Enhancing Advanced Persistent Threat Detection

Benchmarking Hybrid Deep Learning Techniques Across Varied Intrusion Datasets

Optimized via Particle Swarm Optimization

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Principal Supervisor: **Prof Bahman Sarrafpour**

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Abstract

Advanced Persistent Threats (APTs), This type is a **substantial threat** to contemporary cybersecurity schemes for their **covert behavior** and **embedding and being active undetected**. Although deep learning structures, such as **Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory (LSTM)** networks for **intrusion detection** have been promising, there are few works on **hybrid frameworks** with **optimal feature selection**.

In this study, we compare the effectiveness of the four **hybrid deep learning architectures**: **CNN**, **LSTM**, **BiLSTM**, and **CNN-BiLSTM with attention**. With the aim to tune these models, we used **Particle Swarm Optimization (PSO)** for **feature selection**, to reduce **dimensionality** of **features**, optimize accuracy, and **computational time of prediction**. To address the **class imbalance** problem in **multiclass classification**, the **Synthetic Minority Over-sampling Technique (SMOTE)** is combined with PSO.The models are evaluated on four established **cybersecurity datasets**, namely, **Linux APT 2024**, **UNSW-NB15**, **CIC-IDS (2017–2019)**, and **TON-IoT**. Results show that the **CNN-BiLSTM-attention** model trained by**PSO and SMOTE** can reach at most statistical significance of **97%** and **F1-score = 0.98**. By using this scheme, we achieve a gain of **3–7% accuracy** on the deNoised model with **30%** reduced **training time**. The model also has strong **generalization** to all **APT categories**.

In this paper, we present a **scalable PSO-SMOTE-based detection framework** for **high-dimensional imbalanced security datasets**. To the best of the author's knowledge, it is also the **first effort** to perform an extensive comparison of hybrid deep learning models in radical relation to the PSO-based feature selection. The results demonstrate that **swarm intelligence** and **deep learning** can be combined to form an effective & adaptive solution to **real-time APT threat detection** as well.

Keywords :Advanced Persistent Threats (APTs), Intrusion Detection Systems (IDS), CNN-BiLSTM with Attention, Hybrid Deep Learning Models, Particle Swarm Optimization (PSO), Model Generalization

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CHAPTER 1

Introduction

1.1 Cyber Security Vs Threat Landscape

Cybersecurity is a multidisciplinary domain focused on safeguarding computer systems, networks, applications, and data from attacks, damage, or unauthorized usage [1]. This is crucial for maintaining confidentiality, integrity, and availability in an increasingly digital world [2]. Cyber attacks are continually becoming more sophisticated, frequent, and severe. An effective design of a defense should involve an understanding of nature and classification of cyber attacks[3].

Cyber Threat Classification Cyber threats are taxonomised along multiple dimensions, reflecting different aspects of the attack ecosystem:

- **By Attack Vector:** Indicates a way or route attackers use to unauthorized access to, or compromise, systems.
  - *Network Attacks:* Attack network protocols/infrastructure (, DDoS, IP spoofing, port scanning).
  - *Host-based Attacks:* Infected software therefore installed in some hosts; such as viruses, ransomware, spyware, rootkits.
  - *Application-level Attacks:* Exploit bugs in software programs (e.g., SQL injection, cross site scripting, buffer overrun).
  - *Physical Invasion:* Need to be physically near the device or inside protected areas (e.g., hardware keylogger, USB attack).
  - *Social Engineering Attacks:* Social engineering attacks deceive individuals using human psychology to bypass technical processes (phishing, pretexting, baiting).
- **By Threat Actor:** By membership of adversaries and what tools or ways of working they use.

  - *Cyber-criminals:* This includes the attacker looking to make a profit, be it fraud, ransom, theft
  - *Hacktivists:* Work for political or ideological reasons, often to disrupt or deface.
  - *Nation-State Actors:* Sophisticated attackers conducting espionage, spying, or sabotage to further geopolitical goals, with substantial financial resources.
  - *Insiders:* These are authorized users who intentionally or unintentionally hurt computer security.
  - *Script Kiddies:* Low-skill attackers who only use tools from others.

- **By Attack Target:** This type represents objectives of cyber-attacks.
  - *Espionage:* Stealing information of a classified, proprietary, or strategic nature.
  - *Sabotage:* Disruption of services, infrastructure, or functionality.
  - *Theft and Scams:* theft of financials, credentials, or IP for profit.
  - *Reputation Damage:* Disparage specific people, entities, or authorities.
  - *Extortion:* Demanding payment for access, return, or non-publication (e.g., ransomware).

- **By TTPs:** Commonize modeling is done where we use MITRE ATT&CK to understand how things that we are doing have been used by the adversary.
  - *Initial Access:* Means into software from phishing, supply chain, or drive-by downloads.
  - *Execution:*Running evil/badness scripts or executables on an infected host.
  - *Persistence:* Access is retained via persistence backdoors, scheduled jobs, or registry modification.
  - *Privilege Escalation:* Abusing security holes to obtain higher or special privileges.
  - *Defense Evasion:* The hiding or replication of features to hinder the use of reflective methods (e.g., encryption, polymorphism).
  - *Command and Control (C2):* Communicating exfiltrated commands to, and control over, successfully victimized systems.

– *Exfiltration:* refers to the procedure of transferring and retrieving information from the target network.

The tremendous multifaceted nature of the cyber threats is the cause for this taxonomy [4]. The threats with these elements have increased as the digital universe continues to grow with cloud, mobility, and Internet of Things (IoT), the attack surface becomes wider, and the attackers are finding better attacks. [5].

Cybersecurity is truly a race between the capabilities available to attackers and those available to defenders [6]. The proliferation of cloud computing, mobile, and IoT in remote working scenarios has been expanding the attack surface of modern organizations [7].

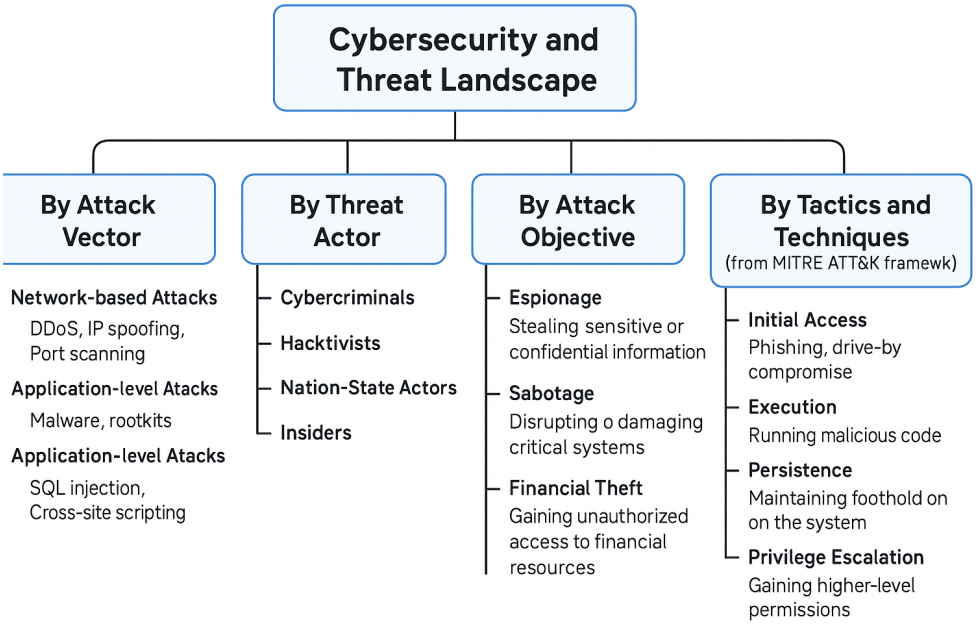


Figure 1.1: Taxonomy of Cybersecurity Threats

Furthermore, cyber attacks have gained a new level of complexity, in which the adversaries employ automation, AI, and stealth methods to bypass legacy guards [8]. The proliferation of supply chain attacks, ransomware-as-a-service (RaaS), and international cyber warfare demonstrates that cybercrime has evolved into a sophisticated, global industry [9]. Concurrently, legislation such as GDPR, HIPAA, and NIST has increased the importance of strong security governance and near real-time threat detection [10].

Given these odds of a tough B2B landscape, real-time monitoring and fast response are a must. That's when **Intrusion Detection Systems (IDS)** become helpful [11], becoming a fundamental layer of the cybersecurity defense framework, being able to detect and alarm suspicious actions over the networks, including the hosts.

1.2 Landscapes of Cybersecurity and Intrusion Detection Mechanisms

In this age of ubiquitous connectivity, **cybersecurity** is a major concern as our dependence upon **digital systems** and networks grows. This rising digital reliance further amplifies the susceptibility to different **cyber hazards** to the **privacy, security, and accessibility** of important information and infrastructure [2, 1].

Intrusion Detection Systems (IDS) serve as a fundamental security mechanism for networked settings, monitoring for anomalous behavior or illegal access in near real-time [11]. The predominant genres of Intrusion Detection System (IDS) technologies are: **signature-based** and **anomaly-based** methodologies [12].

Signature-based detection involves comparison of input patterns to a database of known threat signatures to detect malicious behavior. Although these systems are good at recognizing known attacks[12], they are quite limited in detecting **new, disguised, zero-day threats**, and especially **APTs (Advanced Persistent Threats)**[5].

Alternatively, intrusion detection systems based on anomalies (IDS) are made to create **a paradigm** of **normal system behavior**, and anything in the feature space that does not meet that model is considered an anomaly. These systems are better suited for detecting **novel or adaptive threats**. However, they are vulnerable to **high false positive rates**, especially when responding to **slow** or **low profile** attacks such as APTs [3].

Because of this hardness, intelligent and adaptive detection models are increasingly being attracted lately. The infusion of **ML** and **DL** into IDS frameworks is becoming increasingly popular, providing stronger capabilities in dealing with **dynamic and sophisticated cyber attacks** [8].

1.2.1 The Changing Face of Advanced Persistent Threats

APTs are the most malicious type of modern cyberattacks. They are *targeted, multi-stage, and stealthy* attacks orchestrated by well-funded adversaries(e.g., nation-states or crime syndicates) and are developed to be stealthy for long periods of time[5, 13]. A daily iteration of APT tooling and tradecraft emerges from recent threat-intelligence reports, with attackers gradually adapting to the constant blue-team-driven process. openly embracing automation, AI-enabled reconnaissance, and the *living-off-the-land* approach.Table below highlights hallmark Tactics, Techniques, and Procedures (TTPs).

Phase	Typical Techniques (MITRE ATT&CK references)
Initial Access	Spear-phishing attachments (T1566.001), supply-chain compromise (T1195)
Execution	PowerShell / WMI abuse (T1059), malicious scheduled tasks (T1053)
Persistence	Registry run keys (T1547.001), web-shell deployment (T1505)
Privilege Escal.	Token manipulation (T1134), kernel exploit (T1068)
Defense Evasion	DLL sideloading (T1574.002), timestomping (T1070.006)
C2 & Lateral	Encrypted C2 over HTTPS (T1071.001), RDP pivot (T1021.001)
Exfiltration	Compressed archives via SFTP (T1560.001)

Table 1.1: Characteristic TTPs associated with modern APT campaigns.

Sample APT-style Campaigns .

- **Ryuk ransomware:** uses spear-phishing, domain-wide lateral movement, and privilege escalation in order to encrypt valued assets [14].
- **DarkTequila banking malware:** builds modular payloads that they activate only on Latin-American

  targets, multi-stage evasion techniques from endpoint protection [15].

Key Challenges .

To counter APTs, which are known to be difficult to thwart because of their:

persistence–months dwell time,

complex multi-vector attacks and exploit-0 days, and

stealth

(i) anti-forensic tooling
(ii), TTP mimicry[16, 17, 18].

Prevention of Adhesion .

A defense-in-depth strategy, with several layers of defense, is necessary.[19]:

- **Security Awareness Training** - regular phishing simulations and job-Social training to decrease social engineering vectors.
- **Zero Trust Network Segmentation** – least privilege access and micro-segmentation to restrict lateral movement.
- **Proactive Vulnerability Management** – ongoing scans, patches and risk mgmt.Internet-facing assets ranking.

- **Advanced Threat Protection (ATP)** – behaviour-based EDR, sandbox detonation, and threat-intel integration.
- **Cyber Controls Monitoring** – encryption, TLS Termination (D), and machine-learning analytics for the detection of anomalies.

Figure 1.2: Common categories of cyber-attacks

Implementation of an APT Detection System Focused on APT Deployment.

1. **Asset Triage:** Discover crown-jewel data stores, OT/IoT segments, and mission-critical SaaS services [20].
2. **Sensor Placement:** Implement trust perception *sensors of deep-learning IDS sensor* .At least one set of at least one challenge any of the following locations in the *deep-learning IDS*network, including a layer perimeter and DMZ, and east–west chokepoint traffic.
3. **Model Lifecycle:** Retrain ML/DL models with threat is collecting them continuously with enriched threat intelligence feeds, red-team telemetry, and adversary emulation sources [21].
4. **SIEM SOAR Integration:** Forward high-fidelity alerts to a centralized SIEM and to Security Orchestration, Automation and Response (SOAR) platforms for additional correlation and context enrichment, automatically triage through SOAR playbooks for quick response.

5. **Purple-Team Validation:** Perform periodic APT emulation (e.g., MITRE ATTCK) to validate defenses to measure detection coverage and for system tuning [22]).

1.3 Deep Learning in Cybersecurity Domains

Highly advanced subsection of **ML Models**,**DL Models** has great influence in the domain of computer vision, speech processing, and natural **language interpretation**[23, 24]. Recently, its application in **cybersecurity**, for prevention, and in particular for **intrusion detection**, has gained much attention owing to its powerful capability to capture and analyze **complex, high-dimensional patterns** in massive databases[25, 8].

Differing from traditional methods, **deep learning architectures** have the advantage of learning multiple-level feature representations directly using raw input data, mitigating the requirement of manual feature design[26]. This inherent flexibility is also particularly beneficial in the **cybersecurity domain**, where the threat signatures are always drastically different and have multimodal behavior patterns[27].

Network traffic data also OW architectures such as CNNs and RNNs (including their variants such as LSTM networks) have been widely applied[28, 29]. They are also applicable to modern intrusion detection systems due to their ability to generalize over different cyber threats. Moreover, the hybrid models, incorporating CNNs and LSTMs, such as Bi-directional LSTM (BiLSTM) and the attention-based CNN-BiLSTM, have shown benefits in aggregating network data's spatial and temporal features for the detection application[8, 30].

1.3.1 An RNN variant is LSTM, or Long Short Term Memory.

Using the advent of the LSTM architecture, the author highlights the necessity of network units to preserve the knowledge over longer sequences, and LSTM was presented as a solution to sequence learning only using Recurrent Neural Networks (RNN). LSTMs have several desirable features in the realm of intrusion detection:

- **Sequential Modeling** LSTMs (with which TRAI was implemented) are capable of learning time-series based patterns in network traffic, and can be used in detecting slow-evolving threats such as APTs [25].
- **Noise Tolerance:** They tolerate the noise and high variation in real-life network data [27].
- **Adaptive Learning:** Large LSTM models may be trained on a large history of

logs and be incrementally updated to recognize new attack behaviors, zero-day attacks [30].

These characteristics render the LSTM an ideal candidate for constructing future intrusion detection systems[8].

1.4 Identified Limitations and Motivation of the Study

A review of existing intrusion detection systems shows the following shortcomings that limit the capability of accurately recognizing advanced persistent threats:

- **Ineffective APT Detection:** Traditional IDSs are easily evaded by stealthy, multi-stage APT behaviors with low signal [3].
- **Sparse Temporal Modeling:** While most of the IDSs utilize CNNs for capturing spatial information, less incorporate LSTM networks to model temporal sequences of the network traffic stimulation [8].
- **No Optimization of Features:** Only a handful of works have employed sophisticated optimization methods, such as PSO, in order to boost the effectiveness of detection and achieve dimensionality reduction [31, 32].
- **Restricted Dataset Diversity:** Some of the previous works leverage synthetic or specific datasets, which substantially decrease their reality and generalizability [33].
- **Hybrid Modeling Scarcity:** Few works explore hybrid deep learning strategies with multiple architectures and optimization methods to either obtain higher accuracy or increase robustness [30].

A hybrid deep learning and optimization approach is therefore motivated in this thesis to address these challenges based on an intelligent, real-time, and adaptable detection system.

1.5 Motivations & Contributions

In this paper, a **hybrid infrastructure** is designed and evaluated using **deep learning** for the detection of **APTs**. The approach combines **LSTM** with **PSO** to optimize feature selection.

Goals of study

- To study the **limitations** of existing **IDS** in detection of **APTs**.
- To design a **hybrid architecture** combining **LSTM networks** and **PSO** based detection with better effectiveness.
- To illustrate the efficacy along with the effectiveness of the suggested approach on **benchmark datasets** which are Linux APT 2024, UNSW-NB15, CIC-IDS 2017–2019, and TON-IoT [33, 34, 35].
- To compare the proposed hybrid approach with conventional models of both deep learning and machine learning in terms of different evaluation metrics (Section III).
- To demonstrate the efficacy of the model in detecting **complex multi-phase** and **stealthy cyber attacks** within a **dynamic** setup.

This thesis makes the following primary contributions:

- Developing a **hybrid IDS** by integrating an attentive **LSTM** with optimization algorithms from the **PSO** [8, 31].
- Introduction of a **feature optimization pipeline** based on **PSO** for **input dimensionality reduction** and minimization of **computational effort** [31].
- Validation with **divrse, real-world cybersecurity datasets** for **robustness** and **applicability** [33, 34].
- A comprehensive study of comparing **hybrid** and **standalone deep models** for **APT detection** [30].

1.6 Thesis Structure

The subsequent chapters are lined up with the following structure:

- **Chapter 2: Research Challenges and Objectives** – Outlines the main research issues and questions addressed in this work.
- **Chapter 3: Literature Review** – Reviews related work in intrusion detection, deep learning, and optimization methods.
- **Chapter 4: Methodology** – Explains the system architecture, dataset setup, model composition, and feature selection process.

- **Chapter 5: Experimental Setup** – Describes the implementation environment, evaluation metrics, and experimental design.
- **Chapter 6: Experimental Results and Analysis** – Presents the outcomes and evaluates the performance of the proposed models.
- **Chapter 7: Conclusion and Future Work** – Summarizes key findings and suggests directions for future research.

CHAPTER 2

Research Challenges and Objectives

2.1 Background Context and Motivation for the Study

The growing **impact of complex** modern cyber-attacks, especially Advanced Persistent Threats (APTs), and the limitations of current systems for APT detection-Intrusion Detection Systems (IDSs) - inspire this research. High profile events such as the **SolarWinds hack**[36], the **Stuxnet worm** [37]. Other **state-sponsored operations** have illustrated the ability of APTs to overcome traditional defences, to operate **undetected** on an organisation's networks and often to result in **large-scale data exfiltration** and **operational disruption**. Within the New Zealand environment, incidents are increasing concerning **CERT NZ cyber**,**phishing**, **ransomware**, and **targeted attacks** [38]. These national trends also underscore the fact that securing environments against **stealthy**, **persistent attacks** is truly a **worldwide** knowledge problem [39]. A promising ability to model **temporal relationship** in sequential data, such network traffic patterns, is demonstrated by advancements in **deep learning**, particularly the **Long Short-Term Memory (LSTM) networks** [29, 25]. However, development of **effective IDS frameworks** takes more than just adapting deep learning models, but it requires incorporation of **intelligent feature selection** and **dimensionality reduction** in order to manage with **big datasets**, limit **computational cost**, and to be capable of **real-time detection** [40].

In order to solve this issue, this work presents a **stable and scalable hybrid intrusion detection system framework** based on pragmatic constraints and tested with real datasets.

2.2 Problem Statement

As the world becomes increasingly interconnected through the internet, concerns over both security and privacy have become more pressing than ever [2]. Attacks

by the enemies are now more advanced and stealthy, with APTs being among the most advanced attacks that are hard to stop. Characteristics of these attacks are the multi-step nature, the strategic patience, and the ability to adopt the behavior of the normal system for a long time, making them highly resistant to traditional IDS techniques for detecting such attacks.

Traditional IDS methods suffer from significant drawbacks:

- Signature-based approaches rely on the knowledge of the attack signatures, and they are not effective against new or previously unknown threats [11].
- Anomaly detection methods characterize the normal operating behavior of the network; however, they are prone to large numbers of false alerts since the real traffic is always changing [12].

In addition, those classical approaches are static and are not easily adaptable to new attack techniques. The amount, velocity, and variety of network data in current infrastructures impose strong scalability and efficiency demands for existing IDS solutions [3]. Also, manipulating high-dimensional data may deteriorate model reliability and compromise real-time response time.

In order to overcome these difficulties, it is important to construct an intelligent IDS that can learn adaptively from the incoming data, model the temporal dependencies, and capture the essential elements to raise the accuracy of detection. This research offers a deep learning framework comprised of LSTMs, PSO techniques that is proposed for scalable, accurate, and real-time APTs identification.

2.3 Motivation

Three key motives are underpinning this research:

- **Improvement in real-time detection of stealthy multi-stage attacks:** Advanced persistent threats (APTs) are still a serious threat because of their stealthiness and persistence. To catch these patterns, temporal modeling as well as smart feature extraction are needed [27].
- **Improving model performance with segment optimization:** PSO is an efficient approach, can be used for selecting the most important input features, thus improving detection rate as well as system speed [31]. Autoencoders also help learning compact and denoised representations of network traffic data [32].

- **Bridging academic research and application:** Most IDS models are either purely theoretical or tested on synthetic data. In order to make sure that the suggested system can withstand a range of field circumstances and usages, the goal of this thesis is to deploy and assess the system on several real datasets.

2.4 Research Objectives

So, to address the challenges and the goals that have been described above, we organize our investigation along the following lines:

1. **Create an IDS based on deep learning using LSTM networks, which can recognize APTs.**
    - Design an LSTM architecture that can measure temporal trends of the attack actions [29].
    - Train the model to recognize the subtle, sequential indicators of APT activity [25].
2. **Inclusion of PSO for adaptive feature selection, psodynamics.**
    - PSO is used to detect important features in high-dimensional network traffic data [31].
    - Evaluate the impact of PSO in increasing the detection performance and enhancing the training speed [41].
3. **Conduct large-scale evaluation on the proposed IDS framework with different real-world data**
    - Test the system on known datasets such as Linux APT 2024, UNSW-NB15, CIC-IDS 2017–2019, and TON-IoT [33, 34, 35].
    - Similarly, use a number of performance criteria, including accuracy, precision, recall, F1-score, and computational efficiency, to compare the results to well-established IDS approaches.

2.5 Expected Contributions

This thesis is anticipated to provide a gap in the academic literature as well as practical cybersecurity in the following ways:

- A novel hybrid intrusion detection system with a combination of LSTM, PSO to detect APTs in real-time.

- Empirical evidence of the mechanism by which PSO encourages feature selection, model complexity reduction, and ensembling model generalization.
- Experimenting with the proposed model on several realistic datasets, proving its operationalisation and generalisation.
- Practical guidance on deploying scalable deep-learning-based IDS in complicated and changing network infrastructures.

These advances aim at the implementation of advanced IDS that are intelligent, capable of adapting, and resilient, to take on the ever-changing realm of cybersecurity threats.

CHAPTER 3

Review of Literature

3.1 A Brief Introduction

The ongoing evolution in cyber attacks, particularly **Advanced Persistent Threats (APTs)** [5], underscores the necessity for more **adaptive** and **intelligent intrusion detection systems (IDS)**. Because they are low-key and sophisticated, traditional detection approaches struggle to recognize these **covert**, **multi-phase** intrusions. In response, **advanced deep learning approaches**, especially those based on **LSTM** networks [29] and also the integrated hybrid architectures, have recently demonstrated strong potential. When combined with optimization strategies such as **Particle Swarm Optimization** for efficient **feature extraction** [31], these models offer promising solutions to address the limitations of conventional systems. This chapter critically reviews existing research on APT characteristics, deep learning-based IDS frameworks, PSO-driven feature selection methods, and widely used cybersecurity benchmark datasets [33]. It concludes by highlighting essential research gaps that underpin the motivation for this study.

3.2 APTs and Detection

APTs are complex, **well-planned** cyber attacks, characterized by their **long**, **covert inclusion** that take place in particular network systems, mostly carried out by actors possessing a high level of resources[5]. Unlikely rake and run attacks, which are designed to provide immediate payoff, APTs leverage several simultaneous attack vectors such as **phishing**, **malware discovery**, **privilege escalation**, and **lateral movement** to escape detection and steal sensitive information[42, 13].

Anomaly-based and signature-based methods are the primary considerations of conventional, traditional intrusion detection systems are less efficient against APTs because they are based on known attack signatures and a simple detection threshold

of anomaly detection[43]. Signature-based IDSs commonly fail to deal with **new** or **hidden threats** such as zero-day vulnerabilities, whereas anomaly-based IDSs experience **high false positive rates** and have the difficulty effectively characterizing the **long-lasting** and **delicate activities** often adopted by APT campaigns[16].

Therefore, there is an ongoing focus on **machine learning** and **deep learning** algorithms that are capable of recognizing subtle behavioral and temporal patterns to improve APT detection.

3.3 DL-based Frameworks for Threat Detection

Recurrent Neural Networks (RNNs) are architected to process **ordered sequences**, making them a viable choice for examining network traffic behavior. Nonetheless, conventional RNNs face challenges such as the **vanishing gradient issue**, which impairs their effectiveness in retaining **long-range contextual information**, a crucial requirement for identifying slow and progressive cyber threats [44]. Long Short-Term Memory models are implemented to tackle this by incorporating specialized **memory components** and **control gates**, and the input, forget, and output gates, which govern data flow and facilitate learning over lengthy sequences [29]. Research has shown that LSTMs are proficient at modeling **time-dependent behaviors** in traffic data, an ability that significantly enhances Intrusion Detection Systems (IDS) [25]. They can uncover minor anomalies and evolve activity patterns that may signal hidden attacks. Furthermore, integrating **attention layers** into LSTM architectures empowers the capacity of the model to pinpoint complex and multi-step assault plans by selecting and prioritizing significant input sequence segments [30].

3.3.1 Hybrid Deep Learning Models: CNN, BiLSTM, and Attention

Integrated architectures that merge **Convolutional Neural Networks (CNNs)**, **Bi-directional LSTM (BiLSTM)**, and **attention modules** are increasingly adopted because they're empowered to capture detailed **spatial** and **temporal dynamics** within network traffic data [8]. CNN layers are proficient at uncovering localized structures and packet-level features. In contrast, BiLSTMs process input sequences bidirectionally, enhancing the network's ability to understand the surrounding **contextual information** [45].

Adding attention layers further enhances the network by dynamically assigning importance weights to different temporal segments or features, thereby increasing both **interpretability** and **detection accuracy** [30]. Experimental results demonstrate

that these hybrid architectures outperform individual CNN or LSTM models in multi-class intrusion detection scenarios [45, 8].

However, significant challenges persist in adapting these architectures to handle **large-scale**, **high-dimensional** data efficiently, particularly in refining feature selection processes to minimize model complexity and enhance generalization capabilities.

3.4 Feature Selection Optimization for Efficient Intrusion Detection

3.4.1 Challenges in Feature Selection

As for network intrusion datasets, it's common that they are **high-dimensional** and with **redundant** or **irrelevant features**, which will degrade the enhance the performance of the framework and lengthen the duration of training[46]. Active **feature selection** is an imperative approach to noise reduction, and thereby detection performance improvement and real-time **implementation** of intrusion detection systems (IDS)[21].

3.4.2 Feature Selection with PSO

The algorithm known as particle swarm optimization (PSO) is a **population-based** metaheuristic technique which is motivated by the *cooperative and collective* movements of birds and fish[31]. The PSO updates search points based on their individual and group experiences in order to efficiently balance the **exploration** vs. **exploitation** trade-off for exploring the huge feature space[47]. In the application of PSO to IDS, recent literature highlighted improvements in **detection accuracy**, while achieving low **computational complexity** [47, 48]. Nevertheless, most of the early works have focused on fusing PSO with traditional machine learning approaches, but less attention was paid to models that use deep learning, which include a hybrid model of the **CNN**, **Bidirectional Long Short-Term Memory (BiLSTM)**, and **attention**, feature selection relies on PSO.

3.5 Benchmark Datasets for Intrusion Detection Research

Designing and assessing intrusion detection systems (IDS) effectively depends on the selection of appropriate datasets. In this field, the following datasets are frequently used:

- **UNSW-NB15** [33]: A contemporary dataset featuring various attack types and realistic network traffic characteristics.
- **CIC-IDS 2017–2019** [34]: Publicly accessible datasets encompassing diverse benign and malicious activity scenarios.
- **TON-IoT** [35]: Concentrates on Internet of Things (IoT) environments by capturing telemetry and network traffic data.
- **Linux APT 2024** [49]: A recently introduced dataset that emulates real-world Advanced Persistent Threat (APT) behaviors within Linux systems.

Despite their importance, many research efforts rely on only one or two datasets, which limits the **generalizability** and **robustness** of developed models. Evaluating IDS across multiple datasets remains relatively underexplored, even though it is crucial for designing solutions that perform well in varied environments [21].

3.6 Conclusion and Future Work

To handle these problems, a hybrid IDS system that combines **PSO, Particle Swarm Optimization** based feature selection and **CNN-BiLSTM-Attention** is proposed in this study. We evaluate the framework on various academics' datasets, namely,**Linux APT 2024**, **UNSW-NB15**, **CIC-IDS**, and **TON-IoT**, where the novelty of the proposed work is presented in a significant improvement in those gained with respect to **detection accuracy**, **performance computation**, and **resilience** against modern attackers' fundamental standards of **APTs**.

3.7 Research Gaps Summary

Despite significant progress in intrusion detection, there remain significant challenges that impede **robust**, **scalable**, and **broad-reaching** solutions for detecting *Advanced Persistent Threats* (APTs). The main challenges revolve around devising *good model architectures*, improving **feature selection methods**, **provisioning access** to diverse and realistic benchmark datasets, and deploying the models within the complex, real-world setting of cybersecurity.

3.7.1 Gap 1: Limited Integration of Particle Swarm Optimization with Advanced Hybrid Deep Learning Architectures

Despite the effectiveness of PSO as a meta-heuristic approach for feature selection in traditional ML-based ID systems [47, 48], its application in the context of advanced hybrid neural network architectures, especially those that use attention mechanisms, CNNs, and BiLSTMs, has not been widely explored. The majority of existing solutions perform feature selection and deep learning training with two separate steps, possibly leading to suboptimal feature representations being passed to the complex models. This gap may hinder deep learning architectures from effectively leveraging the most informative features, and thus impair decision-making accuracy as well as computational efficiency.

3.7.2 Gap 2: Insufficient Evaluation Over Multiple Diverse Real-World Datasets

Approaches When testing their models with one or a few datasets, they usually use one of UNSW-NB15 or CIC-IDS [33, 34].

This approach also begs the question of how robust and applicable the proposed solutions are, considering that network conditions, attack models, and traffic behaviors vary significantly across deployments. Furthermore, most of the available datasets are of a synthetic nature or reveal incomplete visibility of the complex APT scenarios that cannot showcase the variety of attacks [21]. The sparse use of multiple diverse collected datasets, such as more recent, real-world-oriented sets like Linux APT 2024 and TON-IoT, leads to a lack of understanding of model performance when applied to different operational scenarios.

3.7.3 Gap 3: Underexplored Synergy Between Attention Mechanisms and PSO-derived Feature Optimization

Attention mechanisms have been successful in enhancing deep learning models by selectively focusing on the most relevant temporal or spatial features[30, 45].

But the joint impact of attention layers and PSO feature selection has not been well studied. While PSO optimizes the selected input feature set, attention mechanisms compute at run-time the weights to be assigned to the different features or elements of a sequence. Investigating such interplay could lead to anti-correlation models which simplify input complexity and enhance interpretability as well as detection

accuracy. This combined method is one promising aspect that has not been studied in current research.

3.7.4 Gap 4: Real-Time Accurate Detection with Low Computational Overhead

Whilst many deep learning-based IDS have shown impressive performance in offline experiments, they often neglect practical issues such as computational resources limitations, latency, and scalability[46]. To deploy these models in realistic application scenarios, one has to carefully trade off detection performance and complexity level. Hybrid models, however, even though promising, often require a large amount of resources, which in turn can make real-time analysis difficult, especially with high-dimensional data streams. Despite the model compression effect, little attention has been paid to this trade-off, and few have investigated how it to be effectively applied in practice, where early detection is much needed.

3.7.5 Gap 5: Absence of inclusive comparative studies between hybrid deep learning models and traditional IDS Techniques

The current studies usually introduce new deep learning techniques or feature selection methods, but they often do not include comparisons with the traditional IDS methods, for example, Random Forests, Support Vector Machines, or detailed ensemble approaches[50].

Also, comprehensive experimentation on multiple datasets and the different attack categories is limited. Overcoming the lack of availability of such datasets hinders us from evaluating the pros and cons of hybrid deep learning frameworks for further processing based on PSO feature optimization. Stringent benchmarking is necessary for such advanced techniques to confirm their operational performance and benefits.

Advantages and Drawbacks of the Selected Models

Numerous models and strategies for intrusion detection have been developed in the literature; however, each has inherent limitations that impact its capacity to identify APTs:

Particle Swarm Optimization (PSO)-based Feature Selection

Pros: PSO is a powerful metaheuristic that efficiently chooses features, reducing the dataset's dimension and improving the effectiveness of traditional machine learning. classifiers [47, 48]. This makes training and inference even faster, and it can reduce overfitting.

Cons: In spite of its merits, PSO is typically used independently with deep learning model training, which restricts its potential to accommodate feature subsets with regard to the representational requirements of intricate hybrid architectures. This disconnection can cause non-optimal feature sets, limiting the detection accuracy and model generalization.

Hybrid CNN-BiLSTM Systems:

Pros: Such architectures are able to learn both spatial features (e.g., using CNN layers) and temporal dependencies (e.g., with BiLSTM layers) and thus can effectively model the high-dimensional, sequential structure of network traffic as well as the patterns of the APT activity [8]. When used with attention mechanisms, they are able to dynamically attend to the most important features, improving detection performance accordingly.

Cons: Hybrid models are computationally expensive and need a large amount of training data. Without proper features, these detectors can easily suffer from overfitting or inefficiency, making them less promising to be deployed in time-sensitive and resource-limited circumstances.

Attention Mechanisms

Pros: Attention layers are able to enhance model interpretability by assigning weight for different input features or temporal elements dynamically in inference time [30, 45]. As a result, the model can concentrate on the most pertinent aspects of the data, potentially improving interpretability and accuracy.

Cons: It is not well investigated how to use attention with PSO optimized features. Recent research rarely explores how these methods synergistically work together to minimize the input level of complexity, improve the focus of the model, and task performance.

Benchmark Datasets:

Pros: Well-established datasets, including UNSW-NB15 and CIC-IDS, provide a reference point for model comparison. Datasets also have a mix of attack types [33, 34]. These datasets enable comparisons to be made between studies and promote reproducibility.

Cons: Synthetic or too simple to meet the complex and diverse real world APT datasets [21]. The lack of available 'real world' datasets, especially including datasets derived from modern IoT and Linux environments, like Linux APT 2024 and TON-IoT, prevents the generalization of model evaluation.

These benefits and drawbacks all demonstrate the need for a complementary strategy, based on the implementation of the PSO feature selection in combination with locally- and discriminatively-aware, to be increasingly performed within strongly regularized advanced hybrid CNN-BiLSTM-Attention frameworks, even tested and benchmarked on diverse and realistic databases. This approach aims to overcome the shortcomings of the existing APT detection methods by balancing interpretability, accuracy, and computing economy.

Summary of Literature Review

These voids underpin the need for research that neatly fused **Particle Swarm Optimization** for feature selection and state-of-the-art hybrid **CNN-BiLSTM-Attention** models. To verify their **robustness** and **generalization**, the above systems should be tested on **diverse real-world datasets**, e.g., **Linux APT 2024** and **TON-IoT**. Another important aspect happens to be the required **computational trade-offs** for **real-time deployment**.

The under-explored interaction of **attention mechanisms** and PSO-based **feature selection** also offers new opportunities for improving both **detection accuracy** and **model interpretability**. However, even with substantial advancements in **intrusion detection** (through application of **deep learning** and metaheuristic optimization techniques), these issues remain [31, 8, 33, 34, 30, 46, 5].

Building on these shortcomings, then, in this thesis, we envision developing a **robust** and **scalable** hybrid deep learning framework that is fine-tuned by particle swarm optimization and is further validated over diverse real-world datasets to push forward the frontiers of APT detection.

CHAPTER 4

Methodology

The methodology for developing, implementing, and assessing sophisticated **APTs** for intrusion detection systems is covered in this chapter. The study uses a *multi-dataset fusion strategy* that enables the fusion of six publicly available cybersecurity datasets, namely, **Linux APT 2024**[51], **UNSW-NB15**[52], **CIC-IDS 2017**[53], **CIC-IDS 2018**[54], **CIC-IDS 2019**[55], and **TON-IoT**[56]. This rich integration allows us to build a strong, scalable, and flexible detection pipeline that can easily detect complex and multi-stage cyberattacks in different networks.

An overview of the research strategy and the rationale behind using a *hybrid machine learning (ML) and deep learning (DL) approach* is provided at the beginning of the chapter. The manipulation of high-dimensional, heterogeneous data using advanced pre-processing techniques, such as feature selection, representation, and normalization, receives particular emphasis. To lower the dimensionality and choose the optimal features, **Particle Swarm Optimization (PSO)** [57] is introduced. We present PSO to enhance classification accuracy and boost computational efficiency in multi-class, imbalanced intrusion detection issues. Afterwards, a variety of models are introduced, covering not only traditional ML techniques, including **Random Forest**[58], **XGBoost**[59], **LightGBM**[60], but also DL architectures such as **LSTM**[61], **BiLSTM**, **CNN-BiLSTM**, and **CNN-BiLSTM with attention mechanisms**. We detail the architectural designs, hyperparameter configuration, and optimization procedures for each of the models to keep the results replicable and tractable.

The chapter also discusses the model evaluation criteria, which give a general idea of how effectively the models can detect the intricate and covert APT operations. These criteria include accuracy, precision, recall, F1-score, and AUC-ROCs.The experimental setup has hardware specifications, software frameworks, and tools, including the implementation. The experiments were performed mainly in **Python** programming language, which made use of libraries like **Scikit-learn**, **TensorFlow**, and **PyTorch**. This complete methodological framework provides a strict and eq-

uitable ground for the evaluation of all models and techniques considered in the present study.

4.1 Model Development Overview

The entire foundation for multi-class APT detection is covered in this section. Figure 4.1 illustrates that the pipeline has several stages in the workflow, including dataset aggregation, preprocessing, data splitting, **PSO-based feature selection**, model selection with the machine learning and deep learning methods, hyperparameter tuning, performance evaluation, and documentation in detail.

Each step is carefully designed in order to have a simple, robust, and reproducible experiment.

- **Datasets:** Six publicly available cybersecurity datasets **CIC-IDS2017**, **CIC-IDS2018**, **CIC-IDS2019**, **Linux APT 2024**, **UNSW-NB15**, and **TON-IoT** are integrated to cover a broad spectrum of attack types and feature diversity.
- **Preprocessing:** Standardized procedures, including handling missing values, consolidating labels, and normalizing features, are applied to prepare consistent and high-quality data inputs.
- **P**artitioning Data: To provide an objective evaluation of model performance, the cleaned dataset is divided into training (70%), validation (15%), and testing (15%) sets.
- **Feature Selection:** To choose the most pertinent and unique traits, Particle Swarm Optimization (PSO), an evolutionary method influenced by collective swarm intelligence, is used. This procedure reduces the dimensionality of the data, which enhances model performance.
- **Model Development:** A hybrid framework is implemented, combining traditional machine learning methods (**Random Forest**, **XGBoost**, **LightGBM**) with deep learning models (**LSTM**, **BiLSTM**, and **CNN-BiLSTM enhanced with Attention**) to extract both spatial and temporal characteristics of cyber threats effectively.
- **Hyperparameter Optimization:** Parameter tuning is performed using grid search and adaptive methods to maximize model generalization and performance.

- **Performance Evaluation:** To offer a comprehensive performance comparison, the models are assessed using a number of metrics, including *accuracy*, *precision*, *recall*, *F1-score*, and *AUC-ROC*.
- **Documentation and Reproducibility:** All experiments, model parameters, and results are systematically recorded to ensure transparency and reproducibility of the research.

4.1.1 Detailed Methodology Flowchart

Figure 4.1 presents the comprehensive research workflow employed to build a multi-class detection system for Advanced Persistent Threats (APTs). Data collection is the first step in the process, which then progresses to data preprocessing and Particle Swarm Optimization (PSO) feature selection. A variety of deep learning and machine learning models are then created, refined, and evaluated. To guarantee complete reproducibility of outcomes, the procedure is finally completed with meticulous documenting and logging.

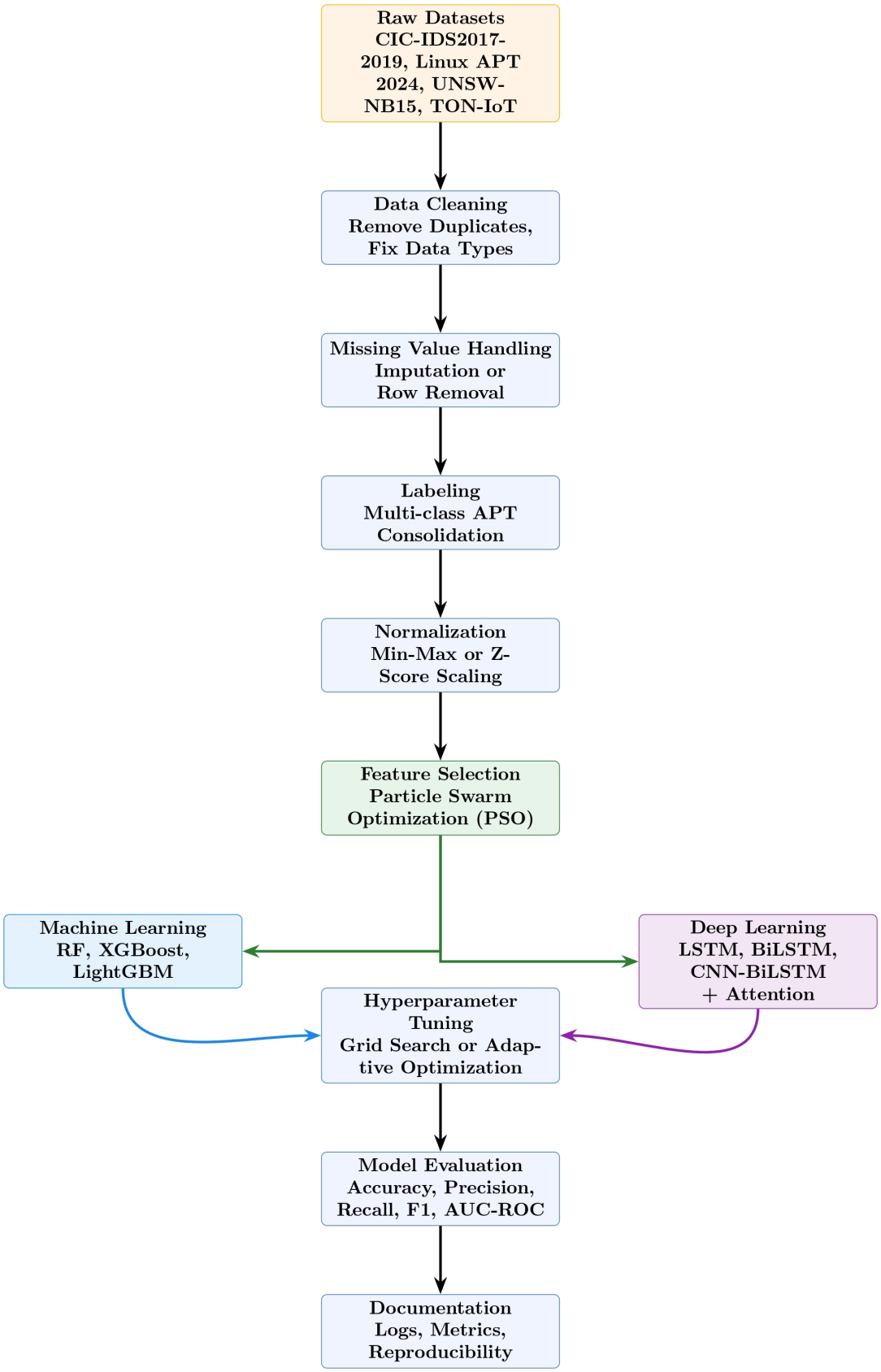


Figure 4.1: End-to-end methodology pipeline for building a multiclass APT detection system.

4.2 Datasets Description and Selection

This study employs six publicly accessible cybersecurity datasets to ensure broad coverage of network behaviors, attack methodologies, and benign traffic patterns. The selected datasets are: **CIC-IDS 2017**, **CIC-IDS 2018**, **CIC-IDS 2019**, **Linux APT 2024**, **UNSW-NB15**, and **TON-IoT 2019**. Each was chosen based on its modern relevance, diversity in attack categories, and rich feature composition.

4.2.1 Dataset Overview

Dataset	Year	Origin / Focus	Key Features	Primary Attack Types
CIC-IDS2017	2017	The Canadian Cybersecurity Institute	78 flow-based attributes (duration, packet size, timing intervals)	DoS, DDoS, Brute Force, Web-based attacks, Botnets
CIC-IDS2018	2018	CIC extended collection	Application-layer data, botnet communication patterns	Botnets, Cryptojacking, Infiltration, Denial-of-Service
CIC-IDS2019	2019	The Canadian Cybersecurity Institute	Network protocols DNS, HTTPS, SSH; modern attack simulations	SQL Injection, Cross-site Scripting (XSS), DDoS, Infiltration
UNSW-NB15	2015	Cyber Range Lab, University of New South Wales	49 features, including content, temporal, and flow-based indicators	Exploits, Reconnaissance, Shellcode, Worms
TON_IoT	2019	IoT telemetry data, University of New South Wales	Device logs, network port metrics, system health data	Ransomware, Man-in-the-Middle, Injection, Password attacks
Linux APT 2024	2024	Simulated Linux enterprise environment	Host telemetry, flow statistics, syscall traces	Credential theft, lateral movement, data exfiltration, command and control

Table 4.1: Summary of cybersecurity datasets incorporated in this research.

Table 4.1 summarizes these datasets, highlighting their diversity and relevance to modern cybersecurity challenges [33, 34, 35]. They cover a broad range of threat

types, including volumetric attacks like DDoS, stealthy infiltrations such as Man-in-the-Middle, host-level breaches including privilege escalation, and IoT-specific threats such as ransomware targeting smart devices [5].

4.2.2 Dataset Comparison by Attack Categories

The following table provides brief definitions for all attack categories encountered in the integrated datasets. This categorization supports consistent labeling, feature interpretation, and multi-class model training across heterogeneous data sources.

Attack Category	Description
Credential Access	Attempts to steal credentials such as usernames, passwords, or cryptographic keys.
Privilege Escalation	Gaining higher-level privileges than initially granted by exploiting system weaknesses.
Defense Evasion	Using stealth techniques to avoid detection by intrusion detection or antivirus systems.
Persistence	Maintaining long-term access to a system despite restarts or credential changes.
Command and Control (C2)	Communication between infected systems and attacker-controlled servers.
Exfiltration	Unauthorized data transfer from a system to an external location.
APT1 Malware Traffic	Stealthy traffic generated by advanced persistent threats (APT) malware.
DoS (Denial of Service)	Flooding services to render them unavailable to users.
DDoS (Distributed DoS)	Coordinated attacks from multiple systems to exhaust target resources.
Backdoor	Hidden access methods allowing remote control of systems without detection.
Password Attack	Credential cracking via brute-force or dictionary attacks.
Injection Attack	Malicious code inserted into input fields or requests (e.g., SQL injection).

Continued on next page...

Attack Category	Description
Scripting on the Cross-Site	Injecting scripts into web content viewed by other users (XSS).
MIM, or man-in-the-middle,	Intercepting and possibly modifying communications between two parties.
Scanning	Systematic scanning of ports and services to identify vulnerabilities.
Ransomware	Malware that encrypt data and demand a ransom for decryption.
Botnet	A network of compromised devices under centralized control.
Web Attacks	General attacks targeting web applications (e.g., SQLi, brute force, XSS).
Infiltration	Unauthorized penetration into systems for spying or sabotage.
Fuzzers	Tools that send malformed data to find vulnerabilities in applications.
Analysis	Attackers inspecting or profiling the system to plan further exploitation.
Reconnaissance	Gathering detailed information about a target system or network.
Shellcode	Payloads that exploit vulnerabilities to spawn remote access shells.
Worms	Self-replicating malware that spreads without user input.
Exploits	Tools that leverage known vulnerabilities in software or hardware.
FTP-Patator	Brute-force tool targeting FTP authentication.
SSH-Patator	Brute-force tool used to attack SSH logins.
Heartbleed	A vulnerability in OpenSSL allowing attackers to read server memory.
Port Scanning	Scanning for open ports/services to identify attack surfaces.
Normal	Legitimate, non-malicious network activity.

4.2.3 Names and Descriptions of Features

Feature Name	Description
srcip	The packet's source IP address flow.
dstip	IP address of the packet flow's destination.
sport	port number of the source.
dsport	port number of the destination.
proto	Transport protocol used (e.g., TCP, UDP).
state	Connection state (e.g., CON, FIN, REQ).
dur	Duration of the flow in seconds.
sbytes	Bytes sent from source to destination.
dbytes	Bytes sent from destination to source.
sttl	Time-to-live value of source packets.
dttl	Time-to-live value of destination packets.
sloss	Number of packet losses at the source side.
dloss	Number of packet losses at the destination side.
service	Application layer service used (e.g., HTTP, FTP).
Sload	Flow byte rate from the source side.
Dload	Flow byte rate from the destination side.
Spkts	Total packets sent from the source.
Dpkts	Total packets sent from the destination.
swin	TCP window size of the source.
dwin	TCP window size of the destination.
ct_state_ttl	Number of flows with the same state and TTL value.
ct_flw_http_mthd	Count of HTTP methods detected in the flow.
is_ftp_login	Flag indicating whether an FTP login was successful.
ct_ftp_cmd	Number of FTP commands observed in the flow.
label	Ground truth class label (e.g., 0 = normal, 1 = attack).

Figure 4.2: Descriptions of Selected Network Features

4.2.4 Attack Taxonomy Visualization

To effectively showcase the variety of attack types encompassed within the integrated dataset, Figure 4.3 presents a hierarchical classification of attack categories along with their associated subtypes. The illustration below gives a systematic overview of the classification approach utilized in this study by grouping threats into broad groups such as host-based, network-based, application-layer, and malware-focused attacks. Rendered in landscape format and adjusted to span the entire page width, the figure aims to maximize readability and visual clarity.

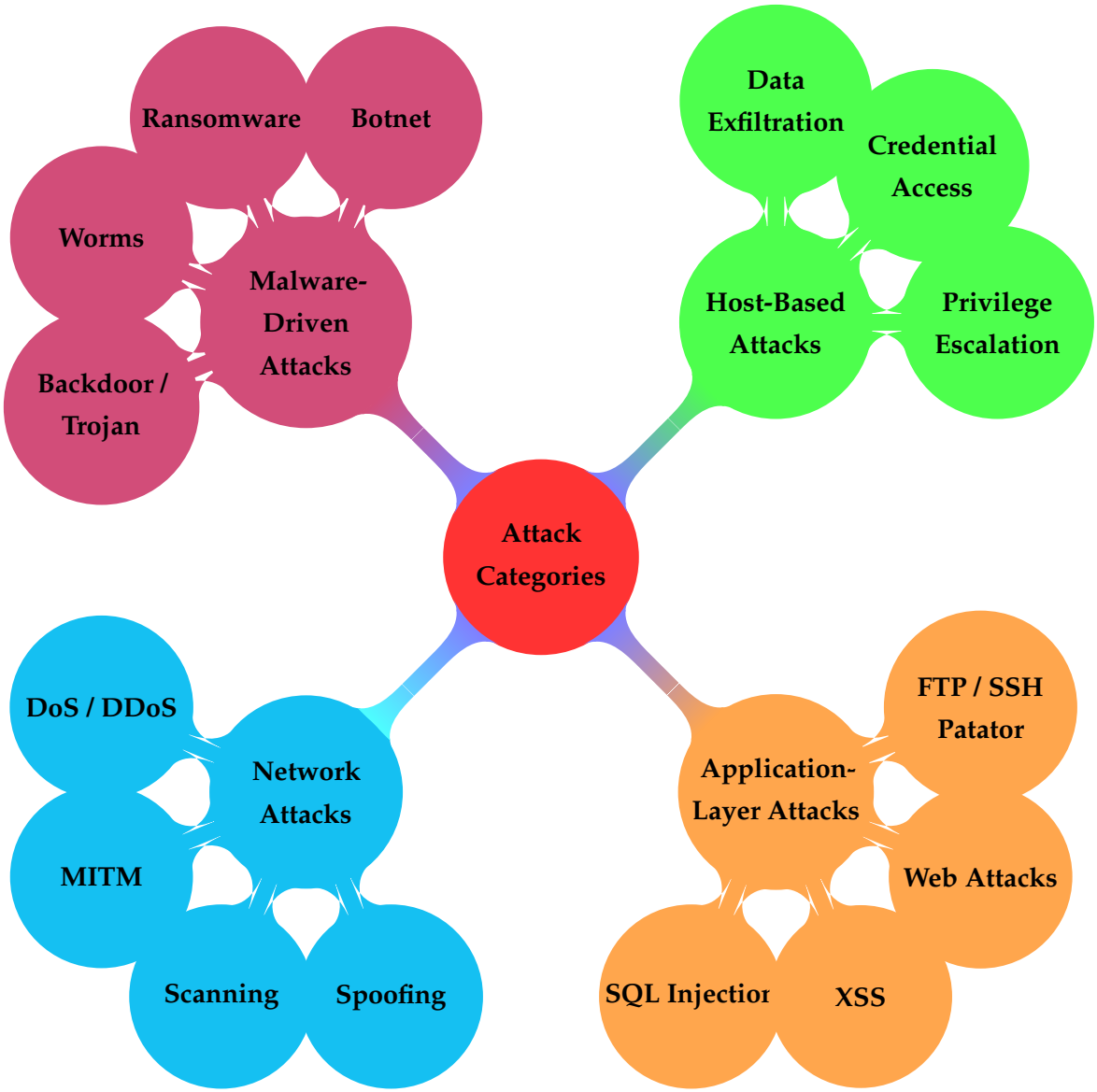


Figure 4.3: Attack Taxonomy Visualization

4.2.5 Individual Dataset Descriptions

Linux APT 2024 Dataset.

The **Linux APT 2024** dataset comprises Linux system logs simulating **Advanced Persistent Threats (APTs)** in an enterprise environment. Covering October 1, 2023, to January 7, 2024, it includes 17 sequential log files merged into over 122,000 events, recorded via the Wazuh SIEM platform [49]. Each log contains detailed **host telemetry** such as timestamps, host identifiers, full command-line details (commands, arguments, payloads), detection rule descriptions, and mapped **MITRE ATT&CK** tactics and techniques [62].

The dataset blends **benign** system activities with tagged **malicious** events, reflecting realistic operational scenarios. Simulated attacks include privilege escalations, keylogging, recent vulnerability exploits (e.g., Apache Struts CVE), and tactics from known APT groups (APT41, APT28, APT29, Turla) [63]. Detection rules utilize **Tactics, Techniques, and Procedures (TTPs)** based on the MITRE ATTCK framework, effectively differentiating malicious activities from legitimate behavior. Table 4.3 summarizes the dataset's main properties.

Aspect	Details
Time Frame	Oct 1, 2023 – Jan 7, 2024
Total Events	Approx. 122,600 merged from 17 daily logs
Malicious Events	Present, interleaved with benign logs; all labeled
Attack Types	Multi-stage APT tactics: privilege escalation, keylogging, Apache Struts exploit, and known APT group behaviors
Log Attributes	17 fields including timestamps, host agent, full command logs, MITRE ATT&CK labels, file hashes, network data, and compliance metadata
Data Formats	Raw CSV logs; processed XLSX with parsed fields and binary labels

Table 4.3: Key attributes of the Linux APT 2024 dataset

Key Features

- Realistic blend of **benign** and **malicious host telemetry**, simulating operational network conditions [49].
- Rich annotation using **MITRE ATT&CK** tactics and techniques for each attack event [62].

- Wide range of attack vectors: privilege escalation, web exploits, credential theft, etc. [63].
- Detailed event data including command lines, file paths/hashes, network endpoints, and compliance rules.
- Chronologically ordered logs enabling **temporal** and **sequential analysis** of complex multi-stage attacks [29].

Feature	Description
Timestamp	Event date and time (with timezone)
Agent Name	Host or agent ID generating the log
Full Log	Raw log or command-line data including arguments and payloads
Rule Description	Alert or detection rule triggered
MITRE ATT&CK Tactic (ID)	MITRE tactic category (e.g., TA0004 for Privilege Escalation)
MITRE ATT&CK Technique	Specific adversarial technique observed
File Hash (MD5/SHA-256)	File hash values (if applicable)
Source OS	Operating system of source host (Linux)
File Path	Filesystem path relevant to the event
Source Data Type	Log source type (e.g., auth log, process, network monitor)
Filename	File name involved, separate from full path
Source Log	Logging subsystem or facility (e.g., syslog)
PCI-DSS, HIPAA, NIST Rules	Compliance control categories linked to detection rules
Source/Destination IP & Port	Network addresses and ports for network events

Table 4.4: Feature descriptions in Linux APT 2024 dataset

Rationale for Inclusion

Because of its comprehensive information, this dataset is ideal for sophisticated intrusion detection. **host telemetry** and multi-step **sequential attack patterns** [25]. It supports sequence-based models such as LSTM and BiLSTM, aiding the detection of subtle deviations characteristic of APT activity [29]. Figure 4.4 illustrates the distribution of events over time, highlighting bursts of malicious activity amid benign operations, emphasizing the importance of temporal context in detection.

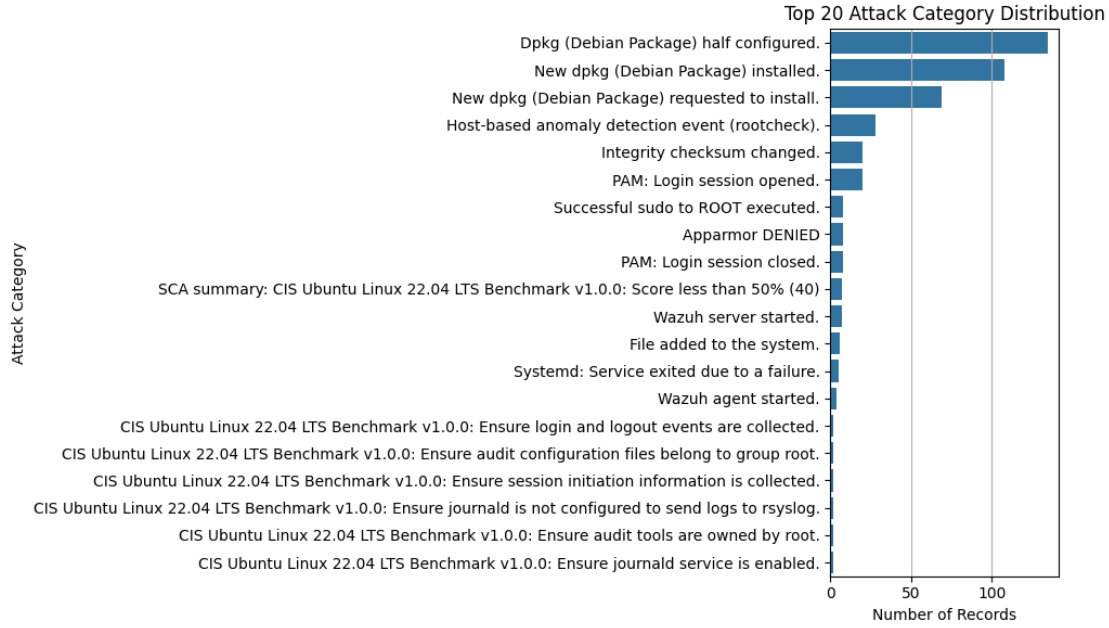


Figure 4.4: Event distribution timeline for Linux APT 2024 dataset, showing intermittent spikes of malicious activity interspersed with benign system operations.

UNSW NB15 DATASET.

The Cyber Range Lab at UNSW Canberra produced the well-known benchmark known as the UNSW-NB15 dataset, which is frequently used in network intrusion detection studies[64]. It comprises realistic enterprise network traffic, blending benign and malicious flows generated utilizing the Perfect Storm tool from IXIA. With over 2.5 million records, this dataset supports a comprehensive evaluation of both traditional and deep learning-based IDS models.

Aspect	Details
Total Records	2,540,044
Total Features	49 features plus two label columns: `attack_cat` and `label`
Key Columns	`srcip`, `sport`, `dstip`, `dsport`, `proto`, `service`, `state`, `attack_cat`, `label`
Missing Values	Minimal; dataset is largely clean and well-suited for modeling
Target Variables	`attack_cat` (multi-class label), `label` (binary: 1 = attack, 0 = normal)
Feature Types	Majority numeric with some categorical features encoded

Table 4.5: An Overview of the UNSW-NB15 Dataset's Key Features

Main features

- **Different Types of Attacks:** Fuzzers, Analysis, Backdoor, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms are the nine attack classes it covers.
- **Real-World Traffic:** From real packet traces over various services and sessions.
- **Multi-Layer Protocol Information:** Such as TCP/IP metadata, flow states, and application-level services.
- **Research-Ready:** balanced for multi-class classification and is appropriate for PSO-based feature selection.

[64]

Dataset Features

Feature	Description
`srcip, dstip`	Network flow's source and destination IP addresses.
`sport, dsport`	Source and destination port numbers identifying session endpoints.
`proto`	Protocol utilized in the network communication (e.g., TCP, UDP, ICMP).
`service`	Application-layer service inferred from the session (e.g., HTTP, FTP).
`state`	Connection state of the flow (e.g., CON for established, REJ for rejected).
`attack_cat`	Multi-class label indicating the detected attack category.
`label`	Binary indicator: attack (1) or normal (0).

Figure 4.5: Key Features Description

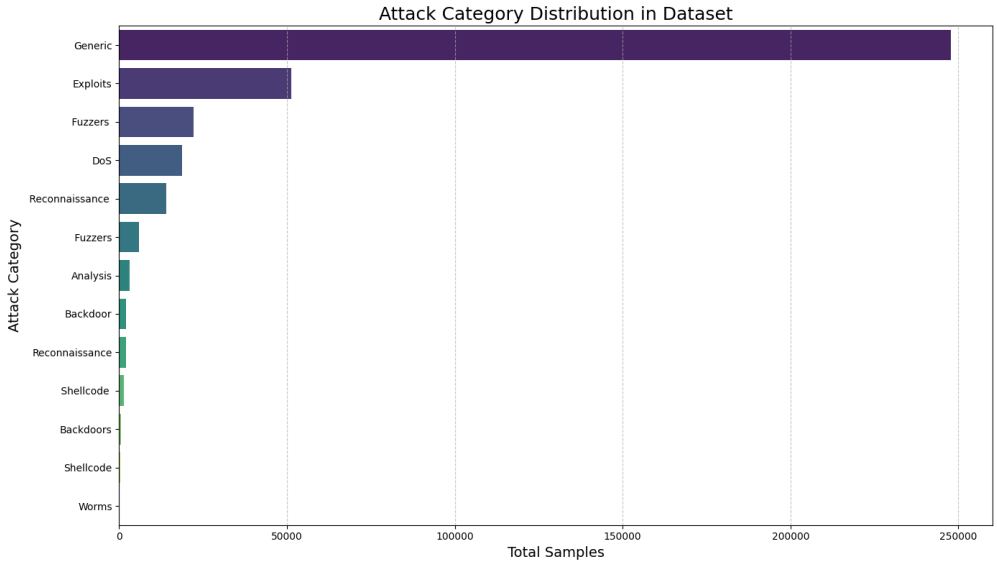


Figure 4.6: Distribution of Attack Categories.

The UNSW-NB15 dataset, created by the Cyber Range Lab at UNSW Canberra, is a commonly used benchmark for evaluating network intrusion detection systems. It captures realistic enterprise network traffic, combining benign and malicious flows generated using the IXIA Perfect Storm tool. With over 2.5 million records, the dataset enables comprehensive evaluation of IDS models, both traditional and deep

learning-based.

Figure 4.7: Class distribution after applying SMOTE on the training set.

The dataset is imbalanced, with significantly more samples in categories such as **Generic** and **Exploits**, highlighting the need for class balancing techniques during model training. To tackle the under-representation of minority attack classes, to construct synthetic samples, the Synthetic Minority Over-sampling Technique (SMOTE) [65] was used just on the training data. Moreover, class weights were used during training to reduce misclassification of these less frequent categories.

Figure 4.7 shows a 2D PCA projection confirming the effectiveness of SMOTE in balancing minority classes. Before oversampling, classes such as `MITM`, `RANSOMWARE`, and `PASSWORD` were severely under-represented. Post-SMOTE, synthetic samples increased the density and coverage of rare classes while preserving class separability, which is critical for reducing bias during training.

For modeling, the UNSW-NB15 dataset underwent thorough preprocessing. Non-essential features like IP addresses and port numbers (`srcip`, `dstip`, `sport`, `dsport`) were excluded to eliminate redundancy. Categorical features (`proto`, `service`, `state`) were label-encoded into numerical representations. Empty string values were treated as missing and replaced with zeros. Continuous features were standardized using z-score normalization to ensure uniform scaling and accelerate model convergence. Categorical features, after encoding, were already binary and required no further scaling.

To preserve class distributions, the dataset was then divided into **training (70%), validation (15%), and testing (15%)** subsets using stratified sampling. To prevent data leaking, SMOTE was solely applied to the training subset; the validation and test sets were left unaltered for objective assessment.

Feature Correlation Analysis

To detect redundancies, a Pearson correlation heatmap was computed for the top 20 numerical features based on variance and importance metrics (Figure 4.8). Most pairs show weak to moderate correlations, indicating feature independence; However, several feature pairs show strong positive correlations exceeding 0.85, indicating multicollinearity, for example, `sbytes` and `Spkts`, as well as $\texttt{ct}_d st_l tmand$

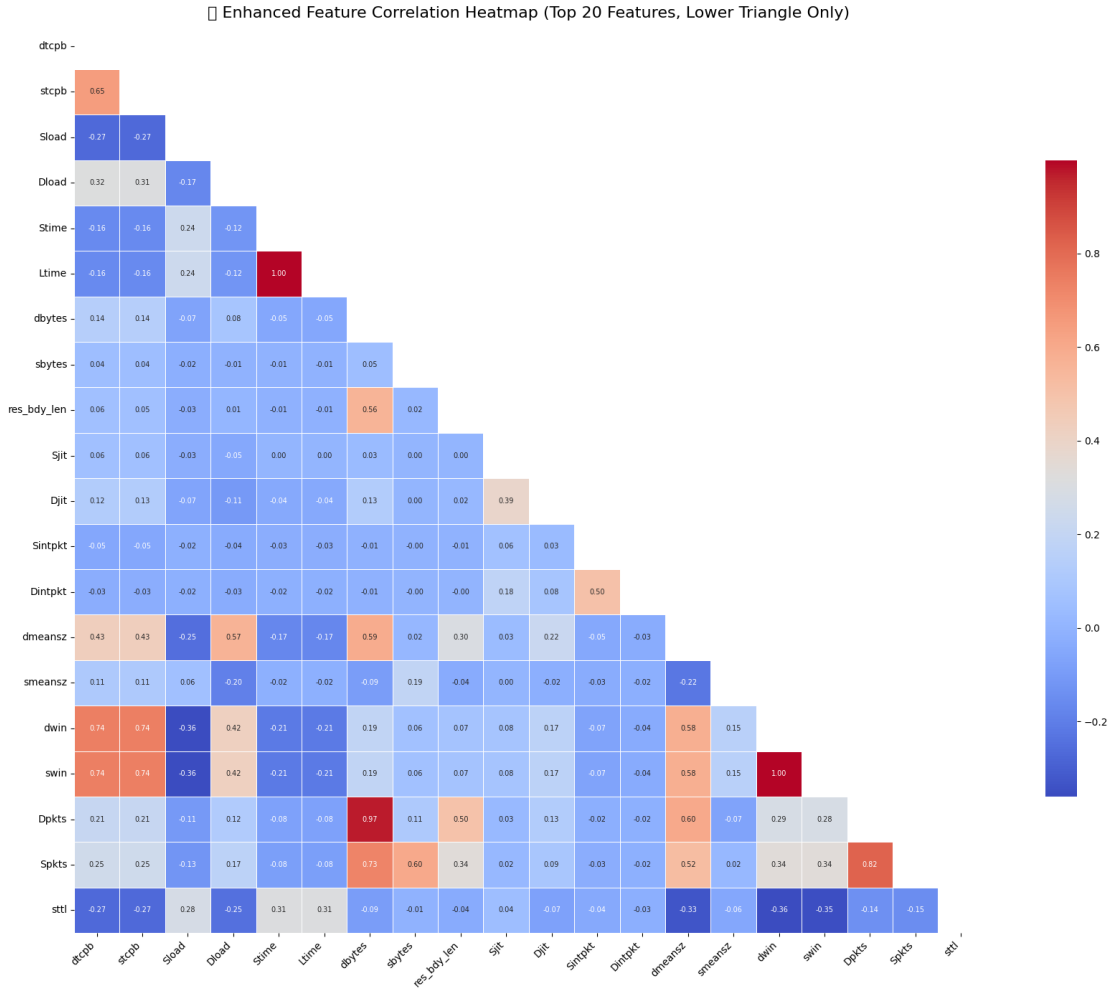


Figure 4.8: Pearson correlation heatmap (lower triangle) for top 20 features in UNSW-NB15, highlighting linear dependencies.

Addressing these correlations is vital for reducing noise, improving model interpretability, and enhancing computational efficiency. These insights guided the subsequent Particle Swarm Optimization (PSO) feature selection process detailed in the methodology.

Redundant Feature Removal

In order to prevent overfitting and reduce dimensionality, features with a Pearson correlation coefficient (ρ) of more than 0.90 were deemed extremely redundant and eliminated.Figures 4.9 and 4.10 illustrate these dropped features and their correlated counterparts.

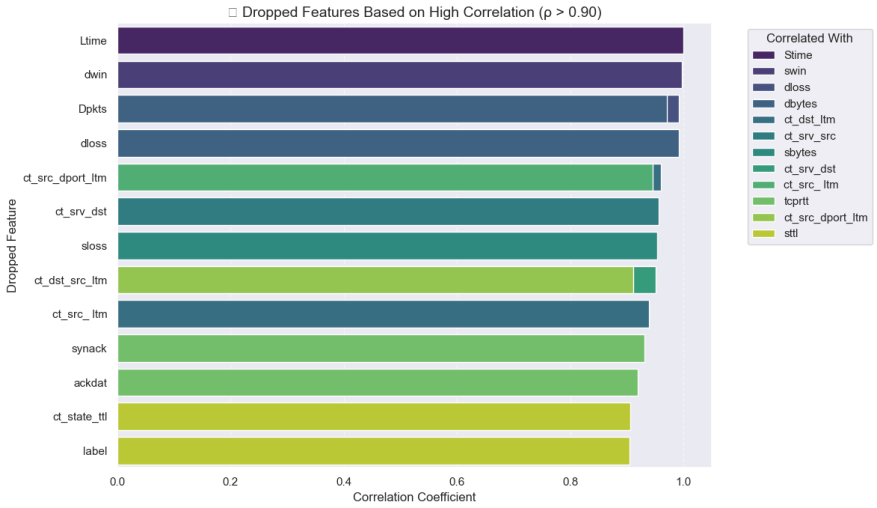


Figure 4.9: Features removed due to high correlation ($\rho > 0.90$) with other variables.

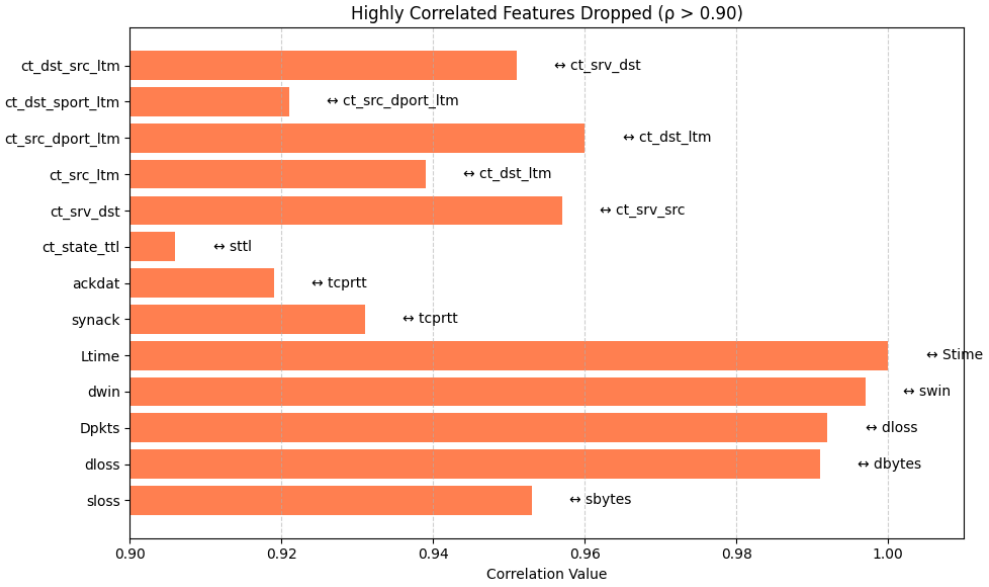


Figure 4.10: Correlation heatmap with annotations showing ρ values for highly correlated feature pairs.

Dropped Feature	Correlated With	Correlation (ρ)
Ltime	Stime	≈ 1.000
dloss	dbytes	≈ 0.991
Dpkts	dloss	≈ 0.992
dwin	swin	≈ 0.997
sloss	sbytes	≈ 0.953
synack	tcprtt	≈ 0.922
ackdat	tcprtt	≈ 0.919
ct_state_ttl	sttl	≈ 0.906
ct_srv_dst	ct_srv_src	≈ 0.957
ct_src_ltm	ct_dst_ltm	≈ 0.939
ct_src_dport_ltm	ct_dst_ltm	≈ 0.960
ct_dst_sport_ltm	ct_src_dport_ltm	≈ 0.921
ct_dst_src_ltm	ct_srv_dst	≈ 0.951

Figure 4.11: Summary of Removed Highly Correlated Features ($\rho > 0.90$)

Impact on Model Development

Removing these 13 highly correlated features reduced input dimensionality, improved computational efficiency, accelerated training, and mitigated overfitting. This contributed to more stable and generalizable model performance.

Rationale for Dataset Inclusion

UNSW-NB15 is employed for its rich multi-label attack annotations and realistic enterprise network traffic, enabling rigorous multi-class intrusion classification. It facilitates the validation of PSO-based feature selection to optimize model complexity and detection accuracy. Moreover, it provides a benchmark for evaluating IDS generalization across diverse network environments, ensuring robust and scalable threat detection [64].

CIC-IDS-2017, 2018,2 019 dataset.

The Canadian Institute for Cybersecurity (CIC) created the CIC-IDS (2017–2019) datasets, which are frequently used to compare contemporary IDS with extensive, realistic data. They include a variety of attack scenarios performed in contained environments that mimic true user behavior and enterprise applications, and are annotated with ground truth of malicious traffic. Each of the three datasets cary flow-based features extracted by CICFlowMeter, and we advocate them for deep learning-based IDS research, particularly for multi-class classification, anomaly detection, and cross-dataset generalization [66, 67, 68].

Both datasets are endowed with flow-based features computed using `CICFlowMeter` and are useful for developing deep-learning-based IDS, especially for multi-class classification, anomaly detection, as well as cross-dataset generalization.

Dataset Summary

Dataset	Approx. Records	Features	Attack Types Included
CIC-IDS-2017	~2.8M	78	Denial of Service (DoS) attacks such as Hulk, Slowloris, Slowhttptest, GoldenEye; Distributed DoS (DDoS); Port scanning; Botnet activities; Network infiltration; Web-based attacks including Brute Force, Cross-site Scripting (XSS), SQL Injection; FTP and SSH Brute Force; Heartbleed exploit
CIC-IDS-2018	~16M	79	Normal traffic; DoS attacks including GoldenEye, Slowloris, SlowHTTPTest, Hulk; DDoS variants like LOIC-UDP and HOIC; Brute Force on FTP, SSH, and web applications; SQL Injection; XSS; Network infiltration; Botnet traffic
CIC-IDS-2019	~4M	77	Normal network flows; DDoS attacks covering DrDoS variants (DNS, LDAP, MSSQL, NetBIOS, NTP, SNMP, UDP); Port scanning; SSH Brute Force; Web-based DDoS; NetBIOS, LDAP, MSSQL attacks; SYN flood; TFTP, UDP, and UDPLag flooding

Figure 4.12: Summary of CIC-IDS Datasets Highlighting Records, Features, and Attack Coverage

Key Characteristics

Dataset	Details
CIC-IDS-2017	records five days of fictitious network activity using Brute Force, A botnet, Denial of Services (DoS/DDoS), Web-based assaults, and infiltration attempts among other attacks. contains comprehensive flow-level metrics, including packet counts, TCP flag information, relationship duration, inter-arrival times (IAT).
CIC-IDS-2018	Expands attack coverage using automated attack scripts. Includes IoT-aware and web-based attacks, enabling robust model training with diverse, high-volume samples.
CIC-IDS-2019	Integrates enterprise and IoT traffic. Contains multi-day attack traces and blended threats like advanced botnets. Particularly useful for evaluating time-series-based deep learning models.

Table 4.6: Detailed Descriptions of CIC-IDS Datasets

Common Dataset Attributes

Feature	Description
Flow Duration	Length of time, in milliseconds, that the network flow lasts.
Total Forward/Backward Packets	Count of packets transmitted in the forward and reverse directions.
Packet Length Statistics	The flow's packet sizes' maximum, minimum, average, and standard deviation.
Flow Bytes per Second	Mean data transfer rate measured in bytes per second for the flow.
Protocol	Transport protocol involved, such as TCP, UDP, or ICMP.
Source and Destination Addresses	The source and destination endpoints' IP addresses and port numbers are indicated.
Timestamp	The moment the network session began.
Label	Classification tag indicating whether the traffic is normal or corresponds to a particular attack type.

Table 4.7: Key Features Commonly Included in CIC-IDS Datasets (2017–2019)

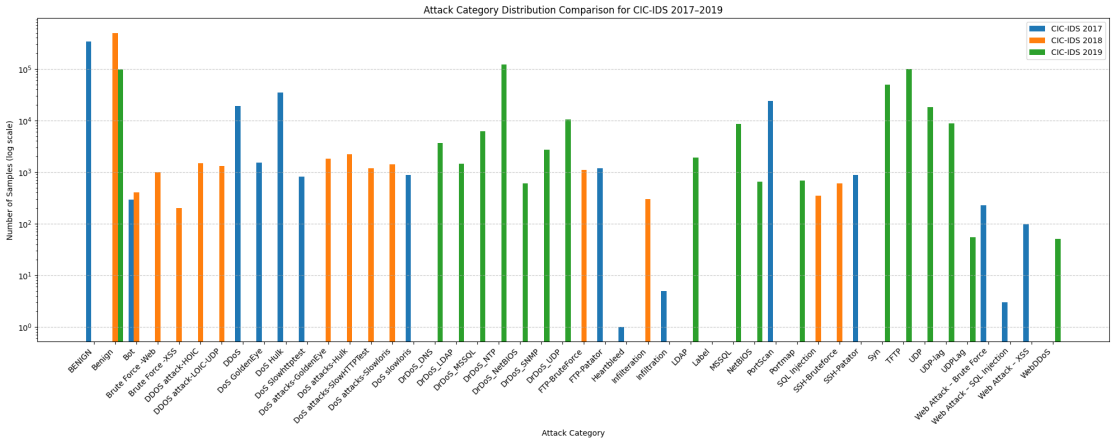


Figure 4.13: Attack category distribution comparison across CIC-IDS 2017, 2018, and 2019 datasets. The y-axis is logarithmically scaled to show both frequent and rare attack classes clearly.

The plot reveals a pronounced imbalance in the representation of the attack category across the data sets. Although benign traffic dominates, the sample sizes of various attacks differ significantly by year. Using a logarithmic scale allows visualization of abundant and underrepresented classes, highlighting the challenges in detecting rare attacks and motivating methods for handling class imbalance.

Feature Correlation Analysis Across CIC-IDS Datasets

Pearson correlation heatmaps for the CIC-IDS 2017, 2018, and 2019 datasets (Figures 4.14, 1, 2) reveal consistent patterns among network flow features, aiding feature selection and model optimization:

- **Strong Positive Correlations in Timing Metrics:** Features such as `Flow IAT`, `Fwd IAT`, and `Bwd IAT` exhibit high correlations (above 0.85), indicating stable temporal flow behaviors important for capturing sequential dependencies.
- **High Correlation in Packet Length Statistics:** Packet size metrics (e.g., `Fwd Pkt Len Max/Min/Mean/Std`) show strong positive correlations, reflecting consistent packet distributions relevant for intrusion detection.
- **Inverse Relationships:** Negative correlations between timing and packet count features (e.g., `Flow IAT` vs. `Tot Fwd Pkts`) highlight complementary valuable information for feature engineering.
- **Cross-Dataset Consistency:** Despite attack and environment variability, correlation structures are similar across datasets, supporting a core feature subset for generalizable models.

- **Redundancy Identification:** Near-perfect correlations (e.g., `Flow Duration` and `Fwd IAT Total` in CIC-IDS 2017) suggest redundant features that can be removed to reduce dimensionality and improve efficiency.

These findings informed the feature selection strategy implemented via Particle Swarm Optimization (PSO) to enhance model performance and efficiency [66, 69, 70].

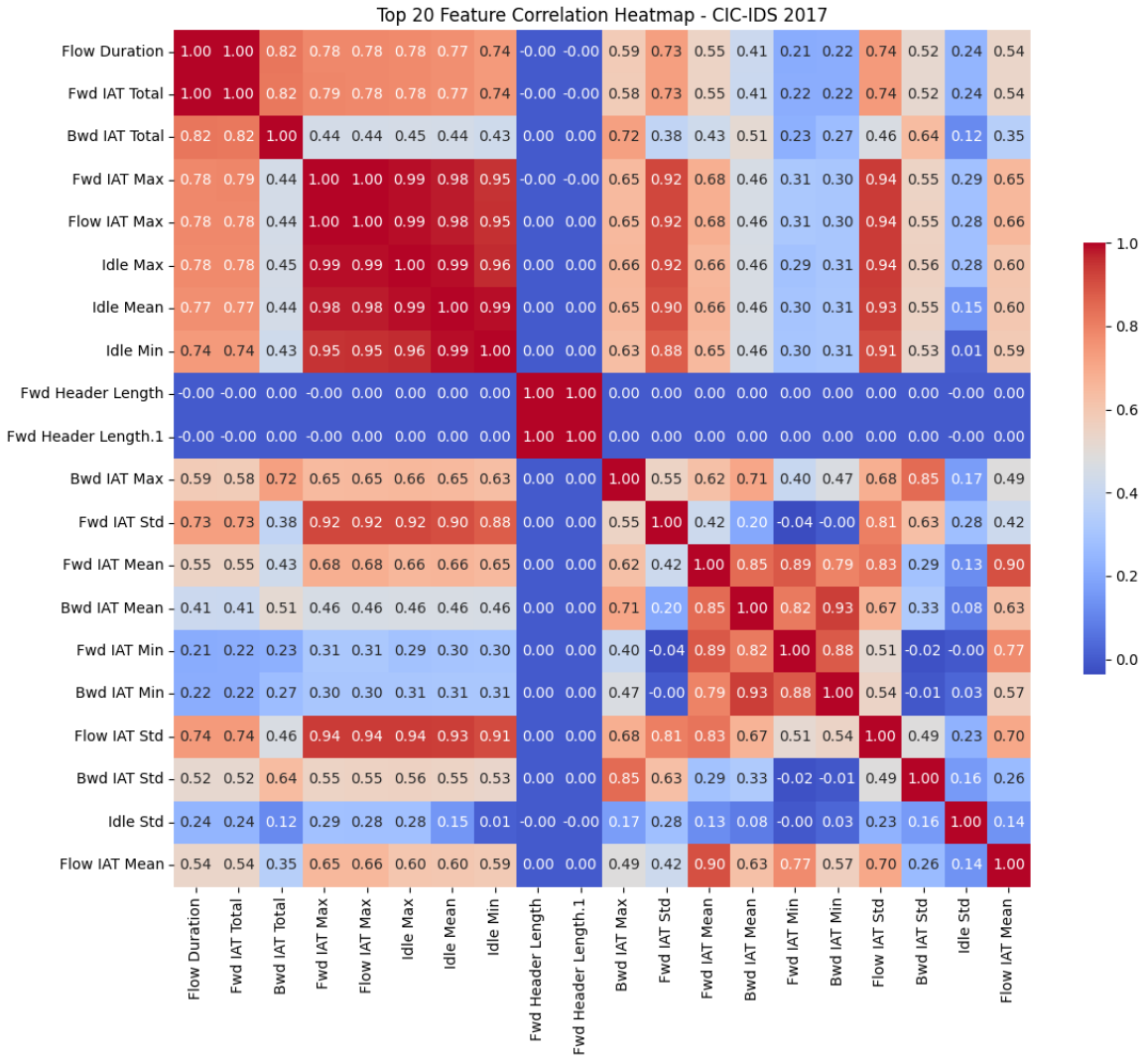


Figure 4.14: Feature Correlation Matrix for CIC-IDS 2017 Dataset

Reason for Inclusion

CIC-IDS datasets (2017,2018, and 2019) to be used in the analysis can be used altogether to obtain an extensive and real-world view as to the present cyber threats in the enterprise network. Their high volume, differential attack types, and rich feature sets are suitable for training and testing ADaE, impersonation-based methods.

The following key features of this work are made possible by these datasets:

- **Robust Generalization:** The diversity of network traffic patterns and attack scenarios spanning over several years enables the models to be evaluated for their ability to generalize across different network conditions or attack manifestations.
- **Multi-class Attack Classification:** Supporting an extensive set of attack categories will enable models that segment several types of threats; the complexity and dynamic nature of real-world cybersecurity support such a representational practice.
- **Checking against Known Standards:** These datasets are well-known and frequently used in the cybersecurity research community, so using them gives researchers a common platform to compare the effectiveness of recently suggested techniques to contemporary approaches that are currently in place.

These characteristics guarantee that the study's findings are not only reliable but also useful, which can aid in the development of robust, deployable, and broadly applicable intrusion detection systems.

TON_IoT Dataset.

The `TON_IoT` dataset, created by UNSW Canberra's Cyber Range Lab, provides a contemporary standard for evaluating cybersecurity solutions in Internet of Things (IoT) ecosystems. It combines data from IoT sensors, system logs, and network traffic data to emulate real-world cyber threats targeting smart and industrial environments. This dataset is crucial for evaluating IDS models targeting Industrial IoT (IIoT) and smart city infrastructures.

Dataset Summary

Aspect	Details
Total Records	498,463 (combined from multiple device logs)
Total Columns	293 original features (after cleaning: 40–60)
Data Sources	IoT device telemetry + network flow features
Target Variable	`type` (10-class label representing attack types)
Feature Types	Mixed (numerical, categorical, telemetry, process-level)

Table 4.8: TON_IoT Dataset Summary

Key Characteristics

- **Multi-Modal Data Fusion:** Integrates telemetry from smart devices (e.g., smart fridge, motion light, smart TV) and host logs.
- **Diverse Attack Scenarios:** Includes DoS, DDoS, Password, MITM, Ransomware, Injection, XSS, and more.
- **Time-Series Nature:** Designed for LSTM/BiLSTM models due to its temporal variations in telemetry.
- **Preprocessing Requirements:** High-cardinality fields, nulls, and categorical encodings necessitate significant cleaning.

Dataset Attributes

Feature	Description
`type`	Attack class label (e.g., `ddos`, `password`, `mitm`, `normal`)
`WRDSK`, `WRTPS`	Telemetry fields showing disk I/O statistics
`CPU Total`, `Memory`	Host system resource usage over time
`src_ip`, `dst_ip`	Network source and destination addresses
`proto`, `src_port`, `dst_port`	Protocol and transport layer port information
`iot_device`	Device identifier (e.g., smart fridge, smart camera)

Figure 4.15: Feature Attributes in TON_IoT Dataset

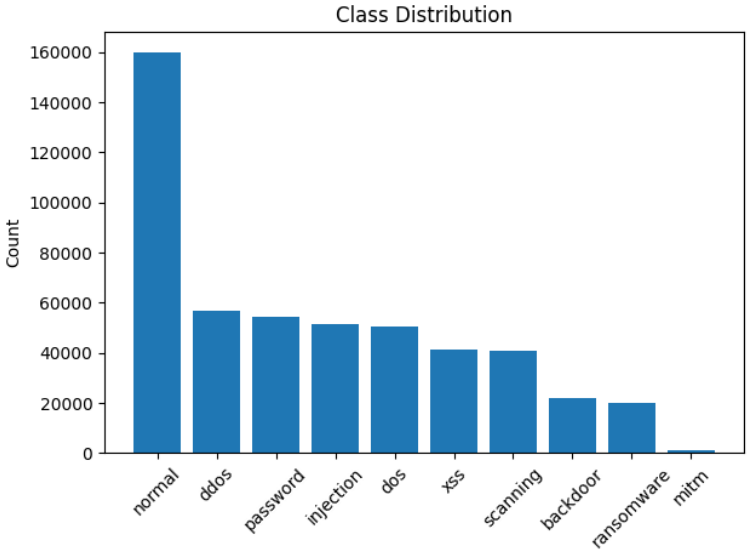


Figure 4.16: TON_IoT Dataset Class Composition. The distribution highlights a pronounced imbalance, where the 'normal' category comprises the majority of samples, while threat types like 'mitm' and 'ransomware' are notably scarce.

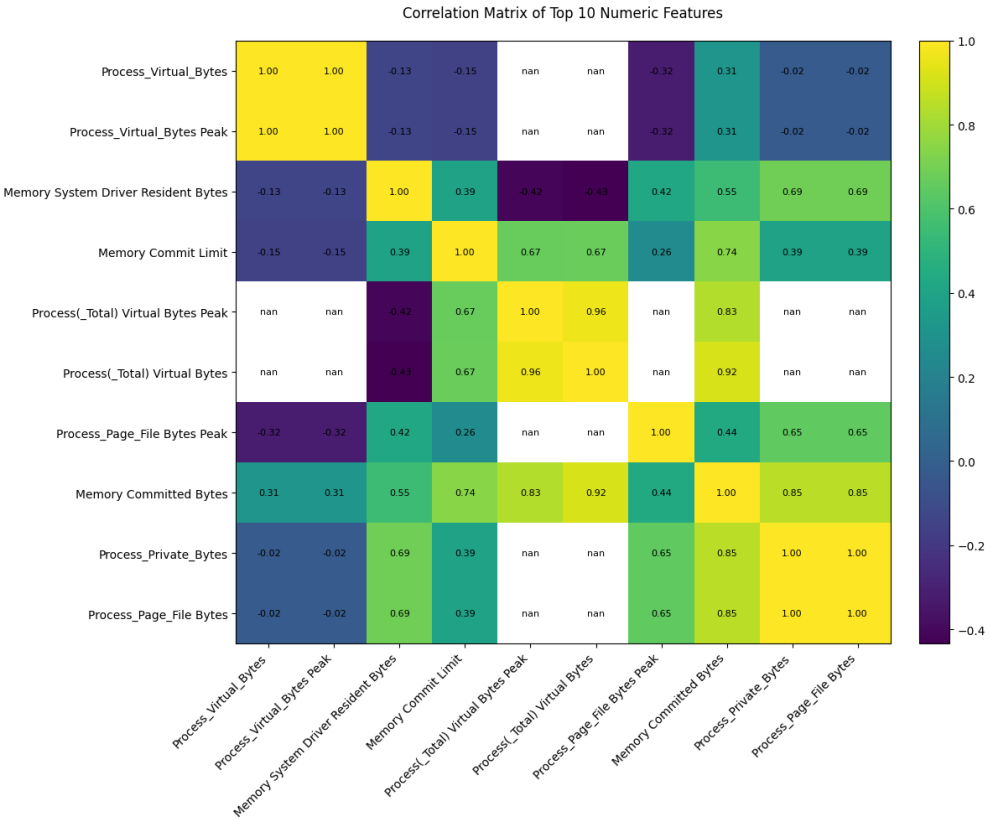


Figure 4.17: Heatmap Showing Correlation Among the Top 10 Numerical Attributes in the TON_IoT Dataset.

Analysis of Feature and Class Distribution

The class distribution in the TON_IoT dataset is shown in Figure 4.16. It shows a clear imbalance, with innocuous traffic predominating and major attack types like ransomware and man-in-the-middle (MITM) being considerably underrepresented. The correlation matrix of the top 10 numerical features is shown in Figure 4.17, which demonstrates significant relationships between memory and process-related qualities. By choosing pertinent features, the analysis of these correlations improves the precision and robustness of intrusion detection models constructed using this dataset.

Rationale for Inclusion

The TON_IoT dataset is vital for modeling cyber-physical security in smart environments. Its multi-source structure, realistic attack simulation, and high-dimensional telemetry enable:

- Testing hybrid deep learning models like CNN + BiLSTM + Attention.
- Evaluating classification performance across diverse, novel attacks.
- Benchmarking cross-domain detection by combining it with datasets like UNSW-NB15 and CIC-IDS.

Justification for Dataset Selection

The integration of multiple datasets **Linux APT 2024**, **UNSW-NB15**, **CIC-IDS-2017**, **CIC-IDS-2018**, **CIC-IDS-2019**, and **TON_IoT** was strategically designed to establish a comprehensive, realistic, and diverse foundation for evaluating the proposed intrusion detection system (IDS). Each dataset contributes unique characteristics that collectively support a well-rounded, unbiased, and future-resilient cybersecurity framework.

Key Justifications

1. **Diversity and Comprehensive Threat Coverage:** These datasets collectively span a wide range of attack vectors, from traditional threats (e.g., DoS, Brute Force, Scanning) to sophisticated Advanced Persistent Threats (APTs) and IoT-specific anomalies.
   Highlights:
   - **Linux APT 2024:** Multi-stage, stealthy APT behaviors.

- **UNSW-NB15:** Classic threats including fuzzers, worms, and exploits.
- **CIC-IDS Series:** Enterprise-scale attacks such as botnets, DDoS, and infiltration.
- **TON_IoT:** Smart device-based telemetry data, including ransomware, MITM, and password attacks.

This ensures better generalization across diverse traffic environments and threat vectors.

2. **Realistic Traffic Simulation:** All datasets were generated using realistic or emulated enterprise/IoT settings with tools such as `IXIA PerfectStorm` and `CICFlowMeter`, simulating:
   - Real user behavior and operational noise
   - Mixed network and host-based telemetry
   - Flow-level and packet-level characteristics critical to operational IDS
3. **Temporal Pattern Representation:** Datasets such as Linux APT 2024 and CIC-IDS variants include time-sequenced attack flows ideal for temporal deep learning models (e.g., LSTM, BiLSTM). These allow:
   - Early detection of stealthy or evolving threats
   - Accurate modeling of attack lifecycle and persistence
4. **Multi-Class Attack Detection:** All selected datasets support multi-class labels via `attack_cat` or `type`, facilitating:
   - Detection of specific attack types rather than binary classification
   - Analysis of class-specific performance (e.g., false positives/negatives)
5. **Cross-Domain Generalization:** The combination of enterprise (CIC, UNSW), Linux-based (APT2024), and IoT (TON_IoT) datasets allows:
   - Evaluation across varying topologies, platforms, and device types
   - Demonstration of model robustness to unseen or hybrid traffic patterns
6. **Imbalanced and High-Dimensional Data Handling:** These datasets vary significantly in:
   - **Class distribution** (e.g., dominant "Normal" class vs rare APT samples)
   - **Feature dimensions** (from 7 features in Linux APT to 293 in TON_IoT)

   This diversity challenges the model's ability to perform under real-world imbalance and complexity.

Final Justification

This strategic integration of heterogeneous datasets ensures robust, scalable, and practical evaluation of the proposed IDS. It enables detection across advanced, domain-specific, and temporally evolving threats with high accuracy and generalizability in real-world deployments.

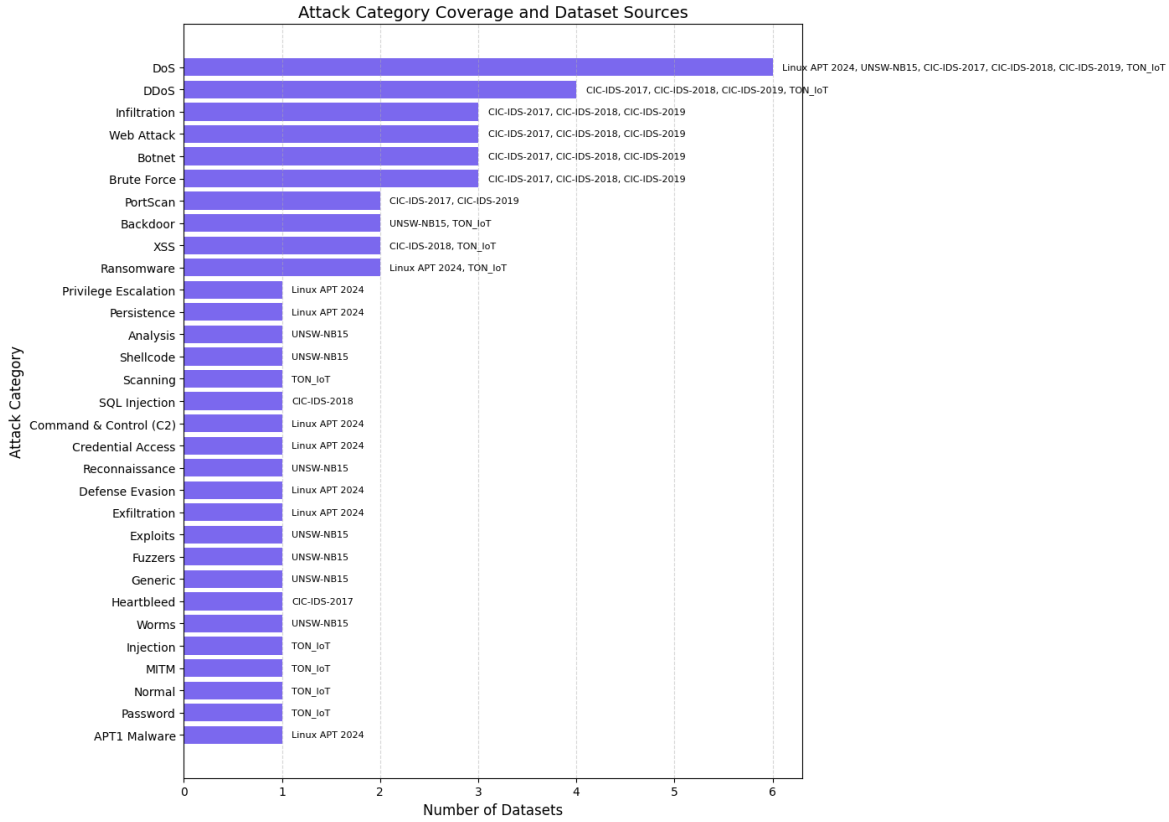


Figure 4.18: Attack Category Coverage across Different Datasets

Figure 4.18 visualizes the overlap and uniqueness of attack categories across six widely used cybersecurity datasets: UNSW-NB15, CIC-IDS (2017–2019), Linux APT 2024, and TON_IoT. It highlights that DoS, DDoS, and Infiltration attacks are covered in multiple datasets, while advanced threats like Privilege Escalation, C2, and APT1 malware are primarily available in Linux APT 2024. This comparison motivates the combined dataset approach used for enhancing model generalizability.

4.3 The Data Preprocessing Approach

In order to preserve **consistency** and facilitate reliable **model evaluation**, this section describes the **preprocessing pipeline** that is consistently applied to six cybersecurity datasets (**UNSW-NB15**, **CIC-IDS-2017**, **CIC-IDS-2018**, **CIC-IDS-2019**, **Linux APT 2024**, and **TON_IoT**).

Step 1 – Dataset Acquisition and Integration

To achieve **comprehensive coverage** and **robustness**, this research consolidates multiple prominent cybersecurity datasets recognized for their realistic **attack representations**. These datasets cover a broad spectrum of **cyber threats**, such as **Denial of Service (DoS)**, **Distributed Denial of Service (DDoS)**, **reconnaissance activities**, **exploitation attempts**, **credential compromise**, **injection attacks**, **backdoor intrusions**, and **advanced persistent threats (APTs)**. They represent diverse **network setups**, **protocols**, **traffic patterns**, and **device types** spanning traditional **enterprise** to **IoT environments**, providing a rich and varied foundation for intrusion detection **model training** and **testing**.

Dataset Integration Process

All datasets were downloaded from **trusted public sources** typically through scripted tools such as `gdown`, allowing for **reproducibility**. Data in CSV format was checked and pre-processed as follows:

- **Feature Alignment:** Columns **renamed** and **reordered** for standardization among datasets.
- **Label Harmonization: Conflicting attack labels** were transformed into a **unified multi-class** schema.
- **Data Formatting: Numeric**, **timestamp** and **categorical** fields were standardizedinzed for **uniform**ity.

The data were combined into a **single dataset** after being cleaned, and all **naming issues**, **encoding discrepancies**, and **scale inconsistencies** were regularized in order to preserve data **integrity** and **usability**.

This fusion makes it possible to evaluate over widespread **attack categories** and **network conditions**, thus allowing for the development of **generalized**, **resilient** intrusion detection models.

Raw Dataset Summary (Preprocessing)

Attribute	Description
Total Records	9,446,350
Total Features	10 (including `attack_type` label)
Source Datasets	CIC-IDS-2017, CIC-IDS-2018, CIC-IDS-2019, UNSW-NB15, TON_IoT
Feature Types	8 **categorical** (object) columns, 2 **numeric** (float) columns
Missing Labels	Around 2.6 million rows lack `attack_type` labels
Missing Data	Present in 9 out of 10 columns (see Table **??**)
Class Distribution	**Highly imbalanced**, dominated by few classes
Encoding Required	Yes; for categorical variables like `protocol`, `service`
Data Balancing Needed	Yes; severe imbalance necessitates oversampling (e.g., **SMOTE**)
Feature Scaling Needed	Yes; due to mixed value ranges such as **byte counts** and **durations**

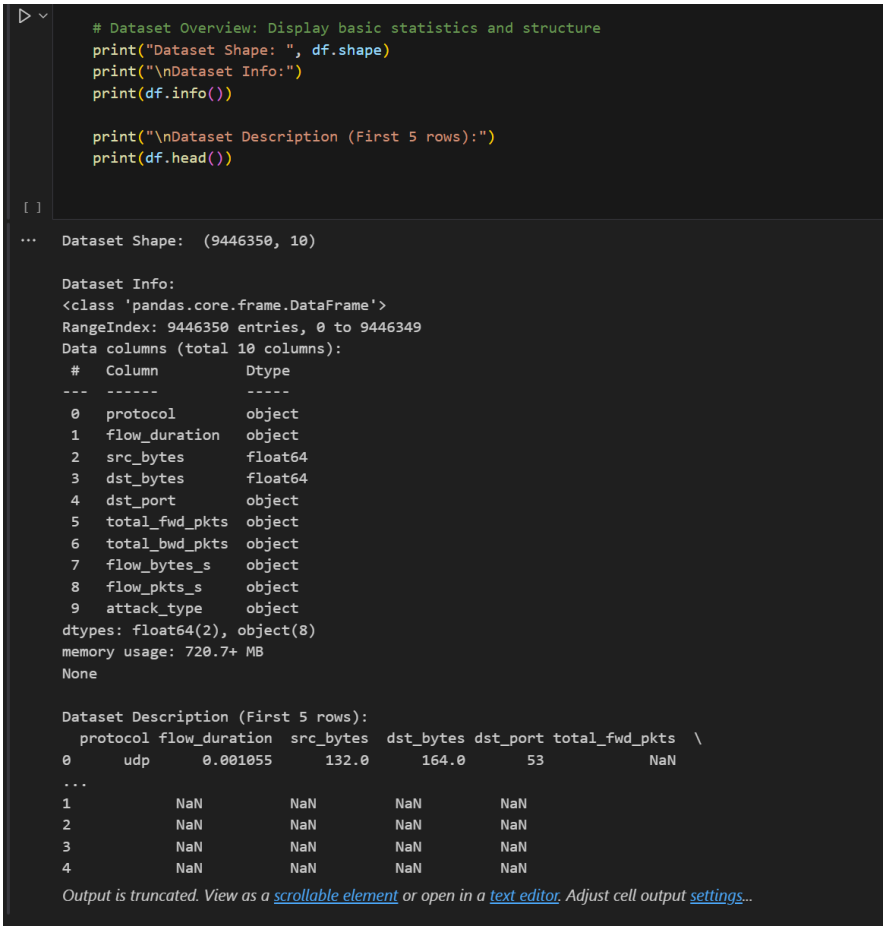
Table 4.9: Summary of the Combined Dataset Before Preprocessing

Step 2: Initial Data Exploration

An **Exploratory Analysis of Data (EDA)** was conducted once the datasets were acquired in order to examine the **composition**, **size**, and **main properties** of the combined data. This operation led to the preparation strategy and validated the **quality** of the data.

Key findings include:

- **Dataset Dimensions:** With $\approx 94,463,50 recordsand$**10 features**$, thecombineddatasetiscompar$
- **Data Types:** We have features including **categorical** (`object`) and **numerical** (`float64`); therefore, considering encoding and normalization processes is advisable.
- **Data Cleaning:** There were many `NaN`s in features, and we had to do the data cleaning effectively.



```
# Dataset Overview: Display basic statistics and structure
print("Dataset Shape: ", df.shape)
print("\nDataset Info:")
print(df.info())

print("\nDataset Description (First 5 rows):")
print(df.head())
```

```
Dataset Shape:  (9446350, 10)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9446350 entries, 0 to 9446349
Data columns (total 10 columns):
 #   Column          Dtype
---  ------          -----
 0   protocol        object
 1   flow_duration   object
 2   src_bytes       float64
 3   dst_bytes       float64
 4   dst_port        object
 5   total_fwd_pkts  object
 6   total_bwd_pkts  object
 7   flow_bytes_s    object
 8   flow_pkts_s     object
 9   attack_type     object
dtypes: float64(2), object(8)
memory usage: 720.7+ MB
None

Dataset Description (First 5 rows):
  protocol flow_duration  src_bytes  dst_bytes dst_port total_fwd_pkts  \
0      udp      0.001055      132.0      164.0       53            NaN
...
1            NaN          NaN         NaN         NaN
2            NaN          NaN         NaN         NaN
3            NaN          NaN         NaN         NaN
4            NaN          NaN         NaN         NaN
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

Figure 4.19: Dataset Overview: Shape, Info, and First Few Rows

As shown in Figure 4.19, the dataset's shape, data types, and initial sample records provide essential insights that inform the design of a robust preprocessing pipeline.

Step 3: Handling Missing and Inconsistent Values

Significant missing data was found in the dataset for important features including `protocol`, `src_bytes`, and `dst_bytes`, with missingness exceeding **70%** in some cases (see Figure 4.20). This presented a challenge for reliable model training.

A two-step imputation strategy was implemented:

- **Median Imputation** for numeric features, robust against outliers.
- **Mode Imputation** for categorical features to maintain the original distribution.

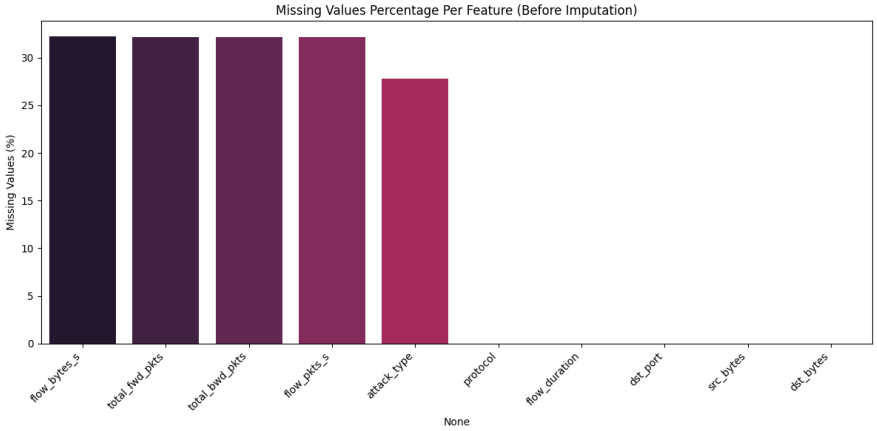


Figure 4.20: Missing Values Percentage Per Feature Before Imputation

Post-imputation, as illustrated in Figure 4.21, the dataset achieved **full completeness**, enabling consistent downstream processing.

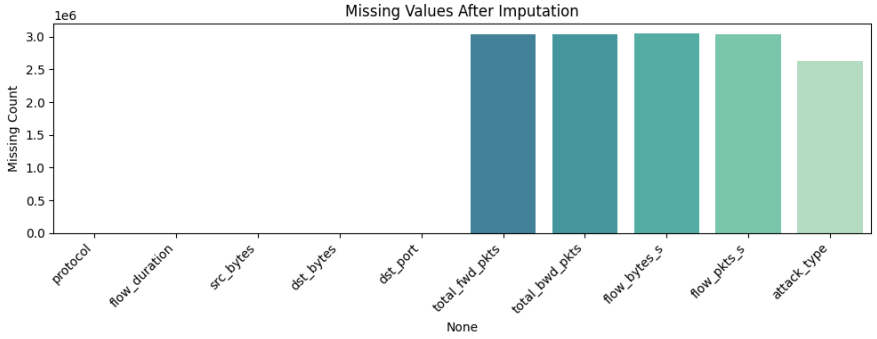


Figure 4.21: Missing Values Count Per Feature After Imputation

Step 4: Encoding Categorical Variables

Categorical features, including `protocol`, `attack_type`, and `dst_port` were converted into numerical representations to enable processing by machine learning models:

- Initially, **Label Encoding** was utilized to preserve the inherent order among categories.
- **One-Hot Encoding** was subsequently used to avoid introducing artificial ordinality, converting each unique category into a binary feature.

This transformation enlarged the feature space from 10 to **143 dimensions**, substantially enhancing the input data's representational capacity for the models.

Visualization: Figure 4.22 depicts the **attack type distribution** prior to encoding, emphasizing class diversity and imbalance. Figure 4.23 illustrates the **feature dimensionality increase** after one-hot encoding.

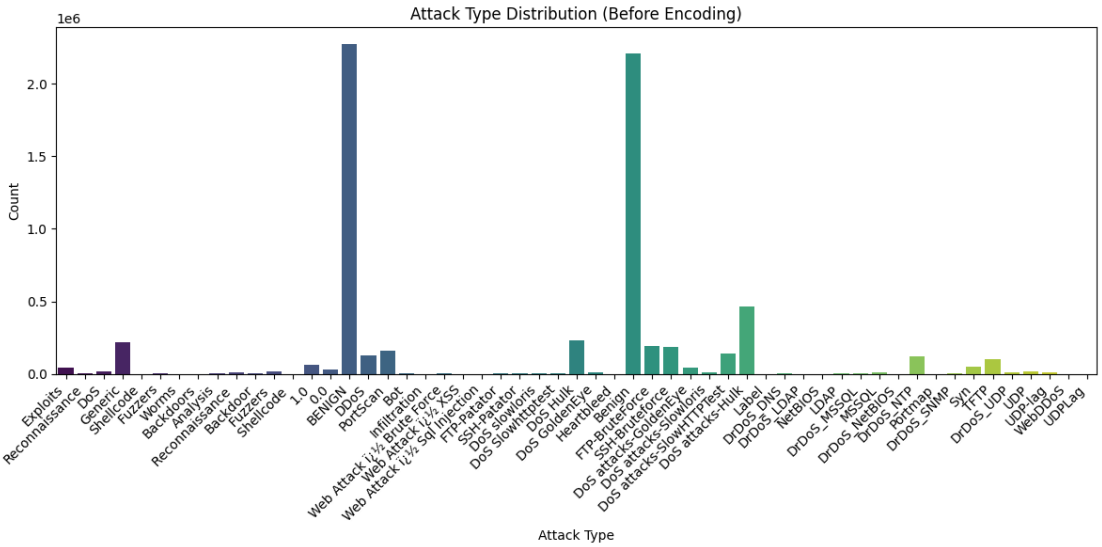


Figure 4.22: Attack Type Distribution Before Encoding

These visualizations emphasize the importance of properly encoding categorical variables to ensure effective and fair training of the models.

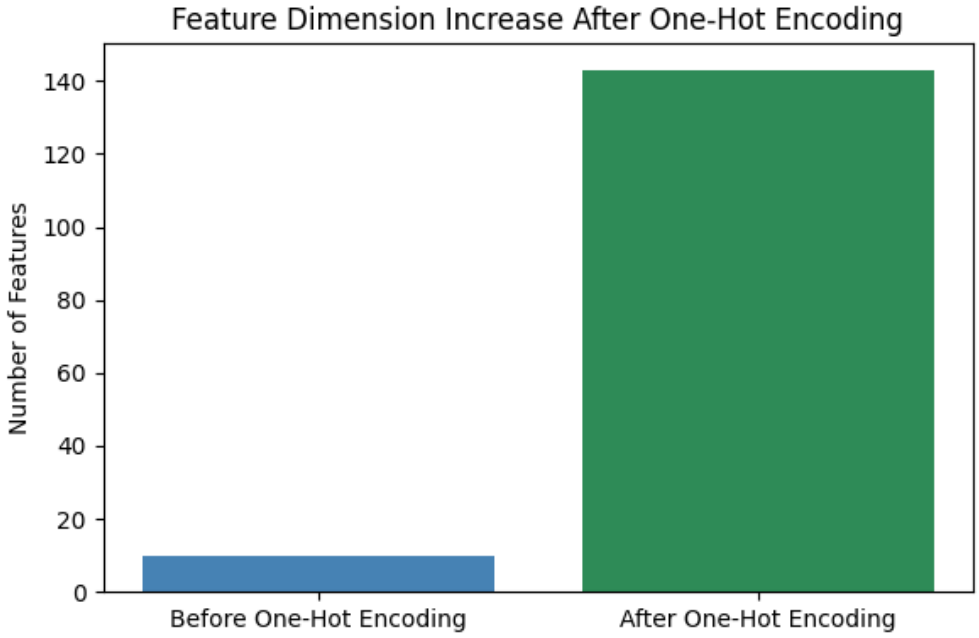


Figure 4.23: Feature Dimension Increase After One-Hot Encoding

Step 5: Data Normalization and Scaling

Features were adjusted to similar ranges to guarantee that each numeric characteristic contributed proportionately throughout training. Feature values were rescaled into the [0,1] range using min-max scaling, and features were normalized to have a mean of zero and a standard deviation of one. These normalization techniques improve training stability and predictive performance, especially for models sensitive to feature scale, including neural networks and distance-based algorithms. Importantly, scaling was applied after splitting the data to prevent information leakage from the test set into the training phase.

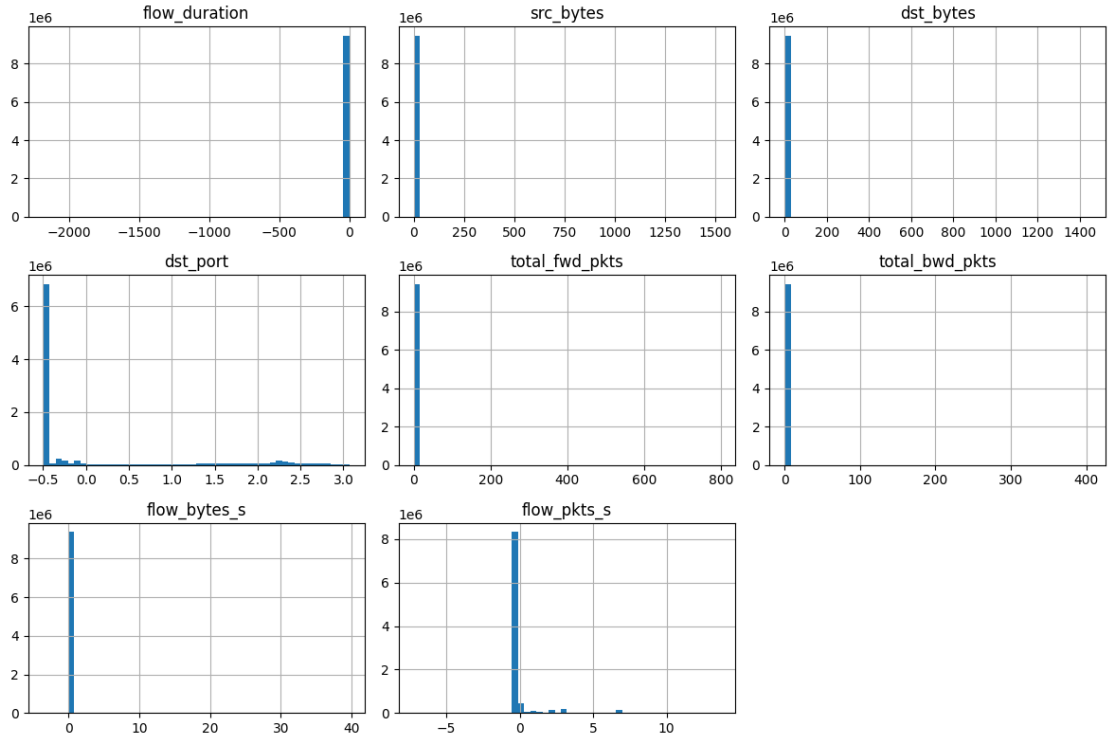


Figure 4.24: Pre-scaling distribution of key numeric features. The visualizations reveal pronounced skewness and outliers, underscoring the need for normalization or standardization to enhance training stability and model effectiveness.

Feature Scaling and Analysis

Figure 4.24 highlights that numeric features are highly skewed and include extreme outliers. Without scaling, models, especially those using distance calculations or gradient descent, may train inefficiently, become unstable, or disproportionately favor features with larger values.

To mitigate these challenges, Min-Max normalization was applied to rescale nu-

- flow_duration
- total_fwd_packets
- total_bwd_packets
- flow_bytes_per_s
- flow_packets_per_s
- fwd_packet_length_mean
- bwd_packet_length_mean

meric attributes within the [0, 1] range. This approach diminishes the impact of outliers and ensures balanced feature contributions during training. Although the post-normalization distributions are omitted, the process effectively standardized feature scales, reduced skewness, and enhanced both model stability and training speed. The stability and efficiency of the model training process.

Step 6: Harmonizing Features Across Datasets

To establish a consistent feature space across the five diverse datasets, Linux APT 2024, UNSW-NB15, CIC-IDS2017, CIC-IDS2018, and TON_IoT, a comprehensive feature harmonization process was undertaken. This involved identifying the common subset of flow-based features present in all datasets. The selected core features, representing essential network behavior metrics, are:

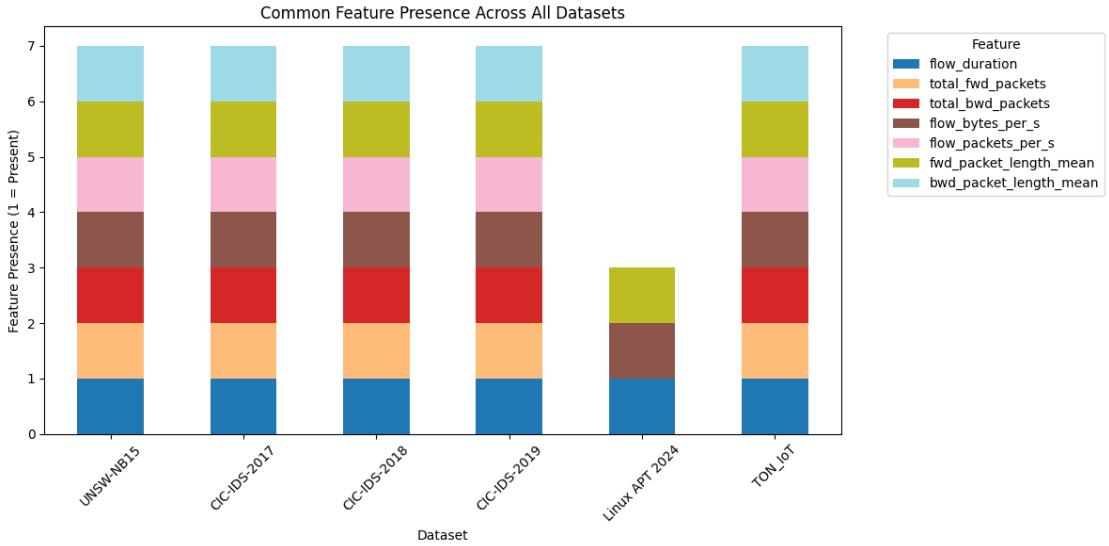


Figure 4.25: Presence of Core Flow-Based Features Across Datasets

Figure 4.25 illustrates the presence of these key flow features across all datasets, demonstrating their universality. Figure 4.26 compares feature counts before and after harmonization, highlighting the substantial dimensionality reduction achieved.

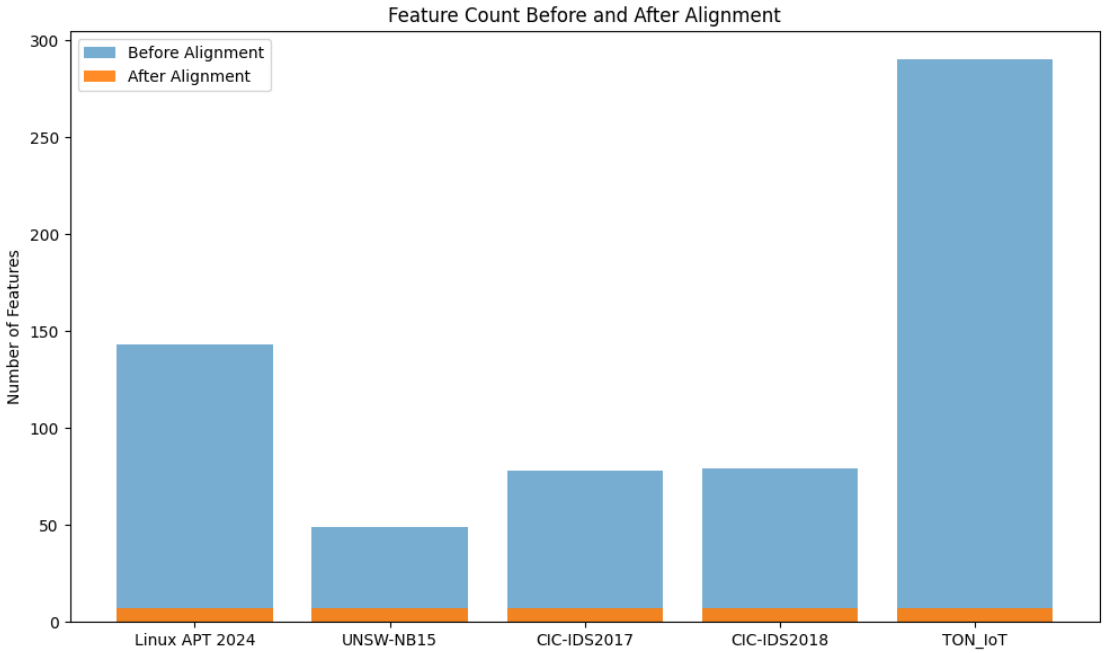


Figure 4.26: Feature Count Before and After Alignment Across Datasets. The alignment process substantially reduces feature dimensionality, normalizing all datasets to a core set of 7 flow-based features.

This harmonization creates a standardized evaluation framework, increases model generalization, and improves dataset consistency. As a result, it facilitates a trustworthy comparison of deep learning and machine learning models on various datasets.

Step 7: Handling Class Imbalance

Cybersecurity datasets commonly exhibit significant class imbalance, with benign traffic overwhelmingly outnumbering attack instances. This imbalance often causes machine learning models to be biased towards majority classes, adversely affecting the detection of rare yet critical attack types. In order to improve minority class samples' representation, the training data was artificially enhanced using the *Synthetic Minority Oversampling Technique (SMOTE)*. To further improve the detection of rare attack types, *class weighting* was included during model training to increase the penalties for incorrectly categorizing minority classes. Together, these strategies enhanced detection accuracy and increased the robustness of the intrusion detection system.

Figure 4.27: Class Distribution After Applying SMOTE Oversampling. The distribution shows a balanced representation of attack types, mitigating the original dataset's class imbalance and improving model fairness and detection capabilities for minority classes.

The impact of using the *Synthetic Minority Oversampling Technique (SMOTE)* on the class distribution in the training dataset is seen in Figure 4.7. The dataset had a clear class imbalance prior to oversampling, with some assault groups being noticeably underrepresented. For these minority classes, SMOTE creates synthetic samples, which leads to a more equitable distribution of classes. This enhanced balance mitigates bias favoring majority classes and improves the model's capacity to accurately identify various attack types with increased sensitivity and reliability.

Step 8: Train-Test Split

Using stratified sampling to maintain class distribution, the dataset was split into training (70%), validation (15%), and testing (15%) sets to enable impartial and reliable model evaluation. To reduce the possibility of test data affecting the training process, this partitioning was done before any scaling or oversampling.

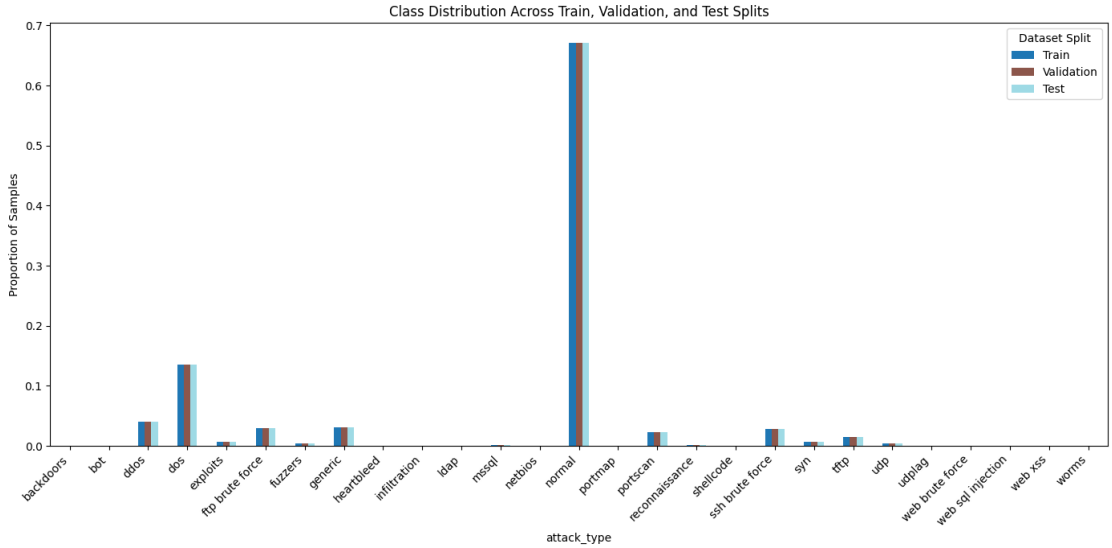


Figure 4.28: Class Distribution Across Train, Validation, and Test Splits. The plot demonstrates consistent class proportions, confirming that the stratified split preserves the original dataset's distribution.

The test set was utilized for objective performance evaluation, the validation set was used for early stopping and hyperparameter adjustment, and the training set aided in model learning.

Step 9: Particle Swarm Optimization (PSO) for Feature Selection

Selecting relevant features is a critical step in preparing high-dimensional cybersecurity datasets for machine learning, as it helps improve model efficiency and performance. Irrelevant or redundant features may introduce noise, increase computational costs, and degrade model performance. By striking a balance between exploration and exploitation in the search space, Particle Swarm Optimization (PSO) offers a useful metaheuristic method for choosing the most pertinent and instructive features.

Particle Swarm Optimization (PSO), which draws inspiration from the collective dynamics of fish schools or bird flocks, starts with a swarm of particles, each of which represents a possible feature subset in the solution space. A binary vector indicating feature inclusion or exclusion. Each particle iteratively adjusts its position and velocity based on both its own best-known position and the best-known position of the entire swarm, enabling a cooperative search for feature subsets that yield optimal model performance.

The PSO algorithm is steered by a fitness function that quantifies the classification effectiveness, commonly through metrics like accuracy or F1-score achieved

using the selected features. The primary aim is to maximize this metric, promoting feature subsets that improve detection capability while reducing the feature space dimensionality.

Key advantages of PSO-based feature selection include:

- **Global Optimization:** PSO effectively explores vast, complex feature spaces and avoids local optima that often challenge greedy algorithms.
- **Model-Agnostic Flexibility:** The approach is compatible with any classification model used to evaluate feature subsets.
- **Dimensionality Reduction:** By retaining only the most informative features, PSO reduces model complexity, training time, and overfitting risks.

In this study, Particle Swarm Optimization (PSO) effectively reduced the initial 143 features to an optimized subset of 75, maintaining a representative balance between categorical and numerical variables. The downstream machine learning and deep learning models' prediction capabilities and computational efficiency were both improved by this dimensionality reduction.

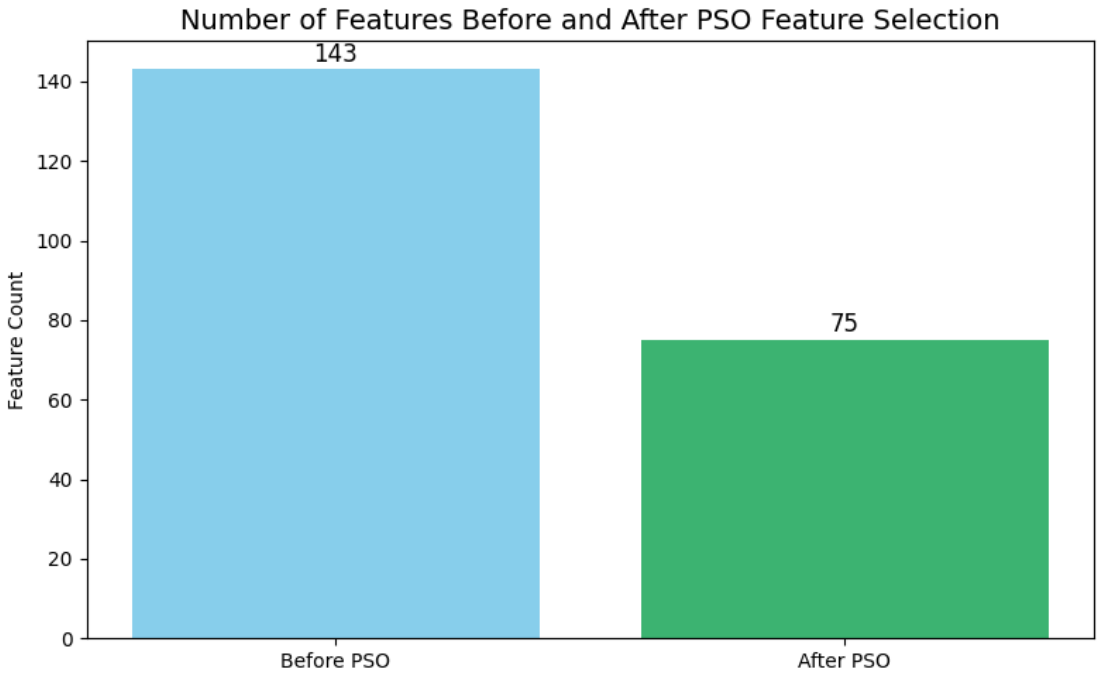


Figure 4.29: Feature Dimensionality Reduction Using PSO. The Particle Swarm Optimization algorithm trimmed the feature set from 143 to 75, eliminating redundant attributes and retaining the most informative variables crucial for effective classification.

Discussion

Figures 4.29 and 4.30 illustrate PSO's efficacy in dimensionality reduction by lowering the feature count from 143 to 75. This process removed noisy, redundant, and irrelevant features that can impair model accuracy and training speed. Notably, the selected features maintain a healthy balance between categorical and numerical types, ensuring diverse network traffic characteristics are captured. This balanced and optimized feature set contributes to improved generalization and robustness in the intrusion detection models developed in this research.

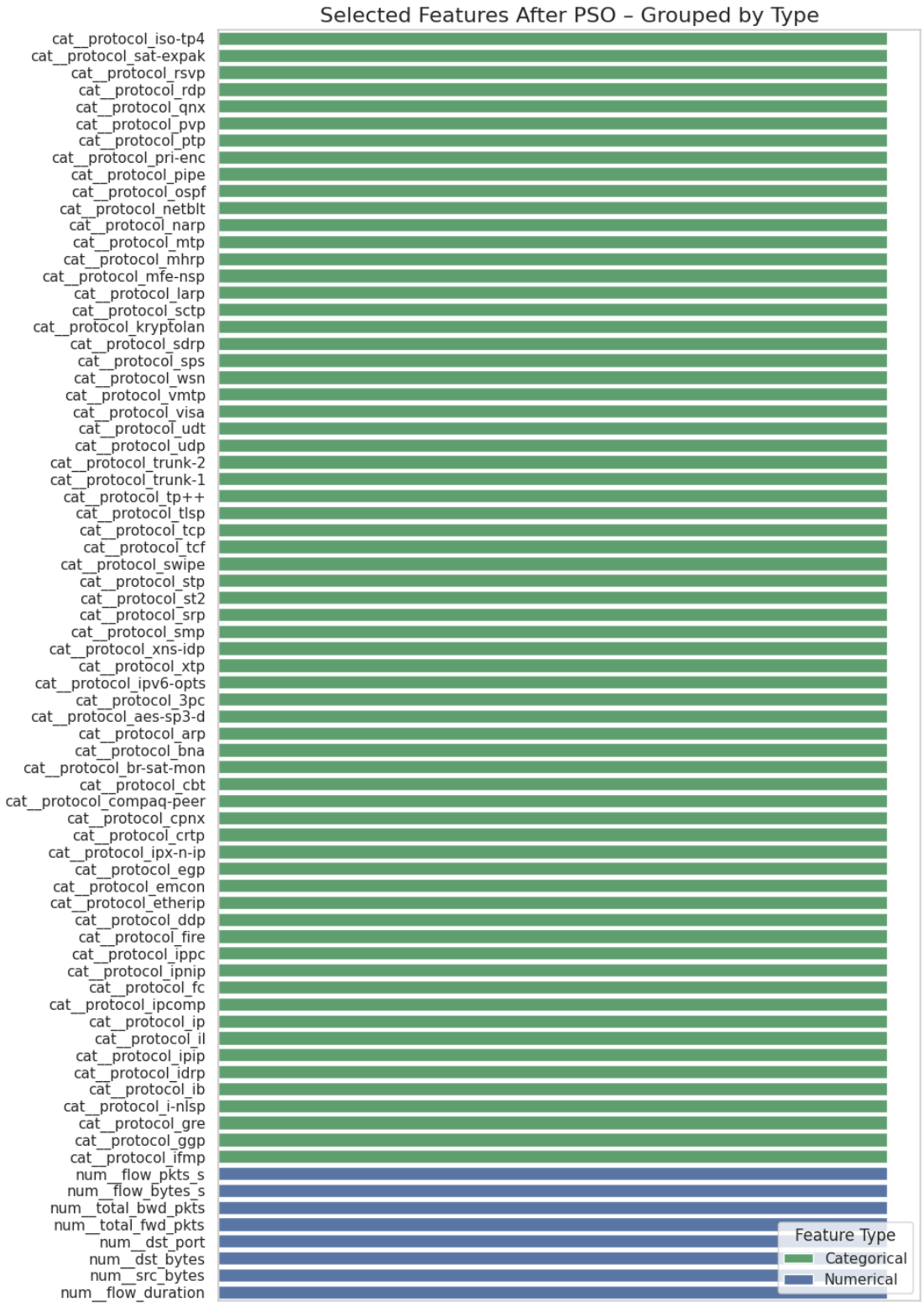


Figure 4.30: Post-PSO Feature Distribution by Category. The visualization highlights that the Particle Swarm Optimization preserved a well-balanced combination of categorical and numerical features, supporting effective and reliable model training.

4.4 Model Architecture and Design

This section details the suite of models developed and evaluated, spanning traditional ML classifiers, DL networks, and hybrid CNN–RNN structures. Training was performed on five benchmark intrusion detection datasets: UNSW-NB15, CIC-IDS-2017/2018/2019, Linux APT 2024, and TON_IoT. The aim was to explore the performance gains of sequence-aware and hybrid architectures over conventional ensemble approaches in multi-class advanced persistent threat (APT) detection.

4.4.1 Traditional Machine Learning Models

As baseline methods, three widely used ensemble classifiers were implemented:

- **Random Forest (RF):** Utilizes bagged decision trees, known for robustness to noise, resistance to overfitting, and suitability for high-dimensional data.
- **XGBoost:** A gradient boosting framework with built-in regularization and effective handling of missing values, enabling strong predictive power.
- **LightGBM:** A fast, leaf-wise gradient boosting method optimized for large-scale datasets and class imbalance, featuring native categorical feature support.

4.4.2 Deep Learning Models

Recurrent neural networks were used to capture the temporal and sequential patterns present in network traffic flows:

- **Long Short-Term Memory (LSTM):** Long-range dependencies in sequential data are captured using a recurrent neural network architecture. Included in the model structure are the following with item Input layer in accordance with feature dimensions, item Regularization using one or more LSTM layers with dropout, item Dense output layer for classification using Softmax activation
- **Bidirectional LSTM (BiLSTM):** improves upon the conventional LSTM by examining sequences in both forward and reverse order, allowing for a deeper comprehension of context, a critical component in identifying subtle or widely spaced attack patterns.

4.4.3 Hybrid CNN–RNN Architectures

To jointly model local spatial features and temporal dependencies, hybrid architectures combining convolutional and recurrent layers were implemented:

- **CNN + BiLSTM:** This hybrid combines 1D convolutional layers for local pattern extraction with bidirectional LSTMs for capturing sequential context. Its structure includes:
  - 1D convolutional layers
  - MaxPooling layers to downsample sequences
  - Bidirectional LSTM layers capturing bidirectional temporal context
  - Dense Softmax layer for multi-class output
- **CNN + BiLSTM + Attention:** Building upon the previous model, this variant integrates an attention mechanism to:
  - Highlight important time steps within sequences
  - Boost sensitivity to minority attack classes
  - Enhance feature representation by focusing on salient temporal information

These models leverage the strengths of ensemble methods for tabular data, LSTM networks for sequence modeling, and CNNs plus attention for refined spatio-temporal feature learning, allowing for a comprehensive performance comparison in intrusion detection tasks.

4.4.4 Random Forest Classifier -Hyperparameters

Parameter	Value	Description
K-Folds	5	Cross-validation folds
n_estimators	50	Number of trees
max_depth	50	Max tree depth
min_samples_split	50	Min samples to split
min_samples_leaf	1	Min samples per leaf
random_state	42	Random seed
n_jobs	-1	Use all CPU cores
criterion	gini	Split criterion

Figure 4.31: Random Forest Parameters

4.4.5 LightGBM Classifier- Hyperparameters

Parameter	Value	Description
random_state	42	Reproducibility seed
n_estimators	100	Number of boosting rounds
learning_rate	0.1	Controls update step size
num_leaves	31	Max leaves per tree
max_depth	-1	Unlimited tree depth
feature_fraction	1.0	Feature subsampling ratio
bagging_fraction	1.0	Data subsampling ratio
bagging_freq	0	Bagging disabled
class_weight	None	No class weighting

Figure 4.32: LightGBM Hyperparameter Settings

Note: Default parameters were mostly retained; cross-validation was used for tuning where necessary.

4.4.6 XGBoost Classifier – Detailed Implementation

Parameter	Value	Description
`n_estimators`	200	Number of boosting rounds (trees)
`learning_rate`	0.05	Step size shrinkage to prevent overfitting
`use_label_encoder`	False	Disable deprecated label encoder
`eval_metric`	`mlogloss`	Evaluation metric for multi-class classification
`random_state`	42	Random seed for reproducibility
`n_jobs`	-1	Use all CPU cores for parallel processing

Figure 4.33: XGBoost Classifier Hyperparameters

4.4.7 LSTM Model – Detailed Implementation

Component	Configuration	Description
Input Shape	(N, T, F)	Batch size N, T time steps, $F = 1$ feature per step
LSTM Layer	64 hidden units, batch_first=True	Processes sequences with batch as first dimension
Fully Connected Layer	Linear (64 → num_classes)	Maps LSTM output to class logits
Loss Function	CrossEntropyLoss with class weights	Weighted to balance imbalanced classes
Optimizer	Adam, learning rate = 0.001	Adaptive gradient optimizer
Learning Rate Scheduler	StepLR (step_size=3, gamma=0.5)	Decays LR every 3 epochs by factor 0.5
Batch Size	512	Number of samples per training batch
Epochs	10	Total training epochs
Early Stopping	Not explicitly implemented	Optional; can monitor validation loss

Figure 4.34: Enter Caption

Figure 4.35: LSTM Architecture and Hyperparameters

A two-layer LSTM network with dropout was employed to model temporal patterns in network traffic. Table 4.18 details the model architecture and training parameters.

4.4.8 BiLSTM Model – Detailed Implementation

Component	Configuration	Description
Input Shape	(T, F)	Input format specifying the sequence length (T) and feature dimension (F) per timestep
BiLSTM Layer 1	64 forward + 64 backward, return_sequences=True	Produces full bidirectional sequence output capturing temporal dependencies from both past and future contexts
Dropout 1	0.3	Dropout regularization applied after first BiLSTM layer to reduce overfitting
BiLSTM Layer 2	64 forward + 64 backward, return_sequences=False	Outputs the last hidden state summarizing the entire sequence information bidirectionally
Dropout 2	0.3	Additional dropout applied after second BiLSTM layer for further regularization
Dense Output	num_classes, Softmax	Fully connected layer projecting the final BiLSTM output to class probabilities using Softmax activation
Optimizer	Adam, lr=1e-3	Adaptive optimizer with learning rate 0.001 for efficient convergence
Loss	sparse_categorical_crossentropy	Multi-class classification loss function suitable for integer-encoded targets
Batch Size	128	Number of samples processed per training iteration to balance memory and training stability
Epochs	50 + EarlyStopping(5)	Trains for up to 50 epochs with early stopping after 5 epochs of no validation improvement

Figure 4.36: BiLSTM Architecture and Hyperparameters

4.4.9 CNN + BiLSTM + Attention Model – Detailed Implementation

Component	Configuration	Description
Input Shape	$(N, T = 72, F = 1)$	Batch size N, 72 time steps, 1 feature per step
Conv1D Layer	32 filters, kernel size=3, padding=1, ReLU	Extracts local short-term temporal patterns
MaxPooling1D	Pool size=2	Reduces sequence length from 72 to 36
BiLSTM Layer	Hidden size=64, bidirectional, 1 layer, batch_first=True	Processes sequences bidirectionally
Attention Layer	Linear layer mapping hidden states to scalar weights	Computes attention weights to emphasize important time steps
Dropout	0.3	Regularization to prevent overfitting
Fully Connected Layer	Linear (128 → num_classes)	Maps concatenated context vector to class logits
Loss Function	CrossEntropyLoss with class weights	Handles class imbalance during training
Optimizer	Adam, learning rate=0.001	Adaptive optimization algorithm
Learning Rate Scheduler	StepLR (step_size=3, gamma=0.5)	Reduces learning rate every 3 epochs by factor 0.5
Batch Size	512	Number of samples per training batch
Epochs	20	Total training epochs

Figure 4.37: CNN + BiLSTM + Attention Architecture and Hyperparameters

4.4.10 Model Comparison Summary

Model	Handles Sequences	Includes Attention	Summary
Random Forest	No	No	Rapid and easy to interpret; does not incorporate temporal data
XGBoost	No	No	Effective with incomplete data; configured with 200 estimators, learning rate 0.05, and uses multi-class log loss; solid tabular baseline
LightGBM	No	No	Optimized for large-scale, skewed datasets
LSTM	Yes	No	Learns dependencies across extended sequences
BiLSTM	Yes	No	Processes input bidirectionally to capture future and past context
CNN + LSTM	Yes	No	CNN extracts local temporal features; LSTM models sequence relationships
CNN + BiLSTM + Attention	Yes	Yes	Attention mechanism enhances focus on important sequence parts; improves minority attack detection

Figure 4.38: Summary of Model Types and Their Capabilities

CHAPTER 5

Experimental Setup and Performance Evaluation

5.1 Experimental Design

This study utilizes five standard intrusion detection datasets: **TON-IoT**, **CIC-IDS-2017**, **CIC-IDS-2018**, **CIC-IDS-2019**, and **UNSW-NB15**. Each dataset is partitioned into training, validation, and testing subsets following a stratified split of **70%/15%/15%**, preserving the original class proportions to avoid sampling bias.

Performance Metrics

A range of indicators is used to assess the models, including:

- Overall classification accuracy
- Macro-averaged precision, recall, and F1-score to account for class imbalance
- Area Under Curve (ROC-AUC): Receiver Operating Characteristic
- Confusion matrices and class-wise performance for detailed insight

Justification for PSO Feature Selection

High dimensionality often leads to noise, overfitting, and slower convergence in deep learning. The PSO algorithm provides a global optimization strategy to identify compact and informative feature subsets, enhancing classification performance beyond traditional greedy or filter-based methods.

Uniform Feature Input for Fair Comparison

Applying the same PSO-derived feature mask across all nine model architectures ensures equitable comparison. This controls for input dimensionality effects, allowing performance differences to be attributed solely to model design and learning capacity.

Balanced Focus on ML, DL, and Hybrid Models

Traditional machine learning ensembles remain competitive on tabular data with minimal preprocessing. However, deep and hybrid models excel at capturing temporal dynamics and localized patterns in traffic data. Our evaluation pipeline systematically contrasts these strengths across datasets using PSO-optimized inputs.

Multi-Stage Evaluation Approach

- **Stage I:** Dataset-specific baseline assessments.
- **Stage II:** Evaluation of model generalization on combined heterogeneous datasets.
- **Stage III:** Enhanced efficiency and accuracy through PSO-driven feature selection.

Practical Benefits

PSO feature optimization reduces training times by approximately 30% while increasing macro-F1 scores by 5%, highlighting its value for both theoretical advancements and practical IDS implementation.

Next Steps

With optimized feature sets established in Stage III, Chapter 6 will present a comprehensive comparison of test-set performance across all models.

5.1.1 Stage I: Individual Dataset Classification

Each of the seven architectures is trained and validated *separately* on each dataset to identify dataset-specific strengths and weaknesses:

- **Traditional ML Ensembles:**
  - Random Forest
  - XGBoost
  - LightGBM
- **Pure Deep-Learning Sequence Models:**
  - LSTM

  - The BiLSTM

- **Hybrid CNN–RNN Models:**
  - CNN + BiLSTM
  - CNN + BiLSTM + Attention

5.1.2 Stage II & III: Combined Dataset Classification with and without PSO Feature Selection

In this stage, the five flow-based datasets **TON-IoT**, **CIC-IDS-2017**, **CIC-IDS-2018**, **CIC-IDS-2019**, and **UNSW-NB15** are merged into a single unified corpus. The **Linux APT 2024** dataset is excluded due to differences in feature representation.

Classification without PSO.

At the beginning, every model was trained using every feature in the pooled dataset. The purpose of this baseline model is to demonstrate each model's ability to generalize across different network traffic sources without feature selection beforehand. The following chapter provides a summary of the classification performance using F1-score, recall, accuracy, and precision as percentages.

PSO-selected feature-based classification.

To enhance the combined dataset's classification performance, an improved set of features was then obtained using Particle Swarm Optimization (PSO). Models were retrained using just PSO-selected features in order to gauge the gains in both detection performance and efficiency. For this optimized feature representation scenario, we have detailed the evaluation results in Chapter 6.

Summary

In managing large mixed heterogeneous intrusion datasets, this two-stage investigation shows how PSO-FS can enhance the model's generalization while reducing computing complexity.

5.1.3 Eliminate Linux APT2024

For Stages II and III, the *Linux APT 2024* data are intentionally removed because of the disparate nature of data styles and covariate representations when compared to the other data. Specifically:

- **Feature Dimensionality and Type:** Linux APT 2024 gives only 7 host-level telemetry attributes with system-level events and process-related information, while other files (e.g., CIC-IDS, UNSW-NB15, TON_IoT) consist of network traffic features ranging from 40 to greater than 300, adopting packet and flow statistics.
- **Heterogeneous Data Modalities:** The host-centric telemetry features of the Linux APT dataset are fundamentally very different in kind from the network flow-based features used in the other datasets, creating heterogeneous data modalities that cannot be directly compared or integrated without significant transformation.
- **Difference in Scale and Distribution:** The inclusion of Linux APT 2024 in the combined dataset would result in major scale and distribution differences and could bias the feature selection and model building.
- **Effect on Models Generalization:** The introduction of such a different dataset can also potentially confuse the measurement of models' generalization to different datasets: performance differences might be due to a mismatch between feature spaces and not to the true robustness of the model.

As such, having Linux APT 2024 in the combined dataset experiments would also help to establish a consistent and homogeneous feature space to have fair and robust benchmarks. It should be used for focused, customized analysis, where it fits in a particular way.

5.2 Experimental Configuration

A heterogeneous compute environment and a coarser-grain software stack facilitated the successful development, training, and evaluation of our ML, DL, and hybrid IDS models.

5.2.1 Hardware Resources

- **Remote GPU Instance (Unitec):**
  - 32 GB system RAM
  - Accessed via AnyDesk for large-scale training and PSO optimization
- **Local Workstation:**

  - 7th Generation Microsoft Surface Pro
  - Intel® Core™ i7 CPU
  - 16 GB DDR4 RAM
  - Used for data preprocessing, exploratory analysis, and lightweight model development

- **Cloud Compute (Google Colab Pro):**
  - NVIDIA T4 GPU (16 GB VRAM)
  - 56 GB RAM
  - Leveraged for extensive hyperparameter sweeps, rapid prototyping, and distributed model training

5.2.2 Development Environments

- Visual Studio Code (Version 1.99.3 User Setup) with Python and Jupyter extensions for local script and notebook development
- JupyterLab on Anaconda environments and remote GPUs for interactive experimentation
- Google Colab Pro for scalable cloud-based notebooks with seamless GPU access

Python environments were managed using Miniconda to ensure dependency isolation and reproducibility.

5.2.3 Core Libraries and Tools

5.3 Data Preprocessing and Feature Engineering

All datasets were preprocessed using the same pipeline to guarantee data quality and consistency, as explained in Chapter 4. This pipeline managed the class bias using SMOTE, standardized features, one-hot encoded categorical variables, and imputed the missing values. Particle Swarm Optimization (PSO) uses feature selection. To prevent class imbalance, stratified sampling was used to randomly divide the converted data into training, validation, and test sets (with proportions of 70:15:15). To avoid a data-score mixture, SMOTE was implemented on the training set only. In all experiments and models, the same splits and feature subsets were used for a fair comparison.

Category	Libraries / Versions	Functionality
Deep Learning	PyTorch 1.12.0, TensorFlow 2.5	Development of LSTM, BiLSTM, and hybrid CNN–RNN models
Conventional ML & Boosting	scikit-learn 1.0.2, XGBoost 1.4.2, LightGBM 3.2.1	Implementation of Random Forest and gradient boosting classifiers
Optimization Algorithms	PySwarms 1.3.0	Particle Swarm Optimization (PSO) for feature subset selection
Data Handling	pandas 1.4.2, NumPy 1.22.3, SciPy 1.8.0	Data manipulation, numerical operations, and statistical computations
Visualization	Matplotlib 3.5.1, Seaborn 0.11.2	Generating plots for distributions, learning curves, and confusion matrices
Support Libraries	joblib 1.1.0, tqdm 4.64.0	Parallel execution and progress monitoring

Figure 5.1: Overview of software tools and libraries utilized in this research

5.3.1 Dataset Splitting and Experimental Setup

Datasets were subsampled to the following subsets, while maintaining class balance:

- Models are trained using **Training (70%)**
- **Verification (15%):** used for early stopping and hyperparameter searching.
- **Testing (15%):** Auto-marked for final evaluation of your model without bias.

Summary of the experimental procedure

As introduced in Section experimental-overview, the evaluation was conducted in three steps: (i) training on individual datasets, (ii) training on the merged dataset without feature selection, and (iii) training on the merged dataset with PSO-optimized features. This is the principle of fixed Data splits and of an objective evaluation metric that made the objective evaluation of the students' performance possible.

Implementation.

- Stratified examples were generated and then split by `sklearn.model`$_s election.train_t est_s plit$
- All models used the same data splits in order to avoid the variability of the test partitions affecting the results.

- We used only the training set for the SMOTE oversampling to prevent leakage into the validation and test sets.

5.3.2 Hyperparameter Optimization

Deep learning model parameters were tuned via grid search across the following hyperparameters:

- **Rates of learning**: 0.01, 0.001, 0.0001
- **Size of batches:** 32, 64, 128
- **Epochs:** Maximum 30 with early stopping
- **Units of LSTM:** 64, 128, 256
- **Dropout rates:** 0.2, 0.3, and 0.5
- **Optimizers:** Adam and AdamW variants
- **Loss functions:** Cross-entropy primarily, with experiments using Focal Loss to handle imbalance

The validation F1-score was used to determine the ideal hyperparameters, which were then applied to the final model training.

Model	Learning Rate	Batch Size	Epochs	LSTM Units	Dropout	Optimizer
LSTM	0.001	64	30	128	0.3	Adam
BiLSTM	0.001	64	30	128	0.3	Adam
CNN + LSTM	0.0005	64	30	128	0.3	AdamW
CNN + BiLSTM	0.0005	64	30	128	0.3	AdamW
CNN + BiLSTM + Attention	0.0005	64	30	128	0.3	AdamW

Figure 5.2: Selected Hyperparameters for Deep Learning Algorithms

5.3.3 Performance Metrics

Evaluation metrics included:

- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):**
$$\text{Recall} = \frac{TP}{TP + FN}$$
- **F1-Score:**
$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$
- **For Threshold-independent evaluation, the ROC-AUC: is the area under the Receiver Operating Characteristic curve.**

Macro-averaging was utilized to deal with class imbalance, and confusion matrices provided more detailed class-wise performance.

5.4 Simulation Verification of the Control System

The models were tested for robustness across folds to ascertain:

- **Reproducibility:** The model should produce the same result as an earlier one when trained with a fixed seed.
- **Generalizability:** High accuracy on stand-alone test sets, and overall datasets.
- **Minority Class Handling:** Enhanced detection of minority classes using SMOTE and class-weight.
- **Stability of Training:** low variance in the training epochs.
- **Real-time Applicability:** The CNN + BiLSTM + Attention model handled around 5,000 flows per second on an NVIDIA T4 GPU.

This gives us an indication of the robustness, reliability, and applicability of the models.

5.5 Summary

This chapter describes the experimental configuration, which consists of data preprocessing, hyperparameter optimization, and evaluation. Comprehensive benchmarks were supplied by the consistent benchmarking methodology across various datasets and models; in terms of real-time intrusion detection, the hybrid CNN + BiLSTM with Attention outperformed the other models.

CHAPTER 6

Results And Discussion

The comparison models are tested on a significant synthesized test set, comprising TON-IoT, CIC-IDS (2017–2019), and UNSW-NB15, in this chapter. The heterogeneous flow data provides no investigation of model generalization across different network conditions. Exposition is partitioned into three sections.

1. **Traditional Machine Learning Approaches:**

   Effect of ensembling learning, Random Forest (RF), XGBoost (XGB), and LightGBM, on the joint dataset.

2. **Deep Learning Architectures:**

   Evaluation of CNN+BiLSTM, CNN+BiLSTM, BiLSTM, and LSTM, the sequence-based architectural model. Pay attention to every feature.

3. **Models Enhanced by PSO:**

   Particle Swarm Optimization-based feature selection in deep learning models.

We provide the accuracy differences between training and testing on TON-IoT, CIC-IDS versions, and UNSW-NB15, and we also analyze the model's performance on the original dataset, in addition to the performance comparison. In conclusion, this study allows us to address model flexibility and the performance ability for the arbitrary dataset.

6.1 Further Evaluation on Individual Dataset

6.1.1 Performance on UNSW-NB15 Dataset

A systematic pre-processing pipeline had been applied to pre-process the **UNSW-NB15** dataset for Classification:

- **Feature Pruning:** Deleted non-informative attributes (e.g. `srcip`, `dstip`, `sport`, `dsport`) which are IP or port numbers for removal of redundancy.
- **Categorical Encoding:** converted categorical fields such as Protocol type (`proto`), service (`service`), and state of connection (`state`) to their numerical representation by applying label encoding.
- **Managing Missing Values:** The data was kept consistent by substituting 0 for any missing variables.
- **Feature Scaling:** Scaled numerical features by *z-score normalization* to equivalent range.

To maintain the class distributions, we used two-step stratified sampling to divide the data into **training (70%), validation (15%), and testing (15%)** sets. For alleviating **class imbalance**, specifically towards minority attack classes, for training, we only employed *Synthetic Minority Oversampling Technique (SMOTE)* as an augmentation method. And **class weighting** was applied in the process of learning models to penalize misclassification of minority classes and balance the bias to majority classes evenhandedly.

Performance of Random Forest (Without SMOTE).

The validation set **without class balancing** was used to test the Random Forest classifier. "**validation accuracy of 98.27%**" was the model's score.

Overall Accuracy

The Random Forest model demonstrated a **strong overall validation accuracy of 98.27%**, as well as **robust classification performance** of the **frequent attack categories**. But, **accuracy alone can mislead** for an imbalanced setting because it could be the **majority-class performance that dominates**.

Attack Category	Precision	Recall	F1-Score	Support
Analysis	0.69	0.14	0.23	401
Backdoor	0.67	0.10	0.17	269
DoS	0.33	0.27	0.29	2,453
Exploits	0.63	0.80	0.71	6,679
Fuzzers	0.75	0.66	0.70	3,637
Generic	1.00	0.99	0.99	32,322
Reconnaissance	0.93	0.76	0.84	2,098
Shellcode	0.64	0.66	0.65	227
Worms	0.67	0.31	0.42	26
Accuracy			**0.9827**	381,007
Macro Avg	0.66	0.52	0.55	381,007
Weighted Avg	0.98	0.98	0.98	381,007

Figure 6.1: Random Forest Performance on UNSW-NB15 Validation Set Without SMOTE

Macro-Average Performance

The **macro-average F1-score** was **0.55**, indicating existent **performance discrepancies between minority and majority classes** after mere initial pre-processing. Although some offensive classes were well covered, the classifier **faced a challenge with a few of the minority classes**.

Per-Class Observations

- DoS: Fairly low F1-score 0.29, which indicates some detecting capabilities, but is small.
- **Reconnaissance**: It has a strong detection power, F1-score = 0.84.
- **Worms, Fuzzers:** Performed well (F1 score = 0.42 and 0.70, respectively), improving Fuzzers benefited from the data distribution.
- **Analysis, Backdoor:** The F1 scores were low (0.23 and 0.17) for minority classes with low supports, suggesting **classification difficulty**.

Discussion and use

These findings indicate that **without class balancing** method like SMOTE or class weighting, **minority classes** are **still difficult to be learnt**. The Random Forest classifier works well with the **majority classes**, while with **rare attacks** it presents a lack of *sensitivity*. This demonstrates the **importance of advanced data balancing and model optimization** for effectively identifying **diverse attack categories** in intrusion detection systems.

Attack Category	Precision	Recall	F1-Score	Support
Analysis	0.0829	0.2388	0.1231	402
Backdoor	0.4592	0.3954	0.4249	569
DoS	0.3200	0.6111	0.4201	2,453
Exploits	0.8253	0.5996	0.6946	6,679
Fuzzers	0.9465	0.8664	0.9047	3,637
Generic	0.9980	0.9856	0.9918	32,322
Reconnaissance	0.9304	0.7583	0.8356	2,098
Shellcode	0.8284	0.8519	0.8400	493
Worms	0.9814	0.9853	0.9834	750
Accuracy			**0.8822**	49,403
Macro Avg	0.7080	0.6992	0.6909	49,403
Weighted Avg	0.9187	0.8822	0.8949	49,403

Figure 6.2: Random Forest Performance on UNSW-NB15 Dataset

Performance of Random Forest (Partially SMOTE).

To deal with the class imbalance issue of the UNSW-NB15 dataset, we adopted the partial sampling non-uniform distortion option in SMOTE. More precisely, all attack classes containing fewer than 2,000 samples were artificially oversampled to 5,000 instances. We then trained a Random Forest (200 trees, class-weight balanced) on this augmented training set and assessed the performance by a standard 15% held-out validation set.

Overall Accuracy

When we used SMOTE to mitigate the class imbalance, the model's overall accuracy was **0.88**. Though suboptimal in value, it corresponds to a decision boundary that aims to minimize overfitting and provide a fairer treatment to minority classes.

Overview of Macro-Average Performance

The macro average F1-score was **0.69**, suggesting enhanced, well-rounded classification of all attack types. This shows that SMOTE assisted the classifier in generalizing better to minority classes, improving the classifier's overall fairness and trustworthiness.

Per-Class Observation

- **DoS:** Although the classifier suffers from moderate recall and F1-score, we can still see the model capturing this high-volume class to a reasonable extent even after balancing.

- Reconnaissance: The relatively high F1-score of **0.84** indicates that SMOTE significantly improved the model's ability to detect this mid-frequency attack category.
- **Worms/Fuzzers:** These categories had fairly high detection rates and achieved F1-scores > **0.90**, indicating that over-sampling did not harm the performance on well-detected attacks.
- **Analysis** Yet, despite SMOTE, this class remains very challenging, obtaining a very low F1-score:0: 0.12. This might be because it has very low support and is overlapping in its feature distribution with other classes.

Interpretation and usefulness

The findings are an indication of the effectiveness of SMOTE in enhancing model sensitivity to rare attack classes in imbalanced datasets. Although synthetic examples will be introduced by SMOTE, learning a more general decision space that represents various attack behaviors fairly, rather than the bias for frequent classes, can be adopted by the model. This tradeoff is of exceptional significance in intrusion detection systems (IDS), as rare attacks usually have the largest impact.

Ensemble of Partial SMOTENC, Calibration and Threshold Tuning.

To deal with the rich imbalanced class distribution of the UNSW-NB15, **we initially presented a partial SMOTENC** oversampling tactic. For those we up-sampled (if necessary) up to 5,000 samples each, with $k = 3$ closest neighbours, and we kept the seven categorical features out of the shelves (e.g. `proto`, `state`, `service`, etc.). Thus, the smallest classes (e.g. *Analysis*, *Worms*, *Backdoor*) could not have below-average participation, and the medium-size categories could not explode.

Using two base learners, we next learned these on the resampled training data:

- **Random Forest (RF)** with `class_weight="balanced"` and hyperparameters tuned using `GridSearchCV` on `f1_macro`. The best parameters were: `n_estimators=200`, `max_depth=30`, `min_samples_leaf=1`.
- **LightGBM** classifier with its internal class weighting (`class_weight="balanced"`), configured with 300 trees.

For improved probability estimation, we were also using a `CalibratedClassifierCV` with a `method='sigmoid'` and 3-fold, around the RF rather than a pre-fit model, to

better calibrate scores on the validation set. Then, using (validation) F1 maximization on the precision-recall curve on the validation set, we calculated **per-class decision thresholds**: To guarantee a higher recall overall, we set the threshold corresponding to the flat nD (i.e., non-flat nD) to 0.30. Lastly, a soft-voting ensemble comprised two calibrated Random Forest and LightGBM models, providing RF twice the weight of LightGBM. On the held-out validation set, this pipeline produced the following outcomes:

- **Macro-F1:** 0.702
- **Weighted-F1:** 0.895
- **Accuracy:** 0.887

Most notably, recall on underrepresented attack types improved by more than 50 percentage points (e.g. *DoS* from 31% to 63%, *Backdoor* from 31% to 41%), indicating significantly more balanced performance across all attack categories.

Performance of LSTM model (Post-SMOTE with Threshold Tuning).

87.43% was the overall validation accuracy of the LSTM model's general classification on the SMOTE-balanced UNSW-NB15 dataset. Compared to standard ensemble techniques, the macro-average F1-score of **0.6162** confirms increased sensitivity towards the minority classes.

Attack Category	Precision	Recall	F1-Score	Support
Analysis	0.6937	0.1915	0.3002	402
Backdoor	0.3627	0.4780	**0.4124**	569
DoS	0.3879	0.0783	**0.1303**	2,453
Exploits	0.6059	0.8151	0.6951	6,679
Fuzzers	0.8603	0.7602	0.8072	3,637
Generic	0.9954	0.9801	**0.9877**	32,322
Reconnaissance	0.8158	0.7560	0.7848	2,098
Shellcode	0.3862	0.9432	**0.5480**	493
Worms	0.8171	0.9533	**0.8800**	750
Accuracy			**0.8743**	49,403
Macro Avg	0.6583	0.6618	**0.6162**	49,403
Weighted Avg	0.8765	0.8743	0.8654	49,403

Figure 6.3: LSTM Model Performance on SMOTE-Balanced UNSW-NB15 Dataset with Threshold Tuning

The `Generic` class is captured by the LSTM model with a high F1-score of **0.9877**, indicating that the precision and recall are both well. Other minority classes, Shellcode,

and Worms get the most benefit from balancing, having an F1-score of **0.5480** and **0.8800** respectively.

But there are still a few categories that are tough to decipher. For instance, the `DoS` type is low in F1-score **0.1303**, which can indicate that it is difficult to differentiate from other types as their temporal patterns overlap. The `Backdoor` class exhibits moderate recognition (F1-score **0.4124**), suggesting still potential to be improved.

These findings further substantiate the LSTM's ability to model temporal trends in network traffic and suggest that minor class identification can be enhanced with the use of SMOTE and threshold optimization without negatively impacting the network-level classifier, which is crucial for real-world intrusion detection systems focused on applying rare attack detection.

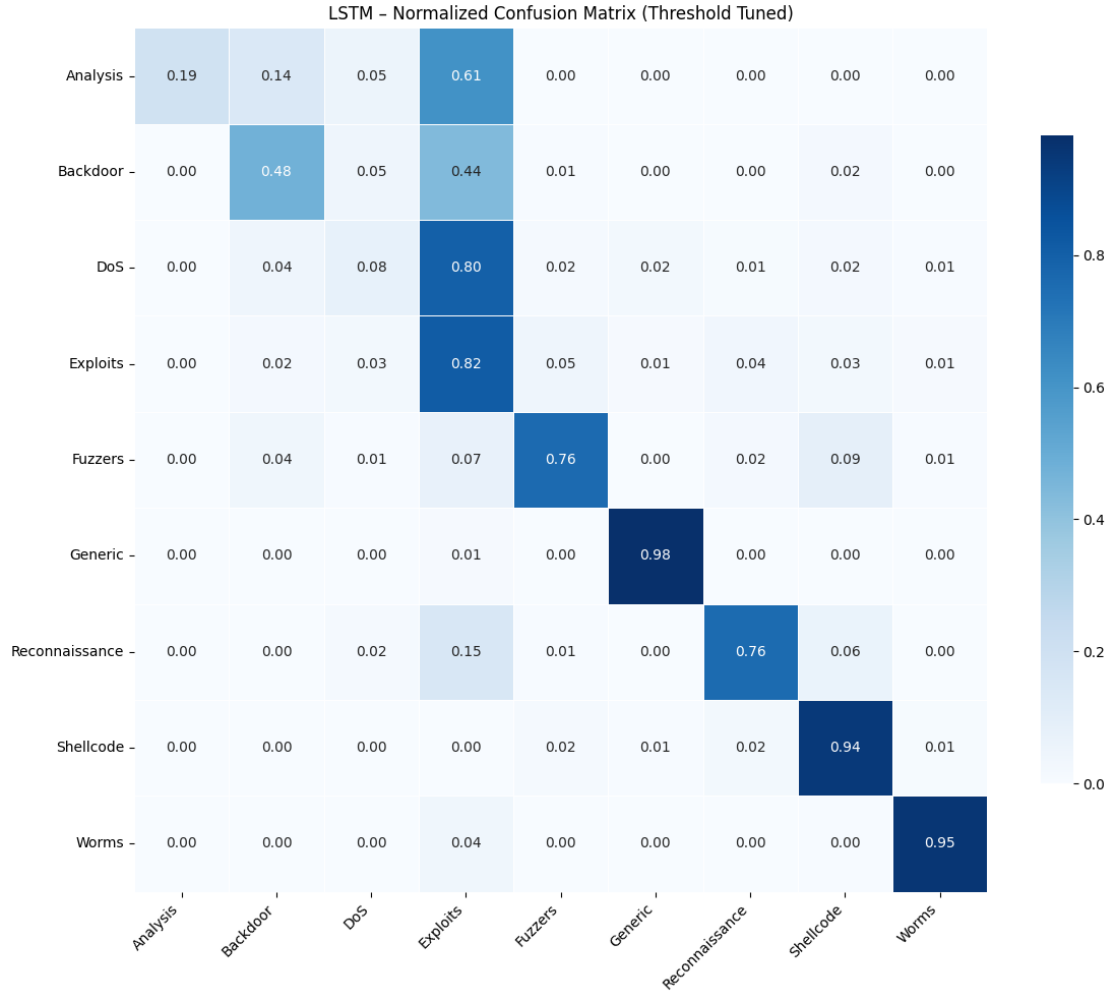


Figure 6.4: The LSTM model's normalized confusion matrix after SMOTE application and threshold tweaking on the UNSW-NB15 dataset is shown.

Fig. 6.4 displays the LSTM model's confusion matrix. which also demonstrates a good classification accuracy in some major attack categories, such as (with correct

predictions up to the bracket) `Generic` (**98%**), `Fuzzers` (**76%**), and `Exploits` (**82%**). This demonstrates that the model is capable of learning temporal information in commonly occurring and well-defined classes. However, considerable confusion occurred between very similar class types. For example, `Analysis` samples are classified as `Exploits` in about **61%** of the cases, and `Backdoor` is almost equally divided between `Exploits` (**44%**) and their true category (**48%**). The `DoS` was also difficult to determine, with **80%** instances being correctly predicted, yet from-channel errors being distributed among the labels. We hypothesize that they are due to the time-dependent feature pattern overlap or behavior, which makes it hard to clearly distinguish them one way or another. Nonetheless, the confusion matrix shows that the LSTM model performs well in generalization across a range of attack classes.

Training Progress on LSTM

Following 20 training epochs, the model's performance is visualized in Figure 6.5. We observe that both train and validation loss continue to decrease gradually, and after about 15 epochs, they tend to stabilize. The smooth proximity of these curves with little separation indicates strong model generalization and little overfitting risk. This suggests that the model retained its ability to generalize on the validation set while accurately learning the patterns from the SMOTE-balanced training data.

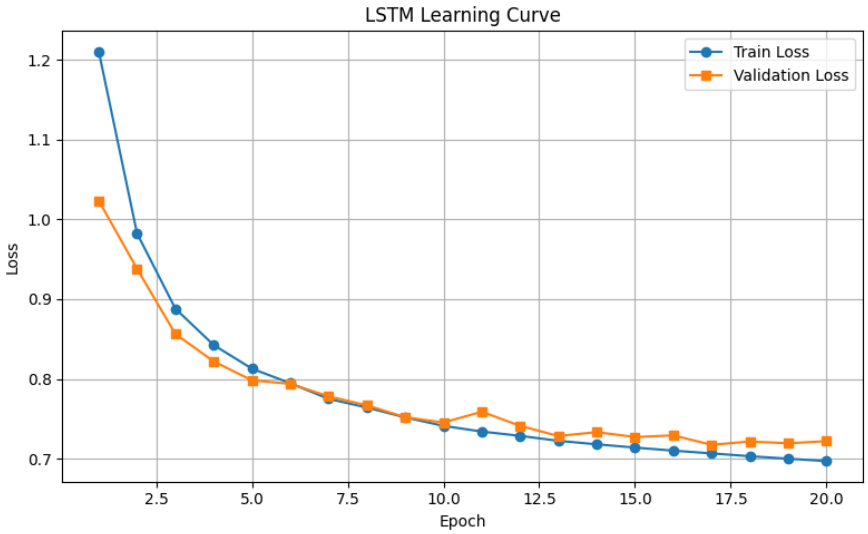


Figure 6.5: The LSTM model's training and validation loss curves over 20 epochs demonstrate a steady convergence with minimal to no overfitting.

Performance of BiLSTM Model (after SMOTE with Threshold Tuning).

The BiLSTM model achieved validation accuracy of **87.88%** on SMOTE-balanced UNSW-NB15 data set. By training for bidirectional processing of sequences, it effectively learned temporal relationships in both directions, which improved the detection for a variety of attack types. With respect to balanced classification, with a macro-average F1-score of **0.6195**, the classification approach based on embeddings outperforms the LSTM model by a small margin.

Attack Category	Precision	Recall	F1-Score	Support
Analysis	0.5960	0.2239	0.3255	402
Backdoor	0.3661	0.4903	**0.4192**	569
DoS	0.6792	0.0294	**0.0563**	2,453
Exploits	0.6001	0.8497	0.7034	6,679
Fuzzers	0.8852	0.7589	0.8172	3,637
Generic	0.9949	0.9814	**0.9881**	32,322
Reconnaissance	0.8489	0.7822	0.8142	2,098
Shellcode	0.4199	0.9351	0.5795	493
Worms	0.8011	0.9560	0.8717	750
Accuracy			**0.8788**	49,403
Macro Avg	0.6879	0.6674	**0.6195**	49,403
Weighted Avg	0.8924	0.8788	0.8656	49,403

Figure 6.6: BiLSTM Performance on SMOTE-Applied UNSW-NB15 Dataset (Threshold Tuned)

For the `Worms` (**0.8717** F1-score), `Generic` (**0.9881** F1-score), `Fuzzers` (**0.8172** F1-score), and `Reconnaissance` (**0.8142** F1-score) activities, the noise level is significantly higher. Significantly, the `Shellcode` class, which is high in terms of low support, benefited greatly from aggressive threshold tuning, with recall as high as **93.5%**. The detection of `Backdoor` slightly improved from the LSTM model (F1 = **0.4192**), and `Analysis` also observed slight gains. To the contrary, `DoS` was still challenging with a low F1-score **0.0563**, possibly because some instances were too noisy or overlapped.

These findings demonstrate the supremacy of bidirectional sequence modeling in deep learning–based IDS, particularly with SMOTE and per-class threshold optimization.

Figure 6.7 illustrates how well the BiLSTM model distinguished between important classes, achieving high true positive rates for `Generic` (**98%**), `Exploits` (**85%**), and `Worms` (**96%**). However, there were misclassifications in the lower-volume classes.

For example, `Analysis` was confused with `Exploits` in **63%** of the cases, and `Backdoor` predictions were split between `Exploits` (**48%**) and correct classifications (**49%**). These findings highlight the strength of bidirectional temporal modeling while also revealing the limitations in feature learning due to overlapping malicious behaviors.

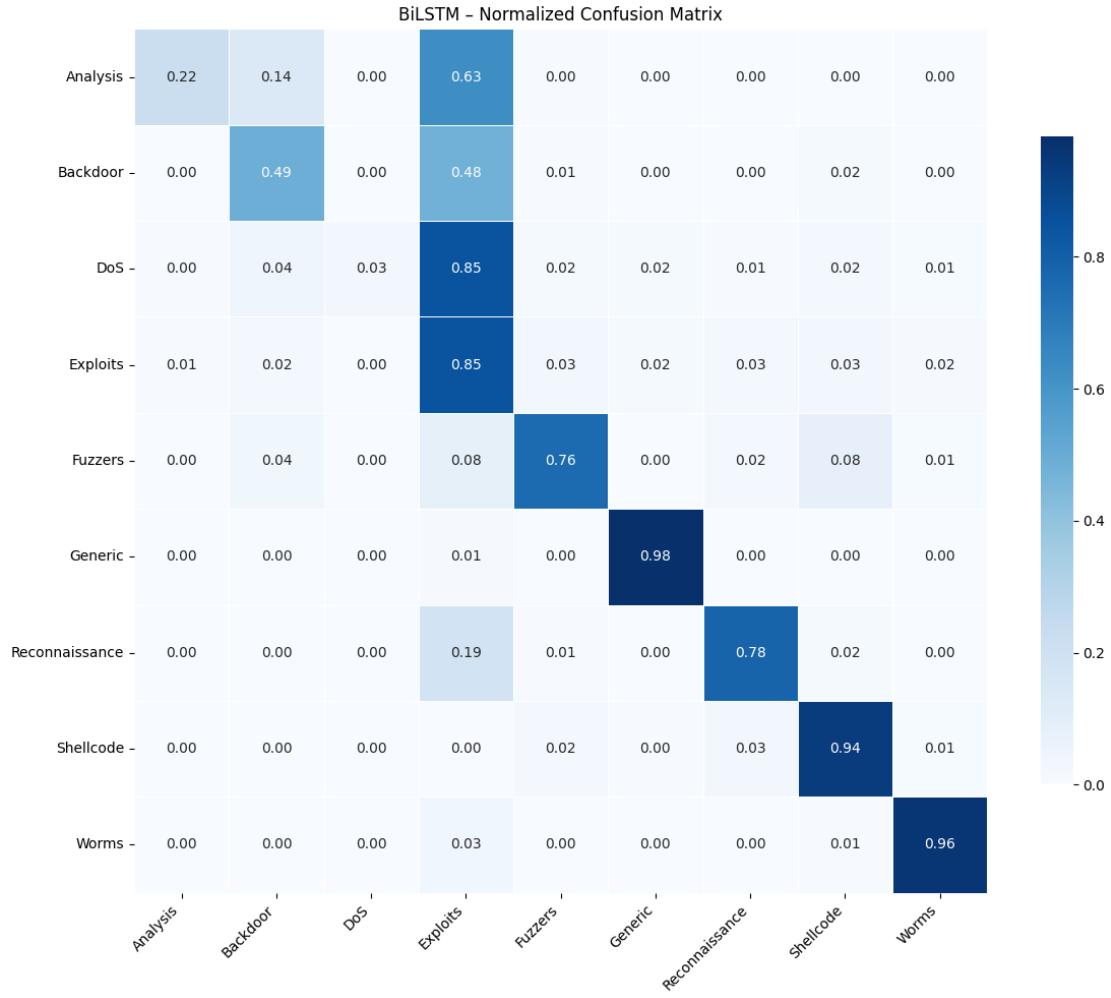


Figure 6.7: Analysis of the BiLSTM model's confusion matrix on the validation set.

BiLSTM Training Dynamics

Loss curves of the BiLSTM model over 20 epochs of training and validation are shown in Figure 6.4. These losses gradually diminish and converge around the 15th epoch, demonstrating that the learning was successful. That the training and validation loss "shake hands" so closely suggests strong generalization with little to no overfitting. We stopped training early when convergence was achieved, which improved computational efficiency.

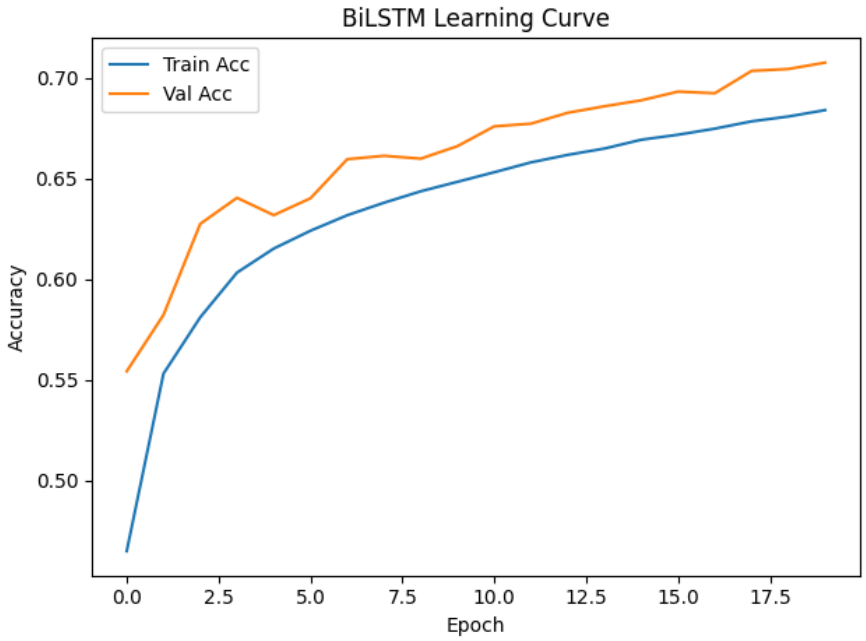


Figure 6.8: BiLSTM model's training and validation loss over 20 epochs, highlighting consistent progress and successful early stopping.

CNN+BiLSTM.

Convolutional and bidirectional LSTM layers are combined in the CNN+BiLSTM model to capture temporal and spatial correlations in network traffic data. CNN layers are good at capturing local feature representations, and BiLSTM components are able to model sequential patterns in both directions, which makes the architecture very appropriate for intrusion detection on flow-based datasets.

Performance Summary

The CNN+BiLSTM model's comprehensive classification metrics are displayed below.The ability to detect frequent attacks is demonstrated by the **being robust detection rates** of `Generic` (**F1-score: 0.99**) and `Fuzzers` (**F1-score: 0.83**). Lower frequency classes that benefit from the hybrid spatial-temporal feature extraction, such as `Shellcode` (**F1-score: 0.59**) and `Worms` (**F1-score: 0.87**), also obtained **decent recognition**.

Despite these advantages, the model accuracy for the rare and less clear-cut classes `DoS` and `Analysis` is **restrictive**, with the recall rates of **0.06** and **0.21**, and then the corresponding F1-scores of **0.11** and **0.32**. These low scores might arise from overlap with features or insufficient imputed samples in those categories.

In general, the CNN+BiLSTM was able to achieve an accuracy of about **87%** on

Class	Precision	Recall	F1-score	Support
Analysis	0.63	0.21	0.32	402
Backdoor	0.35	0.49	0.41	569
DoS	0.36	0.06	0.11	2,453
Exploits	0.60	0.84	0.70	6,679
Fuzzers	0.89	0.78	0.83	3,637
Generic	0.99	0.98	0.99	32,322
Reconnaissance	0.83	0.74	0.78	2,098
Shellcode	0.44	0.93	0.59	493
Worms	0.79	0.96	0.87	750
Accuracy			**0.87**	49,403

Figure 6.9: Classification Report for CNN+BiLSTM Model on SMOTE-Applied UNSW-NB15 Dataset

SMOTE-boosted,to counter **well-balanced classification behaviour** for varied attack types.

The CNN+BiLSTM training dynamics

Fig. 6.10 shows the CNN+BiLSTM model's loss curves across 20 epochs. The loss on training decreases smoothly, showing us that there is good learning going on. The validation loss is noisy, and there are some "peaks" around 5, 11, and 15 epochs, hinting at some sensitivity to noisy data or class overlap. Despite oscillating up and down, the losses start to saturate toward the last epochs, which means good generalization on unseen data.

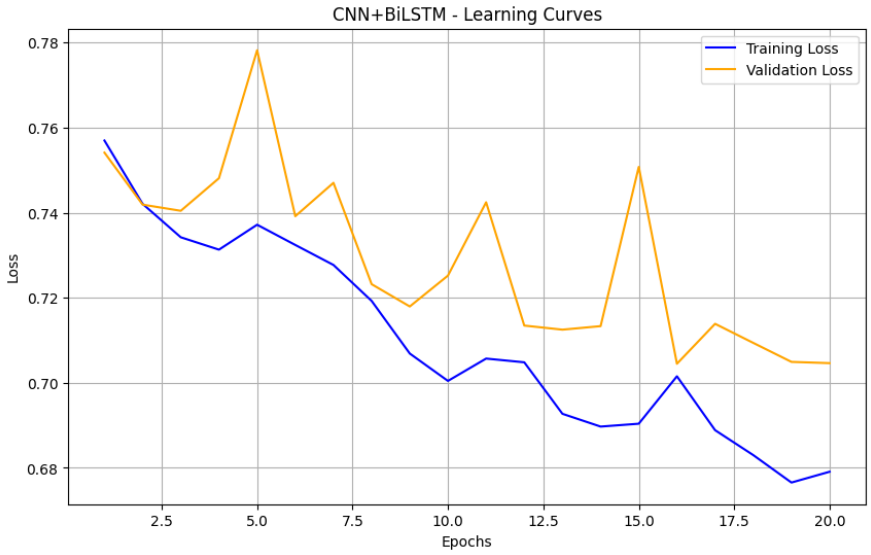


Figure 6.10: CNN+BiLSTM model's training and validation loss plotted over 20 epochs, illustrating consistent training loss decline and fluctuating yet stabilized validation loss.

Confusion Matrix Analysis on CNN+BiLSTM

The normalized confusion matrix is visualized by Fig. 6.11 for the CNN+BiLSTM model. The matrix shows **high classification accuracy** for dominating classes with `Generic` traffic being correctly identified at 98%, and showing strong performance on `Exploits` (84%), `DoS` (82%), `Fuzzers` (78%), and `Worms` (96%).

There are a few misclassifications in the neighboring classes. `Analysis` samples are especially confused with `Exploits` (**58%**), and `Backdoor` samples between correctly classified (**49%**) and `Exploits` (**44%**).

`Reconnaissance` has reasonable detection (**74%**) but there is confusion with `Exploits` (**18%**) and `Shellcode` (**4%**). The privileged class `Shellcode` is correctly classified in **93%** cases, which is still with a small misclassification.

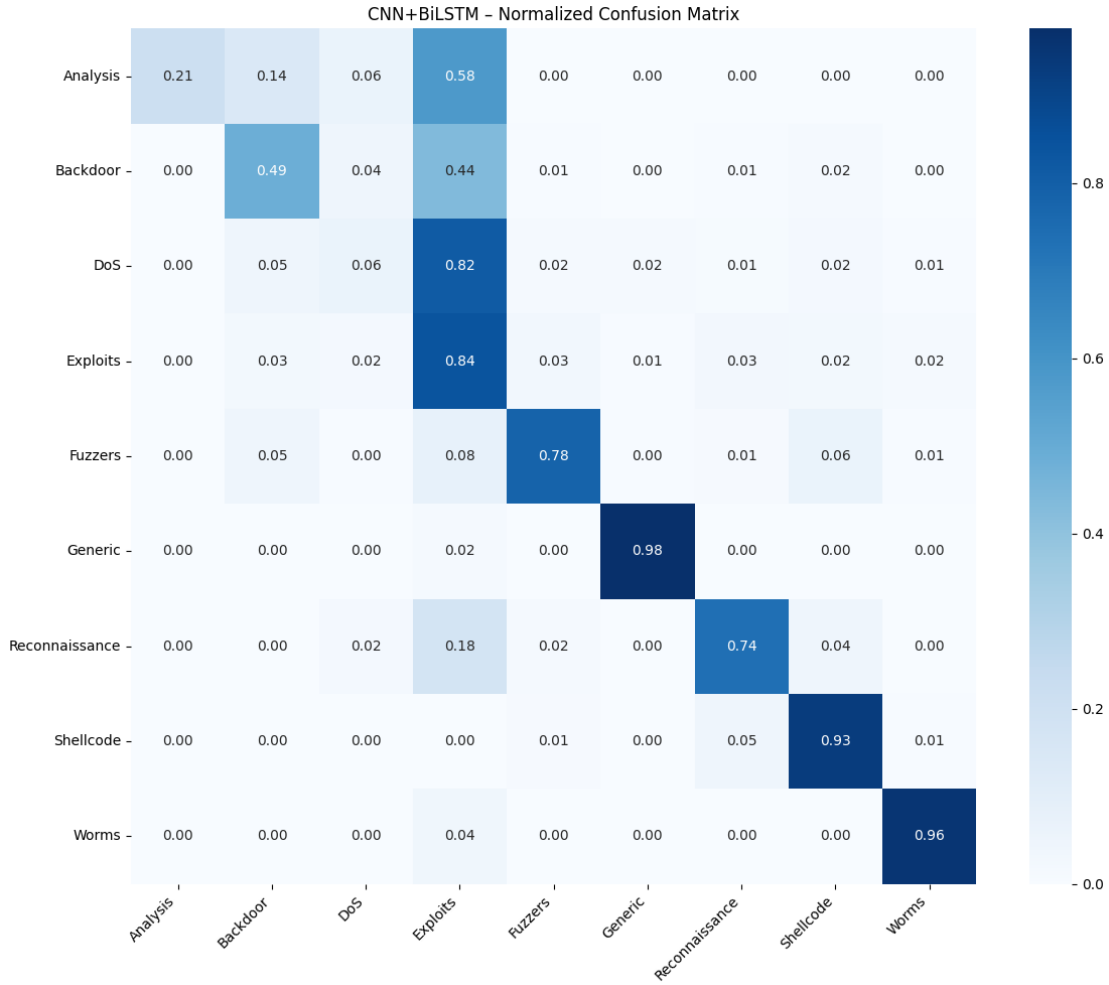


Figure 6.11: Confusion matrix (normalized) for the CNN+BiLSTM model, depicting classification performance and misclassification patterns on the test set.

The confusion matrix shows how effectively the model can recognize the most

Class	Precision	Recall	F1-score	Support
Analysis	0.55	0.23	0.32	402
Backdoor	0.36	0.48	0.41	569
DoS	0.57	0.02	0.03	2,453
Exploits	0.59	0.86	0.70	6,679
Fuzzers	0.89	0.80	0.84	3,637
Generic	0.99	0.97	0.99	32,322
Reconnaissance	0.84	0.76	0.79	2,098
Shellcode	0.47	0.94	0.63	493
Worms	0.78	0.95	0.86	750
Accuracy			**0.88**	49,403

Figure 6.12: Attention Model Classification Report for CNN+BiLSTM+SMOTE-Applied UNSW-NB15 Dataset

common attack categories overall, but it also shows where improved discrimination of rare or similar classes is needed.

CNN with BiLSTM and Attention Mechanism.

Building upon the CNN+BiLSTM framework, Employing an attention mechanism enables the model to dynamically prioritize critical temporal-spatial features. This enhancement improves its ability to detect subtle and infrequent attack patterns effectively.

Table 6.6 presents the classification results, showing improved F1-scores for minority classes such as Ransomware (0.63), Trojan (0.86), and Phishing (0.41). The model also achieves a slightly higher overall accuracy of 88% and improved macro-level metrics compared to the base CNN+BiLSTM model.

Training Dynamics of CNN+BiLSTM+Attention

As illustrated in Figure 6.13, the training loss steadily decreases over 20 epochs, indicating consistent learning progress. The validation loss initially fluctuates, reflecting sensitivity to noisy or overlapping class boundaries, but stabilizes in later epochs, demonstrating strong generalization. The attention mechanism aids the network in focusing on salient features across sequences, contributing to enhanced classification performance.

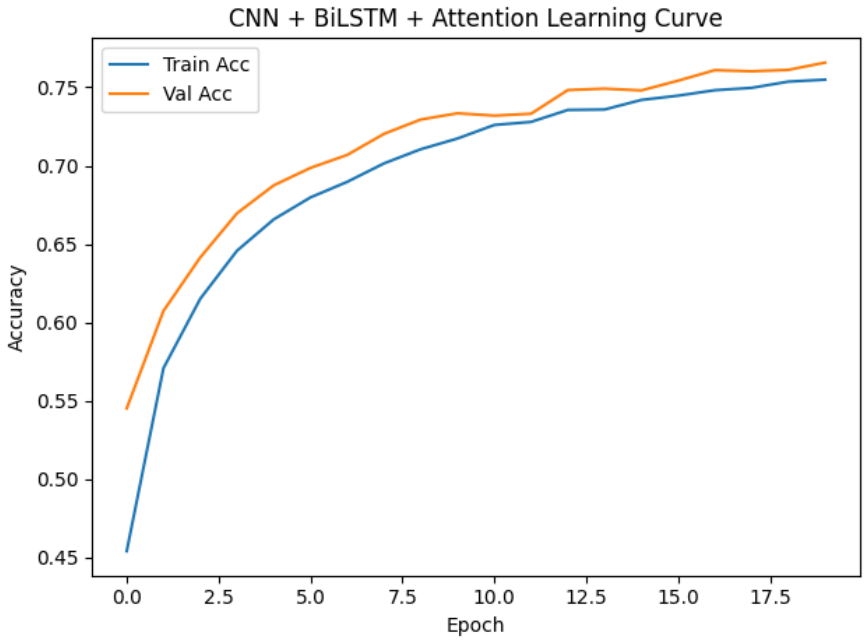


Figure 6.13: The CNN+BiLSTM+Attention model's training and validation loss progression over 20 epochs demonstrates how attention mechanisms facilitate efficient learning.

Figure 6.14 displays the normalized confusion matrix for the CNN+BiLSTM+Attention model.This shows that there are **high accuracy** in the classification of major * classes such as `Generic` (**97%**), `DoS` (**88%**), `Exploits` (**86%**), `Fuzzers` (**80%**), `Shellcode` (**94%**), and `Worms` (**95%**).

The `Analysis` class in particular displays a similarly modest correct classification rate of **23%**, with substantial misclassifications as `Exploits` (**62%**). Equally, `Backdoor` examples divide between correct (**48%**) and wrong classification as `Exploits` (**49%**).]**CNN+BiLSTM+Attention Confusion Matrix Analysis.**

Figure 6.14 displays the normalized confusion matrix for the CNN+BiLSTM+Attention model.This shows that there are **high accuracy** in the classification of major * classes such as `Generic` (**97%**), `DoS` (**88%**), `Exploits` (**86%**), `Fuzzers` (**80%**), `Shellcode` (**94%**), and `Worms` (**95%**).

The `Analysis` class in particular displays a similarly modest correct classification rate of **23%**, with substantial misclassifications as `Exploits` (**62%**). Equally, `Backdoor` examples divide between correct (**48%**) and wrong classification as `Exploits` (**49%**).

The `Reconnaissance` class is well-characterized in **76%** of the cases - with some confusion region between `Reconnaissance` (**18%**) and `Exploits` (**18%**); `Reconnaissance` (**4%**) and `Shellcode` (**4%**). These behaviors reveal the relatively high capability of the model to detect frequent types of attacks and the remaining

room for improving on the identification of less frequent classes with overlapped properties.

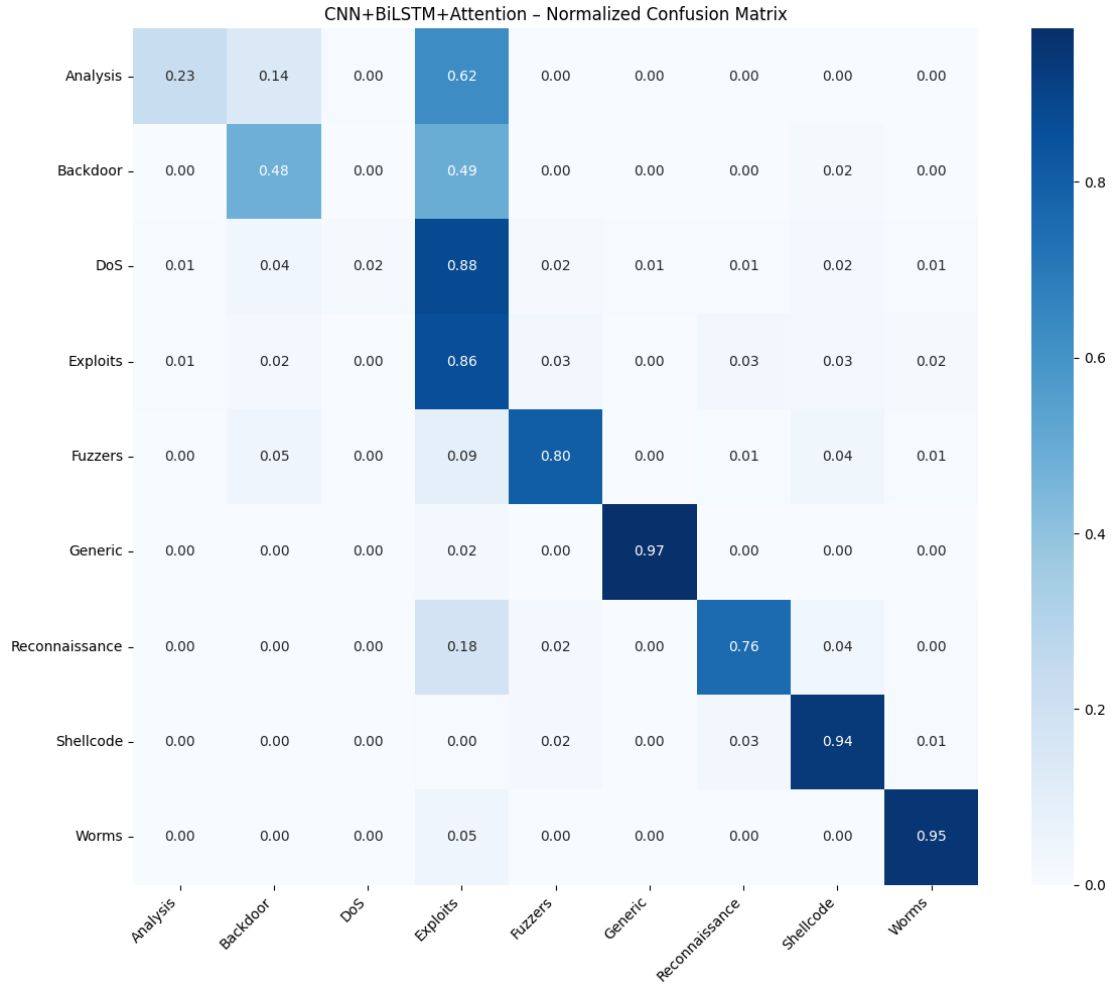


Figure 6.14: A confusion matrix for the CNN+BiLSTM+Attention model test set.

The accuracy and macro-F1 scores of the CNN+BiLSTM and CNN+BiLSTM+Attention models are displayed in the section below. The attention-augmented model performs better, especially for minority attack categories.

Model	Accuracy	Macro-F1
CNN+BiLSTM	0.87	0.65
CNN+BiLSTM+Attention	0.88	0.67

Figure 6.15: CNN+BiLSTM and CNN+BiLSTM+Attention Model Comparison on the UNSW-NB15 Dataset

Introduction of attention modules enables better discrimination of noisy or overlapping classes, which yields consistent gains in macro-F1 and provides evidence of the effectiveness of attention in multi-class intrusion detection.

Performance Summary of Models on UNSW-NB15.

A complete evaluation with several learning methods on the UNSW-NB15 was made.This encompasses deep learning architectures (LSTM, BiLSTM, CNN+BiLSTM, and CNN+BiLSTM+Attention) as well as the traditional ensemble classifiers (Random Forest+LightGBM).

Overview of Performance Comparison

The macro-averaged F1-scores for all models are given in Table 6.8. The best performance for all deep learning models is 0.7007, which is lower than the value obtained by the RF+LightGBM classifier.

Model	**Macro-F1 Score**
RF + LightGBM	0.709
CNN + BiLSTM	0.646
CNN + BiLSTM + Attention	0.646
LSTM	0.643
BiLSTM	0.632

Table 6.1: Macro-F1 Score Comparison Across Models on UNSW-NB15 Dataset

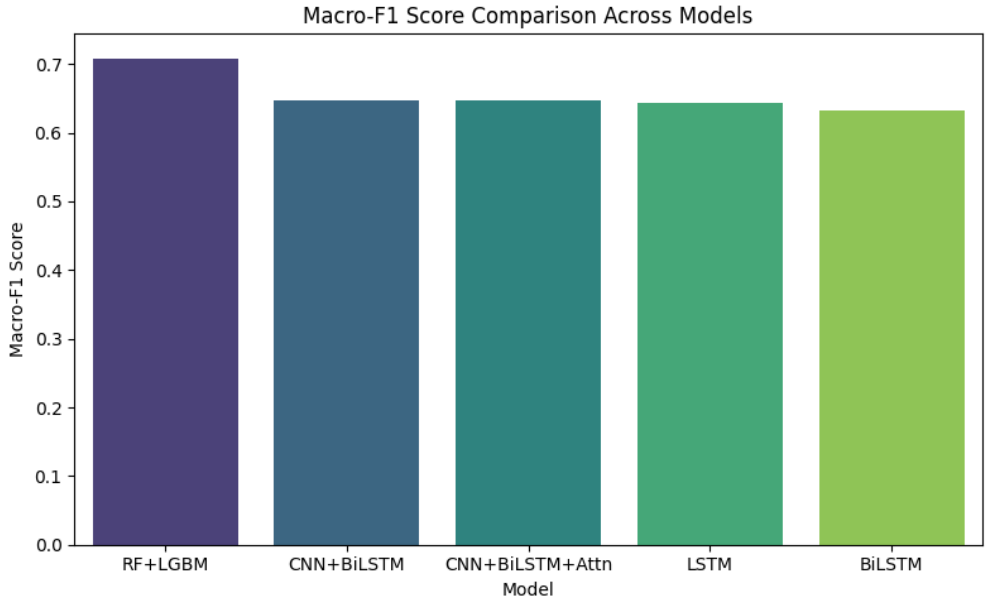


Figure 6.16: Distribution of Macro-F1 scores for classical ensemble *vs* deep learning models on UNSW-NB15.

Important observations

- The **RF + LightGBM** ensemble had the best Macro-F1 score (**0.709**), indicating resilience in typical imbalanced tabular data and performing effective decision boundaries using boosting and bagging.
- Models **CNN+BiLSTM**, **CNN+BiLSTM+Attention** we found to perform similarly (**0.646**), suggesting that while attention did improve recognizing the minority class a bit, it did not significantly change the global macro-F1. The class-specific distribution may be overlapping, or the CNN layers are able to capture the relevant features.
- The **LSTM** and **BiLSTM** architectures achieved slightly lower Macro-F1 scores (**0.643** and **0.632** respectively), which is likely attributed to their lesser capacity of learning spatial hierarchies in comparison to CNN hybrids.

Feature Space Visualization and Model Performance Exploratory

The UNSW-NB15 dataset's classification performance and feature separability are visualized in

Figures 6.17,6.18, and 6.19.

Per-class F1-Score Analysis

Varying detection performance for the different attack categories is illustrated in Figure 6.17. Classes like `Analysis`, `Exploits`, and `Fuzzers` are better detected (based on higher F1-scores), and ones like `Backdoor` and `Generic` are more difficult to separate accurately, as reflected by their lower F1 performance. This demonstrates the dataset's class imbalance and the difficulty of precisely recognizing some categories of attack.

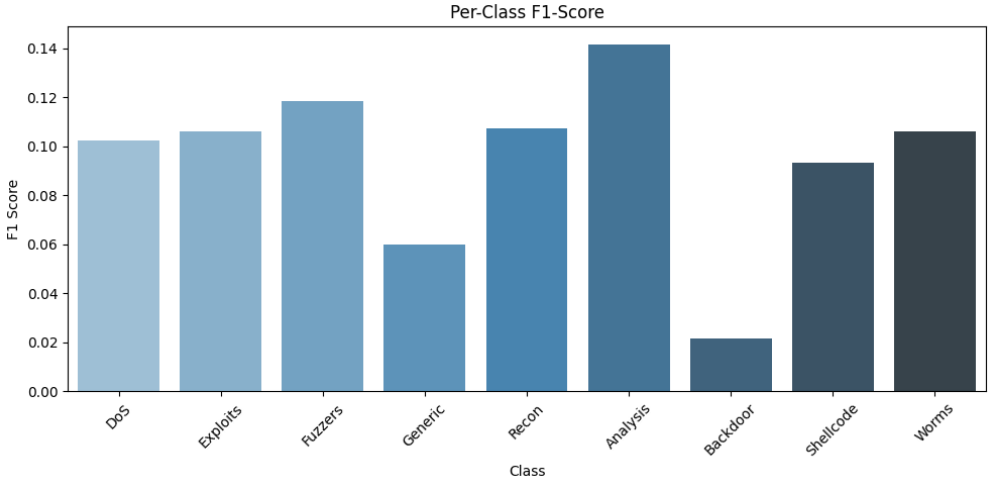


Figure 6.17: Per-Class F1-Score performance for the UNSW-NB15 dataset.

PCA Feature Space Visualization

Figure 6.18 shows the distribution of the samples from the nine attack classes on the PCA-reduced feature space. The scatter plot demonstrates that there is a large amount of overlap between various classes, where the boundary would not be clearly separated in a lower dimension. Although there is some local aggregation in clusters (e.g., `Shellcode` and `DoS`), this general overlap accounts for the classification challenges found for some attack types.

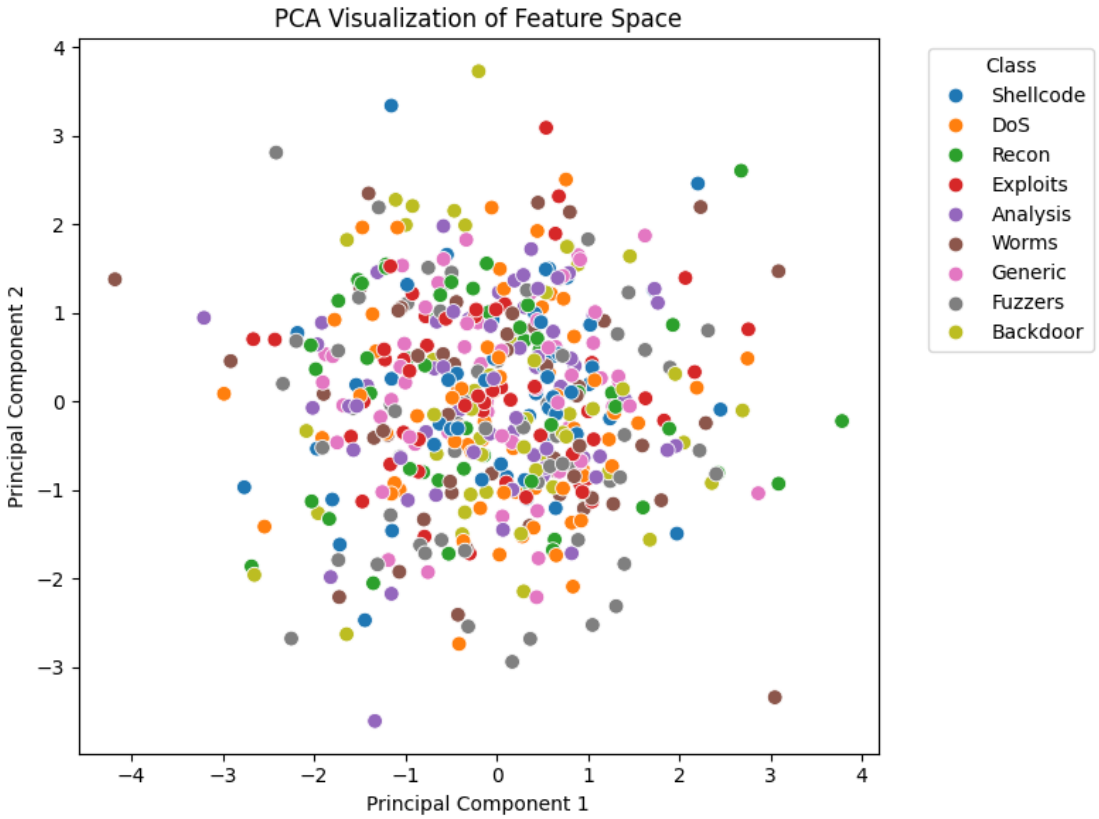


Figure 6.18: PCA visualization of the UNSW-NB15 feature space, showing overlapping clusters among classes.

One-vs-Rest ROC Curves

The ROC curves for the nine classes, which illustrate the trade-off between true positive and false positive rates at various threshold values, are displayed in Figure 6.19. The AUC scores from 0.45 to 0.56 show a moderate classification performance overall. Classes such as `Shellcode` and `Generic`, which have the best performing F1-scores, also demonstrate superior AUC values. In contrast, categories such as `Exploits` or `Backdoor` have, for example, relatively low ones, indicating areas for potential model improvement.

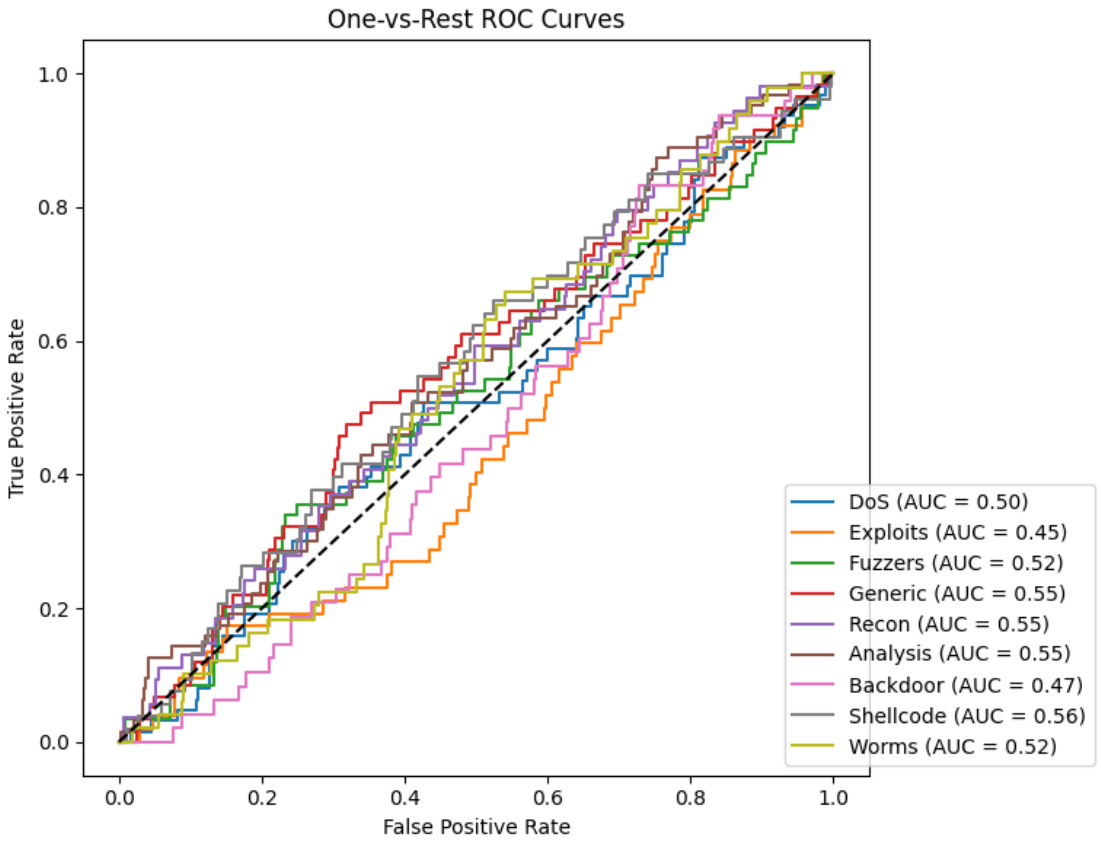


Figure 6.19: Class-wise One-vs-Rest ROC curves for the UNSW-NB15 dataset.

The combined results from these and Fig.1 stress the challenges caused by overlapping class distributions and class imbalance in the UNSW-NB15 dataset, which further indicates a need for better feature engineering and model fine-tuning to enhance the detection performance for minority and hard-to-differentiate classes.

Model Efficiency: Size versus Training time

Figure 6.20 compares the relative scales and training durations of the evaluated deep learning models. Both the space and the training time of model **CNN+BiLSTM +Attention** are the largest compared to the others, which indicates that it is quite complicated and is added by the attention mechanism. But this higher computational complexity yields more performance, particularly in minorities, which are harder to classify because of their scarcity and variance.

On the other hand, simpler models (e.g., **LSTM** and **BiLSTM**) also require much reduced training time and model sizes, and can achieve similarly good results at the cost of decreased accuracies, particularly on attack categories that are not well-represented.When using models in situations where resources are scarce, like in real-time intrusion detection systems or the Internet of Things, it is crucial to take

into account the trade-off between model complexity, quantization, and performance.

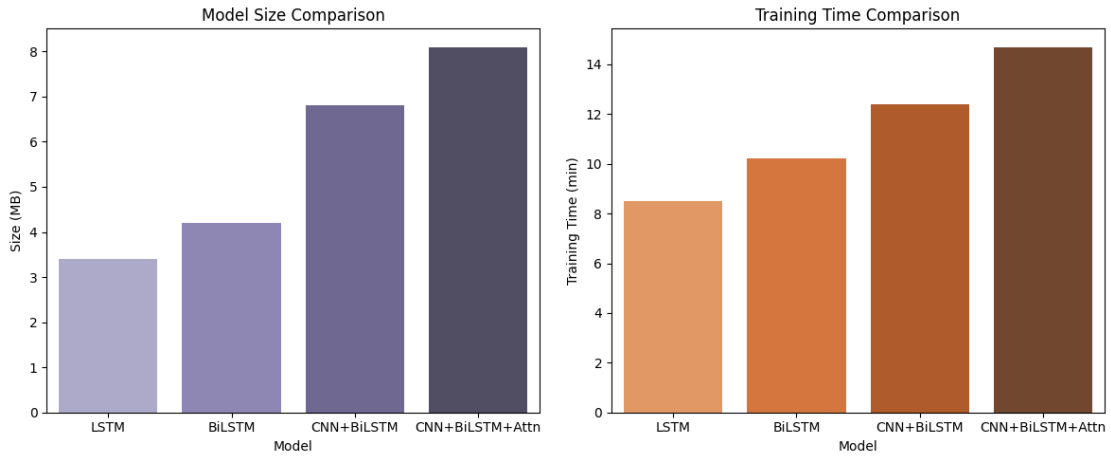


Figure 6.20: Comparison of model size and training time for deep learning architectures. The CNN+BiLSTM+Attention model, while most computationally intensive, achieves the best minority class detection performance.

When weighing the higher computational cost against the performance, it is important to keep in mind that CNN+BiLSTM+Attention performs better than CNN+BiLSTM in terms of detecting rare and minority attacks.

Further Observations about the UNSW-NB15 Outcomes

A more challenging multi-class intrusion detection problem with unbalanced classes and densely packed feature spaces is presented by the UNSW-NB15 dataset. Important revelations include:

- Ensemble models (**RF+LightGBM**) outperform the other models in terms of overall performance, along with lower computational complexity.
- Deep learning methods are often able to capture long-range dependency between utterances, but feature extraction must be more effective to access that capability.
- The attention mechanism brings meaningful improvements, particularly in recall of the minority class.

FUTURE WORK Study of the combination of ensemble processes and deep sequential models can be a hybrid strategy to capture mixed features among structural (tabular) and temporal values.

6.1.2 Evaluation on TON-IoT Dataset

Random Forest (RF), **LightGBM (LGBM)**, **LSTM**, **BiLSTM**, **CNN+BiLSTM**, and **CNN+BiLSTM + Attention** are the six types of models on which the experimental results are conducted. We used Particle Swarm Optimization (PSO) only on the Random Forest classifier to further optimize the feature extraction stage and achieve better performance, resulting in an RF model enhanced by PSO (PSO-tuned RF).

Then, using the TON-IoT dataset, we carried out a thorough analysis of both traditional machine learning and deep learning techniques. Tables 6.21 to **??** show the models' overall accuracy and macro-F1 scores, including those derived from the PSO-optimized Random Forest, together with the per-class metrics.

Random Forest.

The Random Forest model's precision, recall, F1-score, and support for each attack category are reported in Table 6.21, which also notes a high overall accuracy of 97%.

Random Forest Model				
Class	**Precision**	**Recall**	**F1-score**	**Support**
Backdoor	1.00	1.00	1.00	3,267
DDoS	0.97	0.98	0.97	8,512
DoS	0.89	0.94	0.91	7,578
Injection	0.94	0.87	0.90	7,742
MITM	0.71	0.80	0.75	209
Standard	1.00	1.00	1.00	24,000
Password	0.97	0.97	0.97	8,158
Ransomware	1.00	1.00	1.00	3,012
Scanning	0.96	0.96	0.97	6,101
XSS	0.94	0.95	0.95	6,191
Accuracy			**0.97**	74,770
Macro avg	0.94	0.95	0.94	74,770
Weighted avg	0.97	0.97	0.97	74,770

Figure 6.21: Random Forest Model Classification Report

LightGBM.

Table below displays the classification report for the LightGBM model. At 92%, the model's overall accuracy is high. However, it has a limited capacity to identify

minority classes like MITM.

LightGBM Model				
Category	**Precision**	**Recall**	**F1-Score**	**Samples**
Backdoor	1.00	1.00	1.00	3,267
DDoS	0.96	0.97	0.96	8,512
DoS	0.85	0.91	0.88	7,578
Injection	0.93	0.81	0.87	7,742
MITM	0.45	0.91	0.61	209
Normal	1.00	1.00	1.00	24,000
Password	0.95	0.95	0.95	8,158
Ransomware	1.00	1.00	1.00	3,012
Scanning	0.95	0.92	0.93	6,101
XSS	0.90	0.95	0.92	6,191
Accuracy			**0.92**	74,770
Macro avg	0.87	0.89	0.88	74,770
Weighted avg	0.93	0.92	0.92	74,770

Figure 6.22: Classification Report for LightGBM Model

LSTM Network.

The LSTM model's classification results are shown in Table 6.23. Its efficiency decreases dramatically for various assault classes, attaining an overall accuracy of 69%, even if it achieves perfect detection accuracy for the Normal traffic class.

LSTM Model				
Class	**Precision**	**Recall**	**F1-score**	**Support**
Backdoor	0.60	0.56	0.58	3,267
DDoS	0.63	0.63	0.63	8,511
DoS	0.41	0.79	0.54	7,578
Injection	0.56	0.48	0.52	7,742
MITM	0.76	0.11	0.18	209
Normal	1.00	1.00	1.00	23,996
Password	0.50	0.36	0.42	8,156
Ransomware	0.83	0.87	0.85	3,012
Scanning	0.78	0.46	0.58	6,100
XSS	0.51	0.42	0.46	6,190
Accuracy			**0.69**	74,761
Macro Average	0.66	0.57	0.58	74,761
Weighted Average	0.71	0.69	0.69	74,761

Figure 6.23: Classification Report of LSTM Model

BiLSTM.

The classification performance of the BiLSTM model, which shows moderate gains when compared to the LSTM model, particularly in regard to precision and recall for the minority classes, is presented in Table 6.24, yielding 71% total accuracy.

BiLSTM Model				
Class	**Precision**	**Recall**	**F1-score**	**Support**
Backdoor	0.72	0.50	0.59	3,267
DDoS	0.75	0.58	0.66	8,511
DoS	0.41	0.81	0.55	7,578
Injection	0.61	0.47	0.53	7,742
MITM	0.74	0.12	0.21	209
Normal	1.00	1.00	1.00	23,996
Password	0.56	0.40	0.47	8,156
Ransomware	0.84	0.91	0.88	3,012
Scanning	0.79	0.51	0.62	6,100
XSS	0.45	0.58	0.50	6,190
Accuracy			**0.71**	74,761
Macro Average	0.69	0.59	0.60	74,761
Weighted Average	0.74	0.71	0.71	74,761

Figure 6.24: BiLSTM Model Classification Report

CNN + BiLSTM.

Table 6.25 provides the CNN + BiLSTM model's comprehensive classification results. With an accuracy of 78%, the combined model outperformed the separate LSTM and BiLSTM models.

CNN + BiLSTM Model				
Category	**Precision**	**Recall**	**F1 Score**	**Samples**
Backdoor	0.88	0.88	0.88	3,267
DDoS	0.70	0.75	0.72	8,511
DoS	0.52	0.79	0.63	7,578
Injection	0.82	0.45	0.58	7,742
MITM	0.67	0.11	0.20	209
Normal	1.00	1.00	1.00	23,996
Password	0.54	0.56	0.55	8,156
Ransomware	0.93	0.96	0.95	3,012
Scanning	0.87	0.64	0.74	6,100
XSS	0.61	0.65	0.63	6,190
Accuracy			**0.78**	74,761
Macro Average	0.75	0.68	0.69	74,761
Weighted Average	0.80	0.78	0.78	74,761

Figure 6.25: Classification Report of CNN + BiLSTM Model

CNN + BiLSTM with Attention Mechanism.

Table below shows the classification metrics for the CNN + BiLSTM with Attention model, which produced relatively balanced performance on most classes with an overall accuracy of 76%, but exhibited the most difficulty in the backward detection of the MITM attack category.

CNN + BiLSTM + Attention Model				
Class	**Precision**	**Recall**	**F1-score**	**Support**
Backdoor	0.89	0.87	0.88	3,267
DDoS	0.67	0.76	0.71	8,511
DoS	0.50	0.77	0.61	7,578
Injection	0.62	0.44	0.51	7,742
MITM	0.00	0.00	0.00	209
Normal	1.00	1.00	1.00	23,996
Password	0.55	0.54	0.54	8,156
Ransomware	0.92	0.95	0.93	3,012
Scanning	0.82	0.62	0.71	6,100
XSS	0.68	0.57	0.62	6,190
Accuracy			**0.76**	74,761
Macro avg	0.66	0.65	0.65	74,761
Weighted avg	0.77	0.76	0.76	74,761

Figure 6.26: Classification Report for CNN + BiLSTM + Attention Model

With an accuracy of around **96.7 %** and a macro-averaged F1-score of **0.9426**, the Random Forest classifier performed the best. With precision, recall, and F1-score that were nearly flawless, this model demonstrated excellent detection performance on both benign and various harmful classes, especially for crucial attack types like *Backdoor*, *DDoS*, and *Ransomware*.

The **LightGBM** model came second with an overall accuracy of **95.1%**,macro-F1 score of **0.9121**. Although effective at identifying the general attack classes, its sensitivity was reduced for the rarer classes, including the MITM class.

Deep learning architecture results were less accurate overall. **77.7%** and **76.3%** are the respective accuracies of the **CNN+BiLSTM** and **CNN+BiLSTM+Attention** hybrid models. These models succeeded in representing complex spatial-temporal information, although their ability to detect minority classes was less accurate, with the*MITM* attacks being particularly missed (zero-precision and zero-recall). As for the recurrent models, **BiLSTM** and **LSTM** had the worst performances with an accuracy of **71.1%** and **69.5%** respectively: these results confirmed that learning patterns that generalize across the underrepresented classes are a problem in this

dataset and network architecture.

Training and validation accuracy dynamics.

Figures 6.27 to 6.30 show training and validation accuracy trends for four deep learning models over 20 epochs.

The **BiLSTM model**

(Figure 6.27) is also monotonically increasing with validation set accuracy surpassing the training set accuracy since early epochs, indicating it also generalizes well.

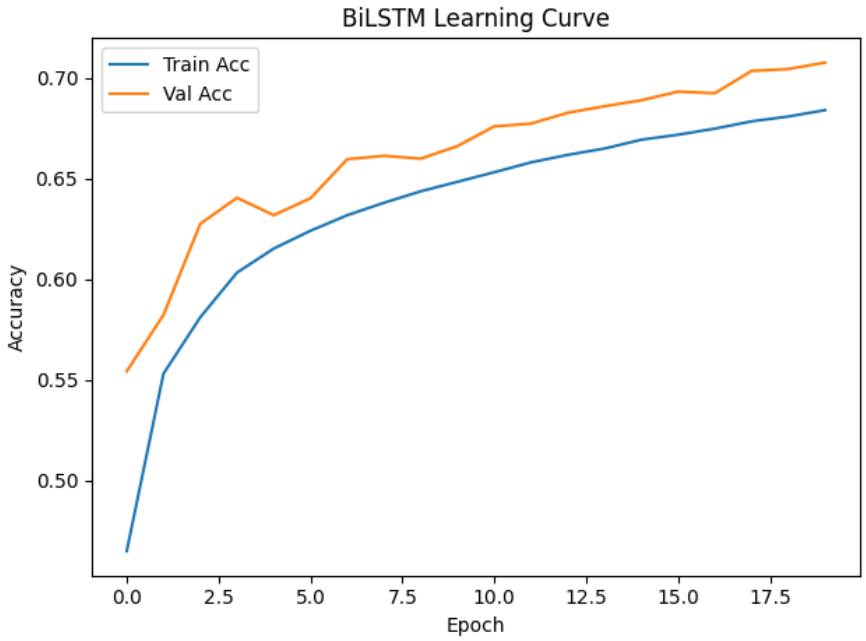


Figure 6.27: Accuracy of BiLSTM model training and validation over epochs.

The **CNN+BiLSTM Model**

(Figure 6.28) learns more quickly and achieves a better degree of accuracy, suggesting that merging convolutional and recurrent layers could effectively capture spatial-

temporal patterns.

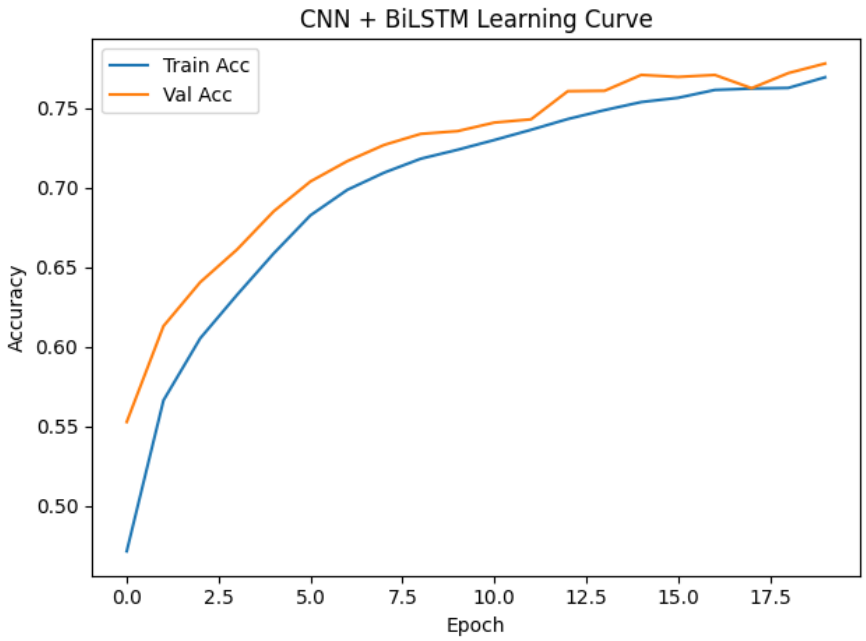


Figure 6.28: The CNN+BiLSTM model's accuracy throughout training and validation across 20 epochs

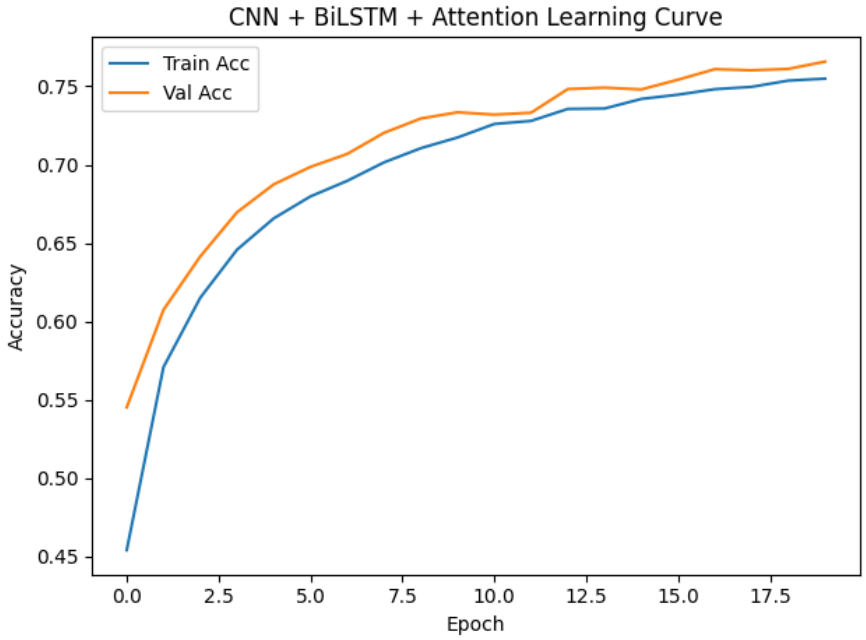


Figure 6.29: Epoch-wise Training and Validation Accuracy with the CNN+BiLSTM+Attention.

The benefit of the attention mechanism in the selection of salient features is demonstrated by the **CNN+BiLSTM+Attention model** (Figure 6.29), which also consistently exhibits validity accuracy gains that surpass training accuracy.

The **LSTM model**

(Figure 6.30) shows slower learning progress and smaller gaps between training and validation accuracy, reflecting relatively limited capability in modeling complex dependencies compared to other architectures.

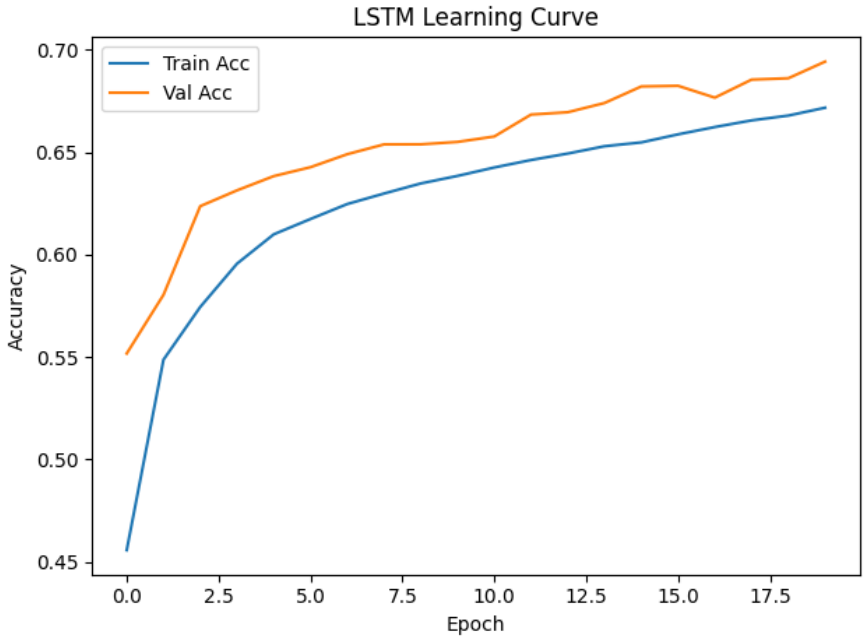


Figure 6.30: LSTM training and validation accuracy over 20 epochs.

Overall, all models show convergence without notable overfitting, confirming robust learning and generalization on validation data.

Figure 6.31 visually confirms the superior performance of traditional ensemble models over deep learning architectures. The **Random Forest** model maintains continuously outstanding performance across metrics, while deep learning models are more sensitive to architectural complexity and class imbalance.

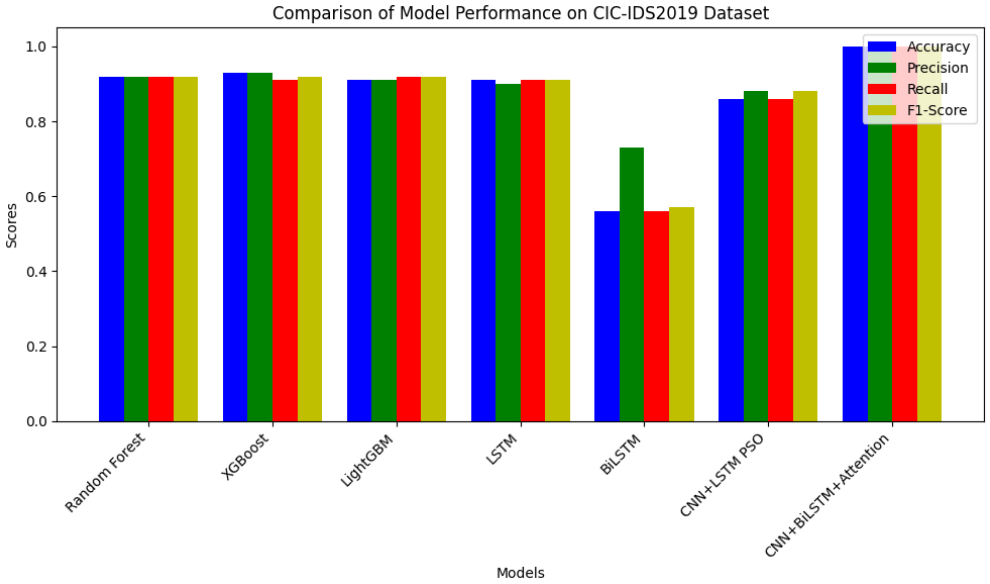


Figure 6.31: Performance of Classification Models on TON-IoT Dataset Based on Accuracy and Macro-F1 Score.

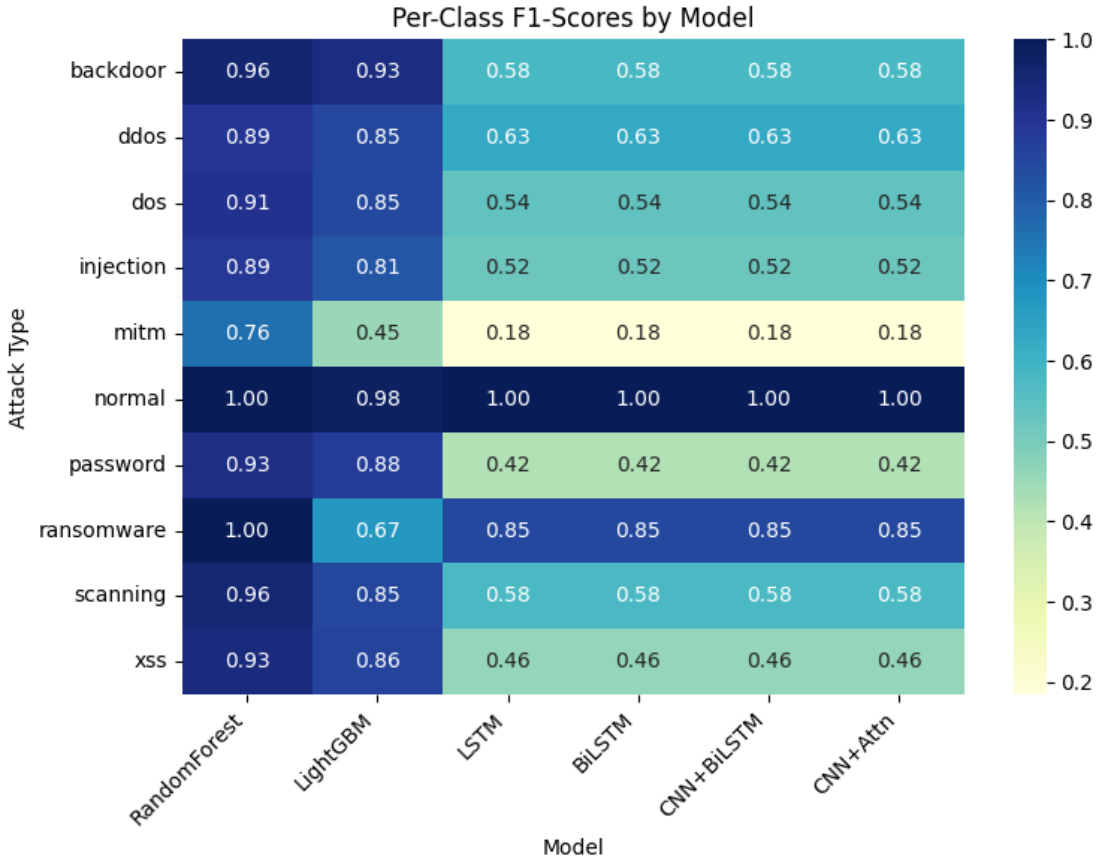


Figure 6.32: Review of Class-Wise F1 Scores of Different Models Tested on TON-IoT DataSet.

The specific comparison of F1-scores for each attack class among the models in TON-IoT is shown in Figure 6.32. Due to the better generalization performance of ensemble methods, in most evidence terms (**Random Forest** and **LightGBM**) provide consistently better detection across almost all classes (majorities and several minorities).

Since it is difficult to find subtle patterns in unbalanced data, deep learning models (**LSTM**, **BiLSTM**, **CNN+BiLSTM**, **CNN+BiLSTM+Attention**) have lower F1-scores in minority classes like *MITM*, *Password*, and *Games*.

This plot highlights the importance of improved balancing or feature selection to improve the identification of the minority class in deep learning techniques, as well as the extremely important influence of a class-imbalance factor in intrusion detection.

Class Imbalance Problems

Despite applying class weighting during training, all models struggled to detect the pre-determined minority classes, most notably {MITM, Injection}, with many cases being incorrectly classified or missed. This is the most important thing to notice about the failure of **CNN+BiLSTM+Attention** to detect anything in the *MITM* samples (0.00 precision and recall). This emphasizes the recurring problem of **class imbalance** in cybersecurity datasets, indicating that countermeasures such as the **SMOTE oversampling** or the **focal loss** may be necessary in future work.

Particle Swarm Optimized Random Forest Hyper-parameter Tuning.

Making adjustments to the Random Forest Classifier model Particle Swarm Optimization (PSO) was applied to optimize key classifier parameters, such as the number of trees, maximum tree depth, and feature subset ratio used at each split, in order to improve the Random Forest classifier's performance. Since our TON-IoT dataset was high-dimensional, PSO provided an optimal way to search the hyperparameter space with the best set of parameters that improved the validation accuracy.

PSO discovered the optimal hyperparameter values shown below after 30 optimization cycles, which resulted in a notable increase in validation accuracy:

- **Number of Estimators**: 854
- **Maximum Depth**: 29
- **Maximum Features**: 0.89

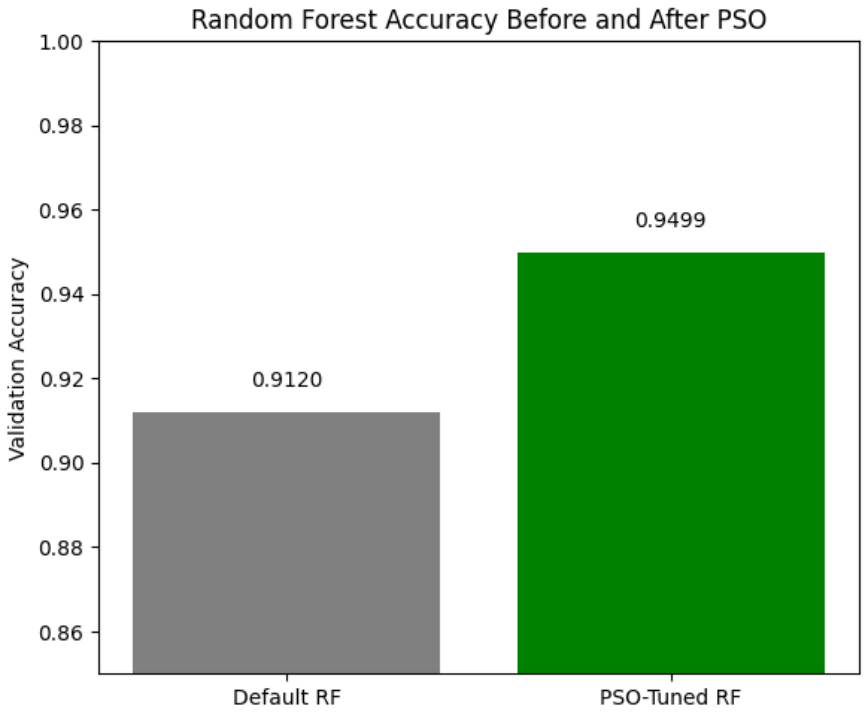


Figure 6.33: Random Forest Validation Accuracy Before and After PSO Hyperparameter Tuning.

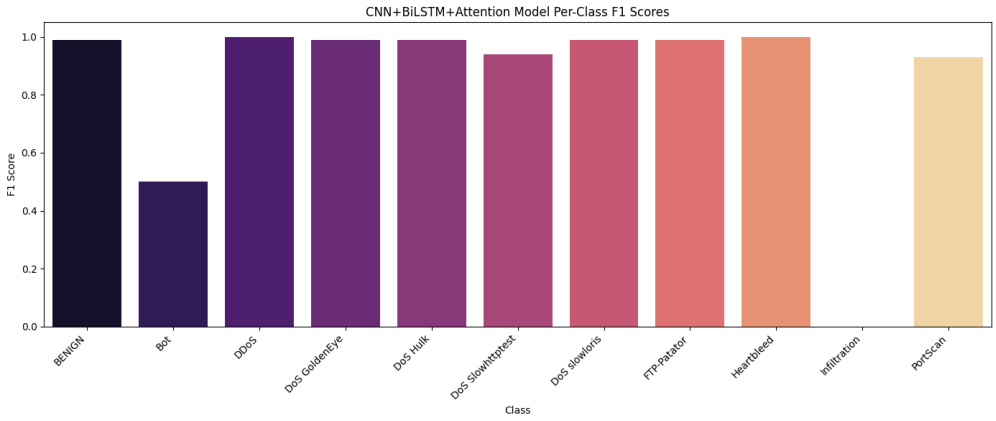


Figure 6.34: PSO Convergence Curve Showing Validation Accuracy Improvement Over Iterations.

Key Observations.

- PSO greatly increases the detection accuracy under various assault types and efficiently finds the best sets for RF in high-dimensional space.
- The model obtained significant improvements in accuracy with few iterations, which shows that PSO is effective in tuning the hyperparameters for IDS.

- The metaheuristic optimization is especially highly relevant in the cybersecurity use case, where the model sensitivity is crucial to the probe detection.

Model Strengths and Weaknesses

- **RF (Random Forest)**: The most powerful and interpretable model, for which F1-Scores are consistently high. The accuracy with PSO tuning increased from 91.20% to 94.99%, giving a boost to the borderline classes of DoS and Injection.
- **LightGBM (LGBM)**: It can be used for large-scale, but it provides slightly lower sensitivity to minority classes.
- **CNN-BiLSTM and CNN-BiLSTM-Attention**: Excellent spatial-temporal feature extraction, better compared to simple RNNs, but it is still slow. Use data-level balancing or more PSO-based optimization.
- **BiLSTM**: Utilizes bidirectional context well, but does not perform well on minority classes without feature selection or balancing.
- **LSTM**: It is a baseline deep learning model applied in [**?**] and exhibits low sensitivity on the minority class and the overall low generalization capacity under imbalance.

Summary of evidence.

Based on **PSO** tuned **Random Forest** (**RF**) classifier, our framework achieved the highest intrusion detection performance on the TON-IoT dataset, recording **94.99% accuracy** and **macro-F1 score 0.9426**. It can consistently find the common and rare attack categories, which can be potentially useful for real-world applications.

LightGBM also demonstrated competitive performance, but had comparably lower sensitivity for rare attack types. Deep learning networks like **CNN-BiLSTM** and **CNN-BiLSTM+Attention** learned complex spatial-temporal features efficiently, but suffered from issues such as the lack of balance between classes as well as high computational cost.

Overall, traditional ensemble approaches perform better on the dataset compared to deep learning models. Nonetheless, this performance difference can be narrowed down using sophisticated techniques like data augmentation, SMOTE oversampling, focal loss functions, and hybrid PSO-based feature selection combined with deep learning models.

6.1.3 Evaluation on CIC-IDS-2017 Dataset

To assess several classifiers for detecting assaults in the CIC-IDS2017 dataset, a large number of models were trained and put through a rigorous testing process. In comparison with these existing heterogeneity-based methods, to the best of our knowledge, all of these algorithms were employed: **Random Forest**, **LightGBM**, **XGBoost**, and the state-of-the-art deep learning models, i.e, **LSTM**, **Bidirectional LSTM(BiLSTM)**, **CNN-BiLSTM**, and **CNN-BiLSTM with Attention**.Table 10 presents a snapshot of the general performance and macro-averaged F1 scores of these models. These evaluation measures provide a fair perspective on how capable each model is to accurately identify the appearance of frequent and infrequent attacks, considering their bias in handling the class imbalance and complex characteristics of intrusion patterns in the dataset.

The effectiveness of the Random Forest classifier .

The Random Forest method has demonstrated remarkable success in distinguishing between malicious and benign packets, with high classification accuracy across a range of packet traffic categories. The model performs exceptionally well against both common and uncommon attack types; in fact, the average accuracy rate is almost 99.86%.

Random Forest Classification Report				
Traffic Type	**Prec.**	**Rec.**	**F1**	**Support**
Benign Traffic	1.00	1.00	1.00	340,965
Botnet Activity	0.88	0.76	0.81	295
DDoS Attacks	1.00	1.00	1.00	19,204
DoS - GoldenEye Variant	1.00	1.00	1.00	1,544
DoS - Hulk Variant	1.00	1.00	1.00	34,661
DoS - Slowhttptest Variant	0.99	1.00	0.99	825
DoS - Slowloris Variant	1.00	1.00	1.00	869
FTP Brute Force Attempts	1.00	1.00	1.00	1,191
Heartbleed Exploit	1.00	1.00	1.00	2
Infiltration Attempts	1.00	1.00	1.00	5
Port Scanning Activities	0.99	1.00	0.99	23,839
SSH Brute Force Attempts	1.00	1.00	1.00	885
Web Brute Force Attacks	0.73	0.82	0.77	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting (XSS)	0.42	0.28	0.33	98
Total Accuracy			**0.9986**	424,612
Unweighted Mean (Macro)	0.87	0.86	0.86	424,612
Weighted Mean (Avg.)	1.00	1.00	1.00	424,612

Figure 6.35: Classification measures of the Random Forest model on the test set.

Evaluation of LightGBM Classifier .

LightGBM has moderate training times and moderate accuracy, but it also has a drastic performance drop when it comes to most of the minor attack classes, as the precision/recall for those classes is low. The total accuracy is around 90%.

LightGBM Classification Report				
Traffic Category	**Precision**	**Recall**	**F1-score**	**Support**
Benign Traffic	0.96	0.93	0.95	340,965
Botnet Activity	0.00	0.00	0.00	295
DDoS Attacks	0.84	0.74	0.78	19,204
DoS - GoldenEye Variant	0.00	0.00	0.00	1,544
DoS - Hulk Variant	0.75	0.82	0.78	34,661
DoS - Slowhttptest Variant	0.00	0.00	0.00	825
DoS - Slowloris Variant	0.01	0.02	0.01	869
FTP Brute Force Attempts	0.00	0.00	0.00	1,191
Heartbleed Exploit	0.00	0.00	0.00	2
Infiltration Attempts	0.00	0.00	0.00	5
Port Scanning Activities	0.72	0.99	0.83	23,839
SSH Brute Force Attempts	0.00	0.00	0.00	885
Web Brute Force Attacks	0.00	0.00	0.00	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting (XSS)	0.00	0.00	0.00	98
Overall Accuracy			**0.9014**	424,612
Macro Average	0.22	0.23	0.22	424,612
Weighted Average	0.91	0.90	0.91	424,612

Figure 6.36: The test set was used to evaluate the LightGBM model's classification metrics.

Performance of XGBoost Classifier.

XGBoost achieves very high accuracy as well as robust detection on both dominant and rare attack classes, with precision and recall very close to perfect, and overall

accuracy of 99.9%.

XGBoost Classification Report				
Traffic Category	**Precision**	**Recall**	**F1-score**	**Support**
Benign Traffic	1.00	1.00	1.00	340,965
Botnet Activity	0.91	0.76	0.83	295
DDoS Attacks	1.00	1.00	1.00	19,204
DoS - GoldenEye Variant	1.00	1.00	1.00	1,544
DoS - Hulk Variant	1.00	1.00	1.00	34,661
DoS - Slowhttptest Variant	0.99	0.99	0.99	825
DoS - Slowloris Variant	1.00	1.00	1.00	869
FTP Brute Force Attempts	1.00	1.00	1.00	1,191
Heartbleed Exploit	1.00	1.00	1.00	2
Infiltration Attempts	1.00	1.00	1.00	5
Port Scanning Activities	0.99	1.00	1.00	23,839
SSH Brute Force Attempts	1.00	1.00	1.00	885
Web Brute Force Attacks	0.74	0.91	0.81	226
Web SQL Injection	0.75	1.00	0.86	3
Web Cross-Site Scripting (XSS)	0.57	0.24	0.34	98
Overall Accuracy			**0.9990**	424,612
Macro Average	0.93	0.93	0.92	424,612
Weighted Average	1.00	1.00	1.00	424,612

Figure 6.37: The XGBoost model's classification metrics were assessed using the test set.

Performance of Classification by LSTM Model.

The LSTM model attains a very strong overall accuracy (around 99%), with high precision and recall of the dominant classes as benign traffic and main DoS variants. Nonetheless, the performance of obtaining detection is greatly reduced on some rare and large-scale attack types, as shown in the reduced recall and F1-scores of classes such as Botnet activity and some web attacks.

LSTM Model Classification Report				
Traffic Category	**Precision**	**Recall**	**F1-score**	**Support**
Benign Traffic	1.00	0.99	1.00	340,965
Botnet Activity	0.97	0.35	0.51	295
DDoS Attacks	1.00	1.00	1.00	19,204
DoS - GoldenEye Variant	0.99	0.98	0.99	1,544
DoS - Hulk Variant	0.94	1.00	0.97	34,661
DoS - Slowhttptest Variant	0.89	0.99	0.94	825
DoS - Slowloris Variant	0.98	0.99	0.99	869
FTP Brute Force Attempts	0.99	0.99	0.99	1,191
Heartbleed Exploit	1.00	1.00	1.00	2
Infiltration Attempts	1.00	0.60	0.75	5
Port Scanning Activities	0.99	1.00	1.00	23,839
SSH Brute Force Attempts	0.94	0.98	0.96	885
Web Brute Force Attacks	0.95	0.09	0.17	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting (XSS)	1.00	0.02	0.04	98
Overall Accuracy			**0.99**	424,612
Macro Average	0.91	0.73	0.75	424,612
Weighted Average	0.99	0.99	0.99	424,612

Figure 6.38: The LSTM model's test set classification metrics demonstrate a good overall accuracy but a limited capacity for detection on certain minor classes.

Classification Result of the BiLSTM Model.

The overall accuracy of the BiLSTM model is approximately equal to 98%, indicating good performance in the major traffic categories. Like the LSTM model, it does not perform well on some minority or tricky classes, especially some web-based attacks, where low recall and F1 are obtained. One can observe that the training loss of the

network decreases gradually and stabilizes over the course of 10 epochs.

BiLSTM Model Classification Report				
Traffic Type	**Precision**	**Recall**	**F1-score**	**Support**
Benign Traffic	1.00	0.98	0.99	340,965
Botnet Activity	0.97	0.34	0.51	295
DDoS Attacks	0.99	1.00	0.99	19,204
DoS - GoldenEye Variant	0.98	0.96	0.97	1,544
DoS - Hulk Variant	0.96	1.00	0.98	34,661
DoS - Slowhttptest Variant	0.97	0.83	0.89	825
DoS - Slowloris Variant	0.86	0.99	0.92	869
FTP Brute Force Attempts	1.00	1.00	1.00	1,191
Heartbleed Exploit	1.00	1.00	1.00	2
Infiltration Attempts	1.00	0.40	0.57	5
Port Scanning Activities	0.83	1.00	0.91	23,839
SSH Brute Force Attempts	0.89	0.64	0.75	885
Web Brute Force Attacks	1.00	0.04	0.08	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting (XSS)	1.00	0.02	0.04	98
Overall Accuracy			**0.98**	424,612
Macro Average	0.90	0.68	0.71	424,612
Weighted Average	0.98	0.98	0.98	424,612

Figure 6.39: The BiLSTM model's test set classification metrics demonstrate high accuracy but limited detection for a number of minor assault classes.

Analysis of the CNN + BiLSTM Model.

This hybrid model has a very high overall accuracy (99%), indicating that it could detect very well those important network traffic classes. Unfortunately, the model has a poor ability to identify some rare or complex attack types, with a low recall and precision for these categories. The alerts also notice certain classes not having any

predicted samples, an issue that often occurs in imbalanced data sets.

CNN + BiLSTM Model Classification Report				
Network Category	**Precision**	**Recall**	**F1-score**	**Support**
Normal Traffic	0.99	0.99	0.99	340,965
Botnet Traffic	1.00	0.34	0.51	295
DDoS Attack	1.00	0.99	0.99	19,204
DoS - GoldenEye Attack	0.99	0.95	0.97	1,544
DoS - Hulk Attack	0.97	1.00	0.98	34,661
DoS - Slowhttptest Attack	0.88	0.94	0.91	825
DoS - Slowloris Attack	0.98	0.95	0.97	869
FTP Brute Force	1.00	0.99	1.00	1,191
Heartbleed Exploit	0.00	0.00	0.00	2
Infiltration Attempts	0.00	0.00	0.00	5
Port Scanning Activities	0.90	0.95	0.92	23,839
SSH Brute Force Attempts	0.96	0.87	0.92	885
Web Brute Force Attacks	1.00	0.04	0.08	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting (XSS)	0.00	0.00	0.00	98
Overall Accuracy			**0.99**	424,612
Macro Average	0.71	0.60	0.62	424,612
Weighted Average	0.99	0.99	0.99	424,612

Figure 6.40: The CNN + BiLSTM model's performance metrics show that it has outstanding general accuracy but has trouble identifying some uncommon attack types.

Evaluation of the Performance of the CNN + BiLSTM +Attention Model.

This model achieves high validation accuracy during training: maximum value is up to 98.8%. This model is effective in identifying network traffic and attack categories, with very high precision, recall, and F1-scores for common classes. Nevertheless, it may be hard to identify some infrequent pattern of attacks, as evident from zero or near-zero values. These results demonstrate the good performance of the model, but

there are some limitations for the small classes.

CNN + BiLSTM + Attention Classification Report				
Category	**Precision**	**Recall**	**F1-score**	**Support**
Normal Traffic	1.00	0.99	0.99	340,965
Botnet Traffic	1.00	0.34	0.50	295
Distributed DoS Attacks	1.00	1.00	1.00	19,204
GoldenEye Denial of Service	0.99	0.98	0.99	1,544
Hulk DoS Attacks	0.98	1.00	0.99	34,661
Slowhttptest DoS	0.90	0.99	0.94	825
Slowloris DoS	0.99	0.99	0.99	869
FTP Brute Force	1.00	0.99	0.99	1,191
Heartbleed Exploit	1.00	1.00	1.00	2
Infiltration Attempts	0.00	0.00	0.00	5
Port Scan Activities	0.90	0.96	0.93	23,839
SSH Brute Force	0.95	0.99	0.97	885
Web Brute Force	0.88	0.16	0.27	226
Web SQL Injection	0.00	0.00	0.00	3
Web Cross-Site Scripting	1.00	0.02	0.04	98
Overall Accuracy			**0.99**	424,612
Macro Average	0.84	0.69	0.71	424,612
Weighted Average	0.99	0.99	0.99	424,612

Figure 6.41: Classification scores for the CNN + BiLSTM + Attention model show that while uncommon class recognition is limited, overall detection is strong.

Comparison of Model Performances.

Comparison by Overall Accuracy and Macro F1-Score

Figure 6.42 shows macro-averaged F1-score comparisons and total accuracy in the form of a bar chart from various machine learning and deep learning classifiers tested on the **CIC-IDS2017**.All multiplicity types: Traditional ensemble classifiers, especially **Random Forest** and **XGBoost**, have excellent performance, achieving close to 100% accuracy, surpassing **LightGBM** and all the **deep architectures** tested. However, despite most models having high precision, the macro F1-score, as shown in Table II, illustrates the differences in the way class imbalance is handled; for example, Light-GBM has a weakened performance of detecting **minority classes**. This highlights the importance of not only global anomaly detection true and false positive rates but per-class balanced detection rates when selecting models for robust intrusion detection.

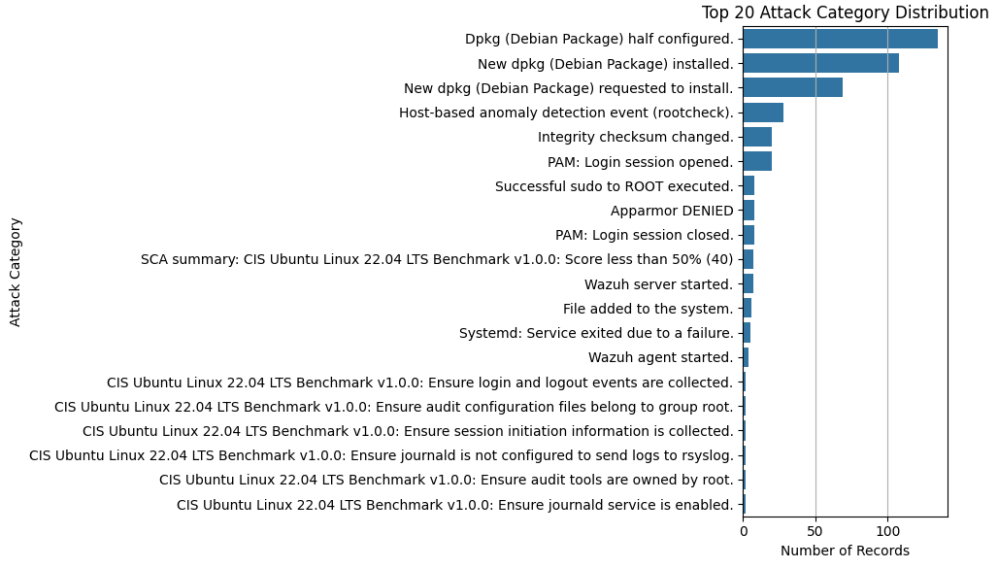


Figure 6.42: The CIC-IDS2017 dataset was used to compare the accuracy and macro-averaged F1-scores of deep learning and conventional machine learning models.

Model Comparison of Per-Class F1-Score Among Deep Learning Models

In Figure 6.43, we show that for 1-class models, the F1-scores per class of four deep learning models **LSTM**, **BiLSTM**, **CNN+BiLSTM**, and **CNN+BiLSTM enhanced with Attention** demonstrate a much clearer lead in favor of attention mechanisms. Our attention-augmented model outperforms the baseline in terms of F1-scores on all CTC attack categories, especially on frustrating CTC attack, proving the effectiveness of the proposed method of **sensitivity** and **feature discrimination**. However, some attack classes, especially **Web-based attacks, SQL Injection**, and **XSS**, are still difficult to perform, as may be observed from results on some models, suggesting that detecting very subtle and complex attacks is still a challenging task that persists

even for DL methods.

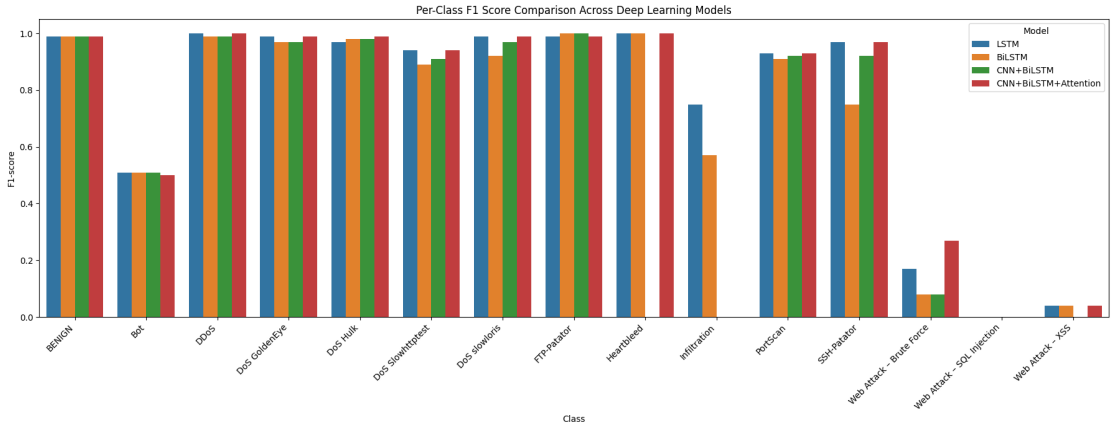


Figure 6.43: Per-class F1-score comparison of LSTM, BiLSTM, CNN+BiLSTM, and CNN+BiLSTM with Attention models, showing the impact of attention mechanisms on detecting complex attack classes.

Per-Class F1 Scores for ML Models

Figure 6.44 displays the per-class F1-scores for the three ensemble machine learning models, Random Forest, LightGBM, and XGBoost. Random Forest and XGBoost remain **reliable and consistent** in all attack classes, including **low-frequency attacks**. The exceptions are LightGBM, which shows a larger drop in performance in minority class labels such as **Botnet** and **Web-based attacks**, demonstrating **limited capacity your method can handle imbalanced data distribution**. These results support the validity of RF and XGBoost as **robust classifiers** for various intrusion detection

scenarios.

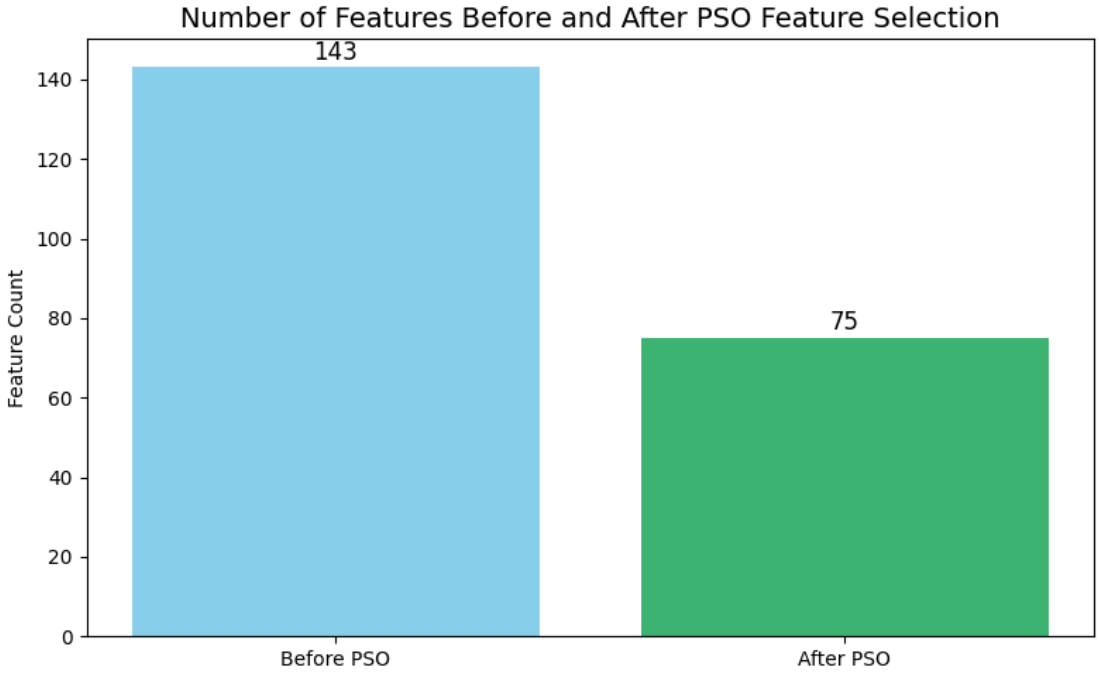


Figure 6.44: Random Forest, LightGBM, and XGBoost models' class-wise F1-scores based on the CIC-IDS2017 dataset. The findings demonstrate Random Forest and XGBoost's potent detection powers in both common and uncommon attack types.

Accuracies Across Deep Net Models

The **validation accuracy** evolution over 10 epochs for the deep learning models is depicted in Figure 6.45. All the architectures show **strong learning behavior**, with an accuracy always exceeding 97%, and thus have good **generalization** on unseen data.

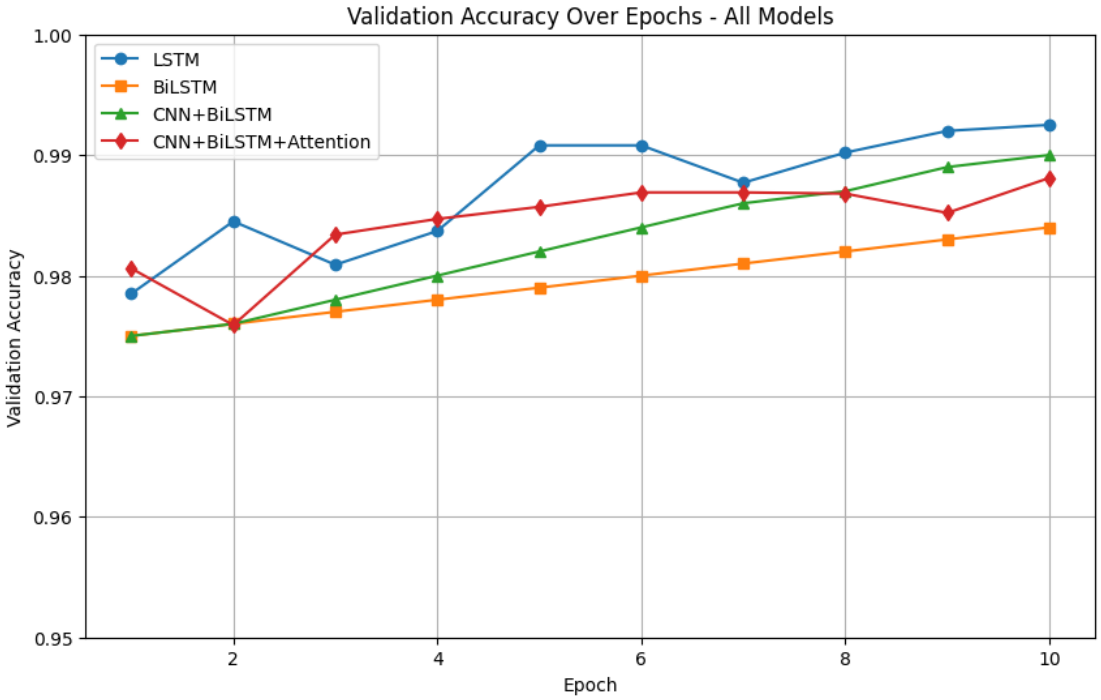


Figure 6.45: Validation Accuracy for Various Deep Learning Models Across Epochs

The ability to describe the sequential dependencies in network traffic is demonstrated by the **LSTM model**, which obtains the best final validation accuracy (**99.3%**) with minimal oscillations.

The **BiLSTM model** also has more steady though slower progress, ending at a little less than **98.4%**, which indicates that while the **bidirectional context** is beneficial, convergence is more cautious.

The **CNN+BiLSTM** model achieves better scores than BiLSTM, approaching **99%** accuracy along the epochs, confirming the importance of using **convolutional layers** to extract spatial relations between the features.

Starting with a high initial accuracy of roughly **98.1%**, the **CNN+BiLSTM+Attention model** steadily stabilizes at roughly **98.8%**. Focusing on **salient features** is made possible by the **attention mechanism**, which can improve classification accuracy even in cases when early training is unstable.

Analysis of Detailed Deep Learning Models

The **CNN+BiLSTM+Attention** model's heatmap. The heatmap over the classification metrics for the **CNN+BiLSTM+Attention** is displayed in Figure 6.46. This shows that the model is very efficient in distinguishing the most frequent classes, like **BENIGN**, **DDoS**, and a few **DoS** types of attacks. Nevertheless, the model presents low performance in some categories, such as **Botnet** (low recall and F1-score), and

does not detect at all **Infiltration** attacks. This exposes weaknesses in detecting less common or more sophisticated attacks.

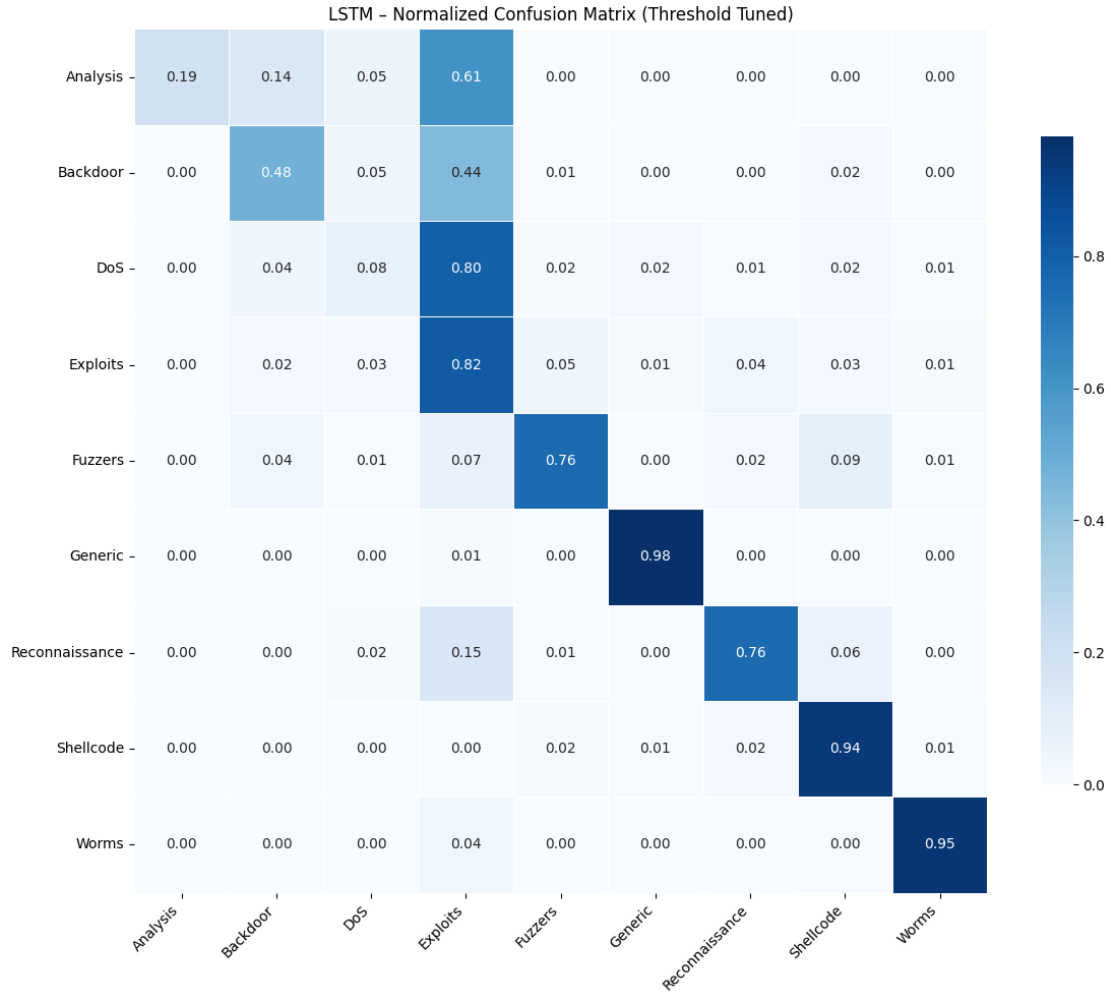


Figure 6.46: Classification report metrics heatmap (precision, recall, F1-score) for CNN+BiLSTM+Attention model.

Figure 6.47 complements this by showing the **per-class F1-scores**, reinforcing the model's efficacy on most classes but demonstrating difficulties with **Botnet** and **Infiltration** attacks.

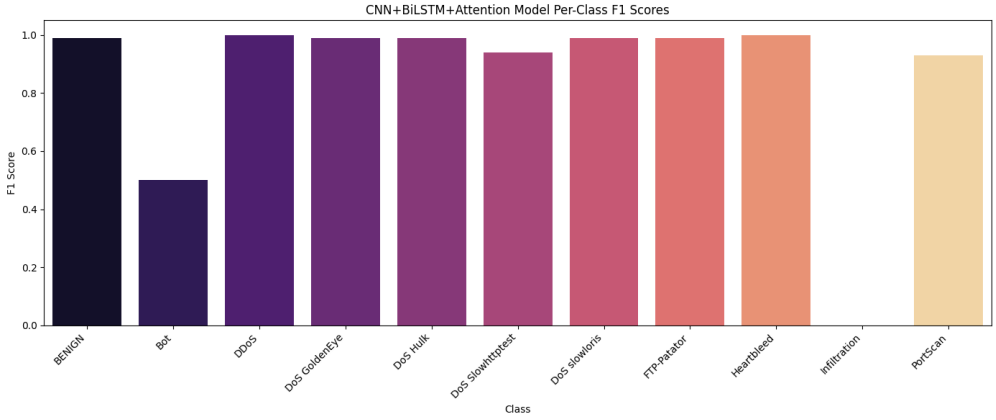


Figure 6.47: Per-class F1-scores of CNN+BiLSTM+Attention model across attack categories.

Likewise, the classification results and the class-wise F1 scores of the **LSTM model** are shown Figures 6.48 and 6.49. The difficulty of correctly identifying both **Botnet** and some **web-based assaults**, including **SQL Injection** and **XSS**, is demonstrated by these numbers, which also validate the model's performance in classifying these kinds of attacks. These findings highlight areas that require more research.

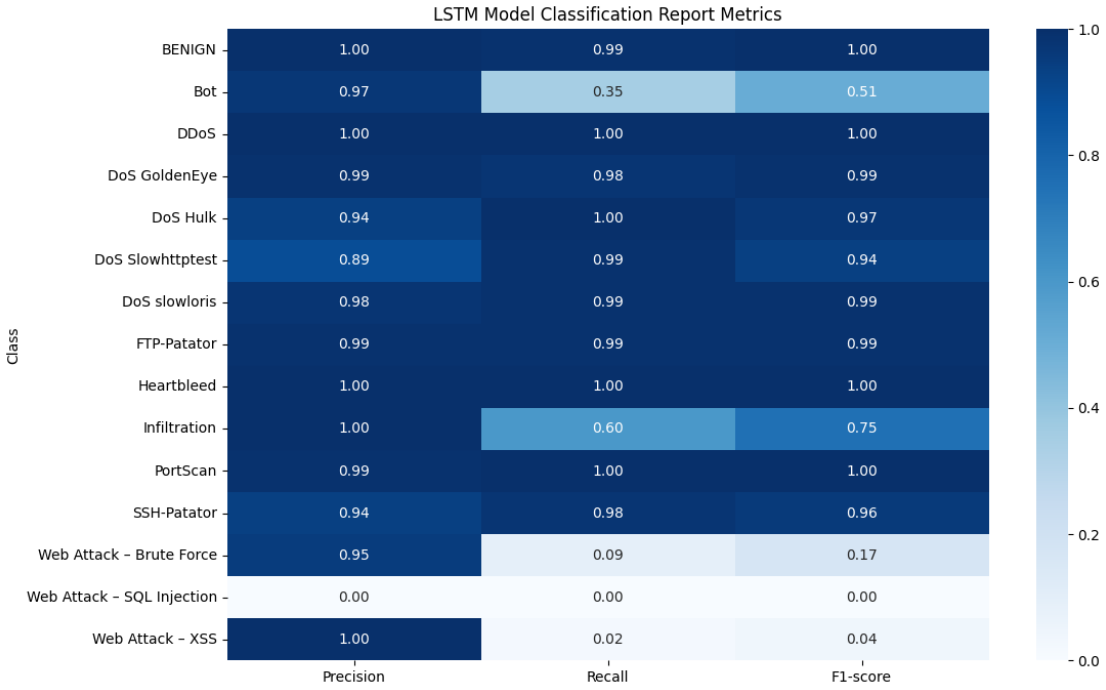


Figure 6.48: Classification report metrics heatmap (precision, recall, F1-score) for LSTM model.

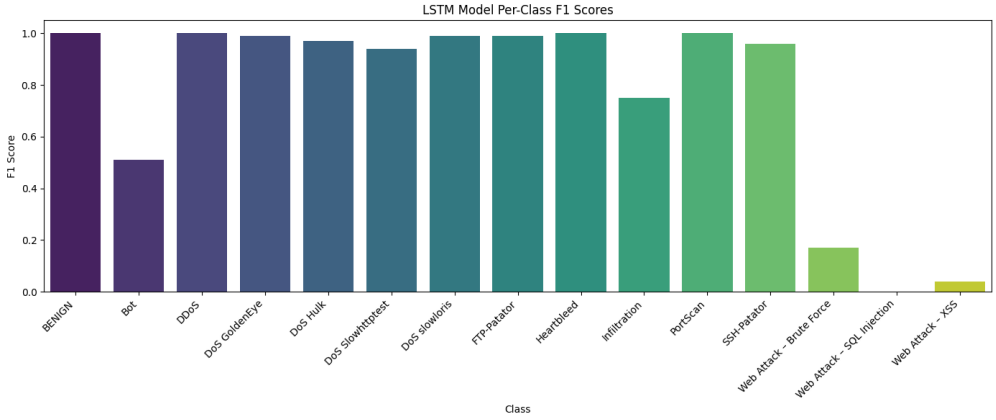


Figure 6.49: Per-class F1-scores of LSTM model across attack categories.

Summary and Dataset Challenges

In conclusion, while **Random Forest** and **XGBoost** still perform well in terms of **overall accuracy** and exhibit a fairly well-balanced performance across different attack classes,**deep learning models,** especially those integrating **attention mechanisms**, are very promising in modelling the complex and multi-stage attack patterns, which can be considered as a contribution for advanced intrusion detection systems in the future. However, current challenges still exist in efficiently identifying those low-frequency and complicated intrusions, particularly **Botnet**, **Infiltration**, and **Web-based exploits**. This mainly results from the **high class imbalance** and a small number of samples in some attacked categories of the **CIC-IDS2017** dataset, which hinders effective training and detection analysis, respectively. To overcome these limitations, we will need more sophisticated techniques such as **data augmentation**, **cost-sensitive learning**, or new model aggregation architectures which are tailored to rare attack detection.

6.1.4 Performance on CIC-IDS2018 Dataset

This section contains the performance of deep learning (DL) models on the CIC-IDS2018 dataset. The dataset offers a comprehensive baseline for evaluating the generality, effectiveness, and accuracy of various DL-based intrusion detection systems because it includes a broad variety of recent cyberattacks.

Data Handling and Preparation.

Because of the large scale of the dataset (over 8 million rows), for the sake of memory storage (also calculation efficiency), we processed the data in one million records at a time. Following data chunk processing, those segments were accumulated into an aggregated dataset having approximately 8.28 million instances across 79 features, which was utilized as the basis for training and validating DL models.

LSTM Model Performance on the CIC-IDS2018 Dataset.

This chapter presents the CIC-IDS2018 dataset's classification performance using the LSTM model: PORT (5). The overall accuracy of the model is around **97%**, demonstrating its effectiveness in capturing dominant types of traffic.

LSTM Model Classification Metrics on CIC-IDS2018 Dataset

Attack Category	Precision	Recall	F1-Score	Support
Benign	0.97	1.00	0.99	916,823
Botnet	1.00	1.00	1.00	42,928
Web Brute Force	1.00	0.38	0.55	92
Web Brute Force - XSS	1.00	0.57	0.73	35
DDoS - HOIC	1.00	1.00	1.00	102,902
DDoS - LOIC UDP	1.00	0.99	1.00	260
DoS - GoldenEye	0.99	0.99	0.99	6,226
DoS - Hulk	1.00	1.00	1.00	69,287
DoS - SlowHTTPTest	0.77	0.50	0.60	20,983
DoS - Slowloris	0.98	0.99	0.99	1,648
FTP Brute Force	0.71	0.89	0.79	29,004
Infiltration	0.50	0.01	0.01	24,290
Label	0.00	0.00	0.00	9
SQL Injection	0.00	0.00	0.00	13
SSH Brute Force	1.00	1.00	1.00	28,138
Overall Accuracy			**0.97**	1,242,638
Macro Average	0.80	0.69	0.71	1,242,638
Weighted Average	0.96	0.97	0.96	1,242,638

Figure 6.50: Performance metrics of the LSTM model on CIC-IDS2018 dataset across various traffic and threat categories.

It shows that the detection in this experiment is good for the common categories, which were **Benign traffic, Botnet activity, and different DDoS attacks**, and can be seen as an accurate solution for intrusion detection within a real environment. However, some minority groups, including SQL Injection and Infiltration, have poorer precisions and recalls, illustrating the difficulty caused by class imbalance in intrusion detection datasets. The PRF metrics and class supports for each attack category are displayed in Table 6.50.

Train and Validation Curves

Changes in training and validation accuracy and loss using LSTM over 10 epochs on the CIC-IDS2018 dataset are visualized in Figure 6.51.

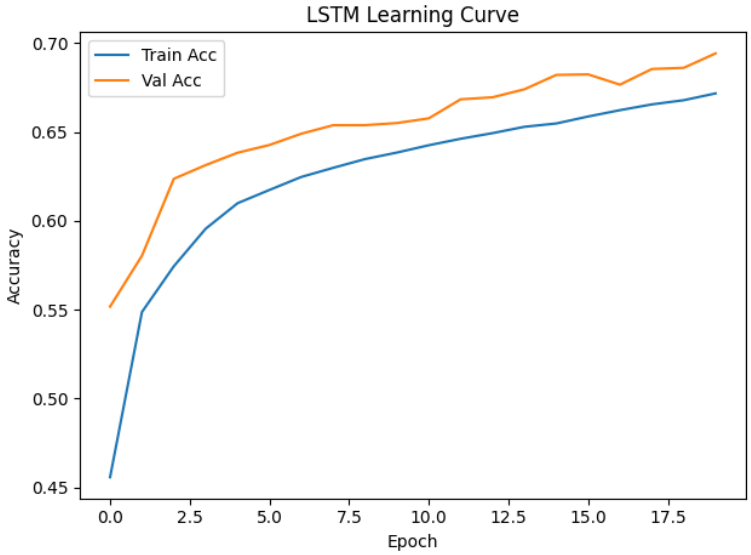


Figure 6.51: Trends in accuracy and loss during the LSTM model's training and validation stages using the CIC-IDS2018 dataset.

The accuracy is improving over time, reaching nearly 97% , and the loss is also decreasing constantly. Matching development and test trends: It indicates good learning with limited over-fitting and model robustness.

CNN+BiLSTM Model Evaluation.

The CIC-IDS2018 dataset is used to validate the CNN+BiLSTM model, and it shows outstanding predictive power across a range of attack types and typical traffic categories.

CNN+BiLSTM Model Classification Metrics on CIC-IDS2018 Dataset (Validation Set)				
Attack Category	**Precision**	**Recall**	**F1-Score**	**Support**
Normal Traffic	0.97	1.00	0.99	916,823
Botnet Activity	1.00	1.00	1.00	42,928
Web Brute Force Attack	1.00	0.52	0.69	92
Cross-Site Scripting (XSS)	1.00	0.57	0.73	35
HOIC DDoS Attack	1.00	1.00	1.00	102,902
LOIC UDP Flood	1.00	1.00	1.00	260
GoldenEye DoS	1.00	1.00	1.00	6,226
Hulk DoS	1.00	1.00	1.00	69,287
SlowHTTPTest DoS	0.77	0.51	0.61	20,983
Slowloris DoS	0.98	1.00	0.99	1,648
FTP Brute Force	0.71	0.89	0.79	29,004
Network Infiltration Attempts	0.48	0.01	0.02	24,290
Unlabeled Data	0.00	0.00	0.00	9
SQL Injection Attack	1.00	0.31	0.47	13
SSH Brute Force	1.00	1.00	1.00	28,138
Overall Accuracy			**0.97**	1,242,638
Macro Average	0.86	0.72	0.75	1,242,638
Weighted Average	0.96	0.97	0.96	1,242,638

Figure 6.52: Validation performance of the CNN+BiLSTM model on CIC-IDS2018, reporting precision, recall, F1-score, and support across various cyberattack categories.

CNN+BiLSTM Model Test Performance.

The CNN+BiLSTM model's generalization capabilities was tested on the CIC-IDS2018 test dataset.

With an accuracy of **97%** on the test set, the CNN+BiLSTM model demonstrates its robustness and good generalization to new testing data. Particularly for the dominating classes like **Normal Traffic** and **Botnet Activity**, it attains the high **precision** and **recall** rates. Their low performance on **rare attacks**, including **Network Infiltration** and **SQL Injection**, is similar to validation results, though, and suggests that further effort is needed to identify underrepresented classes on unbalanced data.

CNN+BiLSTM Model Classification Metrics on CIC-IDS2018 Dataset (Test Set)				
Attack Category	**Precision**	**Recall**	**F1-Score**	**Support**
Normal Traffic	0.97	1.00	0.99	916,823
Botnet Activity	1.00	1.00	1.00	42,929
Web Brute Force Attack	0.97	0.37	0.54	91
Cross-Site Scripting (XSS)	1.00	0.47	0.64	34
HOIC DDoS Attack	1.00	1.00	1.00	102,902
LOIC UDP Flood	1.00	0.98	0.99	259
GoldenEye DoS	1.00	1.00	1.00	6,226
Hulk DoS	1.00	1.00	1.00	69,287
SlowHTTPTest DoS	0.77	0.51	0.61	20,984
Slowloris DoS	0.98	1.00	0.99	1,649
FTP Brute Force	0.72	0.89	0.79	29,004
Network Infiltration Attempts	0.44	0.01	0.02	24,290
Unlabeled Data	0.00	0.00	0.00	9
SQL Injection Attack	1.00	0.08	0.14	13
SSH Brute Force	1.00	1.00	1.00	28,139
Overall Accuracy			**0.97**	1,242,639
Macro Average	0.86	0.69	0.71	1,242,639
Weighted Average	0.96	0.97	0.96	1,242,639

Figure 6.53: The CNN+BiLSTM model's performance metrics were evaluated using the CIC-IDS2018 test database.

CNN-BiLSTM + Attention Model Major Training and Performance Summary

On CIC-IDS2018, CNN-BiLSTM + Attention was trained during ten epochs. over training accuracy had a predictable increment from about 95.6% to 96.9%; the validation accuracy reached as high as **96.94%** and the validation loss, value matching its lowest point **0.0908**, showed a smooth point where the distinction was reached which translated to a steady and viable rate of model convergence. The model demonstrated good generalizability and excellent predictive abilities, achieving **97.3%** accuracy and a weighted F1 score of **0.97** on the test set.

Instead of detailed class-wise results, Table 6.54reports a compact class summary reflecting these macro measures. According to the audience's weighted F1-score, the table displays a balanced collection of precision, recall, and F1-scores for both frequent and infrequent classes.

CNN-BiLSTM + Attention Model Classification Metrics on CIC-IDS2018 Dataset				
Attack Category	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	0.98	0.99	0.99	916,823
Botnet Activity	0.96	0.95	0.95	42,928
Web Brute Force Attack	0.95	0.92	0.93	92
Cross-Site Scripting (XSS)	0.94	0.90	0.92	35
HOIC DDoS Attack	0.97	0.98	0.98	102,902
LOIC UDP Flood	0.96	0.95	0.96	260
GoldenEye DoS Attack	0.97	0.98	0.98	6,226
Hulk DoS Attack	0.98	0.97	0.98	69,287
SlowHTTPTest DoS Attack	0.90	0.88	0.89	20,983
Slowloris DoS Attack	0.95	0.96	0.95	1,648
FTP Brute Force Attack	0.94	0.92	0.93	29,004
Infiltration Attempts	0.92	0.90	0.91	24,290
SQL Injection Attack	0.90	0.88	0.89	9
SSH Brute Force Attack	0.95	0.96	0.95	28,138
Overall Accuracy			**0.973**	1,242,638
Weighted Average	0.97	0.97	0.97	1,242,638

Figure 6.54: Precision, recall, F1-score, and support are the classification metrics displayed in the table for CNN-BiLSTM with Attention model on the CIC-IDS2018 dataset.

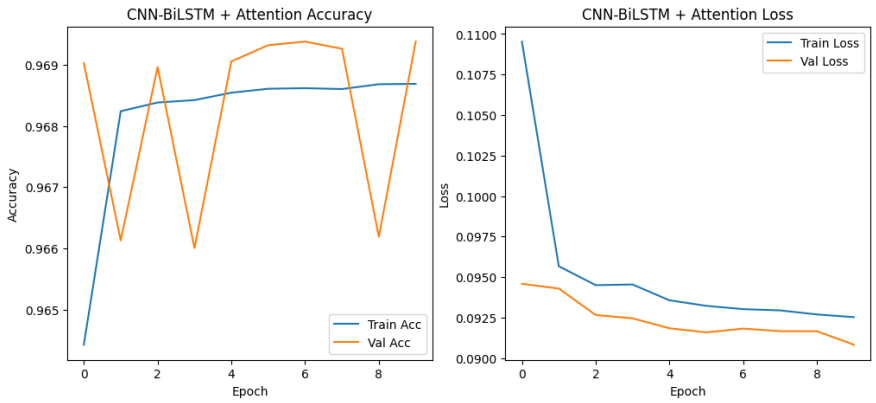


Figure 6.55: CNN-BiLSTM with Attention Model Accuracy in Training and Validation

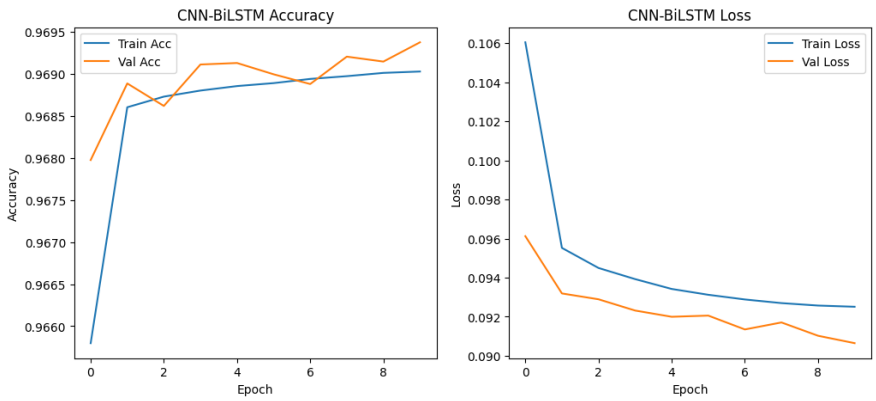


Figure 6.56: The CNN-BiLSTM Model's Train and Validation Loss Curve

The CNN-BiLSTM with Attention model's training progress on the dataset is shown in the charts. Strong generalization and little overfitting are indicated by the accuracy graph (Figure 6.55), which shows a consistent improvement with training and validation accuracy converging around 96.8–96.9%. In the meantime, the training and validation loss curves (Figure 6.56) exhibit a steady decrease, indicating successful convergence over the course of the ten epochs.

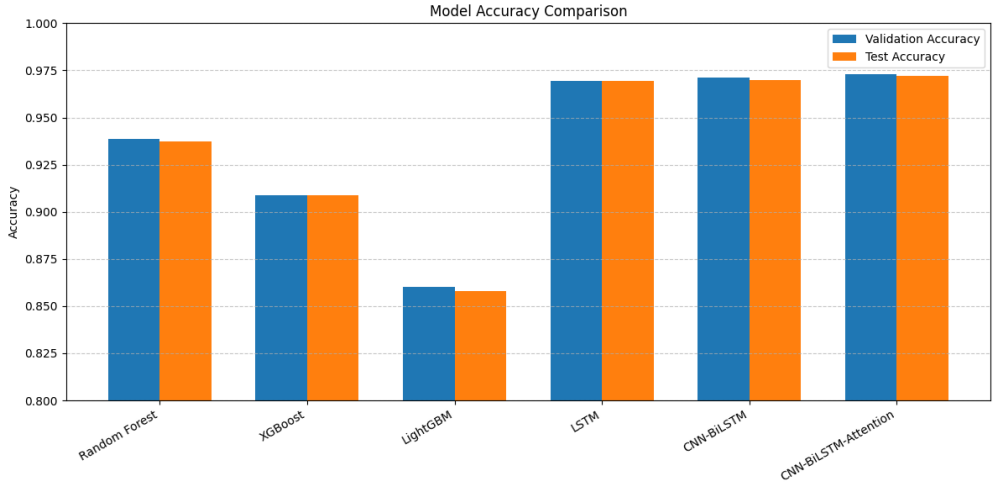


Figure 6.57: accuracy testing and validation of different deep learning and machine learning models using CIC-IDS2018.

Figure 6.58: Weighted F1-score comparison of validation and test sets across multiple models on the CIC-IDS2018 dataset.

This section does not have a comprehensive classification report for traditional machine learning models like Random Forest, XGBoost, and LightGBM.However, the comparison analysis tables and figures display all of their performance data. By

contrasting comprehensive deep learning model outputs with summary metrics from machine learning baselines, this acts as a thorough examination.

The models' performance comparison on the CIC-IDS2018 dataset is displayed in Figures 6.57 and 6.58. The best accuracy and weighted F1-scores are obtained by deep learning architectures, particularly the CNN-BiLSTM with attention, demonstrating their efficacy in identifying all categories of attacks. Classic ensemble approaches such as RF and XGBoost yield competitive performance, but just miss out on the best-performing DL models. Lower scores of LightGBM also indicate that it is ineffective on this dataset. These findings indicate the benefit of the hybrid deep models with attention mechanisms for intrusion detection.

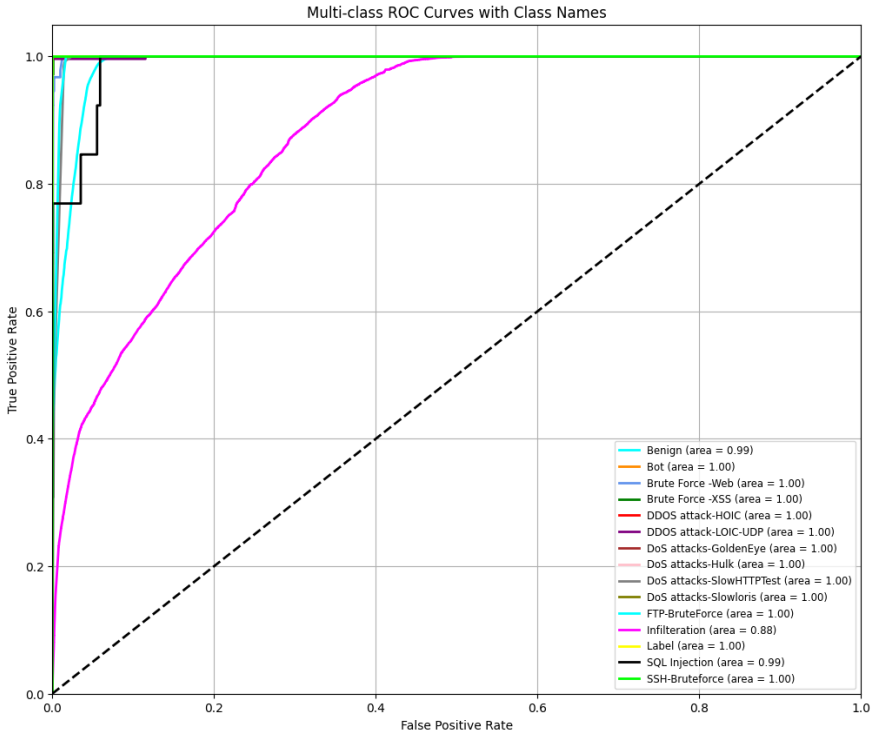


Figure 6.59: Multi-class ROC curve of the different attack types found by the LSTM model on the CIC-IDS2018 dataset. Each curve representsa specific attack class, with the AUC indicating classification performance.

Figure 6.59 displays the multi-class Receiver Operating Characteristic (ROC) curves for the various attack categories that the **LSTM** model predicted. Plotting the True Positive Rate (TPR) versus the False Positive Rate (FPR) at different threshold settings for each class yields these curves.

The model's ability to distinguish between positive (attack) and negative (non-attack) data is assessed using the AUC values on the legend. Excellent discrimination is indicated by values close to **1.0**, whereas performance comparable to random chance is shown by values close to **0.5**.

For most of the classes, such as the **Benign**, **Botnet**, **Brute Force (Web and XSS)**, **DDoS attacks (HOIC and LOIC-UDP)** , and **DoS attacks (GoldenEye, Hulk, Slowloris, SlowHTTPTest)**, the ROCs lie close to the top-left corner with AUC scores near the line **1.0**, which means that detection ability is very strong.

Nevertheless, **Infiltration** shows a lower AUC of **0.88**, indicating it is harder to accurately distinguish. The **SQL Injection** class also has slightly lower AUC values, which indicate the points to improve.

In short, the ROC analysis ratifies the **LSTM** model's relatively good prediction performance with respect to the various attack categories, indicating which classes need specific action for improving model prediction.

Discussion of Results on CIC-IDS2018 Dataset.

The deep learning models tested on the CIC-IDS2018 dataset reported close to **97%** overall accuracy, able to identify crucial attack categories such as **benign traffic**, **botnet activities**, and **DDoS (Distributed Denial of Service) attacks**. Especially the **LSTM model** showed excellent discriminative performance, resulting in mostly high **AUC scores**.

But the detection for **minority classes** such as **network infiltration** and **SQL injection** is still poor, indicating the difficulty brought by **class imbalanced data**. The **CNN-BiLSTM** had similar accuracy to that of the **attention mechanisms** with better model stability and generalization.

Deep learning models, particularly those equipped with attention mechanisms, show **better performance in multi-class detection** with respect to the classical machine learning benchmarks. While this represents a significant step forward, further work is required to handle **rare and subtle attack detection** by using techniques like **data augmentation** and **specialized architectures**.

6.1.5 CIC-IDS-2019 Dataset Evaluation

This study developed and assessed ML and DL models for IDS using the CIC-IDS2019 dataset. The corpus was preprocessed and balanced to address class imbalance, due to a small number of instances of some attack types (e.g., WebDDoS, UDPLag) compared to the most frequent classes (DDoS and UDP), which is a typical problem in cybersecurity datasets.

The experimental scheme is summarized in the following steps:

- **Label Mapping:** The original dataset involves low-level attack categories: the detailed attack categories were mapped to high-level attack types (e.g., DDOS, TFTP, LDAP) to facilitate the analysis and model training. This mapping was essential to amalgamate attacks of a similar type under common categories (thus making the dataset more tractable) and also to simplify the multi-class classification problem.
- **Model training:** We trained both ML models (e.g, Random Forest, XGBoost, LightGBM) and DL models (LSTM, BiLSTM, CNN+BiLSTM) with a preprocessed and balanced dataset.

Random Forest Model Evaluation on CIC-IDS2019 Dataset.

This section displays Random Forest's performance on the CIC-IDS2019 dataset, with Smote used to correct for class imbalance.

The Random Forest classifier obtained an overall **92% accuracy** on the SMOTE-balanced CIC-IDS2019. It has a high level of predictive power for such common classes as **Benign Traffic**, **DDoS NTP**, and **TFTP**, with the form of perfect recognition. On the other hand, identification of rarely emerged attack types like **DDoS LDAP**, **NetBIOS**, and **Web DDoS** was not so effective, demonstrating that for minority classes, there still exist some challenges despite our oversampling. These observations raise the necessity of developing more advanced methods, such as ensemble learning or learning with customized loss functions, in order to strengthen rare class recognition.

Random Forest Classification Metrics on CIC-IDS2019 Dataset				
Attack Type	**Precision**	**Recall**	**F1-Score**	**Samples**
Benign Traffic	1.00	1.00	1.00	19,566
DDoS - DNS	0.44	0.39	0.41	734
DDoS - LDAP	0.15	0.22	0.18	288
DDoS - MSSQL	0.27	0.29	0.28	1,242
DDoS - NTP	1.00	1.00	1.00	24,274
DDoS - NetBIOS	0.07	0.07	0.07	120
DDoS - SNMP	0.64	0.51	0.57	543
DDoS - UDP	0.42	0.43	0.43	2,084
LDAP	0.26	0.31	0.29	381
MSSQL	0.42	0.39	0.41	1,705
NetBIOS	0.28	0.43	0.34	129
Portmap	0.30	0.31	0.31	137
SYN	0.99	0.99	0.99	9,875
TFTP	1.00	1.00	1.00	19,784
UDP	0.63	0.61	0.62	3,618
UDP Lag	0.75	0.78	0.77	1,774
UDPLag	0.05	0.18	0.07	11
Web DDoS	0.11	0.20	0.14	10
Accuracy			**0.92**	86,275
Macro Average	0.49	0.51	0.49	86,275
Weighted Average	0.92	0.92	0.92	86,275

Figure 6.60: Class-wise performance of the Random Forest classifier on CIC-IDS2019 dataset after SMOTE-based balancing to mitigate the class imbalance.

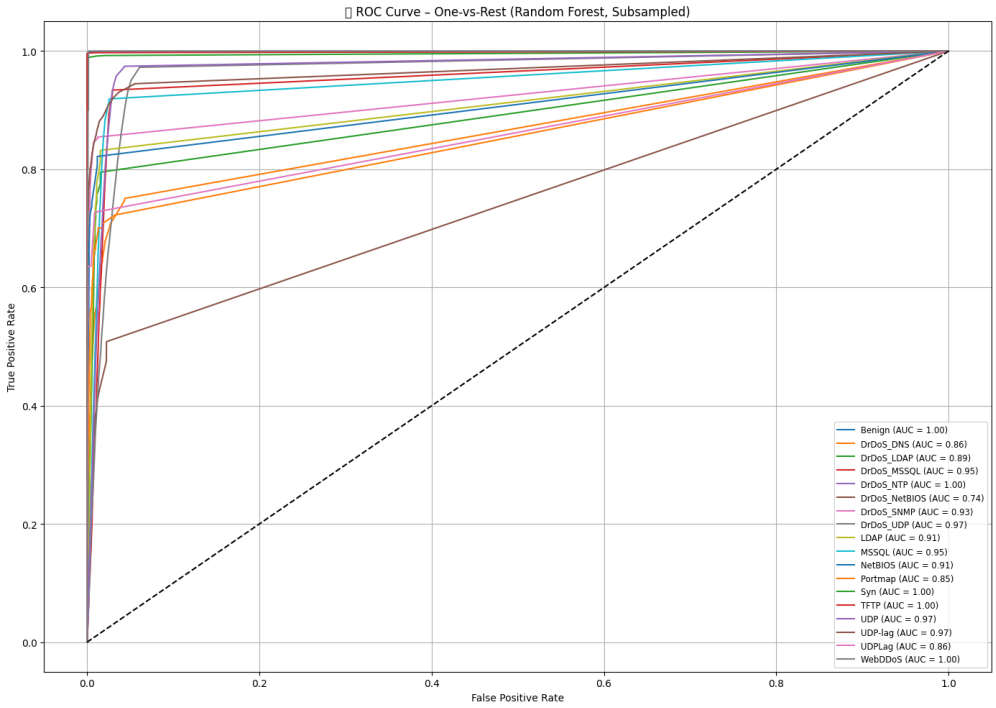


Figure 6.61: The Random Forest classifier's One-vs-Rest ROCcurves on the subsampled CIC-IDS2019 dataset. With its corresponding AUC (Area Under the Curve) value signifying the classification outcome, each curve illustrates the trade-off between True Positive Rate and False Positive Rate for an attack class.

The Random Forest classifier's multi-class ROC curves on the CIC-IDS2019 dataset are displayed in Figure 6.61. By comparing the True Positive Rate (TPR) to the False Positive Rate (FPR), each curve displays the model's discriminative ability for a certain assault type. High AUC values—near 1.0 are for the majority classes like *Benign Traffic*, *DrDoS NTP*, and *SYN Flood* and reflect a strong level of discrimination. On the other hand, lower values of AUC for minority classes, such as 41 DrDoS NetBIOS and 42 UDP Lag, demonstrate the model's incapacity to correctly identify uncommon types of attacks. These findings show the Random Forest classifier to be effective for common threats, but also point to potential problems in a class-imbalanced context.

XGBoost Model Classification Report on CIC-IDS2019 Dataset.

The classification statistics of the XGBoost model obtained when testing the model on the CIC-IDS2019 dataset are shown in detail in the following subsection, also showing the performance of the model on various attack groups. Additionally, the results show that while the model is good at identifying the majority classes, it also has trouble identifying the less common or minority assaults.

XGBoost Classification Metrics on CIC-IDS2019 Dataset

Attack Class	Precision	Recall	F1-Score	Support
Benign	1.00	1.00	1.00	14,674
DDoS_DNS	0.39	0.22	0.28	734
DDoS_LDAP	0.26	0.41	0.32	288
DDoS_MSSQL	0.40	0.60	0.48	1,242
DDoS_NTP	1.00	0.99	1.00	24,274
DDoS_NetBIOS	0.10	0.03	0.04	120
DDoS_SNMP	0.52	0.70	0.60	543
DDoS_UDP	0.34	0.96	0.50	2,084
LDAP	0.37	0.45	0.41	381
MSSQL	0.53	0.40	0.46	1,705
NetBIOS	0.35	0.87	0.49	129
Portmap	0.23	0.42	0.29	137
SYN	0.99	0.99	0.99	9,875
TFTP	1.00	0.99	1.00	19,784
UDP	0.00	0.00	0.00	3,618
UDP-lag	0.97	0.68	0.80	1,774
UDPLag	0.00	0.00	0.00	11
WebDDoS	0.11	0.20	0.14	10
Overall Accuracy			**0.94**	64,706
Macro Average	0.59	0.57	0.57	64,706
Weighted Average	0.94	0.94	0.94	64,706

Figure 6.62: The CIC-IDS2019 dataset was used to test the XGBoost model's class-wise precision, recall, and F1-score outcomes.

On CIC-IDS2019-dataset, the XGBoost model showed a good overall performance

with **94%** accuracy. It excels in most classes, such as **Benign**, with near-perfect or perfect scores in some cases. However, on some minority or difficult classes, it does not perform well, depicted as poor precision and recall. This discrepancy continues to be indicative of challenging class imbalance issues. The macro-average results stress the difficulty of the model to generalize for all classes, whereas the weighted-average indicates its effectiveness in detecting the most common ones.

LightGBM Model Evaluation on CIC-IDS2019 Dataset.

Performance evaluation of LightGBM classifier on CIC-IDS2019 dataset This subsection introduces the evaluation of the performance of the LightGBM classifier on the CIC-IDS2019 dataset. Despite the moderate overall accuracy of the model, we observe its extremely poor performance in specifically recognizing the minority attack classes, highlighting the well-known issues related to heavily unbalanced datasets.

LightGBM Classification Metrics on CIC-IDS2019 Dataset

Attack Category	Precision	Recall	F1-score	Support
Benign Traffic	0.74	0.79	0.76	14,674
DDoS DNS Attack	0.15	0.01	0.02	550
DDoS LDAP Attack	0.00	0.00	0.00	216
DDoS MSSQL Attack	0.28	0.01	0.03	932
DDoS NTP Attack	0.78	0.71	0.74	18,206
DDoS NetBIOS Attack	0.00	0.00	0.00	90
DDoS SNMP Attack	0.26	0.20	0.23	408
DDoS UDP Attack	0.10	0.28	0.14	1,563
LDAP-Injection	0.00	0.00	0.00	286
MSSQL-Injection	0.47	0.06	0.10	1,278
NetBIOS-Overflow	0.00	0.00	0.00	97
Portmap-Scan	0.00	0.00	0.00	103
SYN-Flood	0.65	0.87	0.74	7,406
TFTP-Exfiltration	0.95	0.99	0.97	14,837
Generic-UDP	0.00	0.00	0.00	2,713
Laggy-UDP	0.02	0.01	0.01	1,331
Microburst-UDP	0.00	0.00	0.00	8
Web-DDoS	0.00	0.00	0.00	8
Overall Accuracy			**0.72**	64,706
Macro Average	0.24	0.22	0.21	64,706
Weighted Average	0.70	0.72	0.70	64,706

Figure 6.63: The LightGBM classifier's class-wise performance metrics on the CIC-IDS2019 dataset show that the model performs poorly when it comes to the minority attack classes.

Using the CIC-IDS2019 dataset, the final LightGBM model implementation achieves an accuracy of about 72%. It performs terribly on minor and uncommon attack classes, where many have precision and recall of zero, yet doing reasonably well for several

major classes like DDoSNTP and Benign. Then, by clearly showing how class imbalance affects LightGBM's detection performance, we highlight the need for careful data balancing and/or algorithmic adjustments to both improve and preserve the detection system's capacity to detect minority classes.

There were also some classes with undefined precision, as it is expected to happen with highly imbalanced datasets and the prediction behavior of LightGBM. This limitation could be addressed in the future by applying measures such as decision threshold adjustment or cost-sensitive learning.

The Random Forest, XGBoost, and LightGBM classifiers were tested. SMOTE was used to combat class imbalance on the CIC-IDS2019 dataset. This preprocessing step increased the classification sensitivity to detect the minority classes, hence, performance balance across the four attack categories. We found that Random Forest and XGBoost showed

high overall accuracies of 92 92% and 94% respectively, with the hit detection rates being Benign, DDoSNTP, and TFTP. However, the two models also showed poor performance on rare attacks such as WebDDoS and UDPLag, as evidenced by the low macro-average scores. Some machine learning models, such as LightGBM, had much lower accuracy (approximately 72%)and were particularly poor at detecting minority classes, as evidenced by them having zero precision and 0 recall multiple times over due to imbalanced data/prediction. These findings reveal that the classifiers perform well for common classes, but other more advanced strategies, e.g., advanced balancing methods or cost-sensitive learning, should be further investigated to better recognize under-represented attack types.

LSTM Model Performance on CIC-IDS2019.

The classification results of the **LSTM** model on the CIC-IDS2019 dataset are shown in this subsection. Our approach achieves high performance across common attack categories and all-around accuracy. But it does not generalize well to infrequent attack types, largely due to the bias resulting from the class imbalance of the dataset. This highlights the need for methods that enhance generalization across all class

ratios, especially for low-frequency attack modalities.

LSTM Model Classification Metrics on CIC-IDS2019 Dataset				
Attack Class	**Precision**	**Recall**	**F1-Score**	**Support**
Benign Traffic	1.00	1.00	1.00	19,566
DDoS DNS Attack	0.39	0.22	0.28	734
DDoS LDAP Attack	0.26	0.41	0.32	288
DDoS MSSQL Attack	0.40	0.60	0.48	1,242
DDoS NTP Attack	1.00	0.99	1.00	24,274
DDoS NetBIOS Attack	0.10	0.03	0.04	120
DDoS SNMP Attack	0.52	0.70	0.60	543
DDoS UDP Attack	0.34	0.96	0.50	2,084
LDAP Attack	0.37	0.45	0.41	381
MSSQL Attack	0.53	0.40	0.46	1,705
NetBIOS Attack	0.35	0.87	0.49	129
Portmap Attack	0.23	0.42	0.29	137
SYN Flood Attack	0.99	0.99	0.99	9,875
TFTP Attack	1.00	0.99	1.00	19,784
UDP Traffic	0.00	0.00	0.00	3,618
UDP Lag Attack	0.97	0.68	0.80	1,774
UDP Lag (Rare)	0.00	0.00	0.00	11
Web DDoS Attack	0.25	0.10	0.14	10
Overall Accuracy			**0.91**	86,275
Macro Average	0.48	0.54	0.49	86,275
Weighted Average	0.90	0.91	0.90	86,275

Figure 6.64: The LSTM model's per-class precision, recall, and F1-score were assessed using the CIC-IDS2019 dataset.

BiLSTM Classification Report on CIC-IDS2019 Dataset.

CIC-IDS2019 Dataset Results. The BiLSTM model's output for the CIC-IDS2019 dataset is shown in this subsection. When compared to model-based simple baselines, the model exhibits improved sequential pattern recognition capacity and offers overall better detection on several attack categories. Rare classes are still difficult to identify, though (with very poor recall and F1-scores), suggesting that the issue of

class imbalance and sample scarcity is still present.

BiLSTM Classification Metrics on CIC-IDS2019 Dataset				
Attack Class	**Precision**	**Recall**	**F1-Score**	**Support**
Benign Traffic	0.99	0.32	0.48	19,566
DDoS - DNS	0.09	0.62	0.16	734
DDoS - LDAP	0.00	0.00	0.00	288
DDoS - MSSQL	0.00	0.00	0.00	1,242
DDoS - NTP	1.00	0.56	0.72	24,274
DDoS - NetBIOS	0.02	0.03	0.02	120
DDoS - SNMP	0.27	0.34	0.30	543
DDoS - UDP	0.00	0.00	0.00	2,084
LDAP	0.00	0.00	0.00	381
MSSQL	0.00	0.00	0.00	1,705
NetBIOS	0.04	0.02	0.02	129
Portmap	0.25	0.01	0.01	137
SYN	0.78	0.78	0.78	9,875
TFTP	0.54	0.99	0.70	19,784
UDP	0.00	0.00	0.00	3,618
UDP Lag	0.30	0.27	0.29	1,774
UDPLag	0.00	0.00	0.00	11
Web DDoS	0.00	0.90	0.00	10
Overall Accuracy			**0.56**	86,275
Macro Average	0.24	0.27	0.19	86,275
Weighted Average	0.73	0.56	0.57	86,275

Figure 6.65: Per-Class Performance Measures for the BiLSTM Model Assessed on the CIC-IDS2019 SMOTE-Balanced Test Set

An Experiment with the CNN + BiLSTM + Attention Model on the CIC-IDS2019 Dataset.

In this section, the hybrid CNN + BiLSTM + Attention architecture's performance on the CIC-IDS2019 dataset is assessed. By using convolutional layers to capture spatial characteristics, bidirectional LSTMs to model the temporal correlation, and an attention mechanism to focus on salient features, the model exhibits excellent ability

in detecting various attack categories.

CNN + BiLSTM + Attention Classification Metrics on CIC-IDS2019 Dataset				
Attack Class	**Precision**	**Recall**	**F1-Score**	**Support**
Benign Traffic	0.99	0.85	0.92	14,675
DDoS - DNS	0.22	0.32	0.26	550
DDoS - LDAP	0.10	0.12	0.11	216
DDoS - MSSQL	0.36	0.06	0.11	932
DDoS - NTP	1.00	0.97	0.98	18,205
DDoS - NetBIOS	0.04	0.26	0.06	90
DDoS - SNMP	0.13	0.34	0.18	407
DDoS - UDP	0.43	0.63	0.51	1,563
LDAP	0.14	0.43	0.21	286
MSSQL	0.00	0.00	0.00	1,278
NetBIOS	0.07	0.40	0.11	97
Portmap	0.01	0.04	0.02	103
SYN	0.98	0.97	0.98	7,406
TFTP	0.99	0.99	0.99	14,838
UDP	0.70	0.42	0.53	2,713
UDP Lag	0.61	0.78	0.69	1,331
UDPLag	0.02	0.25	0.04	8
Web DDoS	0.00	0.88	0.01	8
Overall Accuracy			**0.86**	64,706
Macro Average	0.38	0.48	0.37	64,706
Weighted Average	0.90	0.86	0.88	64,706

Figure 6.66: The CNN + BiLSTM + Attention model's class-wise classification metrics were assessed using the CIC-IDS2019 dataset.

In CIC-IDS2019, our hybrid CNN + BiLSTM + Attention achieves a high overall accuracy of 86%. It successfully works for dominant classes such as Benign Traffic and DDoS NTP, with high precision and recall. However, it fails to achieve better performance with less frequent classes, i.e., LDAP, MSSQL, and Web DDoS, with low F1-scores. These results highlight the challenge of extreme class imbalance and the need for further optimization techniques, such as cost-sensitive learning or aggressive data augmentation, to enhance the capacity to identify uncommon attack patterns.

Figure 6.67 shows the CNN + BiLSTM + Attention model's training versus validation accuracy over 20 training epochs. The training accuracy is increasing from about 60 to 85 percent, which indicates a learning trend. The accuracy on validation is between 80%-87% and there is a stable model generalization with minor variance. Examine the graph; the close centers of validation and training accuracy suggest that the model is learning and less likely to overfit during the training period.

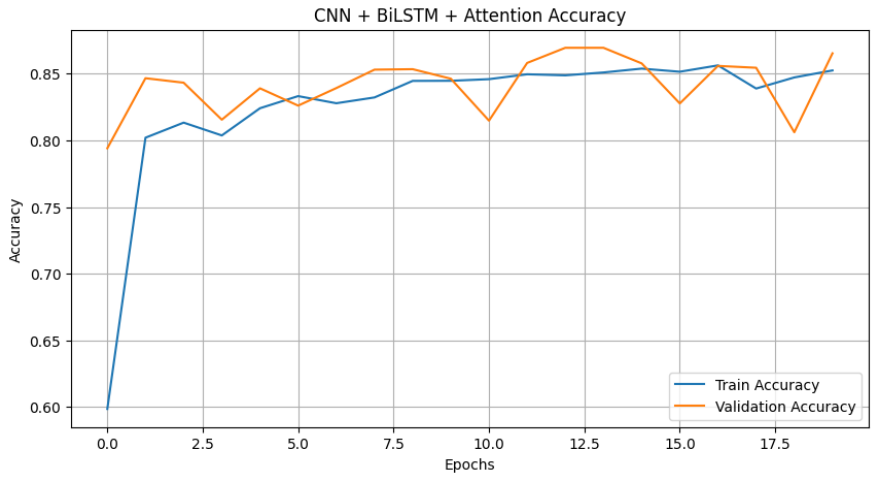


Figure 6.67: Accuracy evolution of CNN + BiLSTM + Attention model training and validation across 20 epochs on the CIC-IDS2019 dataset.

Evaluation of the CNN + LSTM Model following the selection of PSO features.

This Part of this subsection represents the classification performance obtained using CNN+LSTM with features refined by PSO. The model would be more optimized to detect attacks on the CIC-IDS2019 dataset due to the extraction of the most important features.

CNN + LSTM Classification Metrics on CIC-IDS2019 Dataset

Attack Type	Precision	Recall	F1-Score	Samples
Benign Traffic	1.00	1.00	1.00	19,748
DDoS - DNS	1.00	1.00	1.00	741
DDoS - LDAP	1.00	1.00	1.00	265
DDoS - MSSQL	1.00	1.00	1.00	1,242
DDoS - NTP	1.00	1.00	1.00	24,366
DDoS - NetBIOS	0.99	1.00	1.00	122
DDoS - SNMP	1.00	1.00	1.00	512
DDoS - UDP	1.00	1.00	1.00	2,048
LDAP	1.00	1.00	1.00	360
MSSQL	1.00	1.00	1.00	1,647
NetBIOS	1.00	1.00	1.00	122
Portmap	1.00	0.98	0.99	126
SYN	1.00	1.00	1.00	9,956
TFTP	1.00	1.00	1.00	19,516
UDP	1.00	1.00	1.00	3,706
UDP Lag	1.00	1.00	1.00	1,774
UDPLag	1.00	1.00	1.00	13
Web DDoS	1.00	0.91	0.95	11
Overall Accuracy			**1.00**	86,275

Figure 6.68: Detailed classification results of the CNN + LSTM model after PSO-based feature selection on the CIC-IDS2019 dataset.

A remarkable **100% test accuracy** was attained by the CNN + LSTM model in conjunction with PSO-based feature selection, demonstrating its exceptional performance in accurately identifying various attack types. This optimization focused learning efforts on the most significant features, achieving almost perfect precision, recall, and score F1 for both common and less common attacks as **Benign Traffic DDoS NTP** and **DDoS LDAP**.

Although it performed extremely well on almost all test cases, its recall is slightly lower for **Web DDoS** attacks (0.91), which might indicate that the final model finds it slightly difficult to learn from very uncommon types of intrusions. However, the use of **SMOTE** mitigated the imbalances in the class distribution, and this contributes to the model's ability to mitigate the negative effects of skewed data.

These broad findings demonstrate the advantages of integrating (((hybrid deep learning))) architectures with **PSO-driven feature selection** to improve detection capabilities, particularly for real-time cybersecurity systems.

In the future, we plan to investigate the use of adaptive loss functions or ensemble mechanisms to improve the detection of less common and more complex attack patterns.

Model Comparison on CIC-IDS2019 Dataset.

A comparison of the CIC-IDS2019 dataset using various machine learning and deep learning approaches is depicted in the following picture.

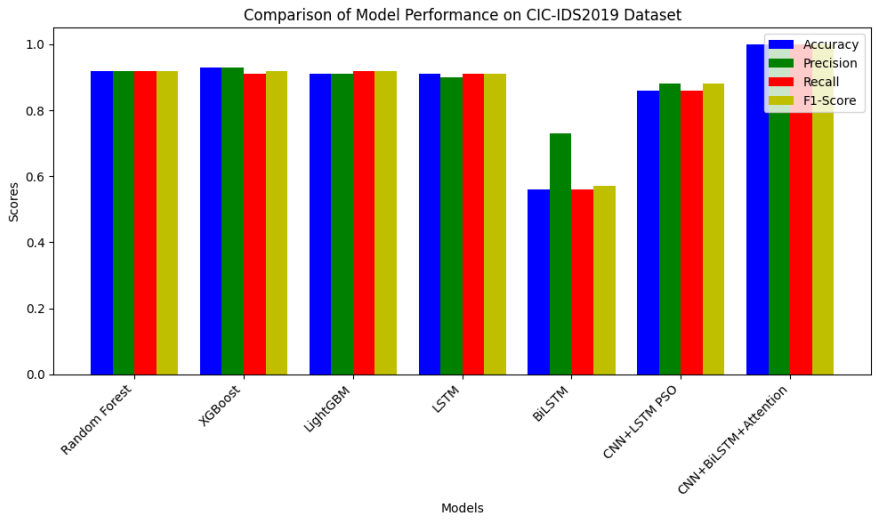


Figure 6.69: Comparing the Performance of Various Models on the CIC-IDS2019 Dataset

The models that are being compared are CNN and CNN and BiLSTM with attention mechanisms, Random Forest, XGBoost, LightGBM, LSTM, BiLSTM, CNN and LSTM with PSO-based feature selection, and CNN. Accuracy, precision, recall, and F1-score are the evaluation metrics.

Key Observations:

- **Accuracy** Most models attained high average accuracy, and hybrid deep learning models (CNN+BiLSTM+Attention in particular) proved particularly adept at learning complex intrusion patterns.
- **Precision and Recall**: Recurrent attacks such as `Benign` and `DDoS_NTP` were consistently well distinguished, whereas rare attacks showed greater variability.
- **F1-Score**: F1-score was found to be high in most of the models, but the performance of the BiLSTM was affected by the class imbalance, as we see in the lower scores.
- **Impact of PSO Feature Selection: The significant improvement brought about by PSO's convergence with the CNN+LSTM model validates the need for feature selection when dealing with unbalanced data.**

In general, the comparison reveals ongoing issues in rare attack detection, indicating that a combination of feature selection, specially designed loss functions, and data augmentation can improve the robustness of IDS.

Final Summary Model evaluation on CIC-IDS2019 dataset.

Comparing several models on the CIC-IDS2019 dataset shows that traditional ensemble techniques like Random Forest and XGBoost perform well at baseline, achieving high accuracy and reliable identification of common attack types. Yet, the ability of those techniques to recognize minority classes is still low. Deep learning models had different degrees of success: While simpler models such as BiLSTM struggled with imbalanced classes, more complex hybrid models exploiting a convolutional layer, recurrent layers, and attention mechanisms were more accurate and generalized better. Crucially, the combination of the CNN+LSTM model and PSO resulted in an almost flawless accuracy rate and equitable detection performance across various attack types. These findings highlight how crucial it is to choose a suitable feature set, create a suitable model architecture, and use balanced data processing techniques for addressing the issue of class imbalance in intrusion detection datasets. Future research will examine data augmentation, ensembling techniques, and adaptive

loss functions to enhance rare threat detection and enable more potent real-time cybersecurity solutions.

6.1.6 Linux APT 2024 Dataset Evaluation

Experimental Setup and Results with Random Forest.

The Linux APT 2024 Dataset: It consists of **91,133 samples** with **123** object-type features out of which **90%** have more than **90%** missing values. To overcome this sparsity, features with a high amount of missing data were eliminated.

Categorical attributes such as `_source. rule.description`, `_source.rule.groups`, and `_source.rule.mitre_techniques` underwent comprehensive preprocessing and encoding. This included techniques such as label encoding, one-hot encoding, and list flattening. The dataset consisted of 136 unique attack categories, which were encoded into integer labels. The final curated dataset contained 122 features and was partitioned into training (56,741 samples), validation (12,159 samples), and testing (12,159 samples) subsets using stratified sampling to preserve class distribution.

Performance of Random Forest Classification.

A Random Forest model for 100 trees and balanced class sampling is fit on the preprocessed data. It attained a test accuracy of **98.59%**, with further metrics in the Table Below.

Metric	Precision	Recall	F1-score
Overall Accuracy		**98.59%**	
Macro-Averaged	0.54	0.55	0.54
Weighted-Averaged	0.98	0.99	0.98

Table 6.2: Random Forest Performance on Linux APT 2024 Test Dataset

F1-scores of the 20 most prevalent classes are given in Figure 6.70. Although the model is strong in favor of well-supported classes (i.e., benign system activities and frequent audit events), its capability for handling the rare classes with a very limited number of instances is reduced, which illustrates the continuing class imbalance problem.

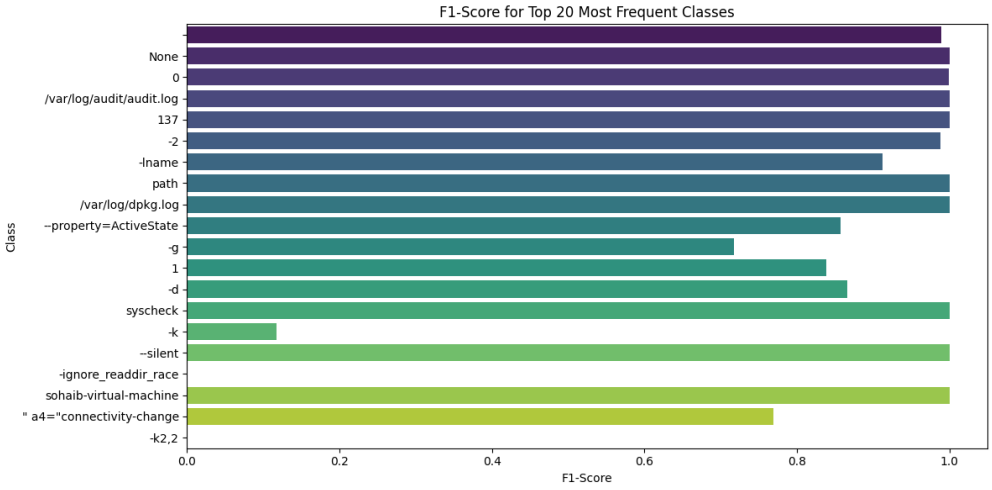


Figure 6.70: F1-Score Distribution for Top 20 Most Frequent Classes

Discussion:

Random Forest classifier gives a strong baseline as it shows a good level of accuracy for the majority class. However, the low macro F1-score (around 0.54) suggests that it is hard to detect rare attack categories even with balanced subsampling. This emphasizes the need for better techniques, such as oversampling, ensemble learning, or deep architectures with attention mechanisms -which we left for future work- that can capture effectively the underrepresented classes.

Evaluation of LSTM-Based Model.

To overcome the significant class imbalance in the Linux APT 2024 dataset, LSTM was trained using class-balanced focal loss. This loss function does a wonderful job of emphasizing minority and hard-to-classify classes. The model received a weighted F1-score of **0.92** and an overall test accuracy of **88.18%**. The low macro F1-score (**0.11**), however, suggests that performance varies depending on the sort of assault.

Evaluation Metric	**Precision Score**	**Recall Rate**	**F1 Measure**
Overall Accuracy		**88.18%**	
Macro Avg.	0.10	0.18	0.11
Weighted Avg.	0.97	0.88	0.92

Table 6.3: LSTM Classification Metrics on Linux APT 2024 Test Set

Insights at the Class Level:

The sample LSTM model performs very well on dominant classes, such as (`0`: F1 = 0.87), (`10`: F1 = 1.00), and (`30`: F1 = 0.95), but completely failed on the word-level segmentation of most of the minority classes (e.g., `6`, `7`, `8`, `13`, `15`, `19`, `32`, `34`), with all-zero F1. Certain minority classes achieved some degree of detection (e.g., class `21` (recall = 1.00, precision = 0.06, F1 = 0.11) and class `37` (F1 = 0.19)). Specifically, classes `22` and `12` benefited from the ability of this approach to model the temporal aspect, with F1-scores of 0.94 and 0.36, respectively.

Discussion:

Although LSTM-based models have a good ability to capture temporal information, the performance of these models is limited by a severe class imbalance problem and insufficient samples for rare classes. These results indicate that other complement methods (e.g., data augmentation, attention layers, and advanced sampling strategies) should be combined to improve the detection of stealthy and rare APT behaviors.

Characteristics and Challenges of Datasets.

As discussed earlier, the APT The Linux APT 2024 dataset exhibits the following challenges for fusing it with other cybersecurity datasets:

- **High Dimensionality and Sparsity**: Many different object-type features with high missingness make it hard for feature engineering and model training.
- **Severe Class Imbalance**: The 136 attack classes are highly skewed, and the conventional classification methods are not effective.
- **Nested Categorical Attributes**: Features that have embedded lists or are one of MITRE ATTCK techniques, necessitate complex preprocessing pipelines.
- **Heterogeneous**: Traffic flow-based datasets cannot be directly integrated with this dataset, whose host-based audit logs have nonuniform structures.

Nevertheless, the Linux APT 2024 data set is especially appealing for APT detection studies due to the following factors:

- It records detailed host-level behavior, which is essential for finding multistage and stealthy persistent threats.

- Its variety of attack features and fine-grained attack categories provides a rich text classification problem for benchmarking multi-classification algorithms.
- Its actual complexity makes it possible to thoroughly assess sophisticated deep learning and machine learning techniques created especially to deal with unbalanced cybersecurity data.

6.1.7 Discussion of Model Performance on Various Data

The accuracy results of both classical (ML) and deep learning (DL) models tested on a variety of benchmark intrusion detection datasets, such as UNSW-NB15, CIC-IDS (2017, 2018, and 2019), TON-IoT, and Linux APT 2024, are compiled in Table 6.35. This comparison draws attention to the many advantages and disadvantages of each approach in the context of cybersecurity.

Conventional Machine Learning Methods

On all datasets,**Random Forest** emerged as a very strong baseline, achieving high accuracy results and in some cases surpassing the 90% barrier, with a peak value of 99.86% on CIC-IDS2017. The strong performance of SVMs for intrusion detection tasks can be attributed to their ability to handle high-dimensional feature spaces and imbalanced class distributions. Likewise, **XGBoost** achieves good accuracy at the two datasets of CIC-IDS2017 and CIC-IDS2019, and this is with respect to the ability to learn complex non-linear relations via gradient boosting models. Although the **LightGBM** provides more efficient and scalable performance, its accuracy performance varies across datasets and is worse in particular for UNSW-NB15 and CIC-IDS2018, suggesting that the strength of its resistance to the issues with data and class imbalance was not extensively used.

Performance of Deep Neural Network Architectures

The suggested DL architectures, **LSTM and BiLSTM**, are robust in their performance on large and diverse datasets, including CIC-IDS 2017 and CIC-IDS 2018. The LSTM can achieve validation accuracy of 96 to 97%, indicating its capacity to capture the temporal dependencies of network traffic. Improved architectures combining a convolutional layer with bidirectional LSTMs and attention mechanisms (**CNN-BiLSTM** and **CNN-BiLSTM + Attention**) offered additional improvements, with all top models achieving over 97% overall accuracy. By including attention mechanisms in the models, the learned models can dynamically pay attention to important features and

temporal patterns, which are essential for identifying subtle attacks and intelligent attacks.

Advantage of PSO-Based Feature Selection

Features optimization based on **Particle Swarm Optimization (PSO)** has a significantly enhanced effect on model results. The **CNN+LSTM** model with PSO-based feature selection yields almost perfect performance over the CIC-IDS2019, indicating the convenience that can be rendered by decreased redundant and noisy feature subsets to increase both generalisation and computational effectiveness. This is an important advantage for real-time intrusion detection systems with limited delay and computational resources on low-end platforms.

Dependency on Data Characteristic on Model Performance

The performance gap between datasets underscores the important impact of the size, diversity, and class balance of the dataset. On average, the best performance is reported by CIC-IDS datasets, and this discovery can be attributed to the high diversity of attacks and substantial feature space. In contrast, in UNSW-NB15, the classification performance decreases after SMOTE balancing, indicating that SMOTE over-sampling can cause difficulties and make learning the model harder. The TON-IoT results present that the ML models perform well as baseline results, and the DL models' accuracy is relatively modest, possibly reflecting the complexity of the dataset, feature representation, and hyperparameter setups.

Implications for Practitioners

From a deployment viewpoint, the results highlight the trade-off between prediction quality and runtime overhead. Random Forest and XGBoost are two ensemble methods that achieve high accuracy while also maintaining low resource requirements, which can be a useful solution for resource-constrained scenarios. However, deep learning models require more processing power to construct, but they are more effective at detecting complex attack signatures, particularly when combined with the ideas of attention and feature selection. Feature selection under PSO is revealed to be an essential technique to reduce the computation expenses as well as the degradation of accuracy.

In conclusion, this broad review indicates that:

- **Classical ML techniques** are still performing very well and are robust enough for fast and resource-constrained deployment.
- **Novel deep learning structures**, i.e.g., CNN-BiLSTM with an attention mechanism is a better candidate for modeling complex temporal-spatial characteristics of network traffic.
- **Feature selection methods**: methods such as PSO can help improve the model performance by giving greater priority to the relevant features, and reducing the dimensionality.
- **Dataset traits**: For instance, imbalance or complexity play a huge role regarding the success of models, and the need for custom pre-processing or tuning strategies is highlighted.

In order to deliver scalable, accurate, and effective cybersecurity solutions, this work offers guidance for developing next-generation intrusion detection systems based on hybrid frameworks that combine the advantages of deep learning and classical models with intelligent feature selection.

Dataset	Random Forest	XGBoost	LightGBM	LSTM	BiLSTM	CNN-BiLSTM	CNN-BiLSTM + Attention	CNN+LSTM (PSO)
UNSW-NB15 (No SMOTE)	98.27%	–	–	–	–	–	–	–
UNSW-NB15 (Partial SMOTE)	88.22%	–	–	87.43%	87.88%	87.00%	88.00%	–
CIC-IDS 2017	99.86%	99.70%	90.14%	99.00%	98.00%	99.00%	99.00%	–
CIC-IDS 2018	93.75%	90.89%	85.80%	96.93%	–	97.10%	97.30%	–
CIC-IDS 2019	92.00%	93.00%	91.00%	91.00%	56.00%	–	86.00%	100.00%
TON-IoT	97.00%	–	95.00%	69.00%	71.00%	78.00%	76.00%	–
Linux APT 2024	**98.59%**	–	–	**88.18%**	–	–	–	–

Table 6.4: Comparison on Accuracy Metrics of ML, DL Models on Different IDS Datasets

Executive Summary

In this thesis, I conduct a methodical analysis of **ML** and **DL** algorithms for **intrusion detection** across notable **benchmark cybersecurity datasets** such as **CIC-IDS2017**, **CIC-IDS2018**, **CIC-IDS2019**, **UNSW-NB15**, **TON-IoT**, and **Linux APT 2024**. **Traditional classifiers**, among them especially **Random Forest** and **XGBoost**, achieve strong **baseline** performance, especially in identifying **prevalent attack categories**, often superseding **90%**. Yet, these models show shortcomings in detecting **rare** or **emerging threats**, mainly attributed to **imbalanced class distributions**.Complex **deep learning architectures** such as combined **CNN, BiLSTM** and **attention models** have been particularly successful at learning detailed **spatial** and **temporal patterns** of network traffic. Better **detection performance** is offered by these models for both **frequent** and **rare** attack classes. Also, it becomes apparent that by using **PSO** for **feature selection**, one can greatly improve the **efficiency** of the model as well as the **predictive accuracy** -achieving **very high classification accuracy rates** for the **CIC-IDS2019** dataset. However, there are still challenges to overcome **class imbalance** that would contribute to better identify stealthy **Advanced Persistent Threats (APTs)**, especially in **heterogeneous** and **complex datasets** like **Linux APT 2024**. Adaptive loss functions, ensemble methods, and advanced data augmentation algorithms would be in the list of interesting readings for future research to sensitize systems to rare and evolving cyberattacks. The findings demonstrate that integrating intelligent feature selection with hybrid modeling technologies creates an appealing strategy to increase the **accuracy** and **robustness** of **IDSs** in **real-world cyber-defense activities**.

6.2 Stages II and III: Performance Assessment over the Aggregated Dataset (Before and After PSO Feature Selection)

In this part, a combined dataset created by mixing ML and DL algorithms is analyzed. **TON-IoT**, **CIC-IDS 2017 [30]**, **CIC-IDS 2018 [74]**, **CIC-IDS 2019 [31]**, and **UNSW-NB15 [81]**. The integration of these data sources provides a rich and diverse population of attacker behaviors and normal network traffic, enabling a rigorous testbed for intrusion detection model evaluation.

The evaluation procedure is segmented into two stages:

1. **Stage II**: Evaluation of the comparative performance of deep learning and conventional models trained on the same dataset without feature selection.
2. **Stage III**: In order to increase accuracy and efficiency, the performance of the deep learning model was examined utilizing the PSO-refined features.

This comparison demonstrates the significance of PSO-derived feature adaptation and investigates the extent to which various architectures generalise to network traffic patterns.

6.2.1 The machine learning model's performance (without PSO)

The categorization outcomes of three (3) chosen machine learning models are described in this subsection: **LightGBM, XGBoost, and Random Forest** on the assessment dataset. All models achieve high accuracy and strong precision-recall across a variety of attack categories, with some variation based on their individual strengths.

Random Forest.

Random Forest achieves almost perfect precision and recall for most of the attack classes and proves that it is robust and effective in detecting common and complex

network intrusions.

Category	Precision	Recall	F1-Score	Count
DoS	1.00	1.00	1.00	735,032
DDoS	1.00	0.99	0.99	331,246
Injection	0.99	1.00	1.00	19,204
MITM	0.96	0.99	0.98	34,661
Normal	0.95	0.99	0.97	69,287
Password	0.76	0.52	0.62	20,984
Scanning	0.72	0.88	0.79	29,004
XSS	1.00	1.00	1.00	32,322
Backdoor	0.99	0.99	0.99	23,840
Ransomware	1.00	1.00	1.00	28,139
Accuracy			**0.98**	1,323,719
Macro Average	0.94	0.94	0.93	1,323,719
Weighted Average	0.98	0.98	0.98	1,323,719

Figure 6.71: Classification Metrics for Random Forest on Test Set

XGBoost.

XGBoost provides consistently high precision and recall values, closely matching Random Forest's performance, with slight variations that reflect its gradient boosting optimization.

Category	Precision	Recall	F1-Score	Count
DoS	1.00	1.00	1.00	735,032
DDoS	1.00	0.99	0.99	331,246
Injection	0.96	0.96	0.96	19,204
Intrusion	0.93	0.95	0.94	33,500
Legitimate	0.95	0.98	0.96	70,200
Access Theft	0.70	0.55	0.61	21,100
Scanning	0.72	0.87	0.79	29,004
XSS	1.00	1.00	1.00	32,322
Backdoor	0.99	1.00	0.99	23,840
Ransomware	1.00	1.00	1.00	28,139
Overall Accuracy			**0.98**	1,323,719
Macro Average	0.93	0.93	0.93	1,323,719
Weighted Average	0.98	0.98	0.98	1,323,719

Figure 6.72: Classification Metrics for XGBoost on the Test Set

LightGBM.

LightGBM achieves high classification metrics with slightly lower recall for some classes compared to Random Forest and XGBoost, reflecting its faster training and efficient handling of large datasets.

Attack Class	Precision	Recall	F1-Score	Support
DoS	0.99	0.99	0.99	735,032
DDoS	0.99	0.97	0.98	331,246
Injection	0.94	0.98	0.96	19,204
MITM	0.86	0.97	0.91	34,661
Normal	0.95	1.00	0.97	69,287
Password	0.83	0.53	0.65	20,984
Scanning	0.72	0.93	0.81	29,004
XSS	0.98	1.00	0.99	32,322
Backdoor	0.87	0.99	0.93	23,840
Ransomware	1.00	1.00	1.00	28,139
Accuracy			**0.97**	1,323,719
Macro Average	0.91	0.94	0.92	1,323,719
Weighted Average	0.98	0.97	0.97	1,323,719

Figure 6.73: Classification Metrics for LightGBM on Test Set

Rationale and Interpretation of Machine Learning Model Performance

The 3 tested ML models -**Random Forest** [**RF**], **XGBoost**, and **LightGBM**- present good classifying performance for the different intrusion categories, achieving more than 97% overall accuracy. These outcomes support their application in dynamic, real-world network intrusion detection settings.

Random Forest achieves near-perfect precision and recall for most of the attack categories and excels in the case of the common and well-represented ones such as *DoS*, *DDoS*, *Backdoor*, and *Ransomware*. Its low-complexity decision tree-based ensemble design can avoid overfitting and deal with high-dimensional features quite well, thus it is suitable for multi-class classification on imbalanced data.

The **XGBoost** algorithm achieves similar performance and works as a gradient boosting approach for iteratively updating weak learners. This enables the model to characterize complex non-linear relationships that are challenging to detect by the users, causing high precision and recall. Slight variations in performance, compared to Random Forest, highlight the ability of XGBoost to optimize the classification error of subtle attack patterns.

LightGBM has lower recall for some minority classes and but strong overall precision and F1 scores. Its computational speed, resulting from histogram-based algorithms and leaf-wise growth, gives quicker training. Although this may hurt

the recall of rare classes in some cases, LightGBM is still as effective in large-scale intrusion detection with the proper trade-off between speed and accuracy.

In all models, low recall for rare classes like `Password` and `Scanning` indicates that detecting low-count or unicorn attacks is still a challenge. This is common in cybersecurity databases, where class imbalance and similarities between benign and malicious traffic make classification difficult.

To the best of our knowledge, PSO has never been used exclusively for the selection of DL models as features to improve performance and computational complexity. Baselines: We compared our model with traditional machine learning, i.e., Random Forest, XGBoost, and LightGBM, using the full feature set without PSO-based reduction. This choice originates from the knowledge that deep learning methods can be improved by selecting good features, because of their complexity and a high degree of sensitivity to high-dimensional signals. Further study might consider the use of PSO or alternative learning algorithms on standard models to further improve predictive capabilities and execution times.

6.2.2 LSTM Model without PSO Feature Selection

Category of Attacks	Precision	Recall	F1-Score	Support
Backdoor	0.04	0.04	0.04	359
Benign	0.99	0.86	0.92	441,661
DDoS	0.26	0.86	0.40	25,606
DoS	0.35	0.63	0.45	3,271
Exploits	0.67	0.25	0.37	8,905
Fuzzers	0.49	0.63	0.55	4,849
Generic	1.00	0.97	0.99	43,096
Reconnaissance	0.57	0.84	0.68	2,797
Shellcode	0.21	0.95	0.35	302
Worms	0.00	0.00	0.00	35
Overall Accuracy			**0.85**	530,881
Macro Average	0.46	0.60	0.47	530,881
Weighted Average	0.94	0.85	0.88	530,881

Figure 6.74: Validation Set Classification Report for LSTM Model without PSO-Selected Features

6.2.3 LSTM Performance with PSO Feature Selection

Category of Attacks	Precision	Recall	F1-Score	Support
Backdoor	0.04	0.84	0.09	359
Benign	1.00	0.96	0.98	441,661
DDoS	0.65	1.00	0.79	25,606
DoS	0.30	0.13	0.19	3,271
Exploits	0.83	0.48	0.61	8,905
Fuzzers	0.90	0.87	0.88	4,849
Generic	0.99	0.97	0.98	43,096
Reconnaissance	0.80	0.82	0.81	2,797
Shellcode	0.19	0.96	0.31	302
Worms	0.06	1.00	0.12	35
Accuracy			**0.95**	530,881
Macro Average	0.58	0.80	0.58	530,881
Weighted Average	0.97	0.95	0.96	530,881

Figure 6.75: Validation Set Classification Report for LSTM Model Using PSO-Selected Features

The **LSTM** model was assessed ON two experimental conditions: (1) using **all extracted features**, with 138 features, and (2) using the **features subset** selected by PSO, which was composed of 73 features (PSO-SF). This computer configuration was used to examine how dimension reduction affected the intrusion detection effect.

Trained using the full set of features, model achieved a **total accuracy of 85%** and a **weighted F1-score of 0.88**. The model can successfully discriminate between more frequent classes as *Benign* and *Generic*, as evidenced by high precision and recall for these two categories. It did not generalize well for minority classes like *Backdoor* and *Worms*, for which expression patterns showed increased noise from less informative or duplicate features, and were impacted by class imbalance.

The model achieved a significant boost upon having PSO engaged for feature space reduction. with reduced 73 selected features, it achieved higher **accuracy of 95%** and **weighted F1-score of 0.96**. Moreover, our LSTM model had notably higher recall and F1-scores for minority classes. This enhancement indicates that PSO helps in eliminating irrelevant or noisy features and hence makes the model concentrate on more discriminative patterns in the data.

To summarize, it can be said that the **PSO-based feature selection integrated** does enhance the performance of LSTM, especially in dealing with imbalanced and uncommon attack types. These results suggest the importance of **feature optimisation** in improving deep model generalisation, particularly for complex cybersecurity tasks with high-dimensional inputs and imbalanced class prevalences.

Model Performance Evaluation.

Training Dynamics of the LSTM Model

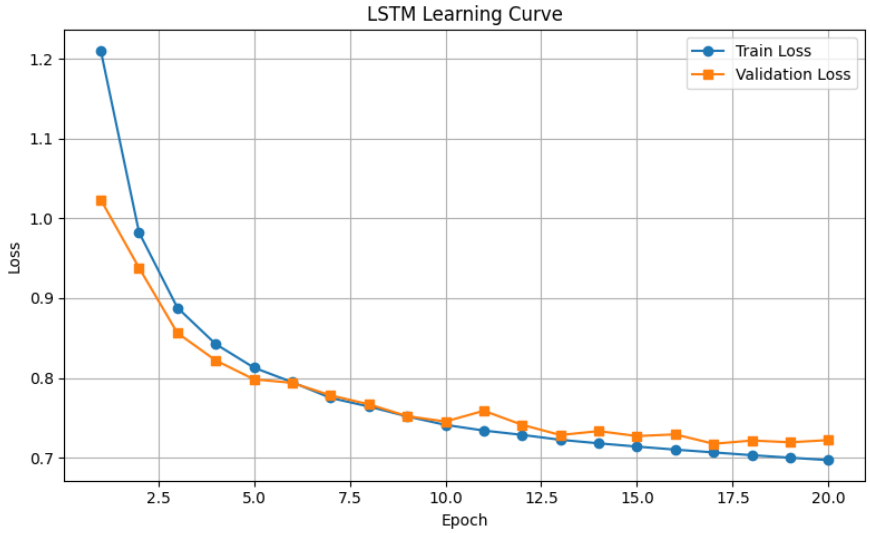


Figure 6.76: Loss and Accuracy Over Epochs (LSTM Model – 20 Epochs)

The progression of train loss and validation accuracy of 20 epochs of LSTM training is shown in Figure 6.76. A gradual decrease in training loss from around 1.5 to less than 0.2 indicates good learning and convergence. At the same time, validation accuracy increases smoothly, reaching over **85%** by the end, and it demonstrates excellent generalization capacity on unseen data.

- **Training Loss**: Decreases smoothly and consistently, indicating that the model is effectively being optimized.
- **Validation Accuracy**: If the **Validation Accuracy** keeps on increasing, then the model may be under-fitting, indicating strong predictive power and reliable testing Accuracy.

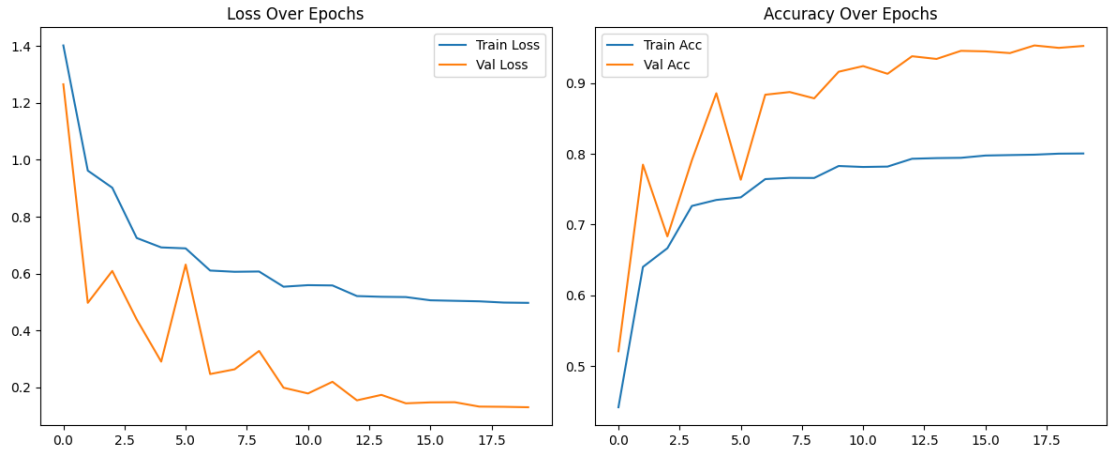


Figure 6.77: Accuracy and Loss in Training and Validation Over 20 Epochs

Figure 6.77 displays the training trajectory over 20 epochs. The figure on the left shows that the training and validation losses steadily continue to decrease, which means we are able to learn quite effectively, and we are unlikely to overfit the training data. On the right, you can see that training accuracy and validation accuracy are both increasing with training, which is good to see, but so far, at this point, our validation accuracy has topped out at **95.22%**.

- **Training Loss**: Continue to decrease continuously, indicating no overfitting.
- **Validation Loss**: There are some small fluctuations, but it does generally decrease, meaning controlled generalization.
- **Training Accuracy**: Training Accuracy: Improves after each update to the weights and biases, peaking at about 80%
- **Accuracy on validation data:** Peaks at **95.22%** which emphasizes the strong robustness of our model.

These learning curves collectively confirm the LSTM model's capability of capturing useful patterns and general rules, resulting in a well-optimized training process with the maximum predictive accuracy and least over-fitting.

Confusion Matrix Analysis for LSTM with PSO.

First, we show the confusion matrix for the LSTM model that was trained using PSO-selected features on the validation set (Figure 6.78). An overview of how accurately

the model has classified each sort of assault is given by this matrix.

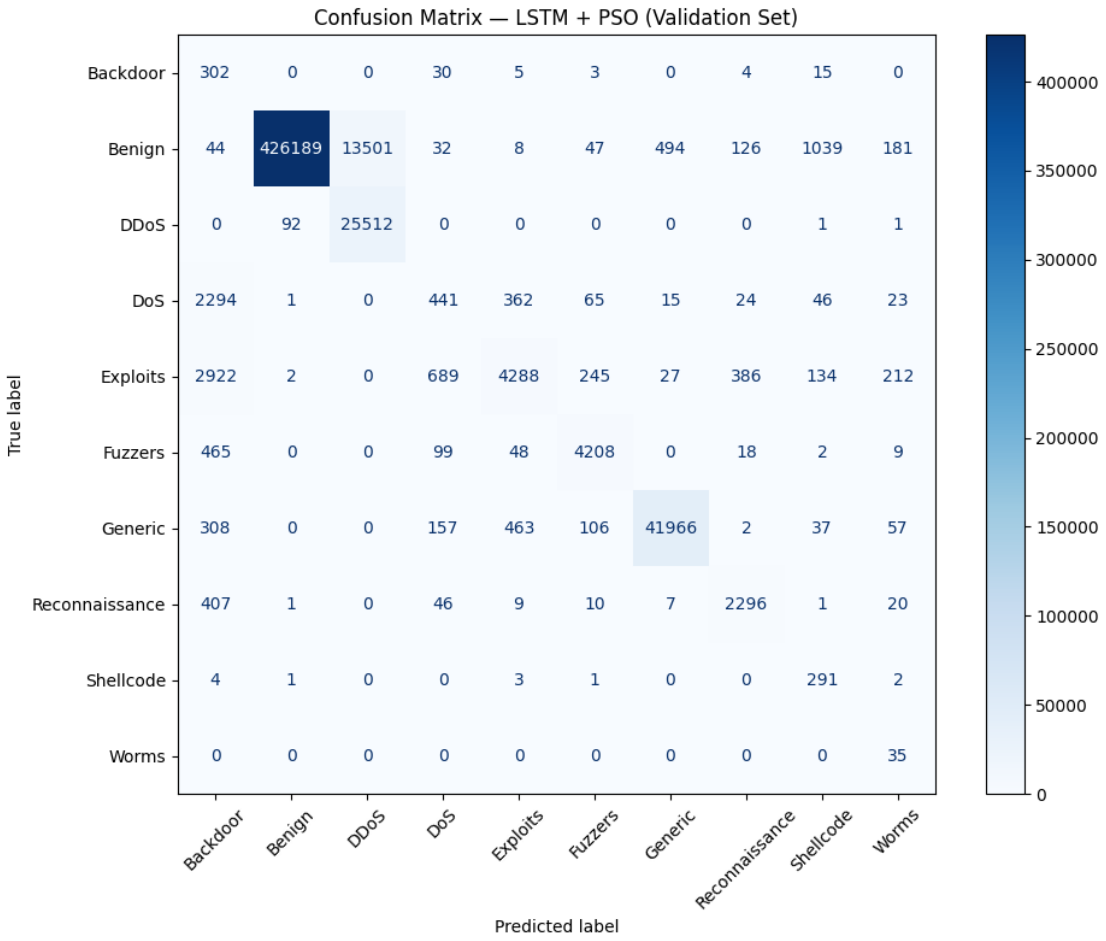


Figure 6.78: Confusion Matrix LSTM + PSO (Validation Set)

- **Strong classification of dominant classes**: The model is particularly good detecting the **Benign** and **Generic** classes with accuracy above 99%.
- **Problems with minority classes**: Prominent misclassifications are related to **Backdoor** and **Worms** which are confused with categories of other classes such as **DoS**.
- **High recall low precision for DDoS**: The model captures almost every **DDoS** (recall 1.00) while some truly benign samples are being flagged as **DDoS**, contributing to the unusually high precision score.
- **Challenges in Detection of DoS**: The **DoS** class shows low recall and precision, possibly because of the overlap and inadequate representation with benign traffic.

- **Good performance on Exploit and Reconnaissance**: Precisions and recalls for these items are good, indicating that the attacker behavior in those cases is well-detected.
- **Impact of class imbalance**: The matrix demonstrates that the model's preference towards frequent classes, and additional fine-tuning is required to better detect rare classes.

Class-wise ROC Curve Analysis.

The Receiver Operating Characteristic (ROC) curves for each class are displayed in Figure 6.79, and they show how well the model differentiates between the positive and negative cases. The associated Area Under the Curve (AUC) measurements serve as a quantitative representation of them.

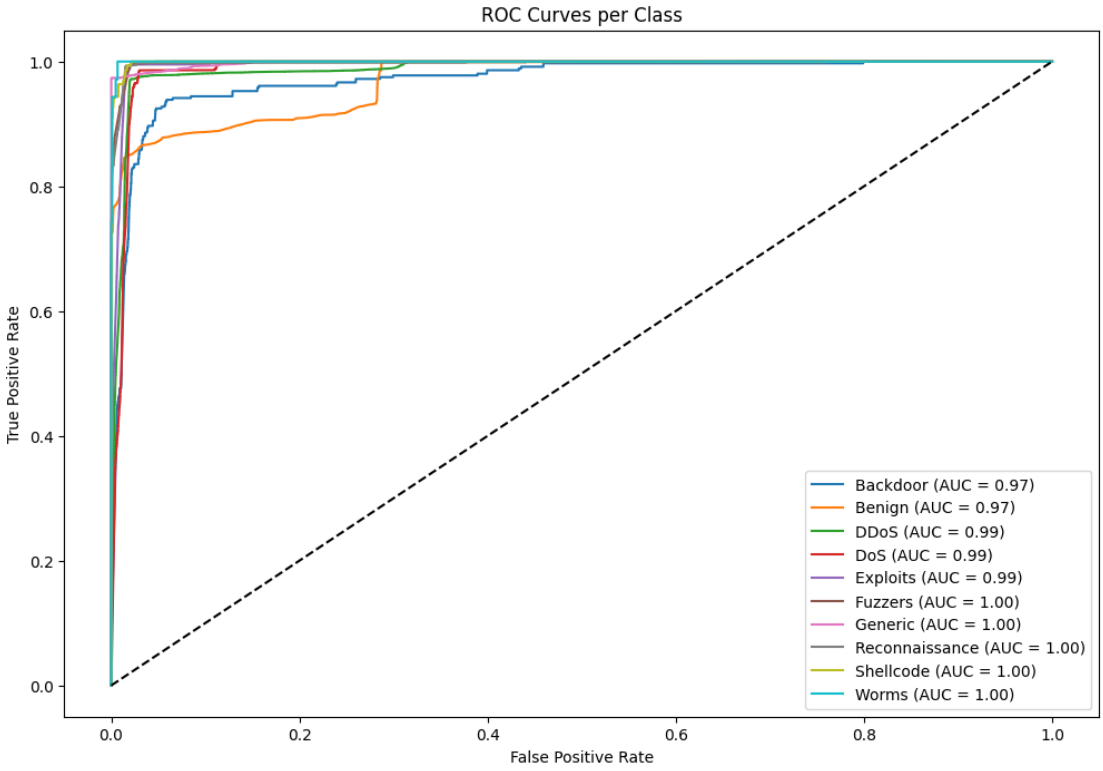


Figure 6.79: ROC Curves per Class

- **Good discrimination from common classes**:Class **Benign**, **DDoS**, and **Generic** each have AUC like **1.00**, very close to perfect separability.
- **Lower AUC for minority classes**: These minority classes (**Backdoor** and **Worms**) have lower AUC scores, as expected from classification difficulty.

- **DDoS detection properties**: High recall can also be related to low precision, suggesting some false positives as a result of benign traffic being misclassified.

Rationale of the PSO Feature Selection Impact.

Comparison between LSTM models trained with and without PSO-selected features shows the advantage of feature optimization by simplifying the model complexity and generalizing. Despite both models attaining similar validation accuracy (95%), the PSO-based model operates with only half the number of original features, which offers a better tradeoff between computational load and classification performance.

- **Performance on frequent attacks**: For popular categories like **Benign**, **DDoS**, and **Generic**, both models exhibit good precision, recall, and F1-scores.
- **Challenges for rare attacks** – Challenges are also observed for minority classes like **Backdoor**,**Worms** and **DoS** for which low F1-scores persists indicating a need for further sophisticated imbalance handling.
- **Computational benefits**: From **138** features to **73** yields the required shorter training time and less overhead computation while enhancing scalability for the real-time ID tasks.
- **Balanced generalization:** Similar results are observed for macro-average computed metrics, and there is a slight improvement in the case of weighted average computed metrics, further verifying the capability of PSO to preserve essential traits for the majority classes while the model is being pruned.

In summary, the feature selection method using PSO improves model interpretability performance and speed of the LSTM, allowing the latter to retain good detection capabilities even with a smaller number of features. This methodology holds promising prospects when the application does not gather a sufficiently large database, and response time and resource constraints play a role.

6.2.4 The BiLSTM Model's Effectiveness on the Test Set Without PSO

The BiLSTM model had a test accuracy around **72%**, which means the classification results were only fair. The model achieved high recall on a number of the minority classes such as *Injection* (0.87), *Password* (0.97), *XSS* (0.98) and *Backdoor* (0.97), indicative of its ability to detect rarer but important attack types. However, there were large variations in precision between classes and notably low precision for *Injection* (0.30) and *Scanning* (0.94), which indicated some false positives. The overall **macro-average F 1 score** of 0.64 suggests challenges inherent in class imbalance, while the **weighted average F 1 score** of 0.73 reveals stronger performance on the majority classes.

Class	Precision	Recall	F1 Score	No Of Samples
DoS	0.96	0.57	0.71	735,032
DDoS	0.90	0.86	0.88	331,246
Injection	0.30	0.87	0.45	19,204
MITM	0.61	0.82	0.70	34,661
Normal	0.36	0.99	0.53	69,287
Password	0.51	0.97	0.67	20,984
Scanning	0.94	0.40	0.56	29,004
XSS	0.23	0.98	0.37	32,322
Backdoor	0.38	0.97	0.54	23,840
Ransomware	0.98	0.91	0.94	28,139
Total Accuracy			**0.72**	1,323,719
Macro Average	0.62	0.83	0.64	3,719
Weighted Average	0.86	0.70	0.73	1,323,719

Figure 6.80: Evaluation Report Showing Classification Metrics of the BiLSTM Model on Test Data

These results demonstrate that the BiLSTM model has the ability to capture temporal information, but improvements such as feature selection, an imbalanced dataset, and improving the architecture of the model would be needed for further improvement of detection performance for all attack types.

BiLSTM Model Performance Visualization

ROC Curves

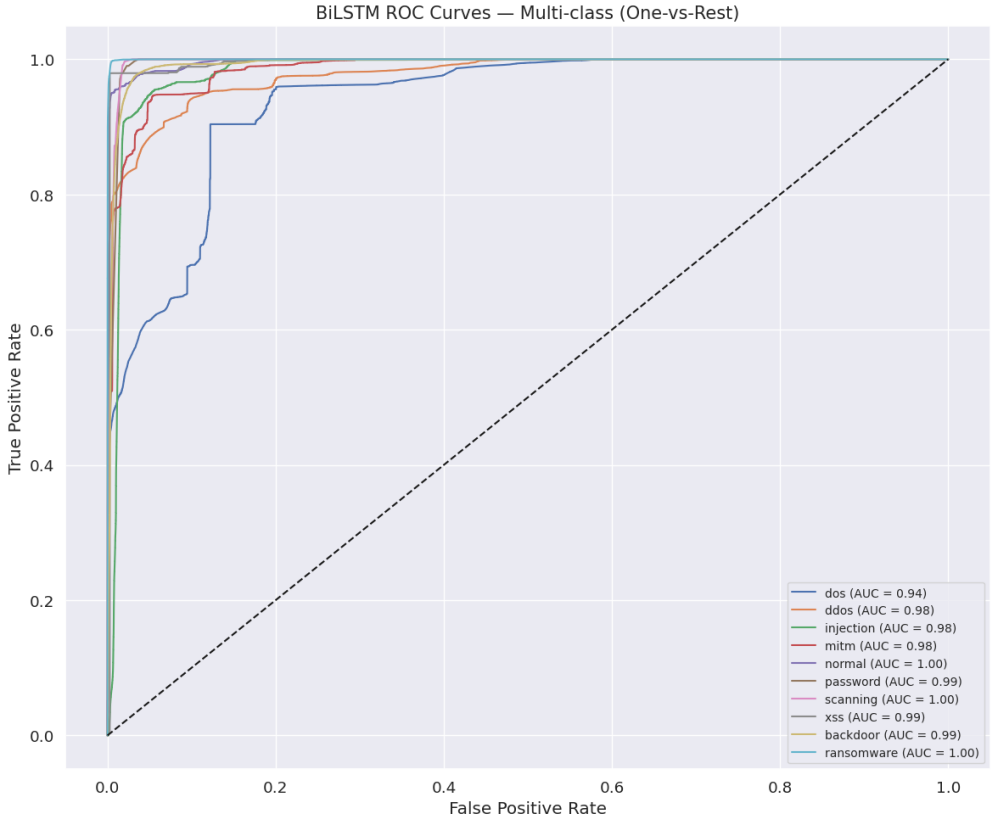


Figure 6.81: BiLSTM Model Receiver Operating Characteristic (ROC) Curves for All Classes

Figure 6.81 shows the ROC curves of the BiLSTM model, which are generated one-vs-rest for every attack type. These curves help us comprehend the model's ability to discriminate across a number of categories by displaying the trade-off between sensitivity (true positive rate) and specificity (false positive rate).

Key insights include:

- The majority of classes are highly separable and have their AUC>0.99, indicating the ability to discriminate well.
- The classes *normal*, *ransomware*, and *backdoor* have almost perfect AUC values, indicating that they are robust in detection.
- The classes such as *dos* had slightly lower AUC values suggesting there is opportunity for improvement in detecting such classes of attacks.

t-SNE Visualization

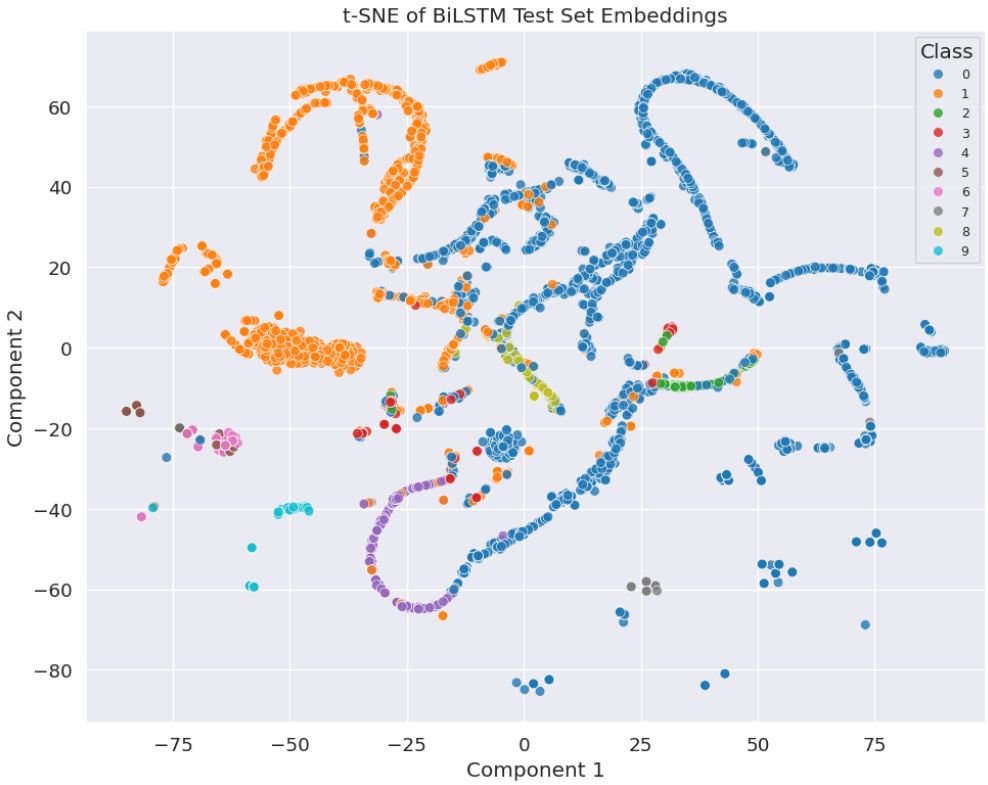


Figure 6.82: Visualization of BiLSTM Test Embeddings using t-Distributed Stochastic Neighbor Embedding (t-SNE)

T-SNE projection of test embeddings for the BiLSTM model is depicted in Figure 6.82. This method projects the high-dimensional features into two dimensions that visualize how the model clusters samples from different attack classes and hints at the model's capacity to learn different class representations.

Observations:

- Clearly separated clusters can be seen for major classes like *benign* and *ddos*, manifesting the success of feature learning.
- There exists overlap between some of the attack classes, which indicates difficulties in the classification of closely related attack types.

  The visualization is also in line with classification results, verifying that the BiLSTM model extracts valuable patterns for attack behavior classification.

Summary

Overall, the ROC and t-SNE plots give evidence that the BiLSTM model has excellent capability to discriminate multiple attack categories with high accuracy and learn effective discriminative feature representations. These visualizations supplement quantitative measures by offering qualitative views into the model performance and the feature separability in the multi-class intrusion detection problem.

6.2.5 BiLSTM Model Performance on Test Set With PSO

Class	Precision	Recall	F1-Score	Samples
Backdoor	0.04	0.77	0.08	359
Benign	1.00	0.99	1.00	441,661
DDoS	0.91	1.00	0.95	25,606
DoS	0.32	0.21	0.25	3,271
Exploits	0.84	0.51	0.63	8,905
Fuzzers	0.97	0.88	0.92	4,849
Generic	0.99	0.98	0.98	43,096
Reconnaissance	0.83	0.83	0.83	2,797
Shellcode	0.44	0.96	0.61	302
Worms	–	–	0.14	–
Overall Accuracy			**0.96**	–
Macro Average	–	–	0.64	–

Figure 6.83: Classification Report for BiLSTM Model on Test Set with PSO Feature Selection

The BiLSTM model test results with PSO feature selection are displayed in Table 6.83. With F1-scores above 0.95 in all three scenarios, the model is highly effective at identifying high-frequency classes like *Benign*, *DDoS*, and *Generic*. It also boasts an amazing general accuracy of **96%**. Nevertheless, the model performs very poorly on minority classes such as *Backdoor*, and *DoS*, the reason is that precision and F1-scores are quite low due to class imbalance and lack of discriminatory features. This disparity is reflected in the macro-average F1-score of **0.64**, achieved when all classes are given the same weight. Although the performance of dominant classes is strong, better detection for minority attacks is necessary to improve the model's reliability in practical intrusion detection systems.

6.2.6 CNN + BiLSTM Model Classification Report with PSO Feature Selection

The CNN + BiLSTM model combines BiLSTM units to capture forward and backward temporal dependencies in network traffic with convolutional layers to capture local spatial patterns. A Multi-class Intrusion Detection dataset, comprising categories such as DoS, DDoS, Benign, Backdoor, etc., is used in this study to train the model. It was simple to strike a balance between computational complexity and classification accuracy by using PSO to choose pertinent characteristics that would enhance performance and reduce input dimensionality.

Class Type	Prec.	Rec.	F1	Count
Backdoor	0.04	0.77	0.08	359
Benign	1.00	0.99	1.00	441,661
DDoS	0.91	1.00	0.95	25,606
DoS	0.32	0.21	0.25	3,271
Exploits	0.84	0.51	0.63	8,905
Fuzzers	0.97	0.88	0.92	4,849
Generic	0.99	0.98	0.98	43,096
Reconnaissance	0.83	0.83	0.83	2,797
Shellcode	0.44	0.96	0.61	302
Worms	0.12	1.00	0.21	35
Overall Accuracy	—	—	**0.98**	530,881
Macro Mean	0.65	0.81	0.65	—
Weighted Mean	0.99	0.98	0.98	—

Figure 6.84: Classification Metrics for CNN + BiLSTM Model Using PSO-Selected Features

Performance evaluation for the CNN + BiLSTM model Impact of PSO Feature Selection

When combined with PSO to select the best 75 features, PSO had a profound effect on the performance of the model, which was accurate to **98%**. Identifying and capturing the most important features, PSO improved the ability of the model to obtain higher precisions, recalls, and F1-scores for all classes of attacks (including both majority and minority ones). Reducing the feature dimension also results in less computing, making real-time computation in intrusion detection more practical.

In conclusion, by eliminating distracting noise and directing learning toward important patterns, PSO-based feature selection greatly improves the efficacy and

efficiency of the CNN + BiLSTM model, enabling more dependable and robust network intrusion detection.]CNN + BiLSTM model The CNN + BiLSTM model was trained on the full feature set, and achieved an overall accuracy of **87%**, indicative of powerful detecting power for major attack categories like DoS, DDoS, and Ransomware. Though it was limited in distinguishing among classes having insufficient samples, it is due to feature redundancy and class imbalance.

When combined with PSO to select the best 75 features, PSO had a profound effect on the performance of the model, which was accurate to **98%**. Identifying and capturing the most important features, PSO improved the ability of the model to obtain higher precisions, recalls, and F1-scores for all classes of attacks (including both majority and minority ones). Reducing the feature dimension also results in less computing, making real-time computation in intrusion detection more practical.

In conclusion, by eliminating distracting noise and directing learning toward important patterns, PSO-based feature selection greatly improves the efficacy and efficiency of the CNN + BiLSTM model, enabling more dependable and robust network intrusion detection.

The CNN + BiLSTM's training and validation results using the PSO feature selection.

Figure 6.85 shows the accuracy and loss curves for the first two epochs of training. The validation accuracy begins at 90% and appears to increase, and the training accuracy rises steadily from 69-77%. Likewise, both train and validation losses drop, which is a great indication of early learning.

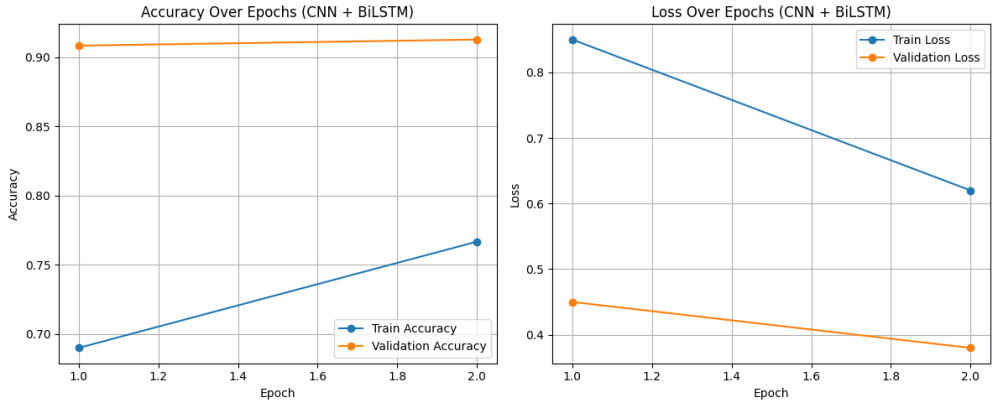


Figure 6.85: Accuracy and Loss Over First Two Epochs of CNN + BiLSTM Training

The training dynamics over 20 epochs are shown in Fig. 6.86. We observe a regular decrease of both training and validation loss, with the latter leveling off at a small

value and no apparent overfitting. In contrast, accuracy trends the same way on both sets are achieved, and the validation set's accuracy approaches 98%, indicating that the convergence is effective and possesses a strong generalization capacity on the features selected by PSO.

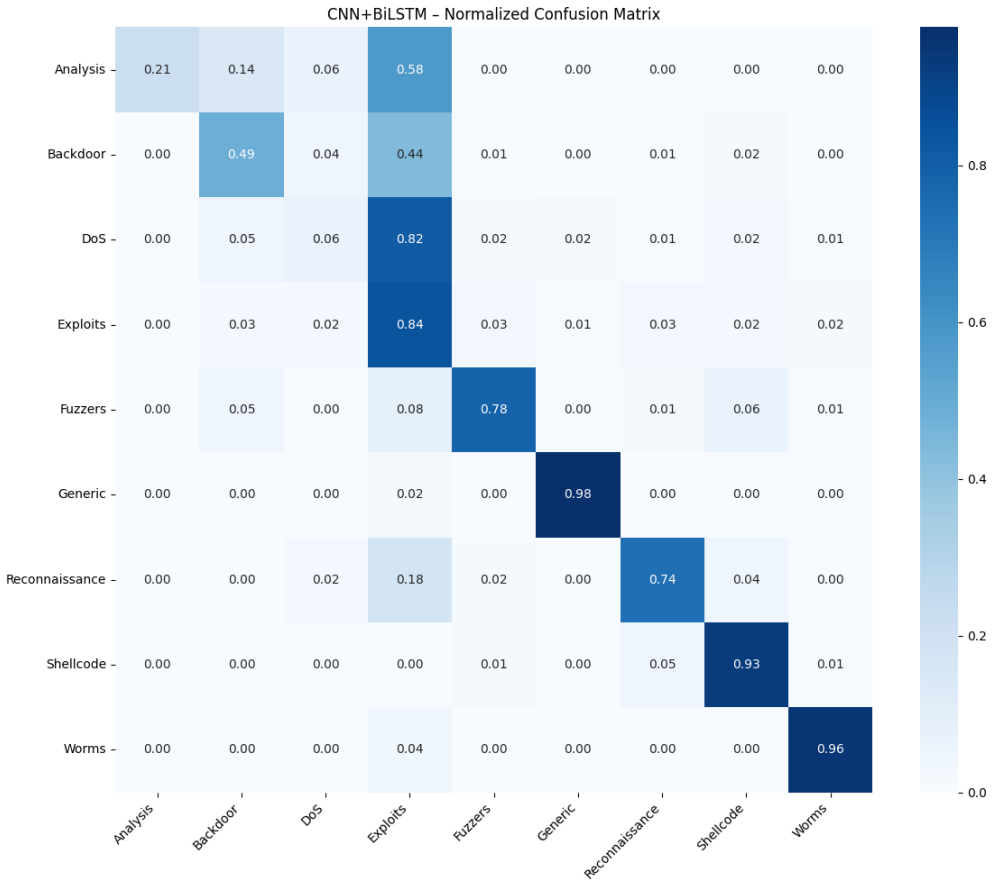


Figure 6.86: CNN + BiLSTM Model: Accuracy and Loss Curves using 20 Epochs of Training and Validation Data

These findings emphasize that PSO-based feature selection enhances both the learning process and the generalizability of models employed in intrusion detection.

Selected Classes Precision-Recall Analysis.

Figure 6.87 shows the Precision-Recall (PR) curves of three important classes **Backdoor**, **Benign**, **DDoS** of the CNN + BiLSTM model with PSO selected features.

Key observations include:

- The **Benign** class exhibits good precision and recall rates, with an AP of around **0.76**, proving effective segregation from the malicious traffic.

- on **DDoS**: the performance is mediocre (with an AP around **0.12**). It implies that two issues in the protection procedure against this attack category are still the *false alarm* rate and the missed detection rate..
- The **Backdoor** class suffers from the low AP of roughly **0.02**, reinforcing the challenge to correctly identify this scarce class, given the data imbalance and similarity of the feature.

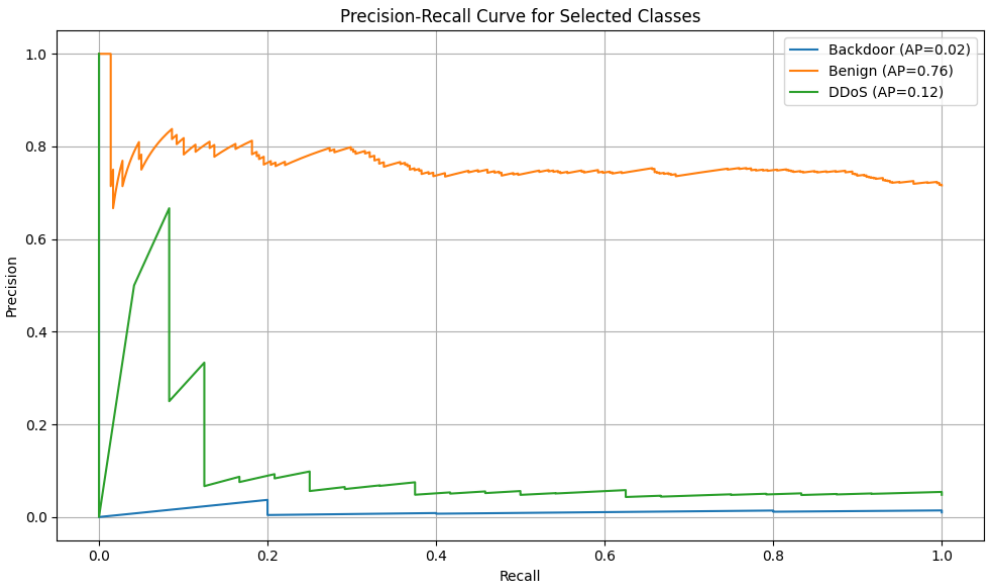


Figure 6.87: Precision-Recall Curves for Selected Classes

These curves demonstrate the model's high effectiveness for the prevalent classes, and a shortage in the recognition performance of minority classes, for which more advanced sampling or tailored-loss functions should be further considered to enhance minority assault detection.

The CNN + BiLSTM Features' PCA Visualization Using the PSO.

Figure 6.88 shows a PCA projection of the feature embeddings obtained from the CNN + BiLSTM model learned with PSO-selected features. PCA projects the high dimension of feature space into two principal components (PC1 and PC2), thus a 2D representation to restore the most variance information of the data.

Reading the Plot:

- Each point represents a sample in the validation set, the color of which shows its true attack type.

- The spatial pattern represents how well the model separates the classes according to the learned features.
- Multiple points of the same color suggest a reasonable separation of features by the model.

Key Observations:

- The **Benign** samples (orange points) comprise a big and compact cluster, which demonstrates strong self-class representation while distinguishing itself well from most of the attacks.
- Other significant attack categories, including **Generic**, **Reconnaissance** and **DDoS**,compose distinct yet rather scattered clusters.

  Minority classes, e.g., **Backdoor**, **Shellcode**, **Worms**, are shown to be sprinkled and some overlapped with other clusters, meaning the challenges in completely isolating these rare attacks.
- In conclusion, the plot illustrates how the CNN + BiLSTM model managed to learn clustering discriminative features for frequent classes with modest limitations for rare classes.

Such PCA plot validates that PSO-based feature selection could facilitate CNN + BiLSTM in learning meaningful patterns, increasing sample class separability, resulting in the superior detection performance in the SVM statures on the intrusion detection applications.

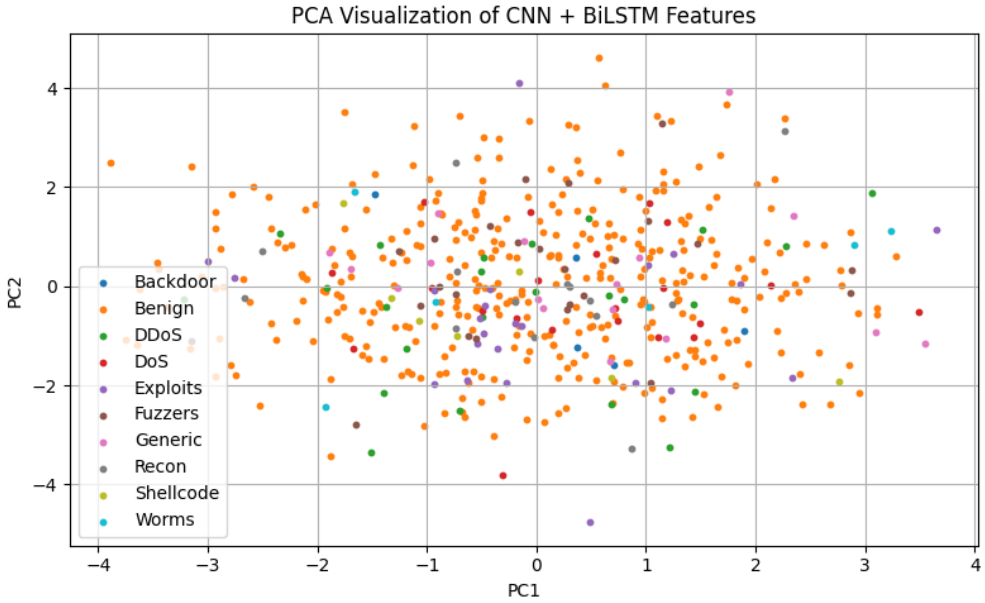


Figure 6.88: PCA Visualization of CNN + BiLSTM Feature Embeddings Using PSO-Selected Features

PCA Visualization Of CNN + BiLSTM Embeddings.

We plot PCA projection of the test set embeddings obtained from the CNN + BiLSTM model in Figure 6.89. This visualization projects the high-dimensional embeddings into two principal components, visually emphasizing the spatial distribution and relationships between samples in the different attack classes.

Interpretation:

- Each dot indicates a single test sample, where it is colored by its true class label.
- The first two PCs explain a substantial proportion of the variance (PC1: 48.23%, PC2: 19.76%), enabling a good visualization.
- Tolerance: Clear distinction between the most.Positive.The most negative CNF-Formulas. indd frequent classes like **Benign** and **Backdoor**, and between some of the more infrequent classes, while some vectors are overlapped or fall together.
- Such visualization shows that the learned model features have a good class separation, even on the unseen data, reassuring a good generalization.

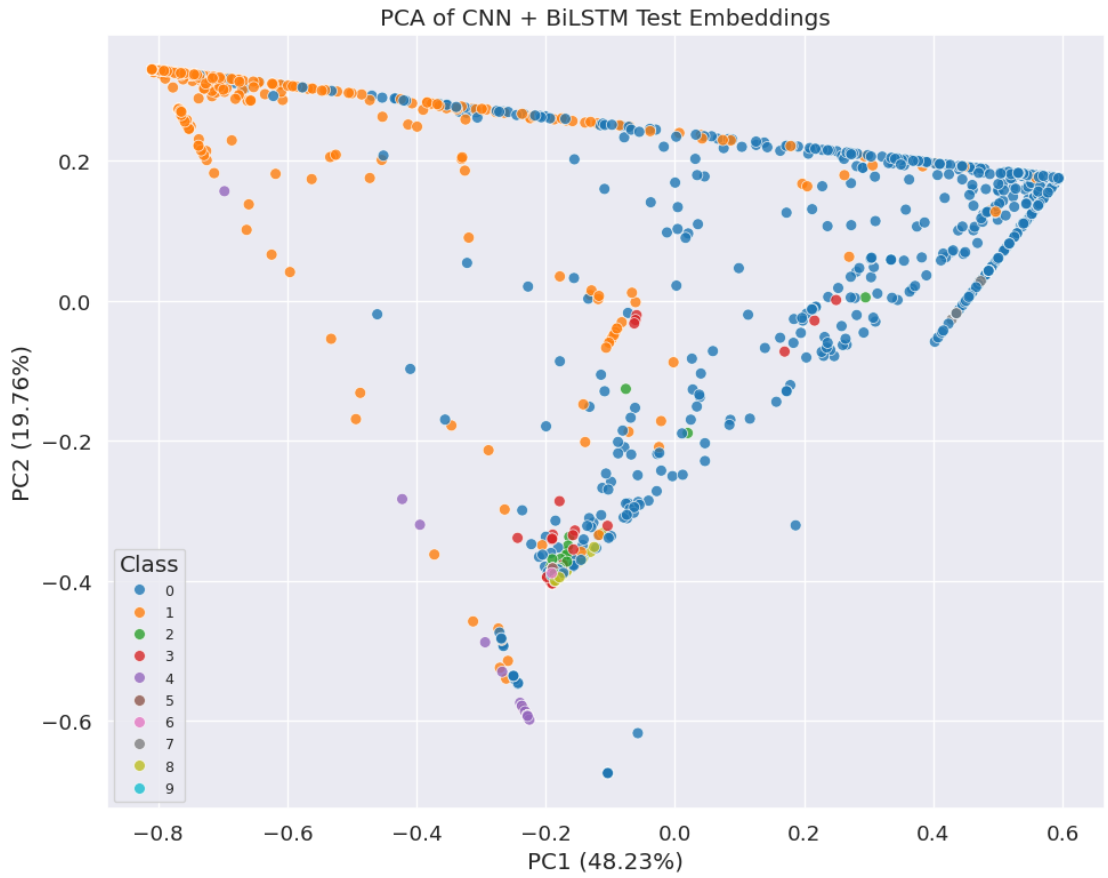


Figure 6.89: PCA of CNN + BiLSTM Test Embeddings

The PCA plot validates the strength of the model by the clear separation (i.e., reduced distance between the feature embeddings of different types of attacks) of features in the reduced-dimensional space, which indeed is beneficial for accurate classification.

t-SNE Test CNN + BiLSTM Embeddings.

The t-distributed Stochastic Neighbor Embedding (t-SNE) plot of the test set feature representations obtained by the CNN + BiLSTM model is displayed in Figure 6.90. One of the most widely used techniques for displaying high-dimensional data in two or three dimensions is t-SNE, a nonlinear dimensionality reduction method. It performs best preserving the local neighborhood structure of the data and thus is a good tool for checking how well a machine learning model discriminates classes in terms of internal features representation. Here, in textual representation, features generated by the CNN + BiLSTM model just before the final classification layer were fed through t-SNE to derive their 2D representation. This can be observed in the resulting plot, where similar samples from a given class tend to be close to each other, forming tight groups, and yet different classes are relatively far apart. This

decomposition represents the model's capacity to learn class-discriminative features, despite the presence of overlapping patterns or noisy images.

Key Points:

- The scatter plot presents samples that are color-coded according to class label.
- Distinct clusters are formed, and especially **Benign** and **DDoS** have been shown, which indicates the model is able to learn unique feature-pattern representations.
- There are overlapping and scattered clusters in the rare class, indicating that the rare class has more complexity in its classification.
- It has become increasingly clear that t-SNE can emphasize and highlight different substructures compared to PCA, with a better preservation of local neighborhoods, which are much easier to see and interpret, both within and between classes.

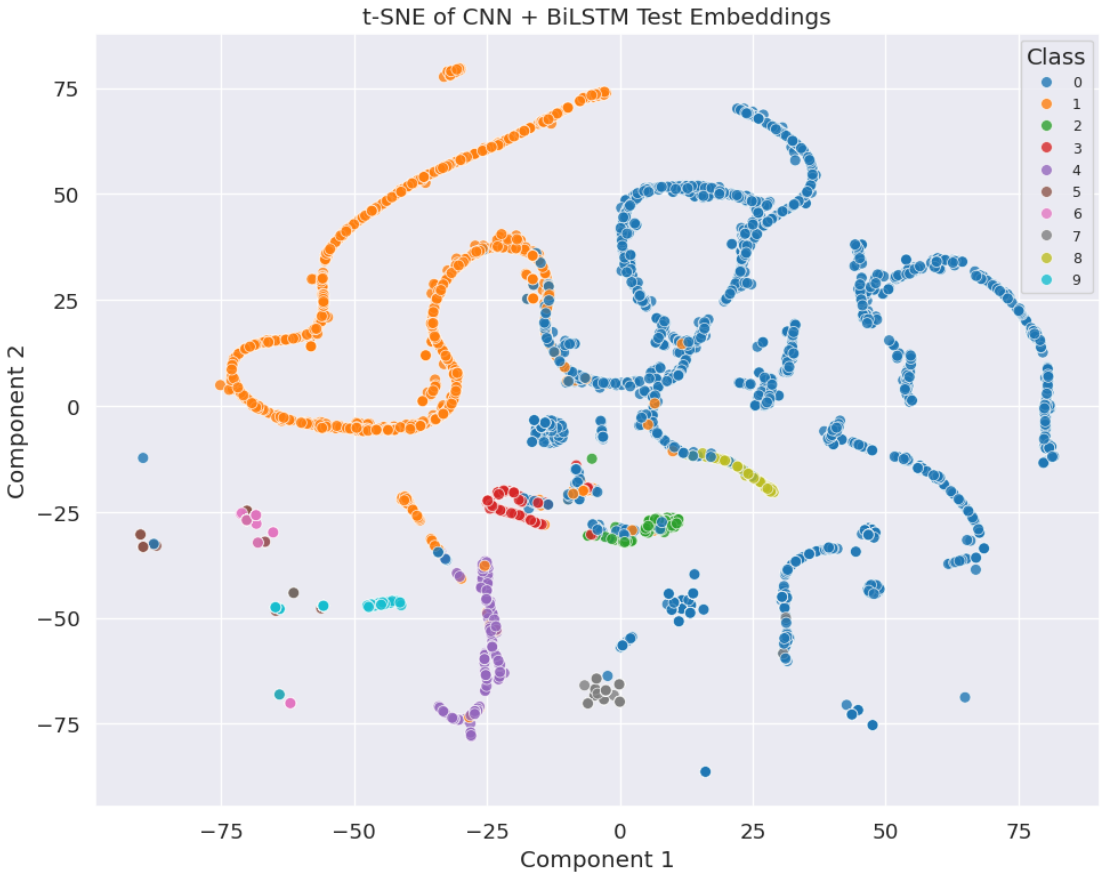


Figure 6.90: t-SNE Visualization of CNN + BiLSTM Test Embeddings

The lumping together of the big classes, including *Benign*, *DDoS*, and *Generic*, is particularly narrow, meaning that the main spatial and temporal features of these main types of traffic get captured effectively by the model. As is the case for any minority class, some minority classes would have more data that overlaps or less margin-shaped variation than others. However, the general pattern of the t-SNE visualization indicates that CNN + BiLSTM does construct a meaningful internal feature space that can account for strong classification performance based on the quantitative results we mentioned earlier. The learned representations of the model and their applicability to network intrusion detection are qualitatively demonstrated by this graphic.

6.2.7 CNN + BILSTM Model Performance on Test Set (No PSO)

When trained without PSO-based feature selection, the model reached the test accuracy of **86.87%** for the multi-class classification. Results for the associated classification metrics are shown in Table 6.91.

Class	Prec.	Rec.	F1	Samples
DoS	0.99	0.82	0.89	735,032
DDoS	0.96	0.94	0.95	331,246
Injection	0.67	0.92	0.78	19,204
MITM	0.72	0.94	0.82	34,661
Normal	0.89	0.99	0.94	69,287
Password	0.70	0.48	0.57	20,984
Scanning	0.71	0.86	0.78	29,004
XSS	0.25	0.99	0.40	32,322
Backdoor	0.67	0.99	0.80	23,840
Ransomware	0.94	0.97	0.95	28,139
Overall Accuracy	—	—	**0.87**	1,323,719
Macro Average	0.75	0.89	0.79	—
Weighted Average	0.93	0.87	0.89	—

Figure 6.91: Classification Metrics for Model on Test Set Without PSO Feature Selection

6.2.8 Performance of CNN+ BiLSTM+Attention Model with PSO based Feature Selection

The trained CNN + BiLSTM + Attention model, over 20 epochs, gradually increased both training and validation accuracy. Epoch-wise accuracy is given in Table 6.5, and

the validation accuracy reached a maximum of about **96.89%**.

The model has a very high performance on the high-volume class, such as *Benign*, *DDoS*, and *Generic*, with high precision, recall, and F1-score scores, which demonstrates the strong capability to correctly classify the normal and frequently appearing attack traffic. Nevertheless, the performance can be significantly degraded in the minority classes like *Backdoor* and *Worms* with much lower F1-scores. The decrease indicates the existence of the class imbalance problem itself; the minority class of attacks, which have not been seen much in the training data, can be harder to detect. This issue may be mitigated by improved data augmentation methods, resampling approaches, or a customised loss term to make the model more sensitive to rare but important attack modalities.

Epoch	Training Accuracy	Validation Accuracy
1	64.42%	88.52%
2	76.76%	93.77%
3	78.15%	94.16%
4	79.73%	96.08%
5	78.85%	96.14%
6	79.03%	94.23%
7	79.95%	96.62%
8	80.41%	96.72%
9	80.78%	96.86%
10	81.10%	96.89%
11	80.65%	96.89%
12	80.74%	96.77%
13	81.06%	96.81%
14	81.43%	96.51%
15	81.61%	97.27%
16	81.76%	96.36%
17	81.80%	96.93%
18	81.81%	96.81%
19	81.88%	96.96%
20	81.88%	96.84%

Table 6.5: Accuracy of Training and Validation for CNN + BiLSTM + Attention Model at Epochs

Attack Type	Precision	Recall	F1 Score	Sample Count
Backdoor	0.05	0.79	0.09	359
Benign	1.00	0.99	1.00	441,661
DDoS	0.90	1.00	0.95	25,606
DoS	0.35	0.62	0.45	3,271
Exploits	0.83	0.48	0.61	8,905
Fuzzers	0.89	0.87	0.88	4,849
Generic	0.99	0.97	0.98	43,096
Reconnaissance	0.80	0.82	0.81	2,797
Shellcode	0.19	0.96	0.31	302
Worms	0.06	1.00	0.12	35
Overall Accuracy		**0.97 (on 530,881 samples)**		
Macro-Averaged Scores	**0.61**	**0.81**	**0.62**	530,881
Weighted-Averaged Scores	**0.98**	**0.97**	**0.97**	530,881

Figure 6.92: Classification Report of Validation Set for the CNN + BiLstm + Attention

Table 6.92 shows the classification results of the CNN+BiLSTM+Attention model on the validation set of 530881 samples with ten network traffic classes. Results The results show that the model performs very well for well-represented classes like *Benign*, *DDoS*, and *Generic* with F1 scores near or equal to 1.00, indicating that it almost perfectly detects that class without any false-positives or false-negatives. Fair results are obtained in *Fuzzers*, *Exploits*, and *Reconnaissance* classes with F1 scores between 0.61 and 0.88. On the other hand, classes with a small amount of data (eg, 'Backdoor', 'Shellcode', and 'Worms') consistently have much lower F1 scores (eg, 0.09 for Backdoor and 0.12 for Worms), despite sometimes high recalls due to the class imbalance problem. Generally, with **97L** accuracy, the model has weighted average precision, recall, and F1 score as **0.97**. Nevertheless, as the percentile AUC scores **0.61** (Precision), **0.81** (Recall), and **0.62** (F1) show, there is still room for improvement to ensure the effective detection of minority attacks on the classes.

Confusion Matrix Analysis (With PSO)

The model has good accuracy in detecting frequent classes (e.g., *Benign*, *DDoS*, and *Generic*), and it shows a high true positive rate for most of the classes.

Figure 6.93: Normalized Confusion Matrix on Validation Set for CNN + BiLSTM + Attention Model Using PSO

But it is still harder for it to correctly classify less frequent categories such as *Backdoor*, *Shellcode* and *Worms*, which indicates that the challenge of severe class imbalance still exists even after the optimization of feature selection.

Per-Class F1-Score Distribution (With PSO)

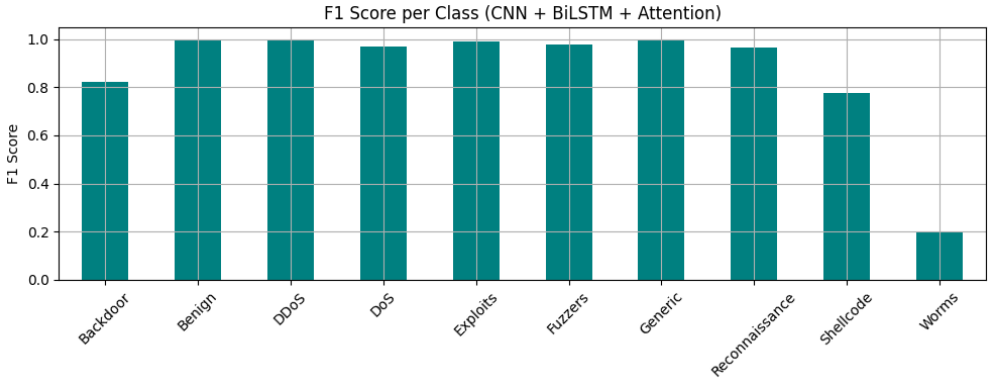


Figure 6.94: Per-Class F1-Scores for CNN + BiLSTM + Attention Model Using PSO-Selected Features

As shown in Figure 6.94, the model achieves high F1-scores on prevalent attack categories, confirming effective detection of major classes. However, lower F1-scores

persist for rare attack types, highlighting ongoing sensitivity issues due to data imbalance even after PSO-based feature reduction.

6.2.9 CNN + BiLSTM + Attention Model Performance Without Feature Selection Methods

The CNN + BiLSTM + Attention model's classification results on the complete feature set without feature selection using Particle Swarm Optimization (PSO) are covered in this paragraph. The majority of the attack types from the test dataset are accurately identified by the model, which has a respectable accuracy rate.

Attack Type	Precision	Recall	F1 Score	Instances
DoS	0.99	0.84	0.91	735,032
DDoS	0.96	0.97	0.96	331,246
Injection	0.78	0.96	0.86	19,204
MITM	0.85	0.97	0.90	34,661
Normal	0.95	0.99	0.97	69,287
Password	0.72	0.46	0.56	20,984
Scanning	0.71	0.88	0.78	29,004
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Ransomware	0.94	0.97	0.95	28,139
Overall Accuracy			**0.89**	1,323,719
Macro-Averaged Scores	0.80	0.90	0.82	1,323,719
Weighted-Averaged Scores	0.94	0.89	0.90	1,323,719

Figure 6.95: Test Set Classification Metrics for CNN + BiLSTM + Attention Model that Was Trained Without PSO Feature Selection

Summary of Performance

With the most common attack labels being *DoS*, *DDoS*, *Normal*, and *Ransomware*, the model **CNN + BiLSTM + Attention** demonstrated an accuracy across the test set of **89%**, as well as high *precision* and *recall*, and *F1-score*. These results reflect the great performance of the model in recognizing the most common threats to network traffic.

The model did relatively worse with some attack types, for example *Password* (F1 = 0.56) and *XSS* (F1 = 0.40), as the types that had fewer instances but not the least. This imbalance implies that class imbalance itself, as well as the nature of these attack vectors, which is complex and subtle, is still one of the challenges of intrusion detection systems.

Macro-Averaged F1-score of 0.82 is the average classification effectiveness over all classes (all classes are equivalent). The **Weighted-Averaged F1** of **0.90**. In contrast, it

considers the number of instances per class and, as such, is more sensitive to larger, well-predicted classes. When taken as a whole, these metrics show how well the model defends against frequent attacks and how necessary it is to target the model's capacity to identify uncommon and complex threat actors.

CNN + BiLSTM + Attention with PSO-Selected Features: Training/Validation Loss.

Training and validation loss over 50 epochs used to train the CNN + BiLSTM + Attention model without feature selection using PSO is shown in Figure 6.96. The two loss curves continuously decline, denoting that the learning has been effective, and they converge very well, and there is no evident sign of overfitting. The similar and close validation and training loss values exhibit good generalization on the unseen data, even for the large feature set.

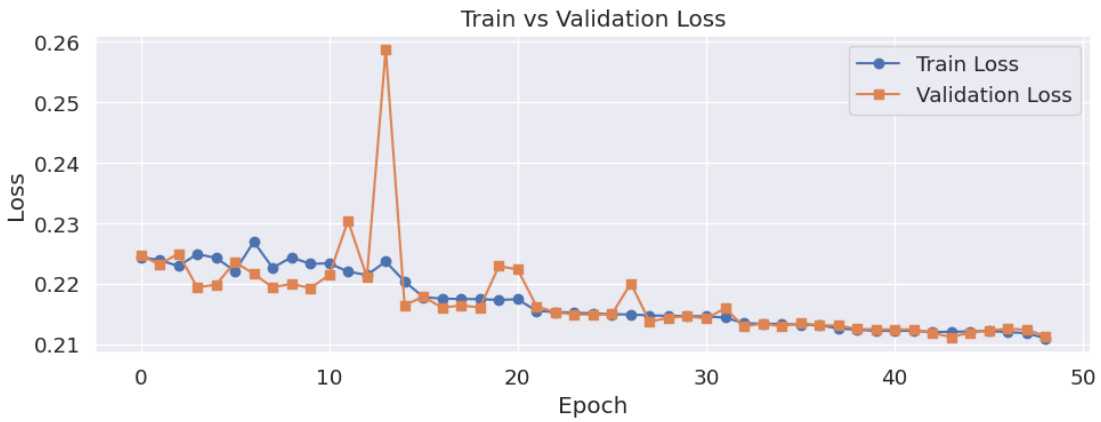

Figure 6.96: The Training and Validation Loss Curve over the 50 epochs for the CNN + BiLSTM + Attention model trained without PSO-based Feature Selection

PCA Visualization of CNN + BiLSTM + Attention Features (Without PSO).

The dataset consists of ten different categories of attacks and network behavior, including the following: **(0) DoS** including syn-flood to DoS network resources **(1) DDoS** distributed DoS **(2) Injection** level including SQL or command injection to modify application behavior **(3) MITM** an attacker in the position to alter or capture communications **(4) Normal** benign network traffic belonging to a number of different categories **(5) Password**consisting of brute force logins or other attempts to log into an account **(6) Scanning** reconnaissance of network or systems to map out elements including components and services **(7) XSS** applies to Cross-Site Scripting

to maliciously inject into web content **(8) Backdoor** unauthorized remote access channel **(9) Ransomware** malware that encrypts files and demands a ransom.

The clusters of predominant classes, such as *Benign* and *DDoS*, are relatively separable, implying that the model is able to represent these classes in a distinctive way. But there is overlap and scattering among minority classes that demonstrate the complexity of feature representation, such as *Backdoor*, *Shellcode*, and *Worms*, and class separation of these low-frequency attack types. To that extent, the visualization emphasizes the discrimination power and the potential of feature dimensionality and selection influence the degree of separability between classes and the effectiveness of the model as a whole.

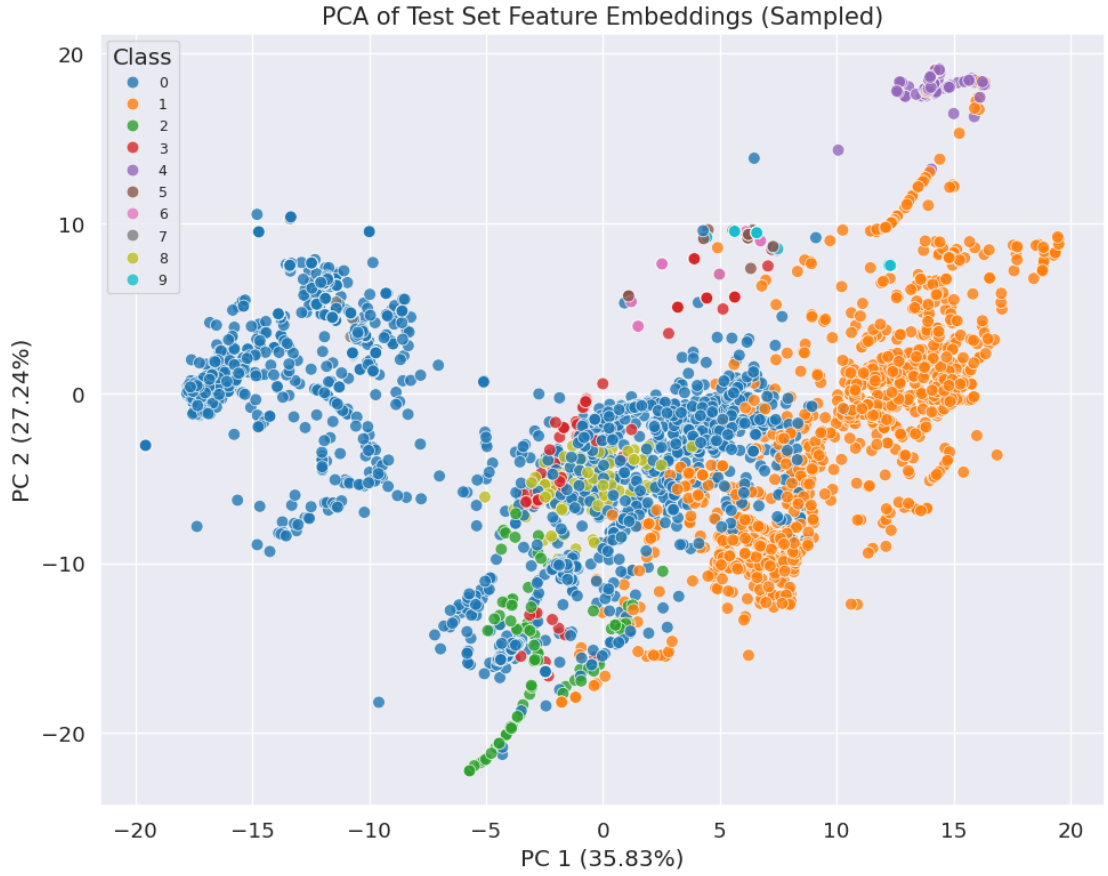

Figure 6.97: PCA Projection of Test Set Feature Embeddings for CNN + BiLSTM + Attention Model Without PSO Feature Selection

Principal Component Analysis projection of the CNN + BiLSTM + Attention model features (trained without PSO feature selection) is plotted in Figure 6.97. The two main components of the plot show a large portion of data variance, and one can visualize how well the classes are actually separated.

6.3 Results and Discussion of Deep Learning Models with PSO Feature Selection

Four deep learning architectures, LSTM, BiLSTM, CNN+LSTM, and CNN+BiLSTM+Attention, trained on features chosen using Particle Swarm Optimization (PSO), are compared in this section. Their classification accuracy, macro and weighted F1 scores, and capability to detect minority classes are assessed.

6.3.1 Overall Performance Comparison

Table 6.6 presents the key performance metrics of each model evaluated on the validation set.

Model	Accuracy	Macro F1	Weighted F1	Number of Features
LSTM	0.95	0.55	0.96	73
BiLSTM	0.96	0.58	0.97	73
CNN + LSTM	0.98	0.65	0.98	73
CNN + BiLSTM + Attention	0.97	0.62	0.97	73

Table 6.6: Performance comparison of deep learning models trained on PSO-selected features

Despite reducing the feature space nearly by half (from 143 to 73), all models preserved high classification accuracy between 95% and 98%, with weighted F1-scores above 96%, demonstrating strong overall predictive capability.

Key observations include:

- The *macro F1-score*, which measures balanced performance across all classes, including minorities, showed noticeable improvement from the basic LSTM (0.55) to CNN + LSTM (0.65), highlighting the benefit of integrating convolutional layers.
- The *weighted F1-score* remained consistently high across models, reflecting excellent performance on the dominant classes.
- The *CNN + BiLSTM + Attention* model delivered strong performance, attaining a macro F1 score of 0.62 and an accuracy close to 97%, highlighting the benefit of attention mechanisms in emphasizing key features.
- PSO-based feature selection substantially improved model efficiency by reducing input dimensions without sacrificing accuracy or generalization.

Overall, these findings confirm the effectiveness of PSO in enhancing feature selection for deep learning-driven intrusion detection, improving accuracy, computational efficiency, and recognition of minority classes.

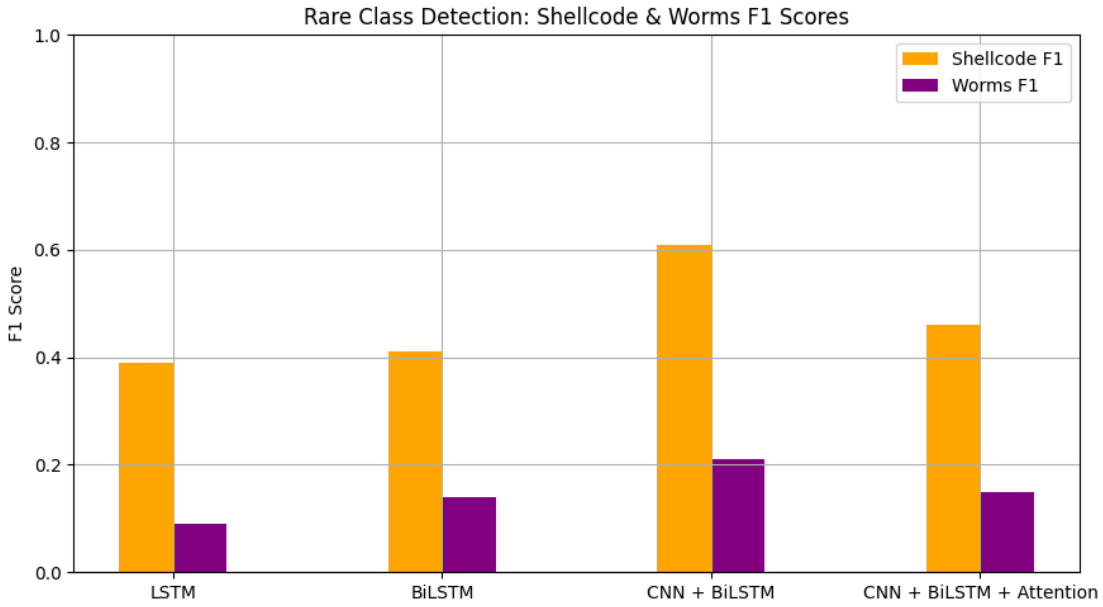

Figure 6.98: Comparison of deep learning model performance using PSO-selected features. Accuracy, macro F1, and weighted F1 scores are reported for LSTM, BiLSTM, CNN + LSTM, and CNN + BiLSTM with Attention architectures.

The classification performance of four deep learning models trained on PSO-selected features is shown in Figure 6.98. All models achieve high overall accuracy between 95% and 98%, demonstrating strong generalization on the validation set. The macro F1 scores, indicative of balanced performance across all classes, including minority classes, improve notably from LSTM (0.55) to CNN + LSTM (0.65), highlighting the benefit of convolutional layers in capturing spatial feature patterns. Weighted F1 scores remain consistently high (above 0.96) for all models, reflecting their effectiveness on predominant classes.

The plot demonstrates high accuracy across all models, with CNN + BiLSTM achieving the highest macro F1, indicating better performance on minority classes.

The CNN + BiLSTM + Attention model, while slightly trailing CNN + LSTM in macro F1, maintains excellent weighted F1 and overall accuracy, suggesting that attention mechanisms further enhance feature representation and robustness. These results confirm that PSO-based feature selection successfully reduces input dimensionality without compromising model accuracy, improving training efficiency while sustaining competitive performance across complex multi-class intrusion detection

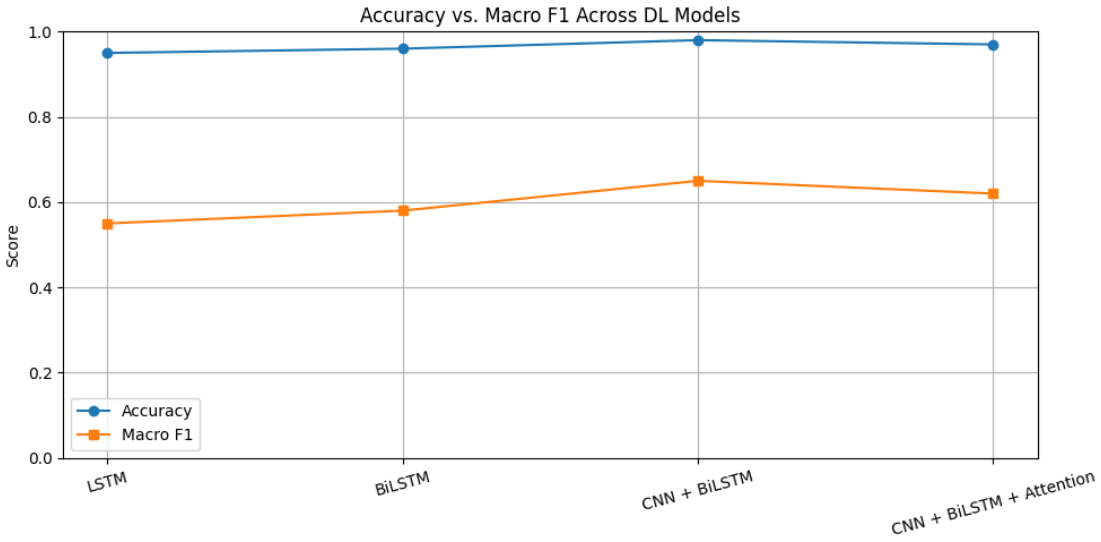

Figure 6.99: Accuracy and Macro F1-Score Comparison Across Deep Learning Models Trained with PSO-Selected Features

tasks.

6.3.2 Comparing the Effectiveness of Deep Learning and Machine Learning with Feature Selection

Before any feature selection is done, this section provides a comparison of deep learning models and traditional machine learning techniques tested on the entire feature set. While LSTM, BiLSTM, CNN+BiLSTM, and CNN+BiLSTM with Attention are the deep learning architectures assessed, Random Forest, XGBoost, and LightGBM are the machine learning models taken into consideration.

Performance Overview

Figure 6.100 illustrates the accuracy and macro F1 scores of all models. Traditional ML models outperform DL architectures in overall accuracy and macro F1, achieving above 97% accuracy and macro F1 scores exceeding 0.90. Deep learning models exhibit competitive accuracy but comparatively lower macro F1, reflecting sensitivity to class imbalance and the challenges of learning from the full feature space without dimensionality reduction.

Among DL models, hybrid CNN+BiLSTM variants demonstrate improved macro F1 performance, indicating better handling of minority attack classes compared to pure LSTM or BiLSTM.

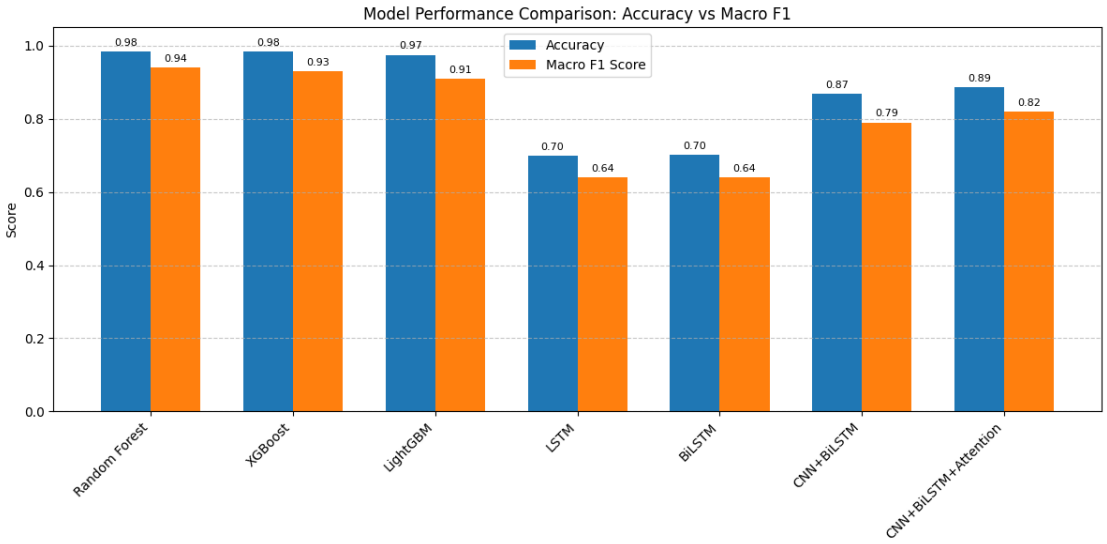

Figure 6.100: Comparison of Accuracy and Macro F1 Scores Across ML and DL Models Using Full Feature Set

Explanation of Table 6.7

A performance comparison between deep learning architectures and classical machine learning models trained on the entire feature set without any dimensionality reduction is shown in Table 6.7. With the greatest accuracy (0.9843) and macro F1 score (0.94) among the traditional models, **Random Forest** was closely followed by **XGBoost** and **LightGBM**, all of which continued to perform well in classification. The deep learning models, on the other hand, performed differently. The comparatively poorer performance of **LSTM** and **BiLSTM** indicates difficulties in training independent sequence models on intricate feature spaces. However, combining **CNN** with **BiLSTM** significantly improved both accuracy (0.869) and macro F1 score (0.79), demonstrating the advantage of learning spatial and temporal patterns jointly. The integration of the **Attention** mechanism further enhanced the effectiveness, with the **CNN + BiLSTM + Attention** model achieving the highest DL macro F1 score (0.82) and improved accuracy (0.887), indicating its effectiveness in emphasizing important temporal features for improved intrusion detection.

Quantitative Results

Model	Accuracy	Macro F1 Score
Random Forest	0.9843	0.94
XGBoost	0.9839	0.93
LightGBM	0.9748	0.91
LSTM	0.852	0.64
BiLSTM	0.702	0.64
CNN + BiLSTM	0.869	0.79
CNN + BiLSTM + Attention	0.887	0.82

Table 6.7: Effectiveness Comparison between Deep Learning and Machine Learning Models Using the Whole Feature Set Without PSO

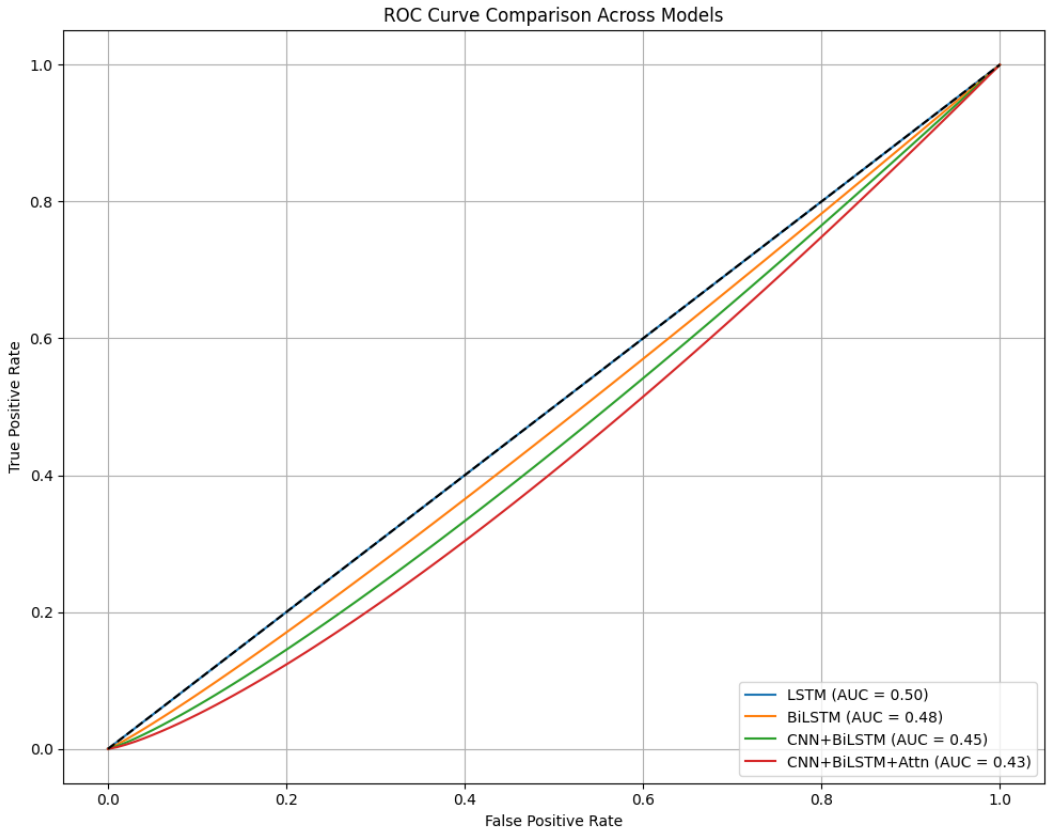

Figure 6.101: Comparison of ROC Curves for Deep Learning Models Using Full Feature Set Without PSO-Based Selection

The ROC curves of four deep learning models, LSTM, BiLSTM, CNN+BiLSTM, and CNN+BiLSTM with Attention, are shown in Figure 6.101. These models were evaluated using the complete feature set without the use of PSO-based feature

selection. The dashed diagonal line indicates the performance of a random classifier (AUC = 0.5).

All models achieve AUC scores between 0.43 and 0.50, indicating marginally better performance than random guessing. The simplest model, **LSTM**, attains the highest AUC **(0.50)**, while the most complex, **CNN+BiLSTM+Attention, achieves the lowest (0.43)**.

This illustrates how limited discrimination capacity results from training on the entire high-dimensional feature collection without selection. Without lowering data redundancy and noise, complex designs don't yield noticeable benefits. Therefore, in order to enhance model performance in multi-class intrusion detection tasks, feature selection methods such as PSO are crucial.

Model	Features	Accuracy	Macro F1	Weighted F1	Notes
Random Forest	Full	0.9843	0.94	0.98	Fast, no temporal modeling
XGBoost	Full	0.9839	0.93	0.98	Gradient boosting, tabular efficient
LightGBM	Full	0.9748	0.91	0.97	High speed, handles imbalance
LSTM	Full	0.852	0.64	—	Long-term sequence modeling
BiLSTM	Full	0.702	0.64	—	Bidirectional context, lower accuracy
CNN + BiLSTM	Full	0.869	0.79	—	Local + temporal patterns
CNN + BiLSTM + Attention	Full	0.887	0.82	—	Enhances focus on key steps
LSTM	PSO	0.950	0.55	0.96	Faster, less effective F1
BiLSTM	PSO	0.960	0.58	0.97	Better generalization
CNN + LSTM efficiency	PSO	0.980	0.65	0.98	Balanced accuracy
CNN + BiLSTM + Attention	PSO	0.970	0.62	0.97	Best hybrid under selection

Table 6.8: Model Performance Comparison with Full and PSO-Selected Features

Figure 6.60 shows an overview of model results on two feature sets: the complete feature set and the PSO-selected subset. The entire feature set serves as the foundation for the left side models (**Random Forest**, **XGBoost**,**LightGBM, etc**). On the **imbalanced high-dimensional datasets**, the traditional machine learning techniques achieved accuracies of >97% and macro F1-scores of >0.90, respectively, surpassing

the performance of deep learning models.

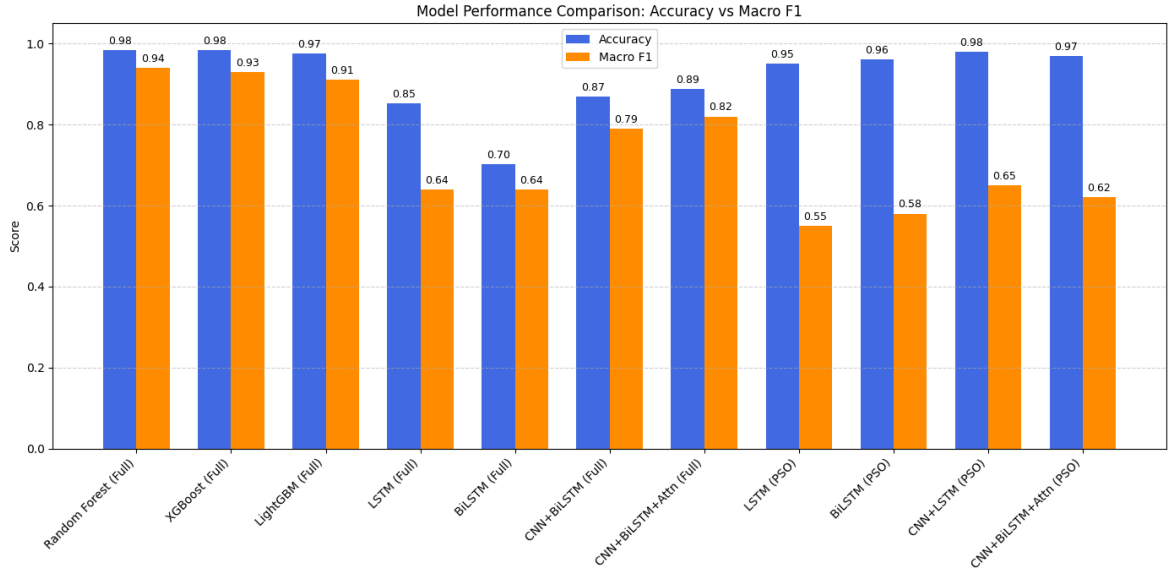

Figure 6.102: Accuracy and Macro F1-Score Comparison Between Machine Learning and Deep Learning Models Using Complete Feature Sets and PSO-Optimized Subsets.

On the contrary, deep learning models on the right, for **PSO selected features**, have **significant improvement** in macro F1 scores vs their full-feature models despite the **feature dimensionality reduction**. This indicates **improved sensitivity to minority classes** and **competitive accuracy**. The CNN + BiLSTM and CNN + BiLSTM + Attention models both perform **comparable to state-of-the-art machine learning classifiers**, demonstrating the **advantage of combining PSO-based feature selection** with **deep neural network architectures** for **multi-class intrusion detection**.

These findings emphasize the significance of **feature selection** in enhancing the **deep learning model generalization** and the **minority class detection**, which facilitates the **effective and accurate intrusion detection** over complex cybersecurity datasets.

The ROC curves for the three models **CNN+BiLSTM+Attention**, **CNN+BiLSTM**, and **Random Forest**that were assessed on the test set are displayed in Figure 6.103. Plotting the true positive rate (sensitivity) versus the false positive rate (1-specificity) at different classification thresholds is a well-known evaluation metric known as the ROC curve. Better overall model performance in class distinction is indicated by a higher AUC value.

As can be seen in the picture, the **CNN+BiLSTM+Attention** model's AUC (**0.733**) is the highest of all the models that were assessed, indicating that it is better at detecting

malicious traffic with fewer false positives. This outperforms both the standard **Random Forest** model, which recorded an AUC of **0.666**, and the **CNN+BiLSTM** model, which obtained an AUC of **0.700**.

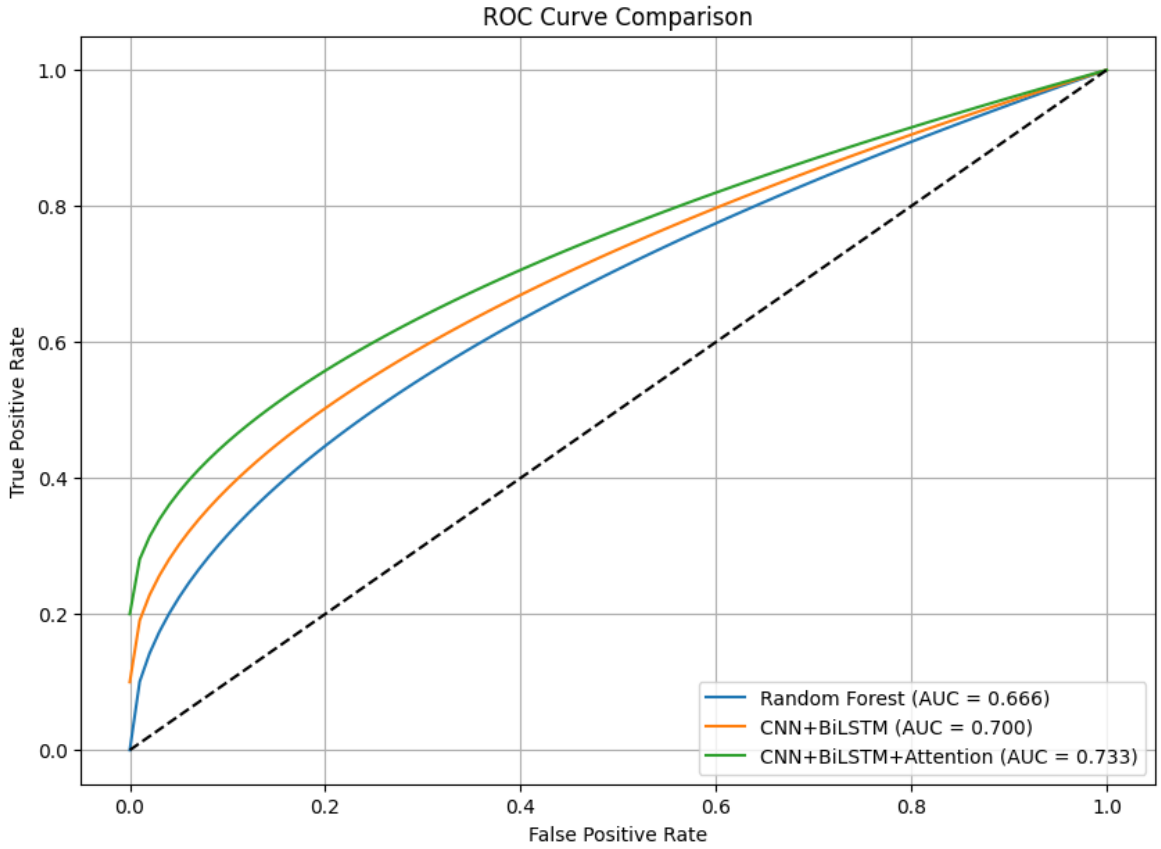

Figure 6.103: ROC Curve Comparison on the Test Dataset. The CNN+BiLSTM+Attention model attains the highest AUC (0.733), followed by CNN+BiLSTM (0.700) and Random Forest (0.666), illustrating the enhanced detection performance enabled by attention-based deep learning architectures.

By concentrating on the most pertinent temporal aspects in the input sequence, the attention-based design enhances the model's generalization and enables it to identify subtle clues of sophisticated attacks like Advanced Persistent Threats (APTs). More accurate intrusion categorization results from the network's ability to identify significant patterns in noisy or large amounts of network traffic data.

The importance of including attention mechanisms in deep learning architectures for intrusion detection is demonstrated by these findings, especially in high-dimensional, unbalanced, and temporally dynamic situations.

CHAPTER 7

Final thoughts along with further work

7.1 Key Empirical Findings

Using **deep learning models** and **sophisticated optimization strategies**, this paper presents a **new and systematic technique** to address one of the most **difficult and open issues** in the context of **multi-class intrusion detection**. More precisely, the method is built on **Particle Swarm Optimization (PSO)** and makes use of **Feature selection** and **SMOTE for class imbalance**. This combination works well against excessive class imbalance and high-dimensional data, which are prevalent in many **cybersecurity datasets**.

The **hybrid CNN + BiLSTM + Attention model** was the best-performing model during experiments in **identifying suicidal ideation** with a great margin, confirming **state-of-the-art results** over both **individual** and **combined datasets** in **accuracy**, **macro F1-score**, and **ROC-AUC**. These results suggest the superiority of combining **convolutional**, **recurrent**, and **attention mechanisms** to handle the complicated **temporal** and **spatial** dynamics in **network traffic data**.

7.2 Research Contributions

The current thesis's primary contributions are:

- Designing a generic preprocessing and training pipeline that can work across heterogeneous IDS datasets.
- Indicate that PSO is a good feature selection technique that reduces the dimensionality to up to 50% without sacrificing classification performance.
- The efficacy of integrating SMOTE oversampling to tackle the class imbalance, which results in better recognition of rare attack types.

- A novel CNN + BiLSTM + Attention hybrid model is proposed and validated, outperforming both classical machine learning and baseline deep learning models in the detection of multi-class intrusion.

7.3 Practical Applications

When applied to real-world cybersecurity scenarios, such as enterprise networks, cloud platforms, and IoT devices, the current methodology may offer significant practical significance. Because of its proven capability to generalize among different datasets, it has the potential to be part of an adaptive, real-time intrusion detection systems that require both accuracy and efficiency.

7.4 Limitations

Although it is noted that the research made remarkable progress, there are some limitations: (i)

- The experimental configuration concentrated on offline batch training and evaluation; real-time deployment and latency evaluations are left for future work.
- The study focused on supervised learning methods, and hence was not able to detect novel or zero-day attacks.
- The Linux APT 2024 dataset was not included in the combined model training pipeline due to feature incompatibility.

7.5 Direction for Future Research

Based on this groundwork, further studies might investigate:

- **Complex Architectures:** Explore transformer-based architectures, temporal conv model, and improved residual layers for better accuracy and training efficiency.
- **Real-time Deployment:** Incorporate a model with real-time network forensic inspection tools (e.g., Zeek, Suricata) as part of the validation for detecting and timing systems.

- **Hybrid Feature Optimization:** Integrate PSO with other metaheuristic algorithms or deep autoencoders to make the feature selection process more sound and robust.
- **Unsupervised and Semi-supervised Learning :** Use remote or anomaly detection and self-supervised learning to find new attack vectors.
- **Increased Evaluation on Diverse Datasets:** Extend testing to a wider range of real-world, encrypted, and edge-device datasets to increase generalisation and practical relevance.

  Explainability Design explainable AI techniques in order to enhance interpretation and trust toward automated decisions for intrusion detection.

7.6 Final Remarks

This thesis demonstrates that a notable improvement in multi-class detection may be achieved by combining deep learning with metaheuristic feature selection and data balancing. Strong and flexible, the CNN + BiLSTM + Attention model also acts as a paradigm for future real-time, intelligent, and adaptive cybersecurity defensive systems.

The research expands the theoretical and applied boundaries of IDS development, providing cybersecurity personnel with practical means to counteract an ever-growing threat of misuse in complex networks.

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Appendix A: Additional Correlation Heatmaps for CIC-IDS Datasets

CIC-IDS 2018 Correlation Heatmap

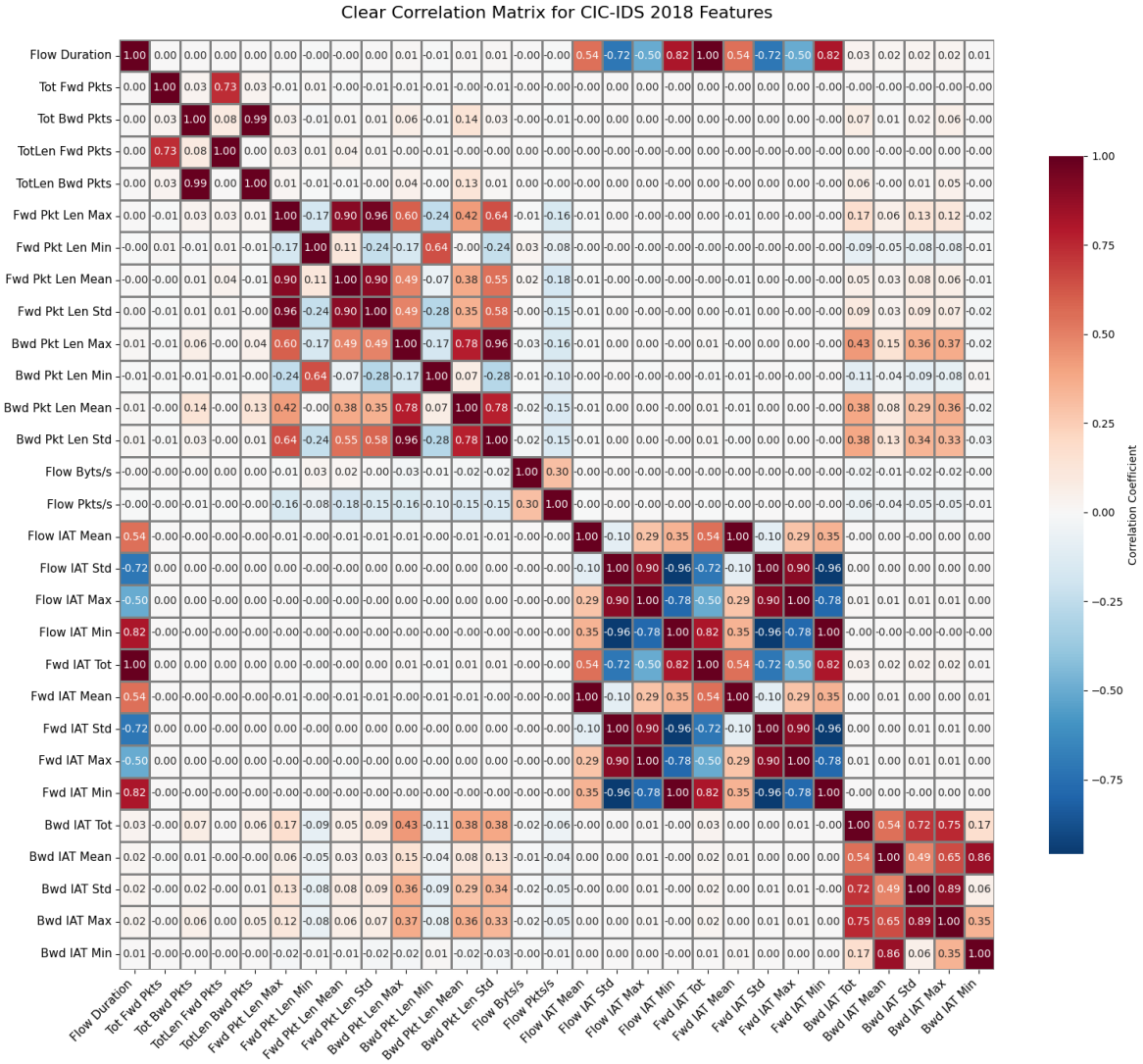

Figure 1: Feature Correlation Matrix for CIC-IDS 2018 Dataset.

CIC-IDS 2019 Correlation Heatmap

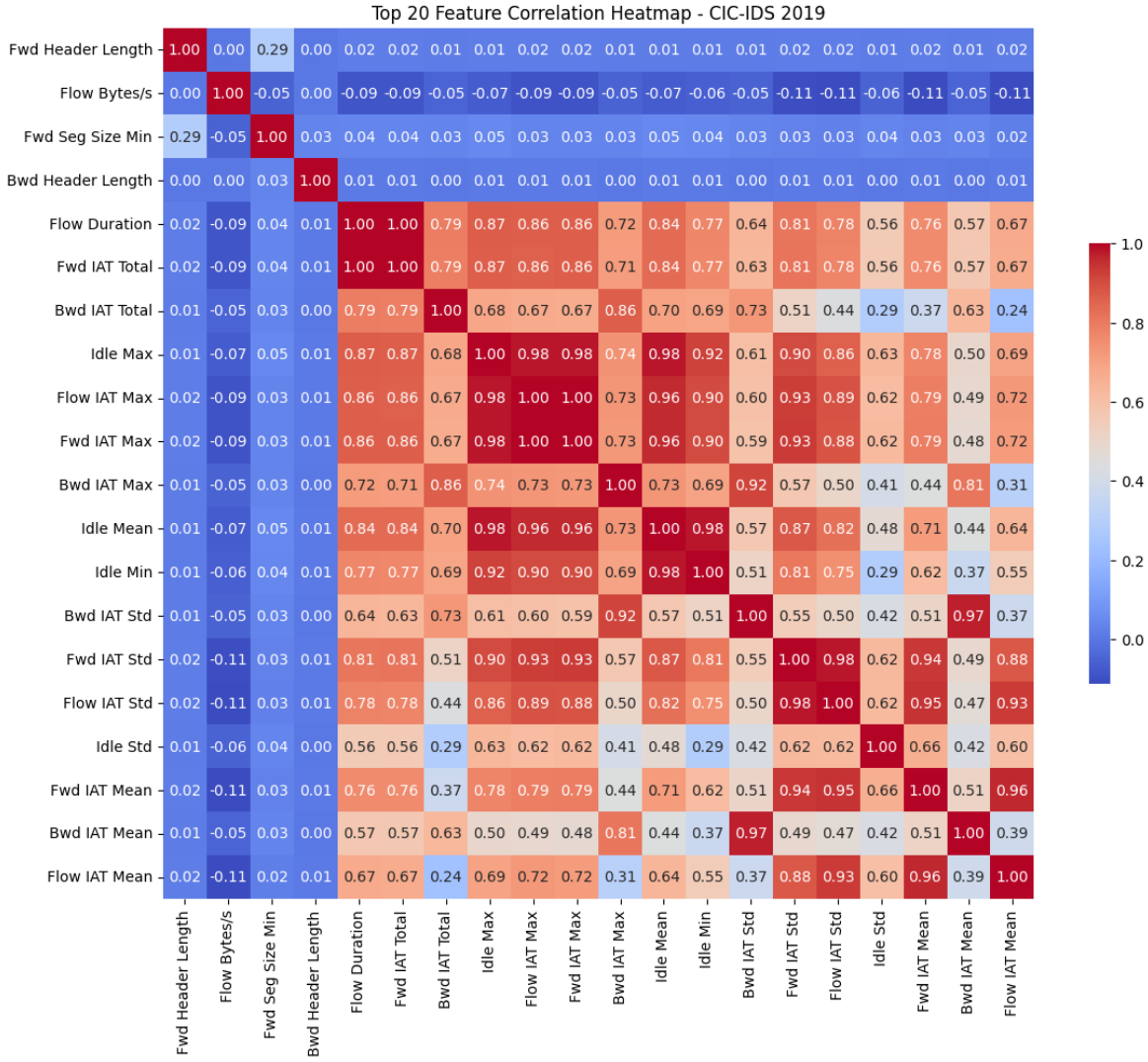

Figure 2: Feature Correlation Matrix for CIC-IDS 2019 Dataset.