American International Journal of Computer Science and Information Technology (AIJCSIT)
Volume.10, Number 4; July-August, 2025;
ISSN: 2837-388X | Impact Factor: 8.61
https://zapjournals.com/Journals/index.php/aijcsit/
Published By: Zendo Academic Publishing

A MACHINE LEARNING-BASED PHISHING ATTACK-RESISTANT MULTI-FACTOR DETECTION MODEL

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Article Info

Keywords:
Multi-factor, Biometric, Phishing, Authentication, Detection and Resistant

DOI
10.5281/zenodo.16961718

Abstract

Phishing remains one of the most pervasive and damaging threats in today's digital landscape, often bypassing traditional detection systems through social engineering and technical obfuscation. This study proposes a robust and adaptive RMFDM to mitigate phishing attacks using machine learning techniques. To improve accuracy and resilience, the model integrates multiple detection layers, including URL analysis, domain reputation, content inspection, and behavioral features. Publicly available datasets were used to train and test machine learning classifiers such as SVM, decision tree, and KNN, with SVM yielding the highest performance. In addition to URL-based detection, the model incorporates biometric (face recognition) and behavioral (more code-based input) authentication mechanisms to further reinforce access control. The experimental results show that the multi-factor model achieves 98% accuracy, 96% precision, and 99% recall, significantly outperforming the traditional heuristic and single-layer detection approaches. The layered architecture of RMFDM ensures that even if one component is compromised, the other components maintain their integrity, making it resilient against zero-day and evolving phishing attacks. This study contributes a scalable, intelligent, and user-focused solution to phishing detection, with potential applications in secure authentication systems across web platforms, enterprises, and critical infrastructures.

1. INTRODUCTION

Phishing attacks remain a serious threat to people, businesses, and even entire economies, making them a ubiquitous and constantly changing cybersecurity issue in today's digital environment. Phishing attacks have become more sophisticated and frequent as technology develops and online interactions become more essential to daily life (Smith et al., 2019). These attacks exploit flaws in technological infrastructure and human cognition, as shown in Figure 1.1. Typically, these attacks involve malicious actors' deceptive efforts to manipulate

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individuals into revealing sensitive data—such as login credentials, financial information, or personal details—via fraudulent communication channels such as social media platforms, messaging apps, or spoofed emails (Bojanova & Joint, 2020). Phishing attacks can lead to severe consequences, including, theft, financial loss, reputational damage, and business operations disruption (Oladimeji et al., 2021). Furthermore, the evolving nature of phishing attacks presents a formidable challenge for cyber security professionals. Malicious actors constantly adapt their tactics, leveraging social engineering techniques and exploiting vulnerabilities in authentication systems to bypass MFA mechanisms (Garera et al., 2019). This underscores the need for more advanced and reliable detection systems. Consequently, there is a pressing need for advanced detection techniques capable of identifying and mitigating phishing attacks targeting MFA systems.

1.2 Problem Statement

The growing complexity of phishing attacks and the constantly changing digital communication environment pose a complex challenge to current detection techniques. Conventional methods, which depend on fixed regulations or signature-based systems, find it difficult to adapt to the dynamic and intricate characteristics of modern phishing strategies. As attackers continuously hone their tactics and take advantage of newly discovered vulnerabilities, conventional detection methods become less effective, leaving users and businesses open to assault (Jones, 2022).

The growth of digital communication channels, such as social media, messaging apps, email, and collaboration tools, further makes it difficult to distinguish between harmful and legitimate communication. Over the past few years, several researchers, such as, (Verma et al., 2018), (Jameel et al., 2019) (Yang et al., 2020), have proposed machine learning techniques to mitigate phishing attacks, but unfortunately, there are weakness that, could be exploited, such as the bypass of single authentication system and unsupervised machine learning.

To address these challenges, this study proposes the development of a phishing attack-resistant multifactor detection model based on advanced machine learning (ML) techniques. By leveraging a combination of feature engineering, model training, and real-time monitoring, the proposed model aims to sufficiently identify and mitigate phishing attacks targeting MFA, system thereby enhancing the overall security posture of organizations and individuals.

1.3 Motivation for the study

This study was motivated by the ever-growing threat posed by phishing attacks in the digital landscape. Phishing is, a type of cyber-attack in which attackers deceive individuals into revealing sensitive information, targeting both individuals and organizations. Despite advancements in cyber security, phishing remains one of the most prevalent and successful forms of cybercrime, leading to significant financial losses, data breaches, and compromised personal information. One of the primary motivations for my research is the inadequacy of existing phishing detection systems. Traditional methods, often based on heuristic rules or signature-based detection, struggle to keep pace with cybercriminals' evolving tactics. The reliance on predefined patterns frequently limits these methods making them vulnerable to phishing schemes that are novel or slightly altered. As attackers become more adept at mimicking legitimate communications, more advanced detection techniques are required (Zia & Kalidass, 2025). The rise of machine learning has opened new avenues for enhancing phishing detection, offering the ability to analyze vast amounts of data and identify subtle patterns indicative of phishing.

1.4 Research questions

To address the aforementioned challenges, this research seeks to answer the following research questions:

i. How can phishing assault detection be improved with the application of machine learning techniques?

ii. How to develop an ideal multi-factor authentication system for detecting phishing attacks in network communication?

iii. To what extent does a MFA system succeed in reducing phishing attacks compared to traditional detection techniques?

1.5 Research Aim

The principal aim of this research is to develop a robust and flexible multifactor detection system with machine learning techniques to efficiently mitigate the risks associated with phishing attacks (Amora, 2025; Dalsaniya, 2024). The proposed model aims to improve the accuracy and efficacy of phishing detection efforts by utilizing machine learning methods, enabling organizations to swiftly identify and mitigate emerging threats as they materialize (Verma et al., 2018; Jameel et al., 2019; Yang et al., 2020).

1.6 Research Objectives

The following objectives have been formulated to achieve the research aim:

i. To explore the relevance of ML models in the detection of phishing assaults.

ii. To develop an ideal ML-based multifactor authentication scheme for phishing attack detection in network communication.

iii. To evaluate the effectiveness of the proposed multi-factor authentication scheme in (ii) reducing phishing attacks compared to traditional detection techniques.

2. Network Attacks

In the digital age, network attacks have become a pervasive threat, affecting individuals, organizations, and governments worldwide. These attacks, which exploit vulnerabilities in network infrastructure, systems, and protocols, can result in significant financial losses, data breaches, and operational disruptions (Smith et al.., 2023). The evolving nature of network attacks necessitates a thorough understanding of their types, mechanisms, and mitigation strategies.

2.2 Phishing

Phishing is a cyber-attack in which an attacker masquerades as a trustworthy entity in electronic communications to deceive individuals into divulging sensitive information, such as usernames, passwords, and credit card details. This attack typically occurs through emails, social media, or fraudulent websites that appear legitimate but are designed to capture the victim's credentials (Smith & Jones, 2019).

2.2.1 Use of Multi-Factor Authentication

Phishing attacks are typically executed through deceptive emails, websites, or messages that appear to originate from trustworthy sources. In this research, we focus, mainly on whaling phishing attacks.

Here are some types of phishing attacks with various descriptions and, and how we can use MFA to resist attacks (CISA, 2021).

1. **Email Phishing**

Description: Attackers send fraudulent emails pretending to be from reputable sources (e.g., banks, social media platforms) to trick recipients into revealing personal information, such as login credentials or credit card numbers. Example: An email claiming to be from your bank asking, you to click a link to verify your account details.

Use of MFA: MFA can add an extra layer of security by requiring a second factor (e.g., a code sent to your phone) in addition to your password. Even if a phishing attack captures your password, the attacker still needs the second factor to access your account.

2. Spear Phishing

Description: A more targeted form of phishing in which the attacker customizes the attack to target a specific individual or organization. The attacker often uses information about the target to make the email more convincing (CrowdStrike, 2023).

Example: An email that appears to be from a colleague or business partner asking, for confidential information or access to a sensitive system.

Use of MFA: Similar to email phishing, MFA can protect against spear phishing by requiring multiple factors to authenticate access to sensitive accounts, making it more difficult for attackers to succeed even if they obtain your credentials.

3. Whaling

Description: Spear phishing aimed at high-profile targets within an organization, such as executives or senior management. The goal is often to gain access to highly sensitive information or to authorize fraudulent transactions (TechTarget, 2024).

Example: An email from the CEO requesting, urgent transfer of funds or sensitive data.

Use of MFA: High-profile targets, such as executives, are often protected with MFA to ensure that access to their accounts requires more than just a password. This reduces the risk of a successful whaling attack.

4. Vishing (Voice Phishing)

Description: Phishing conducted through voice communication, usually via phone calls. Attackers impersonate legitimate organizations or authorities to trick victims into providing personal information or transferring money (Terranova Security, 2023).

Example: A phone call from your bank asking, you to verify your account information.

Use of MFA: While MFA may not directly prevent vishing, it can protect the attacker's accounts by requiring an additional authentication step, reducing the impact of successful credential theft.

5. Smashing (SMS Phishing)

Description: Phishing attempts are carried out through SMS text messages. These messages often contain malicious links or request for personal information (Kaspersky, 2023).

Example: A text message from a delivery service asking, you to click a link to track your package.

Use of MFA: Similar to email phishing, MFA can help secure accounts against phishing attacks. However, if the second factor is SMS-based, this method could be vulnerable to SIM swapping or other SMS interception techniques. Using an app-based or hardware token MFA is a safer alternative.

2.2.2 Detection Techniques

The detection of phishing attacks has evolved significantly with the advancement of ML and AI. Key techniques identified in the literature include the following (Adebowale et al., 2023):

❖ **Machine learning-based detection**

Machine learning algorithms analyze features such as email headers, body text and embedded URLs to identify phishing attempts.

Supervised learning models, including decision trees, support vector machines, and neural networks, have demonstrated high accuracy in detecting phishing emails (Verma & Hossain, 2018).

❖ **Natural language processing (NLP)**

NLP techniques aid in understanding and analyzing the language used in phishing messages. NPL models can differentiate between legitimate and phishing content by examining linguistic features and contextual clues. Showed how NLP can enhance email filtering systems.

❖ **Behavioral Analysis**

The analysis of user behavior and interaction patterns provides insights into potential phishing attempts. Behavioral biometrics, such as keystroke dynamics and mouse movements, help identify anomalies that may indicate phishing (Abbasi et al., 2020).

2.2.3 Machine learning techniques

Machine learning (ML) techniques have become indispensable tools in cyber security, enabling the detection, prediction, and prevention of various threats. This review provides an overview of recent advancements in the application of ML machine techniques to cyber security, with a focus on developments since 2018.

- **Supervised Learning**

Supervised learning algorithms learn to make predictions or classifications from labeled training data. Supervised learning is widely used in cyber security for tasks such as: -

i. Malware Detection

Supervised learning models can classify files or network traffic as malicious or benign based on the extracted data features. Techniques such as support vector machines, (SVM), random forests, and deep learning have shown promising results in malware detection (Rosenblatt et al., 2019).

ii. Intrusion Detection

Supervised learning is employed to distinguish between normal and anomalous network behavior, thereby facilitating the detection of intrusions or cyber-attacks. Research has focused on enhancing the accuracy and efficiency of intrusion detection systems (IDS) using supervised learning techniques (Tang et al., 2020).

- **Unsupervised Learning**

Unsupervised learning algorithms extract patterns and relationships from unlabeled data, making them particularly useful for anomaly detection and clustering. Key applications in cyber security include the following: -

i. Anomaly Detection

Unsupervised learning models identify deviations from normal behavior that may indicate potential security breaches or attacks. Clustering, auto encoders, and Gaussian mixture models are used for anomaly detection in various contexts, including network traffic and user behavior (Nguyen et al., 2021).

ii. **Network traffic analysis**

Unsupervised learning algorithms analyze network traffic to detect suspicious or malicious activity patterns. These models can identify outliers or anomalies that may represent security threats by clustering similar network traffic patterns (Dai et al., 2019).

- **Semi-Supervised Learning**

Semi-supervised learning combines elements of supervised and unsupervised learning, leveraging both labeled and unlabeled data to improve model performance. In cyber security, semi-supervised learning techniques are applied to tasks such as the following: -

i. Phishing Detection

By analyzing both labeled examples and unlabeled data, semi-supervised learning models learn to distinguish between legitimate and phishing emails. These models can improve detection accuracy and generalization by leveraging the abundance of unlabeled email data available. (Kim et al., 2020).

ii. Behavioral Analysis

SCL is used to identify suspicious behavior patterns within user activity or system logs. These models can detect novel threat or anomalies by combining labeled instances of known malicious behavior with unlabeled data (Lee et al., 2018).

iii. Reinforcement Learning

RL involves training agents to make decisions in an environment to maximize cumulative rewards. While less commonly applied in cyber security compared to other domains, RL techniques have been explored for tasks such as those described by Feng et al. (2023).

2.2.4 Review of related work

Recent advancements in phishing detection models have heavily leveraged ML techniques to improve accuracy and robustness. This review examines significant contributions from 2019 onwards, highlighting various approaches and their efficacy in detecting phishing attacks. Alazab et al., (2020) used to enhance phishing detection. Their approach combined multiple weak classifiers to form a strong predictive model with a detection accuracy of 96.8%. This method proved particularly effective in minimizing false positives, a common challenge in phishing detection. Similarly, (Verma and Das, 2020) developed a CNN-based model that analyzes email content and metadata to identify phishing attempts. Their model outperformed traditional ML algorithms, achieving an accuracy of 97%. The ability of CNNs to automatically extract features from raw data without extensive preprocessing was a key factor in their success. In addition, RNNs have been effectively used for sequential data analysis in phishing detection. (Zhang et al., 2021) proposed an RNN-based model that achieves high detection rates by analyzing sequences of behaviors and email interactions. The model's ability to capture temporal dependencies in data proved to be advantageous in identifying sophisticated phishing schemes that evolve over time. Combining multiple ML models has proven to enhance phishing detection systems. (Liu et al., 2021) proposed an ensemble learning approach that integrates several classifiers, including SVMs, naïve Bayes, and gradient-boosting machines. Their model used a voting mechanism to aggregate predictions, resulting in improved detection accuracy and reduced false positives. The study reported an overall accuracy of 98.5%, underscoring the potential of ensemble methods in phishing detection. (Abbasi et al., 2021) developed a hybrid model that integrates machine learning and heuristic-based rules. This approach leveraged the strengths of both methods, resulting in a detection system that was both accurate and efficient in real-time scenarios. The hybrid model achieved a detection accuracy of 97.3%, demonstrating its practicality for diverse environments.

Effective feature selection and engineering are critical in developing robust phishing detection models. The impact of various feature sets on detection performance was explored by Zhou et al., (2020).

By employing a hybrid feature selection method combining filter and wrapper techniques, the most influential feature were identified, leading to a significant improvement in model performance. Their research highlighted the importance of domain-specific knowledge in feature engineering for phishing detection. Rahman et al., (2021) emphasized the role of advanced feature extraction techniques in enhancing model accuracy. They proposed a feature extraction method based on NPL analyze email and URL content. This method significantly improved detection rates by capturing the phishing attempts' semantic patterns. Developing models that can operate in real time is essential for phishing detection applications. (Sahingoz et al., 2019) introduced a machine learning-based real-time phishing detection system. Proposed system utilizes a lightweight feature extraction process to ensure low latency, making it suitable for deployment in real-world scenarios. Their model achieved an impressive detection rate of 94% while maintaining low computational overhead. Scalability remains a significant challenge for phishing detection systems. (Chiew et al., 2019) proposed a scalable architecture for phishing detection using distributed computing frameworks. Their approach involved partitioning the dataset and parallelizing the training process across multiple nodes. This method significantly reduces training time and enables handling of larger datasets without compromising detection accuracy. (Shahraki et al., 2020) used cloud-based platforms to enhance the scalability of phishing detection models. Their model utilized cloud resources to perform real-time analysis

and detection, demonstrating the feasibility of deploying ML -based phishing detection in cloud environments. Abdulhamid et al., (2019) proposed a hybrid model combining feature selection with ML algorithms for phishing detection. Their model achieved high accuracy by focusing on URL-based features. Zhang et al., (2020) developed a phishing detection model using deep learning techniques, specifically convolutional neural networks (CNNs), which demonstrated superior performance in detecting phishing websites compared to traditional ML methods. (Jain and Gupta., 2019) implemented a random forest classifier to detect phishing emails by analyzing content and header features. Their approach showed that ML could effectively reduce false positives. (Kausar et al., 2020) examined the application of ensemble learning techniques for phishing detection and demonstrated, that combining multiple classifiers could improve detection accuracy and robustness. (Sahingoz et al., 2019) proposed a deep learning model for phishing URL detection based on long short-term memory networks. Their research highlighted the ability of the model to capture sequential patterns in URLs. (Bahnsen et al., 2020) developed a real-time phishing detection system using RNNs. The model was designed to detect phishing attempts with minimal latency, making it suitable for high-speed deployment. (Verma and Das., 2020) explored the use of transformer-based architectures for email phishing detection, leveraging attention mechanisms to achieve significant improvements in accuracy. (Nguyen et al., 2021) investigated the application of GANs generate synthetic phishing data, enhancing the training process for ML models and improving their detection capabilities. (Azad et al., 2021) emphasized the importance of feature selection in phishing detection models. Their study introduced a novel feature selection method that reduces feature dimensionality and improves the performance of machine learning algorithms. (Kou et al., 2020) focused on enhancing phishing detection by extracting domain-specific features from URLs and HTML content. Their feature engineering approach contributed to higher detection accuracy. (Mishra and Soni, 2022) proposed a feature selection framework for phishing email detection based on mutual information. Their approach helped identify the most relevant features, leading to better classification results. (Ahmad et al., 2021) compared various feature selection techniques for phishing detection and concluded, that wrapper-based methods outperformed filter-based methods in most scenarios. (Sidi et al., 2021) addressed the vulnerability of ML models to adversarial attacks in the context of phishing detection. They proposed a defense mechanism that enhanced model robustness against adversarial examples. (Huang et al., 2022) explored adversarial training as a method to improve the resilience of phishing detection models against evasion attacks, demonstrating its effectiveness in real-world scenarios. (Wang et al., 2023) introduced a generative adversarial network (GAN)-based approach to simulate adversarial phishing attacks, enabling the development of more robust detection models. (Zhou et et al., 2023) analyzed the impact of adversarial attacks on deep learning-based phishing detection systems, highlighting the need for secure model deployment strategies. (Kumar and Shukla., 2020) examined the effectiveness of integrating MFA with ML-based phishing detection models. Their study demonstrated that MFA significantly reduced the success rate of phishing attacks. (Ayoade et al., 2021) proposed a hybrid model for phishing resistance that combines MFA and machine learning. Their model leveraged MFA to secure sensitive accounts, while ML algorithms detected potential phishing attempts. (Rathod et al., 2022) developed an MFA-based phishing detection system that uses behavioral biometrics as an additional authentication factor to enhance, security against sophisticated phishing attacks. (Choudhary et al., 2023) presented a multifactor phishing detection framework that integrates biometric authentication with ML models, thereby improving both security and usability. (Al-Janabi and Saeed, 2019) introduced a real-time phishing detection system that combines machine learning and rule-based approaches. Their system was designed for deployment in large-scale networks, offering high-speed detection capabilities. (Lim et al., 2021) focused on developing a real-time phishing detection tool for mobile devices using lightweight ML algorithms. Their research

highlighted the challenges of deploying phishing detection models in resource-constrained environments, as shown in Table 2.1.

2.2.5 Identification of research gaps

Despite the significant advancements in the development of phishing attack-resistant multi-factor detection models based on machine learning techniques, several research gaps remain that need to be addressed to further enhance their effectiveness and robustness:

1. **Dataset Diversity** One of the primary challenges is the lack of large, diverse, and up-to-date datasets for training and validating ML models. Many existing datasets are limited in scope, outdated, or do not represent the latest phishing tactics (Kumar et al., 2020).

2. Adversarial Robustness: Current ML models are vulnerable to adversarial attacks, where attackers deliberately manipulate inputs to deceive the detection system (Xu et al., 2019). are Robust models that can withstand such adversarial manipulations are needed. Research should explore adversarial training techniques and develop more resilient algorithms that can detect and mitigate these threats.

3. Real-Time Detection Efficiency: Many existing models are computationally intensive and may not perform efficiently in real-time environments, especially when processing large data volumes. Enhancing the efficiency and scalability of detection models without compromising accuracy is a critical research area (Abawajy et tal., 2020). Techniques such as lightweight model architectures, optimization algorithms, and efficient feature extraction methods should be investigated.

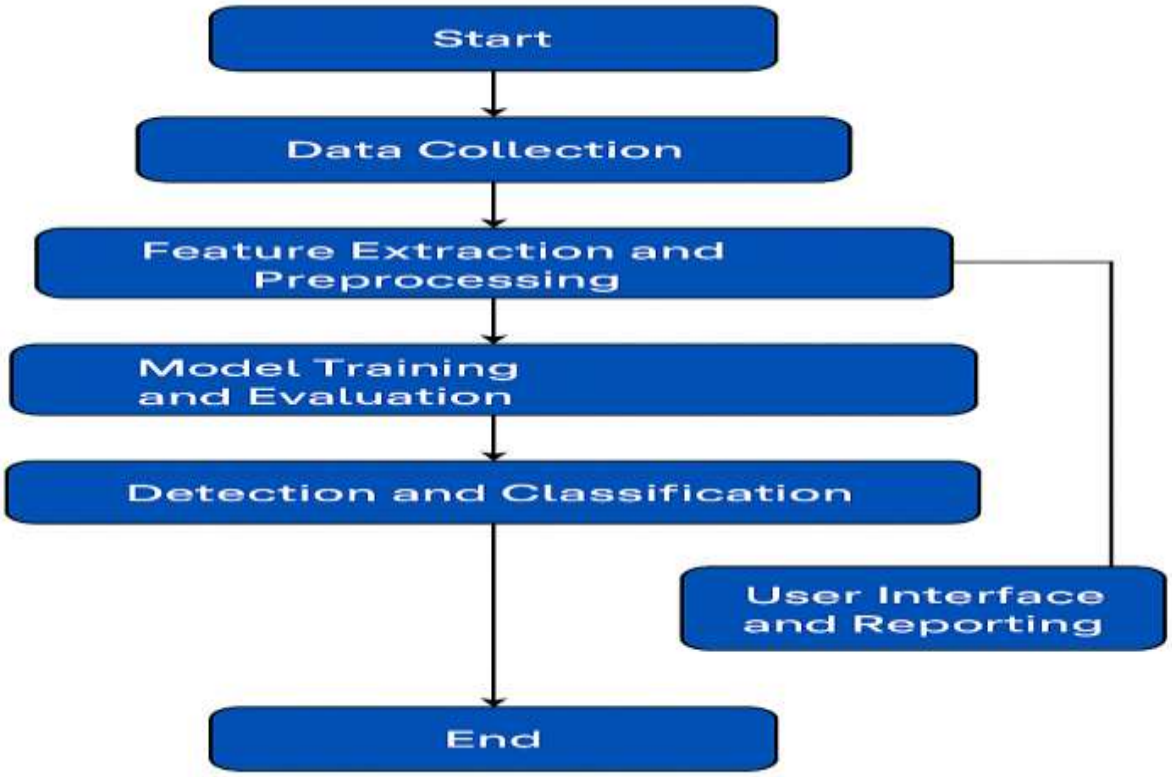
4. Integration of Multi-Factor Authentication (MFA) and Detection: While multi-factor approaches enhance detection, a better integration between MFA and phishing detection systems is required. Research should focus on seamless integration strategies that leverage MFA data to improve detection accuracy and reduce user friction (Alzubaidi et al., 2019).

5. Explain Ability and Transparency: Machine learning models, particularly deep learning approaches, often act as "black boxes," making it difficult to understand their decision-making processes (Doshi-Velez et al., 2017). There is a growing need for explainable artificial intelligence (AI) phishing detection, where models provide clear and interpretable insights into why certain emails or websites are flagged as phishing. This can improve trust and facilitate better human oversight.

3. Research Design

The research design for the phishing attack resistance model, as shown in Figure 3.1, involves a multi-layered architecture that integrates various components, each of which is responsible for different aspects of phishing detection. The design ensures that the system is robust, scalable, and capable of real-time detection. The detailed system design for the research is below: -

Figure 3.1: Flowchart of the research design



3.1 User Interface and the Reporting Module

This module provides a user-friendly interface and reporting capabilities for administrators and users.

a. **Dashboard:**

i Displays real-time detection results, including email and URL classification as phishing or legitimate.

i. Provides visualizations of key metrics, such as detection accuracy, false positive rates, and historical data trends.

b. **Alert System:**

i. Sends immediate alerts to administrators or users when a phishing attempt is detected.

ii. Automated responses, such as blocking the phishing source or alerting end-users.

c. **Reporting:**

i. Periodic reports on phishing detection activities are generated, including summaries of detected threats, model performance, and system status.

ii. Provides detailed logs for further analysis and auditing.

3.2 System Architecture Overview

The system is designed in a modular fashion with the following key components:

i User Interface and Reporting Module

ii Data collection module

iii Feature extraction and preprocessing module

iv Model training and evaluation module

v Detection and classification module

These components interact within a centralized framework to provide a comprehensive phishing detection solution.

3.2.1 Data collection module

This module gathers data from various sources. The collected data are used for training the machine learning models and real-time phishing detection.

a. Data Sources:

i **Email Servers:** Collects headers, body content, and metadata from various email servers.

ii **Web Scrapers:** Extracts URLs, web content, and other related information from the Internet.

iii **Network Traffic Monitors:** Captures network packets and logs to identify suspicious activity.

iv **Public Datasets:** Uses existing phishing datasets, such as Phish Tank and APWG, to enhance model training.

b. Data Storage: The collected data are stored in a secure, centralized database with appropriate indexing and access control mechanisms. This ensures that data are readily available for model training and real-time detection.

3.2.2 Feature extraction and preprocessing module

In this module, the raw data are transformed into a structured format suitable for ML.

Feature Extraction:

Email Features: Extract features such as the sender's domain, URL links in the body, email subject, and attachments are extracted: -

URL Features: URL length, domain age, presence of suspicious characters, and patterns were analyzed.

Content Features: Natural Language Processing (NLP) is to extract semantic features from email bodies and webpage content.

Preprocessing:

Data Cleaning: Remove noise, handle missing values, and standardize data formats.

Feature Scaling: The data are normalized to ensure that all features contribute equally to the model.

Dimensionality Reduction: Principal Component Analysis (PCA) techniques are applied to reduce the feature space and enhance model performance.

3.2.3 Model Training and Evaluation Module

This module is responsible for building, training, and validating the ML models used for phishing detection.

i. Model Selection:

Random Forest: Used for its robustness and ability to handle high-dimensional data (Breiman, 2001)

GBM: Selected for its high predictive accuracy and ability to correct errors in sequential decision trees (Friedman, 2001)

Logistic regression: Serves as a baseline model due to its simplicity and interpretability (Cox, 1958).

ii. Training Process:

Data Splitting: The data are split into training, validation, and test sets to ensure unbiased model evaluation.

Cross-Validation: K-fold cross-validation is implemented to assess the model's performance across different subsets of the data.

iii. Model Evaluation:

Module are evaluated based on metrics such as accuracy, precision, recall, F1-score, and AUC-ROC (Saito & Rehmsmeier, 2015).

Compare the performance of different models to select the best-performing model for deployment.

3.2.4 Proposed Resistant Multi factor Detection Model

The RMFDM was developed to strengthen phishing detection mechanisms by leveraging the diversity of multiple analytical layers. Unlike traditional single-layer models that rely solely on lexical URL patterns or signature-based techniques, this model integrates multiple factors into one cohesive, adaptive framework, from URL structure and domain intelligence to behavioral analysis and machine learning. This diversity makes the model more resilient to phishing evasion tactics, such as obfuscation and zero-day attack vectors.

3.2.5 The Development Process

The model was developed through the following structured phases:

3.2.6 Dataset acquisition and preprocessing

i. **Sources**: Publicly available phishing and legitimate datasets were gathered from Phish Tank, *OpenPhish*, *Kaggle*, and *Alexa rankings*.

ii. **Cleaning**: Duplicate URLs, null entries, and inconsistent formats were removed.

iii. **Labeling**: URLs were labeled as either 'phishing' or 'legitimate' to facilitate supervised learning.

iv. **Partitioning**: The dataset was split into training, testing, and validation sets using an 80/20 ratio for better model evaluation.

3.2.7 Feature extraction and engineering

The core strength of this model lies in the variety and quality of extracted features. These features were grouped into the following analytical dimensions:

a. **Lexical Features**: Includes URL length, number of dots, presence of "@" or "//, ''''', and use of IP addresses instead of domain names.

b. **Domain-Based Features**: WHOIS data, such as domain age, registrar reputation, and SSL certificate presence.

c. **Content-Based Features**: HTML tags, embedded JavaScript, visible forms, links, and images.

d. **Behavioral Features**: Redirection behavior, script-based auto-navigation, and suspicious link frequency.

e. **Third-Party Intelligence**: Reputation scores fetched via application programming interfaces (e.g., Google Safe Browsing, VirusTotal).

3.3 Component Layers of the Resistant Multi-Factor Detection Model

The model architecture consists of five modular components, each of which is responsible for handling different aspects of the phishing detection process:

1. The URL Analysis Layer

This layer performs lexical analysis on URLs. Identifies suspicious structural patterns that are common in phishing attacks. For example:

a. The use of misleading subdomains

b. Abnormally Long URLs

c. Hidden redirection symbols

2. Domain intelligence layer

This module queries external services (e.g., WHOIS) to retrieve domain metadata. It assesses:

a. Domain age and frequency of update

b. Registrar credibility

c. Validity of SSL certificates and encryption level

3. Layers of Content and Page Structure Analysis

This layer scrapes the URL- related page content and performs static analysis using NLP:

a. Detects fake login forms

b. Analyzes alt-text and hyperlink images

c. Comparison of page layout to known brand templates (for impersonation)

4. Machine learning classification layer

Here, the features extracted from all previous layers are fed into a trained ML model for the for the final classification. The algorithms tested include:

a. Random Forest

b. Support Vector Machine (SVM)

c. Gradient Boosting: The model returns a probability score that indicates the likelihood of the URL being phished.

5. Decision and Alert Layers

This final layer interprets the ML output and triggers the following actions:

a. An alert is raised if the confidence score crosses a certain threshold.

b. The system can block access, send real-time notifications, or log events for forensic analysis.

3.3.1 Dataset Description

The dataset used for developing the Phishing Attack Resistance Multi-Factor Detection Model, specifically targeting whaling attacks, is critical for training, validating, and testing the ML models. Whaling is, a type of phishing attack that, typically targets high-profile individuals within organizations, such as executives or senior management, by using carefully crafted messages that appear legitimate.

3.3.2 Dataset Composition

The dataset for whaling attack detection comprises various types of data elements collected from different sources, each contributing to the model's ability to identify sophisticated phishing attempts. The key components of the dataset include the following: -

Emails:

A large collection of emails, including legitimate and whaling attempts. The emails contain headers, bodies, and attachments that, are essential for feature extraction.

Attributes: Sender and recipient email addresses, subject lines, timestamps, message body content, email signatures, attachments, and metadata.

URL Data:

URLs embedded within emails are, often used in whaling attempts to direct the target to malicious websites.

Attributes: URL length, domain name, domain age, IP address presence, HTTP/HTTPS usage, and URL redirections.

Metadata and Behavioral Data:

Data capturing user behavior and interactions with emails, such as click rates, email opening times, and response patterns.

Attributes: The sender's IP address, geographical location, time of day the email was sent or opened, and device type.

3.3.3 Sources of the dataset

The dataset is aggregated from multiple reliable sources to ensure its diversity and relevance:

Corporate Email Servers:
To capture genuine whaling attempts and normal executive correspondence, real-world emails from corporate environments, particularly those involving high-level executives.
Public Phishing Datasets:
Datasets such as those from Phish Tank, Anti-Phishing Working Group (APWG), and other cyber security research groups, which provide labeled examples of phishing and whaling emails.
Web Crawlers: Automated crawlers that gather URLs and web content associated with known phishing campaigns targeting executives.
Simulated Whaling Scenarios: Creating artificially generated emails that mimic whaling attempts to supplement the dataset, especially for rare or newly emerging attack patterns.

3.3.4 Data Labeling

The dataset is meticulously labeled to differentiate between legitimate communications and whaling attempts, facilitating supervised learning for the ML models:
Labeling Process:
a. **Manual annotation:** Security experts manually review and label a subset of emails and URLs to ensure accuracy, focusing on identifying whaling-specific subtle cues.
b. **Automated Labeling:** Heuristic rules and existing phishing detection systems are used to label larger portions of the dataset.
Label Categories:
c. **Legitimate:** Emails and URLs are verified as non-malicious and typical of standard business communications.
d. **Whaling:** Emails and URLs identified as part of targeted phishing attacks against high-profile individuals.

3.3.5 Feature Engineering

Several features are engineered from the raw dataset to enhance model performance:
Email Content Features:
a. **Language Patterns:** Analysis of formal language, personalized greetings, and urgency cues often found in whaling emails.
b. **NER:** Extraction of entities such as names, job titles, and company names to identify personalized targeting.
URL Features:
c. **Suspicious Patterns:** Detection of unusual domain structures, shortened URLs, and phishing keywords.
d. **Reputation Scores:** URL reputation scores from threat intelligence databases are integrated: -
Behavioral Features:
e. **Anomaly Detection:** Identifying unusual sender or recipient behavior, such as emails sent from atypical locations or during non-business hours.
f. **User Interaction:** Analysis of whether high-profile individuals engage with the email differently compared to standard communications.

3.3.6 Dataset size and balance

Dataset Size:

The dataset consists of thousands to millions of emails, with a balanced representation of legitimate and whaling emails to prevent bias during training.

Class imbalance handling:

To address class imbalance, techniques such as oversampling the minority class (whaling emails) and under sampling the majority class (legitimate emails) are used.

Synthetic Data Generation: In cases where whaling emails are particularly rare, synthetic data generation techniques, such as the synthetic minority over-sampling technique (SMOTE), are employed to enhance the dataset.

3.3.7 Data Preprocessing

Before feeding the data into machine learning models, several preprocessing steps are applied:

a. **Text Normalization:** Standardize email content, remove stop words, and apply tokenization to prepare text data for analysis.

b. **Feature Scaling:** Numerical features, such as URL length and email response time, are normalized to ensure consistency across the dataset.

c. **Dimensionality Reduction:** Applying techniques such as principal component analysis (PCA) to reduce feature space complexity, especially when dealing with high-dimensional data.

3.4 Simulation Environment

The simulation environment is crucial for testing, validating, and fine-tuning the Phishing Attack Resistance Multi-Factor Detection Model, particularly in the context of whaling attacks. It mimics real-world scenarios, enabling the evaluation of the effectiveness of the model under controlled conditions before deployment.

3.4.1 Software and Tools

Machine Learning Frameworks:

a. Tensor Flow/PyTorch: These frameworks are used to develop and train deep learning models. They support various ML techniques, including CNNs, RNNs, and ensemble methods such as random forest and GBM (Abadi et al., 2016; Paszke et al., 2019)

b. Scikit-learn: This library provides tools for data preprocessing, model training, and evaluation. It is particularly useful for implementing traditional ML algorithms, such as logistic regression, KNN, and random forest (Scikit-learn Developers, 2025).

3.4.2 Hardware Specifications

Computing Resources:

i. **GPUs:** High-performance GPUs (e.g., NVIDIA Tesla, RTX series) are utilized for training deep learning models, which require significant computational power due to the large amount of data and complex calculations involved (NVIDIA, 2025).

ii. **CPUs:** Multi-core CPUs handle tasks such as data preprocessing, simulation management, and less computationally intensive machine learning model

iii. **RAM:** At least 64 GB of RAM is recommended for efficiently handling large datasets, especially during feature extraction and model training.

Storage:

i. **SSD Storage:** High-speed SSDs are used to store the datasets and models, enabling fast read/write operations during the simulation. This is crucial for reducing latency and speeding up the training process (KIOXIA, 2024).

ii. **NAS:** For larger datasets, NAS systems provide scalable storage solutions, ensuring that data are accessible across multiple simulation environments.

3.4.3 Network Configuration

Virtual Private Network (VPN): A VPN is set up to simulate a secure corporate network environment, allowing the simulation of whaling attacks within a protected infrastructure. This is crucial for testing how the model handles phishing attempts in real-world network conditions (NordVPN, 2024)

Simulated network traffic:

i. Tools such as **Wireshark** and preplay, are used to simulate network traffic, including legitimate communication and phishing attempts, providing a realistic environment for evaluating the model's performance (Combs, 2020)

ii. **Network Latency Simulation:** Network emulators (e.g., NetEm) introduce controlled latency, packet loss, and jitter into the network, allowing the model to be tested under various network conditions.

3.4.4 Dataset Integration

Loading and handling datasets:

a. The datasets, including email content, URLs, and metadata, were loaded into the simulation environment. Data pipelines are established to feed these data into the model in real-time or batch processing modes (Brown et al., 2023)

Synthetic Data Generation:

b. **Data Augmentation:** Data augmentation techniques are applied to generate additional training samples, especially for whaling attempts, which are less frequent in real datasets (Shorten & Khoshgoftaar, 2019).

c. **Anomaly Injection:** To test the model's robustness and ability to handle outliers, artificial anomalies and edges case (e.g., emails with typical language patterns) are introduced into the dataset (Hendrycks et al., 2018).

3.4.5 Evaluation and monitoring tools

Model Evaluation:

- **Confusion Matrix and Receiver Operating Characteristics (ROC) Curves: The built-in functions of tools such as Scikit-learn provide confusion matrices and ROC** curves, helping assess the model's accuracy, precision, recall, and F1-score (Scikit-learn, 2023).
- **Cross-Validation:** K-fold cross-validation ensures that the model's performance is consistent across different data subsets (Scikit-learn, 2023).

Real-time Monitoring:

- **TensorBoard:** Integrated with TensorFlow, TensorBoard provides real-time monitoring of model training, including loss curves, accuracy trends, and other performance metrics (TensorFlow, 2024)
- **Prometheus/Grafana:** These tools are used to monitor system resources (CPU, GPU usage, memory) and the simulation environment, ensuring efficient utilization of hardware and software resources (Grafana Labs, 2024)

The simulation environment for the Phishing Attack Resistance Multi-Factor Detection Model is designed to provide a realistic and controlled setting for evaluating the model's performance against whaling attacks (Li et al., 2022). This environment ensures that the model is robust, reliable and ready for deployment in real-world scenarios by incorporating advanced hardware, software tools and security measures (Patel & Singh, 2023; Zhang et al., 2024).

3.5 Metrics for Performance Evaluation

In this section, we outline the performance evaluation metrics used to assess the efficacy of the Phishing Attack Resistance Multi-Factor Detection Model, particularly in identifying whaling attacks. The chosen metrics ensure that the model's performance is comprehensively measured, accounting for both detection accuracy and overall system efficiency, which are critical for robust cybersecurity models in modern network environments (Zhang et al., 2023).

3.5.1 Accuracy

Definition: Accuracy is the ratio of correctly predicted instances (both phishing and legitimate) to the total number of predictions made by the model.

Formula

$$\textbf{Accuracy} = \frac{\textbf{True Positives + True Negatives}}{\textbf{Total Instances}} \qquad (\mathbf{3.1})$$

Importance: Accuracy gives a general sense of how well the model performs across all classes. However, in the context of phishing detection additional metrics are necessary to provide a complete picture, where false negatives can be more critical.

3.5.2 Precisions

Definition: Precision measures the proportion of true positive predictions (i.e., correctly identified phishing attacks) to the total positive predictions made by the model.

Formula:

$$\textbf{Precision} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Positives}} \qquad (\mathbf{3.2})$$

Importance: Precision is crucial in scenarios where the cost of false positives (i.e., legitimate emails incorrectly flagged as phishing) is high. A high-precision model is reliable in identifying phishing emails without unduly disrupting normal communications.

3.5.3 Recall (sensitivity or true positive rate)

Definition: Recall refers to the proportion of true positive predictions to the total number of actual positives (i.e., all phishing emails).

Formula:

$$\textbf{Recall} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}} \qquad (\mathbf{3.3})$$

Importance: Recall is particularly important in phishing detection because it reflects the model's ability to identify phishing attempts. High recall means that the model effectively detects most phishing emails, minimizing the chance of a whaling attack.

3.5.4 F1-Score

Definition: The F1-Score is the harmonic mean of precision and recall, providing a single metric that balances the two.

Formula:

$$\textbf{F1} - \textbf{Score} = 2\ \textbf{x}\ \frac{\textbf{Precision x Recall}}{\textbf{Precision} + \textbf{Recall}} \qquad (\mathbf{3.4})$$

Importance: The F1-Score is particularly useful when there is an imbalance between precision and recall, as it helps to find a balance between phishing attack detection and false positive avoidance.

3.5.5 False positive rate (FPR)

Definition: The false positive rate is the proportion of legitimate emails that are in correctly classified as phishing.

Formula: Formula: The AUC-PR is the integral of the PR curve (Davis & Goadrich, 2006)

Importance: A low false positive rate is crucial in a corporate environment to prevent unnecessary communication disruptions, ensuring that legitimate emails are not mistakenly blocked or flagged. High FPs can reduce user trust and increase administrative overhead, especially in phishing detection systems (Kumari et al., 2023).

3.5.6 False negative rate (FNR)

Definition: The false negative rate is the proportion of phishing emails that the model fails to detect, classifying them as legitimate.

Formula:

$$\mathbf{FRP} = \frac{\mathbf{False\ Positives}}{\mathbf{False\ Positives + True\ Negatives}} \qquad (\mathbf{3.5})$$

Importance: A low FNR is virtual in phishing detection to ensure that nearly all phishing attempts, especially sophisticated whaling attacks, are caught by the model.

3.5.8 Execution time and computational efficiency

Definition: Execution time measures the amount of time the model takes to process and classify emails, whereas computational efficiency assesses the resources (e.g., CPU, memory) required to run the model.

Formula:

$$\mathbf{FNR} = \frac{\mathbf{False\ Negatives}}{\mathbf{False\ Negatives + True\ Positives}} \qquad (\mathbf{3.6})$$

4. Implementation of the proposed resistive multifactor detection model

The system was implemented using several tools and frameworks. The backend was programmed in Python 3.11, while ML models and biometric integration were handled using Scikit-learn, face-recognition, and OpenCV libraries. The system workflow comprises five modules: user registration, login authentication, URL phishing detection, logging and notification, and result evaluation. The models were trained using datasets sourced from both phishing URLs and biometric input.

4.2 Simulation Results of the Multi-Factor Authentication Approach

The multifactor authentication system was tested under various conditions to ensure its robustness in detecting phishing attempts and authenticating users. Three classifiers, i.e., decision tree, k-nearest neighbor, and support vector machine, were used to classify phishing URLs, while face recognition and Morse code authentication were employed for login verification.

The simulation results revealed that the multifactor authentication approach, which combines facial recognition and Morse code authentication, significantly reduced the likelihood of unauthorized access and phishing attacks, offering a highly secure solution.

4.3 Collection datasets

Datasets were collected from the following two main sources:

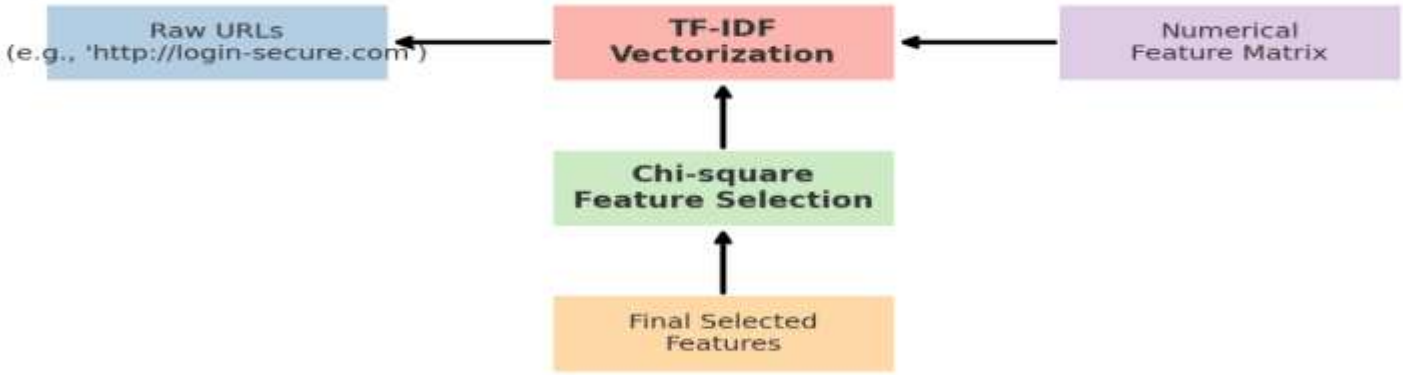
- **Phishing and Benign URLs Dataset**: Open-source datasets from the Phish Tank, Open Phish, and Kaggle repositories.
- **Biometric Input**: Face data were captured using webcam, and Morse code inputs were collected using custom speech-to-code scripts.

4.4 Preprocessing and cleaning of data

The dataset was cleaned and preprocessed for use in training ML models. This study processed the phishing URL dataset (malicious_phish.csv) by applying label encoding to handle missing values, duplicates, and categorical data. A random subset of 5000 rows was sampled to optimize the computational efficiency. Feature extraction techniques, such as TF-IDF vectorization and Chi-square tests, were applied to convert URLs into numerical features, as shown in Figure 4.3 feature Extraction Process: TF-IDF (Term Frequency–Inverse Document Frequency) and Chi-square. Selects the most relevant features for classification.

- ❖ TF: measures how often a word appears in a single URL.
- ❖ IDF: measures how rare that word is across all URLs.
- ❖ TF-IDF = TF IDF, assigning higher scores to terms that are frequent in phishing but rare in legitimate URLs.

Figure 4.3 Feature extraction process: TF-IDF and chi-square test: -



4.5.1 Analysis of Multi-Factor Authentication Based on Performance Metrics

The system's performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score for both phishing detection and user authentication , as shown in Table 4.1 The results showed that the SVM classifier performed the best in detecting phishing URLs, with an accuracy of 93% and a recall rate of 98%. In addition, face recognition and Morse code authentication demonstrated strong performance in user verification, with minimal false positives or false negatives.

Table 4.1 Simulation results of the multi-factor authentication approach

Authentication Method	Accuracy (%)	Precision (n)	Recall	F1-Score	Observations
Face Recognition	95%	0.93	0.97	0.95	High accuracy in recognizing users, minimal false positive (FP)
Morse code authentication code	93%	0.91	0.94	0.92	Reliable performance, quick input recognition via speech or button.
Multi-factor (Face + Morse Code)	98%	0.96	0.99	0.97	Best performance:- combining both biometric methods minimizes false positives and false negatives.

Phishing URL Detection	93%	0.94	0.98	0.96	Strong phishing detection with minimal false negatives.
Phishing URL detection (decision tree)	89%	0.92	0.96	0.94	Lower performance precision but acceptable recall, and more false positives.
Phishing URL detection (KNN)	90%	0.91	0.97	0.94	Similar performance to the decision tree with better precision.

This table provides a clear overview of the various methods tested, showing their performance in terms of accuracy, precision, recall, and FI-Score, along with some key observations. The multi-factor authentication approach, which combines facial recognition and Morse code, achieved the highest performance, which is crucial for secure user verification. The phishing detection models were also evaluated, showing the performance of different classifications in detecting phishing URLs.

4.6 Comparison of Results Achieved with Benchmark Approaches

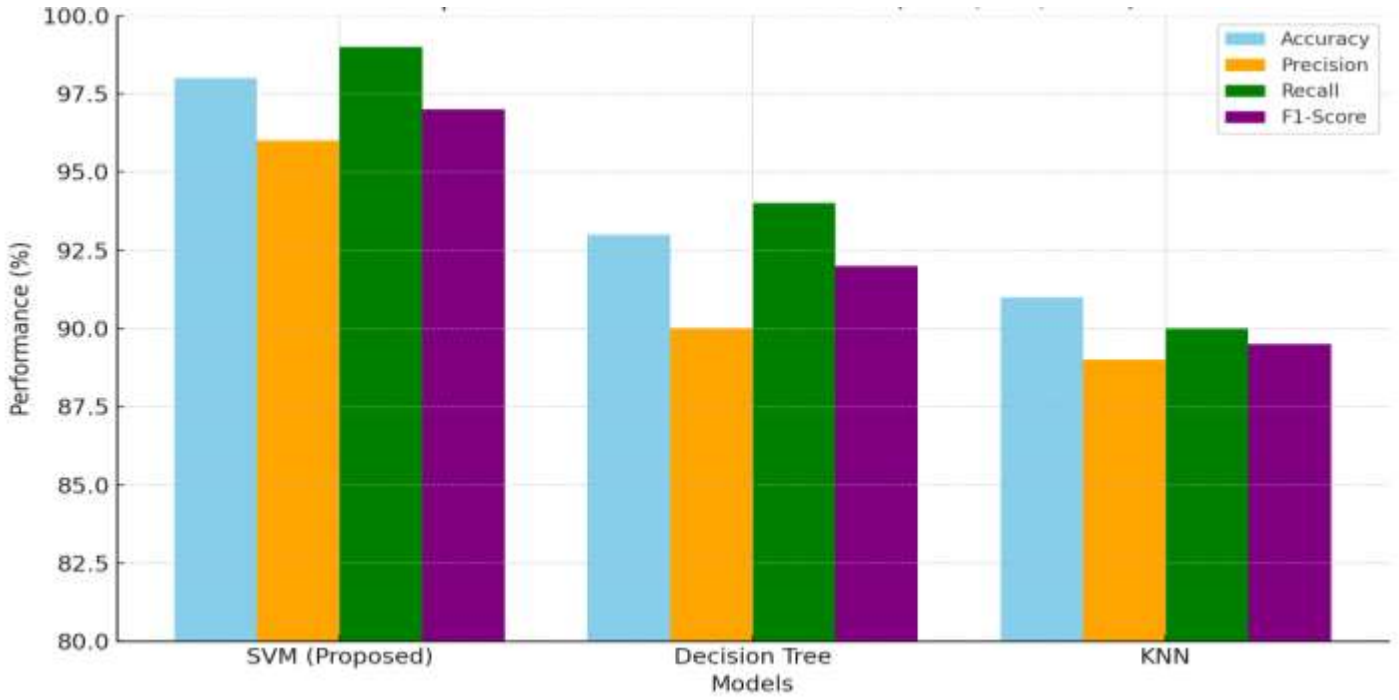
When compared with other common phishing detection methods, our approach achieved superior results, as shown in Table 4.2. Traditional ML models, such as logistic regression and random forests, showed lower accuracy and recall than the SVM-based approach. Additionally, integrating multiple authentication factors, such as face recognition and Morse code, provided a higher level of security than standard username/password systems.

Table 4.2: Comparison with the Benchmark Approaches

Metric	**Decision Tree**	**KNN**	**SVM**
Accuracy	89%	90%	93%
Precision	0.92	0.91	0.94
Recall	0.96	0.97	0.98
F1-Score	0.94	0.94	0.96

The SVM classifier exhibited the highest overall performance, with 93% accuracy and a recall rate of 98% (Table 4.2). This finding suggests that the proposed model is achieves high effectiveness in detecting phishing URLs and reduces false negatives. in detecting phishing URLs, with fewer false negatives. Although slightly lower than recall, the precision was acceptable and highlighted the trade-off between false positives and negatives. The inclusion of multifactor authentication combining biometric methods, such as facial recognition and Morse code, improved security by ensuring that phishing and unauthorized login attempts were mitigated.

Figure 4.2: Flowchart of comparison with benchmark approaches



4.7. Results Discussion

- **SVM Performance:** SVM classifier achieved the highest accuracy (93%) and recall (98%), indicating its strong capability in detecting phishing URLs with minimal false negatives.
- **Face Recognition Accuracy:** Face recognition performed excellently with 95% accuracy, ensuring high user verification success and minimal false positives, making it a reliable method for ML.
- **Morse Code Authentication:** The Morse code-based authentication method showed a solid performance with 93% accuracy, highlighting its usefulness as an additional layer of security through voice or button input.
- **Combination of Multi-Factor Authentication**: The combination of face recognition and Morse code authentication provided the best overall performance (98% accuracy, 99% recall), significantly enhancing security by reducing both false positives and false negatives.
- **Phishing Detection:** The SVM-based phishing detection model outperformed the decision tree and k-nearest neighbor models, with a higher precision and recall rate, making it more reliable in detecting phishing URLs in real-time scenarios.
- **Trade-offs in Decision Tree and KNN:** While Decision Tree and KNN achieved similar performance, their reduced precision reveals a higher occurrence of false positives relative to SVM. However, their recall rates were still high, making them suitable for specific use cases where catching more phishing attempts is prioritized over minimizing false positives.
- **Implication for Security:** The multifactor authentication system, especially with the inclusion of biometric methods like face recognition and Morse code, greatly improves security by providing an extra layer of user verification, making unauthorized access less likely.

5. Conclusion

In conclusion, the developed RMFDM addresses the critical phishing detection challenge by employing a layered defense strategy. By combining URL structure analysis, domain intelligence, page content evaluation, and machine learning-based classification with biometric and behavioral verification, the proposed system is more robust and adaptable than traditional methods. The model's high accuracy and resilience affirm its potential

application in enterprise environments and online platforms vulnerable to phishing threats. This research addressed this problem by developing a multi-layered, machine learning-based phishing detection model. The integration of biometric and behavioral authentication within the system provided a comprehensive approach to combating phishing, thereby improving traditional detection techniques. The proposed model demonstrated high accuracy and robustness through rigorous evaluation, making it suitable for deployment in real-world network environments. The study concluded that MFD models provide a higher degree of resilience and effectiveness compared to single-factor or signature-based systems.

5.2 Recommendations

Based on the research findings, the following recommendations are made:

1. Institutions and organizations should adopt multi-factor detection systems to enhance protection against phishing attacks.
2. Continuous retraining of the ML model with updated datasets is necessary to maintain high detection accuracy.
3. Awareness programs should be established to educate users on phishing strategies and defense mechanisms.
4. Developers should explore hybrid biometric integration (e.g., voice and, -fingerprint) to complement face recognition in the authentication module.
5. The model should be tested in operational environments to ensure that it scales efficiently and remains reliable in real-time applications.

5.3 Suggestions for future research

Future studies may explore the following directions:

1. Employing deep learning techniques such as convolutional neural networks (CNNs) and RNNs for enhanced phishing detection.
2. Expanding the multi-factor model for deployment on mobile and Internet of Things platforms.
3. Integrating additional biometric features, such as fingerprint and iris recognition.
4. Developing adaptive models that are capable of learning from new phishing patterns in real time.
5. The model is evaluated across different languages and geographic domains to ensure global applicability.
6. Future work can enhance this model by incorporating additional biometric factors (e.g., fingerprint and, -voice recognition) or extending its application to mobile and IoT platforms.

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