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**MDDM**

Master’s Degree Program in

**Data-Driven Marketing**

**Improving Intrusion Detection Systems: Challenges with Public Datasets and the Role of Explainable AI**

A Practical Guide Using NFS-2023-TE and HIKARI-2021

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Master Thesis

**NOVA Information Management School**

**Instituto Superior de Estatística e Gestão de Informação**

Universidade Nova de Lisboa

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by

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Master Thesis presented as partial requirement for obtaining the Master’s degree in Data-Driven Marketing, with a specialization in Data Science for Marketing.

**Supervised by**

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July, 2024

# **Statement of Integrity**

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

*Rome, 27/06/2024*

Abstract

Intrusion detection systems based on public datasets deliver results only in academic papers but not in the real world because of flaws in how they are made. Should explainable algorithms be essential when building intrusion detection systems based on a machine learning model? A new paper highlights some of the deficiencies of these studies, but new datasets came out, and practical guides on tackling the problem are missing. Following the paper mentioned above, we have tried to see what improvements have been made and added new suggestions based on our findings. This work found issues on an existing dataset; moreover, we prove with explainable AI why building an intrusion detection system with these datasets should be avoided. Besides adding a contribution on what to avoid while making an intrusion detection system, we also show how some aspects of the process need to be deeply analyzed before proposing a new model.

**Keywords**

intrusion detection; explainable AI; NIDS; public dataset, HIKARI-2021, NFS-2023-TE, Cybersecurity

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# **Introduction**

In recent years, the global landscape of internet usage has undergone a dramatic transformation, with the number of users experiencing significant growth (Xiong et al., 2021). This expansion, driven by technological advancements and worldwide digitalization, has brought numerous benefits to society, including enhanced data sharing, network efficiency, and improved decision-making processes (Ahmetoglu et al., 2022).

However, this digital transformation has also introduced new challenges, particularly in cybersecurity. As the reliance on internet-connected systems grows, so does the potential for network threats and cyber-attacks (Walter et al., 2022). This trend has been further exacerbated by recent global events, such as the COVID-19 pandemic, which led to a surge in internet traffic due to increased remote work and stay-at-home activities. In 2022, global internet traffic reached a staggering 997,301 Gbps, a 30% increase from 2018 (TeleGeography, 2023).

The escalating threat landscape is evidenced by alarming statistics, such as a 29% increase in global cyber-attacks in 2021 (check point, 2021). This underscores the need for robust cybersecurity measures to protect individuals, businesses, and critical infrastructure.

In response to these growing threats, cybersecurity has evolved rapidly. Network Intrusion Detection Systems (NIDS) have become integral to organizational cybersecurity strategies. However, traditional signature-based and rule-based defensive mechanisms face challenges in coping with the increasing volume and complexity of information flowing through the internet (Gümüşbaş et al., 2021).

Researchers and computer engineers have turned to more advanced solutions to address these challenges, particularly in Artificial Intelligence (AI). Machine Learning (ML) and Deep Learning (DL) algorithms have shown promise in enhancing the performance of cyber defensive systems (Louk & Tama, 2023). These AI-based approaches offer the potential for more effective prediction and high-accuracy detection of emerging threats that may be difficult to identify using conventional antivirus programs.

While AI techniques have demonstrated impressive performance in various cybersecurity applications, such as intrusion detection, spam filtering, and malware identification (Sahakyan et al., 2021), a significant challenge lies in the trade-off between model performance and explainability. Interpretability and transparency have come to the forefront, particularly in light of regulations like the European Union's General Data Protection Regulation, which emphasizes the importance of understanding the logic behind AI-driven decisions (Goodman & Flaxman, 2017).

The field of Explainable AI (XAI) has emerged to address these concerns, offering strategies to make AI decisions more intelligible to humans. It has already been implemented in various domains, such as healthcare, business processes, financial and legal decisions, and autonomous vehicle (Nazar et al., 2021).

Building on the issue of explainability, this study practically addresses some specific criticisms raised by (Catillo et al., 2023). Starting from the premise that today, there are ML models that perform IDS work with incredible results, this study highlights how these academic results do not translate into real-world implementation of these models. The problem lies in a series of issues related to public datasets. Besides being a simplified version of reality, these datasets include errors in creating the dataset itself, leading to the easy achievement of good results by machine learning models. A dataset taken as an example in this study is CIC-IDS 2017 (Sharafaldin et al., 2018). The reason this dataset was chosen is that among the various datasets released in recent years, it is the most cited.

Starting from the criticisms developed by (Catillo et al., 2023), we will analyze two new datasets, NFS-2023-TE (Pekar & Jozsa, 2024) and HIKARI-2021 (Ferriyan et al., 2021). The choice of these datasets is not random, as NFS-2023-TE is the latest in a series of datasets created using the same data as CIC-IDS 2017, correcting some issues found in the original dataset. These issues have been addressed by WMTC-2021 (Engelen et al., 2021; L. Liu et al., 2022) and CRiSIS-2022 (Lanvin et al., 2023), leading to NFS-2023-TE, the latest in this series of improvements. Meanwhile, HIKARI-2021 is an entirely new dataset inspired by CIC-IDS 2017 that adds seven new requirements to the eleven used (Gharib et al., 2016) by CIC-IDS 2017.

The need to analyze new datasets instead of a more famous one arises for two reasons. The first is that NFS-2023-TE assumes that CIC-IDS 2017 contains errors, while the other most cited datasets are nowadays outdated. The second reason is that these datasets become obsolete quite quickly (Guerra et al., 2022), so it makes no sense to insist on working on old datasets.

This work aims to minimize the trade-off between explainability of these algorithms and performance. To achieve this result, we will demonstrate how even classical machine learning algorithms can achieve results comparable to deep learning models. After that, we will show how XAI algorithms like Shap (Lundberg & Lee, 2017) are fundamental in demonstrating the validity of a model or the dataset on which this model is based. We will then analyze the HIKARI-2021 dataset, which, to our knowledge, has never been done before. This analysis has led to the discovery of serious problems that make any model developed on these data unsuitable for real-world usage. This analysis will be conducted partly by verifying that the problems found in CIC-IDS 2017 are not present in HIKARI-2021, partly following what is exposed in (Catillo et al., 2023), and finally, use Shap as an XAI algorithm.

Consequently, this study does not want to be yet another attempt to obtain good results with a new model, as starting from flawed data would be a useless exercise. However, it wants to be practical work that brings together some issues already seen in the past to contribute to the drafting of some guidelines that can help develop better datasets in the future.

This thesis is structured to systematically address the challenges in cybersecurity, focusing on developing and evaluating machine learning models for Network Intrusion Detection Systems (NIDS). Chapter 2 provides the necessary background on cybersecurity concepts and the current threat landscape. Chapter 3 reviews related works, examining previous research and identifying gaps this study aims to fill. Chapter 4 details the methodology, including the selection of datasets, an explanation of SHAP for model interpretability, the choice of specific models, evaluation metrics, and preprocessing steps. Chapter 5 presents the results, analyzing dataset characteristics, model performance, and SHAP-based explanations. Finally, Chapter 6 concludes with a summary of findings and discusses their implications for improving dataset quality and model explainability in cybersecurity.

# **Background: Understanding Intrusion Detection Systems and Network Data**

This chapter briefly overviews key concepts in network security and intrusion detection systems (IDS). While not exhaustive, this introduction aims to equip readers with sufficient background knowledge to understand the context of our data science approach to IDS. The following sections offer concise explanations of fundamental ideas and processes in network monitoring and dataset creation for cybersecurity applications.

* 1. **What does an IDS do?**

An Intrusion Detection System (IDS) is a security tool that monitors network traffic for suspicious activities. Its main job is to:

1. Watch all network connections passing through a specific point, usually near the router.

2. Analyze this traffic to identify potential threats or attacks.

3. Alert security teams or automatically respond when it detects something suspicious.

Traditionally, many IDS systems used signature-based detection, which could only identify known attacks. However, according to recent research, machine learning (ML) models are increasingly being used to build more effective IDS. The critical advantage of ML-based IDS is their ability to understand the underlying patterns of attacks. This allows them to potentially detect new, previously unseen threats, unlike signature-based systems limited to recognizing only known attack patterns.

In our analysis, we will focus on how to evaluate the performance of ML models used in IDS. Specifically, we will explore:

1. Metrics for model accuracy: We will examine the advantages and limitations of using different evaluation metrics such as accuracy, precision, recall, and F1 score. This comparison will help us understand which metrics are most suitable for assessing IDS performance in different scenarios.

2. Inference time: We will evaluate the speed at which the model can make predictions. This is crucial for an IDS, as faster detection allows for quicker response to potential threats, minimizing the impact of an attack. For instance, in a data theft scenario, reducing detection time directly correlates with reducing the amount of data that could be stolen.

By focusing on these aspects, we aim to develop a comprehensive understanding of building and evaluating effective ML-based Intrusion Detection Systems that can adapt to new threats and provide robust protection against evolving cyber risks.

* 1. **What is an IP address, and what is a port?**

In the context of a dataset for an Intrusion Detection System (IDS), IP addresses and ports are represented as features. Each host (computer or device on a network) is identified by an IP address, which can be called its network "address". However, it is essential to note that a single host can have multiple active ports, which act like "doors" for different types of network traffic.

Ports, ranging from 0 to 65535, serve specific purposes. For example, port 80 is typically used for HTTP traffic, port 443 for HTTPS, and port 22 for SSH. This means one host can communicate using multiple services simultaneously, each through a different port.

In our dataset, we typically find four key pieces of information for each connection: the source IP address, source port, destination IP address, and destination port. While this information is crucial for network analysis, using it directly in machine learning model training can lead to problems.

The main issue is that IP addresses are often dynamically assigned and can change over time. They are also limited in number, especially with IPv4 (though IPv6 vastly expands this range). Similarly, while there are 65,536 possible ports, many are standardized for specific uses. Training a model on these specific values could create a bias where the model associates certain IPs or ports with malicious activity rather than learning the underlying patterns of the attack.

Attackers could exploit this bias. If they discover that the model considers specific IPs or ports as "safe," they could use these to bypass detection. Therefore, using these features for data correlation and initial analysis is generally better than training the detection model's core.

The primary reason for including IP addresses and ports in the dataset is to correlate records with the raw network traffic data, typically stored in pcap (packet capture) files. However, to make this correlation accurate, a timestamp is also necessary. The combination of IP, port, and timestamp uniquely identifies a specific network connection at a particular moment.

In summary, while IP addresses and ports are crucial for understanding network traffic, their direct use in machine learning models for cybersecurity can lead to vulnerabilities. Instead, they should be used carefully, primarily for data correlation and preprocessing, while the models should focus on more stable and generalizable features of network behavior.

## **What is a flow?**

A flow in these datasets typically represents a single TCP or UDP connection, recorded as one row in the dataset. Each flow is composed of multiple IP packets but is summarized into a single record with various features:

1. Identifier features: These include source and destination IP addresses, ports, and timestamps. They uniquely identify a connection.
2. Statistical features: These are derived from the connection data, such as flag counts, average packet size, maximum payload length, duration, etc. These features capture the behavior of the connection.

The number of features can vary significantly between datasets. Modern public datasets often have 80 or more features, with some new tools potentially offering up to 150 features.

There's a clear start (three-way handshake) and various defined endings for TCP connections. UDP, being connectionless, does not have standard open/close procedures. In datasets, UDP "connections" are typically defined as exchanges starting with the first observed packet and ending after a predefined timeout.

## **How these datasets are made**

Creating a dataset for training an IDS involves several key steps, building upon the concepts of IP addresses, ports, and flows discussed earlier. The process begins with setting up a testbed, which involves creating a network environment including various devices like computers and servers. Some datasets may focus on specific environments, such as IoT networks, which can influence the protocols used.

Once the testbed is established, the next step is traffic generation. This involves programming devices to simulate typical user behavior like web browsing for normal traffic, while also performing controlled attacks within the network to generate attack traffic. The data is then captured using tools like tcpdump, which record network traffic during both typical and attack scenarios. This captured data is stored in pcap (packet capture) files containing detailed packet information.

Following data capture, flow generation takes place. Flowmeter tools such as CICFlowMeter (Lashkari et al., 2017) or NFStream (Aouini & Pekar, 2022) process the pcap files, aggregating individual packets into flows, which form the foundation for dataset samples. These tools then extract features from each flow, including statistical information like packet counts, flow duration, and flag counts. This process transforms raw packet data into a structured format suitable for machine learning.

The next crucial step is labeling, where each flow is categorized as either normal or a specific attack type. This is typically done by analyzing the traffic patterns and correlating them with the known attack times and targets. The labeled flows are then compiled into a CSV file, forming the final dataset. Each row in this file represents a single flow, with columns for various features and labels.

The dataset then undergoes validation to ensure accuracy and consistency. Often, both the processed CSV and original pcap files are made available to researchers. It's worth noting that some datasets, like WTMC-2021, CRiSIS-2022, and NFS-2023-TE, are created by reprocessing pcap files from existing datasets such as CIC-IDS 2017. This approach allows for improving and expanding existing datasets without capturing new network traffic.

The field of NIDS dataset creation continues to evolve. For instance, the authors of CICFlowMeter are developing a new Python-based tool with over 50 new features, potentially offering 130 features in total. This development could lead to more standardized dataset creation, allowing for better comparison of models across different datasets.

## **What is a FIN and RST flag?**

IP packets, in addition to their payload, contain a series of metadata, including so-called flags. These flags perform various functions, including establishing or terminating the connection between two hosts. Specifically, to understand network traffic datasets, we need to know what the RST and FIN flags do.

There are three ways to close a TCP connection. The first is by exchanging a packet with the RST flag set. The second method involves exchanging two packets with the FIN flag set between the two hosts. The third way is through a timeout if the connection is not used after a certain period.

It is essential to know that when monitoring a TCP connection, we should theoretically see either one RST packet or two FIN packets passing through, but not more than one RST or one FIN. Among all the features used for today's datasets, this is one of the few that contains an absolute value that, if exceeded, indicates a malfunction during the dataset creation.

This behavior of RST and FIN flags provides a unique feature in network datasets. Unlike many other features with varying thresholds or patterns, the count of RST or FIN flags per connection has a clear, absolute limit. Exceeding this limit (more than one RST or more than two FIN packets per connection) strongly suggests either an anomaly in the network behavior or an error in the dataset creation process.

For data scientists working with network traffic datasets, understanding these TCP flag behaviors can be crucial for data cleaning and preprocessing, feature engineering, anomaly detection, and understanding the underlying network processes represented in the data.

# **Related work**

This section reviews recent literature on Intrusion Detection Systems (IDS) using machine learning (ML), focusing on studies that employ the HIKARI-2021 and CIC-IDS 2017 datasets. Our analysis aims to identify common trends and challenges in current IDS research.

We selected six papers using HIKARI-2021 (the total available at the time of writing) and six papers using CIC-IDS 2017 (two most cited papers using SHAP and five most cited overall). Some papers include additional datasets beyond these two.

Our analysis utilizes criteria adapted from (Catillo et al., 2023), focusing on ML implications for IDS. We excluded data partitioning issues as they were irrelevant to our non-sequential analysis and transferability due to dataset limitations. We added an explainability criterion for papers employing post hoc explainability algorithms. Before presenting Table 3.1, it's important to explain the criteria used in our evaluation.

We consider whether studies avoid attack-revealing features and ease of detection, which refers to features that inadvertently make attack detection easier due to dataset limitations. For example, in NFS-2023-TE, all attacks use TCP protocol, while the dataset also includes UDP connections. This creates a bias where UDP traffic is automatically classified as non-malicious, which doesn't reflect real-world scenarios. We also observed instances where researchers misunderstood certain features, such as the 'Unnamed' features in HIKARI-2021, which we'll discuss later.

Another criterion is avoiding unmotivated complexity. Some papers propose complex deep learning models without comparing them to simpler, classic models like random forests. Even when comparisons are made, the baseline models often lack proper fine-tuning, potentially skewing results in favor of more complex models.

We also evaluate the use of evaluation metrics. Inappropriate metrics are sometimes used to evaluate models. For instance, using accuracy on an imbalanced dataset with 90% benign traffic can easily yield 90% accuracy by classifying everything as benign, which is misleading.

Source code availability is another important factor. Few papers provide source code, which becomes problematic when crucial details like feature selection or class evaluation are omitted from the paper. Source code could clarify these issues and dispel doubts.

Explainability is assessed to determine whether a model's decisions are explained. Section 5 will analyze model explanations, demonstrating their importance.

We consider whether studies use updated datasets. Despite known errors in datasets like CIC-IDS 2017, some researchers continue using them instead of updated versions that correct them. For HIKARI-2021, the authors have released updated data improving class balance, so we will evaluate this as the update.

Lastly, we examine whether all attacks are used. Not all papers use all available attack types. While this can be justified, some studies don't mention excluded attacks, and their absence only becomes apparent in detailed metrics. This is another reason why publishing source code enhances credibility.

Table 3.1 - Related works \* shap was used, but for feature selection \*\* they use all the features, but they group them (Panigrahi & Borah, 2018)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Paper | *Avoid attack-revealing features and ease of detection* | *Avoid unmotivated complexity* | *Use of the evaluation metrics* | *Source code* | *Explainability* | *Updated dataset* | *All attacks* | *Dataset used* |
| (Kwon et al., 2023) | Yes | Yes | Yes | No | No | No | Yes | Hikari-2021 |
| (Noori et al., 2023) | Yes | Yes | Yes | No | No | No | No | Hikari-2021 |
| (Louk & Tama, 2023) | - | No | Yes | No | No | No | No | Hikari-2021 |
| (Rajak et al., 2022) | - | No | Yes | No | No | No | Yes | Hikari-2021 |
| (Fernandes & Lopes, 2022) | No | Yes | Yes | No | No | No | Yes | Hikari-2021 |
| (Fernandes et al., 2023) | No | Yes | Yes | No | No | No | Yes | Hikari-2021 |
| (Chauhan & Shah Heydari, 2020) | Yes | No | Yes | No | No \* | No | Yes | CIC-IDS 2017 |
| (Zavrak & Iskefiyeli, 2020) | Yes | Yes | No | No | No | No | Yes | CIC-IDS 2017 |
| (Kurniabudi et al., 2020) | Yes | Yes | No | No | No | No | Yes\*\* | CIC-IDS 2017 |
| (Yulianto et al., 2019) | Yes | Yes | Yes | No | No | No | No | CIC-IDS 2017 |
| (Maseer et al., 2021) | Yes | Yes | Yes | No | No | No | Yes\*\* | CIC-IDS 2017 |
| (J. Liu et al., 2021) | Yes | Yes | No | No | No | No | Yes | CIC-IDS 2017 |
| This work | Yes | Yes | Yes | Yes | Yes | Yes | Yes |  |

(Kwon et al., 2023) conducted a study analyzing the HIKARI-2021 dataset, focusing on network anomaly detection and addressing challenges posed by unbalanced data and zero-day attacks. Their research aimed to answer three main questions: how Machine Learning (ML) and Deep Learning (DL) models perform on the highly unbalanced HIKARI-2021 dataset, what strategies can improve model performance on this unbalanced dataset, and whether it's possible to detect previously unseen attack types using these models.

The authors used the HIKARI-2021 dataset, which contains six label categories: Background, Benign, Bruteforce, Bruteforce-XML, Probing, and XMRIGCC CryptoMiner. They noted that this dataset is highly skewed towards normal instances, with a normal-to-attack ratio of approximately 13.7:1. To address these challenges, the researchers employed several ML and DL models, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), Multi-Layer Perceptron (MLP), and Convolutional Neural Network (CNN). They evaluated these models under different data preprocessing scenarios, using the unbalanced dataset as-is and applying random sampling to create balanced datasets of different sizes.

The study's key findings revealed that on the unbalanced dataset, none of the models performed satisfactorily, with F-measures ranging from 0.5384 to 0.6998. However, balancing the dataset through sampling significantly improved performance, with F-measures reaching up to 0.9251. Zero-day detection proved highly challenging, with most models failing to detect untrained attack types.

It is important to note that this study did not use the updated version of the HIKARI-2021 dataset, which could potentially improve the models' performance and impact the results of zero-day detection experiments. Additionally, the Random Forest and XGBoost models were used with default settings, without any fine-tuning, which may have affected their performance, especially in comparison to the neural network models (MLP and CNN) that were more carefully constructed. Lastly, the authors did not provide access to their source code.

(Noori et al., 2023) proposed a novel approach called Dynamic Feature Aware Genetic Programming Ensemble (DFA-GPE) to address several challenges in intrusion detection systems, particularly in the context of data streams. Their work aimed to tackle feature drift, high dimensionality, and data imbalance in modern network traffic data. To address these challenges, the authors proposed DFA-GPE, which extends the GP-combiner framework by incorporating a Dynamic Feature Selection (DFS) block based on an improved multi-objective Particle Swarm Optimization (PSO). This approach allows for variable-length feature selection and optimizes for both accuracy and memory usage.

The authors evaluated their method on two datasets: HIKARI 2021 for network traffic analysis and TON\_IoT 2020 for IoT and IIoT intrusion detection. Their proposed solution included several key components: an intelligent population initialization algorithm using Bernoulli distribution and symmetric uncertainty, a hybrid transfer function set for versatile searching behavior, a novel exemplar selection method to balance exploration and exploitation, and the use of the entire Pareto front for feature selection.

The authors reported significant improvements in performance and efficiency. On the HIKARI 2021 dataset, DFA-GPE achieved 99.09% accuracy while reducing memory usage by 93.49%. On the TON\_IoT 2020 dataset, it achieved 92.64% accuracy with a 62.93% reduction in memory usage. However, it's worth noting that the authors did not use the updated version of the HIKARI 2021 dataset. Furthermore, there is a discrepancy in the attack categories mentioned. In the dataset section related to HIKARI 2021, they only mention three attack categories (Brute Force, Brute Force-XML, and probing) out of the four known categories, without explaining why one has been removed. This missing attack category is also absent in Figure 7, while Figure 4 shows a completely different set of attacks. These unexplained changes highlight the importance of providing source code, which could help clarify these discrepancies and ensure the reproducibility of the research.

(Louk & Tama, 2023) proposed a novel approach called Dual-IDS, which combines bagging with gradient-boosting decision tree (GBDT) models for network anomaly intrusion detection. Their work aimed to improve detection rates and reduce false alarm rates in anomaly-based intrusion detection systems, while enhancing the performance of GBDT algorithms through a dual ensemble technique. The authors evaluated their method on three datasets: HIKARI 2021, NSL-KDD, and UNSW-NB15.

Their proposed solution included a dual ensemble strategy combining bagging with GBDT algorithms, evaluation of multiple GBDT algorithms including GBM, LightGBM, CatBoost, and XGBoost, and hyperparameter tuning using random search for each constituent learner. The authors reported significant improvements in performance across various metrics. For example, on the NSL-KDD KDDTest+ dataset, they achieved 91.57% accuracy, 1.3% false positive rate, 98.67% precision, and an F1 score of 0.915.

However, attempts to reproduce these results were unsuccessful, highlighting the critical importance of providing accessible source code for reproducibility in research. The authors stated that their source code was available upon request, but attempts to obtain it were unsuccessful.

(Rajak et al., 2022) proposed a CNN-LSTM-based Intrusion Detection System (IDS) framework specifically designed for precision farming and Industrial Internet of Things (IIoT) environments. Their work aimed to address security threats to smart agriculture devices and IoT sensors, the need for real-time intrusion detection in precision farming environments, and handling encrypted network traffic in IDS. The authors utilized the HIKARI-2021 dataset to develop and evaluate their model, chosen for its focus on encrypted traffic and representation of modern network behaviors.

The proposed solution included a combined CNN-LSTM architecture for feature extraction and sequence learning, data preprocessing using correlation analysis to select optimal features, and a real-time detection framework for immediate threat identification. The CNN-LSTM model architecture consisted of seven convolutional layers, four max-pooling layers, and four batch normalization layers in the CNN component, two LSTM layers, two dense layers, and two dropout layers in the LSTM component, and a final dense output layer with softmax activation for classification.

The authors reported an accuracy of 93.27% for both training and validation sets, which is competitive but slightly lower than some traditional machine learning approaches they compared against (e.g., SVM and MLP achieved 99% accuracy). However, critical analysis of this work reveals several important points. The authors did not specify using the most recent version of the HIKARI-2021 dataset, which may impact the relevance of their results. Additionally, Table 2 in the paper indicates that both 'traffic\_category' and 'Label' were included in the selected features, which is a critical issue as these columns directly contain the target information, potentially leading to data leakage and overfitting.

Without access to the source code, it's impossible to verify if the inclusion of 'traffic\_category' and 'Label' in Table 2 was an error in reporting or an actual flaw in the methodology. If the reported results are correct, they demonstrate that this complex CNN-LSTM model does not outperform classical machine learning approaches like SVM and MLP. However, the exceptionally high performance of these classical models, combined with the inclusion of both 'traffic\_category' and 'Label' in the feature set, strongly suggests that these results are likely due to incorrect feature selection. This would lead to data leakage, where the model is essentially being given the answers it's trying to predict, resulting in artificially inflated performance metrics.

These issues highlight the importance of transparency in research methodologies and the need for source code availability. The potential inclusion of target variables in the feature set is particularly concerning, as it could lead to unrealistically high performance that wouldn't generalize to real-world scenarios. It also underscores the critical importance of proper feature selection in machine learning studies, especially in the field of intrusion detection where the reliability and generalizability of models are crucial.

(Fernandes et al., 2023; Fernandes & Lopes, 2022) inadvertently included an artificial feature ("unnamed: 0.1") in their analyses, which was not part of the original dataset but rather an artifact created during CSV file loading. This feature, representing row indices, allowed models like Random Forest to learn sequential patterns of attacks, leading to artificially inflated performance metrics. Notably, the inclusion of this feature was not explicitly mentioned in either study. It was only through careful examination of Figure 2 in the first study that this mistake became apparent. The second study revealed a significant performance drop when excluding this feature but failed to recognize its inappropriate inclusion, again highlighting how the source code could help to recognize that there was a mistake in the first study.

(Chauhan & Shah Heydari, 2020) proposed a novel approach to generate polymorphic adversarial DDoS attacks using Generative Adversarial Networks (GANs). Their work aimed to address vulnerabilities of machine learning-based Intrusion Detection Systems (IDS) against new, unknown types of attacks and the ability of attackers to evade detection by continuously changing attack profiles. The authors focused specifically on DDoS attacks, limiting the scope of their study to this particular type of network intrusion. This focused approach allowed for a more in-depth analysis of DDoS attack characteristics and their detection mechanisms.

Key aspects of their methodology include the use of SHAP (SHapley Additive exPlanations) for feature selection, GAN-based adversarial attack generation, and polymorphic attack generation. The authors evaluated their method using the CICIDS2017 dataset and reported significant success in generating adversarial attacks that could evade detection. Their results indicated that by continuously changing the attack profile, even defensive systems employing incremental learning remained vulnerable to new attacks.

This study contributes to the field by demonstrating the potential vulnerabilities of ML-based IDS to adversarial attacks, providing a method for generating polymorphic DDoS attacks, which could be used to improve the robustness of IDS, and showcasing an alternative use of SHAP for feature selection in the context of network security.

(Zavrak & Iskefiyeli, 2020) focused on detecting network intrusions and anomalies using flow-based data and unsupervised deep learning methods, specifically Autoencoder (AE) and Variational Autoencoder (VAE), along with One-Class Support Vector Machine (OCSVM). They used the CICIDS2017 dataset, which contains flow-based network traffic data including normal traffic and various types of attacks. Their methodology employed a semi-supervised learning approach where models were trained only on normal traffic data, and AE, VAE, and OCSVM were used as anomaly detectors.

The model architecture for both AE and VAE used a simple deep autoencoder architecture with two hidden layers in the encoder and decoder, with the bottleneck layer having 64 dimensions. They evaluated their models using Receiver Operating Characteristics (ROC) curves and Area Under the ROC Curve (AUC).

Their results showed that VAE generally performed better than AE and OCSVM in detecting anomalies, although performance varied across different types of attacks. Some attacks (e.g., various DoS attacks) were well-detected, while others (e.g., SSH Patator, Web Attack - SQL Injection) were poorly detected by all methods. The study highlighted the need for additional supervised learning methods to reduce false alarms and suggested considering flow-based features collected at specified time intervals to better model attack characteristics for future work.

(Kurniabudi et al., 2020) conducted a study on feature selection for anomaly detection using the CICIDS-2017 dataset. Their work aimed to address challenges in intrusion detection systems, particularly high dimensionality of data, impact on computational complexity, and computational time. The authors used Information Gain for feature selection and experimented with five classifier algorithms: Random Forest (RF), Bayes Net (BN), Random Tree (RT), Naive Bayes (NB), and J48. They analyzed only 20% of the CICIDS-2017 dataset, which was split into 70% training and 30% testing data.

Their methodology included using Information Gain to rank and group features based on weight scores, evaluating classifier performance using metrics like accuracy, TPR, FPR, precision, recall, and execution time, and implementing 10-fold cross-validation. Their results showed that Random Forest achieved the highest accuracy (99.86%) using 22 selected features, while J48 performed best (99.87% accuracy) using 52 features, but with longer execution time. The number of selected features significantly impacted both detection accuracy and execution time.

However, there are several critical points to consider regarding this study. The authors only used 20% of the CICIDS-2017 dataset, which may not fully represent the dataset's complexity and could impact the generalizability of their results. The study adopts a relabeling approach for attack traffic, as suggested by previous research. While this can help address class imbalance issues, it may also obscure the detection performance for individual, less common attack types. Additionally, while Information Gain was used to rank features, the authors manually determined the minimum weight value for feature selection, introducing a subjective element that could affect reproducibility.

(Yulianto et al., 2019) proposed an approach to enhance the performance of AdaBoost-based Intrusion Detection Systems (IDS) on the CIC IDS 2017 dataset. Their work aimed to address the imbalance in training data, inappropriate selection of classification methods, and the need for effective feature selection. To tackle these issues, the authors proposed a framework combining Synthetic Minority Oversampling Technique (SMOTE) to handle the imbalance in training data, Principal Component Analysis (PCA) and Ensemble Feature Selection (EFS) for selecting important attributes from the dataset, and AdaBoost classifier as the core classification method.

The authors evaluated their method on the CIC IDS 2017 dataset, focusing on DDoS attacks. They used 70% of the data for training and 30% for testing, applied SMOTE with a 200% minority oversampling class, and used a threshold value of T = 0.9 for feature selection. Their results showed significant improvements over previous methods, with the AdaBoost classifier using PCA and SMOTE achieving an Area Under the Receiver Operating Characteristic curve (AUROC) of 92%, and the AdaBoost classifier using EFS and SMOTE producing an accuracy of 81.83%, precision of 81.83%, recall of 100%, and F1 Score of 90.01%. These results demonstrated a substantial improvement over the previous AdaBoost implementation on the same dataset, which had achieved precision, recall, and F1 scores of only 77%, 84%, and 77% respectively. However, two limitations of this study regarding the goal that this thesis set are the fact that explaining the PCA is a problem and that they used only SMOTE.

(Maseer et al., 2021) conducted a comprehensive benchmarking study of machine learning algorithms for anomaly-based intrusion detection systems (AIDS) using the CIC-IDS 2017 dataset. Their work aimed to address several issues in existing AIDS research, including the randomness of selected algorithms, parameters, and testing criteria, the use of outdated datasets, and shallow analyses and validation of results. The authors evaluated 10 popular supervised and unsupervised machine learning algorithms, including Artificial Neural Network (ANN), Decision Tree (DT), k-Nearest Neighbor (k-NN), Naive Bayes (NB), Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Expectation-Maximization (EM), k-Means, and Self-Organizing Maps (SOM).

They tested multiple models and tuning parameters for each algorithm to achieve optimal classifier performance, using evaluation metrics including accuracy, precision, recall, F1-score, training time, and testing time. Key findings revealed that k-NN, DT, and NB algorithms demonstrated the best overall performance in detecting web attacks, supervised learning algorithms generally outperformed unsupervised ones, and DT and k-NN provided the best balance of accuracy and efficiency when considering both training and testing times. However, many models struggled to detect the rarest attack class (SQL Injection) due to class imbalance in the dataset.

The authors highlighted the importance of using comprehensive evaluation metrics beyond just accuracy, especially for imbalanced multi-class datasets like CICIDS2017. They also emphasized the need to consider both effectiveness (detection accuracy) and efficiency (training/testing times) when evaluating AIDS models. However, it's important to note that they did not use the updated version of the CICIDS2017 dataset, which could impact the applicability of their results. Additionally, they focused on only four categories of attacks (BENIGN, Brute Force, XSS, and SQL Injection) out of the multiple attack types available in the full CICIDS2017 dataset. This limited scope, while allowing for a focused analysis, may not represent the full range of intrusion detection challenges present in the complete dataset.

(J. Liu et al., 2021) proposed a network intrusion detection system using ADASYN (Adaptive Synthetic) oversampling and LightGBM. They compared several resampling techniques, including SMOTE and ADASYN, in combination with LightGBM on three datasets: NSL-KDD, UNSW-NB15, and CICIDS2017. The comparison between SMOTE and ADASYN focused primarily on accuracy and false alarm rate. For NSL-KDD,

In light of these observations from related works, it's clear that while each study has its unique approach and objectives, there are common challenges across the field. These include issues with dataset quality, lack of source code availability, and inconsistent evaluation methods. Our work aims to address these challenges by using more recent datasets, implementing standardized preprocessing and evaluation techniques, incorporating explainable AI, and providing full access to our source code. By doing so, we hope to demonstrate how addressing these common issues can lead to the development of more robust and reliable NIDS models, potentially bridging the gap between academic research and real-world applicability.

# **Methodology**

## KDD Cup '99

## NSL-KDD

UNSW-NB15

CIC-IDS 2017

11 criteria set by

(Engelen et al., 2021; L. Liu et al., 2022)

TCP connection closure standards (Brownlee et al., 1999)

NFStream (Aouini & Pekar, 2022)

aligning with most flow analyzers (Hofstede et al., 2014)

HIKARI-2021 (Ferriyan et al., 2021)

(Catillo et al., 2023)

The evolution of Network Intrusion Detection Systems (NIDS) datasets has seen significant progress over the years. Among the most cited datasets according to Google Scholar are KDD Cup '99 (Lee et al., 1999), NSL-KDD (Tavallaee et al., 2009), UNSW-NB15 (Moustafa & Slay, 2015), and CIC-IDS 2017 (Sharafaldin et al., 2017). KDD Cup '99, one of the earliest and most influential datasets, set the foundation for IDS research by providing a large-scale, labeled dataset of network intrusions. Despite its age, it remains a benchmark due to its comprehensive attack types. NSL-KDD, an improvement on KDD Cup '99, addressed key limitations such as redundant records and statistical issues, enhancing the dataset's reliability for evaluating machine learning-based IDSs.

UNSW-NB15 was a completely new dataset created to address the outdated nature of previous benchmarks. It used the IXIA PerfectStorm tool to generate a mix of modern normal and attack traffic, introducing nine contemporary attack categories and 49 features, making it more relevant for current IDS evaluation. CIC-IDS 2017 marked a milestone as it met all 11 criteria set by (Gharib et al., 2016) for IDS datasets, providing a more realistic and comprehensive representation of network behaviors and attack patterns.

As of February 2024, these datasets were among the most cited in Google Scholar, with NSL-KDD leading at 5,131 citations, followed by CIC-IDS 2017 at 3,149 citations, and UNSW-NB15 at 2,740 citations. Despite their popularity, newer datasets have emerged to address limitations in these earlier versions. Our study focuses on two recent datasets: NFS-2023-TE, derived from CIC-IDS 2017, and HIKARI-2021, a new approach to NIDS datasets.

CIC-IDS 2017 was a significant milestone, being the first dataset to cover all 11 criteria set by Gharib et al. It was created over five days, simulating various attack scenarios, including brute force, DoS, infiltration, botnet, DDoS, and port scan attacks. The dataset provides 12 attack labels, 1 benign label, and 80 traffic features. However, subsequent analyses reported several issues. Engelen et al. and L. Liu et al. found over 5% corruption in dataset labeling, with some benign traffic categorized as attacks and others mislabeled. Additionally, CICFlowMeter, the tool used to create the dataset, did not comply with TCP connection closure standards.

These discoveries have significant implications for past research using CIC-IDS 2017, as models may have learned incorrect patterns. The evolution from CIC-IDS 2017 to NFS-2023-TE involved several intermediate steps. WTMC-2021 provided extensive documentation on correct attack labeling, improved CICFlowMeter by fixing various issues and implementing new attributes, and modified connection closure to follow TCP standards. CRiSIS-2022 addressed issues with duplicate packets and packet ordering in pcap files and added a label for port scan attacks.

NFS-2023-TE uses NFStream instead of CICFlowMeter, closes connections after the first FIN or RST flag, aligning with most flow analyzers, and drops duplicates within 10,000 packets instead of 500 microseconds. The authors of NFS-2023-TE reported significant improvements in model scores compared to its predecessors.

HIKARI-2021 brings several key features to the table. It focuses on encrypted traffic, particularly application layer attacks delivered via HTTPS, aligning with the current trend of increasing encrypted network traffic. The dataset offers comprehensive data provision, including pcap files, CSV files, and PKL format, providing researchers with multiple ways to access and analyze the data. It also provides an enhanced feature set of 86 traffic features, including 80 adopted from CICIDS-2017 and 6 additional features derived from Zeek.

Table 4.1- Typical dataset issues

|  |  |  |
| --- | --- | --- |
| Issue | HIKARI-2021 | NFS-2023-TE |
| *Simplification of the data collection environment* | While HIKARI-2021 has made improvements, its environment is still simplified compared to real-world networks. It focuses primarily on web traffic, which is both a strength and a limitation. | Uses the same environment as CIC-IDS 2017, inheriting its simplifications and limitations. |
| *Contemporaneity and effectiveness of the attack* | Focuses on application layer attacks, which the authors claim represent 80% of web attacks. However, the effectiveness of these attacks in real-world scenarios is not thoroughly discussed. | Some attacks in this dataset have been proven ineffective against properly configured systems, as noted in (Catillo et al., 2021). |
| *Representativeness of the normal baselines* | Represents an improvement over previous datasets but still falls short of real-world complexity. It only represents web traffic, which aligns with its goals but remains a limitation. | Inherits the limitations of CIC-IDS 2017 in terms of normal traffic representation, which may not fully capture the complexity of real-world network behavior. |
| *Bugs of the feature extractor and incorrect ﬂow records* | The authors mention using Zeek for feature extraction but don't provide detailed configuration information. They also reference an unspecified Python tool, raising questions about the reproducibility of their method. | Was specifically created to address the flaws in CICFlowMeter and improve upon CIC-IDS 2017, representing a significant improvement in this area. |
| *Data Labeling (Was the traffic analyzed or labeled based on IP, port, and timestamp?)* | The labeling process cannot be fully verified due to the absence of timestamps. However, the authors discovered an unexpected attack during background validation, suggesting a more thorough analysis. | Is the result of multiple iterations and improvements in labeling methodology. From a methodological standpoint, the labeling process should be more robust and less subject to criticism. |
| *Class imbalance* | Shows significant imbalance. The majority class (Benign) represents 71.77% of all data, with the smallest attack class (Bruteforce) at only 1.02% of the total dataset. | Exhibits extreme imbalance. The majority class (BENIGN) accounts for 83.71% of all data, while the smallest attack class (Heartbleed) represents only 0.00035% of the total dataset. |

* + 1. **Future Directions**

The field of NIDS dataset creation continues to evolve. The authors of CICFlowMeter are developing a new Python-based tool with over 50 new features, potentially offering 130 features in total. This development could lead to more standardized dataset creation, allowing for better comparison of models across different datasets.

By selecting NFS-2023-TE and HIKARI-2021 for our study, we aim to leverage the most current and refined datasets reported in the literature. A thorough analysis of these datasets will be conducted as part of our research, with results presented in later sections of this thesis. This analysis will provide deeper insights into these datasets' actual characteristics and potential limitations, contributing to the ongoing discussion on NIDS dataset quality and suitability.

* 1. **Explainable Algorithms in Machine Learning: SHAP and Beyond**

As models become increasingly complex in machine learning, the need for interpretability and explainability has grown significantly. This section explores critical approaches and tools developed to address this need, focusing on SHAP (SHapley Additive exPlanations) and related methodologies. Moreover, we will explain why we have chosen SHAP.

* + 1. **SHAP: A Game-Theoretic Approach to Explainability**

SHAP, introduced by (Lundberg & Lee, 2017), a Python library leverages game theory concepts to provide post hoc explanations for machine learning models. At its core, SHAP computes approximations of Shapley values, a concept from cooperative game theory used to fairly distribute each player's contribution (or, in this case, feature) to the game's outcome (or model prediction).

* + 1. **Understanding Shapley Values**

Shapley values are calculated by considering all possible combinations of features and assessing how each feature's presence or absence affects the model's output. This approach is considered "fair" because it accounts for all possible feature interactions and orders. For example, if we have features A, B, and C, we would consider scenarios like {A}, {B}, {C}, {A,B}, {A,C}, {B,C}, and {A,B,C} to determine each feature's contribution. However, computing exact Shapley values is computationally expensive, especially for models with many features. SHAP addresses this challenge by providing efficient approximation methods.

* + 1. **Key SHAP Explainers**

1. Kernel SHAP: A model-agnostic explainer adapted from LIME (Local Interpretable Model-agnostic Explanations) (Ribeiro et al., 2016). It creates a surrogate linear model to compute Shapley values and can be applied to any machine learning model.

2. Deep SHAP: A model-specific explainer for neural networks based on the DeepLIFT algorithm (Shrikumar et al., 2017).

3. Tree SHAP: Introduced in subsequent papers (Lundberg et al., 2018, 2020), this is a model-specific explainer for tree-based models and ensembles. It is notably faster than Kernel SHAP and Deep SHAP, often capable of explaining entire training sets in seconds.

4. Fast Tree SHAP: An optimized version of Tree SHAP (Yang, 2021), offering improved performance, especially in multi-core environments.

* + 1. **The Choice of SHAP for Explainability**

Our focus on SHAP, particularly TreeExplainer (for tree-based models), is motivated by its unique theoretical guarantees and practical efficiency. As stated by (Lundberg et al., 2020):

TreeExplainer offers several key advantages:

1. Fast Local Explanations: It rapidly computes local explanations, which is crucial for real-time or large-scale applications like intrusion detection systems.
2. Guaranteed Consistency: The explanations maintain consistency across different model outputs, ensuring reliability in interpretation.
3. Polynomial Time Complexity: TreeExplainer reduces the complexity of exact Shapley value computation from exponential to polynomial time, making it feasible for practical use on large datasets and complex models.
4. Theoretical Soundness: Within the class of additive feature attribution methods, Shapley values (as computed by SHAP) are the only approach that satisfies three critical properties:

a) Local Accuracy (Additivity): The explanation's attribution values sum up to the model's output for a specific input, ensuring that the explanation accurately reflects the model's behavior for that instance.

b) Consistency (Monotonicity): If a model changes so that a feature's contribution increases or stays the same regardless of other inputs, that feature's attribution will not decrease. This property ensures that the explanations reflect genuine changes in the model's logic.

c) Missingness: This property ensures that features that do not contribute to a prediction are assigned zero importance.

These properties make SHAP, particularly TreeExplainer for tree-based models, a theoretically sound and practically efficient choice for explaining complex models in intrusion detection systems. The combination of fast computation and guaranteed consistency is precious in security contexts where both speed and reliability of explanations are crucial.

* + 1. **Model-Agnostic vs. Model-Specific Explainers**

Kernel SHAP is model-agnostic, meaning it can work with any machine-learning model. This flexibility comes at the cost of computational efficiency and the need for carefully chosen background data. In contrast, Tree SHAP and Deep SHAP are model-specific, designed to leverage the particular structures of tree-based models and neural networks. This specialization allows for more efficient computations and often more accurate explanations but limits their applicability to specific model types.

* + 1. **True-to-Model vs. True-to-Data Explanations**

An important distinction in explainable AI is between true-to-model and true-to-data explanations (H. Chen et al., 2020):

* True-to-Model Explanations: Provided by Tree SHAP and Linear SHAP, these explanations assign non-zero importance only to features actually used by the model. They break feature dependencies following causal inference principles (Janzing, 2019).
* True-to-Data Explanations: Other explainers provide these, which may assign equal importance to highly correlated features, even if the model only uses one.
  + 1. **Understanding SHAP Mechanics and Perturbation Approaches**

SHAP uses different approaches to assess feature importance, depending on the specific explainer and model type:

1. Kernel SHAP:

* Uses perturbation with background data.
* Background Data: A subset of the dataset used as a reference point.
* Perturbation: Randomly swaps feature values between the explained instance and the background data.
* Accuracy depends on:
  + The size of the background data (typically 100-1000 observations)
  + The number of perturbations per observation
  + For global explanations, the size of the sample being explained
* It's crucial to use realistic background data (e.g., sampled from the dataset or k-means centroids) to avoid skewing the explanations.

2. Tree SHAP:

* Can use tree path-dependent perturbation.
* Does not require separate background data.
* Instead, it follows the nodes of the tree, which contain all the training data.
* This approach allows for efficient computation by leveraging the structure of tree-based models.

3. Linear SHAP:

* Can use interventional feature perturbation.
* Does not require background data.
* Instead, it reads the linear model weights to provide explanations.
* This approach allows for true-to-model explanations by directly interpreting the model's coefficients.
  + 1. **Computational Complexity**

The computational efficiency of SHAP methods varies significantly. Kernel SHAP, being model-agnostic, is the most computationally expensive, especially for high-dimensional data or large datasets. By leveraging the structure of tree-based models, Tree SHAP achieves much faster computation times, often orders of magnitude faster than Kernel SHAP for the same dataset. Linear SHAP is typically the fastest, using the model coefficients directly.

* + 1. **Importance of Background Data**

For Kernel SHAP, the choice of background data is crucial. It serves as a reference point against which feature contributions are measured. Poor selection of background data can lead to misleading explanations. Ideally, background data should represent the features' meaningful "average" or baseline state.

* + 1. **Types of SHAP Explanations**

1. Local Explanations: Explain individual predictions. For example, in an intrusion detection system, a local explanation might show which network traffic features most contributed to classifying a particular connection as malicious.

2. Global Explanations: Provide overall feature importance across the dataset. These can be computed using either the mean absolute SHAP value or the maximum absolute SHAP value across observations. Global explanations in an IDS context might reveal which features are most important for detecting intrusions across all traffic.

* + 1. **Relationship between Local and Global Explanations**

Global explanations are typically derived by aggregating local explanations across many instances. This aggregation can be done by taking the mean or maximum of absolute SHAP values. While global explanations provide an overview of feature importance, they may obscure nuances captured in local explanations, especially for models with complex decision boundaries.

* + 1. **Limitations of SHAP**
* Computational Cost: Especially for Kernel SHAP with large datasets or high-dimensional features.
* Handling of Correlated Features: Kernel SHAP may distribute importance among correlated features in ways that can be counterintuitive.
* Assumption of Feature Independence: Some SHAP methods assume feature independence, which may not be in real-world datasets.
  + 1. **Post Hoc Explanations**

Post hoc explanations refer to interpretability methods applied after a model has been trained. These techniques aim to explain the decisions or predictions of a model without altering its internal structure or training process. SHAP is a prime example of a post hoc explanation method. The key characteristics of post hoc explanations include:

* Applied After Training: They are used to interpret a model's behavior after it has been trained and without modifying it.
* Can Be Model-Specific or Model-Agnostic: Some post hoc methods are designed for specific types of models (like Tree SHAP for tree-based models), while others can be applied to any model (like Kernel SHAP).
* Separate Process: After model training and prediction, the explanation is generated as a separate step.
* No Impact on Model Performance: They do not affect the model's predictive capabilities.
* Flexibility: Can be applied selectively to specific predictions or instances of interest.

While post hoc methods like SHAP offer powerful explanatory capabilities, they do add an additional computational step after model training and prediction. This contrasts inherently interpretable models, which provide explanations as an integral part of their structure or training process.

* + 1. **Alternative Approaches: Glass Box Models**

In contrast to models requiring post hoc explanations, we also explored alternative approaches that offer inherent explainability, specifically the Explainable Boosting Machine (EBM) (Lou et al., 2013). EBM, a Generalized Additive Model with Interactions (GA2M), represents a significant advancement in interpretable machine learning.

As stated by the authors of EBM, this model aims to achieve predictive power comparable to complex deep learning models while providing clear, interpretable explanations similar to simpler glass box models like linear regression. This combination of high performance and inherent interpretability makes EBM particularly interesting for applications where accuracy and explainability are crucial, such as intrusion detection systems.

Our study included EBM as a glass box model for comparison. Our approach focused on comparing the training time of EBM with other models. This comparison is particularly relevant because traditional black box models require additional time to run SHAP to generate explanations after training. In contrast, EBM provides explanations inherently during the training process, potentially offering a more time-efficient solution for scenarios where both model performance and interpretability are crucial.

By including EBM in our analysis, we aimed to evaluate its predictive performance and efficiency in providing interpretable results. This comparison allows us to assess the trade-offs between post hoc explainability methods like SHAP and inherently interpretable models like EBM in the context of intrusion detection systems, considering both predictive power and the time required to obtain explanations.

* 1. **Model Selection and Rationale**

Our choice of models for this study was driven by several key factors, including the unique advantages of Tree SHAP, the performance of boosted models on imbalanced datasets, and the need to balance explainability with performance. This approach aligns with future improvements highlighted in the survey by (Zhang et al., 2022) on explainable AI for cybersecurity, particularly addressing the trade-off between explainability and performance.

* + 1. **Importance of Tree SHAP**

Tree SHAP emerged as a crucial factor in our model selection. Its ability to provide fast, consistent, and theoretically sound explanations for tree-based models made it an ideal choice for our explainability needs. Most importantly, Tree SHAP offers true-to-the-model explanations, meaning they directly reflect the model's decision-making process rather than approximating it. This feature is critical for understanding how our models function, especially in the sensitive domain of intrusion detection.

* + 1. **Focus on Boosted Models**

Nearly all the models we selected, except for the Decision Tree, are boosted. This choice was deliberate and essential, especially given the imbalanced nature of our datasets. Boosted models, such as Random Forest, LightGBM, XGBoost, and CatBoost, have demonstrated superior performance on imbalanced datasets. This is crucial for our case with NFS-2023-TE, where some categories have tiny sample sizes. Combining these boosted models with Tree SHAP allows us to leverage their high performance while maintaining true-to-the-model explainability.

* + 1. **Handling Imbalanced Data**

The imbalanced nature of our datasets significantly influenced our model selection. While we considered deep learning models, they struggled with the imbalanced data. Moreover, the additional complexity of explaining deep learning models and the increased explanation time made them less suitable for our study. We decided against using oversampling techniques to maintain the integrity of the original data distribution.

* + 1. **Balancing Simplicity and Performance**

We included simpler models like Decision Trees to provide a baseline for comparison. This allows us to assess the trade-off between model complexity and performance. The Decision Tree, combined with Tree SHAP, also offers insights into the dataset structure and model behavior, with explanations that are particularly easy to interpret due to the model's simplicity.

* + 1. **Exploration of Other Classic Models**

We tested other classic machine learning models such as SVM, Logistic Regression, and KNN. However, these models did not provide satisfactory results on our datasets, further justifying our focus on tree-based and boosted models.

* + 1. **Inclusion of Explainable Boosting Machine (EBM)**

The EBM model was included as it promises to deliver performance comparable to complex models while maintaining inherent explainability. This aligns with our goal of balancing performance and explainability and provides an interesting contrast to the post-hoc explanations of Tree SHAP.

* + 1. **Selected Models**

Based on these considerations, we chose the following models for our study:

1. Decision Tree (DT): As a baseline model and for its inherent interpretability.

2. Random Forest (Breiman, 2001): A powerful ensemble method known for its robustness.

3. LightGBM (Ke et al., 2017): An efficient gradient boosting framework.

4. XGBoost (T. Chen & Guestrin, 2016): Another popular and highly effective boosting algorithm.

5. CatBoost (Dorogush et al., 2017): Known for its performance and handling of categorical features.

6. Explainable Boosting Machine: For its balance of performance and inherent explainability.

These models, coupled with Tree SHAP for explanation (except for EBM, which provides inherent explanations), allow us to thoroughly explore the trade-off between model performance and explainability in intrusion detection systems. The true-to-the-model nature of Tree SHAP explanations ensures that we can trust the insights gained from our models, which is crucial in a security-critical domain like intrusion detection. This approach enables us to address the challenges of imbalanced datasets while providing meaningful, accurate, and efficient explanations, crucial for the practical application of machine learning in cybersecurity.

* 1. **Data Preprocessing and Sampling Methodology**

To address the challenge of imbalanced datasets and improve our model performance, we implemented a careful under-sampling strategy for both the HIKARI-2021 and NFS-2023-TE datasets. This approach was chosen to balance the classes while maintaining the integrity of the original data distribution.

* + 1. **HIKARI-2021 Dataset**

1. Under-sampling: We reduced all classes to 7,988 samples each. This number was chosen based on the size of the smallest class in the dataset.

2. Class Merging: We merged the Benign and Background traffic classes to create a single non-malicious category. This simplification helps in focusing on distinguishing between normal and malicious traffic.

* + 1. **NFS-2023-TE Dataset**

1. Under-sampling: We reduced most classes to 738 samples each. This number was determined through experimentation as the optimal balance between class representation and overall model performance.

2. Exception for Smaller Classes: Classes with fewer than 738 samples were left unchanged to preserve all available information for rare attack types.

* + 1. **Limitations and Considerations**

1. Data Loss: We acknowledge that under-sampling results in a significant reduction of data, which is a limitation of this study. However, we deemed this preferable to removing entire attack classes, which would have limited the model's ability to detect a full range of attacks.

2. Oversampling Rejection: Given the extreme imbalance in NFS-2023-TE (with the smallest class having only 11 samples), we decided against oversampling. This decision was made to avoid the risk of overfitting on synthetic data, which could lead to unreliable model performance on real-world data.

* + 1. **Training and Validation Methodology**

1. Stratified Split: We used 80% of the under-sampled data for training, ensuring that the class distribution was maintained in training and test sets.

2. Cross-Validation: We implemented 5-fold cross-validation to ensure robust model evaluation and mitigate the overfitting risk.

This methodology represents a balanced approach to handling the challenges presented by our imbalanced datasets. While it involves some compromise regarding data utilization, it allows us to train models that can recognize a full spectrum of attack types while maintaining a balanced view of the problem space. The use of cross-validation further strengthens the reliability of our results, helping to ensure that our models' performance is consistent across different subsets of the data.

* 1. **Evaluation Metrics and Handling Class Imbalance in Multi-class NIDS**

In Network Intrusion Detection Systems (NIDS), choosing appropriate evaluation metrics is crucial, especially when dealing with multi-class, imbalanced datasets. Our approach addresses several key considerations:

* + 1. **Binary vs. Multi-class Classification**
* Some studies simplify NIDS to binary classification (attack vs. benign), where standard metrics like F1 score are straightforward to interpret.
* Our study focuses on multi-class classification to distinguish between different attack types, providing more detailed insights but requiring a more nuanced evaluation approach.
  + 1. **Limitations of Common Metrics**

Accuracy is overly simplistic when evaluating NIDS performance, as it can be misleadingly high in imbalanced datasets even when the model fails to detect rare attacks. While precision and recall provide more insight, they are still insufficient when used individually; precision may be high but recall low (or vice versa), failing to capture the overall effectiveness. Therefore, we opted for the F1 score, which balances precision and recall, providing a more comprehensive measure of the model's performance across common and rare attack classes.

* + 1. **Importance of Detecting All Attack Types**
* We emphasize the critical need to detect all types of attacks, including those with very few instances (e.g., attacks with only 11 samples in NFS-2023-TE).
* This aligns with real-world security requirements where missing a rare attack could have severe consequences.
  + 1. **F1 Macro and F1 Weighted formula**

Where N is the number of classes, i represents a specific class, and wi is the weight of a class in the dataset.

* + 1. **Comparison of F1 Macro and F1 Weighted**

1. F1 Macro:

* Calculates the arithmetic mean of F1 scores for each class.
* Treats all classes equally, regardless of their frequency in the dataset.
* More sensitive to the performance of minority classes.

2. F1 Weighted:

* Calculates a weighted average of F1 scores, where weights are proportional to class frequencies.
* Classes with more samples have a higher impact on the final score.
* Reflects performance with respect to the dataset's class distribution.
  + 1. **Key Insights from F1 Macro and F1 Weighted**

1. Imbalanced Dataset Sensitivity:

* F1 macro is more indicative of performance on rare attacks.
* F1 weighted might show high scores even if rare attacks are misclassified, provided common attacks are correctly identified.

2. Use Case in Our Study:

* For HIKARI 2021 (after under-sampling): These metrics will yield identical results as the dataset becomes balanced.
* For NFS-2023-TE (remains imbalanced):

a) A high F1 weighted with a lower F1 macro would indicate good performance on common attacks but potential struggles with rare ones.

b) Similar F1 macro and weighted scores suggest consistent performance across all classes.

3. Overall Model Assessment:

* F1 macro provides a more stringent evaluation across all attack types.
* F1 weighted reflects performance experienced in a real-world scenario with the given class distribution.

4. Improvement Focus:

* A significant difference between scores can guide improvement efforts:
  + Lower F1 macro suggests the need to improve the detection of minority classes.
  + Low scores in both indicate overall performance issues.

By employing this comprehensive evaluation strategy, we aim to provide a nuanced and accurate assessment of our models' performance across all attack types. This approach helps avoid the pitfalls of oversimplified metrics. It ensures that our evaluation aligns with real-world requirements of intrusion detection systems, where the ability to detect every type of attack, no matter how rare, is crucial for maintaining network security. The combination of F1 macro and F1 weighted, along with supplementary analyses, allows us to balance the assessment of overall effectiveness in real-world scenarios with the critical requirement of detecting all types of network intrusions, regardless of their frequency.

# ***Results***

* 1. ***Data set analysis***

Our analysis of the NFS-2023-TE and HIKARI-2021 datasets revealed essential insights into their quality and potential limitations for intrusion detection research.

* + 1. **NFS-2023-TE Dataset**

While our initial examination of NFS-2023-TE did not identify any significant new flaws, it is essential to note that this does not guarantee the absence of issues. Some inherent problems from CIC-IDS 2017, such as outdated attack types and class imbalance, persist in NFS-2023-TE. These issues can only be fully addressed by completely redoing the data collection process, which was beyond the scope of the authors' aim to improve upon CIC-IDS 2017 rather than create an entirely new dataset from scratch.

Acknowledging that our analysis was primarily based on issues previously identified in other datasets is crucial. Consequently, NFS-2023-TE may have additional problems we did not uncover in this initial examination. Further in-depth analysis might reveal new concerns specific to this dataset.

* + 1. **HIKARI-2021 Dataset**

Our analysis of HIKARI-2021 is noteworthy as it represents the first comprehensive examination of this dataset. By applying the criteria used to identify issues in CIC-IDS 2017, we discovered some problems in HIKARI-2021. Key findings include:

1. TCP Flag Anomalies: We observed unexpectedly high counts for FIN and RST flags, with some flows showing up to 140 FIN and 110 RST packets. This is a significant deviation from expected TCP behavior, where typically, only one RST or up to two FIN packets should be present per connection.

2. Extended Flow Duration: The longest observed flow lasted approximately 4.9 hours (17,942 seconds), which exceeds the stated 3-5 hour capture sessions. This suggests the flow generation tool did not implement proper timeouts or connection closure mechanisms.

3. Inconsistent Connection Handling: Unlike NFS-2023-TE, which closes connections after 120 seconds, HIKARI-2021 lacks a consistent connection termination policy. This leads to unrealistic flow statistics and potential misrepresentation of network behavior.

4. Limited Valid Samples: When filtering for more realistic connection parameters (duration < 181 seconds, RST < 2, FIN < 3), we found only 104 samples for bruteforce and 59 for bruteforce-XML attacks. This severely limits the dataset's utility for training robust intrusion detection models.

5. Lack of Documentation: The absence of detailed documentation on the labeling process and the unavailability of timestamps make it challenging to fully validate the dataset's integrity.

6. Raw Data Issues: Analysis of the pcap files revealed that 0.03% of the packets were duplicated, and 0.23% were out of order. While these percentages are small, they indicate a lack of preprocessing that could impact the dataset's accuracy.

* 1. **Model Evaluation and Performance Analysis**

It is crucial to preface this section by emphasizing its specific role within the broader context of this thesis. The primary purpose of this model evaluation and performance analysis is twofold: firstly, to demonstrate that these models can achieve good performance on the given datasets, and secondly, to maintain transparency regarding our fine-tuning process.

However, it is equally important to note that we are fully aware of the limitations of these datasets for real-world applications. Given this understanding, the objective of this analysis is not to propose models for practical use but rather to provide a basis for comparison with existing works in the field.

That said, even this comparative aim presents challenges. During our literature review, we observed that nearly all analyzed works employed different preprocessing techniques, such as using only a portion of the dataset or eliminating certain classes. These varied approaches make direct and accurate comparisons difficult, if not impossible.

Therefore, while we present detailed performance metrics and analysis, readers should interpret these results within the context of academic exploration rather than as indicators of real-world efficacy. The following evaluation serves primarily as a demonstration of model capabilities on these specific datasets and as a transparent account of our methodology rather than as a proposal for practical implementation.

We evaluated several machine learning models on two datasets: NFS-2023-TE and HIKARI-2021. Our analysis focused on training times, prediction times, and F1 scores (both macro and weighted). All experiments were conducted on a Dell XPS 13 9315 with a 12th gen i7-1250u and 16GB of DDR5 RAM, running Fedora 39 with Linux 6.8. We used Sklearnex and daal4py to optimize inference times, and all models were configured to utilize all available cores.

This introduction clarifies the purpose and limitations of this section, emphasizing its role in academic comparison and methodological transparency rather than real-world application. It also highlights the challenges in directly comparing other works due to varied preprocessing approaches.

* + 1. **Model Parameters - NFS-2023-TE**

Table 5.1 - NFS-2023-TE and NFS-2023-nTe parameters

|  |  |  |
| --- | --- | --- |
| mode | parameter | value |
| Random forest | n\_estimators | 10 |
| max\_depth | 14 |
| max\_features | None |
| bootstrap | False |
| catboost | iterations | 40 |
| depth | 11 |
| learning\_rate | 0.4 |
| loss\_function | MultiClass |
| ebm | learning\_rate | 1 |
| lightgbm | objective | MultiClass |
| num\_class | 15 |
| learning\_rate | 0.01 |
| num\_iterations | 250 |
| max\_depth | 4 |
| num\_leaves | 6 |
| xgboost | n\_estimators | 60 |
| max\_depth | 10 |
| objective | multi:softprob |
| learning\_rate | 0.3 |
| Dt | max\_depth | 14 |

The parameter tuning in Table *5.1* was conducted following the suggestions in the documentation for each library and by observing what worked well across models. We used the F1 macro metric from sklearn to evaluate results, and when different parameters yielded similar results, we favored those that led to shorter training times

* + 1. **Training and Explanation Times - NFS-2023-TE**

Table 5.2 presents the training time, explanation time (using Fast Tree SHAP), and total time for each model based on 6,087 samples.

Table 5.2 - NFS-2023-TE training times



Key observations:

1. EBM has the longest training time but is competitive regarding total time when including explanations.
2. Random Forest and Decision Tree are the fastest, likely due to their simpler structures and the Random Forest using only 10 trees.
3. CatBoost is surprisingly slow despite using fewer trees than LightGBM and XGBoost.

These times show some variance but indicate the order of magnitude necessary to run each model. It's worth noting that while EBM is the slowest during training, it can be faster than LightGBM and XGBoost when considering the explanation time.

* + 1. **Model Performance – NFS-2023-TE**

Table *5.3* shows the average F1 scores (macro and weighted) from 5-fold cross-validation and prediction times for 1,522 samples.

Table 5.3- NFS-2023-TE – average F1 score of 5-fold



For the prediction times, we used the %timeit magic function of IPython to compute the mean of different runs. This approach is crucial because it provides more statistically significant results. With such small durations, a warmup of the function is necessary to reduce computation time. For instance, without the warmup run, the classification time of the decision tree was 3 ms because the first run included the time to load the prediction function into memory.

Key findings:

1. EBM achieves the highest F1 macro score but the lowest F1 weighted score, indicating strong performance on minority classes but potential issues with majority classes.
2. LightGBM offers the best balance of F1 scores but has the slowest prediction time.
3. Random Forest presents a good compromise, with near-top F1 scores and faster prediction times.

Analysis:

* The discrepancy in EBM's performance highlights the challenge of class imbalance in the dataset. Comparing these results with the decision tree shows that the decision tree has problems with Heartbleed and Web Attack - SQL Injection, misclassifying two samples for the first and 4 for the latter. In contrast, EBM misclassifies 111 samples in the DoS Slowhttptest category.
* These results expose the need for a balanced dataset. We can argue that EBM is the best because it can handle each attack well, but on the other hand, building a model over just 11 samples will likely lead to something that will not work in the real world.
* LightGBM's slow prediction time could be problematic for real-time intrusion detection systems, especially during DoS attacks. It is twice as slow as the Random Forest, which scores nearly the same in the F1 metrics.
* The classification time is crucial because, in case of a DoS attack that opens and closes connections at a fast enough speed, the model needs to keep up with each new flow generated; otherwise, the NIDS will run out of service. Another reason this classification time is important is that it can make a difference between enabling or not the use on the edge and lead to less expensive devices when a GPU is not required for running an NIDS.

Given these considerations, while LightGBM shows the best F1 scores, the Random Forest emerges as the best overall alternative, balancing accuracy and speed effectively.

* + 1. **Model Parameters – HIKARI-2021**

Table 5.4 - HIKARI 2021 parameters

|  |  |  |
| --- | --- | --- |
| model | parameter | value |
| cat | iterations | 10 |
| depth | 8 |
| learning\_rate | 0.6 |
| loss\_function | MultiClass |
| dt | max\_depth | 8 |
| ebm | default |  |
| lightgbm | objective | MultiClass |
| num\_leaves | 16 |
| n\_estimators | 5 |
| max\_depth | 6 |
| rf | n\_estimators | 5 |
| max\_depth | 10 |
| max\_features | None |
| bootstrap | False |
| xgb | n\_estimators | 3 |
| max\_depth | 8 |
| learning\_rate | 1 |
| objective | multi:softprob |

Table *5.4* demonstrates how the parameters for HIKARI-2021 lead to less complex models, except for EBM. While balanced datasets typically allow for simpler model structures, the extreme simplicity of these parameters is notable. This level of simplicity, achieving high performance with such basic configurations, raises questions about the complexity and quality of the HIKARI-2021 dataset. Our analysis will further explore these concerns using explainability algorithms, which will provide deeper insights into the models' decision-making processes and the dataset's underlying structure.

* + 1. **Training and Explanation Times – HIKARI-2021**

Table 5.5- HIKARI-2021 training times for 31,952 training samples



Table *5.5* Notable points:

1. Despite using a larger training set (31,952 samples) compared to NFS-2023-TE (6,087 samples), HIKARI-2021 generally shows lower training times.

2. This efficiency can be attributed to two main factors:

a) The balanced nature of the dataset after our under-sampling preprocessing step.

b) The inherent simplicity of the HIKARI-2021 dataset itself, which may lack the complexity typically found in real-world network intrusion scenarios.

3. EBM is the exception, with increased training time due to maintaining its complex structure. Unlike the other models, building a smaller EBM model through fine-tuning without sacrificing performance was impossible.

* + 1. **Model Performance – HIKARI-2021**

Table 5.6 - HIKARI-2021 F1 score and times



Table *5.6* Key insights:

1. All models perform similarly regarding F1 scores, suggesting the dataset might be easier to classify after balancing.
2. The Decision Tree is the fastest model while maintaining competitive performance.

The similarity in F1 scores across models is particularly interesting. For this balanced version of HIKARI-2021, the additional complexity of ensemble methods and boosting algorithms may not provide significant advantages over simpler models like the Decision Tree.

These results should be interpreted cautiously, considering the previously discussed limitations of HIKARI-2021, including issues with its creation process and test bed simplification. Our findings highlight a critical issue: the lack of sufficiently complex, real-world datasets for intrusion detection research.

Given the already good performance of simpler models like decision trees, we argue that training complex deep learning models on these datasets should be avoided. Such efforts are likely to be unproductive and potentially misleading. Instead, researchers should redirect their focus towards improving the datasets themselves.

Future work should concentrate on developing methods to create more realistic and challenging datasets. Our approach of using explainability techniques to uncover dataset flaws is one example of how researchers can contribute to this goal. By focusing on dataset quality and representativeness, we can pave the way for more meaningful advancements in intrusion detection systems that are truly applicable to real-world scenarios.

* 1. ***Model explanations***

In this section, we explore the use of SHAP (SHapley Additive exPlanations) to analyze the NFS-2023-TE and HIKARI-2021 datasets. Our primary goal is to leverage SHAP to uncover potential weaknesses in these datasets and assess their suitability for real-world applications. We focused our analysis on decision trees and CatBoost models, as they provided distinct and insightful explanations.

The decision to limit our detailed analysis to these two models was deliberate. Decision trees were chosen for their inherent interpretability, allowing us to examine the underlying tree structure. CatBoost, on the other hand, was selected because its feature importance often diverged significantly from that of the decision tree, providing a valuable contrasting perspective.

It is important to note that while we examined SHAP explanations for all classes in both datasets, we have chosen to present only the most significant and illustrative examples here. This approach aligns with our objective of identifying critical weaknesses in the datasets; even a single problematic explanation can raise valid concerns about the dataset's integrity and real-world applicability

Figure 5.1 - NFS-2023-TE - decision tree feature importance with shap of bot class

A graph with red and black text

Description automatically generated

Figure *5.1* shows the feature importance of a decision tree for the class bot of NFS-2023-TE. The model has misclassified only 1 sample out of 737 using only a small subset of the available features. The same pattern of using a few features applies to the other attacks. The only exception is benign traffic, which requires more features to be detected. The benign class assigns positive importance to more features because most of the split leads to either attack or benign traffic.

Figure 5.2 - HIKARI-2021 - decision tree feature importance with shap of bruteforce-XML class

Immagine che contiene testo, schermata, numero, linea

Descrizione generata automaticamente

Figure *5.2* illustrates the feature importance for the bruteforce-XML class in the HIKARI-2021 dataset, as determined by a decision tree model using SHAP values. The chart reveals a striking imbalance in feature importance, with 'fwd\_pkts\_payload.max' dominating the model's decision-making process.

Upon closer examination of the decision tree structure, we find that just the first two nodes of the tree are sufficient to achieve a remarkably low gini coefficient of 0.041 for this class. Specifically, if we follow the false path from the root node (which likely corresponds to 'fwd\_pkts\_payload.max' ≤ 737) and then proceed to the second node (likely 'fwd\_pkts\_payload.max' ≤ 761.5), we reach a point where the tree achieves this high level of classification accuracy. Using primarily these two decision points, the model correctly classifies 6,388 out of 6,526 samples.

While this demonstrates the model's effectiveness on this particular dataset, it raises important questions about the dataset's representation of real-world attack scenarios. The ability to achieve such high accuracy with just two decision points based on a single feature is unusual for complex network attacks. In real-world environments, attacks typically exhibit more varied characteristics that require more complex decision boundaries for accurate detection.

This finding underscores the importance of critically evaluating datasets used for intrusion detection research. While the model performs exceptionally well on this data, its reliance on such a simple decision boundary may limit its ability to detect more sophisticated or varied attacks in real-world applications. It highlights the need for datasets that capture a more diverse range of attack behaviors to train models that are more robust and applicable to real-world cybersecurity challenges.

Table 5.7 - fwd\_pkts\_payload.max quintiles

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **category** | **min** | **25%** | **50%** | **75%** | **max** |
| **Background** | 0 | 0 | 40 | 127 | 15741 |
| **Benign** | 0 | 0 | 36 | 426 | 3456 |
| **Bruteforce** | 0 | 357 | 373 | 425 | 786 |
| **Bruteforce-XML** | 0 | 746 | 747 | 748 | 925 |
| **Probing** | 517 | 517 | 517 | 517 | 517 |
| **XMRIGCC CryptoMiner** | 40 | 40 | 50 | 50 | 232 |

Table 5.7 presents the quintile distribution of the 'fwd\_pkts\_payload.max' feature for different categories in the HIKARI-2021 dataset. This feature represents the maximum payload size of forward packets in a network flow. The table provides valuable insights into why this feature is crucial for detecting bruteforce-XML attacks:

1. Bruteforce-XML Distribution: The bruteforce-XML category shows a very narrow distribution, with 50% of the samples having values between 746 and 748 bytes. This tight clustering is highly unusual for real-world network traffic.

2. Decision Tree Split Points: The decision tree's root node splits at 737 bytes, and the subsequent false branch splits at 761.5 bytes. These split points align perfectly with the bruteforce-XML distribution, explaining why this feature is so effective for classification.

3. Contrast with Other Categories: Other categories show much wider distributions. For instance, background traffic ranges from 0 to 15,741 bytes, and benign traffic from 0 to 3,456 bytes. This stark contrast makes the bruteforce-XML traffic stand out.

4. Unrealistic Pattern: In real-world scenarios, attack traffic rarely exhibits consistent payload sizes. The uniformity of the bruteforce-XML category suggests this might be an artifact of the dataset generation process rather than a true representation of attack behavior.

5. Model Vulnerability: A model trained on this dataset would be highly susceptible to evasion. An attacker could easily bypass detection by slightly altering their payload size to fall outside the narrow range identified for bruteforce-XML attacks.

This analysis highlights a significant limitation of the HIKARI-2021 dataset. The unrealistic distribution of the 'fwd\_pkts\_payload.max' feature for bruteforce-XML attacks could lead to developing intrusion detection systems that perform well on this dataset but fail in real-world applications. It underscores the importance of critically evaluating datasets for training security models and the need for more diverse and realistic network traffic data in IDS research.

Figure 5.3- HIKARI-2021 - decision tree feature importance with shap of XMRIGCC CryptoMinerA graph with red bars

Description automatically generated with medium confidence

Figure 5.4- HIKARI-2021 - feature importance with shap of probing attack of decision tree

A graph with red and black text

Description automatically generated

Table 5.8 - Down\_up\_ration mean and std

|  |  |  |
| --- | --- | --- |
| **category** | **mean** | **std** |
| **Background** | 0.810244 | 0.721923 |
| **Benign** | 2.015250 | 32.321667 |
| **Bruteforce** | 8.794107 | 89.440773 |
| **Bruteforce-XML** | 20.071672 | 128.065872 |
| **Probing** | 1.298040 | 0.119266 |
| **XMRIGCC CryptoMiner** | 0.000000 | 0.000000 |

Figure *5.3* shows the importance of the features of XMRIGCC CryptoMiner with the decision tree. Again, only a few selected features have been used; the most important is bwd\_header\_size\_min which for this attack is always zero then we have down\_up\_ratio.

Figure 5.4- HIKARI-2021 - feature importance with shap of probing attack of decision tree

A graph with red and black text

Description automatically generated

Table 5.8 shows that the crypto miner is the only one with always 0 for this feature, making it easy to understand why it is essential for this class. Down\_up\_ratio is also the most critical feature for probing *Figure 5.4*, where we can see that the mean value is around 1.3, with a low standard deviation compared to the other attacks. This is the second most important feature for classifying background, but in this case, we do not have any hypothesis as to why.

Figure 5.5 - NFS-2023-TE - catboost impact on the model output of DDoS with shap sorted by highest magnitude of impact

Immagine che contiene testo, schermata, numero, Carattere

Descrizione generata automaticamente

Before delving into the specific findings, it's important to understand how to interpret the SHAP beeswarm plot shown in Figure *5.5*. This visualization technique, known as a SHAP (SHapley Additive exPlanations) beeswarm plot, illustrates the impact of various features on the model's predictions.

SHAP beeswarm plots can be configured to show either the average impact or the maximum impact of features. The average impact relates to how a feature typically influences the model's decision when the feature remains within its usual range. In contrast, the maximum impact shows how much a feature can affect the model's decision when it reaches its extreme values (maximum or minimum). This distinction is crucial as it can reveal features that may not be impactful under normal circumstances but can significantly alter the model's outcome in rare cases.

In this analysis, we've chosen to display the maximum impact to highlight the most significant potential influence of each feature, including those that might be overlooked when considering only average impacts.

In this plot, each row represents a feature, with the features sorted by their maximum impact on the model's output. The most impactful features appear at the top of the plot. Each dot represents a sample from the dataset. The horizontal position of a dot shows the SHAP value - the impact of that feature for that sample on the model's prediction. Dots to the right increase the likelihood of the prediction, while those to the left decrease it. The color of each dot indicates the feature's value, with red representing high values and blue representing low values.

The spread of dots for each feature demonstrates the range of impacts that feature can have across different samples. Features with wider spreads tend to have more significant potential effects on the model's decisions, especially at their extreme values.

With this understanding of how to interpret the SHAP beeswarm plot and the significance of maximum impact analysis, we can now examine the specific patterns revealed by the SHAP analysis of the CatBoost algorithm on the NFS-2023-TE dataset.

Figure *5.5* illustrates the feature importance analysis of the CatBoost algorithm across various attack types in the NFS-2023-TE dataset. A striking pattern emerges: the 'bidirectional\_fin\_packets' feature consistently ranks as one of the most influential factors for several attack categories, including Bot, DDoS, DoS Slowhttptest, DoS Slowloris, Heartbleed, Infiltration, and Web Attack - XSS.

Table 5.9 - NFS-2023-TE bidirectional\_fin\_packets statistical analysis

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **mean** | **std** | **25%** | **50%** | **75%** |
| **BENIGN** | 0.306362 | 0.460982 | 0.0 | 0.0 | 1.0 |
| **Bot** | 1.000.000 | 0.000000 | 1.0 | 1.0 | 1.0 |
| **DDoS** | 0.999739 | 0.016162 | 1.0 | 1.0 | 1.0 |
| **DoS GoldenEye** | 0.935203 | 0.246183 | 1.0 | 1.0 | 1.0 |
| **DoS Hulk** | 0.999823 | 0.013288 | 1.0 | 1.0 | 1.0 |
| **DoS Slowhttptest** | 0.242679 | 0.428781 | 0.0 | 0.0 | 0.0 |
| **DoS slowloris** | 0.082435 | 0.275052 | 0.0 | 0.0 | 0.0 |
| **FTP-Patator** | 0.689690 | 0.462650 | 0.0 | 1.0 | 1.0 |
| **Heartbleed** | 0.090909 | 0.301511 | 0.0 | 0.0 | 0.0 |
| **Infiltration** | 0.071429 | 0.262265 | 0.0 | 0.0 | 0.0 |
| **PortScan** | 0.001956 | 0.044186 | 0.0 | 0.0 | 0.0 |
| **SSH-Patator** | 0.989597 | 0.101479 | 1.0 | 1.0 | 1.0 |
| **Web Attack - Brute Force** | 1.000.000 | 0.000000 | 1.0 | 1.0 | 1.0 |
| **Web Attack - Sql Injection** | 1.000.000 | 0.000000 | 1.0 | 1.0 | 1.0 |
| **Web Attack - XSS** | 1.000.000 | 0.000000 | 1.0 | 1.0 | 1.0 |

This feature, as *Table 5.9* show which counts the number of FIN packets in a bidirectional connection and shows distinct patterns across different attack types:

1. Binary behavior: We observe exactly 1 FIN packet for Bot and Web Attack- XSS in all instances. Similarly, DDoS attacks show 1 FIN packet in 99% of cases.

2. Low FIN packet counts: Other attack types (DoS Slowhttptest, DoS Slowloris, Heartbleed, and Infiltration) predominantly show 0 FIN packets, with this pattern occurring at the 85th percentile of their distributions.

Table 5.10 - NFS-2023-TE - bidirectional\_duration\_ms

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **mean** | **25%** | **50%** | **75%** | **max** |
| **BENIGN** | 8.455.942.641 | 0.00 | 23.0 | 226.00 | 119999.0 |
| **Bot** | 261.727.642 | 68.00 | 76.0 | 95.00 | 61003.0 |
| **DDoS** | 699.695.919 | 103.00 | 593.0 | 1180.00 | 2236.0 |
| **DoS GoldenEye** | 11.028.957.812 | 10022.00 | 11312.0 | 11793.00 | 106793.0 |
| **DoS Hulk** | 674.306.605 | 63.00 | 148.0 | 182.00 | 110889.0 |
| **DoS Slowhttptest** | 11.832.117.496 | 0.00 | 6.0 | 3004.00 | 119800.0 |
| **DoS slowloris** | 36.721.484.592 | 0.00 | 0.0 | 102650.00 | 105745.0 |
| **FTP-Patator** | 4.520.066.432 | 0.00 | 4099.0 | 8996.00 | 10780.0 |
| **Heartbleed** | 110.679.636.364 | 119259.50 | 119261.0 | 119297.50 | 119303.0 |
| **Infiltration** | 71.705.357.143 | 47004.25 | 79873.0 | 105616.25 | 119992.0 |
| **PortScan** | 2.512.117 | 0.00 | 0.0 | 0.00 | 11012.0 |
| **SSH-Patator** | 12.131.148.322 | 11634.00 | 12109.5 | 12868.50 | 19582.0 |
| **Web Attack - Brute Force** | 20.656.476.821 | 8801.50 | 9856.0 | 34065.00 | 35452.0 |
| **Web Attack - Sql Injection** | 5.023.083.333 | 5006.75 | 5009.5 | 5022.25 | 5087.0 |
| **Web Attack - XSS** | 46.164.407.407 | 6155.50 | 67004.0 | 68090.00 | 70204.0 |

To provide further context, we examined the connection durations for these attack types, as presented in Table 5.10. It is important to note that these durations are in milliseconds:

* Heartbleed and Infiltration have very long mean durations (110,680 ms and 71,705 ms respectively), with 75% of connections lasting over 119,260 ms and 105,616 ms. This supports the hypothesis that these connections often terminate due to timeouts rather than normal closure, as they last for nearly two minutes or more.
* DoS Slowhttptest and DoS Slowloris show widely varying durations. Slowhttptest has a mean of 11,832 ms, but 50% of connections last under 6 ms. Slowloris is even more extreme, with a mean of 36,721 ms, but 50% of connections lasting 0 ms. This high variability, with many connections lasting mere milliseconds, could explain the lack of consistent FIN packets.
* Bot attacks have relatively short durations (mean 262 ms), which aligns with their consistent use of FIN packets for closure. These brief connections suggest rapid, automated interactions.
* DDoS attacks show moderate durations (mean 700 ms), suggesting more prolonged but still relatively short connections.

This pattern raises important questions about the dataset's representation of real-world network behavior and the potential for creating robust intrusion detection systems. The consistent importance of this single feature across multiple attack types suggests it may be an artifact of the dataset generation process rather than a true indicator of attack behavior.

Future research should investigate whether this feature's prominence could lead to overfitting or vulnerabilities in real-world applications, and explore how it interacts with other important features in the classification process.

Our analysis revealed several key insights:

* 1. Feature Importance Imbalance: Both datasets showed a significant imbalance in feature importance. For instance, in HIKARI-2021, the 'fwd\_pkts\_payload.max' feature dominated the decision-making process for the bruteforce-XML class (Figure 5.2). This over-reliance on a single feature raises concerns about the model's robustness in real-world scenarios.
  2. Unrealistic Attack Signatures: The analysis revealed unrealistically consistent patterns for certain attack types. In HIKARI-2021, the bruteforce-XML attacks showed a very narrow distribution of the 'fwd\_pkts\_payload.max' feature (Table 5.7), which is unlikely in real-world attacks. Similarly, in NFS-2023-TE, the 'bidirectional\_fin\_packets' feature showed unexpected consistency across multiple attack types (Table 5.9).
  3. Simplistic Classification Boundaries: Some attack classes could be easily identified using just one or two features. For example, the bruteforce-XML class in HIKARI-2021 could be classified with 97.8% accuracy using just two decision points on a single feature. This simplicity is concerning for a dataset meant to represent complex network attacks.
  4. Potential Dataset Generation Artifacts: The consistent importance of certain features across multiple attack types, such as 'bidirectional\_fin\_packets' in NFS-2023-TE, suggests these might be artifacts of the dataset generation process rather than true indicators of attack behavior.
  5. Unrealistic Traffic Patterns: Analysis of connection durations (Table 5.10) in NFS-2023-TE revealed patterns that may not accurately represent real-world network behavior, particularly for attacks like Heartbleed and Infiltration with unusually long durations.
  6. Limited Feature Utilization: The models relied on a small subset of available features for many attack classes. This is evident in both datasets and across different model types (decision trees and CatBoost), suggesting a potential lack of complexity in the dataset's representation of attacks.
  7. Vulnerability to Evasion: The simplistic nature of some attack signatures, such as the XMRIGCC CryptoMiner in HIKARI-2021 being identifiable by specific values of just two features, suggests that models trained on these datasets could be easily evaded in real-world scenarios.

These findings highlight the limitations of both NFS-2023-TE and HIKARI-2021 for developing robust, real-world intrusion detection systems. While they represent improvements over previous datasets, they still fail to accurately represent the complexity and variability of real-world network environments and attack scenarios.

The use of SHAP in this analysis proved valuable for model interpretation and dataset validation, revealing specific features and decision boundaries that models rely on. This allows for critical assessment of whether these align with expert knowledge of network behavior and attack characteristics.

In conclusion, this analysis underscores the ongoing challenge of creating high-quality, realistic datasets for intrusion detection research. It emphasizes the need for continued refinement in dataset generation methodologies to capture better the complexity and diversity of real-world network traffic and attack patterns.

# **Conclusion**

In this work, we have critically analyzed various aspects of network intrusion detection systems (NIDS), focusing on datasets and methodologies used in current research. Our study presents several key findings and contributions:

1. Analysis of Hikari-2021 Dataset:

We conducted a thorough analysis of the Hikari-2021 dataset, identifying significant issues such as improper handling of TCP connection terminations and class imbalance. This highlights the need for meticulous dataset examination before model development.

2. Enhanced Methodology with SHAP:

A major contribution of our study is the application of SHAP (SHapley Additive exPlanations) for model validation. This method enhances transparency by explaining model decisions clearly, ensuring that selected features are relevant to attack detection.

3. Evaluation Metrics:

Our study emphasizes the importance of using comprehensive evaluation metrics beyond simple accuracy. Metrics like the F1 score are crucial for a more accurate assessment, especially in imbalanced datasets.

4. Dataset Issues and Limitations:

We highlighted the limitations of current datasets, noting that while we employed techniques like random stratified undersampling to address class imbalance in Hikari-2021 and NFS-2023, these measures are insufficient. The need for more robust and representative datasets remains critical.

5. gReproducibility and Transparency:

Addressing the lack of reproducibility in many studies, we ensured the release of our source code and the use of up-to-date datasets. This promotes transparency and allows for the validation and comparison of different models.

6. Transferability to Real-World Applications:

We recognized the challenge of ensuring that models trained on public datasets perform well in real-world scenarios. This ongoing problem highlights the necessity for future research to bridge the gap between academic studies and practical applications.

* 1. **Main Contributions**

The main contributions of our study are:

* In-Depth Analysis of the Hikari-2021 Dataset: Identifying critical issues and underscoring the importance of thorough dataset examination.
* Introduction of SHAP for Model Validation: Enhancing model transparency and explainability by providing deeper insights into decision-making processes.
* Comprehensive Methodology: Promoting the use of diverse evaluation metrics and addressing the limitations of current datasets, though acknowledging the need for further improvements.

In conclusion, our study calls on the NIDS research community to shift focus from developing new models on flawed datasets to improving dataset quality and representativeness. Our methodology provides a foundation for a standardized approach to NIDS research, emphasizing transparency, reproducibility, and practical applicability. By addressing these core issues, we can advance towards developing NIDS models that are both academically robust and practically effective in real-world cybersecurity contexts.

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# **Appendix A**

Source code available at: <https://github.com/ludotosk/tesi>

A picture containing text, screenshot, font, design

Description automatically generated