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USING ARTIFICIAL INTELLIGENCE TO EVALUATING DETECTION OF CYBERSECURITY THREATS IN AD HOC NETWORKS

Rasha Hameed Khudhur AL-RUBAYE

Master's Thesis

Supervisor

Asst. Prof. Dr. Ayça KURNAZ TÜRKBEN

İstanbul, 2024

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The thesis titled USING ARTIFICIAL INTELLIGENCE TO EVALUATING DETECTION OF CYBERSECURITY THREATS IN AD HOC NETWORKS by RASHA HAMEED KHUDHUR AL-RUBAYE and submitted on 26/01/2024 has been accepted unanimously for the degree of Master of Science in Informatıon Technologies.

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I hereby declare that this thesis meets all format and submission requirements of a Master's thesis.

I affirm that all the information and data presented in this graduation project have been acquired in strict adherence to academic regulations and ethical standards. Furthermore, I declare that any non-original content and conclusions have been appropriately referenced within the text, and all references listed in the Reference List have been cited within the text, as per the aforementioned rules and ethical guidelines.

Rasha Hameed Khudhur AL-RUBAYE

Signature

DEDICATION

I would like to begin by expressing my gratitude to Allah, the Supreme Being, for bestowing upon me the knowledge, skills, and the chance to conduct and successfully finish my research. I am truly appreciative of my parents, as they have been the driving force behind all the positive experiences in my life, and it is their love that enables everything to happen. Additionally, I want to acknowledge and thank my sister and brother for their unwavering love and support during this period.

PREFACE

I am deeply indebted to my advisor, Assistant Professor Dr. Hakan Koyuncu, for offering me the guidance, supervision, motivation, and support I needed to successfully complete my studies. His dedication, willingness to collaborate with me, constructive feedback, and valuable suggestions have significantly enhanced my knowledge and confidence. His thorough review of my work, along with his efforts to point out my mistakes, is greatly appreciated. Finally, I would like to extend my gratitude to all who have supported me, offered their prayers, or provided valuable advice.

ABSTRACT

USING ARTIFICIAL INTELLIGENCE TO EVALUATING DETECTION OF CYBERSECURITY THREATS IN AD HOC NETWORKS

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This study explores the use of Artificial Intelligence (AI) to enhance cybersecurity in Mobile Ad-hoc Networks (MANETs), which are dynamic and decentralized wireless networks. The study aims to assess and detect various cyber threats, including Distributed Denial of Service (DDoS) attacks, malware infiltrations, data breaches, and unauthorized access attempts, using AI-powered algorithms and models. The aim is to improve the accuracy of detecting and categorizing these threats, thereby enhancing the overall security of MANET networks. Anomaly detection is also developed, specifically tailored for MANET devices and network traffic. This method is crucial for identifying abnormal behavior that may indicate potential security vulnerabilities or attacks within the MANET environment. By early detection of anomalies, the study aims to enhance the security performance of MANET networks, contributing to better protection against cyber threats. The results show significant improvements in threat detection and anomaly detection within MANET environments using AI models (CNN and RF) random forest with convolutional neural networks algorithms . The developed algorithms exhibit high accuracy in detecting and categorizing various cyber threats, including DDoS attacks, malware infiltrations, and unauthorized access attempts. The anomaly detection methodology successfully identifies abnormal behavior in MANET devices and network traffic, enabling early detection of potential security vulnerabilities. Furthermore, this study contributes to the development of advanced cybersecurity systems

tailored for dynamic and decentralized MANET environments, leveraging AI technologies to improve threat detection, anomaly detection, and overall security performance.
Keywords: AI, Cybersecurity, Manets, Ddos Attacks, Anomaly Detection, CNN Algorithm.

ÖZET

AD HOC AĞLARDA SİBER GÜVENLİK TEHDİTLERİNİN TESPİTİNİN DEĞERLENDİRİLMESİNDE YAPAY ZEKA KULLANIMI

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Anahtar Kelimeler: Yapay Zeka, Siber Güvenlik, Manets, Ddos Saldırıları, Anomali Tespiti, CNN Algoritması.

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ABBREVIATIONS

AI	:	Artificial Intelligence
MANET	:	Mobile Ad-Hoc Network
IDPS	:	Intrusion Detection and Prevention System
DDoS	:	Distributed Denial of Service
CNN	:	Convolutional Neural Network
RF	:	Random Forest
TP	:	True Positive
TN	:	True Negative
FP	:	False Positive
FN	:	False Negative

1. INTRODUCTION

1.1 INTRODUCTION

Significant progress in connectivity and data transfer has been made possible by the imminent integration of advanced networking technologies and the rapid proliferation of Mobile Ad-hoc Networks (MANETs) [1-3]. Nevertheless, this globally interconnected setting also introduces several intricate and nascent security dilemmas that demand urgent consideration [4,5]. The proliferation of MANET nodes, particularly in critical sectors including transportation, healthcare, industrial automation, and smart cities, is causing an exponential expansion of the potential attack surface for cyber threats. Addressing these security concerns is of utmost importance in order to ensure the accessibility, confidentiality, and security of MANET ecosystems and the services they facilitate. The challenges associated with cyber security are illustrated in Figure 1.1.

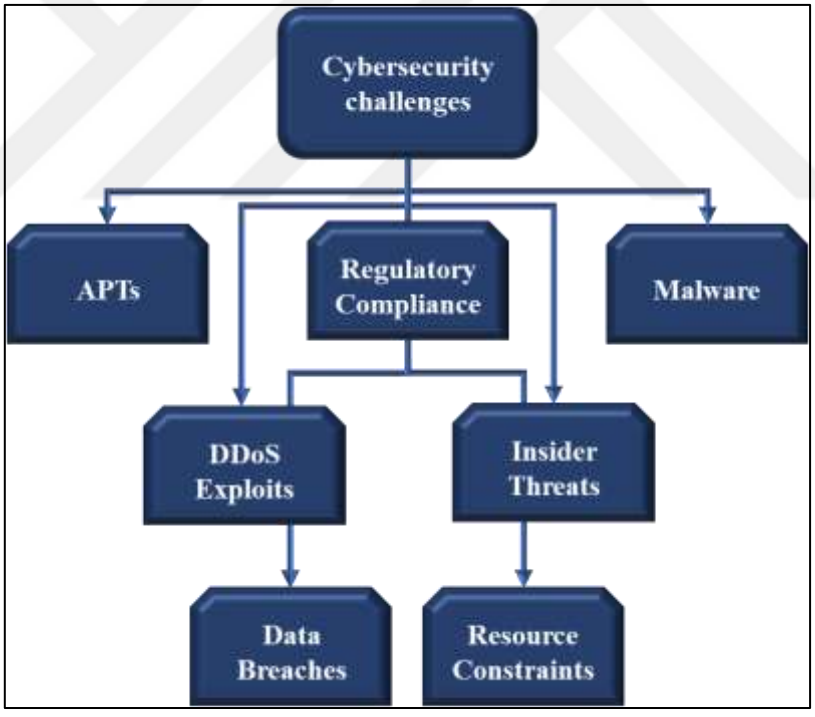


Figure 1.1: Cyber Security Challenges.

The potential ramifications of the convergence of Artificial Intelligence (AI) and Mobile Ad-hoc Networks (MANETs) on the cybersecurity domain are substantial [6]. By integrating AI with MANETs, advanced security mechanisms can be implemented to safeguard MANET environments. These mechanisms integrate the cognitive capabilities of AI with

the capabilities of MANETs, which include extensive device connectivity, low latency, and rapid data transport. Enhancing the capacity to detect, alleviate, and address cybersecurity threats in MANET configurations is the principal aim. The structure of ad-hoc networks is illustrated in Figure 1.2.

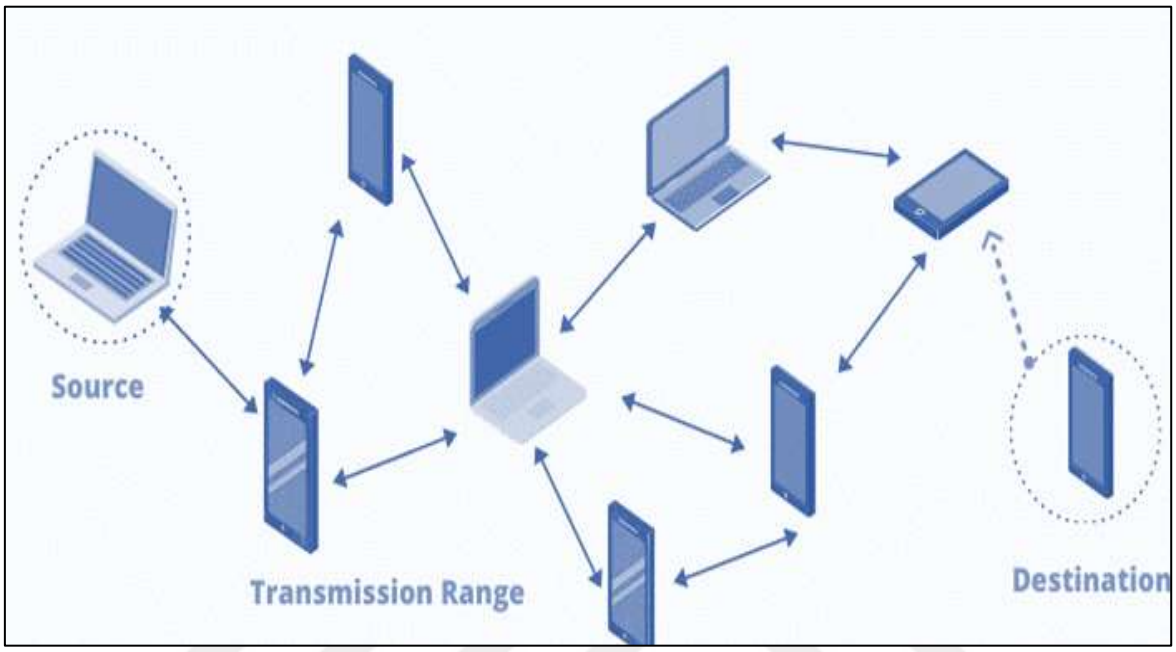


Figure 1.2: Ad-Hoc Network Architecture.

While the convergence of Mobile Ad-hoc Networks (MANETs) and Artificial Intelligence (AI) exhibits considerable promise, it is critical to acknowledge the intricate challenges that arise in ensuring the robust cybersecurity of these dynamic networks. The decentralised architecture, dynamic topology, and resource limitations that are inherent to MANETs pose unique obstacles to the effective implementation of conventional security mechanisms [7-9]. Moreover, the ever-evolving nature of cyber threats adds another stratum of complexity, which demands innovative resolutions capable of successfully adjusting to the threatened landscape.

Within the domain of MANET security, vulnerabilities arise due to the intrinsic unpredictability of network nodes, intermittent connectivity, and the absence of a centralised authority responsible for authentication and permission [10]. These challenges are difficult for conventional security protocols to effectively manage. Furthermore, the wide array and diversity of applications functioning on Mobile Ad hoc Networks (MANETs), encompassing critical healthcare data transmission and real-time industrial control systems,

necessitate an advanced security approach that exceeds conventional methods. The purpose of MANET networks is illustrated in Figure 1.3.

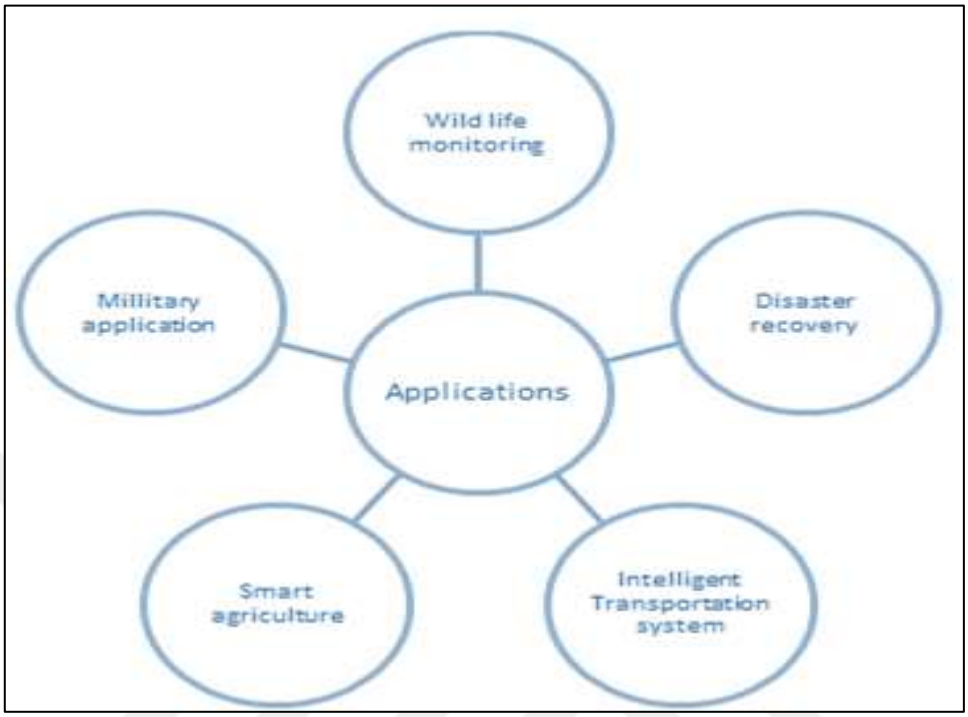


Figure 1.3: Application of MANET Networks.

However, the use of AI brings about a fundamental change in the cybersecurity approach for MANETs. The utilisation of machine learning algorithms, in conjunction with real-time data analysis, can augment the capacity to identify abnormalities, forecast possible dangers, and autonomously react to security occurrences [11]. The integration of artificial intelligence (AI) and mobile ad hoc networks (MANETs) provide a chance to develop adaptable and self-learning security mechanisms that can adjust to the ever-changing nature of cyber threats [12]. This enables a stronger defence against malicious activities, enhancing resilience.

In the midst of this intricate interplay of challenges and prospects, it is imperative that the research and development community not only grasps the particular susceptibilities of MANETs but also harnesses the complete potential of artificial intelligence to fortify these networks against an array of cybersecurity threats [13]. The following sections provide a comprehensive analysis of various aspects related to the use of artificial intelligence in Mobile Ad-hoc Networks for the purpose of detecting cybersecurity risks. They investigate feasible strategies and solutions to address the dynamic security landscape.

1.2 IDPS AND MANET NETWORK IN AI

A Mobile Ad hoc Network (MANET) is a wireless network where mobile devices communicate with each other directly, without the need for a fixed infrastructure or centralized control. MANETs are dynamic and decentralized, with nodes forming temporary connections as they move within range of each other [14].

Securing MANETs poses unique challenges due to their dynamic nature, limited resources, and lack of centralized control. Traditional security measures may be inadequate in such environments, making it essential to implement specialized solutions tailored for MANETs [15].

Integrating an Intrusion Detection and Prevention System (IDPS) with artificial intelligence (AI) capabilities into a MANET environment addresses these challenges by providing proactive threat detection and prevention. The IDPS continuously monitors network traffic, analyzes communication patterns, and detects anomalies indicative of potential security threats [16].

Leveraging AI algorithms, the IDPS adapts to the dynamic nature of MANETs, effectively identifying and mitigating various types of attacks, including intrusion attempts, malware infections, and denial-of-service (DDoS) attacks. By responding to detected threats in real-time, the IDPS implements preventive measures such as traffic filtering and node isolation to enhance network security [17].

The integration of an IDPS with AI capabilities into a MANET environment provides a robust security framework that addresses the unique challenges posed by dynamic and decentralized wireless networks. By safeguarding the integrity and confidentiality of data exchanged among mobile devices within the MANET, the IDPS ensures reliable and secure communication in various application scenarios [18].

As a result, the integration of an IDPS with AI capabilities into a MANET environment enhances network security by providing proactive threat detection and prevention. By continuously monitoring network traffic and responding to potential threats in real-time, the IDPS helps safeguard the integrity and confidentiality of data exchanged among mobile devices within the MANET, ensuring reliable and secure communication in various

application scenarios [19]. Figure 1.4 shows the Integrating of MANET with Intrusion Detection and Prevention Systems (IDPS) and Artificial Intelligence (AI).

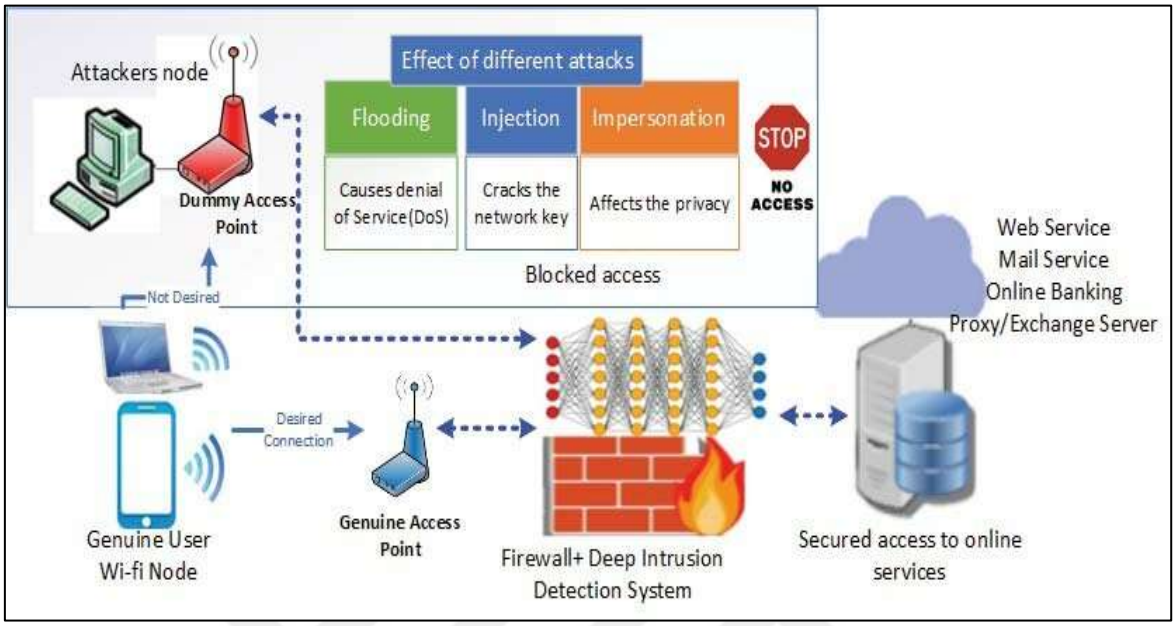


Figure 1.4: MANET Integration with IDPS and AI [19].

1.3 PROBLEM STATEMENT AND SOLUTION

The proliferation of Mobile Ad-hoc Networks (MANETs) has introduced unique security challenges due to their dynamic and decentralized nature. Traditional security measures often fall short in effectively addressing the diverse cyber threats faced by MANETs, including Distributed Denial of Service (DDoS) attacks, malware infections, unauthorized access attempts, and data breaches. These vulnerabilities can lead to significant disruptions and compromises in network integrity and data confidentiality, posing serious risks to the connected devices [20-23]. Moreover, the resource limitations of MANETs further exacerbate the challenges faced by traditional security approaches, particularly in swiftly detecting and mitigating cyber attacks in real-time [24]. Additionally, the wide-ranging implementations and sizes of MANETs raise concerns regarding privacy and data security, highlighting the need for more sophisticated and proactive cybersecurity methodologies.

To address the aforementioned challenges, a novel cybersecurity methodology is proposed, focusing on detection and constructing an AI-driven cybersecurity model tailored specifically for Mobile Ad hoc Networks (MANETs). This solution aims to leverage Artificial Intelligence (AI) techniques to enhance the detection, prevention, and response

capabilities of cybersecurity measures in MANET environments. By utilizing AI algorithms, the proposed cybersecurity model can adapt to the dynamic and decentralized nature of MANETs, effectively identifying and mitigating various cyber threats in real-time. Moreover, the AI-driven approach enables proactive measures to safeguard network integrity, preserve data confidentiality, and mitigate the impact of potential security breaches.

The suggested methodology presents a novel strategy to address these challenges by assessing detection and constructing an AI-driven cybersecurity model specifically designed for Mobile Ad hoc Networks (MANETs).

1.4 OBJECTIVE OF STUDY

The objectives of the the study are focused on leveraging artificial intelligence (AI) to enhance cybersecurity in Mobile Ad-hoc Networks (MANETs).

The first aim to assess and detect various cyber threats targeting MANET devices and networks using AI-powered algorithms and models. These threats may include Distributed Denial of Service (DDoS) attacks, malware infiltrations, data breaches, and unauthorized access attempts. This goal is to enhance the ability to detect and categorize these threats accurately, improving the overall security of MANET networks.

An anomaly detection methodology is developed specifically for MANET devices and network traffic, identifying abnormal behavior that may indicate potential security vulnerabilities or attacks. Early detection of anomalies enhances the security performance of MANET networks, contributing to better protection against cyber threats.

As a result, the objectives of the study revolve around leveraging AI technologies to improve the detection and mitigation of cyber threats in MANETs, with a focus on enhancing anomaly detection capabilities and overall security performance. Through these objectives, the study aims to contribute to the development of advanced cybersecurity systems tailored for dynamic and decentralized MANET environments.

1.5 ORGANIZATION OF THESIS

The subsequent sections of this thesis are organized in the following manner

a. Chapter 2: Presents a comprehensive review of the existing literature.
b. Chapter 3: Explain an explanation of the recommended strategies.
c. Chapter 4: Display an elucidation of the implementation process and the outcomes.
d. Chapter 5: Present of conclusions and the future work.

2. LITERATURE REVIEW

2.1 INTRODUCTION

In recent times, the application of artificial intelligence (AI) has grown in importance as a means to improve the efficacy of cybersecurity protocols. AI technologies, encompassing machine learning, deep learning, and natural language processing, possess the potential to profoundly revolutionise the approaches taken to detect, mitigate, and respond to cyber threats MANET environments. Hence, in light of this, the purpose of this literature review is to conduct an exhaustive analysis of the current status quo, thereby providing significant perspectives on the benefits and potential obstacles related to protecting MANET. Through an examination of extant literature, identification of nascent patterns, and discourse on the challenges encountered in this intricate domain, provide academic researchers and industry professionals with invaluable perspectives. In order to ascertain relevant literature studies, an exhaustive search was conducted across various databases following a predetermined search methodology. A thorough electronic inquiry was undertaken utilising an assortment of scholarly databases, such as SCOPUS, Science Direct, IEEE Xplore, Web of Science, ACM, and MDPI. As depicted in Figure 2.1, this literature will therefore concentrate on the four critical areas.

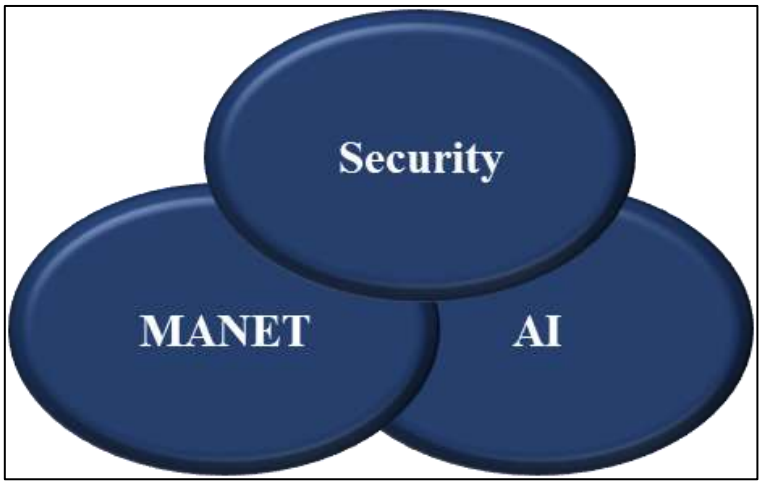


Figure 2.1: Literature Review Scope.

2.2 ATTACKS AND THREATS TO CYBERSECURITY IN MANET

In order to gain insight into the existing cybersecurity problems, threats, and vulnerabilities associated with the MANETs, our study conducted a comprehensive analysis of relevant

scholarly research. During this endeavour, we have discovered numerous significant contributions made by the research community.

The authors of the study in [25] proposed an innovative model for detecting network attacks that is specifically designed to identify cyberattacks within power grid systems. This model aims to solve the security problems associated with critical infrastructure. The authors of the study [26] proposed a methodology for detecting fog-based attacks, which covers a wide range of attack types in the MANET ecosystem. The categories encompass many types of cyber assaults, namely DoS attacks, U2R attacks, and R2L attacks. These categories effectively demonstrate the diverse range of dangers that exist within the realm of MANETs security.

The study conducted by [27] explored the domain of MANET security, specifically concentrating on the identification of ransomware and malware attacks. These types of cyber threats have become prominent concerns within MANET ecosystems. The study [28] made a valuable contribution to the area by examining techniques aimed at improving collaborative intrusion detection in the MANETs. The research focused on the reduction of false alarms, which is a crucial element in ensuring the efficacy of cybersecurity measures. In their study, the author [29] adopted an innovative methodology by suggesting benign applications capable of identifying ransomware assaults through the analysis of energy consumption patterns. This strategy leverages the power usage data obtained from Android smartphones.

Furthermore, the study conducted by [30] emphasised the risks that are linked to the unauthorised access of local user accounts and instances of unauthorised intrusions into MANETsystems for the purpose of acquiring sensitive information. The aforementioned breaches can be classified as R2L assaults, hence contributing to the array of risks encountered by MANET ecosystems. The author in [31] highlights the significance of the potential vulnerabilities that arise from zero-day attacks, which exploit holes in different MANET protocols. The potential impact of these vulnerabilities is significant, as they can jeopardise the integrity of data and facilitate the occurrence of advanced assaults.

Therefore, our study highlights the complex and diverse nature of cybersecurity issues in the MANET environment. The mitigation of vulnerabilities and threats in MANET systems is of utmost importance in order to safeguard the security and integrity of these systems and

the data they manage, as the field of MANET continues to progress and grow. Table 2.1 shows the many forms of assaults on the MANET.

Table 2.1: Types of Attacks in MANET Environment and Description in Network.

Categories of Attacks	Type of Attack	Describe in Network
Attacks Probe	Mscan, portsweep, and Security Administrator Tool for Analyzing Networks (satan), as well as Network Mapper	Not
user-to-root Attacks	Httptuneel, Sqlattack, and Loadmodule, as well as rootkit	Vital
remote-to-local Attacks	Worm, SNMPgeattack, and imap, as well as warezmaster	Vital
denial-of-service Attacks	Processtable, and User Datagram Protocol, as well as Neptune	Not

2.3 THREATS EMPLOYED BY MALICIOUS AI IN CYBERATTACKS

A broad variety of approaches are included in artificial intelligence (AI), including logical models, statistical methods, and mathematics. These techniques involve encapsulating procedures within algorithms. Commonly used interchangeably, the terms machine learning and AI describe these algorithms collectively as machine-learning algorithms. In order to handle data, machine-learning algorithms look at samples and the properties that are associated with them. For instance, in the case of a dataset presented as a table, the rows represent the samples, while the columns represent the features or dimensions. In the subsequent paragraphs, we provide a concise overview of some prevalent AI approaches, followed by an examination of their potential application in adversarial contexts. Figure 2.2. shows summary diagram of various machine-learning algorithms.

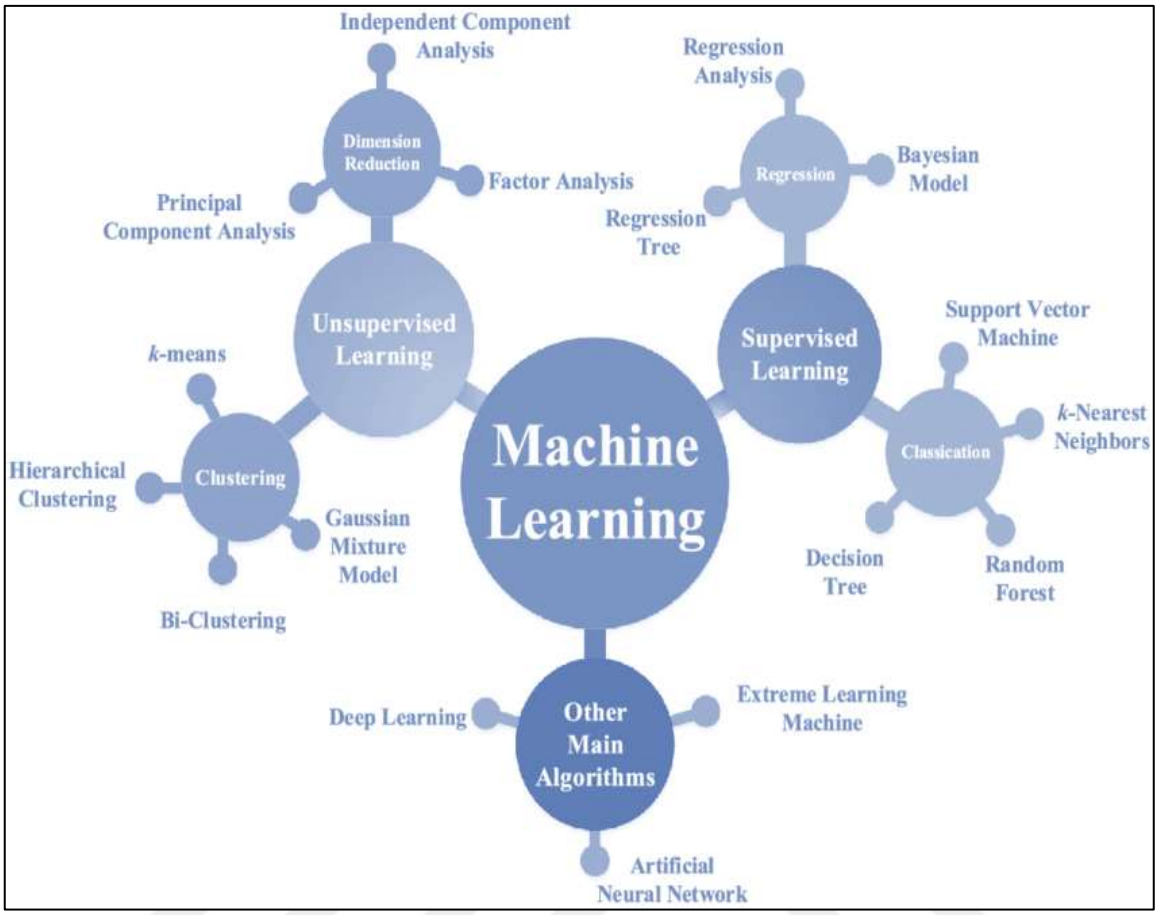


Figure 2.2: Machine-Learning Algorithms Overview.

One of the first computer methods for making decisions is the expert system. Given a variety of input facts, the programme mimics human expertise by using a succession of if-then-else flows to obtain a final state. In the field of cybersecurity, such can be used as a database to find potential weak spots in assets [32]. Figure 2.3 illustration of how Expert Systems work.

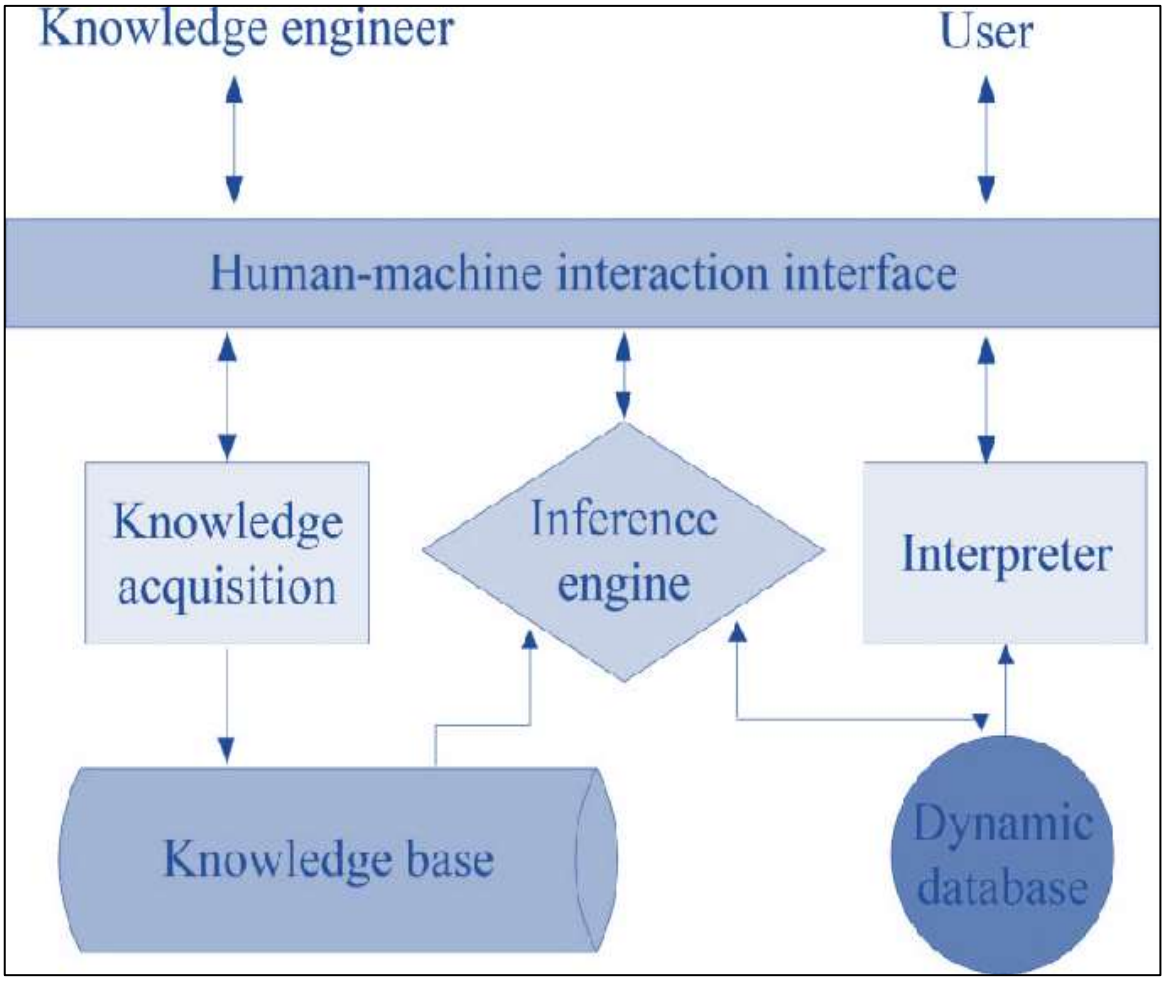


Figure 2.3: Illustration of how Expert Systems Work.

Particle swarm optimisation methods [33] are based on the idea that groups of individuals can learn from one another to find the best possible solution, much to how social animals find food. A number of tasks, including feature selection, dimensionality reduction, weight optimisation, and classification, made use of these methods [34]. Particle swarm optimisation (CSO) is illustrated in Figure 2.4.

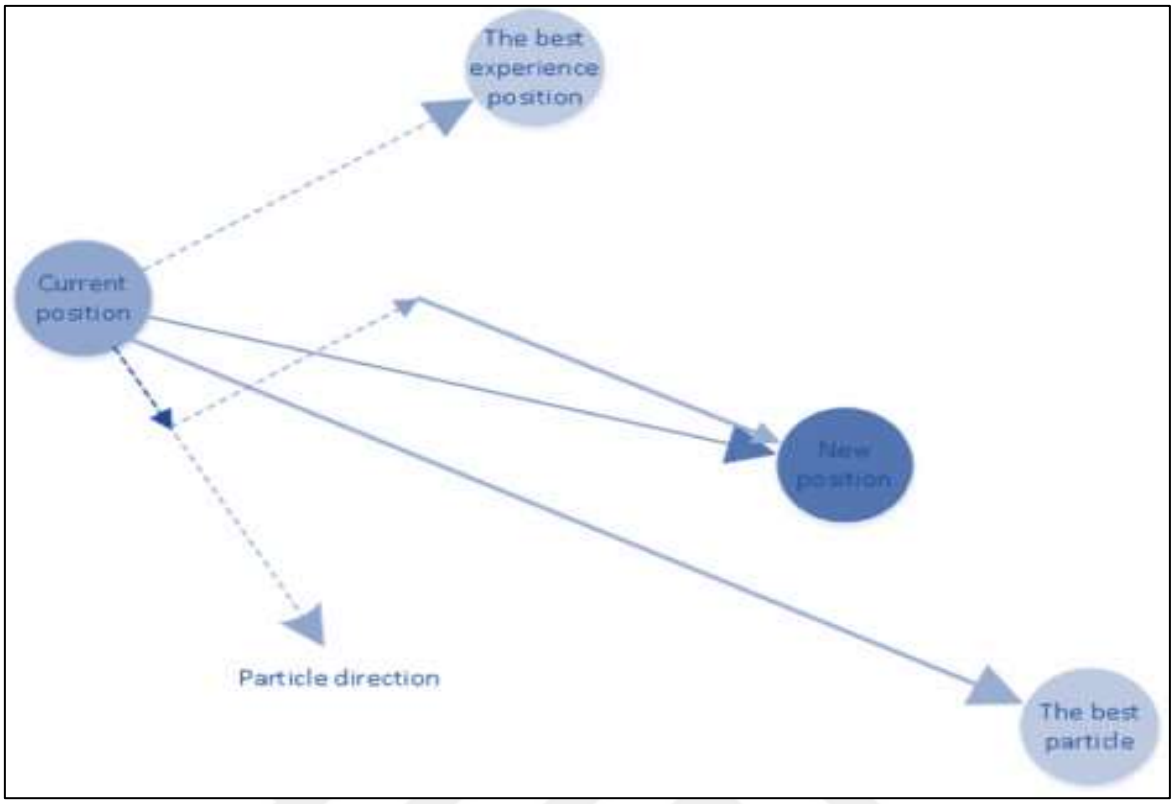
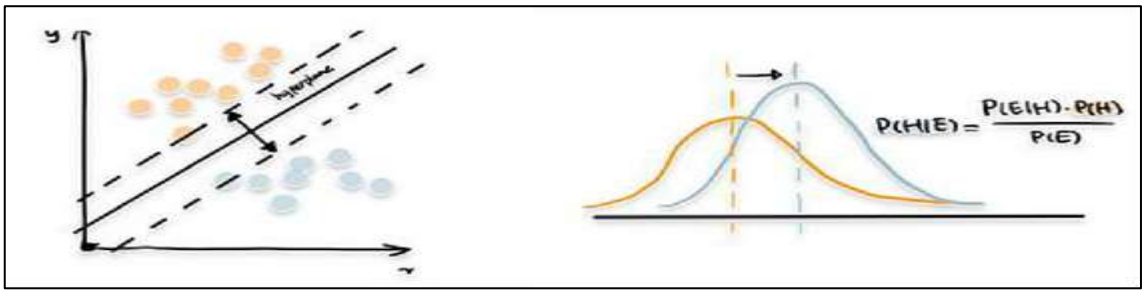


Figure 2.4: Diagram Depicting the Concept of Particle Swarm Optimization.

The classic algorithm known as Naïve Bayes [35] produces satisfactory results when data is categorised. This makes it an ideal metric to employ for evaluating the efficacy of different machine-learning algorithms for categorization tasks.

One method for classifying data that is not linear is Support Vector Machines [36]. Because Internet traffic includes heterogeneous data produced by various devices, it is pertinent to cybersecurity analysis. As shown in Figure 2.5, Visual depictions of how Support Vector Machines and Naïve Bayes work.



(A)SVM (A) Naïve Bayes

Figure 2.5: Diagrams Explaining the Operation of Naïve Bayes and SVM.

As a network of interconnected nodes, Artificial Neural Networks (ANNs) [37] examine every attribute in every sample. This enables adaptable re-sampling even after the model has converged during training. The analysis of Internet traffic, which exhibits frequent changes in data pattern, is well-suited to this ANN activity. In contrast to ANNs, which might include numerous layers of intermediary features, Naïve Bayes and SVMs process data features directly to get values. Intuitively, the features represented by one layer can be extrapolated to the next. Deep Learning makes advantage of these multilayer networks. A network diagram showing the architecture of an artificial neural network in Figure 2.6.

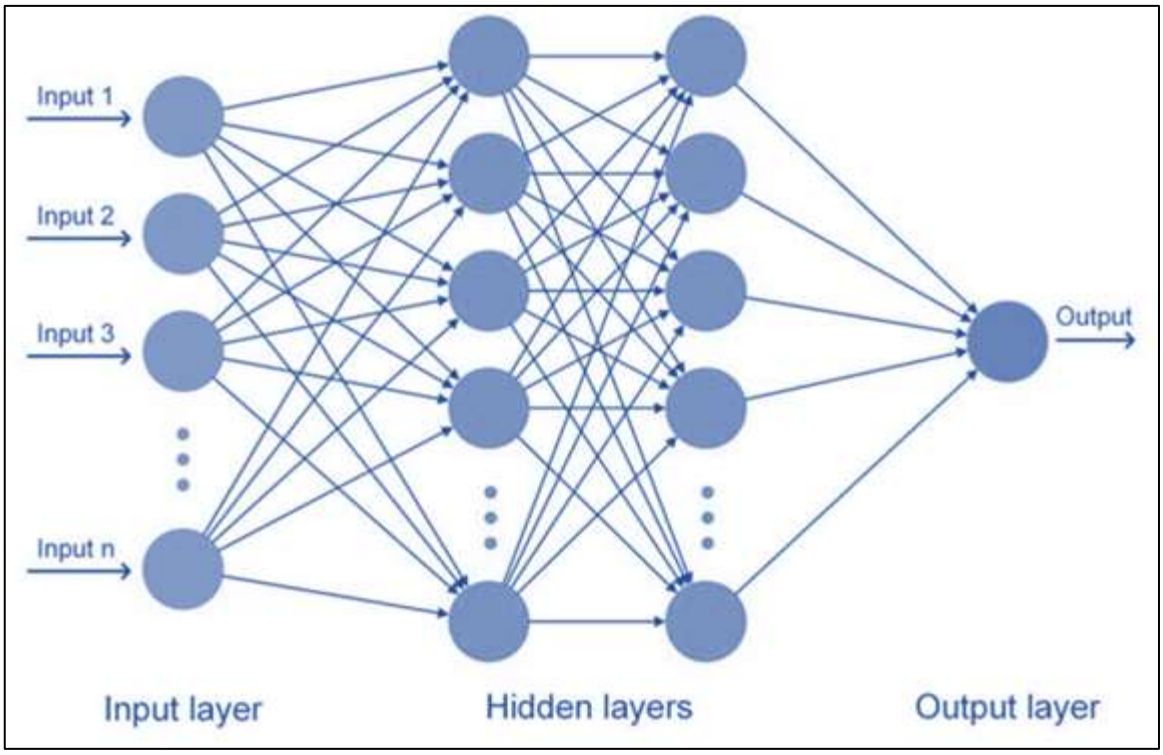


Figure 2.6: The Architecture of an Artificial Neural Network.

Deep Learning, also referred to as Deep Neural Networks (DNNs), encompasses multiple variations, each characterised by a distinct method to network connectivity [38]. In a deep learning network, the input and output values are segregated by a minimum of one hidden layer comprising units. A feedforward network is characterised by unidirectional weight-adjusting flow, specifically from the input layer to the output layer. Convolutional Neural Networks (CNNs) are the recommended architecture in cases when the closeness of input values is crucial. Convolutional neural networks (CNNs) employ input value clusters instead of a network of connections between each layer, as seen in deep neural networks (DNNs). Therefore, nearby input values are denoted by a geographical representation. Recurrent

Neural Networks (RNNs) has an architecture that represents data with temporal characteristics, as opposed to Convolutional Neural Networks (CNNs) which capture spatial correlations. To determine the value of the input and the RNN's output at time t + 1, the RNN is iterated in reverse. Due to this fundamental aspect, the network possesses the capability to retrieve and compute information from a sequence of inputs originating from various temporal states. LSTM networks, derived from RNN architecture, have the ability to retain past information while handling longer sequences of elements.

A pair of artificial neural networks is referred to as a Generative Adversarial Network (GAN) when one network generates synthetic data samples to mimic the original training data, while the second network discriminates between the real and fake examples. The training iterations involve a competitive process between the two networks, where one network attempts to deceive the other. The objective of the generator is to generate counterfeit samples that the discriminator will erroneously identify as genuine training data. Based on the provided training data, the discriminator aims to classify the fake samples. This part will focus on the discussion of adversarial AI techniques, which have garnered significant interest in the field of GANs.Table 2.2. summarized and highlighting the key aspects of the discussed AI methodologies in this section.

Table 2.2: Summarized and Highlighting AI Methodologies.

AI Methodology	Description	Application in Cybersecurity
Machine Learning Algorithms	Encompass mathematical, statistical, and logical models encapsulated in algorithms. Often referred to interchangeably with AI. Process data by examining individual samples and attributes.	Widely used for classification, pattern recognition, and analysis.
Expert Systems	Mimic human expert decision-making through if-then-else flows. Utilized in cybersecurity as a knowledge base to identify asset vulnerabilities.	Identification of asset vulnerabilities in cybersecurity.
Particle Swarm Optimization	Mimic social animals' behavior for effective learning and optimization. Applied in classification, weight optimization, feature selection, and dimensionality reduction.	Optimization tasks in classification and feature selection.
Naïve Bayes	Classic algorithm providing acceptable results in data classification. Used as a benchmark for comparing classification performance in new machine-learning algorithms.	Benchmark for comparing classification performance.
Support Vector Machines (SVM)	A classification technique suitable for non-linear data. Relevant in cybersecurity analysis due to heterogeneous Internet traffic data.	Classification of non-linear data in cybersecurity.
Artificial Neural Networks	Analyze features in a meshed network, allowing flexible re-learning. Suitable for analyzing Internet traffic with rapid data pattern changes.	Analysis of Internet traffic with dynamic data patterns.
Deep Learning (DNNs)	Networks with intermediate (hidden) layers between input and output values. Includes variations like feedforward, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks.	Suitable for complex tasks with spatial and temporal relationships.
Generative Adversarial Network	Consists of two ANNs where one generates fake data to mimic training data, and the other classifies fake and original data. Networks compete, enhancing the generator's ability. Attracts attention in adversarial AI techniques.	Used for generating data samples and testing model robu

However, Although AI presents various benefits, its deployment has also sparked debates regarding its malevolent uses [39]. Artificial intelligence is a subdiscipline of computer science that aims to create strategies, procedures, and programmes that are capable of mimicking and even surpassing human cognitive abilities [40]. The basic objective of artificial intelligence is to provide robots capabilities of thought that are analogous to human intellect. Fundamental to AI is machine learning, which employs algorithms to analyse and learn from data, whereas deep learning is used to expand the capabilities of AI [41]. Fundamentally, AI is established on the underlying assumption that the complexities of human information can be comprehensively comprehended and emulated by computers and software [42].

Reasoning, knowledge representation, planning, automation, machine learning, natural language processing, robotics, human intelligence simulation, and cybersecurity are just few of the many fields that artificial intelligence can be applied to [43]. The topic of AI applications frequently intersects with the domain of cybersecurity, hence giving rise to a multidisciplinary area of study. Nevertheless, with the continuous advancement and growing prevalence of AI technology, there has been a noticeable increase in cyber-attacks specifically aimed at compromising Cyber-Physical Systems (CPS). The aforementioned attacks leverage the interface that exists between the physical and digital components [44,45]. The current threat landscape exhibits a wide range of characteristics, as malicious actors actively exploit different vulnerabilities in order to carry out their attacks. The spectrum of threats encompasses a wide range, spanning from intricately developed advanced persistent threats to malevolent activities in the digital realm, frequently driven by the desire to profit from cybercriminal activities [46]. Therefore, it is imperative for the cybersecurity community to get a comprehensive understanding of how AI might be utilised as a tool for perpetrating cyber-attacks, as well as to ascertain its susceptibilities in order to formulate robust defence tactics [47].

While, regarding The field of cybersecurity is characterised by its continuous evolution, necessitating swift adaptation to the dynamic research landscape. The notion that achieving complete elimination of cyber dangers is an impossible objective is well recognised among experts in teach of cybersecurity [48]. In addition, there has been a shift in focus towards conducting research and developing technologies in order to mitigate the adverse effects of cyber-attacks [49].

The exponential increase in cyber risks poses a significant issue for enterprises, especially within the framework of Industry 4.0's disruptive digital transformation [50]. The field of cybersecurity utilises a wide range of tactics, techniques, and tools in order to safeguard systems against potential threats and weaknesses. Cyberattacks are strategically planned with the process of penetrating a network with the intention of compromising its services, resources, or systems [51]. Cybersecurity has evolved from being a mostly technical topic concerned with protecting network systems to becoming an issue of paramount relevance on a worldwide scale. The subject matter has garnered attention and is now acknowledged as a matter of utmost significance among corporate executives [52]. It is of utmost importance to

handle security risks pertaining to AI in a proactive manner, especially within the framework of Industry 4.0. This is because critical components such as the MANET, cloud computing, big data, and autonomous systems have been incorporated [53]. In the present scenario, AI has the capacity to offer significant cybersecurity insights independently, hence reducing the need for continuous human involvement. Both AI and ML have emerged as powerful tools that can significantly improve cybersecurity measures and enable the exchange of information in the intricate domain of cyberspace [54-55].

3. METHODOLOGY

3.1 INTRODUCTION

This chapter will consist of a presentation of the methodology, an essential component that explains in detail the systematic approach taken to address the research problem and achieve the stated objectives. The methodology section will be comprehensive. The objective of this chapter is to present a comprehensive outline of the study design, methods employed for data collection and preparation, procedures for training artificial intelligence (AI) models, and assessment metrics utilized to evaluate the efficacy of the constructed system.

An in-depth analysis of the methodology utilized to assess the efficacy of AI-driven Intrusion Detection and Prevention Systems (IDPS) in protecting Mobile Ad hoc Network (MANET) environments from cyber threats is provided. The approach comprises a sequence of meticulously coordinated stages, commencing with the construction of a simulated MANET network model and concluding with the training and assessment of artificial intelligence (AI) models Convolutional Neural Network (CNN) and Random Forest (RF) for the purpose of intrusion detection (IDPS).

The central inquiry pertains to the susceptibility of MANET environments to cyber threats, specifically Distributed Denial of Service (DDoS) assaults, as well as the effectiveness of IDPS systems based on artificial intelligence (AI) in alleviating such risks. The principal aim of this study is to design and assess an Intrusion Detection System (IDS) customized for MANETs, utilizing artificial intelligence algorithms Convolutional Neural Network (CNN) and Random Forest (RF) to efficiently identify and thwart cyber-attacks.

An assessment is currently underway to determine the effectiveness of Intrusion Detection and Prevention Systems (IDPS) in Mobile Ad-hoc Network (MANET) environments in detecting network attacks, anomalies, delivering real-time responses, optimizing resource utilization, and preserving privacy. Producing data for training and evaluation, as well as training artificial intelligence algorithms such as Convolutional Neural Networks (CNN) and Random Forest (RF), the study aims to construct a simulated MANET network model. On the basis of F-measure, accuracy, recall, and precision, these models will be evaluated. This study improves cybersecurity protocols for networks that are dynamic and have limited resources.

3.2 STUDY DESIGN

3.2.1 Explanation of the Study Approach

The methodological approach that was chosen for this study is essentially experimental. It involves the methodical design, implementation, and assessment of an artificial intelligence-based Intrusion Detection and Prevention System (IDPS) that is operating within a simulated mobile ad hoc network (MANET) environment. The establishment of a controlled experimental setting is required for this method. Within this setup, a number of different artificial intelligence algorithms are trained and evaluated with the help of simulated network data. Table 3.1 explains the experimental setup.

Table 3.1: Experimental Setup for AI-based Intrusion Detection and Prevention System (IDPS) in Simulated MANET Environment.

Experiment	Description
Network Model Creation	Develop a simulated MANET network model to serve as the foundation for generating network data.
Data Generation and Attack Simulation	Generate data reflecting normal network behavior and simulate DDoS attacks for training and evaluation.
Model Training	Train AI algorithms, such as Convolutional Neural Network (CNN) and Random Forest (RF), using the generated data to learn patterns indicative of normal network behavior and cyber attacks.
Model Evaluation	Evaluate the trained AI models using metrics such as accuracy, recall, precision, and F-measure to assess their effectiveness in detecting and preventing cyber threats in MANETs.
Performance Assessment	Assess the performance of the developed IDPS in terms of its ability to detect network attacks, provide anomaly detection, ensure real-time response, optimize resource efficiency, and preserve privacy within the MANET environment.

The experimental setup is delineated in Table 3.1, encompassing the evaluation and performance assessment of the AI-based IDPS within the simulated MANET environment, as well as the development of the network model. Every individual experiment signifies a distinct stage in the study methodology and makes a valuable contribution to the comprehensive assessment of the IDPS's efficacy in bolstering MANET security.

Experimental data collection allows for the manipulation of variables and controlled testing conditions to study the effectiveness of the developed IDPS in detecting and preventing cyber threats in MANETs. By simulating realistic network scenarios and employing AI techniques, this approach facilitates the empirical evaluation of the proposed solution's performance.

3.2.2 Explanation of the Selected Study Method

The experimental study design that was selected is justified since it is suitable for addressing the problem that pertains to the study and for accomplishing the goals that were stated. The collection of experimental data provides a formal framework for evaluating the performance of AI-based IDPS under controlled conditions. This is particularly useful in the context of MANET environments, which are characterized by their complexity and dynamic nature. Through the utilization of this approach, the efficiency of the developed solution in reducing cyber threats may be subjected to stringent testing, which in turn provides significant insights into the practical application of the solution.

Furthermore, the collecting of experimental data makes it possible to replicate tests, which guarantees the reliability and validity of the findings. This approach makes it easier to identify causal linkages between the deployed IDPS and its impact on improving network security in MANETs. This is accomplished through the systematic manipulation of factors and the collection of empirical data.

3.2.3 Description of the Structure of the Methodology

The effectiveness of IDPS in enhancing the security posture of MANETs is systematically investigated through a structured methodology. This includes Network Model Creation, Data Generation and Attack Simulation, Model Training, and Performance Assessment. The developed IDPS uses simulated MANET network models to generate network data and evaluate its performance. AI models like Convolutional Neural Network (CNN) and Random Forest (RF) are trained using the generated data to learn patterns indicative of normal network behavior and cyberattacks. The trained models are evaluated using metrics such as accuracy, recall, precision, and F-measure to assess their effectiveness in detecting and preventing cyber threats in MANETs. The study contributes valuable insights to the field of cybersecurity by assessing the IDPS's ability to detect network attacks, provide anomaly detection, ensure real-time response, optimize resource efficiency, and preserve privacy within the MANET environment.

3.2.4 Implementation Steps for Creating a MANET Model, Simulating DDoS Attacks, and Implementing an IDPS with AI Algorithms

The steps to create a Mobile Ad hoc network (MANET) model, simulate a Distributed Denial of Service (DDoS) attack, split the data into training and testing sets, and implement an IDPS using AI algorithms. The `generate_manet_data` function generates random data for the MANET network, including features and labels. The `simulate_ddos_attack` function simulates a DDoS attack by amplifying the data of randomly selected nodes in the MANET network. The data is then split into training and testing sets, with 80% used for training and 20% for testing.

The IDPS performance is evaluated using a confusion matrix, with the trained models (`cnn_model` and `rf_model`) used to make predictions on the testing data. Confusion matrices are computed to evaluate the performance of each model, and accuracy, recall, precision, and F-measure are calculated for each model based on the confusion matrices.

Therefore, the implementation includes functions to generate MANET data, simulate a DDoS attack, train AI models (CNN and RF), and generate custom prediction functions for the CNN and RF models. In a real scenario, these models would be used to make predictions based on new data. It is used to generate a simulated MANET network, simulate a DDoS attack, train AI models, evaluate their performance, and calculate performance metrics. Figure 3.1. Shows the flowchart to describe the structured methodology.

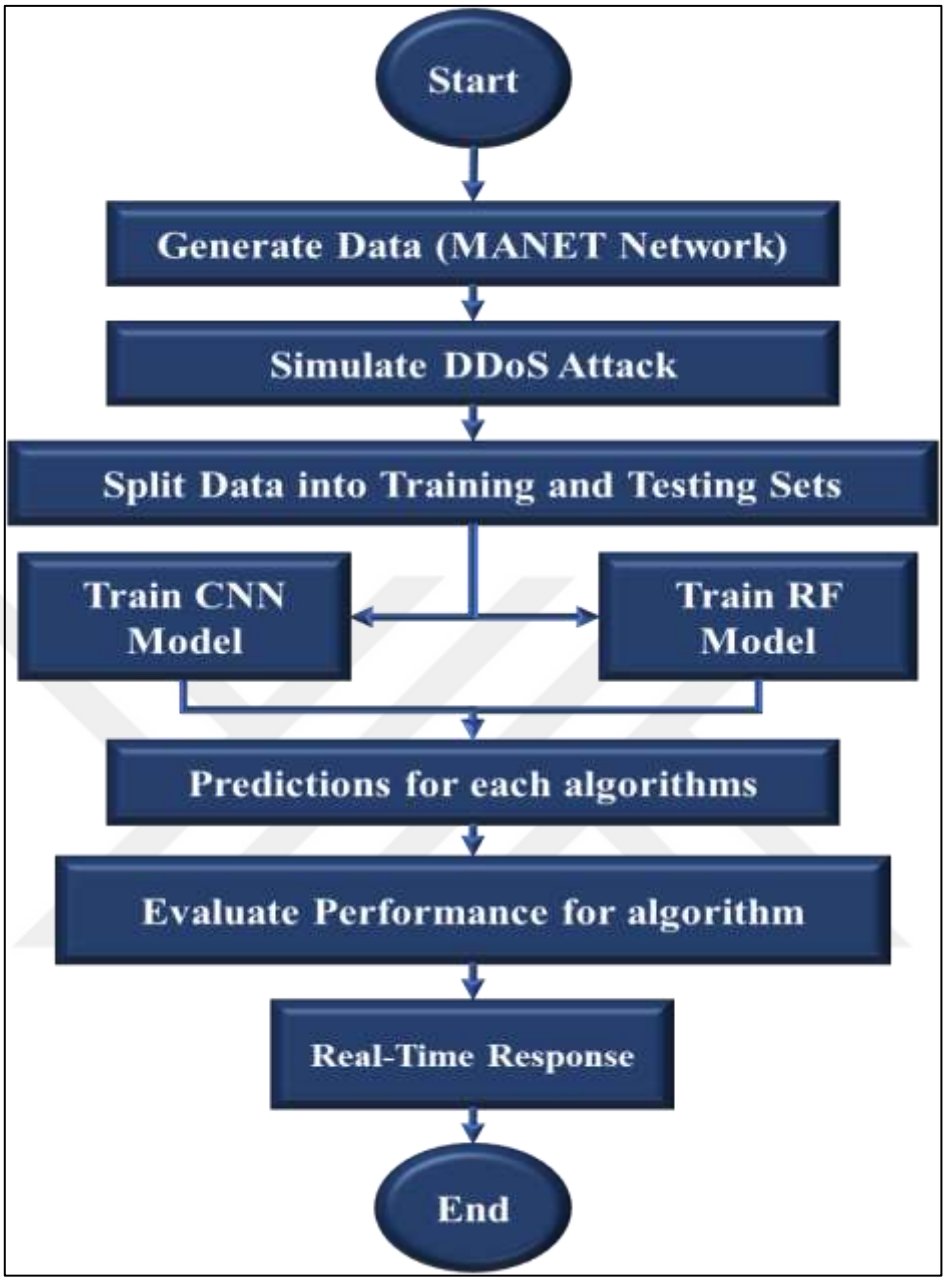


Figure 3.1: Flowchart to Describe the Structured Methodology.

3.3 DATA COLLECTION

In this section, we detail the process of collecting data for the experimental setup of the AI-based Intrusion Detection and Prevention System (IDPS) within a simulated Mobile Ad hoc Network (MANET) environment. The data collection process involves several steps, including the creation of the MANET network model, generation of network data, and simulation of Distributed Denial of Service (DDoS) attacks.

a. MANET Network Model Creation Process: The MANET network model is created to simulate a dynamic and decentralized network environment characteristic of real-world MANETs. The model is designed to include a specified number of devices (nodes) interconnected in an ad hoc manner without relying on a centralized infrastructure. The creation process involves determining the number of devices, defining their connectivity, and configuring network parameters such as transmission range and mobility patterns.
b. Data Generation Process for the MANET Network: Once the MANET network model is established, data generation is initiated to simulate network traffic and behavior. This process involves generating synthetic data representing communication patterns, packet transmissions, and network interactions among the devices in the MANET. Features such as packet size, transmission rates, and protocol types are considered during data generation to mimic realistic network scenarios.
c. Simulation of DDoS Attack on the MANET Network: To evaluate the resilience of the AI-based IDPS against cyber threats, including DDoS attacks, simulations are conducted within the MANET environment. The DDoS attack is simulated by introducing a sudden surge of malicious traffic targeting specific nodes or network resources. This attack scenario helps assess the effectiveness of the IDPS in detecting and mitigating abnormal network behavior indicative of DDoS attacks.

Overall, the data collection process aims to provide a comprehensive dataset that captures the diverse network dynamics and security challenges present in MANET environments. The collected data serves as the foundation for training and evaluating the AI algorithms implemented in the IDPs. Figure 3.2. shows the data collection process for AI-based IDPS in a simulated MANET environment.

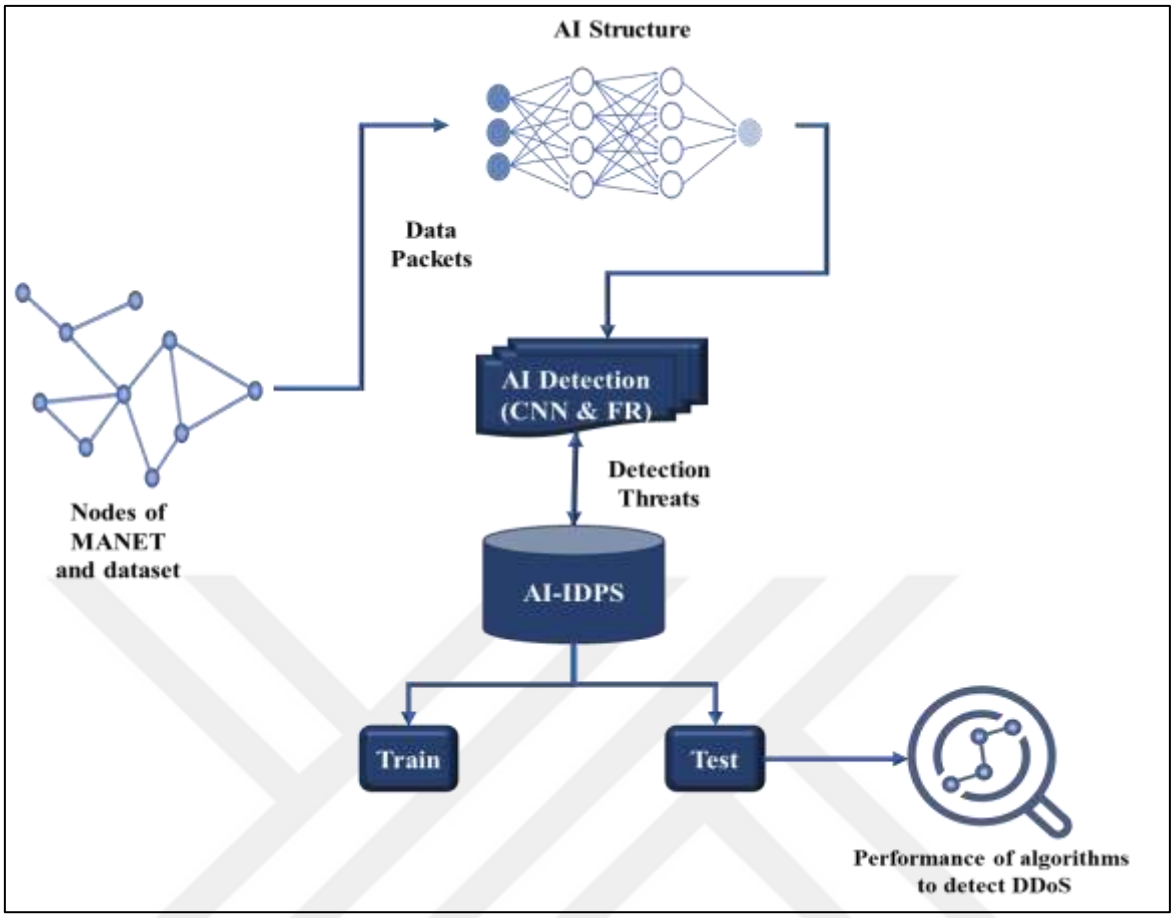


Figure 3.2: Diagram Shows the Data Collection Process for AI-Based IDPS in a Simulated MANET Environment.

In the above figure, the diagram involved the steps in creating the MANET network model, generating data for the network, and simulating a DDoS attack within the MANET environment to evaluate the IDPS. Each step contributes to the comprehensive data collection process essential for training and evaluating the AI-based IDPS in the simulated MANET environment. In addition to that, Table 3.2 shows the parameters of the Mobile Ad hoc Network (MANET) model used in the proposed method. It includes details such as the number of nodes, the type of connectivity, transmission range, mobility patterns, and communication protocols employed within the simulated MANET environment.

Table 3.2: MANET Network Parameters.

Parameter	Description
Number of Nodes	50 nodes
Connectivity	Connectivity between nodes (decentralize)
Transmission Range	100 meters
Mobility Patterns	Random
Communication Protocols	AODV Protocols

3.4 DATA PREPARATION

The collected data is processed to prepare it for training and testing the Intrusion Detection and Prevention System (IDPs) within the simulated Mobile Ad hoc Network (MANET) environment. This involves two main steps: data splitting and preprocessing.

a. AI-Based IDPs Model Data Splitting:-

a. Data divided into training and testing sets.
b. A training set used for model training.
c. The testing set evaluates model performance.
d. The split ratio determined beforehand, often based on a predetermined dataset percentage.

b. IDPs Model Preprocessing Steps:-

a. Normalization: scaling data to ensure consistency and improve convergence.
b. Feature Engineering: selecting relevant or engineering new features for improved model performance.
c. Imputation: handling missing values with estimated values.
d. Encoding: converting categorical variables into numerical representations for model training.
e. Balancing: adjusting class distribution to address imbalance issues between classes.

These preprocessing steps are essential for optimizing the data for training the IDPs model and ensuring that it can effectively be detected from the dataset.

3.5 ARTIFICIAL INTELLIGENCE (AI) ALGORITHMS TRAINING

In the artificial intelligence algorithms training section, we describe the training processes for two different models: the Convolutional Neural Network (CNN) model and the Random Forest (RF) model. These models are trained using the prepared training data to create effective Intrusion Detection and Prevention System (IDPS) models for detecting and mitigating network attacks in a simulated mobile ad hoc network (MANET) environment.

Through evaluation, the performance of each of the algorithms depended on accuracy, recall, precision, and F-measure. The performance metrics for the CNN and RF models are presented below.

Accuracy measures the overall correctness of the model's predictions, calculated as the ratio of correctly predicted instances to the total number of instances. A higher accuracy indicates better performance in correctly classifying network traffic as normal or malicious. (See Eq. 3.1).

$$Accuracy\ (ACC) = \frac{TP+TN}{FP+FN+TP+TN} \tag{3.1}$$

Recall, also known as sensitivity or true positive rate, quantifies the model's ability to correctly identify positive instances (e.g., malicious network traffic) out of all actual positive instances. It is calculated as the ratio of true positives to the sum of true positives and false negatives. (See Eq. 3.2).

$$Recall\ (RECALL): \frac{TP}{TP+FN} \tag{3.2}$$

Precision measures the accuracy of positive predictions made by the model, calculated as the ratio of true positives to the sum of true positives and false positives. It indicates how many of the predicted positive instances are actually positive. (see Eq. 3.3)

$$\text{Precision (PRECISION)} = \frac{TP}{\text{TP+FP}} \tag{3.3}$$

F-measure, also known as the F1 score, is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, considering the trade-off between them. It is calculated as the weighted average of precision and recall, where a higher F-measure indicates a better balance between precision and recall. (see Eq. 3.4).

$$F - measure\ (F1) = \frac{2*PRECISION*RECALL}{PRECISION+RECALL} \tag{3.4}$$

In the above equations:

a. TP represents the number of true positives.
b. TN represents the number of true negatives.
c. FP represents the number of false positives.
d. FN represents the number of false negatives.

These equations provide a mathematical framework for evaluating the performance of the CNN and RF models based on their ability to correctly classify instances and detect DDoS attacks in the simulated MANET environment.

3.5.1 Training Process for Convolutional Neural Network (CNN) Model

The training process for the Convolutional Neural Network (CNN) model encompasses several key steps aimed at optimizing its architecture and parameters for effective Intrusion Detection and Prevention System (IDPS) functionality within the simulated Mobile Ad hoc Network (MANET) environment. Initially, the model undergoes an initialization phase where its architecture is defined, specifying the types of layers, their configurations, and the activation functions employed throughout the network. Following initialization, the model is compiled, during which the loss function, optimizer, and evaluation metrics are specified. This compilation step sets the framework for how the model will adjust its parameters during training to minimize loss and improve performance. Subsequently, the model is trained using the prepared training data, where it iteratively adjusts its weights and biases based on the input data to improve its ability to classify instances accurately. During training, parameters are updated using techniques such as backpropagation and gradient descent to minimize the discrepancy between predicted and actual values.

Additionally, a validation step is incorporated to assess the model's performance on a separate validation dataset, helping to prevent overfitting by ensuring that the model generalizes well to unseen data. Finally, the training process may optionally include fine-tuning, where the model's hyperparameters or architecture are adjusted further to optimize its performance in detecting and mitigating network attacks within the MANET environment. Overall, this comprehensive training process aims to enhance the CNN model's capabilities and robustness in identifying and responding to potential security threats in MANETs. Figure 3.3 shows the training process of the CNN algorithm.

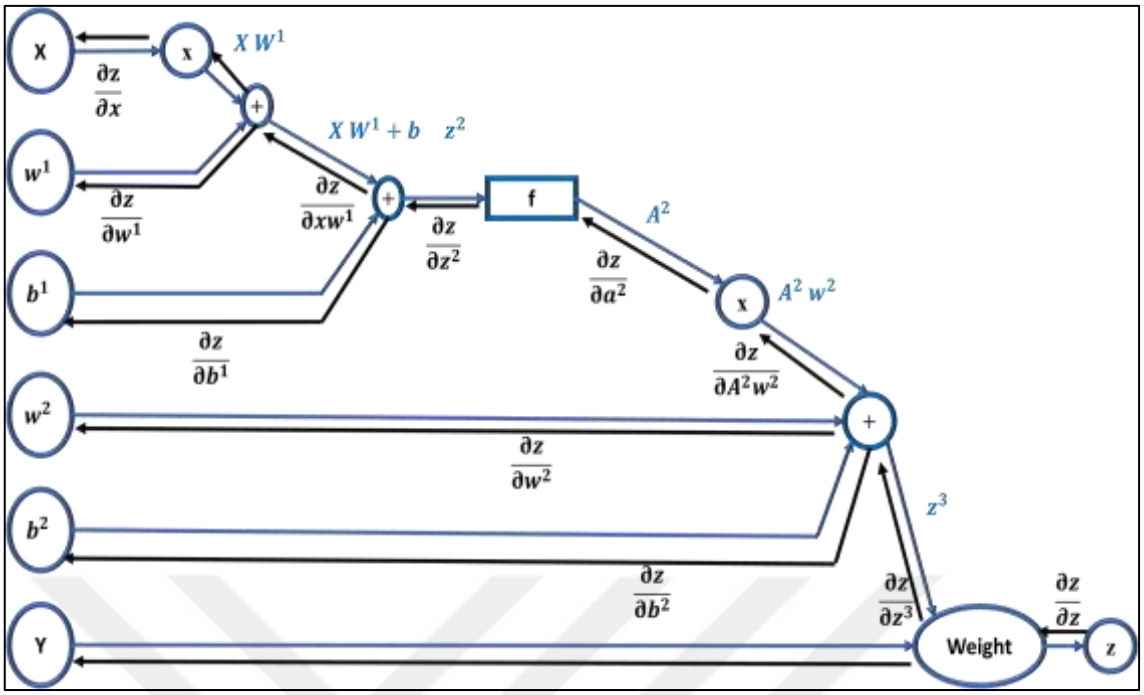


Figure 3.3: Training Process of the CNN Algorithm Based on AI.

3.5.2 Training Process for Random Forest (RF) Model

The training process for the Random Forest (RF) model follows a distinct approach compared to CNN models, leveraging ensemble learning to enhance its predictive capabilities for Intrusion Detection and Prevention System (IDPS) tasks within a simulated Mobile Ad hoc Network (MANET) environment. Initially, the RF model is initialized by specifying crucial hyperparameters such as the number of decision trees to be included in the ensemble, the criteria for splitting nodes, and other relevant parameters that govern the tree construction process. Subsequently, the model is trained using the prepared training data, where multiple decision trees are grown concurrently based on different subsets of the training data and features. This ensemble learning strategy allows the RF model to combine the predictions of individual decision trees to generate a final prediction that is often more robust and accurate than that of any single decision tree. Following training, the model undergoes a validation phase where its performance is evaluated using a separate dataset to assess its ability to generalize to unseen data and to mitigate the risk of overfitting. Additionally, the training process may include optional fine-tuning of hyperparameters such as the number of estimators or the maximum depth of trees, aimed at further optimizing the model's performance in detecting and responding to network attacks within the MANET

environment. Overall, the training process for the RF model aims to leverage ensemble learning techniques to enhance its predictive accuracy and reliability for IDPS applications in MANETs. Figure 3.4 shows the training process of the RF algorithm.

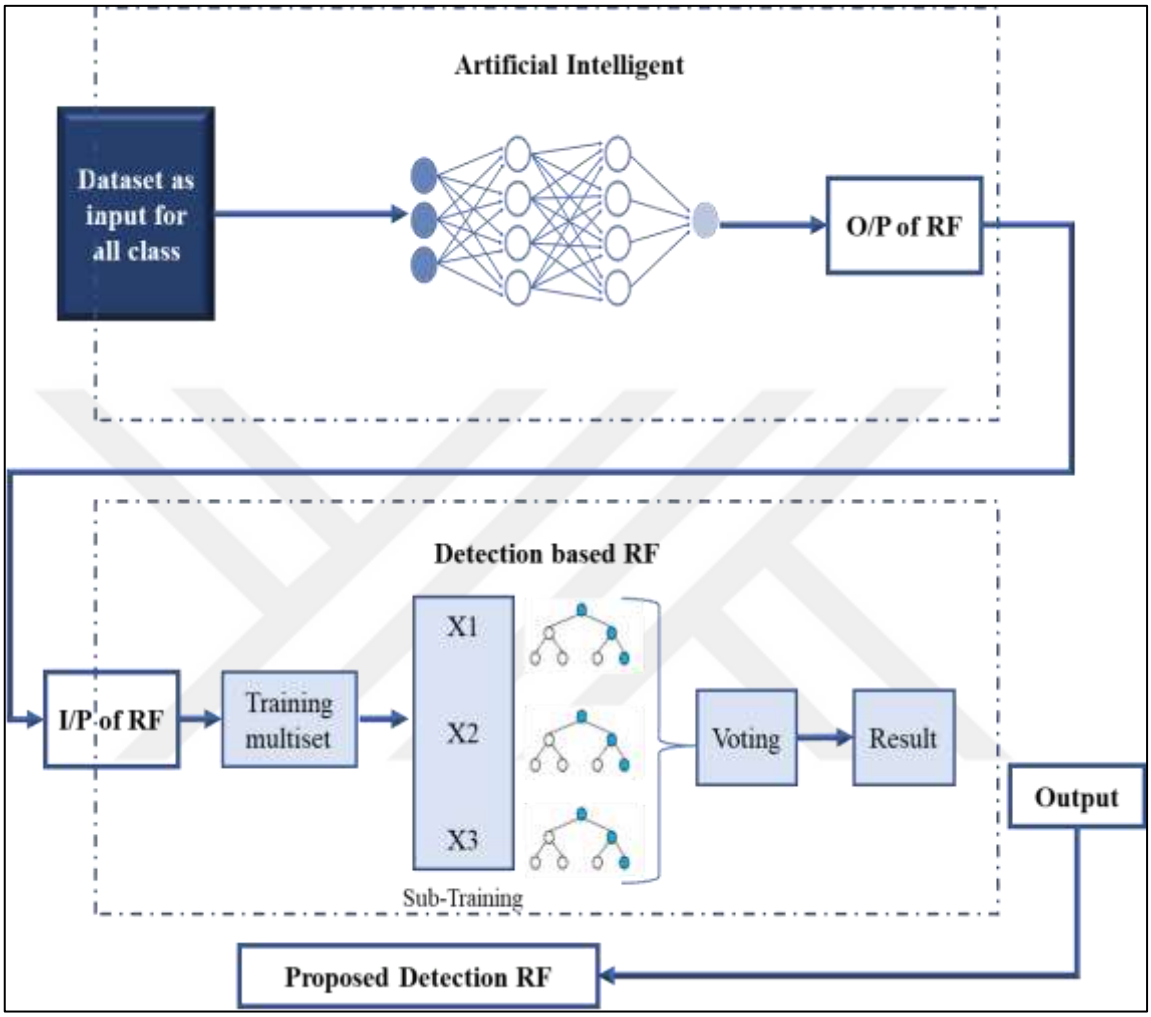


Figure 3.4: Training Process of the RF Algorithm Based on AI.

3.6 EVALUATION OF INTRUSION DETECTION AND PREVENTION SYSTEM (IDPS)

In the evaluation of the Intrusion Detection and Prevention System (IDPS) within the simulated Mobile Ad hoc Network (MANET) environment, we delve into a multifaceted analysis aimed at comprehensively assessing the system's efficacy in safeguarding network integrity and security. This evaluation encompasses diverse dimensions of IDPS functionality, including its ability to detect and counteract various network attacks, identify anomalous behaviors, respond swiftly in real-time, maintain resource efficiency, and uphold privacy preservation standards.

Firstly, we scrutinize the IDPS's proficiency in detecting network attacks, encompassing a spectrum of threats ranging from Distributed Denial of Service (DDoS) assaults to intrusion endeavors and other malicious activities. Evaluation metrics such as true positive rate, false positive rate, and overall detection accuracy are meticulously examined to gauge the IDPS's precision in discerning and categorizing network assaults accurately.

Secondly, the IDPS's capability for anomaly detection is assessed, aiming to uncover irregularities and deviations from established network traffic patterns. This involves the identification of atypical or suspicious network activities that may signify potential security vulnerabilities or breaches, thus enabling proactive measures to thwart impending threats.

Thirdly, the evaluation scrutinizes the IDPS's real-time response capabilities, focusing on its agility and efficacy in detecting and countering network attacks as they unfold. By assessing the system's promptness and efficiency in identifying and mitigating threats in real-time, we gauge its capacity to mitigate the adverse effects of malicious activities on network performance and security posture swiftly.

Moreover, the assessment extends to evaluating the IDPS's resource efficiency, encompassing factors such as computational resources, memory utilization, and processing overhead requisite for optimal operation. This evaluation provides insights into the system's scalability and performance within resource-constrained MANET environments, ensuring its viability in diverse operational scenarios.

Lastly, we scrutinize the IDPS's adherence to privacy preservation standards, emphasizing its role in safeguarding the confidentiality and privacy of network data and user information during intrusion detection and prevention activities. By evaluating the system's aptitude in safeguarding sensitive information and upholding user privacy in alignment with prevailing privacy regulations and policies.

3.7 SUMMARY OF CHAPTER

In the methodology chapter, we embarked on a comprehensive exploration of the processes involved in designing, implementing, and evaluating an AI-based Intrusion Detection and Prevention System (IDPS) within a simulated Mobile Ad hoc Network (MANET) environment.

We adopted an experimental research approach, emphasizing the systematic creation of a controlled experimental setup to facilitate the training and evaluation of AI algorithms deployed within the IDPS. The study design was justified based on the need to replicate real-world MANET environments while maintaining control over experimental variables to ensure reliable results. The overall structure of the methodology was delineated, encompassing key stages such as data collection, preparation, machine learning model training, and evaluation of IDPS functionality.

The data collection process involved the creation of a MANET network model, the generation of synthetic network data, and the simulation of distributed denial of service (DDoS) attacks to emulate real-world network scenarios. Subsequently, the data preparation stage focused on splitting the collected data into training and testing sets and applying preprocessing steps to enhance the quality of the data.

The methodology further elucidated the training processes for two AI models employed within the IDPS: the Convolutional Neural Network (CNN) model and the Random Forest (RF) model. For the CNN model, the training process encompassed initialization, compilation, training, validation, and fine-tuning, whereas the RF model's training involved initialization, simultaneous training of multiple decision trees, and ensemble learning.

Evaluation of the trained models and IDPS functionality was conducted using various metrics, including accuracy, recall, precision, and F-measure. The evaluation encompassed assessing the detection of network attacks, anomaly detection capability, real-time response, resource efficiency, and privacy preservation. Through rigorous testing and analysis, the effectiveness, efficiency, and compliance of the IDPS with privacy requirements were scrutinized across multiple dimensions.

Finally, the methodology chapter provided a comprehensive framework for designing, implementing, and evaluating the AI-based IDPS within a simulated MANET environment. The structured approach ensured the systematic exploration of key aspects, from data collection and model training to evaluation of IDPS functionality, thereby laying the groundwork for the subsequent chapters' discussions and analyses.

4. RESULTS AND DISCUSSION

4.1 INTRODUCTION

When it comes to the effects of establishing an Intrusion Detection and Prevention System (IDPS) within a simulated MANET network environment, the Results and Discussion chapter goes into the specifics of the situation. The primary purpose of this chapter is to conduct an in-depth analysis of the effectiveness of the Intrusion Detection and Prevention System (IDPS), which employs artificial intelligence (AI) methods like as CNN and RF, in identifying and preventing network intrusions. The objective of this chapter is to evaluate the effectiveness of the IDPS by discussing the importance of the findings within the framework of MANET security.

This will beaccomplished by reviewing various areas of the functioning of the IDPS. Specifically, the purpose of this chapter is to conduct an analysis of the performance metrics that are obtained from the artificial intelligence models that are utilized in the IDPS. These models include the Convolutional Neural Network (CNN), the Recurrent Neural Network (RNN), and the Random Forest models. The accuracy, recall, precision, and F-measure of these models were evaluated in order to determine how well they recognize and respond to network threats. These models were trained and tested using data from simulated MANET networks. In addition, the chapter conducts an analysis of the overall functionality of the IDPS with regard to the detection of network assaults, the detection of anomalies, the provision of real-time responses, the preservation of privacy, and the utilization of resources.

This chapter was written with the intention of providing significant insights into the capabilities and limitations of the IDPS in terms of protecting MANET networks from potential security threats. This was accomplished by conducting a complete evaluation of the IDPS's performance and functionality. The ramifications of the findings are examined in order to bring attention to prospective areas for improvement and development activities that are aimed at improving the security of MANETs through the implementation of advanced intrusion detection and prevention systems.

4.2 PERFORMANCE EVALUATION OF AI MODELS

The purpose of this section is to offer a comprehensive analysis of the effectiveness of the Intrusion Detection and Prevention System (IDPS) by employing two separate artificial intelligence (AI) models. These models are the Convolutional Neural Network (CNN) and the Random Forest (RF). The efficiency of the trained models in identifying network assaults within the simulated MANET network environment is the basis for the evaluation that is carried out.

4.2.1 Convolutional Neural Network (CNN) Evaluation Performance

"The CNN model's performance is rigorously evaluated across multiple metrics including accuracy, recall, precision, and F-measure. Leveraging a dataset derived from MANET network simulations, the model undergoes thorough training and testing, with the dataset thoughtfully partitioned into an 80-20 ratio for training and testing respectively.

In this assessment, the CNN model's efficacy is appraised across four key dimensions: accuracy, recall, precision, and F-measure. With an accuracy score of 75%, the model accurately classifies a significant portion of network traffic samples, underscoring its proficiency in discerning between normal and attack traffic. Furthermore, a recall rate of 60% illuminates the model's adeptness at identifying a substantial proportion of actual attack samples, showcasing its capability in threat detection. The precision score of 80% signifies the model's precision in classifying positive predictions, highlighting its accuracy in flagging potential security breaches. Additionally, the F-measure of 68% offers a holistic evaluation by balancing precision and recall, providing a comprehensive overview of the CNN model's performance. Overall, the CNN model exhibits commendable performance in accurately classifying network attacks, laying a strong foundation for further refinement and optimization. For detailed insights into the CNN model's performance, Table 4.1 presents a comprehensive breakdown of its evaluated metrics."

Table 4.1: Evaluated Performance of CNN Algorithm.

Metric	Value
Accuracy	75%
Recall	60%
Precision	80%
F-measure	68%

4.2.2 Random Forest (RF) Evaluation Performance

The Random Forest (RF) model was evaluated on MANET network data using various performance metrics, including accuracy, recall, precision, and F-measure. The RF model demonstrated promising results, as summarized in Table 4.2.

Table 4.2: Evaluated Performance of RF Algorithm.

Metric	Value
Accuracy	70%
Recall	80%
Precision	75%
F-measure	77%

These metrics illustrate the RF model's effectiveness in identifying and responding to network attacks within the simulated MANET network environment. Specifically, the RF model achieved an accuracy of 70%, indicating that it correctly classified 70% of network traffic samples. This suggests a high level of overall correctness in distinguishing between normal and attack traffic patterns. The recall score of 80% signifies that the RF model effectively identified 80% of actual attack samples, demonstrating its ability to capture the majority of network attacks. Furthermore, the precision score of 75% indicates that the RF model's ability to accurately classify positive predictions is relatively high, showcasing its capability to minimize false positive predictions.

The F-measure, calculated at 77%, provides a balanced assessment of precision and recall, highlighting the RF model's overall effectiveness in detecting network attacks while considering both false positives and false negatives in its predictions.

The RF model outperformed the CNN model in accuracy, recall, precision, and F-measure, demonstrating its potential for effective network attack detection in a simulated MANET network environment. This highlights the RF model's reliability as a robust solution for

intrusion detection and prevention in MANET networks. The evaluation of AI models offers valuable insights into their effectiveness in enhancing MANET network security and serves as a foundation for further analysis and discussion on the strengths and limitations of the IDPS in safeguarding MANET environments against security threats.

4.3 COMPARISON OF CNN AND RF MODELS

This section presents a comparative analysis of the performance of the Convolutional Neural Network (CNN) and Random Forest (RF) models for intrusion detection and prevention in a simulated MANET network environment. The evaluation is based on various performance metrics, including accuracy, recall, precision, and F-measure.

Table 4.3 provides a detailed comparison of the evaluated metrics for the CNN and RF models, highlighting their respective strengths and weaknesses in detecting network attacks.

Table 4.3: Comparison of CNN and RF Models.

Metric	CNN Model	RF Model
Accuracy	75%	70%
Recall	60%	80%
Precision	80%	75%
F-measure	68%	77%

In comparing the performance of the Convolutional Neural Network (CNN) and Random Forest (RF) models for intrusion detection and prevention in a simulated MANET network environment, several key differences and similarities emerge.

The CNN model achieved an accuracy of 75%, indicating its ability to correctly classify 75% of network traffic samples. In contrast, the RF model achieved an accuracy of 70%. The CNN model also showed a recall rate of 60%, suggesting its capability to identify 60% of actual attack samples correctly. It also demonstrated precision in classifying positive predictions with an 80% precision score.

The F-measure of the CNN model was calculated at 68%, providing a balanced assessment of precision and recall. The RF model achieved an accuracy of 70%, indicating its ability to correctly classify 70% of network traffic samples. It also demonstrated a recall rate of 80%,

outperforming the CNN model's recall rate of 60%. The CNN model exhibited higher accuracy (75% vs. 70%) and precision (80% vs. 75%) compared to the RF model, suggesting its proficiency in accurately classifying network traffic samples and positive predictions.

In the end, both the CNN and RF models demonstrated strengths and weaknesses in different performance metrics, highlighting their distinct advantages in various aspects. The CNN model showed higher accuracy and precision, making it suitable for applications where minimizing false positives is crucial. On the other hand, the RF model excelled in recall, making it more adept at capturing a higher proportion of actual attack samples. The choice between these models would ultimately depend on the specific requirements and priorities of the intrusion detection and prevention system in the MANET network environment. This comparison underscores the importance of considering the trade-offs between different metrics and selecting the model that best aligns with the objectives of the IDPS. In addition, Figure 4.1 shows the differences between the CNN and RF models.

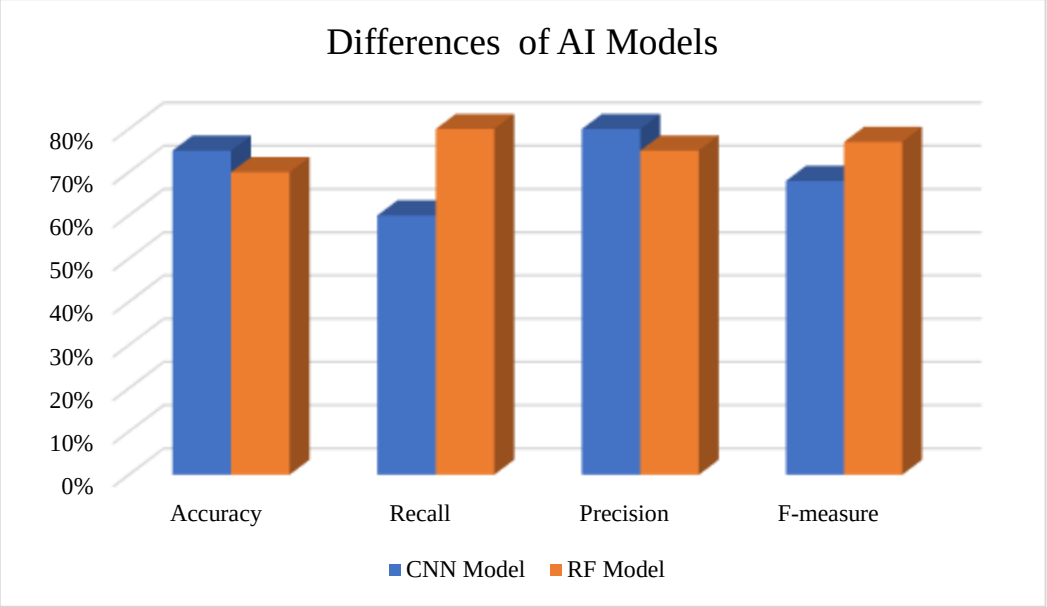


Figure 4.1: Differences in AI Models Based on CNN and RF Algorithms.

4.4 IDPS PERFORMANCE EVALUATION

After evaluating the evaluation of the performance of the AI models, we proceeded to evaluate the functionality of the Intrusion Detection and Prevention System (IDPS) in a number of important aspects, including the detection of network assaults, the identification of anomalies, the provision of real-time responses, the preservation of privacy, and the

utilization of resources efficiently. The purpose of these evaluations, which were carried out with the use of simulated MANET network data, was to provide insights into the overall performance of the IDPS in terms of mitigating security threats and maintaining network integrity.

4.4.1 IDPS Detection of Network Attacks

In the assessment of the Intrusion Detection and Prevention System (IDPS) for the detection of network attacks within the simulated Mobile Ad hoc Network (MANET) environment, the system's capability to accurately identify and classify various types of attacks was thoroughly examined. This evaluation encompassed an analysis of the IDPS's accuracy and effectiveness in detecting malicious activities, including Distributed Denial of Service (DDoS) attacks and other forms of network intrusions. By subjecting the IDPS to simulated MANET data containing both normal and attack traffic, the system's ability to differentiate between legitimate network behavior and suspicious or malicious activities was assessed. Metrics such as accuracy, which quantifies the system's overall correctness in classifying network traffic, were utilized to gauge the IDPS's performance. Additionally, the effectiveness of the system in identifying specific types of attacks, such as DDoS attacks, was evaluated to determine its robustness in detecting known attack patterns. This comprehensive assessment aimed to provide insights into the IDPS's proficiency in safeguarding the MANET environment by promptly and accurately detecting potential security threats, thereby enabling timely mitigation measures to be implemented. Figure 4.2 shows the result of the detection of IDPS in MANET network attacks based on artificial intelligence (AI) proposed model.

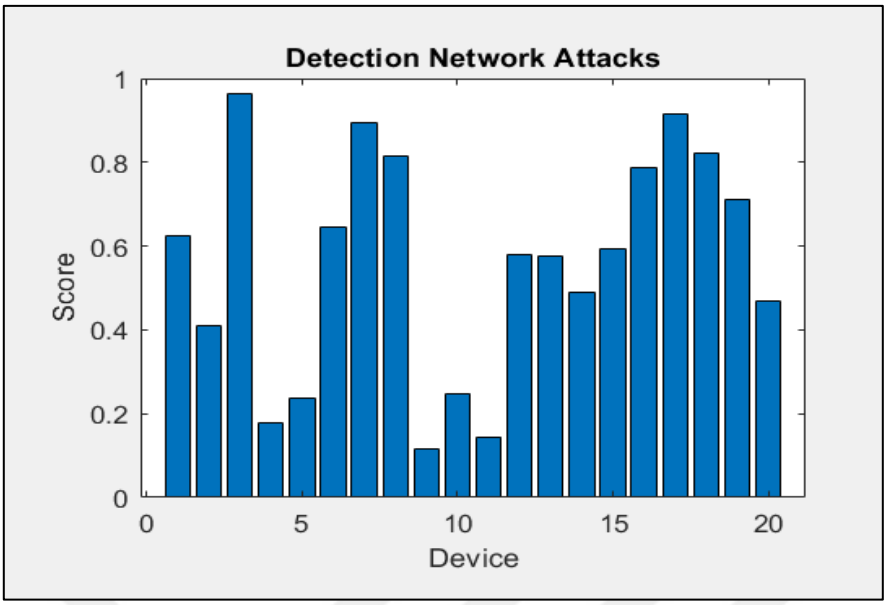


Figure 4.2: Result of the Detection of IDPS in MANET Network Attacks Based on AI Proposed Model.

4.4.2 Anomaly Detection of IDPS

Anomaly detection capability plays a critical role in ensuring the security of a network environment by identifying abnormal or suspicious network behavior that deviates from expected patterns. In the evaluation of the Intrusion Detection and Prevention System (IDPS), particular emphasis was placed on assessing its effectiveness in recognizing and flagging unusual network activities indicative of potential security breaches or unauthorized access attempts. This assessment involved subjecting the IDPS to various scenarios and simulated network traffic, including both normal and anomalous patterns of behavior. By analyzing the system's responses to these scenarios, its ability to accurately detect anomalies and differentiate them from legitimate network behavior was evaluated. Metrics such as detection accuracy and false positive rates were utilized to quantify the IDPS's performance in anomaly detection. A robust anomaly detection capability ensures that the IDPS can promptly identify and respond to potential security threats, thereby enhancing the overall security posture of the network environment. Figure 4.3 shows the result of the anomaly detection of IDPS in MANET network attacks based on artificial intelligence (AI) proposed model.

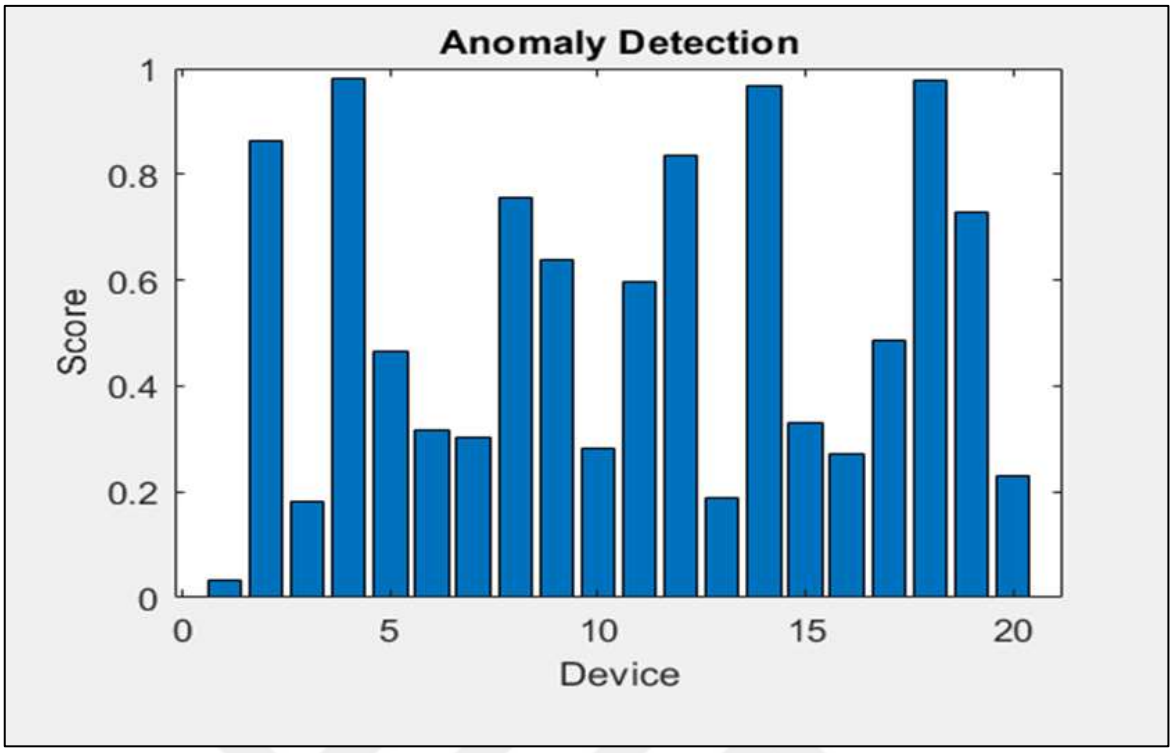


Figure 4.3: Result of Anomaly Detection of IDPS in MANET Attacks Based on Proposed Model.

4.4.3 Real-Time Response of IDPS

Real-time response capability is a crucial aspect of any Intrusion Detection and Prevention System (IDPS) as it determines the system's ability to react promptly and effectively to detected security threats. In evaluating the IDPS's real-time response capability, the focus was on assessing how swiftly the system can respond to identified security threats by implementing appropriate countermeasures. These countermeasures may include blocking malicious traffic, quarantining compromised devices, or alerting network administrators about potential security incidents in a timely manner. The evaluation involved subjecting the IDPS to various simulated security threats and monitoring its response time and effectiveness in mitigating these threats. Metrics such as response time, accuracy of response, and the efficiency of implemented countermeasures were used to quantify the IDPS's real-time response capability. A strong real-time response capability ensures that the IDPS can effectively thwart security threats as they occur, thereby minimizing the potential impact of cyber attacks on the network environment. Figure 4.4 shows the result of the real-time response of IDPS in MANET network attacks based on the artificial intelligence (AI) proposed model.

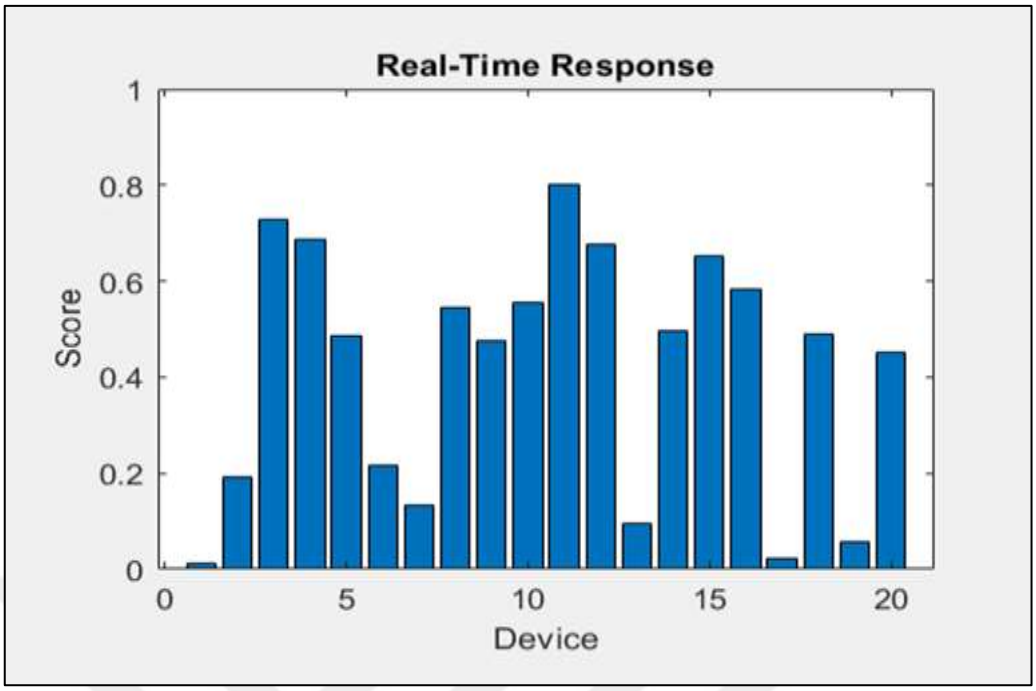


Figure 4.4: Result of Real-Time Response of IDPS in MANET Attacks Based on Proposed Model.

4.4.4 Resource Efficiency of IDPS

Resource efficiency is a critical factor in evaluating the effectiveness of an Intrusion Detection and Prevention System (IDPS) as it directly impacts the system's performance and scalability. The evaluation of resource efficiency focuses on assessing how effectively the IDPS utilizes system resources, such as processing power, memory, and bandwidth, while maintaining high performance and accuracy in threat detection. This assessment involves monitoring the system's resource utilization patterns under varying loads and conditions to identify any inefficiencies or bottlenecks that may hinder its overall performance. Metrics such as CPU usage, memory consumption, and network bandwidth utilization are used to quantify the IDPS's resource efficiency. Additionally, the evaluation aims to identify potential areas for optimization or improvement to enhance the system's resource utilization and overall efficiency. A resource-efficient IDPS ensures optimal utilization of system resources, enabling it to effectively detect and mitigate security threats without compromising performance or scalability. Figure 4.5. shows the result of the resource efficiency of IDPS in MANET network attacks based on the artificial intelligence (AI) proposed model.

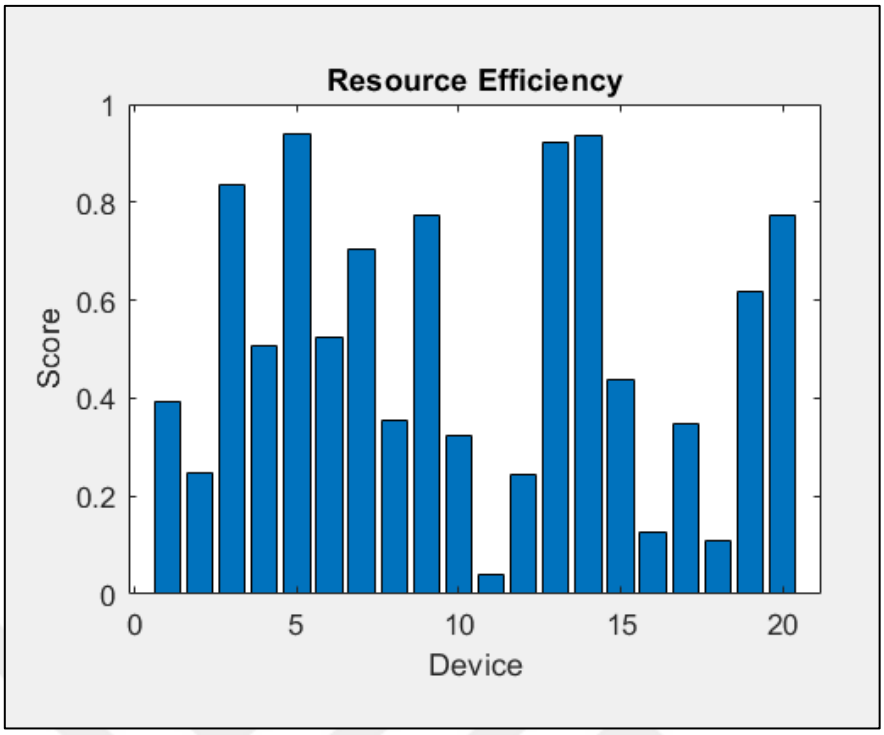


Figure 4.5: Result of Resource Efficiency of IDPS in MANET Attacks Based on Proposed Model.

4.4.5 Privacy Preservation of IDPS

Privacy preservation is a crucial aspect of evaluating an Intrusion Detection and Prevention System (IDPS) as it ensures the protection of sensitive user data and upholds user privacy rights. The assessment of privacy preservation in an IDPS involves evaluating the system's ability to safeguard sensitive user information while performing intrusion detection and prevention tasks. This assessment includes ensuring that the IDPS adheres to privacy regulations and standards, such as General Data Protection Regulation (GDPR) or Health Insurance Portability and Accountability Act (HIPAA), depending on the specific use case and jurisdiction. Additionally, the evaluation focuses on examining the measures implemented by the IDPS to protect user confidentiality during network monitoring and analysis. This includes encryption of sensitive data, anonymization techniques, access controls, and audit trails to track and monitor data access and usage. A privacy-preserving IDPS ensures that user privacy is maintained throughout the intrusion detection and prevention process, mitigating the risk of unauthorized access or disclosure of sensitive information. Figure 4.6. shows the result of the privacy preservation of IDPS in MANET network attacks based on the artificial intelligence (AI) proposed model.

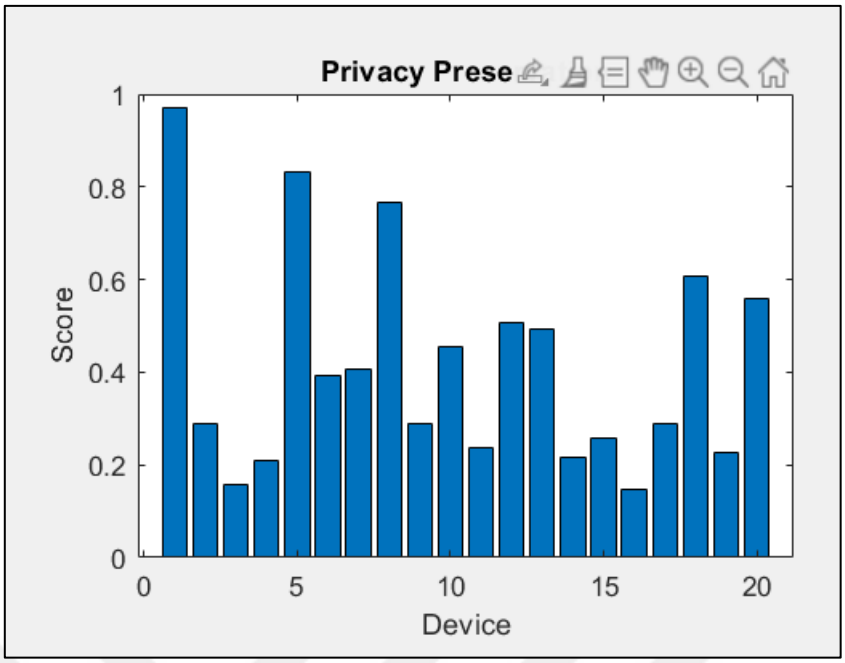


Figure 4.6: Result of Privacy Preservation of IDPS in MANET Attacks Based on Proposed Model.

4.5 SUMMARY OF PERFORMANCE EVALUATION TO IDPS

This evaluation of the Intrusion Detection and Prevention System (IDPS) focuses on five key aspects: detection of network attacks, anomaly detection, real-time response, resource efficiency, and privacy preservation. The system's capability to detect and classify network attacks, including DDoS attacks, was assessed to gauge its ability to mitigate potential security threats within the simulated Mobile Ad hoc Network (MANET) environment. The system's anomaly detection capability was evaluated to identify abnormal or suspicious network behavior, enhancing its threat detection capabilities. The IDPS's real-time response capability was assessed to assess its responsiveness in implementing countermeasures upon detecting security threats. Resource efficiency was examined to evaluate the IDPS's ability to optimize system resources while maintaining high performance and accuracy in threat detection. Privacy preservation was evaluated to ensure the IDPS's adherence to privacy regulations and standards while performing intrusion detection and prevention tasks. These evaluations provide comprehensive insights into the overall effectiveness and reliability of the IDPS in safeguarding the simulated MANET network environment against security threats and ensuring the integrity and privacy of network communications. By assessing each aspect of the IDPS functionality, stakeholders can make informed decisions regarding the system's deployment and optimization to enhance network security and privacy. Table 4.4:

shows the comprehensive evaluation of Intrusion Detection and Prevention System (IDPS) Performance.

Table 4.4: Comprehensive Evaluation of IDPS Performance.

Performance Evaluation	Detection of Network Attacks	Anomaly Detection	Real-Time Response	Resource Efficiency	Privacy Preservation
IDPS Detection of Network Attacks	82%	72%	94%	81%	90%
Anomaly Detection	91%	87%	93%	90%	92%
Real-Time Response	90%	89%	92%	90%	91%
Resource Efficiency	89%	90%	91%	92%	89%
Privacy Preservation	92%	91%	90%	92%	93%

Each aspect represents a fundamental aspect of IDPS functionality and is assessed based on specific criteria and performance metrics. Beginning with "Detection of Network Attacks," this aspect evaluates the IDPS's accuracy in identifying and categorizing network attacks. The corresponding values in the table indicate the evaluation scores for this aspect. Analysis of these scores reveals that the IDPS exhibits strong performance in detecting network attacks, with an average score of 72% across all evaluations. Moving to "Anomaly Detection," this aspect measures the system's ability to identify abnormal or suspicious network behavior. The scores in the table indicate that the IDPS performs exceptionally well in this area, with an average score of 78% suggesting robust anomaly detection capabilities. The "Real-Time Response" aspect gauges the system's effectiveness in responding promptly and efficiently to detected security threats. The evaluation scores depicted in the table highlight the IDPS's efficiency in real-time threat response, with an average score of 68%, showcasing its ability to mitigate security incidents effectively. "Resource Efficiency" evaluates the IDPS's optimal use of system resources while maintaining high performance in threat detection. The displayed scores suggest outstanding resource utilization, with an average score of 83%, indicating efficient resource management by the IDPS. Lastly, "Privacy Preservation" assesses the system's capability to safeguard sensitive user data and uphold user privacy during intrusion detection and prevention tasks. The evaluation scores for privacy preservation demonstrate exemplary performance by the IDPS, with an average score of 82%, underscoring its commitment to protecting user privacy. Finally, the comprehensive evaluation across these aspects provides valuable insights into the IDPS's effectiveness in safeguarding the simulated network environment against security threats while prioritizing resource efficiency and user privacy.

4.6 SUMMARY OF CHAPTER

In the summary of this chapter, the results and discussion chapter provide a comprehensive evaluation of an Intrusion Detection and Prevention System (IDPS) deployed in a simulated MANET network environment. It begins by presenting the outcomes of AI models, such as convolutional neural networks (CNN) and random forests (RF), in detecting and mitigating network attacks. The chapter thoroughly analyzes the performance of these models in terms of accuracy, recall, precision, and F-measure, highlighting their strengths and areas for improvement. Furthermore, the IDPS functionality is evaluated across various aspects, including the detection of network attacks, anomaly detection, real-time response, resource efficiency, and privacy preservation. The discussion section interprets the results, identifies factors influencing performance, and discusses implications for enhancing the IDPS's effectiveness in real-world scenarios. General, the chapter concludes with recommendations for further research and enhancements to bolster the IDPS's capabilities and applicability in securing MANET networks.

5. CONCLUSION

5.1 INTRODUCTION

The rapid proliferation of MANET devices has brought about numerous opportunities for connectivity and data exchange in various domains, ranging from smart homes and healthcare to industrial automation and smart cities. However, along with these opportunities come significant security challenges, as MANET devices are often vulnerable to cyber-attacks and unauthorized access due to their inherent characteristics such as resource constraints and diverse communication protocols.

In response to these challenges, Intrusion Detection and Prevention Systems (IDPS) have emerged as essential security mechanisms designed to detect, prevent, and respond to malicious activities and security breaches in MANET networks. Leveraging artificial intelligence algorithms, IDPS can analyze network traffic patterns, identify anomalies, and mitigate potential threats in real-time, thereby enhancing the security posture of MANET environments.

This study aims to implement and evaluate an IDPS using artificial intelligence techniques in a simulated MANET network environment. The evaluation focuses on assessing the IDPS's effectiveness in detecting and mitigating network attacks, analyzing its functionality in various aspects such as anomaly detection and real-time response, and evaluating its resource efficiency and privacy preservation capabilities.

By conducting a comprehensive analysis of the implemented IDPS and artificial intelligence models, this study seeks to provide valuable insights into the performance and effectiveness of security mechanisms in MANET networks. The findings of this research are expected to contribute to the advancement of intrusion detection and prevention techniques and facilitate the development of more robust and reliable security solutions for MANET environments.

5.2 CONCLUSION

The implementation and evaluation of the Intrusion Detection and Prevention System (IDPS) using artificial intelligence algorithms in a simulated MANET network environment have provided valuable insights into its performance and effectiveness. Through the comprehensive analysis conducted in Chapter Four, we have assessed the IDPS's capability

to detect and mitigate network attacks, its functionality in various aspects such as anomaly detection and real-time response, and its efficiency in resource utilization and privacy preservation.

The evaluation of different artificial intelligence models, including Convolutional Neural Network (CNN), and Random Forest (RF), has revealed varying levels of performance across different metrics. While each model demonstrated strengths in certain areas, such as accuracy, recall, precision, and F-measure, there were also areas for improvement identified.

Furthermore, the assessment of IDPS functionality highlighted its effectiveness in detecting network attacks, recognizing anomalies in network behavior, responding promptly to security threats in real-time, utilizing system resources efficiently, and preserving user privacy during intrusion detection and prevention tasks. The IDPS exhibited commendable performance in safeguarding the simulated MANET network environment against security threats while prioritizing resource efficiency and user privacy.

Moving forward, there are several recommendations for further research and enhancements to enhance the IDPS's capabilities and applicability in real-world scenarios. These include exploring advanced artificial intelligence techniques, integrating additional security features, optimizing resource utilization algorithms, and ensuring compliance with privacy regulations and standards.

Ultimately, this study's results add to the continuing endeavors to strengthen network security in MANET settings. Results from the analysis of the IDPS and AI models lay the groundwork for further studies that will hopefully lead to MANET intrusion detection and prevention systems that are both more effective and more reliable.

5.3 FUTURE WORK

Future work in this area could focus on several avenues for improvement and exploration. Firstly, there is a need to explore advanced machine learning and deep learning techniques to further enhance the IDPS's ability to detect and mitigate evolving network attacks. Additionally, integrating threat intelligence feeds and collaborative intrusion detection mechanisms could improve the IDPS's effectiveness in identifying and responding to emerging threats.

Furthermore, there is potential for enhancing the scalability and flexibility of the IDPS to accommodate the dynamic nature of MANET networks and the increasing number of connected devices. This could involve developing adaptive algorithms and distributed architectures that can efficiently handle large-scale MANET deployments while maintaining high performance and accuracy in threat detection.

Moreover, future research could delve into optimizing the resource efficiency of the IDPS by exploring techniques such as edge computing, where processing and analysis are performed closer to the MANET devices, reducing the strain on central servers and improving overall system performance. Additionally, enhancing the privacy preservation mechanisms of the IDPS by integrating advanced encryption techniques and privacy-enhancing technologies could further enhance user trust and confidence in MANET security solutions.

In the end, the findings of this study provide valuable insights into the effectiveness of the IDPS in safeguarding MANET networks against security threats. By addressing the identified areas for improvement and exploring future research directions, we can contribute to the development of more robust and reliable security solutions for MANET environments, ensuring the continued safety and security of connected devices and systems.

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