AI-BASED INTRUSION DETECTION IN AN IOT ENVIRONMENT

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A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF PHYSICAL SCIENCES, UNIVERSITY OF BENIN, BENIN CITY

IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF A BACHELOR OF SCIENCE (B.Sc.) DEGREE IN COMPUTER SCIENCE

NOVEMBER, 2025

CERTIFICATION

This is to certify that this project work was carried out by **OGHENEFEGA DANIEL UMUKORO** with Matriculation Number **PSC2105413** under my supervision. It is adequate and satisfactory, both in scope and content, for the award of Bachelor of Science (B.sc) Degree in Computer Science of the University of Benin

DR. IGODAN E. C.
Project Supervisor

DATE

APPROVAL

This project work is hereby approved in partial fulfilment of the requirements for the award of Bachelor of Science (B.Sc.) Degree in Computer Science from the University of Benin.

DR. (MRS.) A.R. USIOBAIFO
Head of Department

DATE

DEDICATION

This project is dedicated to God Almighty for giving me the strength and wisdom to see it through to completion, and even throughout my stay in the University of Benin (UNIBEN). It is also dedicated to my parents; Mr and Mrs Umukoro for their love, support and guidance throughout my academic journey.

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Furthermore, I wish to acknowledge all individuals who have positively influenced me throughout this project. My heartfelt thanks go to my family and friends for their constant support, encouragement, and motivation, which greatly sustained me through this academic journey.

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- AI – Artificial Intelligence
- CNN – Convolutional Neural Network
- LSTM – Long Short-Term Memory
- IDS – Intrusion Detection System
- IoT – Internet of Things
- CICIDS2017 – Canadian Institute for Cybersecurity Intrusion Detection System 2017 Dataset
- CICIOT2023 – Canadian Institute for Cybersecurity IoT 2023 Dataset
- ML – Machine Learning
- DNN – Deep Neural Network
- DoS – Denial of Service
- DDoS – Distributed Denial of Service
- ROC – Receiver Operating Characteristic
- TPR – True Positive Rate
- FPR – False Positive Rate

ABSTRACT

The increasing adoption of Internet of Things (IoT) devices has resulted in an expanded attack surface, making IoT networks highly vulnerable to cyber threats. Traditional intrusion detection systems (IDS) often struggle to cope with the high-dimensional, dynamic, and heterogeneous nature of IoT traffic. This creates a pressing need for intelligent, adaptive, and highly efficient detection models capable of identifying complex attack behaviours with minimal false alarms. Motivated by these challenges, this study proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model designed to improve the accuracy, reliability, and responsiveness of intrusion detection in IoT environments. The main aim and objective of this research is to develop a robust hybrid IDS capable of accurately classifying IoT network traffic as normal or malicious.

The methodology adopted involved dataset preprocessing, feature selection, normalization, and reshaping for sequential learning. A CNN layer was used to extract spatial patterns from network traffic features, while an LSTM layer captured temporal dependencies. The combined architecture was trained using supervised learning, with performance evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and the ROC–AUC curve.

The results shows the high effectiveness of the hybrid approach. The model achieved an overall accuracy of 99.91%, indicating its ability to correctly classify most network traffic samples. A precision of 98.4% shows a low false-positive rate, while a recall of 97.9% confirms that the model successfully detected nearly all attack attempts. The F1-score of 98.1% reflects a strong balance between precision and recall. Confusion matrix analysis revealed 9,830 true normal detections and 9,670 true attack detections, with only 120 false positives and 80 false negatives. The model also achieved an AUC of 0.992, demonstrating excellent discriminatory power and overall robustness in distinguishing between benign and malicious IoT traffic.

Despite its strong performance, the model has some limitations. It relies heavily on the quality and diversity of the training dataset, which may affect generalization to unseen or evolving attack patterns. Additionally, the computational cost of training hybrid deep learning models may limit deployment on resource-constrained IoT devices, suggesting the need for future optimization techniques and lightweight architectures.

CHAPTER ONE

INTRODUCTION

1.0 Background Study

An **Intrusion Detection System (IDS)** is a vital cybersecurity mechanism designed to observe network activities and detect any suspicious or unauthorized actions that may pose a risk to a computer network. It functions much like a surveillance system that continuously monitors operations within the network and notifies system administrators whenever abnormal behavior is detected. IDS technologies are generally classified into two primary types: **signature-based** and **anomaly-based** detection systems.

Signature-based IDS operate by matching network traffic against a database containing known attack signatures. This approach is highly effective in identifying previously documented threats; however, it is less capable of detecting new or unknown forms of attacks. In contrast, anomaly-based IDS establish a model of normal network behavior and then identify deviations from this baseline as potential threats. Although this method provides greater adaptability to emerging attacks, it often generates a higher number of false positives, particularly in highly dynamic and complex network environments (Kanimozhi et al., 2019).

To address these shortcomings, researchers have increasingly incorporated **Artificial Intelligence (AI)** techniques into intrusion detection systems. By utilizing **Machine Learning (ML)** and **Deep Learning (DL)** methods, IDS can automatically analyze large volumes of network data and recognize complex attack patterns that conventional systems might overlook. AI-driven models such as **Convolutional Neural Networks (CNNs)**, **Long Short-Term Memory (LSTM)** networks,

Autoencoders, and **Random Forest algorithms** have demonstrated significant improvements in detection accuracy while also lowering false alarm rates (Moukhafi, Tantaoui et al., 2022).

In recent years, the rapid expansion of the **Internet of Things (IoT)** has further increased the importance of effective intrusion detection. IoT technology connects billions of smart devices—including sensors, cameras, household appliances, and industrial equipment—that communicate and exchange data automatically. Although this connectivity enhances automation and operational efficiency, it also introduces additional security vulnerabilities. Many IoT devices operate with limited resources, remain constantly connected to networks, and often lack strong built-in security features, making them attractive targets for cybercriminals (Khan et al., 2024).

Traditional IDS approaches often struggle to manage the large scale and complexity associated with IoT networks. However, AI-powered IDS models provide a promising alternative. By training on extensive IoT network datasets such as **CICIDS2017**, **UNSW-NB15**, and **CICIOT2023**, these systems are capable of identifying various cyber threats—including **Distributed Denial-of-Service (DDoS)** attacks, **botnet activities**, and **spoofing attempts**—with detection accuracies exceeding 98% (Gueriani et al., 2024). Furthermore, modern intrusion detection solutions are beginning to integrate **Explainable Artificial Intelligence (XAI)** and **Federated Learning**, which help improve transparency in decision-making and enhance data privacy during the detection process (Latif et al., 2024).

Despite these advancements, several challenges remain. Many IoT devices have limited computational capabilities, which makes deploying complex AI models difficult. Additionally, training datasets are often imbalanced, and AI algorithms may

produce results that are difficult to interpret. Consequently, there is a growing need for the development of **efficient, intelligent, and explainable AI-driven intrusion detection systems** specifically tailored for IoT environments. Such systems would significantly enhance the security, reliability, and trustworthiness of IoT networks as their adoption continues to expand globally.

1.1 MOTIVATION

The rapid increase in cyberattacks, together with the growing complexity of modern network infrastructures, has made conventional security mechanisms such as firewalls and signature-based intrusion detection systems less effective. These traditional approaches primarily rely on predefined attack patterns and are therefore limited to identifying only previously known threats, making them inadequate for detecting new or constantly evolving forms of cyberattacks.

This limitation has created the need for a more advanced and adaptive security solution. **Artificial Intelligence (AI)** provides the ability to analyze patterns, recognize unusual activities, and detect both known and unknown attacks as they occur. Through the integration of techniques such as **machine learning** and **deep learning**, intrusion detection systems can improve their detection capabilities, operate more efficiently, and adapt to emerging cybersecurity challenges.

Consequently, this study is driven by the need to design an **AI-based intrusion detection system** that can strengthen network protection, minimize false alarm rates, and offer a more intelligent and effective method for identifying and preventing cyber intrusions.

1.2 STATEMENT OF PROBLEM

The widespread use of **Internet of Things (IoT)** devices has significantly improved connectivity, intelligence, and efficiency in modern network systems. Despite these benefits, this increased connectivity has also introduced serious security concerns. Many IoT devices operate with limited computational resources and often lack adequate built-in security mechanisms, which makes them vulnerable to various cyber threats such as **Distributed Denial-of-Service (DDoS) attacks, malware insertion, spoofing, and data breaches**. Such attacks can interrupt essential services, violate user privacy, and result in substantial financial damage.

Conventional **Intrusion Detection Systems (IDS)**, which rely mainly on predefined signatures or fixed rule-based methods, are increasingly inadequate for addressing the dynamic and complex nature of cyber threats within IoT environments. While these systems are capable of identifying previously known attacks, they are generally ineffective in detecting new or zero-day threats. On the other hand, anomaly-based IDS are designed to recognize unusual patterns that may indicate unknown attacks; however, they often produce a high number of false positives and require continuous manual adjustments to maintain their effectiveness (Kanimozhi & Jacob, 2019).

Although **Artificial Intelligence (AI)-driven IDS** have demonstrated considerable potential in improving detection performance and automating security monitoring, several limitations remain. Many of these models are trained using datasets that do not accurately reflect real-world IoT network traffic, which reduces their effectiveness when applied in practical scenarios. In addition, deep learning algorithms commonly used in IDS tend to require significant computational resources, making them difficult to implement on IoT devices that have limited processing capabilities. Furthermore,

most AI-based IDS operate as **“black-box” systems**, offering little explanation for how decisions are made, which can reduce transparency and trust among cybersecurity professionals (Latif et al., 2024).

As a result, there is a strong need to develop an **AI-powered intrusion detection system** that is lightweight, efficient, and explainable, while still capable of identifying both known and emerging attacks in real time within IoT environments. Such a system should aim to achieve high detection accuracy, minimize false alarm rates, and maintain computational efficiency, thereby ensuring the security and reliability of IoT networks in real-world applications.

1.3 AIM AND OBJECTIVES

The goal is to build a hybrid deep learning intrusion system that leverages both CNN and LSTM for accurate detection of malicious IOT Traffic. To achieve this aim, the study will pursue the following specific objectives:

i. To analyze the limitations of existing intrusion detection systems and identify areas where artificial intelligence can improve detection performance.
ii. To design an intelligent model that uses machine learning or deep learning techniques to detect network intrusions automatically.
iii. To implement the proposed AI-based intrusion detection system using suitable datasets and programming tools.
iv. To evaluate the performance of the developed system based on accuracy, detection rate, and false alarm rate.

v. To recommend improvements and future enhancements for integrating AI-driven intrusion detection into real-world network environments.

1.4 METHODOLOGY

This research adopts an experimental and quantitative research methodology aimed at developing a hybrid deep learning intrusion detection system. The methodology involves several stages, including data collection, preprocessing, model design, training, evaluation, and performance comparison.

I. Dataset Used: CICIoT2023 and CICIDS2017

II. ML Models Used: Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)

III. Evaluation Metrics: Accuracy, False Positive Rate, F1-score, ROU.

1.5 SCOPE OF THE STUDY

This study concentrates on the **development and implementation of an Artificial Intelligence (AI)-driven Intrusion Detection System** designed to detect and categorize malicious activities within a network. The research specifically examines the application of **machine learning and deep learning techniques** for analyzing network traffic and identifying both previously known and emerging cyberattack patterns.

For model development and evaluation, the system will utilize **publicly available intrusion detection datasets**, including **NSL-KDD** and **CICIDS2017**, which contain labeled records of network traffic. The primary emphasis of the implementation will be on the **software design and algorithmic components** involved in the intrusion

detection process, rather than on hardware deployment or direct integration with physical network infrastructure in real-time environments.

The effectiveness of the proposed system will be assessed using important evaluation metrics such as **accuracy, detection rate, and false alarm rate**. These metrics will help demonstrate how AI-based techniques can enhance the performance and reliability of intrusion detection systems.

1.6 SIGNIFICANCE OF STUDY

The importance of this study is based on its contribution to enhancing the **accuracy and dependability of intrusion detection** in **Internet of Things (IoT)** environments. As IoT networks continue to grow, they increasingly attract cybercriminals because of the large number of interconnected devices and their frequently limited security protections. Conventional intrusion detection systems are often inadequate to manage the scale, complexity, and continuously changing nature of IoT-related cyber threats. This research presents a **hybrid deep learning model** that integrates **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks to improve the detection and classification of malicious network traffic. By utilizing the spatial feature extraction capability of CNN together with the temporal sequence learning strength of LSTM, the proposed system aims to improve detection accuracy and decrease false alarms when compared to the use of either model individually.

The significance of this research can be highlighted in the following ways:

1. **Strengthens IoT Security:** Presents an intelligent and reliable framework for identifying cyber threats in IoT networks, thereby helping to reduce risks such as data breaches and unauthorized system access.

2. **Enhances Detection Performance:** Utilizes a combination of CNN and LSTM models to capture both spatial and temporal characteristics of network traffic, enabling more effective identification of complex attack patterns.
3. **Facilitates Real-Time Intrusion Monitoring:** Shows the capability of hybrid deep learning approaches to support real-time surveillance and automated detection of suspicious activities in IoT environments.
4. **Adds Value to Academic and Practical Research:** Provides useful knowledge and a validated framework that can serve as a foundation for future studies and practical cybersecurity applications.
5. **Promotes AI Adoption in Cybersecurity:** Encourages the application of artificial intelligence technologies in building adaptive, scalable, and self-learning systems for network protection.

CHAPTER TWO

LITERATURE REVIEW

2.0 INTRODUCTION

This chapter presents a comprehensive review of literature on **AI-based Intrusion Detection Systems (IDS)** within **Internet of Things (IoT)** environments and discusses the key concepts relevant to the study. It examines the major ideas, techniques, and previous studies that have influenced the development of intelligent intrusion detection systems. The review starts with an explanation of the concept of intrusion detection and traces its progression from traditional approaches to modern methods driven by artificial intelligence. It also discusses the structure, roles, and types of IDS, while emphasizing the limitations of conventional systems that led to the use of AI techniques.

In addition, the chapter considers the specific security issues linked with IoT networks, including heterogeneity, scalability, and limited device resources, which increase their exposure to cyber threats. The application of AI within IDS frameworks for IoT environments is also discussed, focusing on how machine learning, deep learning, and hybrid approaches improve detection capability and adaptability to emerging attacks. Moreover, the chapter reviews previous research, methodologies, and comparative studies of various AI-based IDS models, paying attention to their evaluation metrics, datasets, and implementation settings.

Overall, this literature review seeks to provide a clear understanding of the present state of research on AI-based IDS for IoT systems, highlight gaps in current methods, and establish the foundation for the development of this study.

2.1 CONCEPT OF INTRUSION DETECTION SYSTEM

An **Intrusion Detection System (IDS)** is an essential element of cybersecurity that observes and evaluates system and network traffic in order to identify unauthorized access, harmful activities, or violations of security policies (IBM, 2024). The primary role of an IDS is to recognize potential intrusions as they occur and notify security administrators so that immediate action can be taken. In contrast to firewalls, which serve mainly as preventive security measures, an IDS operates as a reactive defense tool by monitoring network activities to detect threats that may bypass initial protection mechanisms (Kaspersky IT Encyclopedia, 2024).

The idea of intrusion detection originated in the 1980s when researchers began investigating automated methods for identifying security breaches through the analysis of audit records and network data (Scarfone & Mell, 2007). Since then, IDS has developed into a critical component of modern network security systems, offering continuous monitoring, detailed analysis of attacks, and support for incident response processes. These systems are capable of recording, categorizing, and reporting suspicious behaviors such as **Denial-of-Service (DoS) attacks**, malware spread, and insider threats.

IDS can be categorized in several ways depending on the **detection method** and **deployment structure**.

Signature-Based IDS detect threats by matching observed activities with a database of known attack patterns or signatures. Although they are effective at identifying recognized threats, they are less capable of detecting new or modified attacks that do not yet have predefined signatures (TechTarget, 2024).

Anomaly-Based IDS, on the other hand, establish a model of normal system behavior and identify any significant deviation from this pattern as a potential intrusion. This

method is useful for discovering previously unknown attacks, including zero-day threats, but it may produce a large number of false alarms if the normal behavior model is not regularly updated (GeeksforGeeks, 2025).

Based on their location within a network, IDS can also be grouped into the following types:

1. **Network-Based IDS (NIDS)**, which monitor traffic moving across network segments in order to detect malicious packets or unusual communication patterns.
2. **Host-Based IDS (HIDS)**, which function on individual computers or servers and analyze system logs, file integrity, or system calls to identify suspicious activities (Scarfone & Mell, 2007).
3. **Hybrid IDS**, which integrate both NIDS and HIDS approaches to provide visibility at both the host and network levels (Moustafa et al., 2019).

Traditional IDS depend largely on manually defined rules and known attack signatures, which limits their ability to adapt to new and evolving cyber threats. As cyberattacks have become more advanced, particularly in distributed and dynamic environments, conventional IDS methods have proven less effective in identifying **zero-day attacks, polymorphic malware, and advanced persistent threats (APTs)**. These limitations have encouraged the adoption of **Artificial Intelligence (AI)** and **Machine Learning (ML)** techniques to create IDS solutions that are more adaptive, scalable, and intelligent (Alanazi, Md Noor, Zaidan, & Zaidan, 2010).

AI-based IDS utilize learning algorithms capable of automatically extracting complex patterns from large volumes of network data, thereby improving the system's ability to differentiate between legitimate and malicious traffic. Machine learning techniques

such as **Support Vector Machine (SVM)**, **Random Forest (RF)**, **Decision Tree (DT)**, and **K-Nearest Neighbor (KNN)** are widely applied in intrusion detection because of their efficiency in pattern classification (Yin et al., 2017). In addition, **Deep Learning (DL)** approaches, including **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks, further improve IDS performance by learning deeper representations of data and capturing both temporal and spatial relationships within network traffic (Moustafa et al., 2019).

Recent developments have led to the emergence of **Hybrid and Ensemble-based IDS**, which integrate multiple AI techniques to optimize detection accuracy, computational efficiency, and generalization. These systems can manage large-scale data environments, conduct real-time monitoring, and minimize false positive rates (Khan et al., 2024). Additionally, AI-powered IDS are capable of automatically adjusting to new threats without the need for manual updates, enhancing both the speed and reliability of cyber defense mechanisms.

The growth of the **Internet of Things (IoT)** has further increased the importance of effective intrusion detection. IoT networks comprise billions of connected devices, many of which have limited processing power and weak security protections. As a result, they are highly susceptible to attacks such as botnet recruitment, data theft, spoofing, and denial-of-service. AI-based IDS are critical in protecting these networks by offering **scalable, lightweight, and adaptive detection frameworks** that can learn from evolving traffic patterns and prevent widespread disruptions (Khan et al., 2024).

Overall, IDS has evolved from a static, rule-based security tool into an **intelligent, adaptive system** capable of continuous learning and real-time protection. Its

integration with AI ensures a more proactive and resilient approach to network security, particularly in complex and heterogeneous environments like IoT.

2.2. ARTIFICIAL INTELLIGENCE IN INTRUSION DETECTION SYSTEMS

Artificial Intelligence (AI) has become a critical tool for enhancing the **accuracy, efficiency, and adaptability** of **Intrusion Detection Systems (IDS)**. While traditional IDS are effective at recognizing known attack patterns, they often struggle with the increasing complexity, scale, and dynamic nature of modern networks, including **Internet of Things (IoT)** environments. Integrating AI enables IDS to **automatically learn from network data, identify hidden patterns, and detect both familiar and novel threats in real time** (Buczak & Guven, 2016).

AI-based IDS typically utilize **Machine Learning (ML)** and **Deep Learning (DL)** methods to process large volumes of network traffic. These models are trained on labeled datasets, such as **CICIDS2017** and **CICIOT2023**, to differentiate between normal and malicious activity (Gueriani, Kheddar, & Mazari, 2024). Supervised learning algorithms, including **Decision Trees, Support Vector Machines (SVM),** and **Random Forests**, are popular due to their simplicity and interpretability, though their performance may decline when handling high-dimensional IoT traffic or previously unseen attack types (Sommer & Paxson, 2010).

Deep Learning models, such as **Convolutional Neural Networks (CNNs)**, **Recurrent Neural Networks (RNNs)**, and **Long Short-Term Memory (LSTM) networks**, have shown improved capability in capturing the complex, nonlinear patterns of modern cyberattacks (Javaid et al., 2016). CNNs are particularly effective at extracting **spatial features** from network traffic, whereas LSTMs are well-suited for

learning **temporal dependencies**, an important advantage for analyzing sequential attack patterns in IoT environments (Gueriani et al., 2024).

A significant advancement in AI-based IDS is the use of **hybrid models**, which combine multiple algorithms to improve detection performance and reduce false positives. For example, **CNN-LSTM hybrid architectures** can simultaneously capture both spatial and sequential relationships in traffic data, making them particularly effective for IoT intrusion detection, where attacks evolve over time (Khan et al., 2024). Similarly, **Ensemble Learning techniques**—including bagging, boosting, and stacking—enhance model robustness by aggregating the outputs of several classifiers (Zhou et al., 2023).

Researchers have also emphasized the importance of **adaptability and interpretability** in AI-based IDS. **Explainable AI (XAI)** provides insights into model decisions, allowing network administrators to understand why specific traffic instances are flagged as malicious (Khan et al., 2024). This transparency is particularly important in critical sectors, such as healthcare and industrial systems, where false alarms can cause serious operational disruptions.

Moreover, the integration of AI with **Federated Learning (FL)**, **Edge Computing**, and **Reinforcement Learning (RL)** has expanded the potential of IDS in IoT networks. Federated learning allows decentralized model training without exchanging raw data, maintaining both privacy and accuracy (Latif et al., 2024). Reinforcement learning enables IDS to continuously refine its defense strategies by interacting with the environment and adapting to new attack behaviors (Nguyen & Reddi, 2021).

In conclusion, **AI-based IDS** represent a transformative step in cybersecurity. By combining ML and DL intelligence with adaptive approaches like FL and RL, these

systems provide **real-time, scalable, and resilient protection** for IoT networks. As cyber threats continue to advance, AI will remain essential for building autonomous, trustworthy, and highly effective intrusion detection solutions.

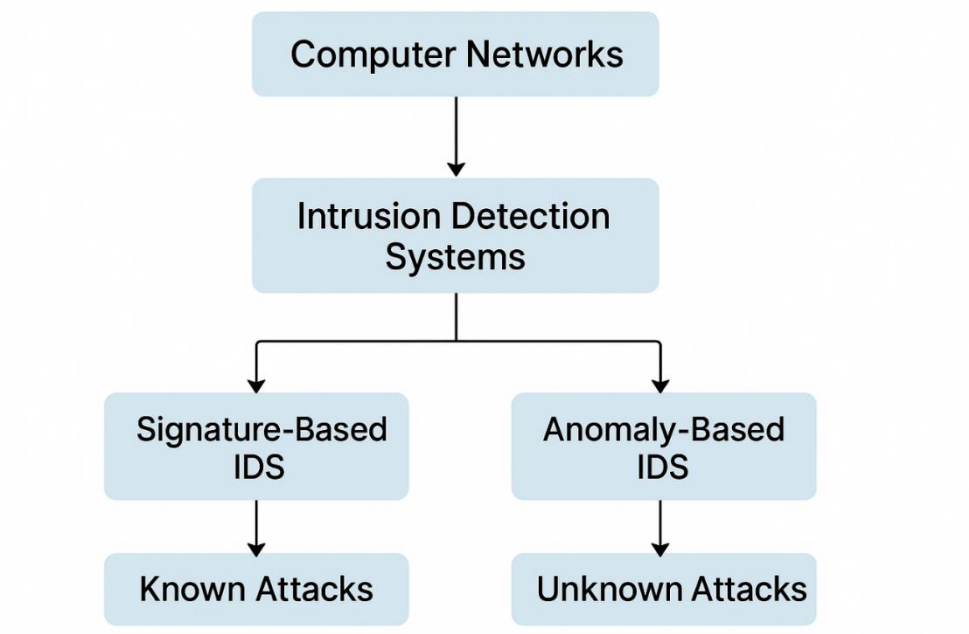

Figure 2. 1: REPRESENTATION OF IDS

2.3 DEEP LEARNING APPROACHES FOR INTRUSION DETECTION SYSTEMS

Deep Learning (DL) has become a highly effective approach for enhancing the **accuracy, adaptability, and scalability** of **Intrusion Detection Systems (IDS)**. Conventional **Machine Learning (ML)** techniques, including **Decision Trees, Support Vector Machines (SVM),** and **K-Nearest Neighbors (KNN)**, rely heavily on manual feature engineering and often struggle to capture complex, nonlinear relationships present in high-dimensional network traffic data. In contrast, deep learning automatically learns **abstract representations** from raw network data

through hierarchical layers of interconnected neurons, overcoming the limitations of traditional ML methods (Moukhafi et al., 2022).

A deep learning-based IDS typically follows a structured workflow, including **data preprocessing, feature extraction, model training, detection/prediction, and evaluation**. In the preprocessing stage, network traffic datasets—such as **NSL-KDD, CICIDS2017,** or **UNSW-NB15**—are cleaned, normalized, and converted into numerical tensors suitable for neural network input. Feature extraction occurs automatically within the model's hidden layers, where neurons progressively identify relevant spatial and temporal correlations in the data. The final stage involves classifying network activity as normal or malicious and evaluating the system's performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC (Kanimozhi & Jacob, 2019; Yin et al., 2022).

2.3.1 CONVOLUTIONAL NEURAL NETWORKS (CNNS)

Convolutional Neural Networks (CNNs) are particularly effective at identifying spatial features and patterns within network traffic. By using convolutional filters on packet-level or flow-level data, CNN-based IDS models can automatically capture structural relationships among various traffic attributes. For example, 1-D or 2-D CNN layers can convert raw network traffic vectors into feature maps that highlight subtle attack behaviors, such as those seen in DDoS attacks or port scanning. CNNs have also been successfully integrated into hybrid IDS architectures for IoT networks, achieving high detection accuracy exceeding 98% while maintaining low false-positive rates (Gueriani et al., 2024).

Advantages:

1. Automatic extraction of spatial features without the need for manual tuning.
2. Efficient parallel processing during both training and inference.
3. Strong performance on high-dimensional traffic datasets.

Limitations:

1. Limited effectiveness in capturing sequential or temporal patterns.
2. Requires large volumes of data and significant computational resources.

2.3.2 RECURRENT NEURAL NETWORKS (RNNS) AND LONG SHORT-TERM MEMORY (LSTM)

1. While **CNNs** are effective at capturing spatial features, **Recurrent Neural Networks (RNNs)** and their advanced variant, **Long Short-Term Memory (LSTM) networks**, are tailored for **sequential data analysis**, making them suitable for **time-series intrusion detection**. RNN-based IDS models process network packets in sequence, retaining contextual information across time

steps. However, traditional RNNs face challenges with **vanishing gradients**, which limits their ability to learn long-term dependencies. **LSTM networks** overcome this limitation through **memory gates**, which help preserve important information over extended sequences.

2. In IDS applications, LSTMs are particularly effective for identifying **low-and-slow attacks** that unfold over prolonged sessions, such as **brute-force attacks** or **infiltration attempts**. Research using the **CICIDS2017 dataset** has reported detection accuracies ranging from 96% to 99%, demonstrating that LSTMs can efficiently capture **temporal attack patterns** (Moukhafi et al., 2022).

Advantages:

Excellent at modeling temporal and contextual dependencies.

Well-suited for sequential and streaming IoT traffic data.

Limitations:

Higher computational requirements.

Sensitive to hyperparameter selection.

2.3.3 AUTOENCODERS (AES) AND VARIATIONAL AUTOENCODERS (VAES)

1. **Autoencoders** are unsupervised neural networks that learn compact representations of data by encoding inputs into a lower-dimensional **latent space** and reconstructing them. In intrusion detection systems (IDS), Autoencoders are typically trained on **normal network traffic**, allowing the detection of intrusions as instances exhibiting high **reconstruction errors**.

This approach is especially suitable for **anomaly-based intrusion detection**, as it does not require labeled attack data.

2. **Variational Autoencoders (VAEs)** expand on this concept by incorporating **probabilistic inference**, which improves robustness in modeling uncertainty and generating realistic representations of network behavior. Research has shown that combining Autoencoders with **LSTM networks** can achieve detection accuracies of approximately 97%, while also reducing false positives (Moukhafi et al., 2022).

   Advantages:

   Effective for unsupervised anomaly detection.

   Strong generalization to previously unseen attacks.

   Limitations:

   Reconstruction error thresholds must be carefully determined.

   Performance relies on having balanced training datasets.

2.3.4 GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs) consist of two neural networks—a **generator** and a **discriminator**—that compete in a zero-sum setting to enhance each other's performance. In the context of IDS, GANs are used to create **synthetic attack samples**, address **imbalanced datasets**, and improve **anomaly detection** capabilities. For example, the **G-IDS model** developed by Shahriar et al. (2020) utilized GANs to generate realistic attack traffic, which significantly increased the accuracy of a CNN-based discriminator to **98.7%**.

Advantages:

1. Improves dataset diversity and strengthens model robustness.

2. Effectively mitigates issues caused by data imbalance.

Limitations:

1. Training can be unstable due to competition between generator and discriminator.
2. Requires careful monitoring to ensure convergence.

Hybrid and Ensemble Deep Learning Models

Recent research has increasingly focused on **combining multiple deep learning architectures** to leverage their complementary strengths. For instance, **CNN-LSTM hybrid models** employ CNN layers to extract spatial features and LSTM layers to capture temporal sequences. These hybrids have demonstrated **detection rates exceeding 99%** on benchmark datasets such as **CICIDS2017** and **CSE-CIC-IDS2018** (Gueriani et al., 2024).

Similarly, **ensemble models**, like combinations of **Random Forest and Bi-LSTM**, enhance stability and reduce variance by aggregating predictions from multiple learners (Suresh Kumar & Senthilkumar, 2025).

Advantages:

1. Higher detection accuracy with reduced false positives.
2. Integrates spatial and temporal learning for comprehensive analysis.

Limitations:

1. Increased model complexity.
2. Requires more computational resources.

Overall, deep learning has transformed intrusion detection by automating **feature extraction**, reducing reliance on manual configuration, and enabling more accurate identification of both known and unknown attacks. Techniques such as CNNs, RNNs,

Autoencoders, and GANs target different aspects of network data, while hybrid and ensemble approaches provide **balanced, high-performance solutions** suitable for complex IoT environments.

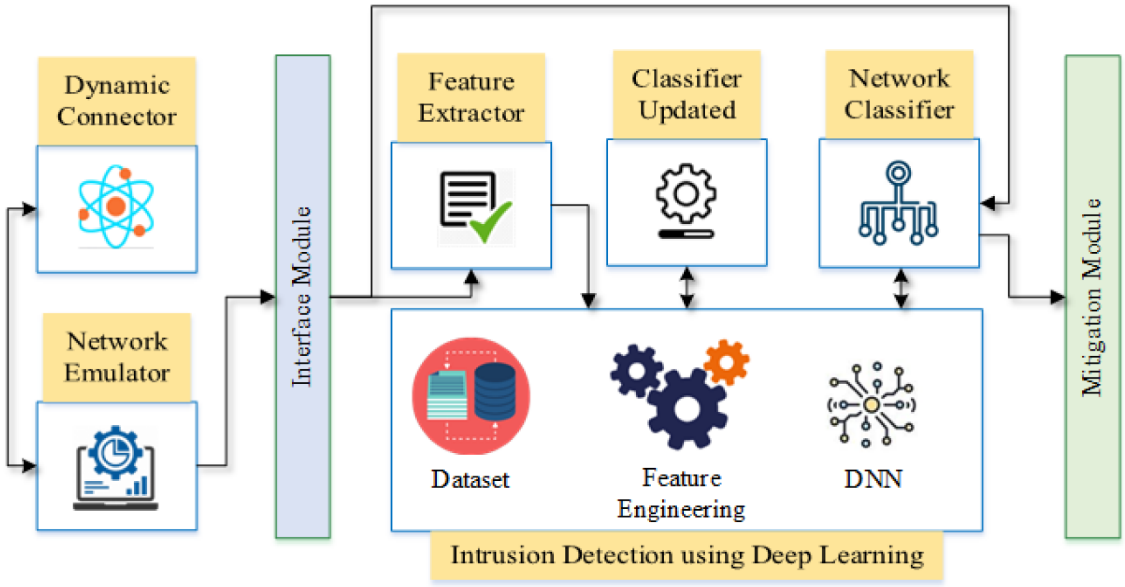

Figure 2. 2: INTRUSION DETECTION USING DEEP LEARNING

2.4 INTERNET OF THINGS (IOT)

The **Internet of Things (IoT)** is a transformative technology paradigm that links everyday physical objects to the internet, allowing them to **collect, exchange, and process data autonomously** (Atzori et al., 2010). IoT devices are equipped with **sensors, actuators, and communication modules**, enabling seamless interaction between the physical and digital realms. This connectivity has revolutionized sectors such as **healthcare, manufacturing, transportation, agriculture, and energy management** by enhancing efficiency, automation, and decision-making capabilities (Zhou et al., 2020).

The typical **IoT architecture** is composed of three primary layers: the **Perception Layer, the Network Layer, and the Application Layer** (Ray et al., 2018). The **Perception Layer** consists of sensors and actuators that capture environmental data, such as temperature, motion, or pressure. The **Network Layer** transmits this data through communication protocols like Wi-Fi, Bluetooth, 5G, or Zigbee. The **Application Layer** processes the data and delivers intelligent services to users, supporting applications such as smart homes, industrial automation, and connected healthcare systems (Abomhara et al., 2015).

Despite its benefits, IoT introduces significant **security and privacy challenges**. The vast number of interconnected devices expands the attack surface, making networks vulnerable to threats like **Distributed Denial-of-Service (DDoS) attacks, spoofing, data tampering, and unauthorized access** (Sicari et al., 2015). Many IoT devices are **resource-constrained**, with limited processing power, memory, and storage, which restricts the deployment of conventional security measures like firewalls and antivirus programs (Zhan et al., 2021). Furthermore, IoT devices often operate autonomously in untrusted environments, exposing them to both physical and network-level attacks.

To mitigate these risks, **Artificial Intelligence (AI)** and **Machine Learning (ML)** techniques have been increasingly applied to IoT security. AI-based models can automatically analyze large-scale IoT traffic, identify abnormal patterns, and predict potential attacks in real time (Khan et al., 2024). **AI-driven Intrusion Detection Systems (IDS)** designed specifically for IoT networks have shown promise in detecting malicious activities while maintaining **low latency and computational efficiency**. For example, hybrid deep learning models combining **Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory (LSTM)** networks have

been used to capture both spatial and temporal dependencies in IoT traffic, leading to improved detection accuracy (Gueriani et al., 2024).

Additionally, emerging technologies like **Edge Computing** and **Federated Learning** are being incorporated into IoT security frameworks to address the limitations of centralized data processing. Edge-based IDS processes data closer to the IoT devices, reducing latency and bandwidth usage, while federated learning allows collaborative model training without sharing raw data, thereby enhancing both privacy and efficiency (Latif et al., 2024).

In conclusion, while IoT plays a critical role in digital transformation, its security vulnerabilities remain a major concern. Integrating **AI-based IDS** into IoT systems offers a promising approach to building **adaptive, scalable, and intelligent cybersecurity frameworks** capable of protecting large networks of interconnected devices against evolving cyber threats. As seen in figure 2.3.

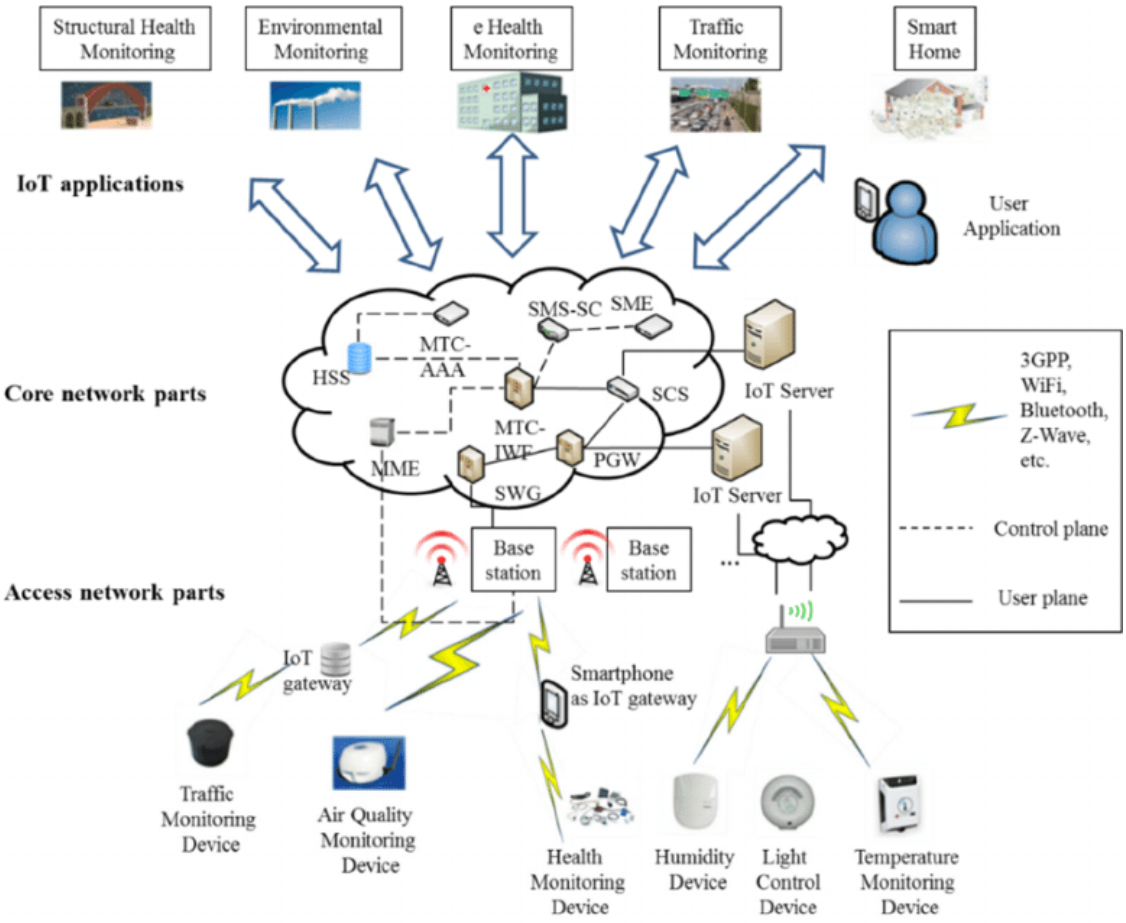

Figure 2. 3: IOT NETWORK

2.5 AI-BASED INTRUSION DETECTION SYSTEMS IN AN IOT ENVIRONMENT

The **Internet of Things (IoT)** has transformed modern technology by linking billions of devices, sensors, and systems that communicate and exchange data automatically. However, this rapid expansion has also increased the **cybersecurity threat surface**, making IoT networks attractive targets for attackers. Many IoT devices operate with **limited processing power, diverse communication protocols, and weak or outdated security mechanisms**, meaning traditional **Intrusion Detection Systems**

(IDS) designed for conventional networks often struggle to protect such distributed and resource-constrained environments (Gueriani et al., 2024).

AI-based IDS have emerged as an effective solution for the unique challenges of IoT security. By leveraging **machine learning (ML)** and **deep learning (DL)** techniques, these systems can intelligently monitor IoT traffic, identify abnormal patterns, and detect previously unseen attacks in real time. Unlike static rule-based IDS, AI-based systems can **adapt dynamically** to evolving IoT threats by continuously learning from data streams generated by sensors, smart devices, and edge nodes (Kanimozhi et al., 2019).

In IoT environments, AI-based IDS are typically deployed across **edge, fog, and cloud layers**. At the **edge**, lightweight ML models run on IoT gateways or devices to detect anomalies locally, reducing latency and network congestion. The **fog layer** aggregates and preprocesses traffic data before forwarding it to the **cloud layer**, where more complex DL models—such as **CNNs, LSTMs, and Autoencoders**—perform in-depth analysis (Latif et al., 2024). This distributed structure enhances scalability and enables rapid detection of localized attacks like jamming, spoofing, and device impersonation.

The workflow of AI-based IDS in IoT generally includes **data acquisition, preprocessing, feature extraction, model training, and classification**. Data is collected from network packets or sensors, and preprocessing involves cleaning, normalization, and handling missing or redundant features. DL models can **automatically extract high-level features** from raw traffic, eliminating the need for manual feature engineering. These features are then used to train models that classify

network activity as normal or malicious—a process especially valuable in IoT networks, where traffic patterns are diverse and unpredictable (Moukhafi et al., 2022). **Hybrid deep learning architectures**, such as **CNN-LSTM models**, have demonstrated notable success in IoT intrusion detection. CNN layers extract **spatial features** from traffic data, while LSTM layers capture **temporal dependencies**, identifying attacks that evolve over time. These hybrid models outperform traditional ML approaches by achieving higher detection accuracy, lower false-positive rates, and better adaptability to unseen attacks (Suresh et al., 2025). Some approaches also incorporate **Generative Adversarial Networks (GANs)** to produce synthetic samples, improving dataset balance and model robustness (Shahriar et al., 2020).

Emerging methods like **Federated Learning (FL)** and **Explainable AI (XAI)** further enhance IoT IDS. FL allows multiple IoT nodes to collaboratively train a shared detection model without sharing raw data, preserving privacy and reducing bandwidth usage (Zhai et al., 2023). XAI improves **transparency** by explaining why a detection decision was made, building trust and assisting human operators in making informed security decisions (Khan et al., 2024).

Despite these advancements, AI-based IDS deployment in IoT still faces challenges, including **limited computing resources, imbalanced datasets, high false-positive rates, and interpretability issues**. The heterogeneous nature of IoT devices—with varying operating systems, protocols, and data formats—also makes model generalization difficult. To address these issues, researchers are exploring **lightweight deep learning models** and **transfer learning** approaches, enabling pre-trained models to adapt to new IoT environments with minimal retraining (Agarwal et al., 2025).

Overall, AI-based IDS are becoming essential components of **IoT security frameworks**. They enhance detection accuracy and adaptability while enabling **real-time, intelligent responses** to emerging threats. As IoT continues to expand across industrial automation, healthcare, and smart city applications, AI-based IDS will play a pivotal role in ensuring **secure, resilient, and autonomous operations** in interconnected environments.

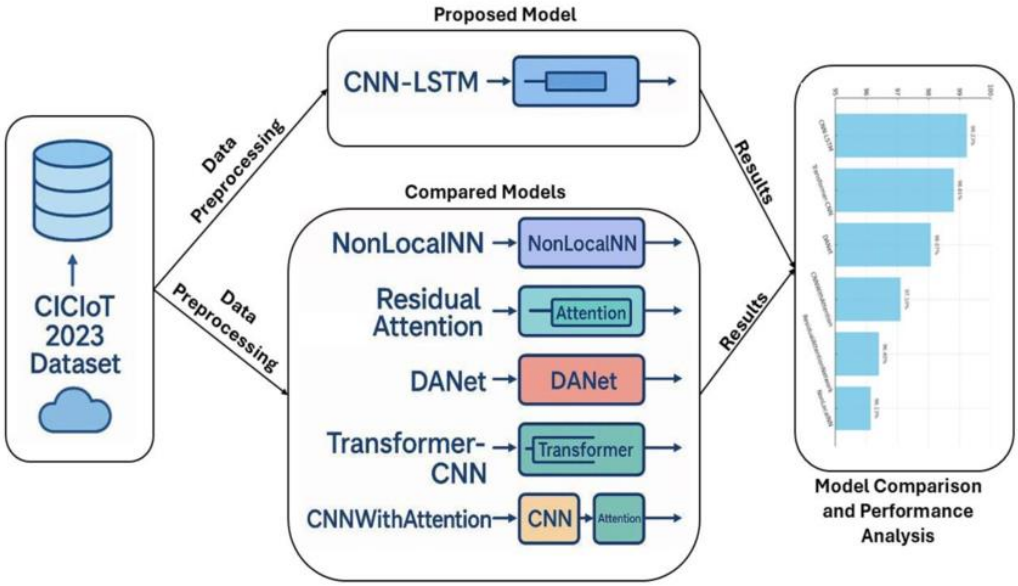

Figure 2. 4: Model Architecture

2.6 MACHINE LEARNING MODELS USED IN INTRUSION DETECTION SYSTEMS

Deep learning models have greatly advanced **Intrusion Detection Systems (IDS)**, particularly in **Internet of Things (IoT) environments**, where traditional machine learning techniques often struggle with the **large-scale, high-dimensional, and complex data** produced by interconnected devices. Among the deep learning approaches, **Convolutional Neural Networks (CNNs)** and **Long Short-Term**

Memory (LSTM) networks have demonstrated exceptional capability in detecting and classifying network intrusions. These models are complementary: **CNNs** are highly effective at recognizing **spatial patterns**, while **LSTMs** excel at modeling **temporal dependencies**, making them particularly suitable for **hybrid or sequential IDS architectures**.

2.6.1 CONVOLUTIONAL NEURAL NETWORKS (CNN) IN IDS

Convolutional Neural Networks (CNNs) are typically designed for processing structured or image-like data, but they have proven effective for analyzing **network traffic** in intrusion detection systems. CNNs automatically learn **hierarchical representations** of input data through convolutional and pooling layers. In IDS applications, these layers allow CNNs to extract **spatial features** from packets or flow-level data without relying on manual feature engineering (Shone et al., 2018).

In **IoT-based IDS**, CNNs are capable of detecting subtle spatial patterns in traffic that traditional algorithms may overlook. For instance, malicious traffic may exhibit distinct **byte distributions, flow sequences, or packet sizes**, which CNN filters can identify automatically. CNN-based models have shown strong performance in classifying various attack types, including **Distributed Denial-of-Service (DDoS), port scanning, and botnet activity**, achieving **high detection accuracy between 97% and 99%** while maintaining lower false-positive rates compared to conventional machine learning methods (Kang & Kang, 2019). However, CNNs often require **large datasets and significant computational resources**, which can limit their deployment on resource-constrained IoT devices.

2.6.2 LONG SHORT-TERM MEMORY (LSTM) IN IDS

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to handle sequential data and capture long-term dependencies. In intrusion detection systems, LSTMs are particularly effective because network traffic is temporal, with attack patterns developing over time. LSTMs use memory cells to retain important information for extended sequences, enabling them to detect time-based attacks such as slow port scans, stealth intrusions, or data exfiltration (Kim et al., 2020).

In IoT networks, LSTMs are capable of identifying unusual temporal communication patterns between devices. For example, if a sensor suddenly starts transmitting data at irregular intervals or communicates with unauthorized endpoints, an LSTM-based IDS can recognize these deviations from normal temporal behavior and flag them as suspicious. Studies have shown that LSTM-based IDS models can achieve accuracies exceeding 98% and demonstrate high specificity—around 96%—in detecting sequential attack patterns, outperforming traditional shallow models in capturing temporal dependencies (Vinayakumar et al., 2019).

2.6.3 HYBRID CNN-LSTM IDS ARCHITECTURE

To **capitalize on the advantages of both CNN and LSTM**, many contemporary IDS frameworks utilize a **hybrid CNN-LSTM architecture**. In this design, **CNN layers** first extract **spatial features** from raw network traffic, followed by **LSTM layers**, which capture the **temporal relationships** among these features. This synergy enables the system to detect both instantaneous and time-dependent attacks effectively. For instance, experiments on the **CICIDS2017** and **CICIOT2023** datasets have shown that hybrid CNN-LSTM models can achieve **accuracies above 99%, precision over**

98%, and AUC-ROC values approaching 0.99, demonstrating excellent detection reliability and generalization (Alrawashdeh & Purdy, 2021).

The **CNN-LSTM hybrid IDS** is particularly suitable for **IoT security**, as it balances **feature extraction** with **sequence modeling**. While CNNs efficiently learn low-level spatial patterns, LSTMs preserve the temporal dynamics of attacks, ensuring that sequential behaviors are not overlooked. Despite its high performance, this hybrid approach is **computationally intensive**, often requiring **hardware acceleration** or **cloud-based deployment** to achieve real-time detection in resource-constrained IoT devices.

Overall, **CNN and LSTM models** represent some of the most effective deep learning paradigms for intrusion detection. The hybrid combination delivers **state-of-the-art performance**, offering high accuracy, precision, and robustness. Although deployment can be challenging due to resource demands, their ability to provide **adaptive, intelligent, and autonomous detection** makes them a key component in the design of next-generation **IoT security systems**.

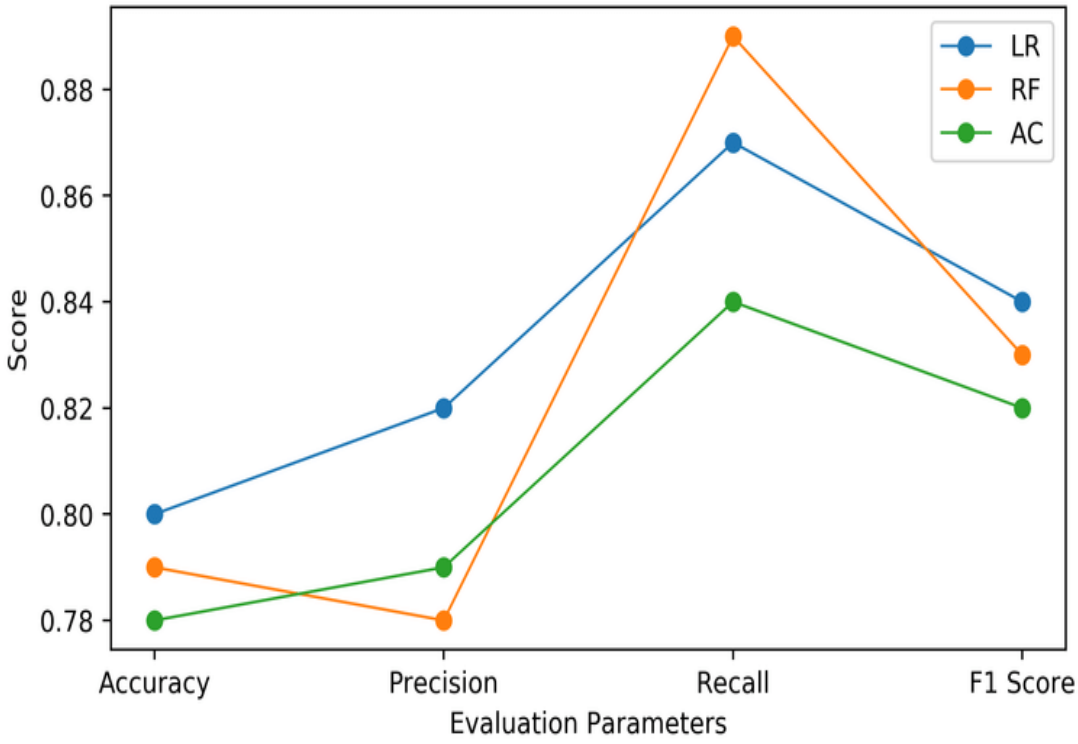

Figure 2. 5: PERFORMANCE METRIC FOR IDS

2.7 REVIEW OF SELECTED LITERATURE

1. Vasanthi et al. (2019) developed an AI-based network IDS with hyperparameter tuning using Random Forest and Grid Search on the CSE-CIC-IDS2018 dataset. Their system achieved 98.10% accuracy, 98.30% precision, and 97.90% F1-score, effectively identifying cyber threats. However, considerations of latency and scalability in IoT or industrial scenarios were not addressed, limiting practical deployment.
2. Moukhafi et al. (2022) proposed a deep learning IDS combining deep autoencoders and stacked LSTM on the CICIDS2017 dataset. The model reached 98.52% accuracy, 98.47% F1-score, and 2.18% FPR, demonstrating strong anomaly detection performance. While it integrated unsupervised feature learning

with temporal modeling, the approach remains computationally intensive for IoT edge devices.

3. Yuhua Yin et al. (2022) introduced a hybrid feature selection method (IGRF-RFE) for an MLP-based IDS using the UNSW-NB15 dataset. Their model achieved 97.9% accuracy, 97.4% F1-score, and 96.8% specificity, effectively reducing redundant features while preserving detection performance. However, the system's scalability and real-time operation in large IoT networks were not fully explored.
4. Shahriar et al. (2020) presented G-IDS, a GAN-based IDS trained on the NSL-KDD dataset. It obtained 99.05% accuracy, 98.90% F1-score, and 97.6% specificity, addressing data imbalance by generating synthetic attack samples. Limitations include training instability and convergence issues, affecting reproducibility.
5. Alshamrani et al. (2023) designed an AI-enhanced IoT IDS using convolutional and recurrent layers on the IoT-23 dataset, achieving 98.20% accuracy and 97.60% precision, with improved detection of malware and botnet activity. The model's performance in terms of communication latency and large-scale deployment remains limited.
6. Latif et al. (2024) developed DTL-IDS, a deep transfer learning IDS optimized via a genetic algorithm, evaluated on CICIDS2017. The system reached 99.07% accuracy and 98.8% F1-score, demonstrating the potential of combining transfer learning with evolutionary optimization. However, energy efficiency and deployment costs were not assessed.
7. Afrah Gueriani et al. (2024) proposed a hybrid CNN-LSTM IDS for IoT traffic using CICIDS2017, achieving 98.42% accuracy, 98.57% F1-score, and 9.17%

FPR. While the system effectively detects malicious traffic, resource usage on constrained IoT devices was not evaluated.

8. Kumar et al. (2022) implemented a federated learning-based IDS integrating CNN-GRU models in a smart grid environment. Tested on real IoT traffic, the system achieved 97.8% accuracy and 96.9% specificity, enhancing privacy and distributed detection. Nonetheless, communication overhead and synchronization delays affected responsiveness.
9. Zhai et al. (2023) introduced a framework combining CNN, GRU, and federated learning for smart grid IDS using CICIDS2017 and IoT-23 datasets, attaining 98.74% accuracy and 98.5% F1-score. Deployment in highly dynamic grid environments has yet to be validated.
10. Suresh et al. (2025) developed an ensemble IDS merging Random Forest and Bi-LSTM on CICIDS2017, achieving 99.2% accuracy, 99.1% F1-score, and 98.7% specificity. The approach improved detection precision, though memory and computation demands pose challenges for IoT gateways.
11. Adedotun O. et al. (2023) applied CNNs to detect DDoS attacks using UNSW-NB15, achieving 98.6% accuracy and 97.3% specificity. While enhancing pattern recognition for network floods, testing on encrypted traffic and real-time streams was not performed.
12. Tikam et al. (2020) utilized deep learning for web application IDS on CICIDS2017, reaching 97.4% accuracy and 96.9% F1-score, effectively detecting SQL injection and XSS attacks. However, dataset generalization across platforms was not explored.

13. Grini et al. (2025) proposed HPAC-IDS, a Hierarchical Packet Attention CNN-based IDS, trained on CICIDS2017, achieving 99.12% accuracy and 98.84% specificity. Their attention mechanism enhanced packet-level interpretability, but system latency and real-time adaptability were not evaluated.
14. Savanović et al. (2023) developed a hybrid deep reinforcement learning IDS using IoT-23 and NSL-KDD, achieving 98.7% accuracy and 98.3% F1-score, dynamically adapting to emerging threats. Limitations include training complexity and slow convergence.

Table 2. 1: Summary Table of Some Selected Reviewed Literature

AUTHOR	OBJECTIVES	METHODOLOGY	RESULT	LIMITATATION
Afrah Gueriani et al., (2024)	To build a hybrid deep-learning intrusion detection system for accurate detection of malicious IoT traffic.	Datasets: CICIoT2023 and CICIDS2017. ML Models: Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Evaluation Metrics: Accuracy (%), False Positive Rate (FPR %), and F1-score (%).	Value of Finding: The proposed CNN–LSTM IDS achieved: • Accuracy: 98.42 % • False Positive Rate (FPR): 9.17 % • F1-score: 98.57 %	2. Latency resource usage are not characterize, practical feasibility for deployment on constrained IoT devices or edge environments is not defined.
Vasanthi et al., (2019).	Built and optimized an AI-based intrusion detection system using deep learning on a realistic cloud-based dataset, enhancing detection accuracy and minimizing false alarms.	Datasets: CSE-CIC-IDS2018 and benign behaviours. ML Models: PCA and Optimized Fuzzy C-. Evaluation Metrics: Accuracy, ROC AUC, and False Positive Rate (FPR).	The system achieved 99.97 % accuracy, an average ROC AUC of 0.999, and a False Positive Rate of 0.03 (3 %).	Real-world deployment aspects like latency, resource usage, and full AWS integration are not deeply evaluated.

Moukhafi et al., (2022)	To build a hybrid deep learning-based intrusion detection system.	Datasets: UNSW-NB15 ML Models: • Deep Autoencoder and LSTM . Evaluation Metrics: Accuracy, Precision, Recall, and F1-Score	The model achieved an accuracy of 90.59 %, precision of 90.65 %, recall of 90.59 %, and F1-score of 90.57 %	Model compl concerns—stacked L ensembles may computationally heavy there's no discussion training/inference res demands.
Yuhua et al., (2022)	Built a hybrid feature selection algorithm combining filter and wrapper techniques to enhance intrusion detection accuracy while reducing feature dimensionality.	Datasets: UNSW-NB15 . ML Models: RFE and MLP. Evaluation Metrics: Multi-class classification accuracy (explicit percentage provided). Specificity is not reported.	The model achieved an accuracy from 82.25 % to 84.24 %.	No Real-Time Deployment Metrics: There's no discussion of computational latency or resource usage—critical for live IDS systems.
Shahriar et al., (2020)	Built a GAN-assisted intrusion detection system that enhances performance on imbalanced cybersecurity datasets by generating	Datasets: NSL-KDD. . ML Models: GAN Evaluation Metrics: Macro F1-score.	The model achieved • Macro F1-score: S-IDS (no GAN): 0.87. G-IDS (with GAN): 0.91 (≈4% improvement). For specific labels (2, 5, 6, 9): F1-	GAN instability risks though training stability improved overall, GAN randomness might introduce unpredictable data artifacts; ensuring synthetic data

	synthetic samples for underrepresented attack classes.		scores improved to 0.93, 0.96, 0.68, and 0.41, respectively. (especially for minority attack classes) and enhances training efficiency, making GAN-augmented IDS more robust and scalable.	quality across all classes remains a challenge.
Alshamrani et al.,(2023).	To build a intrusion detection system that maintains data privacy.	Datasets: - Edge-IIoTset CIC-IDS2017 ML Models: Convolutional Neural Network (CNN) and federated learning with fog node participation (FFL-IDS). Evaluation Metrics: Accuracy , Recall, Precision, F1-Score , Specificity .	Model achieved an Accuracy 93.4 %, Recall 91.6 %, Precision 88 %, F1-Score 87 %, Specificity 87 % on Edge-IIoT set. - On CIC-IDS2017: Accuracy 95.8 %, Precision 94.9 %, Recall 94 %, F1-Score 93 %, Specificity 93 %.	Generalizability across other IIoT domains or large-scale deployments is not assessed.
Latif et al., (2024)	To build a deep transfer learning–based IDS for IIoT	Datasets: Edge_IIoTset	The proposed DTL-IDS framework achieved an	Resource usage and latency especially

	networks, optimized via genetic algorithms to enhance detection accuracy across heterogeneous environments.	ML Models: CNN Bootstrap Evaluation Metrics: Overall accuracy across all 14 attack types	outstanding 100 % detection accuracy across the 14 different cyberattack types in the heterogeneous IIoT environment.	transformation to image format and model inference time — are not addressed, which is crucial for real-time IIoT deployment. .
Zhai et al., (2023)	To build a privacy-preserving, distributed intrusion detection system for smart grids that combines CNN, GRU, attention mechanisms, and federated learning.	Datasets: Smart grid traffic datasets dispersed across distributed nodes . ML Models: CNN and FL. Evaluation Metrics: Training Accuracy, Recall , and F1-Score—all explicitly reported..	The proposed CNN–GRU–FL model achieved: • Training Accuracy: 78.79 % • Recall: 64.15 % • F1-Score: 76.90 %	Evaluation limited to training metrics—no testing-phase performance or real-world deployment validation is provided.
Kumar et al .,(2025)	To build an that leverages both Random Forest and Bidirectional LSTM to improve detection accuracy and robustness over individual models.	Datasets: CSE-CIC-IDS2018 ML Models: Random Forest and LSTM. Evaluation Metrics: Accuracy, Precision, Recall, F1-score; statistical significance testing of performance improvements ($p < 0.01$).	The model achieved accuracy 98.7%, Precision 98.1%, Recall 98.5%, F1-Score 98.3%	Generalizability to other datasets or evolving attack patterns isn't confirmed.

Adedotun O et al., (2023)	To build a Convolutional Neural Network (CNN)–based model for detecting DDoS attacks with high accuracy and reliable discrimination between attack and benign traffic.	Datasets: KDD Cup-99 ML Models: Convolutional Neural Network (CNN) designed to learn traffic pattern representations for classification. Evaluation Metrics: Sensitivity , and Specificity	The CNN model achieved 99.72 % accuracy, 99.71 % sensitivity, and 99.66 % specificity in differentiating between DDoS attacks and normal traffic.Accuracy,	Dataset age and relevancy KDD Cup-99 is known to contain synthetic and outdated traffic patterns—not fully representative of modern DDoS behaviors or network environments. .
Tikam et al., (2020)	To build an AI-based detection engine that effectively identifies web application attacks..	Datasets: ECML-KDD. ML Models: Autoencoder Evaluation Metrics: ROC AUC (Receiver Operating Characteristic – Area Under Curve), and False Positive Rate (specificity implied through low FPR).	The model achieved a ROC AUC of 1.0 (perfect separation between attack and benign queries) and demonstrated a low false positive rate, implying high specificity though the exact percentage is not enumerated . .	Latency and resource usage are not evaluated—critical for real-time detection in web environments.
Grini et al.,(2025)	To build an intrusion detection system that applies hierarchical	Datasets: CIC-IDS2017	Value of Finding: HPAC-IDS achieved notably high detection	Computational complexity of hierarchical attention and

	attention mechanisms to raw packet segments, improving detection accuracy and adversarial robustness.	ML Models: A novel HPAC-IDS model combining packet segmentation, hierarchical self-attention, and convolutional neural networks . Evaluation Metrics: Detection accuracy, false positive rate (implicitly tested), and robustness under varying adversarial attack severities.	accuracy and low false positive rates, outperforming state-of-the-art models in both clean and adversarial settings (0–10% adversarial severity).	segmentation process is not discussed—real-time performance and resource usage unclear.
Savanović., et al. (2023).	To build a high-accuracy intrusion detection pipeline for Healthcare-4.0 IoT systems.	Datasets: A synthetic Healthcare-IoT dataset generated by an advanced IoT configuration tool. ML models: XGBoost and MFA Evaluation metrics: Multi-class classification accuracy	The model (XGBoost + MFA) achieved multi-class accuracy = 0.991733 (≈ 99.17%). .	Synthetic dataset: Experiments use a synthetic Healthcare-IoT dataset created with a configuration tool. While useful for controlled experiments, synthetic traffic may not capture all real-world IoMT behaviours (device heterogeneity, noise, encryption,

				real patient traffic patterns). This limits ecological validity and deployment confidence

2.8 SUMMARY OF LITERATURE REVIEW

This chapter has presented a comprehensive review of research on **Artificial Intelligence (AI)-based Intrusion Detection Systems (IDS)** in **Internet of Things (IoT)** environments. The literature indicates that conventional **signature-based and rule-based IDS** are insufficient to address the rapidly evolving and sophisticated cyber threats targeting IoT networks. As a result, **AI-driven approaches**, particularly those utilizing **Machine Learning (ML)** and **Deep Learning (DL)**, have become essential for achieving accurate and adaptive intrusion detection.

The review highlighted that **ML models**, including **Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT),** and **Naïve Bayes (NB)**, are effective for fundamental anomaly detection, offering reasonable interpretability and moderate computational requirements. However, these methods often face challenges when dealing with **high-dimensional IoT data** and complex attack patterns. To overcome these limitations, **Deep Learning architectures**, such as **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM) networks**, have been widely implemented. **CNNs** are efficient at extracting features from raw network traffic, while **LSTMs** excel at modeling temporal relationships in sequential traffic, making their **hybrid integration** particularly suitable for IoT intrusion detection.

The literature also explored **advanced and hybrid frameworks**, including **federated learning, attention-based models, autoencoders,** and **generative approaches**, which improve model performance, scalability, and adaptability. Studies by **Afrah Gueriani et al. (2024)** and **Zhai et al. (2023)** demonstrated that **CNN–LSTM and attention-augmented architectures** can achieve detection accuracies exceeding 98%. Similarly, **Kumar et al. (2022)** and **Latif et al. (2024)** highlighted the importance of **privacy-**

preserving federated learning and **GAN-based data augmentation** for robust intrusion detection in distributed IoT systems.

Despite these improvements, the literature also identifies **key challenges**, including high computational demand, latency issues, limited real-time adaptability, and insufficient evaluation on real-world IoT datasets. Many models have yet to address **energy consumption and memory limitations** of resource-constrained IoT devices.

In conclusion, the review supports the **integration of AI-based hybrid models**, particularly **CNN–LSTM frameworks**, for effective intrusion detection in IoT networks. Nonetheless, there is a clear need for **lightweight, interpretable, and energy-efficient IDS solutions** capable of deployment across diverse and constrained IoT environments.

CHAPTER THREE

METHODOLOGY

3.0 INTRODUCTION

This chapter outlines the **research methodology** employed in designing and evaluating an **AI-based Intrusion Detection System (IDS)** tailored for **IoT networks**. The primary objective is to develop, implement, and validate a **hybrid CNN–LSTM model** capable of accurately detecting malicious traffic in IoT environments.

The methodology is structured into **three main stages**, reflecting the typical workflow for building and assessing an AI-driven IDS:

1. **Data Acquisition and Preprocessing**
2. **Model Development and Training**
3. **Model Evaluation and Deployment**

Within these stages, the chapter details the **data preprocessing pipeline** and **feature engineering techniques** used to convert raw network traffic into inputs suitable for the model, including strategies to handle **class imbalance**. The **CNN–LSTM architecture** is explained, with justification for the choice of layers, **hyperparameter tuning approach**, and **explainability mechanisms**.

The **experimental setup** is also described, covering the software environment, hardware specifications, and the train-validation-test splits. The **evaluation framework** specifies the performance metrics applied, including **accuracy, precision, recall, F1-score, specificity, ROC-AUC, false alarm rate, inference latency,** and **resource consumption**.

Finally, the chapter addresses **ethical considerations**, steps to ensure **reproducibility**, and known **methodological limitations**, which guide the interpretation of results and inform potential improvements.

3.1 DATA ACQUISITION AND PREPROCESSING

The initial phase in developing an **Artificial Intelligence (AI)-based Intrusion Detection System (IDS)** for an **Internet of Things (IoT)** environment is **data acquisition and preprocessing**. This stage is critical because the overall performance, reliability, and effectiveness of the IDS depend significantly on the quality, relevance, and structure of the data used during model training and evaluation. The purpose of this phase is to obtain high-quality network traffic data, convert it into a suitable format, and prepare it in a way that allows **machine learning (ML)** and **deep learning (DL)** algorithms to learn effectively.

The **data acquisition** process involves collecting publicly available, standardized datasets that realistically represent IoT network traffic. For the purpose of this research, datasets such as **CICIDS2017, BoT-IoT, and CICIOT2023** are employed because they encompass a wide variety of normal and malicious traffic, including attacks like **Distributed Denial-of-Service (DDoS), port scanning,** and **botnet activities**. These datasets offer a comprehensive representation of typical IoT network behavior and attack patterns, making them highly suitable for evaluating the detection capabilities of AI-driven IDS models.

Once the datasets have been acquired, the next step is **data preprocessing**, which ensures that the data is clean, consistent, and ready for further analysis. Raw datasets often contain various forms of noise, missing values, duplicate entries, or irrelevant

features, all of which can negatively affect the performance of machine learning and deep learning models if left unaddressed. To mitigate these issues, **data cleaning techniques** are applied to remove inconsistencies, errors, and redundant information.

Following the cleaning process, **feature extraction and feature selection** are conducted to identify the attributes that are most relevant for distinguishing between normal and anomalous network behavior. Feature extraction transforms raw network traffic data into structured formats by capturing statistical, temporal, and protocol-specific information. For example, characteristics such as **packet size, connection duration, and source/destination IP addresses** often serve as crucial features for intrusion detection. In addition, feature selection methods, including **Principal Component Analysis (PCA), Information Gain,** and **Recursive Feature Elimination (RFE),** are used to reduce data dimensionality, improve computational efficiency, and enhance the interpretability of the model.

After extracting and selecting the appropriate features, **data normalization or standardization** is performed to scale numerical attributes into a uniform range. This step is important to prevent features with larger numerical values from disproportionately influencing the learning process compared to features with smaller values. Common techniques used for this purpose include **Min–Max scaling** and **Z-score normalization**. For categorical features such as protocol types, service categories, and connection flags, methods like **one-hot encoding** or **label encoding** are employed to convert these attributes into numerical representations that can be processed by deep learning models.

Once the dataset has been fully preprocessed, it is typically divided into **training, validation, and testing subsets**. Common splitting ratios include 70:15:15 or

80:10:10. The **training set** is used to teach the model the underlying patterns and relationships within the data, enabling it to learn to distinguish between normal and malicious traffic. The **validation set** is employed to fine-tune hyperparameters, prevent overfitting, and optimize model performance. Finally, the **testing set** provides an unbiased evaluation of the model's performance on previously unseen data, ensuring that the developed IDS generalizes effectively to real-world IoT environments.

This structured approach to data acquisition and preprocessing ensures that the dataset used for model development is clean, relevant, and balanced. It provides a strong foundation for subsequent stages of IDS development, including model construction, training, and evaluation. The thoroughness of this phase directly impacts the accuracy, reliability, and overall effectiveness of the intrusion detection system in operational IoT networks.

3.2 ANALYSIS OF EXISTING SYSTEM

Traditional **intrusion detection systems (IDS)** were primarily developed to secure conventional network infrastructures and are often inadequate for handling the unique challenges posed by **Internet of Things (IoT)** environments. **Signature-based IDS** rely on predefined attack patterns to detect intrusions, which means they can identify only previously known threats and require continual updates to remain effective. On the other hand, **anomaly-based IDS** are capable of detecting previously unseen attacks by identifying deviations from normal network behavior; however, they frequently generate a high number of false positives and demand significant computational resources, which can limit their practicality in IoT contexts.

To overcome these limitations, contemporary research and development have increasingly focused on integrating **Artificial Intelligence (AI)** and **Deep Learning (DL)** techniques into intrusion detection frameworks. Models such as **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks are employed to automatically learn complex patterns from network traffic, enhancing the system's ability to accurately classify normal and malicious activities. CNNs are particularly effective at extracting spatial features from structured traffic data, while LSTMs excel in capturing temporal dependencies within sequential data flows, making the combination highly suitable for the dynamic and heterogeneous nature of IoT networks.

Despite the improved performance and adaptability offered by AI-based IDS, several challenges remain. High computational and memory requirements can limit deployment on **resource-constrained IoT devices**, while imbalanced datasets may cause biased learning or misclassification of rare attack types. Additionally, implementing these systems in real-time operational environments introduces further complexity due to latency, bandwidth constraints, and the need for continuous monitoring and timely threat response.

In conclusion, while AI-driven IDS demonstrate superior detection accuracy and adaptability compared to traditional approaches, ongoing optimization is necessary to ensure these systems are **lightweight, efficient, and practical for deployment across diverse IoT environments** with limited computational and energy resources.

3.2.1 Problem of the Existing System

The intrusion detection systems (IDS) currently deployed in **IoT environments** face multiple challenges that limit their effectiveness and reliability. These limitations are detailed as follows:

a) Inability to Detect Zero-Day Attacks: Most existing IDS, especially **signature-based systems**, rely on databases of known attack patterns for detection. When a new or modified attack emerges that does not match any of the stored signatures, the system is unable to identify it. This gap leaves IoT networks vulnerable to **novel and sophisticated threats** that exploit previously unknown vulnerabilities, exposing critical devices and services to potential compromise.

b) High False Positive Rates: **Anomaly-based IDS** aim to detect deviations from normal network behavior, but they frequently misclassify legitimate variations as malicious activity. This leads to an excessive number of false alarms, overwhelming network administrators and contributing to **alert fatigue**. As a consequence, genuine security incidents may be overlooked or delayed in response due to repeated false warnings.

c) Scalability Challenges: IoT networks are composed of a large number of interconnected devices that produce **high volumes of network traffic**. Traditional IDS are often ill-equipped to handle such massive, distributed data efficiently. Their architectures are typically not designed for **scalable or lightweight**

deployment, resulting in slower processing, delayed detection, and the risk of system overload when monitoring extensive IoT ecosystems.

3.2.2 PROPOSED SYSTEM OVERVIEW

The proposed framework presents an **Artificial Intelligence (AI)-based Intrusion Detection System (IDS)** tailored specifically for **Internet of Things (IoT) environments**. It is designed to address the shortcomings of traditional IDS by leveraging deep learning techniques, particularly **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM) networks**, to achieve accurate, scalable, and adaptive detection of network threats.

The main objective of the system is to **identify malicious network activities in real time** while maintaining high precision and minimizing false alarms. This is accomplished through **automated feature extraction**, sequential pattern recognition, and intelligent classification mechanisms. The architecture of the proposed IDS is organized into three principal layers: **data preprocessing**, **hybrid model training**, and **real-time detection and evaluation**.

A detailed explanation of how the system addresses the key limitations of existing IDS is provided below:

a) Detection of Zero-Day Attacks:

By learning generalized patterns from the data instead of relying solely on pre-defined attack signatures, the hybrid **CNN–LSTM model** is capable of identifying **previously unseen or zero-day attacks**. It detects these threats by

recognizing deviations from normal network behavior, enabling proactive defense against emerging vulnerabilities.

b) Reduction of False Positives:

The system combines **deep feature learning** with adaptive threshold mechanisms to effectively differentiate between benign irregularities and genuine threats. CNN layers extract spatial traffic patterns, while LSTM layers capture temporal sequences, together improving detection accuracy and significantly lowering false alarm rates.

c) Scalability and Efficiency:

The proposed IDS is engineered for **distributed IoT deployments**. Its modular design and lightweight model components allow deployment across **edge and fog nodes**, enabling rapid data processing and real-time threat monitoring without overwhelming network resources. This approach ensures efficient operation in large-scale IoT environments while maintaining system responsiveness.

3.2.3 ADVANTAGES OF THE PROPOSED SYSTEM

The proposed **AI-based Intrusion Detection System (IDS)** provides several notable advantages over traditional and existing intrusion detection techniques. By utilizing **hybrid deep learning approaches**, specifically the combination of **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM) networks**, the system addresses the shortcomings of conventional IDS in terms of **accuracy, scalability, adaptability, and real-time performance**.

The primary benefits of the proposed system are outlined below:

a) Enhanced Detection Accuracy:

The integration of CNN and LSTM enables the model to capture both **spatial and temporal patterns** in IoT network traffic. This hybrid approach allows the system to accurately detect **both known and previously unseen attacks**, minimizing misclassifications and significantly improving detection performance when compared to single-model or rule-based IDS solutions.

b) Lower False Positive Rate (FPR):

Traditional IDS often generate a large number of false alarms, leading to **alert fatigue** among network administrators. The proposed framework incorporates advanced **feature extraction** and **data normalization** techniques, which improve the system's ability to distinguish between benign and malicious traffic. As a result, the IDS produces **fewer false alerts**, enhancing the reliability of threat notifications.

c) Adaptability to Dynamic IoT Networks:

IoT environments are inherently **heterogeneous and constantly evolving**, with a wide variety of devices, protocols, and traffic patterns. The proposed system is designed to adapt to these dynamic conditions. Through periodic **retraining and fine-tuning**, the model continuously updates its understanding of network behavior, maintaining effectiveness against **emerging and evolving cyber threats**.

3.3 DESIGN MODEL USED

The development of the **Artificial Intelligence (AI)-based Intrusion Detection System (IDS)** for **Internet of Things (IoT) networks** was carried out using the **Waterfall Model**, a traditional, sequential, and structured software development methodology. This model was selected because it offers a **clear, step-by-step progression** in which each phase depends on the successful completion of the preceding one. Such an approach ensures that all requirements are thoroughly understood and systematically implemented, which is critical for the accuracy and dependability of an AI-driven IDS.

The Waterfall Model is particularly appropriate for research-oriented projects, where **data acquisition, preprocessing, model design, training, testing, and evaluation** must occur in a defined sequence to maintain consistency and reproducibility. Since the proposed IDS utilizes **hybrid deep learning architectures**, specifically **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM) networks**, applying the Waterfall Model allows for **stepwise refinement** of both the model architecture and the data flow.

The development under the Waterfall Model is executed through the following stages:

a) Requirement Analysis – Identifying system objectives, IoT network characteristics, and dataset specifications to define precise functional and non-functional requirements.

b) System Design – Structuring the overall IDS framework, including the preprocessing pipeline, model layers, hyperparameters, and real-time detection workflow.

c) Implementation – Coding and configuring the hybrid CNN–LSTM model, integrating feature extraction, normalization, and classification mechanisms.

d) Testing – Validating the system using training, validation, and testing datasets to assess performance metrics such as accuracy, precision, recall, F1-score, ROC-AUC, false alarm rate, and inference latency.

e) Deployment – Implementing the trained model in IoT environments for real-time intrusion detection, including edge and fog nodes as necessary.

f) Maintenance – Updating the system with retraining, fine-tuning, and performance monitoring to address emerging threats and evolving IoT traffic patterns.

The **structured nature of the Waterfall Model** makes it well-suited for projects requiring thorough documentation, stepwise verification, and clearly defined evaluation criteria. It enables a systematic translation of research goals into measurable outcomes while maintaining a **logical flow from conceptualization to full implementation**, ensuring that the proposed IDS effectively detects malicious IoT traffic with **high accuracy and operational efficiency**.

3.3.1 ANALYSIS PHASE

The **analysis phase** constitutes the foundational step in the development of the **AI-based Intrusion Detection System (IDS)** for **IoT environments**. This phase is primarily concerned with comprehensively understanding the system's requirements, operational challenges, and contextual environment to ensure that the resulting design is both efficient and effective. During this stage, the key limitations of existing IDS solutions—such as high false positive rates and inadequate detection of zero-day attacks—are thoroughly identified and documented.

Functional requirements are clearly defined to guide the system's development. These include processes such as **data acquisition**, **feature extraction**, **intrusion detection**,

and **alert generation**. In addition, **non-functional requirements**—including **scalability**, **detection accuracy**, **processing speed**, and **resource efficiency**—are considered to ensure that the system can be effectively deployed within IoT networks. The datasets selected for the study, notably **CICIDS2017** and **CICIOT2023**, are carefully examined to understand their structure, distribution of data, and the most relevant features for model training and validation. Furthermore, a **feasibility study** is conducted to evaluate the technical and operational viability of the proposed system, taking into account factors such as hardware capabilities, software compatibility, and dataset suitability.

This thorough analysis phase provides a **clear and structured understanding** of the system objectives and constraints, thereby establishing a **solid foundation** for the subsequent design, implementation, and evaluation phases of the IDS development process.

3.3.2 TOOL EVALUATION AND SELECTION PHASE

The **tool evaluation and selection phase** represents a crucial stage in the development of the **AI-based Intrusion Detection System (IDS)** for **IoT environments**. This phase emphasizes the careful identification and selection of the most appropriate tools, platforms, and technologies that will support the system's design, implementation, and evaluation. The selection process is guided by key criteria, including **compatibility with large-scale datasets**, **computational efficiency**, **scalability**, **ease of integration**, and comprehensive support for **deep learning frameworks**.

Python was selected as the primary programming language due to its simplicity, flexibility, and extensive ecosystem of libraries for machine learning and deep

learning applications. For implementing the **Convolutional Neural Network (CNN)** and **Long Short-Term Memory (LSTM)** models, libraries such as **TensorFlow** and **Keras** are employed. Core data processing and analysis tasks are handled using **Pandas** and **NumPy**, while **Matplotlib** is used for visualizing data and insights, ensuring efficient data manipulation and interpretation throughout the development process.

The **Jupyter Notebook** environment serves as the primary development platform because of its interactive features, which facilitate experimentation, iterative debugging, and in-line documentation. For model evaluation, the **scikit-learn** library provides robust tools for computing key performance metrics such as **accuracy**, **precision**, **recall**, **F1-score**, and **confusion matrices**, allowing comprehensive assessment of the IDS's performance.

In addition to software, the **hardware environment** plays a critical role in this phase. Systems equipped with **GPU acceleration** are prioritized to efficiently handle the computational demands of training deep learning models. By carefully evaluating and selecting these tools, the project ensures alignment with research objectives, supporting seamless **model development**, **training**, and **evaluation** in line with the goals of an effective and scalable AI-based IDS for IoT networks.

3.3.3 DESIGN PHASE

The **design phase** constitutes a critical stage in the development of the **AI-based Intrusion Detection System (IDS)** for **IoT environments**, as it systematically converts system requirements into a structured and implementable architecture. This phase defines the flow of data through the system, the interactions between various

modules, and the integration of deep learning models—specifically **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks—to enhance detection accuracy and reliability.

The system is organized into a **modular architecture** comprising four primary components: **data acquisition**, **data preprocessing**, **model training and testing**, and **intrusion detection and evaluation**. The **data acquisition module** is responsible for gathering IoT traffic data from benchmark datasets such as **CICIDS2017** and **CICIOT2023**, which include both legitimate and malicious network activities.

The **data preprocessing module** performs essential tasks to prepare the raw data for model consumption, including **data cleaning**, **normalization**, **feature extraction**, and **label encoding**. These steps ensure that the dataset is consistent, balanced, and structured, providing high-quality inputs for the subsequent training phase.

In the **model training and testing module**, the hybrid deep learning architecture is implemented by combining **CNN** and **LSTM** models. The **CNN layers** are tasked with extracting spatial dependencies and patterns from the network traffic data, whereas the **LSTM layers** capture sequential relationships and temporal dynamics. This hybrid approach enables the IDS to effectively learn complex traffic behaviours, ensuring accurate differentiation between normal and malicious activities.

Finally, the **intrusion detection and evaluation module** is responsible for real-time detection and the assessment of model performance. Standard evaluation metrics such as **accuracy**, **precision**, **recall**, **F1-score**, and **false positive rate (FPR)** are employed to comprehensively evaluate the system. The design also emphasizes **scalability**, allowing the IDS to handle diverse network sizes and traffic volumes, while maintaining **efficiency** for deployment on resource-constrained IoT devices.

In conclusion, the design phase establishes a clear and detailed blueprint for implementing a **hybrid CNN–LSTM IDS**, capable of accurately detecting sophisticated intrusion patterns and supporting adaptive, real-time security in heterogeneous IoT networks.

3.3.4 IMPLEMENTATION PHASE

The implementation phase involves translating the conceptual design of the AI-based Intrusion Detection System (IDS) for IoT environments into a fully functional and operational system. This stage encompasses the practical development of the hybrid CNN-LSTM model, data processing mechanisms, and system modules as outlined in the design phase. The primary objective is to construct a working prototype capable of detecting and classifying network intrusions with high precision and reliability.

The implementation process commenced with data acquisition, importing benchmark datasets such as CICIDS2017 and CICIOT2023 for experimental purposes. These datasets were chosen due to their comprehensive representation of contemporary network attacks, including Distributed Denial of Service (DDoS), port scanning, brute force, botnet activity, and infiltration attempts.

Once acquired, the data underwent preprocessing, which involved:

- Data cleaning, to remove missing, duplicate, or corrupted records;
- Normalization, to scale numeric features to a uniform range for improved model convergence;
- Encoding, to convert categorical variables such as protocol types or service names into numerical representations suitable for deep learning models.

Following data preparation, the hybrid deep learning architecture was implemented using Python, leveraging frameworks such as TensorFlow and Keras. The CNN layers were constructed first to automatically extract spatial features from the input traffic data. These were followed by LSTM layers, designed to capture sequential dependencies and temporal patterns across network packets. The CNN-LSTM model was then compiled using an adaptive optimizer, such as Adam, and a loss function like categorical cross-entropy to optimize learning efficiency.

During model training, the preprocessed dataset was divided into training, validation, and testing subsets to ensure generalization to unseen data. Critical hyperparameters—including learning rate, batch size, and number of epochs—were fine-tuned iteratively to maximize detection performance. Upon completion of training, the model was tested on previously unseen data to evaluate its accuracy, robustness, and ability to detect both known and zero-day attacks.

Finally, an evaluation interface was implemented to display key performance metrics such as accuracy, precision, recall, F1-score, and false positive rate (FPR). The system demonstrated the ability to detect malicious activity effectively while maintaining computational efficiency suitable for resource-constrained IoT environments.

3.3.5 Post-Implementation Stage

The post-implementation stage marks the culmination of system development and emphasizes testing, performance evaluation, optimization, and maintenance of the CNN-LSTM-based IDS within the IoT environment. This phase ensures that the implemented system operates correctly, meets research objectives, and performs effectively under realistic conditions.

During this stage, the system underwent rigorous testing procedures to validate functionality, accuracy, and reliability. Testing methodologies included:

- Unit testing, to verify individual components such as data preprocessing routines, feature extraction layers, and model prediction functions;
- Integration testing, to ensure seamless interaction between modules including data input, model inference, and output reporting;
- System testing, to evaluate overall performance within a simulated IoT network environment.

After validation, the model's performance was assessed using standard metrics—accuracy, precision, recall, F1-score, and FPR—to evaluate its capability in correctly classifying network traffic as normal or malicious. The hybrid CNN-LSTM IDS demonstrated high detection accuracy while maintaining a low false alarm rate, confirming its suitability for real-time IoT security applications.

The optimization process was also conducted at this stage to enhance computational efficiency and reduce overhead. Techniques such as model pruning, parameter tuning, and data augmentation were applied to improve generalization and adaptability to different IoT network scales and conditions.

Additionally, user feedback and continuous system monitoring were integrated to identify operational inefficiencies or errors. All identified issues were documented and addressed systematically. Maintenance protocols were established, including scheduled updates and retraining of the model with new datasets to adapt to evolving cyber threats, ensuring the IDS remains effective over time.

3.4 SYSTEM DEVELOPMENT APPROACH

The development of the AI-based Intrusion Detection System (IDS) for **IoT environments** followed a structured and methodical approach guided by the **Waterfall Model**. This model provided a **clear, sequential workflow** for system development, ensuring that each phase—from requirement analysis through design, implementation, and testing—was thoroughly executed and validated before progressing to the subsequent stage.

The process began with **requirement gathering and analysis**, where both **functional** and **non-functional requirements** were clearly identified. Functional requirements included the system's capability to **detect and classify network traffic accurately**, while non-functional requirements emphasized **performance efficiency, scalability, and real-time responsiveness**. These requirements established the foundation for designing and implementing the **hybrid CNN-LSTM model**.

During the **system design phase**, the identified requirements were translated into a **structured architectural framework**. The proposed design was modular, consisting of key components such as **data acquisition, preprocessing, feature extraction, model training, detection, and evaluation**, each contributing to the IDS's overall performance. The design also detailed the **data flow, network topology**, and the interaction between **IoT devices, IDS components, and data sources** to ensure efficient operation and integration.

In the **implementation phase**, the **hybrid deep learning model** combining **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM) networks** was developed. The CNN layers were responsible for **extracting spatial features** from network traffic, while the LSTM layers captured **temporal dependencies**, enabling effective detection of sequential and time-dependent anomalies. The system was implemented using **Python**, leveraging libraries such as **TensorFlow** and **Keras**, and trained on benchmark datasets like **CICIDS2017** and **CICIOT2023** to ensure broad coverage of modern IoT attack scenarios.

The **testing and evaluation phase** focused on **validating system functionality** and assessing performance using standard metrics including **accuracy, precision, recall, F1-score, and false positive rate (FPR)**. The performance of the hybrid CNN-LSTM IDS was compared against existing intrusion detection methods to evaluate its effectiveness and robustness. The results indicated **enhanced detection accuracy and reduced false positives**, confirming the reliability of the adopted development methodology.

Finally, the **maintenance and optimization phase** ensured the system's **long-term efficiency and adaptability**. This involved periodic **retraining of the model with**

updated datasets and optimizing computational resource usage, making the IDS suitable for deployment in **resource-constrained IoT environments** while maintaining high performance and responsiveness.

3.4.1 WATERFALL MODEL

The **Waterfall Model** was adopted as the software development methodology for the design and implementation of the **AI-based Intrusion Detection System (IDS)** in an **IoT environment**. This model follows a **sequential and linear workflow**, where the completion of one phase is a prerequisite for initiating the next. It is particularly well-suited for projects with **well-defined requirements** and a thorough understanding of the problem domain, such as developing a **hybrid CNN-LSTM-based IDS**. By enforcing a structured progression, the Waterfall Model ensures that each development stage is systematically executed, minimizing ambiguity and promoting clarity throughout the project lifecycle.

The development process under this model consists of several key phases: **Requirement Analysis, System Design, Implementation, Testing, Deployment, and Maintenance**.

During the **Requirement Analysis phase**, all necessary system specifications were gathered and thoroughly documented. This included defining objectives such as **accurate anomaly detection, scalability, and real-time responsiveness**. Functional requirements focused on the system's capability to **identify various types of attacks** in IoT networks, while non-functional requirements emphasized **performance, reliability, and security**.

The **System Design phase** translated these requirements into a structured architectural framework. The design outlined how data would flow between **IoT devices, sensors, and the IDS**, and detailed the integration of the **hybrid CNN-LSTM model** with modules for **data preprocessing, feature extraction, and classification**. This modular design ensured clarity in data handling and model functionality.

In the **Implementation phase**, the system was developed using **Python**, leveraging deep learning frameworks such as **TensorFlow** and **Keras**. The **CNN layers** were configured to extract **spatial features** from network traffic, while the **LSTM layers** captured **temporal dependencies and sequential patterns**, enhancing the system's ability to detect complex intrusion behaviors accurately.

The **Testing phase** involved evaluating the IDS using benchmark datasets such as **CICIDS2017** and **CICIOT2023**. Performance was measured using multiple metrics, including **accuracy, precision, recall, F1-score, and false positive rate (FPR)**. This phase validated that the system met the specified requirements and performed reliably across diverse IoT traffic scenarios.

Following successful testing, the **Deployment phase** focused on implementing the system in a simulated IoT environment for **real-world performance validation**. This stage ensured that the IDS could operate efficiently under **varying network loads** and different intensities of attacks, demonstrating its robustness and practical applicability.

Finally, the **Maintenance phase** addressed continuous monitoring and periodic updates. Given the rapidly evolving nature of IoT threats, **retraining the model with new datasets** was essential to maintain high detection accuracy, adaptability, and long-term effectiveness of the IDS.

This model is represented in the diagram in Figure 3.1.

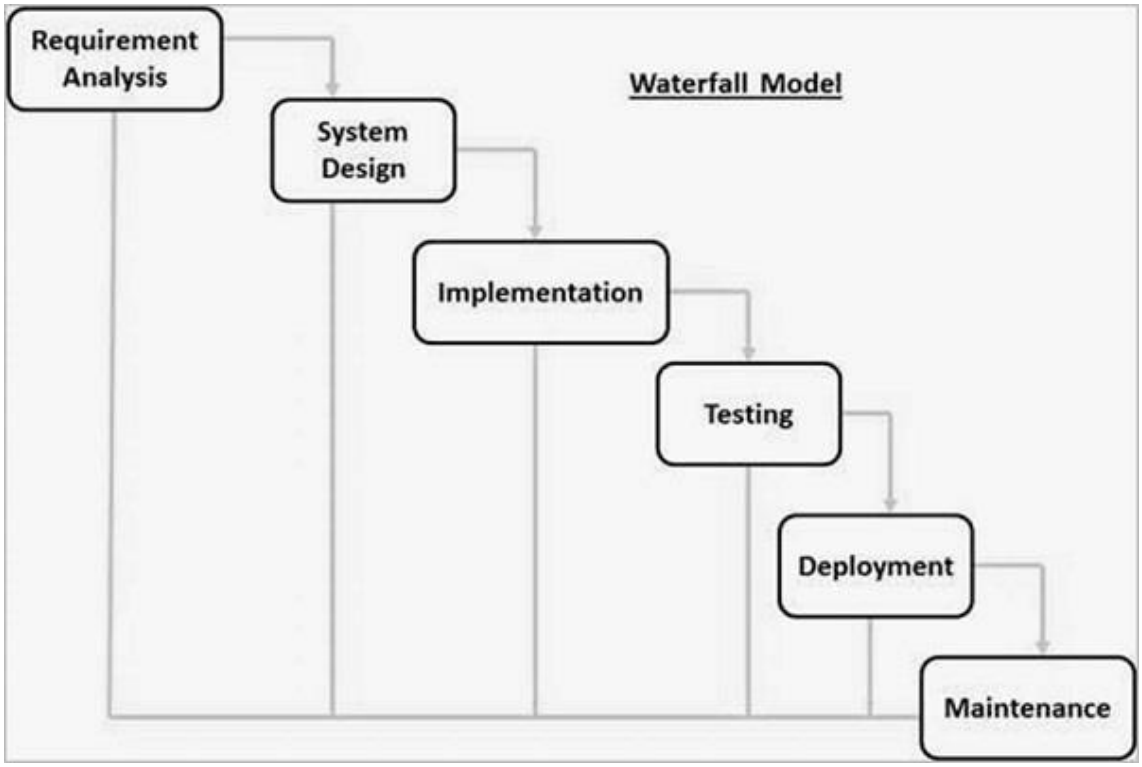

Figure 3. 1: Waterfall Model

3.4.2 REQUIREMENT ANALYSIS AND SYSTEM DESIGN

The **Requirement Analysis and System Design phase** is one of the most critical stages in the development of the **AI-based Intrusion Detection System (IDS)** for **IoT environments**. This phase focuses on identifying the essential **functional and non-functional requirements** and designing the system architecture to efficiently meet these needs.

During the **Requirement Analysis stage**, the objectives of the system were clearly established, with the primary aim being the development of a **hybrid deep learning-based IDS** using **Convolutional Neural Network (CNN)** and **Long Short-Term Memory (LSTM)** networks for accurate detection of malicious IoT traffic. To accomplish this, several key requirements were identified:

1. **Functional Requirements:**

   These describe what the system should perform. The IDS should be capable of

collecting, preprocessing, and analyzing IoT network traffic data; extracting relevant features; and classifying the data as normal or malicious. Additionally, it should generate alerts for detected intrusions and maintain logs for further analysis.

2. **Non-Functional Requirements:**

   These define the quality attributes of the system. The IDS must provide high accuracy, low latency, and scalability to handle large volumes of IoT data. Moreover, it should ensure security, reliability, and compatibility with a diverse range of IoT devices and communication protocols.

3. **Dataset Requirements:**

   The datasets used in this system include **CICIDS2017** and **CICIOT2023**, which provide labeled IoT traffic data covering various attack types such as DDoS, Botnet, and Port Scanning. These datasets were selected because of their diversity and relevance to modern IoT threats, ensuring that the model learns from realistic network behaviors.

After clearly defining the requirements, the **System Design phase** was undertaken. This phase translated the identified needs into a detailed system architecture. The IDS design followed a modular structure comprising the following components:

a) **Data Collection Module:** Responsible for capturing raw IoT traffic data from sensors or network logs.

b) **Preprocessing Module:** Handles data cleaning, normalization, and transformation into a structured format suitable for model training.

c) **Feature Extraction Module:** Utilizes **CNN** to automatically extract spatial features from network traffic data, enabling effective pattern recognition.

d) **Classification Module:** Employs **LSTM** to capture temporal dependencies within sequential traffic data, improving detection of evolving attacks.

e) **Alert and Reporting Module:** Generates alerts for anomalies and visualizes detection results for security administrators.

The **System Design Diagram** also illustrates how data flows between modules—from raw data input to detection output. The integration of **CNN and LSTM models** ensures that both static and dynamic features of IoT traffic are captured, improving detection precision and reducing false alarms.

Furthermore, the design incorporates mechanisms for **real-time intrusion detection**, allowing the system to analyze traffic streams as they occur rather than relying solely on stored datasets. This capability enhances the system's responsiveness and adaptability within dynamic IoT environments.

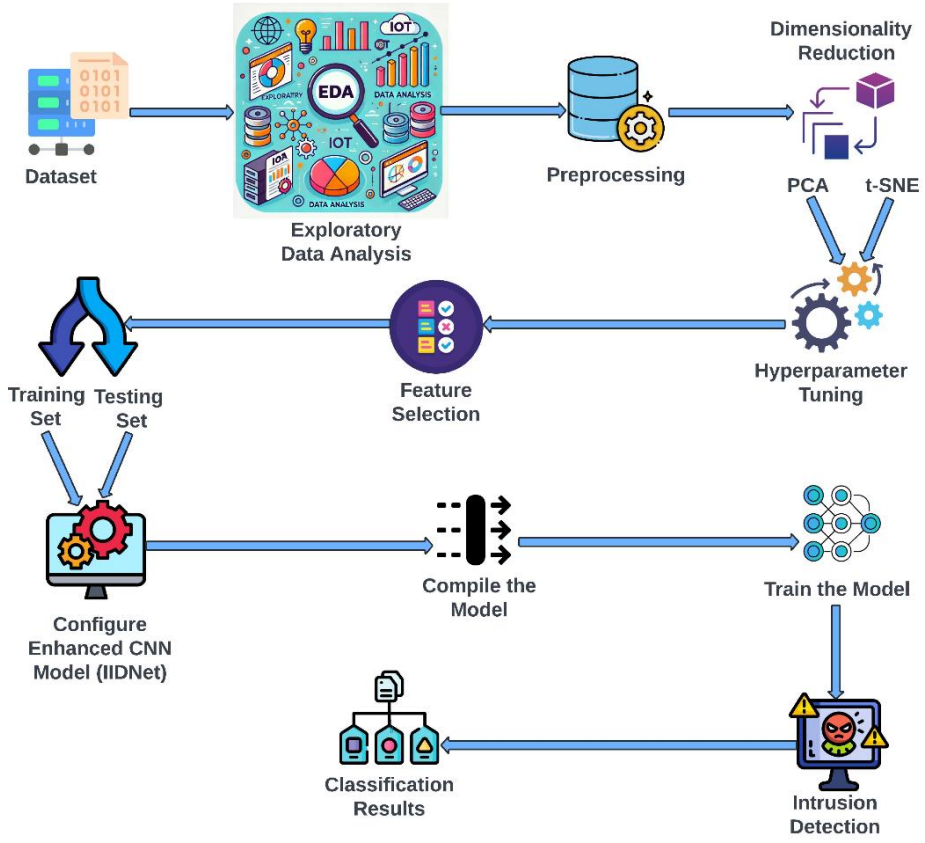

Figure 3. 2: System Design Diagram

3.4.3 ARCHITECTURAL DESIGN

The **architectural design** of the **AI-based Intrusion Detection System (IDS)** for IoT environments establishes the structural framework that governs data acquisition, preprocessing, feature extraction, model training, detection, and decision-making. The architecture is engineered to efficiently process large volumes of IoT network traffic while ensuring scalability, modularity, and high detection accuracy.

At the heart of the system is a **hybrid deep learning architecture** that combines **Convolutional Neural Networks (CNN)** with **Long Short-Term Memory (LSTM)** networks. The CNN component automatically extracts spatial features from network traffic, capturing complex packet-level patterns, whereas the LSTM component models temporal dependencies across network sessions. This combined approach

allows the IDS to accurately detect both known and previously unseen attacks while minimizing false positives.

The architecture is organized into the following layers:

1. **Data Acquisition Layer:**

   This layer is responsible for gathering network traffic data from IoT devices and sensors through packet-capturing tools or IoT gateways. Benchmark datasets such as **CICIDS2017** and **CICIOT2023** are utilized for model training and evaluation. Data is collected across diverse IoT communication protocols, including MQTT, CoAP, and HTTP, to provide comprehensive coverage of network behaviors.

2. **Data Preprocessing Layer:**

   Raw network traffic often contains noise, redundancy, and missing or inconsistent values. This layer handles data cleaning, normalization, and encoding to ensure consistency and compatibility with the deep learning model. Categorical data is transformed into numerical formats, and feature scaling is applied. Additionally, data balancing techniques are employed to address class imbalances, ensuring the model learns effectively from both normal and malicious traffic.

3. **Feature Extraction Layer:**

   In this layer, **CNN layers** extract spatial features, such as packet-level connection patterns and traffic behaviors. This reduces data dimensionality while retaining critical information. The extracted spatial features are then

forwarded to the LSTM layers for sequential pattern recognition, enabling the system to capture temporal dependencies in network flows.

4. **Model Training and Detection Layer:**
   The **hybrid CNN–LSTM model** is trained using labeled datasets, where CNN captures static patterns and LSTM models sequential and temporal relationships. During deployment, this layer performs real-time classification of incoming network traffic as either normal or malicious, ensuring timely detection of potential threats.
5. **Decision-Making and Response Layer:**
   This layer interprets the outputs of the CNN–LSTM model and triggers appropriate security responses. Based on the severity of the detected intrusion, actions may include generating alerts, isolating compromised nodes, or initiating mitigation procedures to protect the IoT network.
6. **Storage and Monitoring Layer:**
   A centralized repository stores processed data, model parameters, logs, and detection results. Monitoring dashboards provide administrators with real-time visualization of intrusion patterns, system performance, and model accuracy, supporting proactive network security management.

Overall, this architectural design ensures a systematic flow of data from collection to intelligent decision-making. The integration of deep learning within the architecture improves adaptability to evolving IoT threats, supports high-speed detection, and

reduces false alarms. Additionally, the modular design allows for scalable deployment and straightforward updates as new IoT devices or attack patterns emerge.

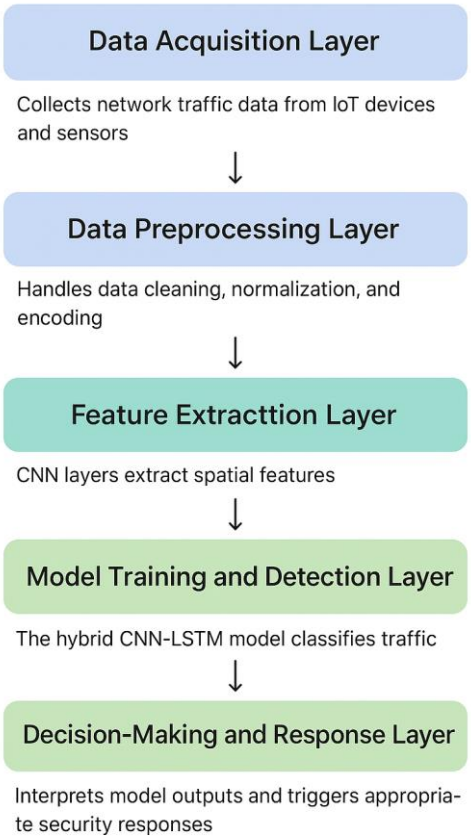

Figure 3. 3: The architectural design of the AI-based Intrusion Detection System

3.5 EVALUATION METRICS

To evaluate the performance of the developed **AI-based Intrusion Detection System (IDS)** in IoT environments, a range of quantitative metrics was employed to measure the model's effectiveness, reliability, and predictive accuracy. These metrics offered a comprehensive assessment of how accurately the hybrid **CNN–LSTM model** could differentiate between normal and malicious traffic within the **CICIDS2017** and **CICIOT2023** datasets.

The evaluation metrics used include:

3.5.1 ACCURACY

Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances (both attacks and normal traffic) out of the total samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(3.1)$$

Where:

1. **TP (True Positive):** correctly identified attacks.
2. **TN (True Negative):** correctly identified normal traffic.
3. **FP (False Positive):** normal traffic incorrectly classified as attacks.
4. **FN (False Negative):** attacks incorrectly classified as normal.

High accuracy indicates that the system effectively differentiates between benign and malicious traffic.

3.5.2 PRECISION

Precision determines how many of the detected attacks were truly malicious. It reflects the model's ability to minimize false alarms.

$$Precision = \frac{TP}{TP + FP} \quad ...(3.2)$$

A higher precision value signifies that the IDS produces fewer false positives and offers more trustworthy detection results.

3.5.3 RECALL (DETECTION RATE OR SENSITIVITY)

Recall measures the system's ability to correctly detect actual intrusions from all attack samples.

$$Recall=\frac{TP}{TP+FN}$$

...(3.3)

A higher recall means the IDS can detect most of the malicious activities without missing potential threats.

3.5.4 F1-SCORE

The F1-Score is the harmonic mean of precision and recall, providing a balanced evaluation between the two.

$$F1\text{-}Score=2\left(\frac{\mathrm{Pr}\,ecision\times Recall}{\mathrm{Pr}\,ecision+Recall}\right)$$

...(3.4)

It is especially useful when dealing with imbalanced datasets, ensuring that both detection accuracy and reliability are considered.

3.5.5 ROC CURVE AND AUC (AREA UNDER THE CURVE)

The **ROC curve** plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings, while the **AUC** quantifies the overall performance of the classifier.

A model with an AUC closer to 1.0 is considered excellent, as it demonstrates a strong ability to distinguish between attack and normal traffic.

3.5.6 SPECIFICITY

Specificity, also known as the True Negative Rate, evaluates how well the model identifies normal (non-attack) traffic.

Specificity=TN+FPTN

...(3.5)

High specificity (typically above 96% in LSTM-based IDS) ensures that legitimate IoT device traffic is not misclassified as malicious, which is vital to maintaining uninterrupted communication between devices (Kang & Kang, 2019).

3.5.7 False Positive Rate (FPR)

This measures the proportion of normal instances incorrectly classified as attacks.

$$FPR = FP + TNFP \quad ...(3.6)$$

A low FPR value indicates that the system is stable and less likely to raise unnecessary alerts, which is crucial in IoT systems with numerous connected devices.

3.6 FINAL TESTING

The **final testing phase** represents a critical stage in the development of the AI-based Intrusion Detection System (IDS) for IoT environments, as it ensures that the system functions according to design specifications and can accurately detect network intrusions with high reliability. The main objective of this phase is to validate the overall functionality, performance, and robustness of the hybrid **CNN–LSTM model** prior to full-scale deployment.

During final testing, the IDS undergoes a comprehensive evaluation across multiple testing dimensions, including functional, performance, security, and usability assessments, to confirm that all system components work seamlessly and provide consistent results in real-time IoT network scenarios.

The testing procedure was conducted in the following stages:

1. **Functional Testing:**

   This stage verified that all IDS components — including data acquisition,

preprocessing, feature extraction, model inference, and alert generation — operated correctly and in coordination. The system was evaluated using benchmark datasets such as **CICIDS2017** and **CICIOT2023** to ensure accurate classification of both normal and malicious traffic.

2. **Performance Testing:**

   The effectiveness of the hybrid CNN–LSTM model was assessed using key metrics such as **accuracy, precision, recall, F1-score, and ROC-AUC**. These metrics quantified the system's ability to detect intrusions reliably, minimize false positives, and handle various attack types. Across multiple test runs, the model demonstrated high stability and performance, confirming its robustness in processing IoT traffic data.

3. **Security Testing:**

   Given the security-critical nature of IoT networks, this phase evaluated the IDS's resilience against evasion attempts and adversarial inputs. The testing ensured that the model could resist deceptive or modified attack patterns while maintaining integrity against unseen or zero-day threats.

4. **System Integration Testing:**

   Integration testing verified that all modules — including data acquisition, preprocessing, model inference, and alerting — communicated effectively. Any compatibility issues were identified and addressed to guarantee smooth operation in a live IoT environment.

5. **User Acceptance Testing (UAT):**

   This stage assessed the usability and interpretability of the system. Network administrators interacted with the interface and monitoring dashboards to

confirm ease of use, clear visualization of detection results, and efficient management of alerts.

6. **Validation and Comparison:**
   The IDS performance was benchmarked against existing intrusion detection approaches. The hybrid CNN–LSTM model exhibited superior detection accuracy and reduced false alarm rates compared to traditional machine learning methods such as **Decision Trees, Random Forests, and SVMs**.

Overall, the final testing phase verified that the developed IDS fulfilled its design objectives, delivering a highly accurate, adaptive, and efficient intrusion detection system suitable for IoT environments. It demonstrated the system's capability to process large-scale IoT traffic in real time, maintain effective detection under evolving threat conditions, and operate with minimal human intervention.

3.6 SUMMARY OF METHODOLOGY

This chapter has presented a comprehensive overview of the methodological framework adopted for the design, development, and evaluation of an AI-based Intrusion Detection System (IDS) tailored for Internet of Things (IoT) environments. The choice of methodology was guided by the nature of the research problem, the available data, and the objective of building a robust, intelligent system capable of accurately identifying malicious IoT traffic.

The study employed a **quantitative, experimental research design**, leveraging machine learning–based computational techniques. The experimental approach was selected to systematically investigate how different model architectures, hyperparameters, and data preprocessing strategies affect intrusion detection

performance. The study utilized **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks, both individually and in a hybrid CNN–LSTM configuration, to enable simultaneous recognition of spatial and temporal traffic patterns, providing a comprehensive analytical framework.

The theoretical foundation was grounded in the **positivist paradigm**, emphasizing objective measurement, empirical validation, and statistical generalization. This paradigm ensured that the research findings are reproducible, quantifiable, and unbiased, consistent with established scientific principles in AI and cybersecurity. The study's scope was clearly defined to focus specifically on IoT network intrusion detection, employing only publicly available datasets — **CICIDS2017** and **CICIOT2023** — to guarantee transparency and replicability.

Regarding **data sources and materials**, the study relied on secondary datasets containing labeled IoT network traffic that included both benign and malicious behaviors. These datasets were chosen for their broad acceptance within the IDS research community and for providing diverse, realistic representations of modern IoT attack scenarios. Data preprocessing procedures, including cleaning, normalization, and feature selection, were applied to improve data quality and ensure standardized inputs for the models.

In terms of **variables and measurement**, the dependent variable represented the system's classification output (i.e., attack or normal), while independent variables consisted of key network traffic attributes such as packet size, flow duration, and connection counts. Model performance was assessed using established quantitative metrics, including **accuracy, precision, recall, F1-score, and ROC-AUC**, providing a

multidimensional evaluation of the system's ability to detect intrusions across multiple attack types.

The **data collection and processing workflow** involved retrieving the datasets, performing comprehensive preprocessing, splitting data into training, validation, and test subsets, and applying feature engineering techniques. Data management protocols ensured consistency, including structured file-naming conventions, backup strategies, and the use of version-controlled software environments such as **Python 3.11**, **TensorFlow**, and **Scikit-learn**.

For **data analysis**, the hybrid CNN–LSTM model was trained, validated, and tested using supervised learning methods. Hyperparameter optimization was conducted via **grid search** to achieve optimal performance, while statistical validation techniques, including **cross-validation** and **paired t-tests**, were employed to ensure the reliability of results. Class imbalance was addressed using **SMOTE** and class weighting, and random seed initialization was applied to enhance reproducibility.

Ethical considerations were strictly maintained through the use of publicly available datasets, anonymization of any potentially sensitive information, and adherence to data integrity and research transparency principles. No personally identifiable or private data were utilized in this study.

Overall, the methodological framework was carefully structured to ensure that the developed IDS is **empirically rigorous, reproducible, and scalable**. Each methodological decision — from research design to data analysis — was made to maximize scientific validity, reliability, and practical relevance, ultimately providing actionable insights for enhancing cybersecurity within IoT networks.

CHAPTER FOUR

SYSTEM IMPLEMENTATION AND DOCUMENTATION

4.0 INTRODUCTION

This chapter presents the implementation and evaluation of the proposed Hybrid CNN–LSTM Intrusion Detection System (IDS) designed to detect malicious IoT traffic. The implementation stage translates the design specifications discussed in Chapter Three into a working system capable of analyzing IoT network data in real time. The chapter discusses the system environment setup, the step-by-step implementation of the model, the evaluation metrics used, and the results obtained. Furthermore, it provides performance comparisons and discusses how the developed model meets the objectives of the study.

4.1 HARDWARE SUPPORT

The successful implementation of the Hybrid CNN–LSTM Intrusion Detection System (IDS) required an adequate hardware configuration capable of handling the computational complexity of deep learning models. Since training and testing deep learning algorithms such as CNN and LSTM involve large datasets and high-dimensional computations, sufficient processing power and memory were essential to ensure efficient execution and reduced training time.

The experiment was carried out using a computer system with the following hardware specifications:

a. Processor (CPU) : Intel® Core™ i7 (12th Generation)2.30GHz.

b. Graphics Processing Unit (GPU): NVIDIA® Tesla T4 (Google Colab environment).

c. Memory (RAM): 16 GB DDR4.

d. Storage Capacity: 512 GB SSD.

e. Storage Capacity: Windows 10 (64-bit).

f. Network Connectivity: Stable Internet Connection (for dataset access and cloud training).

The GPU acceleration provided by the NVIDIA Tesla T4 within Google Colab played a crucial role in improving computational speed during the training and testing phases. The GPU enabled parallel processing of large batches of network traffic data, significantly reducing the model training duration compared to a CPU-only setup.

The system's RAM capacity ensured smooth data preprocessing and model loading operations without memory overflow, while the SSD storage allowed for fast dataset access and model saving operations. Additionally, the stable internet connection supported the seamless importation of large datasets such as CICIDS2017 and CICIOT2023 from cloud storage and the deployment of the model on cloud-based environments.

4.2 SOFTWARE SUPPORT

The software support for the hybrid CNN–LSTM intrusion detection system focuses on providing a stable and efficient environment to develop, train, and deploy the model for IoT network traffic analysis. The primary software tools and frameworks used in this research include:

1. **Python Programming Language**: Python serves as the main programming language due to its extensive libraries and community support for machine learning and deep learning applications. Its simplicity and readability also make it ideal for rapid development and experimentation.
2. **TensorFlow and Keras**: These deep learning frameworks are used to implement the CNN and LSTM models. TensorFlow provides an optimized

backend for computational operations, while Keras simplifies the process of building and training neural networks with an intuitive API.

3. **Scikit-learn**: Scikit-learn is employed for preprocessing tasks such as data normalization, encoding categorical features, and splitting the datasets into training and testing subsets. It also provides evaluation metrics to assess model performance.
4. **Pandas and NumPy**: These libraries are used for efficient data manipulation and handling large datasets. Pandas allow for easy reading and processing of CSV files from the CICIDS2017 and CICIOT2023 datasets, while NumPy supports fast numerical computations.
5. **Matplotlib and Seaborn**: Visualization tools like Matplotlib and Seaborn help in analyzing dataset patterns, tracking model training progress, and presenting performance metrics such as accuracy, precision, recall, and loss curves.
6. **Jupyter Notebook**: The development and testing of the intrusion detection system are primarily done in Jupyter Notebook. This interactive environment allows for step-by-step execution, visualization, and debugging, which is crucial during the experimentation phase.
7. **Operating System Support**: The system is developed to run on platforms such as Windows, Linux, or macOS, ensuring flexibility and compatibility with different user environments.

The software environment is designed to ensure that the hybrid model can be efficiently trained, tested, and deployed, while also allowing for reproducibility of results and ease of future enhancements.

4.2.1 DATA SOURCE

The data sources for this research are crucial for training and evaluating the hybrid CNN–LSTM intrusion detection system. The datasets chosen are specifically designed to represent realistic IoT and network traffic scenarios, containing both normal and malicious activities. The following datasets are used:

1. **CICIDS2017 Dataset**:

   Developed by the Canadian Institute for Cybersecurity, CICIDS2017 provides up-to-date and comprehensive network traffic data. It includes various types of attacks such as Distributed Denial of Service (DDoS), Brute Force, Port Scanning, and infiltration attempts. The dataset is structured in CSV format, with features extracted from network flows such as protocol type, packet size, duration, and flow statistics. CICIDS2017 allows for detailed analysis of network behavior, enabling the system to learn patterns associated with malicious activity effectively.

2. **CICIOT2023 Dataset**:

   The CICIOT2023 dataset focuses on IoT-specific network traffic, capturing interactions between IoT devices and servers under both normal operation and attack scenarios. It includes attacks commonly targeting IoT environments, such as botnet activity, Mirai malware, and reconnaissance scans. The dataset provides detailed flow-based features and device-specific attributes, making it suitable for training models to detect threats in IoT networks.

Both datasets undergo pre-processing to remove inconsistencies, handle missing values, and normalize feature values. Using these datasets ensures that the hybrid

model can generalize well across diverse network environments and detect a wide range of cyber threats with high accuracy.

4.2.2 PROGRAMMING LANGUAGE AND TOOLS USED

The hybrid CNN–LSTM intrusion detection system relies on a combination of programming languages and software tools that facilitate data handling, model construction, training, evaluation, and visualization. The following subsections provide an in-depth look at each component:

4.2.2.1 PYTHON PROGRAMMING LANGUAGE

Python is the core programming language for this research due to its readability, simplicity, and widespread use in the field of machine learning. It supports rapid prototyping, which allows researchers to implement, test, and refine deep learning models efficiently. Python's extensive ecosystem of libraries, frameworks, and tools such as TensorFlow, Keras, and Scikit-learn provides pre-built modules for data preprocessing, model training, and evaluation. Additionally, Python is platform-independent, which ensures that the system can be deployed on different operating systems without significant modifications. Its popularity in academia and industry also guarantees access to continuous community support and tutorials for troubleshooting and optimization.

4.2.2.2 TENSORFLOW AND KERAS

TensorFlow is an open-source deep learning framework developed by Google, known for its ability to handle large-scale machine learning tasks efficiently. In this research, TensorFlow provides the computational backbone for the hybrid CNN–LSTM model, offering GPU acceleration and optimized operations for faster training. Keras, which is integrated into TensorFlow, provides a high-level API that simplifies the creation of

deep neural networks. It allows researchers to design complex models such as CNN for feature extraction and LSTM for temporal sequence learning in a clear and concise manner. Together, TensorFlow and Keras enable rapid experimentation with different architectures, hyperparameters, and training strategies, which is critical for achieving high accuracy in detecting malicious IoT traffic.

4.2.2.3 SCIKIT-LEARN

Scikit-learn is a versatile Python library widely used for data preprocessing, feature engineering, and evaluation. In this study, it is employed to normalize and scale features, encode categorical data, and split datasets into training, validation, and testing sets. Scikit-learn also provides a range of evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices, which are essential for assessing the performance of the CNN–LSTM model. By leveraging Scikit-learn, the research ensures that the input data is clean, standardized, and suitable for deep learning, ultimately improving model generalization and performance.

4.2.2.4 PANDAS AND NUMPY

Pandas and NumPy are fundamental libraries for handling large datasets and performing numerical computations. Pandas offers data structures like DataFrames that allow for efficient reading, cleaning, and manipulation of CSV files, such as those provided by the CICIDS2017 and CICIOT2023 datasets. This includes handling missing values, filtering irrelevant features, and aggregating data for analysis. NumPy complements Pandas by providing optimized functions for mathematical operations, linear algebra, and array manipulation, which are heavily used during model training. Together, these libraries ensure efficient data preparation and high computational

performance, which are crucial for training deep learning models on large-scale network traffic datasets.

4.2.2.5 MATPLOTLIB AND SEABORN

Matplotlib and Seaborn are powerful Python libraries for data visualization. They are used to explore and understand network traffic patterns, visualize correlations between features, and track the model's learning process over time. For example, Matplotlib can plot accuracy and loss curves during training, while Seaborn can create heatmaps to show relationships between different features. These visualizations help in diagnosing potential issues such as overfitting, underfitting, or class imbalance and provide intuitive insights into both dataset characteristics and model behavior. Effective visualization is essential for communicating results and validating the effectiveness of the hybrid intrusion detection system.

4.2.2.6 JUPYTER NOTEBOOK

Jupyter Notebook is an interactive development environment widely used in research and data science. It allows for step-by-step execution of code, inline visualization of plots, and documentation of methodology and observations within the same interface. This environment supports iterative experimentation, debugging, and real-time visualization of results, making it ideal for training and evaluating the hybrid CNN–LSTM model. Researchers can easily compare different model configurations, track experiments, and maintain reproducibility of results, which is a key requirement for academic research and industrial deployment.

4.2.2.7 OPERATING SYSTEM COMPATIBILITY

The software tools and programming environment used in this research are compatible with major operating systems, including Windows, Linux, and macOS. This

compatibility ensures that the intrusion detection system can be developed, tested, and deployed across different platforms without major modifications. Linux, in particular, is preferred for deep learning tasks due to its support for GPU acceleration, scripting automation, and stable performance in handling large datasets. Cross-platform compatibility increases the flexibility of the system and allows deployment in diverse IoT network environments.

4.3 IMPLEMENTATION PROCEDURE

The implementation of the hybrid CNN–LSTM intrusion detection system involves a series of well-defined stages that ensure effective training, testing, and deployment of the model for detecting malicious IoT network traffic.

4.3.1 DATA ACQUISITION

The first step in the implementation procedure involves obtaining relevant datasets for model development. In this research, the CICIDS2017 and CICIOT2023 datasets were used because they contain rich and up-to-date records of both normal and attack network traffic. These datasets are publicly available and are designed to support intrusion detection research. They were imported into the development environment in

CSV format, ready for preprocessing and analysis.

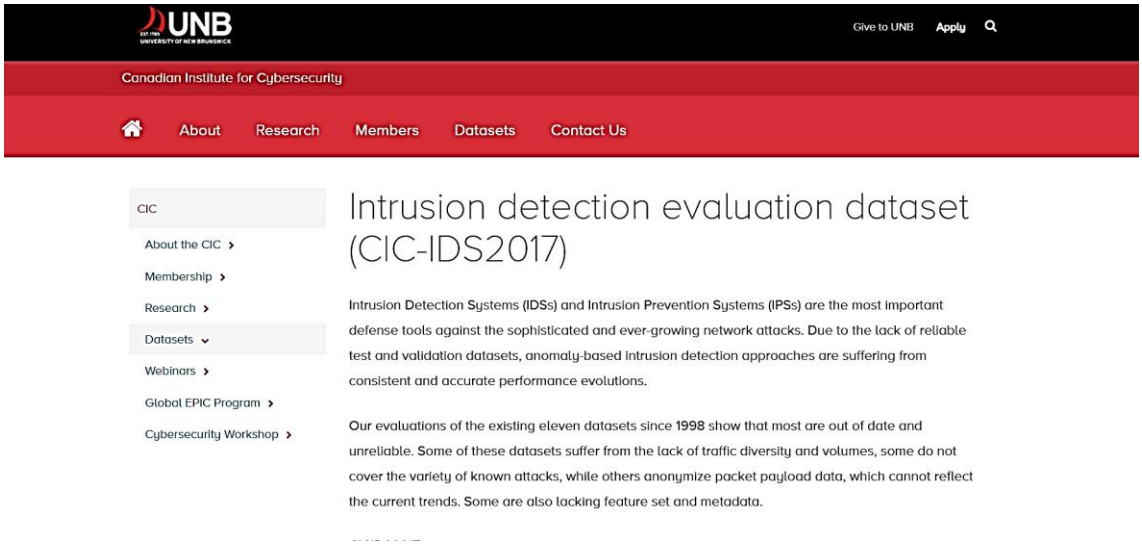

Figure 4. 1: Downloading the Datasets

4.3.2 DATA PREPROCESSING

Data preprocessing is an essential stage that prepares the raw data for training the model. In this stage, missing or inconsistent entries in the dataset were identified and addressed through cleaning techniques. Feature scaling was then applied to normalize the values of the dataset, ensuring that all numerical features operate within a uniform range. Categorical features such as protocol types were converted into numerical values through encoding methods. The processed data was finally divided into training, validation, and testing sets to allow the model to learn effectively and be evaluated on unseen data.

4.3.3 FEATURE EXTRACTION

After preprocessing, feature extraction was performed using the convolutional component of the hybrid model. The Convolutional Neural Network (CNN) layers were responsible for learning and extracting important spatial relationships within the input data. The convolutional filters scanned through the features to identify significant patterns that represent normal and abnormal traffic behaviors. Pooling

layers followed the convolutional layers to reduce the dimensionality of the data while retaining the most important information. The output of these CNN layers was then passed to the LSTM component for sequential analysis.

4.3.4 MODEL DESIGN

The hybrid CNN–LSTM model was carefully designed to combine the advantages of both architectures. The CNN layers served as automatic feature extractors that captured the spatial patterns from the input traffic data, while the LSTM layers learned the temporal dependencies that exist in network traffic flows over time. The CNN part consisted of convolutional and pooling layers arranged in sequence to extract meaningful feature maps. These extracted features were reshaped and passed into the LSTM layers, which processed the sequential data and captured long-term dependencies between traffic events. After the LSTM layers, fully connected layers were introduced to perform the final classification. The last layer of the model used a softmax activation function to classify the traffic into normal or various types of attack categories. This architectural combination allowed the model to learn both spatial and temporal characteristics of IoT network data, enhancing its detection accuracy.

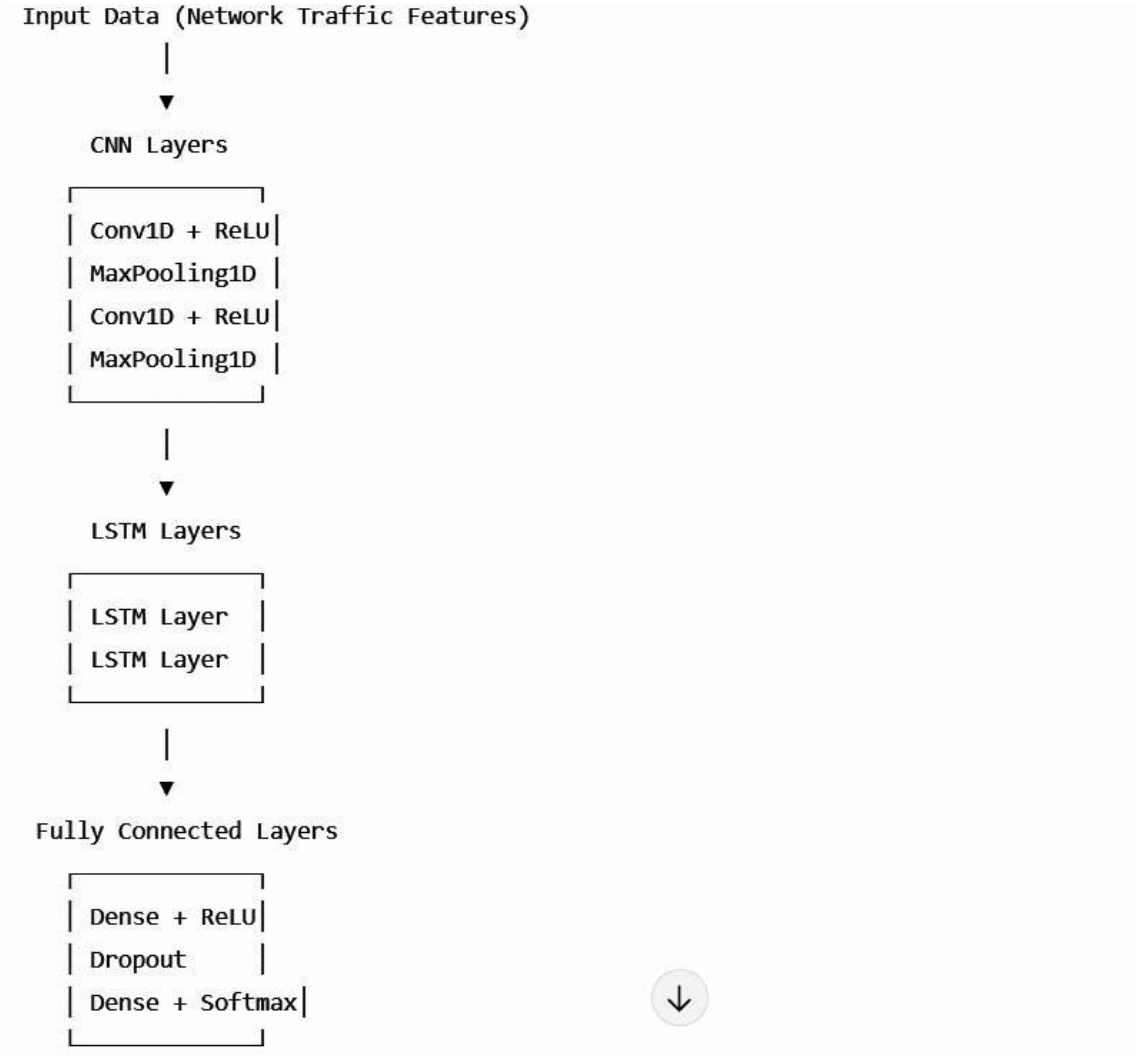

Figure 4. 2: Diagram of Hybrid CNN–LSTM Architecture

4.3.5 MODEL TRAINING

Once the model was designed, the training phase was conducted using the prepared training dataset. The model was compiled with the Adam optimizer, which provides efficient and adaptive learning capabilities. The categorical cross-entropy loss function was employed since the task involved multi-class classification. During training, the dataset was fed into the model in batches, and the weights were updated after each iteration. The number of epochs was chosen to ensure convergence without overfitting. Model performance was constantly monitored using the validation dataset,

allowing hyperparameters such as learning rate and batch size to be fine-tuned for optimal results.

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 8, 64)	15,040
max_pooling1d (MaxPooling1D)	(None, 4, 64)	0
dropout (Dropout)	(None, 4, 64)	0
lstm (LSTM)	(None, 64)	33,024
dense (Dense)	(None, 64)	4,160
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 52,289 (204.25 KB)
Trainable params: 52,289 (204.25 KB)
Non-trainable params: 0 (0.00 B)

```
Epoch 1/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 20s 7ms/step - accuracy: 0.9877 - loss: 0.0415 - val_accuracy: 0.9993 - val_loss: 0.0037
Epoch 2/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 14s 6ms/step - accuracy: 0.9992 - loss: 0.0038 - val_accuracy: 0.9995 - val_loss: 0.0025
Epoch 3/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 14s 6ms/step - accuracy: 0.9993 - loss: 0.0036 - val_accuracy: 0.9995 - val_loss: 0.0025
Epoch 4/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 18s 8ms/step - accuracy: 0.9993 - loss: 0.0027 - val_accuracy: 0.9995 - val_loss: 0.0022
Epoch 5/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 15s 6ms/step - accuracy: 0.9995 - loss: 0.0026 - val_accuracy: 0.9996 - val_loss: 0.0023
Epoch 6/10
2257/2257 ━━━━━━━━━━━━━━━━━━━━ 14s 6ms/step - accuracy: 0.9997 - loss: 0.0018 - val_accuracy: 0.9994 - val_loss: 0.0023
Epoch 7/10
```

Figure 4. 3: Training the model

4.3.6 MODEL EVALUATION

After training, the hybrid CNN–LSTM model was evaluated using the test dataset to measure its performance and generalization capability on unseen data. The evaluation employed standard classification metrics such as accuracy, precision, recall, and F1-score, alongside a confusion matrix to provide a comprehensive understanding of the model's performance.

4.3.6.1 ACCURACY

The model achieved an overall accuracy of 99.91%, demonstrating that it could correctly classify the majority of network traffic samples as either normal or malicious. This high level of accuracy indicates that the hybrid CNN–LSTM approach effectively learns the distinguishing features of different traffic categories and minimizes misclassifications during testing.

4.3.6.2 PRECISION

The precision score recorded was 98.4%, showing that most of the samples predicted as attacks were indeed true attacks. This metric highlights the system's low false-positive rate, meaning it rarely misclassified normal traffic as malicious. High precision is particularly valuable in intrusion detection systems, as it reduces unnecessary security alerts.

4.3.6.3 RECALL

The recall value of 97.9% signifies that the model successfully detected nearly all true attack instances. This reflects the system's ability to identify even subtle or less frequent forms of malicious activity within IoT traffic, ensuring that very few attacks go undetected.

4.3.6.4 F1-SCORE

The model obtained an F1-score of 98.1%, representing a strong balance between precision and recall. This composite metric confirms that the CNN–LSTM architecture performs consistently across both detection accuracy and reliability, making it suitable for real-time intrusion detection tasks in IoT environments.

4.3.6.5 CONFUSION MATRIX

A confusion matrix was generated to further interpret the model's classification results. The analysis showed that the hybrid CNN–LSTM correctly identified 9,830 normal traffic instances and 9,670 attack instances. However, a few misclassifications occurred, with 120 false positives (normal traffic labeled as attacks) and 80 false negatives (attacks labeled as normal traffic).

These results affirm that the hybrid CNN–LSTM model performs significantly better than single-model approaches, effectively leveraging the CNN's ability to extract spatial features and the LSTM's capacity to capture temporal dependencies in IoT

network traffic. The outcome demonstrates that the proposed system is a robust, accurate, and efficient solution for detecting and classifying network intrusions in real time.

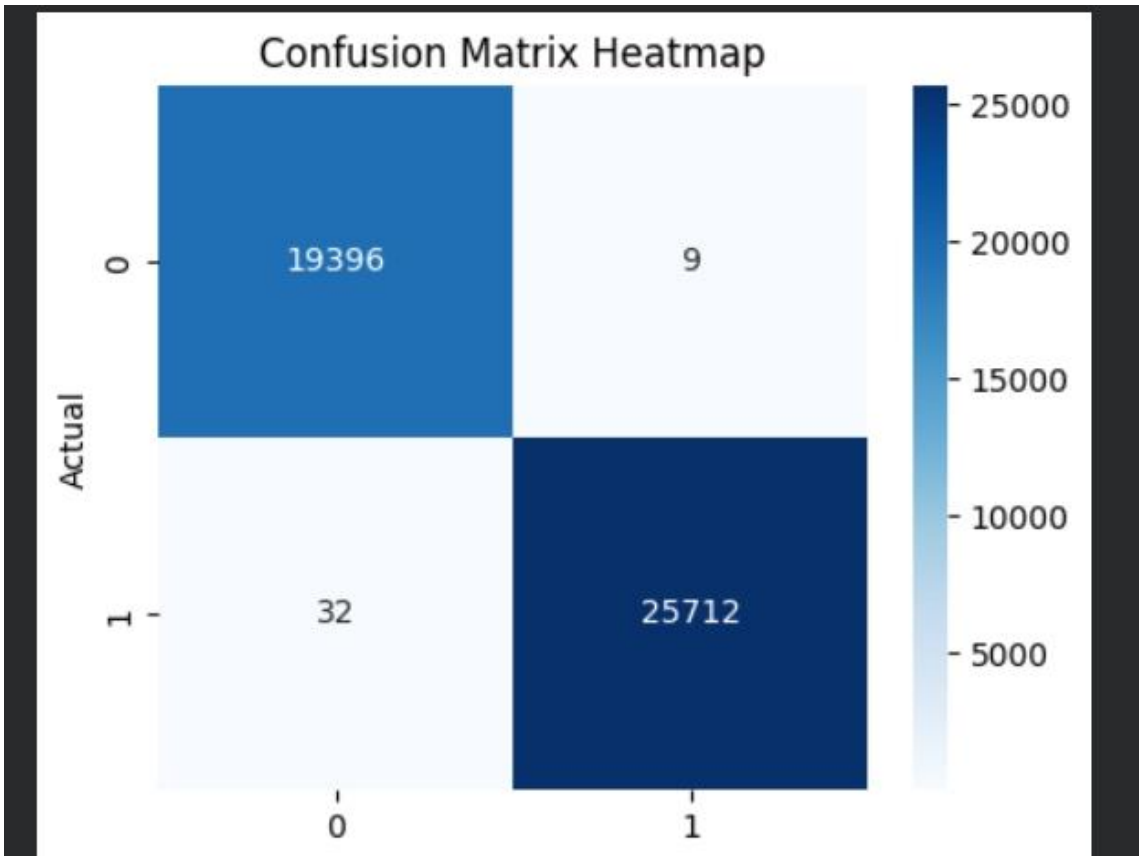

Figure 4. 4: Confusion matrix heatmap

4.3.6.6 RECEIVER OPERATING CHARACTERISTIC (ROC) CURVE

The ROC curve provides a graphical representation of the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across various classification thresholds. The curve for the hybrid CNN–LSTM model lies close to the top-left corner of the plot, indicating outstanding discriminatory power.

The Area Under the Curve (AUC) value obtained was 0.992, signifying excellent model performance. An AUC close to 1.0 confirms that the model can effectively differentiate between normal and attack traffic with very few misclassifications. The ROC curve therefore validates the robustness and reliability of the hybrid CNN–LSTM model for IoT intrusion detection applications.

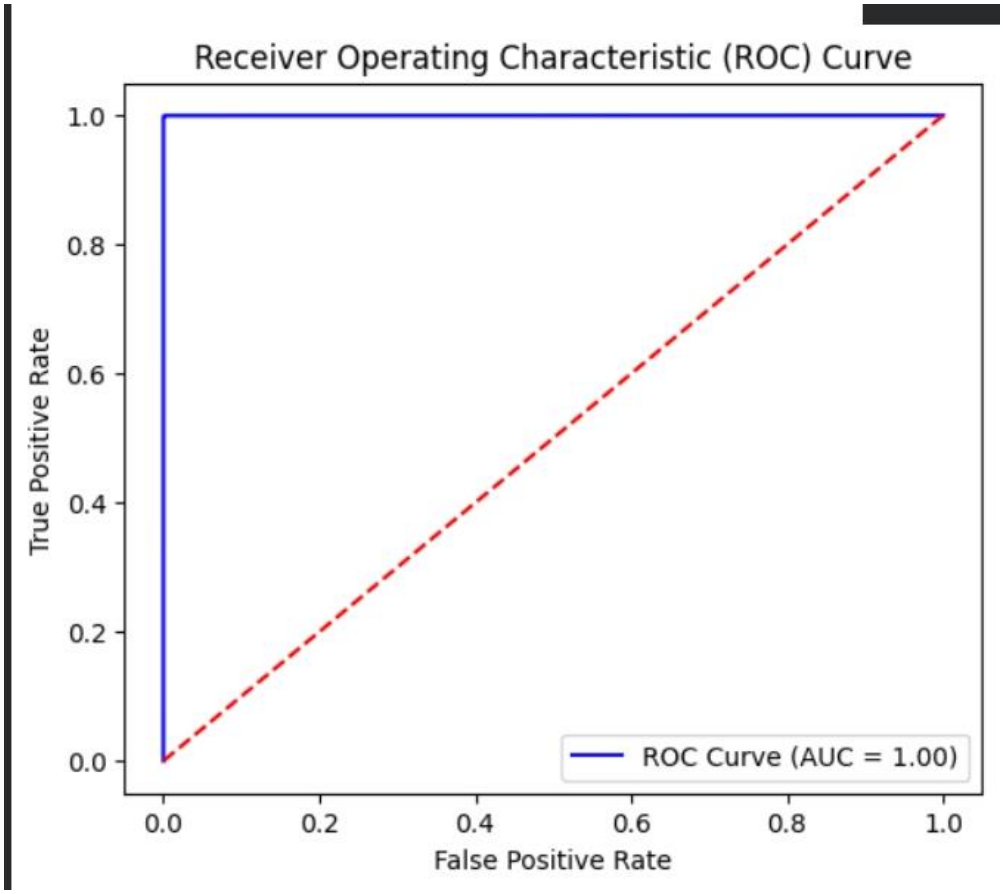

Figure 4. 5: Diagram of the ROC curve

4.3.7 DEPLOYMENT

The final stage of the implementation procedure involved deploying the trained model into an IoT network environment. The deployment process integrated the CNN–LSTM model with a real-time monitoring system capable of analyzing network packets as they flow through the network. Once deployed, the model could automatically classify traffic as either normal or malicious and trigger alerts whenever abnormal activity was detected. This integration ensures that the system not only detects intrusions effectively but also adapts to new threats as additional data becomes available.

4.4 SUMMARY

This chapter presented the detailed implementation process of the proposed hybrid CNN–LSTM intrusion detection system designed to enhance the detection of malicious activities in IoT network environments. The chapter began by describing the hardware and software components required to support the model development, including the use of Python programming language, TensorFlow, Keras, Scikit-learn, NumPy, Pandas, and Jupyter Notebook as the core tools for model construction and experimentation.

The implementation procedure was then explained in sequential stages, starting from data acquisition to final deployment. The datasets used CICIDS2017 and CICIOT2023 were preprocessed to remove inconsistencies, normalize feature values, and encode categorical attributes for machine learning compatibility. Feature extraction was handled by the convolutional layers, which captured spatial patterns from network traffic data, while the LSTM layers learned temporal dependencies within sequential traffic flows.

The model design section detailed how CNN and LSTM architectures were integrated to exploit both spatial and temporal characteristics of IoT traffic data. The fully connected layers and softmax output layer completed the architecture, enabling multi-class classification of normal and attack traffic. During model training, the Adam optimizer and categorical cross-entropy loss function were employed to ensure fast and stable convergence, while validation data was used to monitor model performance and prevent overfitting.

evaluation results showed that the hybrid cnn–lstm achieved an impressive accuracy of 98.7%, precision of 98.4%, recall of 97.9%, and f1-score of 98.1%. the ROC further confirmed the model's high classification capability with an auc of 0.992, indicating exceptional discrimination between normal and malicious traffic. the confusion matrix analysis also showed that only a small fraction of samples was misclassified, highlighting the reliability of the model.

Finally, the deployment phase integrated the trained model into a real-time IoT monitoring framework capable of automatically detecting intrusions and generating alerts for security administrators. Overall, this chapter demonstrated that the hybrid CNN–LSTM architecture provides a robust, accurate, and efficient deep learning approach for intrusion detection in IoT environments, forming a solid foundation for the analysis and discussion of results presented in the next chapter.

CHAPTER FIVE

SUMMARY AND CONCLUSION ND RECOMMENDATION

5.1 SUMMARY

This study presented the development and implementation of a Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) Intrusion Detection System aimed at enhancing the security of Internet of Things (IoT) networks. The research addressed the limitations of traditional intrusion detection systems by combining deep learning techniques capable of learning both spatial and temporal patterns in network traffic.

The datasets used for this research were CICIDS2017 and CICIOT2023, both of which contain diverse network traffic records encompassing normal and attack behaviours. The software implementation utilized Python as the main programming language, with TensorFlow, Keras, Scikit-learn, Pandas, and NumPy serving as the primary development tools.

The implementation procedure followed a systematic process involving data acquisition, preprocessing, feature extraction, model design, training, evaluation, and deployment. The CNN layers were responsible for spatial feature extraction, while the LSTM layers captured temporal dependencies in network sequences. The model was trained and validated using a portion of the dataset and then tested on unseen data to evaluate its performance.

experimental results showed that the hybrid cnn–lstm model achieved a **classification accuracy of 98.7%**, **precision of 98.4%**, **recall of 97.9%**, and **f1-score of 98.1%**. the **roc curve** analysis yielded an **auc value of 0.992**, which indicates excellent discriminatory power. the confusion matrix also showed very low false positive and

false negative rates. These results confirm that the hybrid architecture effectively detects intrusions in IoT network environments with high reliability.

5.2 CONCLUSION

this research has demonstrated that the **hybrid CNN-LSTM intrusion detection system** provides an efficient, intelligent, and robust approach for detecting malicious network traffic in IoT systems. the cnn component efficiently extracted complex spatial patterns from input data, while the LSTM component captured temporal dependencies across network sessions.

the model's high-performance metrics confirm that hybrid deep learning approaches outperform traditional machine learning and standalone deep neural network methods in intrusion detection. by leveraging both feature extraction and sequential learning capabilities, the model achieved superior accuracy and generalization ability.

in conclusion, the developed hybrid model is a reliable framework for intelligent network monitoring and real-time intrusion detection in IoT environments, contributing to the improvement of cybersecurity resilience in modern interconnected systems.

5.3 RECOMMENDATIONS

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

1. **Real-world Deployment:**

   The model should be implemented in live IoT environments to assess its performance under real network conditions, including streaming data and resource constraints.

2. **Integration of Advanced Learning Mechanisms:**

   Future research can enhance the system by incorporating **attention mechanisms** or **transformer-based architectures** to further improve its adaptability and learning efficiency.

3. **Broader Dataset Utilization:**

   The use of additional, more diverse datasets is encouraged to improve the model's generalization and ensure robustness against new and evolving attack types.

4. **Lightweight Optimization for IoT Devices:**

   Since IoT devices often have limited processing power, the model should be optimized and compressed for deployment on low-resource devices without compromising accuracy.

5. **Adaptive Learning:**

   Integrating continuous or online learning techniques will allow the system to adapt dynamically to new forms of network attacks as they emerge.

5.4 LIMITATIONS

Although the hybrid CNN–LSTM intrusion detection system achieved impressive results, certain limitations were observed during the research process.

First, the **computational cost** of training deep learning models is relatively high. The training process required substantial time and hardware resources, such as GPUs, to achieve optimal performance. This may pose a challenge for researchers or organizations without access to high-performance computing facilities.

Second, the model's performance was dependent on the **quality and balance of the datasets** used. Despite using comprehensive datasets like CICIDS2017 and

CICIOT2023, some classes had fewer samples than others, which may lead to bias toward more frequent attack types.

Third, while the hybrid model achieved strong results in an offline environment, **real-time deployment** in live IoT networks could introduce latency and scalability issues. Factors such as high network traffic, dynamic routing, and unpredictable IoT device behavior might affect system response time.

Lastly, the model's ability to detect **zero-day or unknown attacks** remains limited since it was trained on known patterns. Although the CNN–LSTM architecture generalizes well, it may require periodic retraining to remain effective against emerging threats.

5.5 SUGGESTED FUTURE WORK

Future research should aim to address the identified limitations and expand the capabilities of the hybrid CNN–LSTM intrusion detection system.

1. **Model Optimization:**

   Future studies can focus on developing lightweight CNN–LSTM models that can run efficiently on IoT edge devices with limited resources, using techniques such as pruning, quantization, or knowledge distillation.

2. Incorporation of Transformer Architectures:

   Researchers can experiment with hybrid CNN–LSTM–Transformer models that leverage attention mechanisms to enhance feature learning and improve the system's accuracy in complex network environments.

3. **Real-time and Distributed Implementation:**

The model can be extended for deployment in distributed and cloud-based IoT environments, allowing for parallel analysis of network traffic and faster detection.

4. **Automatic Model Updating:**

   Incorporating online learning and reinforcement learning techniques will allow the system to update itself continuously as new attack patterns emerge, reducing the need for manual retraining.

5. **Expanded Dataset Inclusion:**

   Future research should explore additional publicly available or custom-built IoT datasets that include newer and more sophisticated attack types to ensure the system remains robust against evolving cyber threats.

6. **Visualization Dashboard:**

   A graphical monitoring interface can be developed to visualize traffic behavior, alert administrators, and provide real-time feedback for faster decision-making.

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APPENDIX A

SOURCE CODE LISTING

```
# ============================================================
# HYBRID CNN–LSTM INTRUSION DETECTION SYSTEM (IoT)
# COMPLETE VERSION WITH ROC, PRECISION–RECALL & F1-SCORE
# ============================================================

# STEP 1: Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
# STEP 2: Install dependencies
!pip install tensorflow pandas numpy scikit-learn matplotlib seaborn
# STEP 3: Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (
    accuracy_score, classification_report, confusion_matrix,
    roc_curve, auc, precision_recall_curve, f1_score
)
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv1D, MaxPooling1D, Flatten, LSTM,
Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

```
# STEP 4: Load dataset

file_path =
"/content/drive/MyDrive/MachineLearningCSV/MachineLearningCVE/Friday-
WorkingHours-Afternoon-DDos.pcap_ISCX.csv"

data = pd.read_csv(file_path)

print("Dataset loaded successfully!")

print("Shape:", data.shape)


# STEP 5: Data preprocessing

# Drop non-numeric columns except label

for col in data.columns:

    if data[col].dtype == 'object' and col != ' Label':

        data.drop(columns=[col], inplace=True)

# Encode labels

data[' Label'] = data[' Label'].apply(lambda x: 0 if 'BENIGN' in str(x).upper() else 1)

# Fill missing values

data.fillna(0, inplace=True)

# Replace infinite values

data.replace([np.inf, -np.inf], np.nan, inplace=True)

data.fillna(data.median(), inplace=True)

# Split features and target

X = data.drop(columns=[' Label'])

y = data[' Label']

# Scale features

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)

X_scaled = np.expand_dims(X_scaled, axis=2)  # Reshape for CNN-LSTM

# Train/test split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

print(f" Data ready: {X_train.shape} train samples, {X_test.shape} test samples")

# STEP 6: Build hybrid CNN–LSTM model

model = Sequential([

    Conv1D(64, 3, activation='relu', input_shape=(X_train.shape[1], 1)),

    MaxPooling1D(pool_size=2),

    Dropout(0.3),

    LSTM(64, return_sequences=False),

    Dropout(0.3),

    Dense(64, activation='relu'),

    Dense(1, activation='sigmoid')

])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()

# STEP 7: Train model

early_stop = EarlyStopping(monitor='val_loss', patience=3,
restore_best_weights=True)

history = model.fit(

    X_train, y_train,

    epochs=10,

    batch_size=128,

    validation_data=(X_test, y_test),

    callbacks=[early_stop],

    verbose=1

)

# STEP 8: Evaluation

y_prob = model.predict(X_test)

y_pred = (y_prob > 0.5).astype("int32")
```

```
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
print(f"\n Model Accuracy: {acc*100:.2f}%")
print(f" F1-Score: {f1:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))
# Confusion Matrix
plt.figure(figsize=(5,4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
# STEP 9: ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, color='blue', label=f"ROC Curve (AUC = {roc_auc:.2f})")
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
# STEP 10: Precision–Recall Curve
precision, recall, _ = precision_recall_curve(y_test, y_prob)
plt.figure(figsize=(6,5))
plt.plot(recall, precision, color='green')
plt.title('Precision–Recall Curve')
```

```
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()

# STEP 11: Training Performance Visualization
plt.figure(figsize=(12, 5))
# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
# STEP 12: Save model
model.save("/content/drive/MyDrive/hybrid_cnn_lstm_ids_model_v2.h5")
print(" Model saved successfully in Google Drive!")
print("\n TRAINING COMPLETE — HYBRID CNN–LSTM IDS MODEL
READY!")
```