PHISHING BASED SOCIAL ENGINEERING DETECTION IN AI

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PHISHING BASED SOCIAL ENGINEERING DETECTION IN AI

NURSYUHADAH BINTI AHMAD SUDERMAN

This report is submitted in partial fulfillment of the requirements for the

Bachelor of [Computer Science (Computer Security)] with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

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# DEDICATION

This work is dedicated to Allah Almighty, my creator, pillar, and source of wisdom, knowledge, and insight. Throughout this journey, He has been my source of strength, and I have only been able to fly on His wings.

To my beloved parents, Ahmad Suderman Bin Mohd Yaacob and Norayzuazlin Binti Mohd Ayob whom I wholeheartedly dedicate this study to. Thank you for being my source of inspiration and for your unwavering support and trust. To my brothers, whom I hold very dear to my heart.

To my supervisor, Dr Zaheera binti Zainal Abidin, for supporting and believing in me to accomplish this project. Finally, I want to thank my friends for being there for me during my bachelor's degree, sharing words of advice and support to help me accomplish this study.

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# ABSTRACT

Social engineering attacks pose a significant and growing threat in the cybersecurity landscape, exploiting human psychology rather than technical vulnerabilities to manipulate individuals into compromising sensitive information. Among various social engineering techniques, phishing has emerged as the most prevalent and damaging, driven by its scalability, low execution cost, and evolving tactics such as spear phishing and smishing. As traditional rule-based detection methods struggle to keep up with these dynamic threats, Artificial Intelligence (AI) offers a robust and adaptive solution. This study explores AI-based approaches—specifically Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL)—for the detection of phishing attacks. It provides a comprehensive literature review, analysis of current research trends (2020–2024), and detailed examination of relevant datasets and algorithms including Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and Deep Q-Networks (DQN). The research highlights the advantages of AI in automating threat detection, enhancing accuracy, and enabling systems to adapt to new attack vectors. By focusing on phishing as a primary social engineering threat, this work aims to contribute to the development of intelligent, scalable, and real-time defenses against increasingly sophisticated cyber threats.

# ABSTRAK

Serangan kejuruteraan sosial merupakan ancaman yang semakin ketara dalam landskap keselamatan siber, di mana ia mengeksploitasi psikologi manusia dan bukannya kelemahan teknikal untuk memanipulasi individu agar mendedahkan maklumat sensitif. Dalam pelbagai teknik kejuruteraan sosial, serangan *phishing* telah muncul sebagai bentuk yang paling meluas dan merosakkan, didorong oleh keupayaannya untuk berkembang secara besar-besaran, kos pelaksanaan yang rendah, serta taktik yang sentiasa berubah seperti *spear phishing* dan *smishing*. Oleh kerana kaedah pengesanan berasaskan peraturan tradisional semakin sukar menandingi ancaman yang dinamik ini, Kecerdasan Buatan (AI) menawarkan penyelesaian yang kukuh dan adaptif. Kajian ini meneroka pendekatan berasaskan AI—khususnya Pembelajaran Mesin (ML), Pembelajaran Mendalam (DL), dan Pembelajaran Penguatan (RL)—dalam pengesanan serangan *phishing*. Ia merangkumi ulasan literatur yang komprehensif, analisis *trend* penyelidikan semasa, serta pemeriksaan terperinci terhadap set data dan algoritma yang relevan termasuk *Support Vector Machines* (SVM), *Long Short-Term Memory* (LSTM), dan *Deep Q-Networks* (DQN). Kajian ini menekankan kelebihan AI dalam mengautomasikan pengesanan ancaman, meningkatkan ketepatan, dan membolehkan sistem menyesuaikan diri dengan vektor serangan baharu. Dengan memberi tumpuan kepada *phishing* sebagai ancaman utama kejuruteraan sosial, kajian ini bertujuan menyumbang kepada pembangunan sistem pertahanan yang pintar, berskala, dan masa nyata terhadap ancaman siber yang semakin canggih.

# TABLE OF CONTENTS

[DECLARATION ii](#_Toc197372189)

[DEDICATION iii](#_Toc197372190)

[ACKNOWLEDGEMENTS iv](#_Toc197372191)

[ABSTRACT v](#_Toc197372192)

[ABSTRAK vi](#_Toc197372193)

[TABLE OF CONTENTS vii](#_Toc197372194)

[list of tables x](#_Toc197372195)

[list of figures xi](#_Toc197372196)

[List of Abbreviations xiii](#_Toc197372197)

[List of ATTACHMENTS xiv](#_Toc197372198)

[Chapter 1: INTRODUCTION 1](#_Toc197372199)

[1.1 Introduction 1](#_Toc197372200)

[1.2 Problem Statement 2](#_Toc197372201)

[1.3 Project Question 3](#_Toc197372202)

[1.4 Objective 4](#_Toc197372203)

[1.5 Project Scope 4](#_Toc197372204)

[1.6 Project Contribution 5](#_Toc197372205)

[1.7 Thesis Organization 5](#_Toc197372206)

[1.8 Summary 6](#_Toc197372207)

[Chapter 2: literature review 7](#_Toc197372208)

[2.1 Introduction 7](#_Toc197372209)

[2.2 Related Work 9](#_Toc197372210)

[2.2.1 Phishing 10](#_Toc197372211)

[2.2.2 Machine Language Approaches 11](#_Toc197372212)

[2.2.3 Deep Learning Approaches 19](#_Toc197372213)

[2.2.4 Reinforcement Learning Approaches 23](#_Toc197372214)

[2.3 Critical Review 27](#_Toc197372215)

[2.3.1 Features and Mathematical Formulations 27](#_Toc197372216)

[2.3.2 Comparative Summary 34](#_Toc197372217)

[2.3.3 Justification 34](#_Toc197372218)

[2.4 Project Solution (Draft) 37](#_Toc197372219)

[2.4.1 Overview of Proposed Solution 37](#_Toc197372220)

[2.4.2 System Architecture 37](#_Toc197372221)

[2.4.3 Justification for Model Choice 39](#_Toc197372222)

[2.4.4 Anticipated Benefits 39](#_Toc197372223)

[2.4.5 Limitations and Future Work 39](#_Toc197372224)

[2.5 Summary 40](#_Toc197372225)

[Chapter 3: METHODOLOGY 42](#_Toc197372226)

[3.1 Introduction 42](#_Toc197372227)

[3.2 Methodology 42](#_Toc197372228)

[3.2.1 Requirement Analysis 42](#_Toc197372229)

[3.2.2 System Design 43](#_Toc197372230)

[3.2.3 Implementation 43](#_Toc197372231)

[3.2.4 Testing 43](#_Toc197372232)

[3.2.5 Deployment 43](#_Toc197372233)

[3.2.6 Maintenance 43](#_Toc197372234)

[3.3 Project Schedule and Milestones 45](#_Toc197372235)

[3.3.1 Project Milestones 45](#_Toc197372236)

[3.3.2 Project Gantt Chart 46](#_Toc197372237)

[3.4 Summary 47](#_Toc197372238)

[Chapter 4: ANALYSIS AND DESIGN 48](#_Toc197372239)

[4.1 Introduction 48](#_Toc197372240)

[4.2 Summary 48](#_Toc197372241)

[Chapter 5: IMPLEMENTATION 49](#_Toc197372242)

[5.1 Introduction 49](#_Toc197372243)

[5.2 Summary 49](#_Toc197372244)

[Chapter 6: discussion 49](#_Toc197372245)

[6.1 Introduction 49](#_Toc197372246)

[6.2 Result and Analysis 49](#_Toc197372247)

[6.3 Summary 49](#_Toc197372248)

[Chapter 7: CONCLUSION 50](#_Toc197372249)

[7.1 Introduction 50](#_Toc197372250)

[7.2 Project Summarization 50](#_Toc197372251)

[7.3 Project Contribution 50](#_Toc197372252)

[7.4 Project Limitation 50](#_Toc197372253)

[7.5 Future Works 50](#_Toc197372254)

[7.6 Summary 50](#_Toc197372255)

[references 51](#_Toc197372256)

# list of tables

|  |  |
| --- | --- |
|  | **PAGE** |

[Table 1.2‑1 Problem Statement 2](#_Toc112842306)

[Table 1.3‑1 Project Question 3](#_Toc112842307)

[Table 1.4‑1 Project Objective 4](#_Toc112842308)

[Table 1.6‑1 Project Contribution 5](#_Toc112842309)

[Table 2.4‑1: Summary of Research Papers Reviewed 22](#_Toc112842310)

[Table 3.2‑1: Hardware Requirement 28](#_Toc112842311)

[Table 3.2‑2: Software Requirement 29](#_Toc112842312)

[Table 3.2‑3: Example of Comparison Table generated after analysis of data is finished 31](#_Toc112842313)

[Table 4.4‑1: Possible Scenarios 40](#_Toc112842314)

[Table 5.4‑1 below shows the value of bandwidth usage, latency and throughput respective to the three protocols studied. 56](#_Toc112842315)

[Table 5.4‑1: Comparison Table from Collected Data 56](#_Toc112842316)

[Table 5.5‑1: Implementation Status 57](#_Toc112842317)

# list of figures

|  |  |
| --- | --- |
|  | **PAGE** |

Figure 1: Literature Review Structure Diagram 8

Figure 2: Action varieties in Social Engineering incidents 9

Figure 3: CoAP Protocol Layers (payatu.com) 10

Figure 4: Confirmable Message (payatu.com) 11

Figure 5: Non-confirmable message (payatu.com) 11

Figure 6: Publish/Subscribe model in MQTT (Martí et al., 2019) 13

Figure 7: QoS0 (Sueda et al., 2019) 14

Figure 8: QoS1 (Sueda et al., 2019) 15

Figure 9: QoS2 (Sueda et al., 2019) 15

Figure 10: AMQP Architecture (Anusha, et al., 2017) 16

Figure 11: Sensors used to collect temperature, humidity and light (Corak et al., 2018) 18

Figure 12: Diagram of testbed’s processing unit (Corak et al., 2018) 18

Figure 13: Topology for (a) Experiment I and (b) Experiment II (Moraes et al., 2019) 19

Figure 14: Diagram of hardware used for the testbed (Pohl et al., 2018) 20

Figure 15: Experimental setup (Mijovic et al., 2016) 21

Figure 16 Waterfall Model 28

Figure 17: Data Processing and Obtaining Result 30

Figure 18: Example of Graph that compares three protocols based on Bandwidth Utilisation 31

Figure 19: Network System Architecture 36

Figure 20: Logical Design 38

Figure 21: Physical Design 39

Figure 22: Scenario 1: CoAP 40

Figure 23: Scenario 2: AMQP 40

Figure 24: Scenario 3: MQTT 41

Figure 25: CoAP server running at Server 44

Figure 26: CoAP client running at PC1 44

Figure 27: CoAP Client sending GET message 45

Figure 28: Server received CoAP messages from PC1 45

Figure 29: Wireshark Packet Capture (CoAP) 46

Figure 30: RabbitMQ installed in Server browser 46

Figure 31: Python code for sending message 47

Figure 32: Python code for receiving message 48

Figure 33: RabbitMQ Management Interface 48

Figure 34: Wireshark Packet Capture (AMQP) 49

Figure 35: Moisquitto loaded and running 50

Figure 36: Connection details 50

Figure 37: PC1 MQTTlens interface 51

Figure 38: PC2 MQTTlens interface 51

Figure 39: PC2 received 100 messages from PC1 52

Figure 40: Wireshark Packet Capture (MQTT) 52

Figure 41: Protocol Hierarchy for CoAP 53

Figure 42: Protocol Hierarchy for AMQP 53

Figure 43: Protocol Hierarchy for MQTT 54

Figure 44: Packet Length for CoAP 54

Figure 45: Packet Length for AMQP 55

Figure 46: Packet Length for MQTT 55

Figure 47: Conversations Statistics for CoAP 56

Figure 48: Conversations Statistics for AMQP 56

Figure 49: Conversations Statistics for MQTT 56

Figure 50: Bandwidth Usage Graph 60

Figure 51: Latency Graph 61

Figure 52: Throughput Graph 61

Figure 53: Average Packet Size, B (CoAP) from Wireshark 62

Figure 54: Average Packet Size, B (MQTT) from Wireshark 62

# List of Abbreviations

|  |  |  |
| --- | --- | --- |
| **IoT** | **-** | **Internet of Things** |
| **CoAP** | **-** | **Constrained Application Protocol** |
| **AMQP** | **-** | **Advanced Message Queuing Protocol** |
| **MQTT** | **-** | **Message Queue Telemetry Transport** |
| **TCP** | **-** | **Transmission Control Protocol** |
| **UDP** | **-** | **User Datagram Protocol** |

# List of ATTACHMENTS

|  |  |  |  |
| --- | --- | --- | --- |
|  | | | **PAGE** |
|  | | |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

# INTRODUCTION

## Introduction

Social engineering attacks are among the most persistent and evolving cybersecurity threats, leveraging psychological manipulation to deceive individuals into disclosing confidential information or compromising systems. Techniques such as phishing, baiting, and pretexting exploit trust, urgency, or curiosity, making them difficult to detect using traditional, rule-based security systems. Phishing stands out as a dominant threat due to its scalability, ease of execution, and the increasing sophistication of its tactics.

This study explores the role of Artificial Intelligence (AI) in detecting social engineering attacks, with a primary focus on phishing. The research involves a comprehensive analysis of existing AI approaches—specifically Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL)—to evaluate their effectiveness, challenges, and potential in improving detection accuracy. Rather than developing a prototype, this study critically reviews current methods, datasets, and models to identify strengths, limitations, and areas for improvement in AI-based social engineering detection systems.

## Problem Statement

The problem that has been identified is summarized in Table 1-1 below:

Table 1.2‑1 Problem Statement

|  |  |
| --- | --- |
| **PS** | **Problem Statement** |
| **PS1** | Existing AI models struggle to detect the constantly changing nature of social engineering attacks, resulting in lower detection accuracy. |

**PS1: Existing AI models struggle to detect the constantly changing nature of social engineering attacks, resulting in lower detection accuracy.**

Existing AI models face challenges in accurately detecting social engineering attacks due to the dynamic and evolving tactics used by attackers. Machine learning has gradually introduced a huge basket of “AI capabilities” that can be harnessed for social engineering and phishing attacks (Schmitt & Flechais, 2024). This constant change reduces the effectiveness of traditional detection approaches, leading to lower overall detection accuracy.

## Project Question

Three Project Question (PQ) is constructed based on the problem statement that needs to be answered in this project. The summary of project question is shown in Table 1-2.

Table 1.3‑1 Project Question

|  |  |  |
| --- | --- | --- |
| **PS** | **PQ** | **Project Question** |
| PS1 | PQ1 | |  | | --- | |  |  |  | | --- | | What are the factors causing low detection accuracy in existing AI models when identifying evolving social engineering attacks? | |
| PQ2 | How can AI models be improved to adapt to the evolving tactics of social engineering attacks? |
| PQ3 | Which AI techniques or features are most effective in enhancing the detection accuracy against dynamic social engineering attacks? |

**PQ1: What are the factors causing low detection accuracy in existing AI models when identifying evolving social engineering attacks?**

Investigate and analyze the main factors that contribute to low detection accuracy of AI models against evolving social engineering tactics.

**PQ2: How can AI models be improved to adapt to the evolving tactics of social engineering attacks?**

Propose potential improvements and techniques to enhance AI models' adaptability to new and dynamic social engineering strategies.

**PQ3: Which AI techniques or features are most effective in enhancing the detection accuracy against dynamic social engineering attacks?**

Identify and evaluate the most effective AI techniques or feature combinations that improve detection accuracy against constantly evolving social engineering attacks.

## Objective

Based on the project questions formulated in the previous section, appropriate project objectives (PO) are developed. The Project Objective (PO) is summarized in Table 1-3.

Table 1.4‑1 Project Objective

|  |  |  |  |
| --- | --- | --- | --- |
| **PS** | **PQ** | **PO** | **Project Objective** |
| PS1 | PQ1 | PO1 | To investigate existing phishing techniques for detecting social engineering attacks in AI environment. |
| PQ2 | PO2 | To analyze accuracy performance of phishing in detecting social engineering attacks. |
| PQ3 | PO3 | To compare accuracy performance of proposed approach with existing phishing techniques. |

**PO1: To investigate existing phishing techniques for detecting social engineering attacks in AI environment.**

**PO2: To analyze accuracy performance of phishing in detecting social engineering attacks.**

**PO3: To compare accuracy performance of proposed approach with existing phishing techniques.**

## Project Scope

The project’s scopes are focused on the following aspects:

1. The AI tools considered for social engineering attack detection are Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL).
2. The performance of the AI model will be evaluated based on accuracy, precision, recall, and F1-score.
3. The platform used for training and testing the AI models is WEKA and KNIME

## Project Contribution

## Thesis Organization

This report is divided into six chapters, namely Chapter 1: Introduction, Chapter 2: Literature Review, Chapter 3: Methodology, Chapter 4: Design, Chapter 5: Implementation, Chapter 6: Discussion and Chapter 7: Conclusion.

**Chapter 1: Introduction**

This chapter discusses the project's introduction, background, research problem, research questions, objectives, scope, significance of the project, and report organization. It sets the stage for the problem addressed and outlines the goals of the project in the context of AI-based social engineering attack detection.

**Chapter 2: Literature Review**

This chapter provides a review of relevant literature, discussing previous research on social engineering attacks, existing detection methods, and AI techniques such as Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL). It also identifies gaps in the current literature and frames the research questions and objectives.

**Chapter 3: Methodology**

This chapter outlines the research methodology adopted for the project, including the datasets used, AI techniques implemented (ML, DL, RL), and the performance evaluation metrics. It provides a step-by-step explanation of the model development, data preprocessing, feature extraction, and model training processes.

**Chapter 4: Analysis and Design**

**Chapter 5: Implementation**

**Chapter 6: Discussion**

**Chapter 7: Project Conclusion**

## Summary

# literature review

## Introduction

**Social engineering** is a psychological manipulation technique where cybercriminals exploit human trust, fear, or urgency to deceive individuals into performing actions that compromise security, such as disclosing confidential information or enabling system access. Instead of relying on traditional hacking tools to exploit software or hardware vulnerabilities, social engineering exploits human behavior, making it one of the most dangerous and successful forms of attack in the modern threat landscape. Techniques include phishing, baiting, pretexting, vishing, and quid pro quo.

Among these techniques, **phishing remains the most widespread and damaging form of social engineering attack**, and its prevalence has been supported by numerous global studies and industry analyses. Research shows that phishing is consistently ranked as the most common social engineering threat due to its effectiveness, ease of execution, and adaptability across communication channels (Alzahrani et al., 2021; Basit et al., 2022). Attackers exploit digital platforms, particularly email, to impersonate legitimate institutions and deceive users into providing sensitive information.

What sets phishing apart from other social engineering methods is its ability to scale rapidly and target both individuals and organizations with minimal resources. Unlike baiting or pretexting, phishing campaigns can be automated and distributed widely using email bots and phishing kits available on underground forums. These features make phishing a recurring top threat in annual cybersecurity threat reports by multiple academic and professional organizations.

The continued evolution of phishing tactics, from generic spam to personalized spear phishing and smishing (SMS phishing), has contributed to its resilience and growth. This explains why, compared to other forms of social engineering attacks, phishing is the focus of this research. It provides not only a well-documented attack vector but also a diverse set of datasets and practical applications for testing AI-based detection models.

As the complexity and frequency of phishing attacks grow, the need for intelligent, adaptive defense systems becomes critical. Traditional security measures often fall short, especially against zero-day phishing attacks or personalized spear phishing. This has led to a strong shift toward **Artificial Intelligence (AI)**, specifically **Machine Learning (ML)**, **Deep Learning (DL)**, and **Reinforcement Learning (RL)**, as a robust solution for phishing detection. AI-based models can process large volumes of data, identify hidden patterns, and adapt over time, enabling more accurate and timely threat detection.

Given phishing's prominence and evolving nature, this study focuses exclusively on AI-based phishing detection. Compared to other forms of social engineering, phishing offers both a greater volume of research data and clearer use cases for AI implementation, making it an ideal focal point for academic and practical analysis. The subsequent sections provide a deep dive into AI techniques, available software tools, datasets, and recent research that contribute to building effective, intelligent phishing detection systems.



Figure 1: Literature Review Structure Diagram

## Related Work

Recent advancements between 2020 and 2024 have demonstrated the growing impact of AI in combating phishing threats. Researchers have developed increasingly sophisticated models leveraging ML, DL, and RL to classify, detect, and respond to phishing activities in real time.

Rahman et al. (2022) introduced a hybrid model combining Decision Trees and anomaly detection, achieving improved phishing email detection rates in enterprise environments. Their work highlighted the effectiveness of ensemble methods in capturing varied attack patterns. Aljohani and Hossain (2021) employed the BERT transformer model to detect phishing content by analyzing contextual semantics within emails. Their results showed significant accuracy improvements over traditional ML models.

Zhao et al. (2020) used Long Short-Term Memory (LSTM) networks to detect phishing attempts in mobile text messages. LSTM’s ability to process sequential information proved critical in identifying suspicious messages that mimic legitimate communications. Nasir et al. (2023) proposed a CNN-based phishing detection system that integrated user behavior logs with content analysis. The combination of behavioral and textual features enhanced detection performance, particularly for spear-phishing cases.

Asker and Essa (2024) emphasized the potential of unsupervised models, such as Autoencoders, to identify phishing emails without labelled data. Their findings suggest these models are well-suited for environments where phishing strategies evolve rapidly and labelled examples are scarce. Zhang et al. (2023) explored the use of Reinforcement Learning to create adaptive phishing detection systems. Their RL-based framework optimized decision-making policies in real-time, improving resilience against evolving attack vectors while minimizing false positives.

These studies demonstrate a transition from static rule-based systems to adaptive, intelligent models that integrate language understanding, behavior analysis, and real-time learning. They underscore the importance of hybrid approaches and model interpretability in building effective phishing detection solutions.

### Phishing

Phishing is a cyber-attack technique in which malicious actors impersonate trustworthy entities to deceive victims into revealing sensitive information, such as usernames, passwords, credit card details, or login credentials. These attacks often take the form of emails, websites, or messages that closely resemble legitimate communication from known organizations. The purpose of phishing is typically to commit fraud, gain unauthorized access to systems, or install malware.

Phishing continues to be the most prevalent type of social engineering attack globally. Its popularity among attackers stems from its high success rate, scalability, and ability to exploit human behavior rather than technical vulnerabilities. According to the 2023 Verizon Data Breach Investigations Report, phishing accounted for more than one-third of all social engineering-related incidents. The Anti-Phishing Working Group (APWG) also reported over 1.2 million phishing attacks in a single quarter, indicating a steady and alarming upward trend. These attacks have evolved from generic bulk emails to more targeted approaches such as spear phishing, business email compromise (BEC), and smishing (SMS phishing), which are increasingly difficult to detect. The figure below shows that Pretexting is now more prevalent than Phishing in Social Engineering incidents. However, when we look at confirmed breaches, Phishing is still on top (Verizon, 2023).



**Figure 2: Action varieties in Social Engineering incidents (Verizon, 2023)**

Due to the sophistication and frequency of phishing, AI-based techniques have become central to its detection. Machine Learning approaches such as Support Vector Machine (SVM) and Random Forest are commonly used due to their strong classification capabilities on structured datasets. These models analyze features such as email headers, URL characteristics, and content patterns., models like Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT) have proven effective in understanding the semantic structure of emails, enabling the identification of sophisticated phishing attempts that evade traditional filters.

Recently, Reinforcement Learning (RL) has emerged as a powerful approach for dynamic and adaptive phishing detection. Unlike ML and DL, which learn from static datasets, RL enables an agent to learn optimal policies through interactions with an environment, receiving feedback in the form of rewards or penalties. Techniques such as Q-learning, Deep Q-Networks (DQN), and Policy Gradient Methods are used to develop adaptive systems that can fine-tune detection thresholds based on evolving user behavior and attack strategies. These RL-based methods are especially useful in real-time systems, where phishing tactics change frequently and require continuous learning to maintain detection accuracy.

### Machine Language Approaches

**Machine Learning (ML)** is a core subset of Artificial Intelligence (AI) that focuses on creating algorithms and models that enable computers to automatically learn and improve from experience without being explicitly programmed for specific tasks. At its essence, ML empowers systems to identify patterns, make predictions, and adapt to new data through iterative learning processes. This adaptability is achieved by training models on vast amounts of labelled or unlabelled data and optimizing performance based on measurable outcomes (GeeksforGeeks, 2023).

Modern ML approaches are categorized into three main types: supervised learning, where models learn from labelled data; unsupervised learning, where models uncover hidden structures in unlabelled data; and reinforcement learning, where agents learn optimal behaviors by interacting with environments and receiving feedback in the form of rewards or penalties (Kelleher, 2020). ML is widely applied across domains such as cybersecurity, finance, healthcare, and e-commerce due to its ability to process and learn from high-dimensional, complex datasets.

In the context of cybersecurity, ML plays a pivotal role in the detection and mitigation of threats like phishing attacks, malware, and network intrusions. Techniques such as Support Vector Machines (SVM), Random Forest, and Naïve Bayes have demonstrated high effectiveness in classifying malicious content by learning from historical attack patterns and extracting relevant features from structured or textual data (Alzahrani et al., 2021; Kaur & Arora, 2023).

#### Support Vector Machines (SVM)

Support Vector Machine (SVM) model as a hyper plane in which several classes are represented. So that we may reduce the amount of mistakes we make, SVM will create the hyper plane in an iterative fashion. SVM's purpose is to classify datasets such that a maximum marginal hyper plane may be discovered (Jain & Gupta, 2023).

The high accuracy of SVMs in phishing detection has been demonstrated in various studies. For instance, research by Gupta et al. (2023) highlights that SVMs, when properly tuned, can achieve remarkable detection rates and low false positive rates, making them a reliable choice for cybersecurity applications. However, the effectiveness of SVMs comes with certain challenges. The considerable parameter adjustment necessary to maximize the model's performance is one of its primary drawbacks. It can take some time to carefully choose parameters like the kernel parameters and the penalty parameter (C) to balance the choices between variance and bias.

The computational expense associated with Support Vector Machines (SVMs), particularly when using non-linear kernels, can be significant. Training an SVM model involves solving a complex optimization problem, which can be computationally intensive, especially when dealing with large datasets typically encountered in phishing detection systems. This computational burden can limit the practicality of SVMs in real-time phishing detection, where fast processing is crucial to ensure timely responses and effective protection. Despite these challenges, the high precision and robustness of SVMs in identifying complex patterns in data make them a valuable asset in phishing detection frameworks.

To mitigate these limitations, hybrid approaches that combine SVMs with other machine learning techniques have been explored. These methods aim to capitalize on the strengths of SVMs while addressing their computational drawbacks. For example, integrating SVMs with feature selection techniques can reduce data dimensionality, lessening the computational load and improving real-time applicability. As cyber threats continue to evolve, the role of SVMs in phishing detection remains critical, providing a balance of high accuracy and adaptability necessary for effective cybersecurity defences.



Figure 3: SVM algorithm (Jain & Gupta, 2023)

#### Random Forest

Random Forest is a well-known machine learning method that performs excellently when dealing with regression and classification problems. It creates a lot of decision trees during training, outputs the mode of classes for classification tasks or the mean prediction for regression tasks and increases accuracy and generalization ability by voting or averaging over all trees. Because of the ensemble technique, the model resists overfitting. Because Random Forest can handle big datasets with high dimensionality and is flexible and effective, it is widely employed. It is also resistant to noise and outliers and provides insights into feature importance. Visualization techniques can aid in model evaluation and decision-making (Gunjan & Prasad, 2024).

**Random Forest Technique**

Random Forest (RF) is a powerful ensemble learning algorithm that has shown strong performance in phishing detection due to its ability to handle complex patterns and noisy data. It operates by building multiple decision trees using different random subsets of the training dataset—a process known as bootstrapping. Each tree is trained independently, which introduces diversity and reduces the risk of overfitting. This is especially beneficial in phishing detection, where malicious patterns can be subtle and varied across different instances. Once the forest is constructed, each decision tree contributes to the prediction process. In classification tasks such as distinguishing between phishing and legitimate activities, each tree casts a "vote" for a class label. The final decision is based on majority voting, where the class with the most votes becomes the output. This collective decision-making mechanism improves both accuracy and stability, making Random Forest well-suited for phishing detection systems that require consistent performance under diverse threat scenarios. Refer to the figure below, which illustrates how multiple decision trees independently classify an instance and then combine their outputs through majority voting to determine the final class.



**Figure 4: Random Forest Algorithm**

### Deep Learning Approaches

**Deep Learning (DL)** is a specialized subfield of Machine Learning (ML) that utilizes artificial neural networks with multiple layers—referred to as **deep neural networks**—to automatically learn complex patterns from large volumes of data. Inspired by the structure and function of the human brain, DL systems can model intricate relationships and hierarchical representations in data, enabling them to outperform traditional ML algorithms in tasks involving high-dimensional, unstructured inputs such as images, audio, and text.

In the context of cybersecurity, and particularly phishing detection, deep learning techniques offer significant advantages. Unlike conventional ML models that rely heavily on manually engineered features, DL models can perform **automatic feature extraction**, allowing them to learn hidden patterns in raw email content, URLs, or user interaction logs. Common DL models applied in phishing detection include:

* **Long Short-Term Memory (LSTM)**: A type of Recurrent Neural Network (RNN) that is effective in capturing sequential dependencies in phishing emails or SMS messages.
* **Transformer models (e.g., BERT)**: These models understand the contextual meaning of words in sentences, making them highly effective in detecting sophisticated and linguistically deceptive phishing emails.

The adaptability and high accuracy of DL models make them increasingly vital for building robust, intelligent, and real-time phishing detection systems.

#### Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to effectively capture long-term dependencies in sequential data. In the context of phishing website detection, LSTM plays a crucial role in modeling temporal patterns and contextual features that may not be apparent in static data. As described by Elberri et al. (2024), LSTM was integrated with a Convolutional Neural Network (CNN) in a hybrid deep learning architecture aimed at improving phishing detection accuracy. While CNN excels at extracting spatial features from grayscale images generated from URL and web content data, LSTM contributes by analyzing the sequential behavior and dependencies within the data. This combination allows the model to better understand complex relationships, such as those found in URL structures and embedded script behavior typical of phishing attacks. The study demonstrated that the CNN-LSTM hybrid model outperformed standalone CNN and LSTM models in terms of accuracy, sensitivity, and precision, highlighting LSTM’s effectiveness in enhancing the classification of phishing and legitimate websites.

**S****tructure of an LSTM neural network cell**

LSTM is a variant of the RNN deep learning architecture designed specifically for tasks like time series analysis and classification. LSTM effectively uses a gating mechanism to deal with vanishing gradient problems in the training process.The LSTM memory cell has four gates named forgetting f, input gate i, control gate c, and output gate o. The fundamental configuration of the LSTM cell is presented in Figure 4 and it consists of the output of the previous memory cell Ct-1. (Elberri et al., 2024)

This neural network uses components such as the input signal at each time step Xt, the current memory cell Ct output, the previously hidden unit Ht − 1, and the currently hidden unit Ht. The forget gate determines the way in which the contribution from the previous time step is incorporated, resulting in a value ranging from zero to one for each datapoint in Ct-1. The input gate regulates the amount of input that is stored in the memory cell from the current time step. Meanwhile, the control gate updates the memory cell contents from Ct-1 to Ct. The output gate dictates the extent to which the internal state influences the external state at the current time step. The symbol ⊗ represents the element-wise multiplication of vector elements, while ⊕ signifies the summation of vector along with the application of the σ (sigma) function. To formulate the LSTM artificial neural network. (Elberri et al., 2024)

Diagram of a diagram of a cell state

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**Figure 5: Structure of an LSTM neural network cell (Elberri et al., 2024)**

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**Figure 6: Equations of LSTM (Elberri et al., 2024)**

#### Bidirectional Encoder Representations from Transformers (BERT)

Bidirectional Encoder Representations from Transformers (BERT) is a powerful deep learning model that has shown great effectiveness in detecting phishing attacks, particularly those involving social engineering through text-based communication. Phishing often relies on carefully crafted language to manipulate users into revealing sensitive information or clicking malicious links. BERT’s unique bidirectional architecture allows it to analyze both the left and right context of each word in a sentence, enabling it to detect subtle linguistic patterns and deceptive cues used in phishing attempts. In recent studies, BERT has been applied to phishing detection by transforming message content into 768-dimensional contextual embeddings using the [CLS] token, which captures the overall semantics of the text. These embeddings, when combined with other extracted features such as URLs, email addresses, or phone numbers, are used as inputs for neural network classifiers to distinguish phishing messages from legitimate ones. Compared to traditional text classification techniques, BERT has demonstrated superior performance in identifying context-based phishing strategies, making it a valuable AI tool for building intelligent systems that can proactively detect and prevent social engineering-based cyber threats.



**Figure 7: Transformer Model Architecture (Jain et al., 2025)**

### Reinforcement Learning Approaches

Reinforcement learning (RL) is one of the sub-domains of machine learning. The goal is to let the agent learn how to act based on the environment state to maximize the expected long-term rewards, where the learning problem can usually be modeled as Markov decision problems (MDPs). Figure 8 shows the interactive feedback loop between the agent and the environment. (Wang et al.,2020)



**Figure 8: Interaction between the agent and the environment: at each time step, after the agent observes the environment, it chooses an action according to its policy. After the action is executed, the environment gives a reward signal to the agent and transit to a new state.**

Reinforcement learning (RL) agents are generally trained in episodes, each consisting of a certain number of steps. Given an episode, the sequence of states, actions, and rewards builds the trajectory or rollout of π. Let *k* be the index assigned to an episode; the *cumulative discounted reward* is defined as = . Then, the objective function to be optimized can be indicated as and the maximization problem, which the agent tries to solve, aims at finding for all and .

#### Q- Learning

Q-learning is a value-based reinforcement learning algorithm. The goal of Q-learning is to learn the optimal action-selection policy for an agent interacting with an environment. The agent learns this by updating a table of values called the Q-table where each entry represents the value of taking a particular action in each state (Kovalchuk, 2024).

The Q-learning algorithm uses the following formula to update the Q-value for a state-action pair based on figure below:

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**Figure 9: Q – Learning equation (Kovalchuk, 2024)**

Where:  
- Q(s, a) is the Q-value for state s and action a.  
- alpha is the learning rate, controlling how much new information overrides old information.  
- R is the immediate reward for taking action a in state s.  
- gammais the discount factor, representing the importance of future rewards.  
- max\_a Q(s’, a’) is the maximum Q-value for the next state s’, representing the best possible reward achievable from that state.

#### Deep Q-Learning

Deep Q-Learning or Deep Q Network (DQN) is an extension of the basic Q-Learning algorithm, which uses deep neural networks to approximate the Q-values. Traditional Q-Learning works well for environments with a small and finite number of states, but it struggles with large or continuous state spaces due to the size of the Q-table. Deep Q-Learning overcomes this limitation by replacing the Q-table with a neural network that can approximate the Q-values for every state-action pair (Amin, 2024).

A diagram of a network

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Figure 10: Structure of DQN

**Concepts of Deep Q-Learning**

1. **Q-Function Approximation**: Instead of using a table to store Q-values for each state-action pair, DQN uses a neural network to approximate the Q-values. The input to the network is the state, and the output is a set of Q-values for all possible actions.
2. **Experience Replay**: To stabilize the training, DQN uses a memory buffer (replay buffer) to store experiences (state, action, reward, next state). The network is trained on random mini-batches of experiences from this buffer, breaking the correlation between consecutive experiences and improving sample efficiency.
3. **Target Network**: DQN introduces a second neural network, called the target network, which is used to calculate the target Q-values. This target network is updated less frequently than the main network to prevent rapid oscillations in learning.
4. **Bellman Equation in DQN**: The update rule for DQN is based on the Bellman equation, like Q-Learning:



Figure 11: Bellman equation i

Where:

* θ are the weights of the main Q-network,
* θ− are the weights of the target Q-network,
* s is the current state,
* a is the action taken,
* ris the reward received,
* s′ is the next state,
* maxa′Q​Q(s′,a′) is the maximum Q-value for the next state.

## Analysis

### Analysis of Dataset

Data description

The presented dataset was collected and prepared for the purpose of building and evaluating various classification methods for the task of detecting phishing websites based on the uniform resource locator (URL) properties, URL resolving metrics, and external services. The attributes of the prepared dataset can be divided into six groups (Vrbančič et al., 2020).

* attributes based on the whole URL properties presented in Table 1,
* attributes based on the domain properties presented in Table 2,
* attributes based on the URL directory properties presented in Table 3,
* attributes based on the URL file properties presented in Table 4,
* attributes based on the URL parameter properties presented in Table 5, and
* attributes based on the URL resolving data and external metrics presented in Table 6.

A screenshot of a computer

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**Figure 12: Table 1 of dataset attributes based on URL (Vrbančič et al., 2020)**

A screenshot of a computer

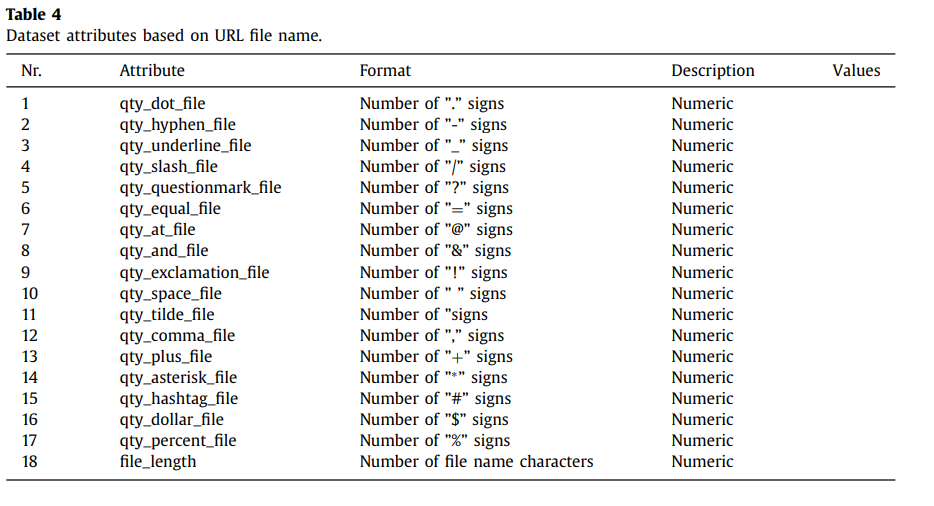
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**Figure 13: Table 2 of dataset attributes based on domain URL (Vrbančič et al., 2020)**

**A table of numbers and symbols

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**Figure 14: Table 3 of dataset attributes based on URL directory (Vrbančič et al., 2020).**



**Figure 15: Table 4 of dataset attributes based on URL file name (Vrbančič et al., 2020)**

## Critical Review

Primary studies on Machine Learning techniques.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ref | Applied Approach | Used Algorithm | Used Data set | Main Findings | Limitation/Challenges |
| Rashid et al., 2020 | Machine Learning | Support Vector Machine | Alexa, Common Crawl archive (5000 URL) | The suggested method categorizes phishing and legal websites with 95.66% of Accuracy. | The study is very shallow and has used only one classifier, i.e., SVM, and five features for detecting phishing websites. A small data set was collected using GNU and Python scripts. Moreover, only one performance metric, i.e., Accuracy, was used for model evaluation. |
| Basit et al., 2020 | Machine Learning | Random Forest  K-Nearest Neighbor Decision tree  Artificial Neural Network | UCI machine learning repository 11,055 instances 30 features | The combination of K-Nearest Neighbors and Random Forest classifier detects phishing attacks with 97.33% accuracy. | The study has not used multiple data sets to evaluate their ensemble model. Further, the UCI dataset is open source and has normalized features. It does not include the Original URL. The study has also not included any feature selection procedure. The study has picked the open-source data set and existing ML algorithms for their study. It still needs to include the calibration values of each selected ML approach. |
| Saha et al., 2020 | Machine Learning | Random Forest  Decision tree | Kaggle 11,504 URL 32 attributes | The highest Accuracy of 97.00% was achieved through the Random Forest classifier. | The study has used only two Machine Learning approaches and only a single dataset. They used the PCA feature selection technique for analyzing data set characteristics. The study intended to use CNN for anticipating phishing attacks. They did not compare the results with existing equivalent techniques. It is a very shallow study. |
| Kasim, 2021 | Machine Learning & Heuristic | Support Vector Machine LightGBM  Multilayer Perceptron Convolution Neural Network | ISCXURL-2016 2978 instances and 77 different features | The current technique uses the Light Gradient Boosted Machine model to classify the features encoded with SAE-PCA at a rate of 99.60% accuracy. | The study has done the experiment on a limited dataset of 2978 instances, and PCA has reduced the feature selection from 77 to 20; these are also very limited. |
| Geyik et al., 2021 | Machine Learning | Decision tree  Logistic Regression Naive Bayes  Random Forest | PhishTank  Alexa  Common-crawl | The highest Accuracy produced by the Random Forest classifier is 83.0%. | Performance achieved with the dataset is very low compared to other studies with similar classifiers and datasets. |
|  |  |  |  |  |  |

## Project Solution

## Summary

# METHODOLOGY

## Introduction

## Methodology

### Requirement Analysis

#### Hardware Requirement

A laptop is used as a workstation for all tasks, from researching to documenting. The laptop specifications are shown in the table below.

Table 3.2‑1: Hardware Requirement

|  |  |
| --- | --- |
| **Specification** | **Description** |
| Processor Type | AMD Ryzen 5 5600U with Radeon Graphics 2.30 GHz |
| Operating System | Windows 11 Version 21H2 |
| Operating System Type | 64-bit operating system, x64-based processor |
| RAM | 8.00 GB (7.35 GB usable) |
| Storage | 476 GB |
| Display Resolution | 1920 x 1200 |

#### Software Requirement

This project's development includes the usage of some software. The software used in this project is listed in the table below.

Table 3.2‑2: Software Requirement

|  |  |
| --- | --- |
| **Software** | **Description** |
| Windows 10 | An environment of operating system used for project execution. |
| GNS3 | Software used to execute the simulation/experiment based on the topology selected. |
| VMware Workstation Pro | Software to run virtual machines |
| Wireshark | Capture network traffic for analysing purpose. |
| Microsoft Word 365 | Software used to complete the project reporting and documentation. |
| Microsoft Excel 365 | Software used to sort the data according to attributes and instances, also to create graph. |
| Microsoft PowerPoint 365 | Software used to create charts or framework. |

### System Design

### Implementation

### Testing

### Deployment

### Maintenance

During this phase, if the testing fails, some maintenance is made to determine the cause and resolve the problem. To locate the mistake, every configuration made to measure the metrics are examined. The testing stage then is performed several times until a better result is attained. As a result, the maintenance phase occurs during testing and can also be applied if the project encounters an error. Recommendations to improve IoT performance may be made based on the simulation results. This section also discusses the difficulties encountered during the implementation process, from setting up the environment to gathering findings.

## Project Schedule and Milestones

### Project Milestones

A milestone is a project marker that denotes a shift or stage of progress. Thus, project milestones is essential in keeping track of upcoming events or goals across the timeline.

|  |  |  |
| --- | --- | --- |
| **Week** | **Phase** | **Activity** |
| 1-6 | Requirement Analysis | * Gather information regarding IoT protocol. * Studies on related work and previous research of performance analysis of IoT protocol. * Analyse the methods used by previous researchers to do their study. * Studies on hardware and software used to run the experiment. |
| 7-14 | System Design | * Information collection and analysis. * Project design – where to implement and topology selection. * Project demonstration and report submission to supervisor and evaluator. |
| ***SEM BREAK*** | | |
| 15-18 | Implementation | * Installation of GNS3 and ISO used. * Setup selected topology in simulator, GNS3. * Configure nodes, switches, servers based on the needs. * Configure topology so it can measure the chosen metrics (bandwidth utilisation, latency, and throughput) * Integrate VMware with topology in GNS3 |
| 19-22 | Testing | * Test the configuration done. * Monitor performance for each protocol at different topology. |
| 23-25 | Deployment | * Describe the results gain from the simulation. * Critical review of findings from the simulation done. |
| 26-28 | Maintenance | * Provide recommendation to improve IoT performance. * Project demonstration and final report submission to supervisor and evaluator. |

### Project Gantt Chart

Gantt Charts provide a thorough overview of the project from start to finish, as well as all the activities required to complete the project. It aids in demonstrating how far the tasks have progressed.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **PHASE** | **WEEK** | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
| Requirement Analysis |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| System Design |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Implementation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Testing |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Deployment |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Maintenance |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

## Summary

# ANALYSIS AND DESIGN

## Introduction

This chapter briefly outline the project's design that is going to be implemented in order to make the project clearer. This chapter provides logical and physical design with explanation. Possible scenarios in this project are also stated. In addition, the simulation's topology design is discussed during this phase. As a result, this chapter provides a good understanding of the specific topology that is implemented in the next chapter.

## Summary

To summarize, this chapter is vital as it contains the clear idea on how to develop the project, in this case, to analyse the performance of IoT protocol. The chapter goes through system architecture, physical and logical design of the simulation and also includes the proper measurement of metrics. The upcoming phase, implementation phase, must be carried out using the analysis and design achieved in this chapter.

# IMPLEMENTATION

## Introduction

## Summary

# discussion

## Introduction

## Result and Analysis

## Summary

# CONCLUSION

## Introduction

## Project Summarization

## Project Contribution

## Project Limitation

## Future Works

## Summary

# references