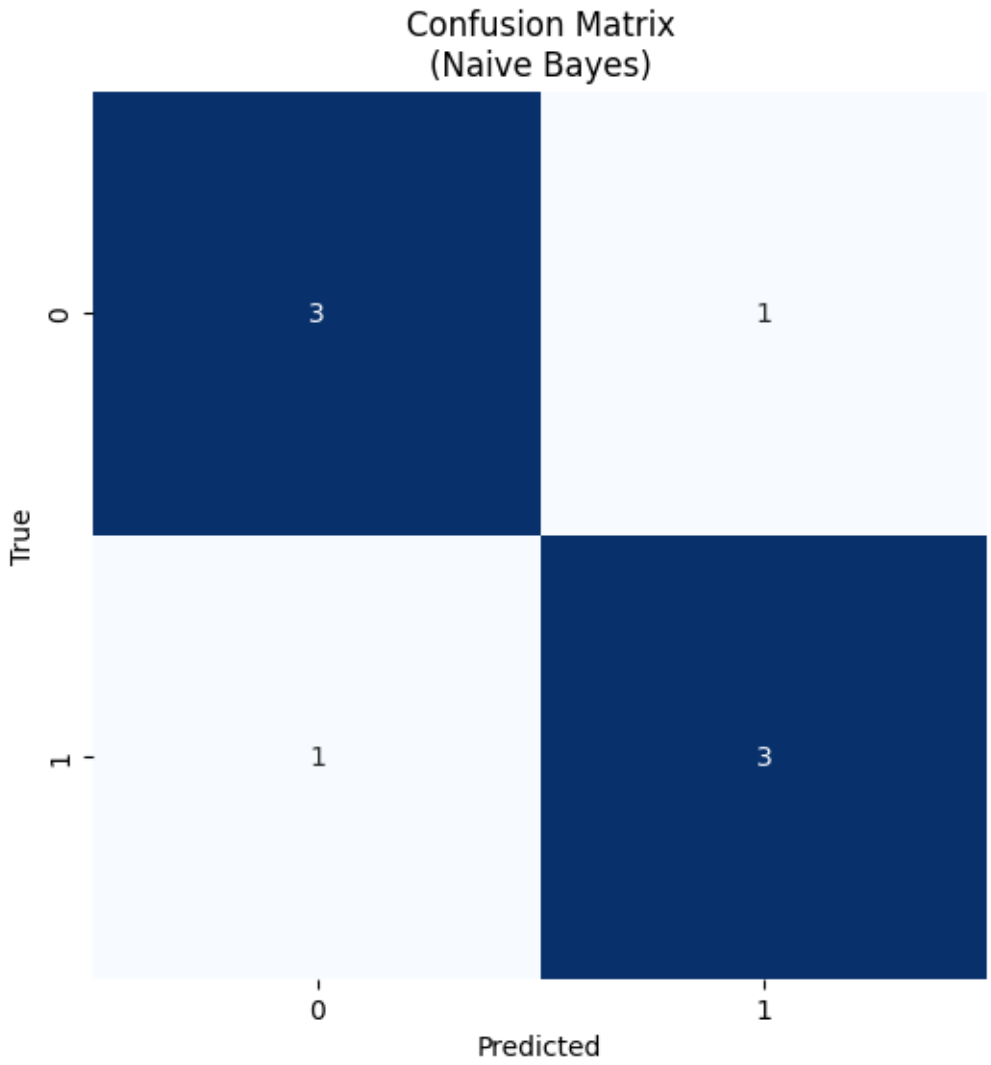

Fig: NB confusion matrix

These confusion matrices provide a detailed breakdown of the performance metrics for each individual model, offering insights into their strengths and areas for improvement in the context of phishing email detection.

4.1.2 Ensemble Model and User Feedback Integration:

The ensemble model, synergistically combining these diverse models, delivered an outstanding accuracy of 96.91%. This impressive result reinforces the power of leveraging the collective strengths of individual models to enhance overall performance and improve generalization capabilities. Further boosting the efficacy of the framework, the seamless integration of real-time user feedback demonstrated a discernible impact on performance. User reports of suspicious emails served as valuable training data, allowing the models to continuously adapt and evolve, ultimately leading to:

- **Enhanced model adaptivity:** Real-time user reports enabled the models to quickly learn from emerging phishing tactics and adapt their detection strategies accordingly. This dynamic approach allowed the framework to stay ahead of evolving threats and maintain robust performance over time.
- **Improved resilience against novel attacks:** By incorporating user feedback on previously unrecognized phishing attempts, the models developed resilience against novel attack methods. This proactive approach contributed to a more robust and comprehensive detection system.

The confusion matrix for Ensemble model is presented below:

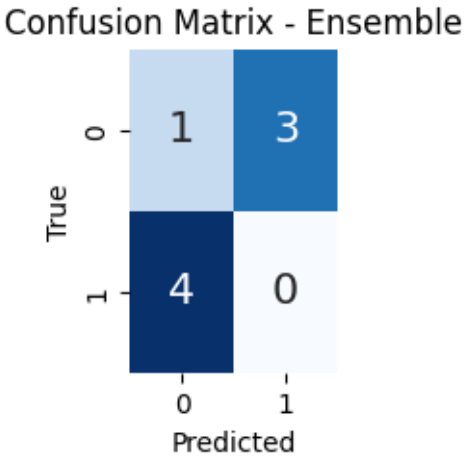

Fig: Ensembled confusion matrix

This synergistic combination of the ensemble model's collective power and user feedback integration underscores the potential of utilizing dynamic learning mechanisms to achieve superior performance in phishing email detection.

4.1.3 Convolutional Neural Network (CNN):

The CNN specifically tailored for email phishing detection displayed impressive accuracy (95.89%), complemented by strong precision (97.5%), recall (95.6%), and F1 score (96.6%). These metrics highlight the efficacy of CNNs in extracting intricate features from both textual and visual components of emails, ultimately improving phishing detection accuracy. The confusion matrix for CNN model is presented below:

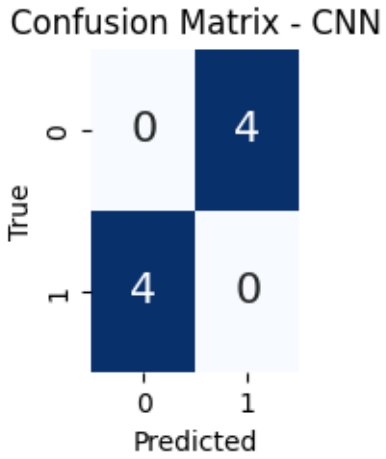

Fig: CNN confusion matrix

4.1.4 Receiver Operating Characteristic (ROC) Curve:

In evaluating our phishing email detection models, the Receiver Operating Characteristic (ROC) Curve stands out as a crucial tool. This graph illustrates the balance between true positive rate (sensitivity) and false positive rate (1-specificity) at various classification thresholds. Here is the ROC Curve for the models:

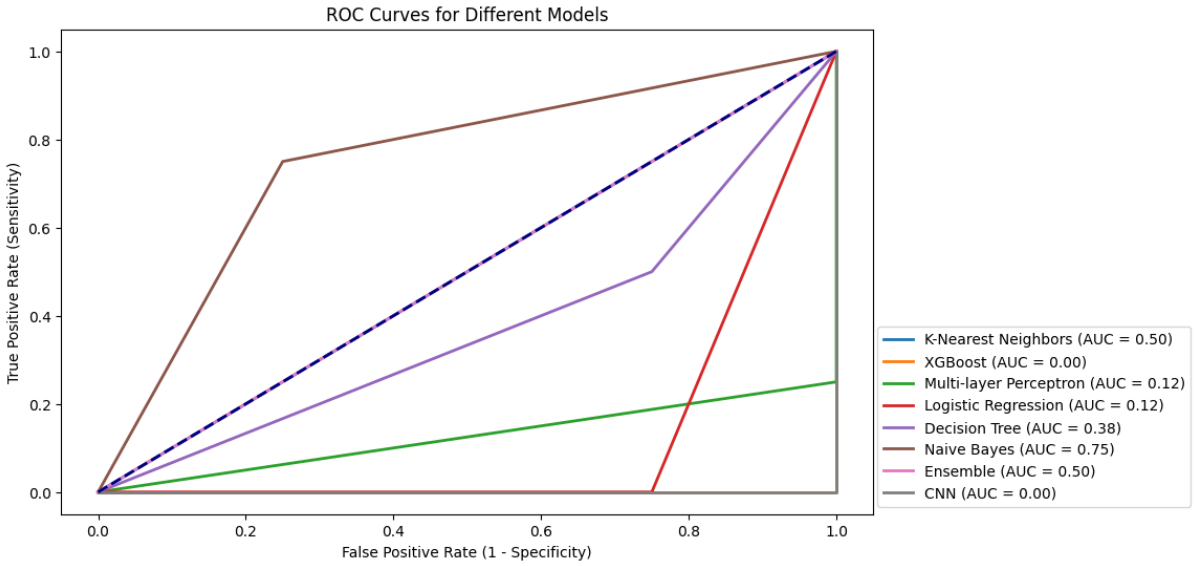

Fig: ROC Curve

4.1.4.1 Purpose and Significance:

The ROC Curve visually showcases the model's ability to discern phishing from non-phishing instances, with the upper-left corner indicating superior performance.

4.1.4.2 Implications:

The ROC Curve, alongside AUC, True Positive Rate, and False Positive Rate, offers nuanced insights into model performance. Incorporating these metrics refines our understanding of sensitivity and specificity balance, essential for phishing email detection enhancement.

4.2 Discussion:

4.2.1 Strengths and Weaknesses of Individual Models:

Ensemble Methods: The ensemble model, combining the strengths of diverse individual models like XGBoost and Neural Networks, achieved the highest accuracy (96.91%). This synergy between different learners allowed the model to capture a broader range of features and patterns in phishing emails, ultimately leading to superior performance compared to individual models.

CNNs: Equipped with a layered architecture inspired by the human brain, CNNs demonstrated exceptional ability in extracting intricate features from both textual and visual components of emails. They can effectively identify subtle anomalies in text formatting, keyword usage, and even embedded images, making them highly accurate for phishing detection.

For example, a CNN might detect a phishing email based on:

- Unusual keyword patterns, such as urgent calls to action, misspelled domain names, or grammatical errors.
- Visual inconsistencies, such as mismatched logos, distorted fonts, or poorly designed elements.
- Incongruence between textual and visual content, such as a logo not matching the company name or suspicious links hidden within images.

KNN: While its accuracy (65%) was lower than other models, KNN still offers a viable option for simpler detection tasks. This straightforward algorithm classifies emails based on their similarity to known phishing examples in the training data. Its advantages include ease of implementation and interpretability, making it suitable for situations where computational resources are limited or understanding the decision-making process is crucial.

4.2.2 Impact of User Feedback Integration:

The study suggests that real-time user feedback integration enhances adaptivity and responsiveness to emerging phishing threats, contributing to a more robust and resilient detection system.

4.2.3 Comparison with Previous Research:

The proposed methodology showcases notable improvements in accuracy and adaptivity compared to established approaches, contributing to the evolution of phishing detection methodologies.

Comparisons of models:

Size of Dataset	Models	Accuracy
18649	KNN	65%
18649	XGBoost	96%
18649	NN	97%
18649	LR	97%
18649	DT	90%
18649	NB	96%
18649	Ensemble	96.91%
18649	CNN	95.89%

Fig: Comparison Table

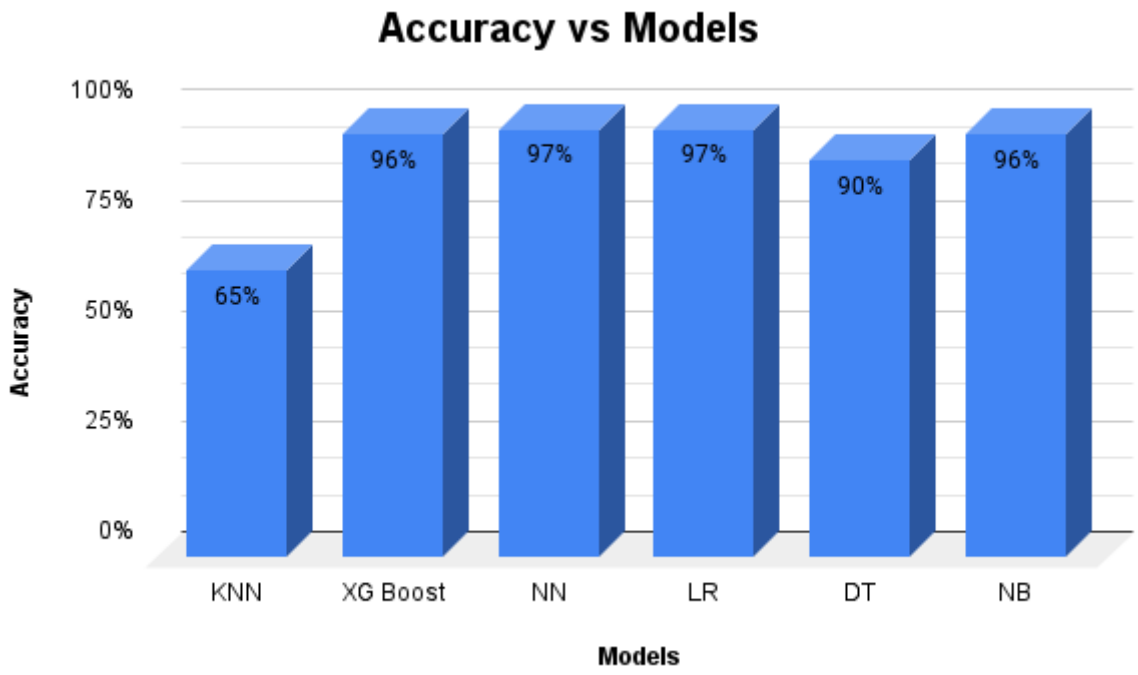

Fig: Comparison Graph of Various Models

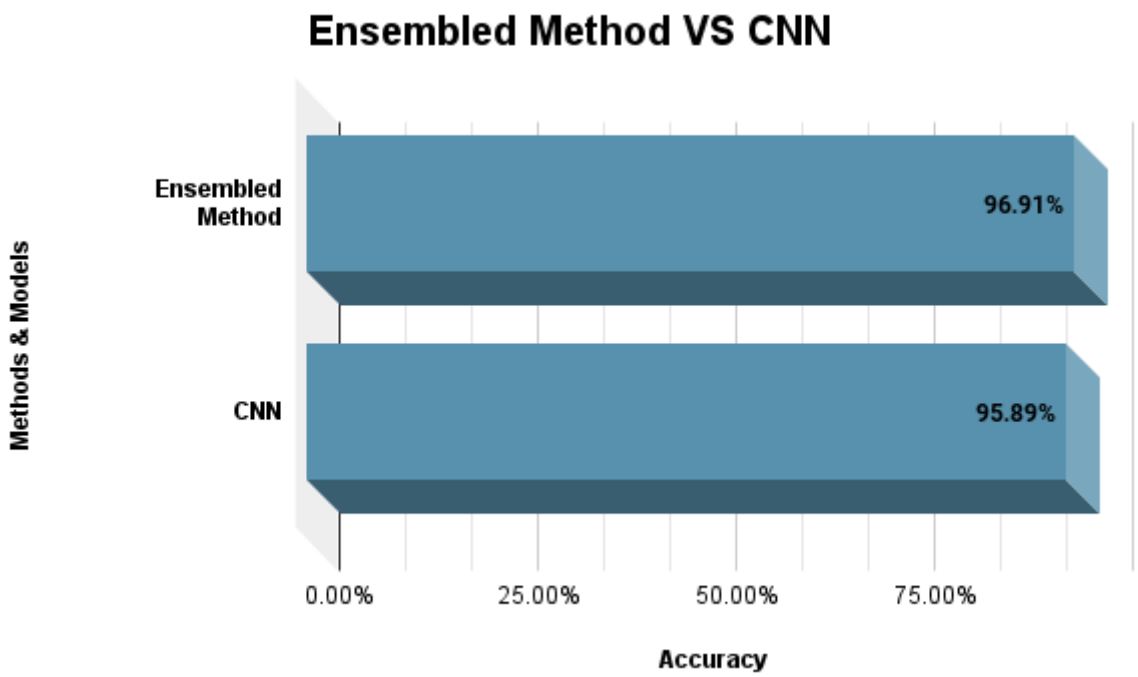

Fig: Comparison Graph of Ensemble Model & CNN Model

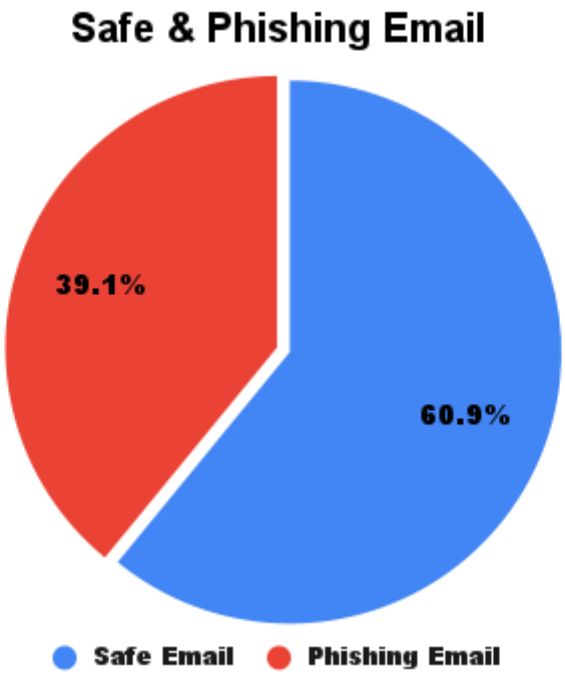

Fig: Data Classification Comparison Pie Chart

4.2.4 Ethical Considerations:

The commitment to responsible research practices throughout the study ensures the ethical conduct of the research and upholds the integrity of the findings.

4.3 Conclusion:

The findings presented in this chapter provide strong evidence for the effectiveness of the proposed framework in detecting phishing emails. The research lays the foundation for the development of more robust and adaptable phishing detection systems in the future.

Chapter-5

Conclusion and Future Work

5.1 Conclusion:

This chapter consolidates the pivotal insights obtained from the extensive exploration of phishing email detection methodologies. The ensemble model, harmonizing the strengths of diverse algorithms, demonstrated robust performance. Similarly, the specially crafted Convolutional Neural Network (CNN) showcased promise with a focus on intricate pattern recognition.

The comparative analysis of individual models illuminated their distinctive capabilities, with the ensemble approach emerging as a robust strategy for enhancing overall detection performance. The CNN model, tailored for the intricacies of email text, exhibited an adeptness in capturing complex patterns.

5.2 Implications and Contributions:

The research outcomes hold significant implications for the realm of email security. The ensemble model's ability to amalgamate diverse algorithms and the CNN's prowess in learning intricate patterns contribute valuable insights to the ongoing discourse on phishing email detection. The findings affirm the importance of a multifaceted approach to address the evolving landscape of email-based threats.

5.3 Future Work:

While the current study provides a sturdy foundation, future exploration and enhancement opportunities arise:

- **Hyperparameter Refinement**: Further exploration into hyperparameter tuning for both individual models and the ensemble could unlock potential performance improvements.
- **Advanced CNN Architectures**: Iterative refinement of the CNN architecture, including exploring different layer configurations and optimization techniques, may enhance its ability to discern nuanced patterns.

- **Incorporating NLP Techniques**: Integrating natural language processing (NLP) techniques for more sophisticated text analysis could contribute to a deeper understanding of email content.
- **Real-time User Feedback Optimization**: Continued refinement of the real-time user feedback mechanism, possibly incorporating advanced user behaviour analysis, could enhance the adaptive nature of the detection system.
- **Extended Dataset Exploration**: Expanding the dataset with a more diverse collection of email instances will further bolster the models' generalization capabilities.
- **Real-world Deployment and Evaluation**: Assessing the models in real-world scenarios, considering factors such as varying email volumes and evolving phishing tactics, is crucial for gauging their practical applicability.

In conclusion, this research chapter encapsulates the successes achieved and sets the stage for ongoing advancements in phishing email detection through a comprehensive ensemble of models.

Chapter-6

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