



Transferability and Explainability of Machine Learning Models for Network Intrusion Detection

Final Project Report

Author: Ahmed Bedair

Supervisor: Dr. Fabio Pierazzi

Student ID: K2105577

April 8, 2024

Abstract

Machine learning-based network intrusion detection systems (NIDS) can detect novel cyber threats by learning patterns from network traffic data. This dissertation investigates the transferability of learned patterns across datasets using random forests and support vector machines (SVMs).

It analyzes flow-based features to uncover characteristics distinguishing malicious and benign traffic, and employs explainable AI techniques to identify relevant features. The findings contribute to developing effective NIDS solutions by providing insights into the transferability of learned patterns, dataset biases, and explainability.

Originality Avowal

I verify that I am the sole author of this report, except where explicitly stated to the contrary.
I grant the right to King's College London to make paper and electronic copies of the submitted work for purposes of marking, plagiarism detection and archival, and to upload a copy of the work to Turnitin or another trusted plagiarism detection service. I confirm this report does not exceed 25,000 words.

Ahmed Bedair

April 8, 2024

Acknowledgements

Thank you to my supervisor, Dr. Fabio Pierazzi, for his guidance and support throughout the project. The supervision and support were very much appreciated and helped me stay on track and complete the project successfully. I would also like to thank my family and friends for their encouragement and support.

Contents

1	Introduction	3
2	Background	5
2.1	CTU13 and CICIDS2017 Datasets	6
2.2	Machine Learning Classifiers	9
2.3	Explainable AI Techniques	10
3	Relevant Work	12
3.1	Botnet Detection using CTU13 Dataset	12
3.2	Intrusion Detection using CICIDS2017 Dataset	13
3.3	Random Forest for Intrusion Detection	14
3.4	Support Vector Machines for Intrusion Detection	14
3.5	Explainable AI Techniques for Intrusion Detection	15
3.6	Challenges and Limitations	16
3.7	Summary and Positioning	17
4	Specification & Design	19
4.1	Experimental Setup	20
4.2	Classifier Configurations	22
4.3	Transferability Evaluation	23
4.4	Summary	24
5	Implementation	26
5.1	Experimental Setup	26
5.2	Package Implementation	29
6	Evaluation	34
7	Legal, Social, Ethical and Professional Issues	35
7.1	Legal Considerations	35
7.2	Ethical & Social Considerations	35
7.3	Professional Considerations	36
7.4	Societal Impact and Sustainability	37
7.5	British Computing Society Code of Conduct	38

8 Conclusion and Future Work	40
Bibliography	43

Chapter 1

Introduction

In an increasingly interconnected world, the security of computer networks is of paramount importance. However, the rapid evolution of cyber threats has made it challenging for traditional signature-based network intrusion detection systems (NIDS) to keep pace with novel and sophisticated attacks [17]. To address this issue, researchers have turned to machine learning approaches, which have the potential to detect previously unseen intrusions by learning patterns and anomalies from network traffic data [5].

The effectiveness of machine learning-based NIDS heavily relies on the quality and representativeness of the datasets used for training and evaluation [8]. Two widely used datasets in this domain are CTU13 [10], which contains real botnet traffic mixed with background traffic, and CICIDS2017 [21], a more recent dataset that includes a diverse range of modern attacks. However, the transferability and generalisability of machine learning models trained on one dataset to detect intrusions in another remain largely unexplored.

This dissertation aims to address this gap by investigating the efficacy of using machine learning algorithms trained on the CICIDS2017 dataset to detect botnet attacks in the CTU13 dataset. Specifically, two popular classifiers, Random Forest and Support Vector Machine (SVM), were trained on CICIDS2017 and evaluated their performance on CTU13. This approach allows us to assess the transferability of learned features and patterns across different datasets, simulating a real-world scenario where a model is trained on one dataset and deployed to detect intrusions in the wild.

To guide our experimental design and analysis, we draw upon the recommendations of Arp et al. [3] on the best practices for applying machine learning in security. Furthermore, we employ explainable AI techniques, such as SHAP (SHapley Additive exPlanations) [15], to gain insights into the decision-making process of our trained models. By identifying the most important features contributing to the detection of botnet traffic, we aim to uncover the key patterns and characteristics that distinguish malicious and benign network flows.

Additionally, we conduct a comparative analysis of the network flow features extracted from the CTU13 and CICIDS2017 datasets. By exploring the statistical properties and distributions of various features, such as flow duration, packet counts, and inter-arrival times, we seek to understand the inherent differences between actual and simulated network traffic. This analysis sheds light on the challenges and limitations of using synthetic datasets for training NIDS models and emphasises the importance of considering dataset biases in performance evaluation.

Including Random Forest and SVM classifiers in our study enables a more comprehensive assessment of model transferability and generalisability. By comparing their performance and interpreting their predictions using SHAP, we gain valuable insights into the robustness and adaptability of these algorithms in detecting botnet attacks across different datasets.

We organise the remainder of this dissertation as follows: Section 2 provides background information on the CTU13 and CICIDS2017 datasets, machine learning classifiers, and explainable AI techniques. Section 3 presents a literature review of relevant work in machine learning-based NIDS. Section 4 describes the specification and design of our experiments, while Section 5 details the implementation aspects. Section 6 presents the evaluation results and discusses the implications of our findings. Section 7 addresses the legal, social, ethical, and professional issues related to using machine learning in network intrusion detection. Finally, Section 8 concludes the dissertation and outlines future research directions.

Chapter 2

Background

Section 2.1 provides an overview of two widely used datasets in the field of network intrusion detection: the CTU13 dataset [10] and the CICIDS2017 dataset [21]. Researchers have extensively utilised these datasets to develop and evaluate machine learning-based NIDS. Understanding the datasets' characteristics, strengths, and limitations used to train machine learning models is essential for designing robust and effective intrusion detection systems.

Section 2.2 discusses two popular machine learning classifiers, Random Forest and Support Vector Machine, widely used in network intrusion detection systems. The strengths and limitations of these classifiers are highlighted, along with their performance on different datasets. Understanding the capabilities and trade-offs of the classifiers used in a machine learning NIDS is crucial for selecting appropriate models for intrusion detection.

Section 2.3 introduces explainable AI techniques, which aim to provide insights into the decision-making process of machine learning models. These techniques help us understand the factors that contribute to the predictions made by the models and offer interpretable explanations for their outputs. Understanding the importance of the features a model uses to predict benign or malicious network flows is essential for validating the reliability of machine learning models and gaining insights into their decision-making process.

2.1 CTU13 and CICIDS2017 Datasets

The availability of representative and labelled datasets is crucial for developing and evaluating machine learning-based network intrusion detection systems. Two widely used benchmark datasets in this domain are the CTU13 dataset [10] and the CICIDS2017 dataset [21].

Garcia et al. [10] introduced the CTU13 dataset, which contains real botnet traffic captured in a controlled environment. The dataset consists of 13 scenarios, each representing specific botnet behaviours such as port scanning, DDoS attacks, click fraud, and spam. The authors provide a detailed description of the dataset creation methodology, including the setup of the controlled environment, the use of actual botnet samples, and the labelling process based on the known behaviour of the captured botnets. They also present an evaluation of the dataset using various machine learning algorithms, demonstrating its utility for botnet detection research. The realistic nature of the CTU13 dataset and the variety of botnet scenarios it covers have made it a popular choice among researchers.

Table 2.1 shows the breakdown of classes in the CTU13 dataset.

Class	Benign	Botnet
Count	213,326	15,559

Table 2.1: CTU13 Dataset Class Breakdown

Sharafaldin et al. [21] created the CICIDS2017 dataset, a more recent and comprehensive dataset for evaluating network intrusion detection systems. The dataset contains many modern attacks, including DoS, DDoS, brute force, XSS, SQL injection, and infiltration. The authors describe the dataset generation process, which involved creating a controlled lab environment resembling a real-world network infrastructure. They used tools and scripts to generate realistic benign traffic and attack scenarios. The dataset also includes a combination of manually labelled and time-based labelled data. The authors evaluate the dataset using different machine learning algorithms and demonstrate its effectiveness in detecting various types of attacks.

Table 2.2 shows the breakdown of classes in the CICIDS2017 dataset.

Class	Count
Benign	908,528
Botnet	745
DDoS	51,234
DoS GoldenEye	4,189
DoS Hulk	91,856
DoS Slowhttptest	2,191
DoS slowloris	2,355
FTP-Patator	3,184
Heartbleed	6
Infiltration	18
PortScan	63,633
SSH-Patator	2,342
Web Attack Brute Force	601
Web Attack SQL Injection	9
Web Attack XSS	260

Table 2.2: CICIDS2017 Dataset Class Breakdown

Comparing the two datasets, it is evident that botnet attacks in the CTU13 dataset share similar characteristics with various attack types in the CICIDS2017 dataset, such as DDoS/DoS attacks, Web attacks, and Bot attacks. These similarities in attack structure and behaviour suggest that machine learning models trained on the CICIDS2017 dataset may be transferable to detecting botnet attacks in the CTU13 dataset.

Several studies have utilised these datasets to develop and evaluate network intrusion detection systems. Chowdhury et al. [6] proposed a graph-based approach for botnet detection using the CTU13 dataset. They constructed a graph representation of the communication patterns among botnet-infected hosts and applied graph analysis techniques to identify botnets. Their approach achieved high accuracy in detecting botnets and demonstrated the potential of leveraging graph-based features for botnet detection.

Pektaş and Acarman [19] applied deep learning techniques to the CTU13 dataset for botnet detection. They used a convolutional neural network (CNN) to learn discriminative features from raw network traffic data. Their proposed model achieved high detection accuracy and

showcased the effectiveness of deep learning in capturing complex patterns and behaviours associated with botnets.

Ustebay et al. [24] proposed an intrusion detection system based on a multi-layer perceptron (MLP) classifier using the CICIDS2017 dataset. They performed extensive preprocessing and feature selection to optimise the input data for the MLP classifier. Their approach achieved high detection accuracy for various attack types in the dataset, demonstrating the potential of neural network-based models for network intrusion detection.

Aksu and Aydin [1] conducted a comparative study of different machine learning algorithms for network intrusion detection using the CICIDS2017 dataset. They evaluated the performance of decision trees, random forests, and support vector machines. Their results showed that random forests outperformed other algorithms regarding accuracy and false-positive rates, highlighting the effectiveness of ensemble learning methods for intrusion detection.

While these studies demonstrate the utility of the CTU13 and CICIDS2017 datasets, it is crucial to acknowledge their limitations. Sommer and Paxson [22] discuss the challenges of using synthetic datasets for network intrusion detection. They argue that synthetic datasets may only partially capture the complexity and diversity of real-world network traffic and may need more crucial contextual information. They emphasise the need for more realistic and representative datasets considering intrusion detection systems' operational aspects and deployment challenges.

Lashkari and colleagues have presented a solution to the constraints surrounding network traffic dataset generation in their study [11]. Their framework utilises methods for producing authentic benign traffic and modelling user actions, resulting in diverse and comprehensive datasets. Additionally, they have introduced the CICFlowMeter tool, which facilitates the extraction of flow-based attributes from unprocessed network traffic data. This tool has become famous for feature extraction and analysis alongside the CICIDS2017 dataset.

However, Engelen et al. [8] identified limitations and issues in the CICFlowMeter tool that affect the quality of the extracted features in the CICIDS2017 dataset. They conducted an in-depth dataset analysis and discovered problems related to flow construction, feature extraction, and labelling. They proposed improvements to the CICFlowMeter tool and generated a revised version of the dataset to address these limitations, enhancing the reliability and utility of the dataset for intrusion detection research.

Sommer and Paxson [22] underscore the significance of utilising unbiased and representative datasets when training machine learning models in network intrusion detection. They draw attention to the obstacles posed by the ever-changing nature of network traffic and attack patterns, which can impact the models' long-term efficacy. Buczak and Guven [5] present a comprehensive survey of data mining and machine learning techniques for cyber security intrusion detection. They delve into the challenges and considerations of applying machine learning methods to network intrusion detection, such as selecting appropriate algorithms, feature engineering, and model evaluation.

2.2 Machine Learning Classifiers

Machine learning classifiers have been widely used in network intrusion detection systems to identify malicious activities and automatically distinguish them from benign traffic. Random Forest (RF) and Support Vector Machine (SVM) are popular classifiers with promising results in this domain.

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions [12]. It constructs many decision trees during the training phase and outputs the majority vote of the individual trees for classification tasks. Random Forest has advantages such as handling high-dimensional data, robustness to noise and outliers, and capturing complex interactions among features.

Farnaaz and Jabbar [9] proposed a Random Forest-based model for intrusion detection and evaluated its performance on the NSL-KDD dataset. They performed feature selection using the Chi-square test and trained the Random Forest classifier on the selected features. Their model achieved an accuracy of 99.67% and a low false positive rate of 0.06%, demonstrating Random Forest's effectiveness in detecting various types of network attacks.

Belouch et al. [4] applied Random Forest to the CICIDS2017 dataset for network intrusion detection. They compared the performance of Random Forest with other machine learning algorithms, including Decision Tree, Naive Bayes, and k-Nearest Neighbors. Their results showed that Random Forest outperformed other algorithms, achieving an accuracy of 99.98% and a false positive rate of 0.01%. They also analysed the importance of different features in the dataset and identified the most discriminative features for intrusion detection.

Support Vector Machine (SVM) is another widely used classifier in network intrusion detection.

SVM aims to find the optimal hyperplane that maximally separates different classes in a high-dimensional feature space [7]. It can handle both linear and non-linear classification tasks using kernel functions. SVM is known for its ability to generalise well, even with limited training data, making it suitable for network intrusion detection scenarios where labelled data may be scarce.

Kabir et al. [13] proposed an SVM-based intrusion detection system and evaluated its performance on the NSL-KDD dataset. They used a genetic algorithm for feature selection and optimised the SVM parameters using grid search. Their proposed system achieved an accuracy of 99.91% and a detection rate of 99.93%, showcasing SVM's effectiveness in detecting various types of network attacks.

Teng et al. [23] applied SVM with different kernel functions for intrusion detection on the CICIDS2017 dataset. They compared the performance of linear, polynomial, and radial basis function (RBF) kernels. Their results showed that the RBF kernel achieved the highest accuracy of 97.80% and a low false positive rate of 0.12%. They also highlighted the importance of selecting appropriate kernel functions and tuning the SVM parameters for optimal performance.

The choice of a machine learning classifier depends on various factors, such as the dataset's characteristics, the nature of the attacks, and the computational resources available. Buczak and Guven [5] provide a comprehensive survey of machine learning methods for cyber security intrusion detection. They discuss the strengths and limitations of different classifiers and emphasise the importance of selecting appropriate features, handling imbalanced data, and evaluating the performance of classifiers using relevant metrics.

Comparing the performance of different classifiers on multiple datasets provides valuable insights into their generalisation capabilities and transferability. Training classifiers on one dataset and testing them on another helps assess how well the learned patterns and features can be applied to detect intrusions in different network environments. This approach helps understand the robustness and adaptability of the classifiers across various scenarios.

2.3 Explainable AI Techniques

While machine learning classifiers have shown promising results in network intrusion detection, their decision-making process is often considered a 'black box', lacking transparency and interpretability. Explainable AI techniques aim to bridge this gap by providing insights into the

reasoning behind the predictions made by these models.

SHAP (SHapley Additive exPlanations) [15] is a popular technique for model interpretation. It is based on the concept of Shapley values from cooperative game theory and provides a unified framework for explaining the output of any machine learning model. SHAP assigns importance scores to each feature, indicating their contribution to the model's prediction for a specific instance. By applying SHAP to trained classifiers, researchers can identify the key features that contribute to detecting particular types of attacks.

Warnecke et al. [25] evaluated various explanation methods for deep learning-based intrusion detection systems, including SHAP. They applied SHAP to a convolutional neural network (CNN) trained on the NSL-KDD dataset and analysed the importance of different features in the model's predictions. They demonstrated that SHAP can provide meaningful insights into the decision-making process of deep learning models and help identify the most influential features for detecting specific attack types.

Amarasinghe et al. [2] employed SHAP to interpret the predictions of a deep learning-based NIDS. They trained a deep neural network on the NSL-KDD dataset and applied SHAP to explain the model's predictions. They analysed the SHAP values to understand the impact of different features on the model's decisions and identified the most discriminative features for detecting specific types of attacks. Their study highlights the potential of SHAP in providing interpretable explanations for deep learning-based NIDS.

Mane and Rao [16] used SHAP to explain the predictions of a random forest classifier for network intrusion detection. They trained the classifier on the NSL-KDD dataset and applied SHAP to interpret the model's predictions. They visualised the SHAP values to understand the contribution of each feature towards the model's output and identified the most critical features for detecting various types of network attacks. Their study demonstrates the effectiveness of SHAP in providing interpretable explanations for ensemble learning methods like random forests.

The insights gained from explainable AI techniques can help validate the reliability of the trained models, identify potential biases or limitations in the datasets, and guide future improvements in feature engineering and model development. Moreover, these insights can be valuable for network security analysts and practitioners in understanding the key factors contributing to detecting specific attacks and developing more targeted defence strategies.

Chapter 3

Relevant Work

This chapter comprehensively reviews related work in machine learning-based network intrusion detection. It covers state-of-the-art approaches for botnet detection using the CTU13 dataset, intrusion detection using the CICIDS2017 dataset, and the application of Random Forest and Support Vector Machines for intrusion detection tasks. Furthermore, it explores the use of explainable AI techniques, such as SHAP, to provide insights into the decision-making process of machine learning models in the context of intrusion detection. The chapter also discusses the challenges and limitations associated with using synthetic datasets and the importance of considering dataset biases and the dynamic nature of network traffic when developing and evaluating intrusion detection systems.

3.1 Botnet Detection using CTU13 Dataset

Several studies have utilized the CTU13 dataset for developing and evaluating botnet detection systems. Chowdhury et al. [6] proposed a graph-based approach for botnet detection using the CTU13 dataset. They constructed a graph representation of the communication patterns among botnet-infected hosts and applied graph analysis techniques to identify botnets. The authors extracted features such as in-degree, out-degree, and betweenness centrality from the graph and used them to train a Random Forest classifier. Their approach achieved an accuracy of 99.86% in detecting botnets, demonstrating the potential of leveraging graph-based features for botnet detection. In contrast, this dissertation investigates the transferability of models trained on the CICIDS2017 dataset to detect botnet attacks in the CTU13 dataset, exploring

the generalization capabilities of machine learning classifiers across different datasets.

Pektaş and Acarman [19] applied deep learning techniques to the CTU13 dataset for botnet detection. They used a convolutional neural network (CNN) to learn discriminative features from raw network traffic data. The authors converted the traffic data of the CTU13 dataset into grayscale images through preprocessing and then fed them as input to the CNN. The proposed model achieved an accuracy of 99.99% and a false positive rate of 0.01% in detecting botnet traffic, showcasing the effectiveness of deep learning in capturing complex patterns and behaviours associated with botnets. While deep learning approaches have shown promising results, this dissertation explores the potential of traditional machine learning classifiers, such as Random Forest and Support Vector Machines, in detecting botnet attacks and investigates their transferability across datasets.

3.2 Intrusion Detection using CICIDS2017 Dataset

Many researchers have widely used the CICIDS2017 dataset to evaluate intrusion detection systems. Ustebay et al. [24] proposed an intrusion detection system based on a multi-layer perceptron (MLP) classifier using the CICIDS2017 dataset. They performed extensive preprocessing on the dataset, including handling missing values, encoding categorical features, and scaling numerical features. The authors also applied recursive feature elimination with random forest to select the most relevant features for intrusion detection. Their MLP-based approach achieved an accuracy of 97.29% and an F1-score of 97.30%, demonstrating the potential of neural network-based models for network intrusion detection. In this dissertation, we leverage the CICIDS2017 dataset to train machine learning classifiers and investigate their transferability to detect botnet attacks in the CTU13 dataset, focusing on the generalization capabilities of the learned patterns and features.

Aksu and Aydin [1] conducted a comparative study of different machine learning algorithms for network intrusion detection using the CICIDS2017 dataset. They evaluated the performance of decision trees, random forests, and support vector machines. The authors preprocessed the dataset by removing redundant records, handling missing values, and applying normalization techniques. They also performed feature selection using information gain and correlation-based methods. The experimental results showed that random forests outperformed other algorithms, achieving an accuracy of 99.77% and a false positive rate of 0.04%, highlighting the effectiveness of ensemble learning methods for intrusion detection. This dissertation takes

inspiration from their findings and employs Random Forest as one of the classifiers to investigate its transferability across datasets.

3.3 Random Forest for Intrusion Detection

Farnaaz and Jabbar [9] utilized Random Forest for intrusion detection tasks and presented a model based on it. They evaluated the model's performance on the NSL-KDD dataset. They performed feature selection using the Chi-square test to identify the most relevant features for intrusion detection, then proceeded to train the Random Forest classifier using the selected features. The proposed model achieved an accuracy of 99.67% and a false positive rate of 0.06%, demonstrating Random Forest's effectiveness in detecting various types of network attacks. While their work focused on a single dataset, this dissertation explores the transferability of Random Forest classifiers trained on the CICIDS2017 dataset to detect botnet attacks in the CTU13 dataset, investigating the generalization capabilities of the learned patterns across different network environments.

Belouch et al. [4] applied Random Forest to the CICIDS2017 dataset for network intrusion detection. They compared the performance of Random Forest with other machine learning algorithms, including Decision Tree, Naive Bayes, and k-Nearest Neighbors. The authors pre-processed the dataset by removing redundant records and handling missing values. They also analyzed the importance of different features in the dataset using the Random Forest feature importance measure. The experimental results showed that Random Forest outperformed other algorithms, achieving an accuracy of 99.98% and a false positive rate of 0.01%, further validating the effectiveness of Random Forest for intrusion detection. This dissertation builds upon their findings by employing Random Forest as one of the classifiers. It investigates its transferability to detect botnet attacks in a different dataset, exploring the robustness and adaptability of the learned patterns.

3.4 Support Vector Machines for Intrusion Detection

Intrusion detection tasks have extensively utilized Support Vector Machines (SVM). Kabir et al. [13] proposed an SVM-based intrusion detection system and evaluated its performance on the NSL-KDD dataset. They used a genetic algorithm for feature selection to identify the most discriminative features for intrusion detection. The authors also optimized the SVM parameters

using grid search to improve the model’s performance. The proposed system achieved an accuracy of 99.91% and a detection rate of 99.93%, showcasing SVM’s effectiveness in detecting various types of network attacks. In contrast to their work, this dissertation focuses on the transferability of SVM classifiers trained on the CICIDS2017 dataset to detect botnet attacks in the CTU13 dataset, exploring the generalization capabilities of the learned patterns across different datasets.

Teng et al. [23] applied SVM with different kernel functions for intrusion detection on the CICIDS2017 dataset. They compared the performance of linear, polynomial, and radial basis function (RBF) kernels. The authors preprocessed the dataset by removing redundant records and scaling the features. They also applied principal component analysis (PCA) for dimensionality reduction. The experimental results showed that the RBF kernel achieved the highest accuracy of 97.80% and a low false positive rate of 0.12%, highlighting the importance of selecting appropriate kernel functions and tuning the SVM parameters for optimal performance. This dissertation takes inspiration from their findings and employs SVM as one of the classifiers to investigate its transferability in detecting botnet attacks across different datasets, exploring the robustness and adaptability of the learned patterns.

3.5 Explainable AI Techniques for Intrusion Detection

Explainable AI techniques have gained attention in intrusion detection to provide insights into the decision-making process of machine learning models. Warnecke et al. [25] evaluated various explanation methods for deep learning-based intrusion detection systems, including SHAP. They applied SHAP to a convolutional neural network (CNN) trained on the NSL-KDD dataset and analyzed the importance of different features in the model’s predictions. The authors demonstrated that SHAP can provide meaningful insights into the decision-making process of deep learning models and help identify the most influential features for detecting specific attack types. This dissertation takes inspiration from their approach and employs SHAP to interpret the predictions of Random Forest and SVM classifiers trained on the CICIDS2017 dataset, providing insights into the transferability of the learned patterns and the most relevant features for detecting botnet attacks in the CTU13 dataset.

Amarasinghe et al. [2] employed SHAP to interpret the predictions of a deep learning-based network intrusion detection system. They trained a deep neural network on the NSL-KDD dataset and applied SHAP to explain the model’s predictions. The authors analyzed the SHAP

values to understand the impact of different features on the model’s decisions and identified the most discriminative features for detecting specific types of attacks. Their study highlights the potential of SHAP in providing interpretable explanations for deep learning-based intrusion detection systems. In this dissertation, we leverage SHAP to interpret the predictions of traditional machine learning classifiers, such as Random Forest and SVM, and investigate the transferability of the learned patterns and the most relevant features for detecting botnet attacks across different datasets.

Mane and Rao [16] used SHAP to explain the predictions of a random forest classifier for network intrusion detection. They trained the classifier on the NSL-KDD dataset and applied SHAP to interpret the model’s predictions. The authors visualized the SHAP values to understand the contribution of each feature towards the model’s output and identified the most critical features for detecting various types of network attacks. Their study demonstrates the effectiveness of SHAP in providing interpretable explanations for ensemble learning methods like random forests. This dissertation builds upon their findings by employing SHAP to interpret the predictions of Random Forest and SVM classifiers trained on the CICIDS2017 dataset. It investigates the transferability of the learned patterns and the most relevant features for detecting botnet attacks in the CTU13 dataset.

3.6 Challenges and Limitations

Intrusion detection system developers and evaluators frequently employ the CTU13 and CICIDS2017 datasets. Nonetheless, it is necessary to recognize their limitations. Sommer and Paxson [22] have addressed the challenges of utilizing synthetic datasets for network intrusion detection. They contend that these datasets may only partially capture the intricacy and variety of network traffic and require additional contextual information. Furthermore, the authors stress the necessity of more authentic and comprehensive datasets that consider the operational aspects and deployment hurdles of intrusion detection systems. This dissertation acknowledges these limitations and emphasizes the importance of considering dataset biases and the representativeness of training data when developing and evaluating intrusion detection systems.

Furthermore, Sommer and Paxson [22] highlight the importance of using representative and unbiased datasets for training machine learning models in network intrusion detection. They discuss the challenges posed by the dynamic nature of network traffic and the constant evolution of attack patterns, which can impact the long-term performance of the trained models.

Buczak and Guven [5] provide a comprehensive survey of machine learning and data mining methods for cyber security intrusion detection. They discuss the considerations and challenges in applying machine learning techniques to network intrusion detection, including selecting appropriate algorithms, feature engineering, and model evaluation. This dissertation considers these challenges and aims to address them by investigating the transferability of machine learning models across different datasets and employing explainable AI techniques to gain insights into the decision-making process.

3.7 Summary and Positioning

This chapter reviews relevant work in machine learning-based network intrusion detection, focusing on botnet detection using the CTU13 dataset, intrusion detection using the CICIDS2017 dataset, and the application of Random Forests and Support Vector Machines for intrusion detection tasks. While previous studies have demonstrated the effectiveness of various machine learning algorithms in detecting network attacks, this dissertation explores a novel aspect by investigating machine learning models' transferability and generalization capabilities across different datasets.

This dissertation takes inspiration from existing approaches that have utilized Random Forest and Support Vector Machines for intrusion detection and applies these classifiers to the CICIDS2017 dataset. However, this work goes beyond previous studies by evaluating the performance of these classifiers in detecting botnet attacks in the CTU13 dataset, which represents a different network environment. This dissertation aims to assess the robustness and adaptability of the learned patterns and features across datasets, simulating a real-world scenario where a model is trained on one dataset and deployed to detect intrusions in the wild.

Furthermore, while the use of explainable AI techniques, such as SHAP, has been explored in previous studies for interpreting the predictions of intrusion detection models, this dissertation employs SHAP in a novel context. Specifically, it leverages SHAP to provide insights into the transferability of learned patterns and the most relevant features for detecting botnet attacks when applying classifiers trained on the CICIDS2017 dataset to the CTU13 dataset. This aspect of the research distinguishes it from previous studies, as it focuses on understanding the transferability of the learned patterns and the key characteristics that distinguish malicious and benign traffic across different datasets.

In summary, this dissertation builds upon existing research by investigating machine learning models' transferability and generalization capabilities for network intrusion detection, emphasizing the importance of dataset representativeness and biases. By employing Random Forest and Support Vector Machines classifiers and leveraging explainable AI techniques in the context of cross-dataset transferability, this work aims to provide valuable insights into the robustness and adaptability of these algorithms in detecting botnet attacks across different datasets, contributing to the development of more effective and practical intrusion detection solutions.

Chapter 4

Specification & Design

This chapter outlines the experiments conducted in this dissertation, focusing on three classifiers: the Dummy Classifier, the Random Forest Classifier, and the Support Vector Machine Classifier. The experimental setup has been designed based on a thorough literature review to address the following research questions:

- RQ1** How well do machine learning models trained on one dataset transfer and generalise to another dataset in the context of network intrusion detection?
- RQ2** What is the impact of dataset biases and representativeness on the performance of machine learning-based intrusion detection systems?
- RQ3** How can explainable AI techniques, such as SHAP, provide insights into the transferability of learned patterns and the most relevant features for detecting specific types of attacks across different datasets?

The CTU13 and CICIDS2017 datasets are chosen for this dissertation as they contain specific types of attacks and possess distinct properties that make them suitable for addressing the research questions. CTU13 consists of real botnet traffic captured in a controlled environment [10], while CICIDS2017 is a more recent and comprehensive dataset designed for evaluating network intrusion detection systems, containing a wide range of modern attacks [21]. By training models on CICIDS2017 and testing them on CTU13, this dissertation aims to assess the transferability of learned patterns and features from one dataset to another, addressing RQ1.

The scripts 5.2.2 and 5.2.1 are utilised during pre-processing to ensure uniformity and coherence across all datasets. These scripts facilitate mapping dataset features to a standardised naming convention and removing features that only appear in one dataset (which would not be transferrable between datasets), promoting equitable comparisons and analysis. This approach effectively addresses RQ2 by mitigating the impact of dataset biases and representativeness.

This dissertation comprehensively analyses network intrusion detection classifiers, utilising a range of evaluation metrics, including accuracy, recall, precision, the confusion matrix, and F1 score. Additionally, the SHAP library interprets the classifiers' predictions, offering valuable insights into their decision-making process. An essential aspect of this dissertation is the exploration of RQ3, where we utilise explainable AI techniques to uncover the transferability of learned patterns and identify critical features for detecting specific types of attacks across multiple datasets.

A common practice in machine learning is to split data into training and testing sets using a 60/40 ratio. This approach ensures a fair data distribution between the two sets, which helps prevent overfitting and promotes unbiased testing. This partitioning ratio has been widely accepted in the field as it balances training and assessing models, as noted in a research survey by Buczak et al. [5].

Alternative designs and dataset selections were considered, such as using neural network-based classifiers (e.g., MLP and CNN) and other datasets. However, the focus on interpretability using SHAP and the comparative study by Belouch et al. [4] influenced the decision to use Random Forest and SVM classifiers. The combination of CICIDS2017 and CTU13 datasets aligns with the research objectives of assessing the effectiveness of machine learning classifiers in detecting botnet attacks and understanding the challenges and limitations of transferring learned patterns across datasets.

4.1 Experimental Setup

The experimental setup consists of three classifiers: a Dummy Classifier, a Random Forest Classifier, and a Support Vector Machine Classifier. Each classifier is trained on the CICIDS2017 dataset and tested on both the CICIDS2017 and CTU13 datasets to assess its transferability and generalisation capabilities.

4.1.1 Data Pre-processing

During the pre-processing stage, the datasets undergo relabeling using the scripts 5.2.2 and 5.2.1 to ensure consistency and compatibility. Subsequently, the CICIDS2017 dataset is processed to generate binary and multi-class classification tasks. In contrast, we only process the CTU13 dataset to generate binary classification tasks, aiming to detect botnet attacks and benign traffic because it only includes botnet attacks, whereas CICIDS2017 contains various types of attacks.

4.1.2 Training and Testing Split

We partitioned the datasets into training and testing sets to ensure precise results with a 60/40 ratio. Our team trained the classifiers using the training set from the CICIDS2017 dataset and subsequently tested them on both the testing set of the same dataset and the full CTU13 dataset. This approach allows us to evaluate the classifiers' effectiveness on the dataset we trained them on and their performance on a separate dataset.

4.1.3 Evaluation Metrics

Several metrics evaluate the classifiers' performance, including confusion matrix, accuracy, precision, recall, and F1 score. These metrics comprehensively assess the classifiers' effectiveness in detecting network intrusions and their ability to transfer learned patterns across datasets.

4.1.4 Explainable AI

The SHAP library is utilised to interpret the predictions made by the trained classifiers and offer valuable insights into their decision-making process. We compute SHAP values for the Random Forest and Support Vector Machine classifiers to pinpoint the most significant features that aid in detecting particular types of attacks. This aspect of explainability is critical in comprehending the transferability of learned patterns and the essential attributes that differentiate between malicious and benign traffic, even across diverse datasets.

4.2 Classifier Configurations

4.2.1 Dummy Classifier

Purpose: The Dummy Classifier serves as a baseline for evaluating the performance of the more advanced classifiers. It randomly assigns labels to the data, providing a reference point for comparison.

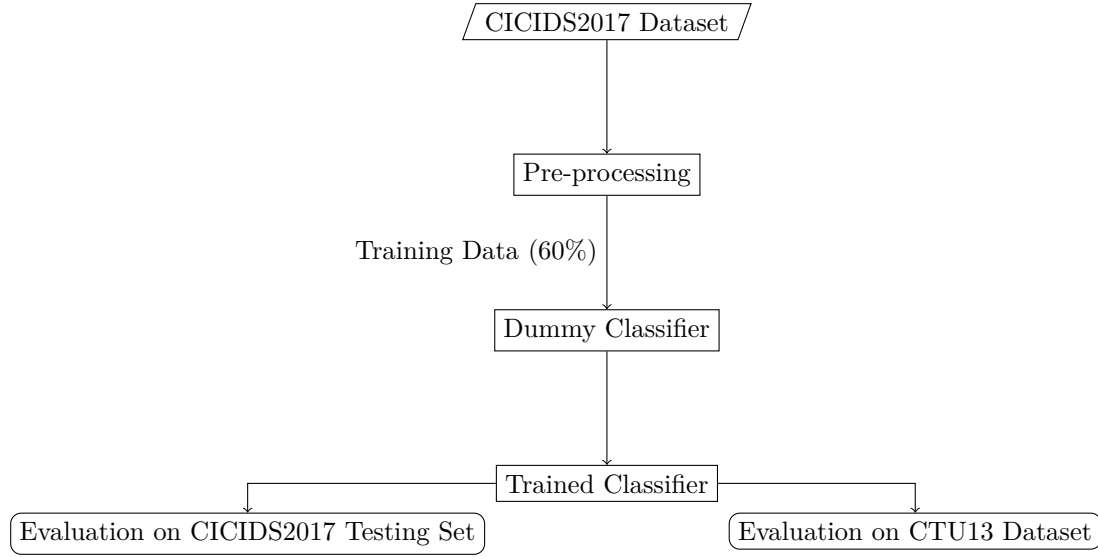


Figure 4.1: Dummy Classifier Configuration

4.2.2 Random Forest and SVM Classifiers

Purpose: The Random Forest and Support Vector Machine (SVM) classifiers are employed to evaluate the performance of more advanced machine learning models in detecting network intrusions. These classifiers are trained on the CICIDS2017 dataset and tested on both the CICIDS2017 testing set and the CTU13 dataset to assess their transferability and generalisation capabilities.

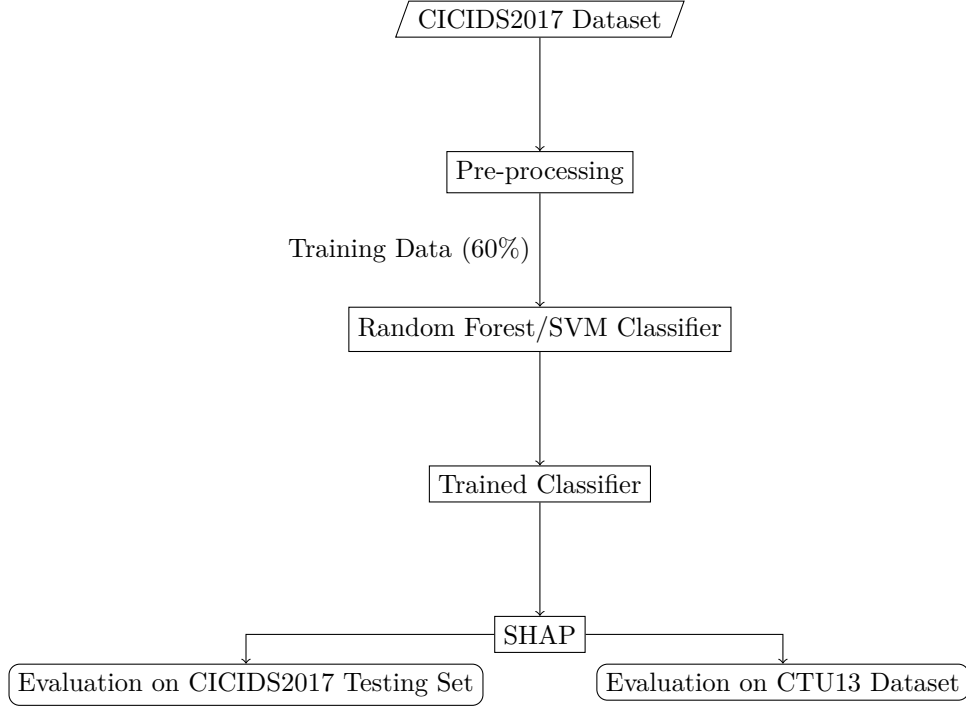


Figure 4.2: Random Forest Classifier Configuration

4.3 Transferability Evaluation

To ensure the applicability of our findings, we took great care in constructing the experimental setup for our dissertation. Our goal was to assess the classifiers' ability to apply the learned patterns from the CICIDS2017 dataset to the CTU13 dataset. We recognise the significance of transferability and thus designed the setup to test the classifiers' capability to transfer their learned patterns. During the training process, the classifiers were trained on the CICIDS2017 dataset and assessed on its testing set and the entire CTU13 dataset.

In order to assess the transferability of the classifiers, we consider the following performance metrics:

- Accuracy: The overall correctness of the classifier's predictions on the target dataset.
- Precision: The proportion of true positive predictions among all positive predictions.
- Recall: The proportion of true positive predictions among all real positive instances.
- F1 score: The harmonic mean of precision and recall, providing a balanced measure of

the classifier’s performance.

Calculating these metrics for each classifier on both the CICIDS2017 testing set and the CTU13 dataset enables evaluation of the transferability of the learned patterns. A classifier that maintains high-performance metrics on both datasets demonstrates good transferability, whereas a significant drop in performance on the CTU13 dataset indicates limited transferability.

Furthermore, the SHAP values generated through the explainable AI analysis provide valuable insights into the essential attributes that facilitate the identification of distinct attack types across a range of datasets. By carefully examining the consistency of the most significant features across these datasets, we can assess the applicability of the acquired patterns. The SHAP values obtained through the explainable AI analysis also offer crucial information on the features that contribute the most to detecting particular attack types across various datasets. By thoroughly examining the top-ranked features’ consistency across datasets, we can further evaluate the transferability of the learned patterns.

4.4 Summary

This chapter presents the specification and design of the experiments conducted in this dissertation, focusing on three classifiers: a Dummy Classifier, a Random Forest Classifier, and a Support Vector Machine Classifier. The experimental setup addresses three key research questions related to the transferability and generalisation of machine learning models, the impact of dataset biases, and the insights provided by explainable AI techniques in the context of network intrusion detection.

We chose the CTU13 and CICIDS2017 datasets for their distinct properties and the presence of specific types of attacks. The data pre-processing step involves relabeling the datasets to ensure consistency and compatibility, while the training and testing split follows a 60/40 ratio. The classifiers are trained on the CICIDS2017 dataset and tested on both the CICIDS2017 testing set and the entire CTU13 dataset to evaluate their transferability.

We assess the classifiers’ performance using various evaluation metrics, including accuracy, precision, recall, and F1 score. The SHAP library is employed to interpret the predictions of the trained classifiers and identify the most relevant features contributing to the detection of specific types of attacks across different datasets.

The evaluation of transferability is of immense importance to this dissertation. We utilise quality metrics and SHAP values to assess the classifiers' proficiency in transferring learned patterns from CICIDS2017 to CTU13. By analysing the consistency of the top-ranking features and comparing the classifiers' performance on both datasets, we can gauge the transferability of the learned patterns.

Chapter 5

Implementation

This chapter provides a comprehensive overview of the experiments conducted in this dissertation, detailing the experimental setup, dataset usage, and the design of each experiment. We also explore the implementation of key package modules, accompanied by relevant code excerpts highlighting essential functionality.

5.1 Experimental Setup

The experiments in this dissertation involve training and evaluating three classifiers: a Dummy Classifier, a Random Forest Classifier, and a Support Vector Machine (SVM) Classifier. Each classifier is trained on the CICIDS2017 dataset [21] and tested on both the CICIDS2017 and CTU13 [10] datasets to assess transferability and generalization capabilities.

The choice of Random Forest and SVM classifiers is justified by their proven effectiveness in handling large, high-dimensional datasets and unbalanced class distributions [9, 23], which are common in network traffic classification. We employ the SHAP library [15] for explainability due to its ability to provide insights into the decision-making process of machine learning models and identify important features.

5.1.1 Data Pre-processing

Proper data preprocessing is crucial for ensuring the effectiveness of the trained classifiers. The relabelling scripts, `relabelCICIDS2017.py` (Section 5.2.2) and `relabelCTU13.py` (Sec-

tion 5.2.1), standardize feature names and class labels across the datasets. This process involves mapping dataset features to a consistent naming convention, removing features unique to one dataset to avoid overfitting, and ensuring class labels are compatible. For example, the CTU13 dataset’s binary labels ‘0’ and ‘1’ are converted to ‘Benign’ and ‘Botnet’ to match the CICIDS2017 labelling scheme.

During the preprocessing stage, several data quality issues and inconsistencies were encountered, such as missing values and differing feature names across datasets. We address these issues through careful data cleaning, imputation, and feature mapping techniques to ensure the datasets’ compatibility and integrity.

5.1.2 Experiment 1: Dummy Classifier

The Dummy Classifier from the scikit-learn library [18] serves as a baseline for evaluating the performance of the more advanced classifiers. It predicts the most frequent class in the training data. Three Dummy Classifiers are trained: one on the CTU13 dataset for binary classification and two on the CICIDS2017 dataset for binary and multiclass classification. The Dummy Classifiers use the same features as the Random Forest and SVM classifiers, and their performance metrics (accuracy, precision, recall, and F1 score) provide a baseline for comparison.

5.1.3 Experiment 2: Random Forest Classifier

Random Forest, an ensemble learning method constructing multiple decision trees [12], is well-suited for handling large, high-dimensional datasets and unbalanced class distributions [9], which are common in network traffic classification. The CTU13 and CICIDS2017 datasets exhibit such class imbalances (Tables 2.1 and 2.2).

Three Random Forest Classifiers are trained (`trainRandomForest.ipynb`, Section 5.2.4): one on the CTU13 dataset, and two on the CICIDS2017 dataset for binary and multiclass classification. The classifiers are evaluated on their respective datasets and then tested on the other dataset to assess transferability. The SHapley Additive exPlanations (SHAP) library [15] is employed to explain the classifiers’ predictions and identify the essential features.

5.1.4 Experiment 3: Support Vector Machine Classifier

Support Vector Machines (SVMs) effectively handle large, high-dimensional, non-linear data [7, 20]. They have been successfully applied to network intrusion detection tasks [14, 23].

The experimental setup for the SVM Classifiers (`trainSVM.ipynb`, Section 5.2.5) mirrors that of the Random Forest Classifiers: we train three SVMs on the CTU13 and CICIDS2017 datasets, evaluated on their respective datasets, and tested on the other dataset. SHAP is used to interpret the SVM predictions and identify important features.

5.1.5 Testing and Evaluation

A comprehensive testing and evaluation strategy is employed to ensure the robustness and reliability of the results. We assess the performance of the classifiers using various metrics, including accuracy, precision, recall, and F1 score. We calculate these metrics for each classifier on their respective test sets and when evaluated on the other dataset for transferability analysis.

5.1.6 Novelty and Originality

The novelty and originality of this research lie in the combination of the chosen datasets (CTU13 and CICIDS2017), classifiers (Random Forest and SVM), and the use of SHAP for explainability. This dissertation provides a unique perspective on network intrusion detection by investigating the transferability and generalization of machine learning models across different datasets.

The application of SHAP to interpret the predictions of the trained classifiers and identify the most relevant features for detecting specific types of attacks across datasets is a novel approach. This aspect of the research contributes to a deeper understanding of the transferability of learned patterns and the key characteristics distinguishing malicious and benign traffic.

5.1.7 Strengths and Limitations

The chosen methodology has several strengths. Random Forest and SVM classifiers are well-suited for handling the imbalanced and high-dimensional nature of the CTU13 and CICIDS2017 datasets. These classifiers have demonstrated their effectiveness in network intrusion detection tasks [9, 23].

However, there are also limitations to consider. The potential impact of dataset biases and

the training data’s representativeness on the models’ transferability is a concern. The computational complexity of the SHAP explanations may also pose challenges when dealing with large-scale datasets.

5.2 Package Implementation

5.2.1 relabelCTU13.py

Algorithm 1 Relabeling CTU13 Dataset

Require: Raw CTU13 dataset

Ensure: Preprocessed CTU13 dataset with consistent feature names and class labels

```

1: Import necessary libraries
2: Load the raw CTU13 dataset
3: Define a dictionary for mapping feature names
4: for each feature in the CTU13 dataset do
5:     if the feature name exists in the mapping dictionary then
6:         Rename the feature using the corresponding value from the dictionary
7:     end if
8: end for
9: Replace the class labels '0' and '1' with 'Benign' and 'Botnet', respectively
10: Define the desired order of features based on the CICIDS2017 dataset
11: Reorder the features in the CTU13 dataset according to the desired order
12: Save the preprocessed CTU13 dataset

```

Like `relabelCICIDS2017.py` (Section 5.2.2), this script preprocesses the CTU13 dataset by renaming features, relabeling traffic classes, and reordering features to match the CICIDS2017 dataset’s structure.

5.2.2 relabelCICIDS2017.py

Algorithm 2 Relabeling CICIDS2017 Dataset

Require: Raw CICIDS2017 and preprocessed CTU13 datasets

Ensure: Preprocessed CICIDS2017 dataset with consistent feature names and class labels

```
1: Import necessary libraries
2: Load the raw CICIDS2017 dataset
3: Load the preprocessed CTU13 dataset
4: Define a dictionary for mapping feature names from CTU13 to CICIDS2017
5: for each feature in the CTU13 dataset do
6:     if the feature name exists in the CICIDS2017 dataset then
7:         Rename the feature in the CTU13 dataset using the corresponding value from the
           mapping dictionary
8:     end if
9: end for
10: Change the label of benign traffic from '0' to 'Benign'
11: Change the label of attack traffic from '1' to 'Botnet'
12: Get the list of columns in the preprocessed CTU13 dataset
13: Get the common columns between the preprocessed CTU13 and raw CICIDS2017 datasets
14: Reorder and select the common columns in the CICIDS2017 dataset
15: Save the preprocessed CICIDS2017 dataset
```

This script preprocesses the CICIDS2017 dataset by mapping feature names to match the CTU13 dataset, relabeling traffic classes, identifying common features, and reordering the CICIDS2017 features to align with the CTU13 dataset.

5.2.3 trainDummyClassifier.ipynb

Algorithm 3 Training Dummy Classifiers

Require: Preprocessed CTU13 and CICIDS2017 datasets

Ensure: Trained Dummy Classifiers and performance metrics

```
1: Import necessary libraries
2: Read preprocessed CTU13 and CICIDS2017 datasets
3: Define common features for training and testing
4: for dataset in [CTU13, CICIDS2017] do
5:   if dataset is CTU13 then
6:     Train Dummy Classifier on CTU13 dataset (binary classification)
7:     Save the trained classifier
8:   else if dataset is CICIDS2017 then
9:     Train Dummy Classifier on CICIDS2017 dataset (binary classification)
10:    Train Dummy Classifier on CICIDS2017 dataset (multiclass classification)
11:    Save the trained classifiers
12:   end if
13: end for
14: for each trained Dummy Classifier do
15:   Load the trained classifier
16:   Test the classifier on its corresponding test set as well as the other dataset
17:   Calculate performance metrics (accuracy, precision, recall, F1 score) for each experiment
18:   Save performance metrics for analysis and comparison
19: end for
```

This Jupyter Notebook trains and evaluates the Dummy Classifiers on the CTU13 and CICIDS2017 datasets. The classifiers' performance is a baseline for comparing the Random Forest and SVM Classifiers.

5.2.4 trainRandomForest.ipynb

Algorithm 4 Training Random Forest Classifiers

Require: Preprocessed CTU13 and CICIDS2017 datasets**Ensure:** Trained Random Forest Classifiers, performance metrics, and SHAP values

```
1: Import necessary libraries
2: Read preprocessed CTU13 and CICIDS2017 datasets
3: Define common features for training and testing
4: for dataset in [CTU13, CICIDS2017] do
5:   if dataset is CTU13 then
6:     Train Dummy Classifier on CTU13 dataset (binary classification)
7:     Save the trained classifier
8:   else if dataset is CICIDS2017 then
9:     Train Dummy Classifier on CICIDS2017 dataset (binary classification)
10:    Train Dummy Classifier on CICIDS2017 dataset (multiclass classification)
11:    Save the trained classifiers
12:   end if
13: end for
14: for each trained Random Forest Classifier do
15:   Load the trained classifier
16:   Test the classifier on its corresponding test set as well as the other dataset
17:   Calculate performance metrics (accuracy, precision, recall, F1 score) for each experiment
18:   Save performance metrics for analysis and comparison
19:   Create a SHAP explainer object for the classifier
20:   Calculate SHAP values for the test set
21:   Save SHAP values for analysis and comparison
22: end for
```

This Jupyter Notebook trains and evaluates the Random Forest Classifiers on the CTU13 and CICIDS2017 datasets. It tests the classifiers' transferability by evaluating their performance on the dataset for which they were not trained. The notebook also utilizes the SHAP library to explain the classifiers' predictions and identify important features.

5.2.5 trainSVM.ipynb

Algorithm 5 Training Support Vector Machine Classifiers

Require: Preprocessed CTU13 and CICIDS2017 datasets

Ensure: Trained SVM Classifiers, performance metrics, and SHAP values

```
1: Import necessary libraries
2: Read preprocessed CTU13 and CICIDS2017 datasets
3: Define common features for training and testing
4: for dataset in [CTU13, CICIDS2017] do
5:   if dataset is CTU13 then
6:     Train Dummy Classifier on CTU13 dataset (binary classification)
7:     Save the trained classifier
8:   else if dataset is CICIDS2017 then
9:     Train Dummy Classifier on CICIDS2017 dataset (binary classification)
10:    Train Dummy Classifier on CICIDS2017 dataset (multiclass classification)
11:    Save the trained classifiers
12:   end if
13: end for
14: for each trained SVM Classifier do
15:   Load the trained classifier
16:   Test the classifier on its corresponding test set as well as the other dataset
17:   Calculate performance metrics (accuracy, precision, recall, F1 score) for each experiment
18:   Save performance metrics for analysis and comparison
19:   Create a SHAP explainer object for the classifier
20:   Calculate SHAP values for the test set
21:   Save SHAP values for analysis and comparison
22: end for
```

Similar to `trainRandomForest.ipynb` (Section 5.2.4), this Jupyter Notebook trains and evaluates the SVM Classifiers on the CTU13 and CICIDS2017 datasets, tests their transferability, and employs SHAP to interpret the classifiers' predictions and identify important features.

Chapter 6

Evaluation

Chapter 7

Legal, Social, Ethical and Professional Issues

This chapter evaluates potential legal, social, ethical, and professional issues that may arise during the research process. It also explains how the research adheres to the British Computing Society’s Code of Conduct.

7.1 Legal Considerations

The research utilises two publicly available datasets: CTU13[10] and CICIDS2017[21]. These datasets are accessible for research purposes and are not subject to legal restrictions. The research does not involve the use of personal data, as CICIDS2017 is a synthetic dataset, and CTU13 has excluded passive network flows that could potentially contain sensitive information. By avoiding the use of personal data, the research ensures compliance with the UK Data Protection Act 2018.

7.2 Ethical & Social Considerations

This research evaluates the transferability and generalisation of machine learning models across different datasets. The study does not involve human subjects; the datasets used are publicly available. Consequently, no direct ethical or social issues are associated with this research. However, it is vital to consider the broader implications of developing effective network intru-

sion detection systems. By enhancing the ability to detect and prevent cyber attacks, this research improves individuals' and organisations' overall security and privacy. Developing robust and transferable machine learning models for intrusion detection can help protect sensitive information, prevent data breaches, and mitigate the risks associated with malicious activities in networked environments.

On the other hand, using explainable AI techniques, such as SHAP, in network intrusion detection raises some ethical concerns. While SHAP provides valuable insights into the decision-making process of machine learning models, it can also potentially expose the most influential features for detecting specific types of attacks. If this information falls into the wrong hands, malicious actors could exploit it to evade detection by manipulating or spoofing the relevant features. Therefore, ensuring that the insights gained from SHAP are handled with utmost care and not disclosed to unauthorised parties is crucial. Proper security measures should be in place to protect the confidentiality and integrity of the explainability results.

Furthermore, developing highly effective intrusion detection systems may also have unintended consequences. For instance, it could lead to an overreliance on automated systems for security, potentially diminishing the role of human expertise and judgment. It is essential to balance leveraging machine learning models' capabilities and maintaining human oversight and intervention in the decision-making process. When considering intrusion detection systems, carefully evaluating the potential for false positives is crucial. These can cause unnecessary disruptions and result in the misallocation of resources, making it essential to take proactive steps to avoid them. Adequate safeguards and human review processes should be in place to mitigate the impact of false positives.

7.3 Professional Considerations

The research findings indicate that machine learning model transferability across different datasets is limited, which can be problematic for organisations relying on these models for cybersecurity purposes. The study suggests that organisations exercise caution when deploying machine learning models across different environments. They must ensure that the models are better generalised to avoid potential issues. However, the explainability results provide insights into the reasons behind this limitation, paving the way for future work to improve the transferability of machine learning models.

From a professional perspective, this research highlights the importance of thoroughly evaluating and validating machine learning models in network intrusion detection. It emphasises the need for organisations to carefully consider the limitations and potential biases of the datasets used for training and testing these models. The findings underscore the significance of explainable AI techniques, such as SHAP, in providing insights into the decision-making process of machine learning models. These insights can aid in identifying the most relevant features for detecting specific types of attacks and guide the development of more robust and reliable intrusion detection systems.

However, professionals should also know the potential risks of using explainable AI techniques in cybersecurity. The insights gained from techniques like SHAP should be treated as sensitive information and protected from unauthorised access. Professionals have a crucial responsibility to ensure the ethical and responsible use of explainability results and to prevent any unintentional assistance to malicious actors in evading detection. Establishing clear guidelines and protocols for handling and sharing the insights derived from explainable AI techniques is crucial to minimising the risk of misuse.

Furthermore, professionals should actively engage in ongoing research and development efforts to improve the transferability and generalisability of machine learning models in the context of network intrusion detection. Collaborative efforts within the cybersecurity community can help address the limitations identified in this study and contribute to developing more robust and adaptable intrusion detection solutions.

7.4 Societal Impact and Sustainability

The development of effective network intrusion detection systems has significant societal implications. In an increasingly interconnected world, the security and integrity of computer networks are crucial for maintaining public trust, protecting sensitive information, and ensuring the smooth functioning of critical infrastructure. This research contributes to developing more robust and transferable machine learning models for intrusion detection, which can help safeguard against cyber attacks and minimise the potential for data breaches. By enhancing the security of networked systems, this research promotes a more sustainable and resilient digital environment.

From a sustainability perspective, the research findings can guide the development of more

adaptable and scalable intrusion detection solutions. This research supports the long-term sustainability of cybersecurity measures by improving the transferability of machine learning models across different datasets and network environments. It enables organisations to leverage existing knowledge and models to detect and respond to emerging threats, reducing the need for extensive retraining and resource-intensive model development processes. This sustainability aspect is critical in the face of constantly evolving cyber attack landscapes and the increasing complexity of networked systems.

However, it is essential to acknowledge that developing advanced intrusion detection systems may also have unintended consequences for society. The increasing reliance on automated systems for cybersecurity could lead to a false sense of security and complacency. It is crucial to raise awareness among individuals and organisations about the limitations of these systems and the importance of maintaining vigilance and adopting a multi-layered approach to security. When considering intrusion detection systems, it is crucial to carefully weigh the potential societal impact of false positives they generate. False positives can cause unnecessary disruptions and erode trust in these systems, so it is crucial to minimise them, which may involve providing clear communication and redress mechanisms to help mitigate their impact on individuals and organisations.

7.5 British Computing Society Code of Conduct

This research is conducted with integrity and professionalism, following the Code of Conduct of the British Computing Society. They present the results accurately and transparently, using publicly available datasets without legal restrictions. The study does not involve any direct ethical or social issues. The researchers present the findings clearly and understandably and acknowledge the study's limitations.

The research aligns with the principles of the BCS Code of Conduct by promoting the responsible use of technology and contributing to the advancement of knowledge in the field of cybersecurity. The study adheres to the principles of honesty, integrity, and objectivity in conducting research and disseminating findings. The research also demonstrates a commitment to the public interest by addressing the critical issue of network intrusion detection and working towards developing more effective and reliable security solutions.

Furthermore, the research acknowledges the importance of professional competence and the

need for continuous learning and improvement. The study builds upon existing knowledge in the field and seeks to advance the understanding of machine learning model transferability and explainability in the context of intrusion detection. The research findings provide valuable insights that can inform future research directions and contribute to the ongoing development of cybersecurity professionals.

However, the research also recognises the potential risks and ethical considerations of using explainable AI techniques in cybersecurity. In adherence to the BCS Code of Conduct, the research emphasises the need for responsible handling and protection of the insights gained from techniques like SHAP. It highlights the importance of establishing clear guidelines and protocols to prevent malicious actors' misuse of explainability results. By addressing these ethical considerations and promoting the responsible use of AI in cybersecurity, the research demonstrates alignment with the BCS Code of Conduct principles.

Chapter 8

Conclusion and Future Work

References

- [1] Dogukan Aksu and M Ali Aydin. Detecting port scan attempts with comparative analysis of deep learning and support vector machine algorithms. In *2018 International congress on big data, deep learning and fighting cyber terrorism (IBIGDELFT)*, pages 77–80. IEEE, 2018.
- [2] Kasun Amarasinghe, Kevin Kenney, and Milos Manic. Toward explainable deep neural network based anomaly detection. In *2018 11th international conference on human system interaction (HSI)*, pages 311–317. IEEE, 2018.
- [3] Daniel Arp, Erwin Quiring, Feargus Pendlebury, Alexander Warnecke, Fabio Pierazzi, Christian Wressnegger, Lorenzo Cavallaro, and Konrad Rieck. Dos and don’ts of machine learning in computer security. In *31st USENIX Security Symposium (USENIX Security 22)*, pages 3971–3988, 2022.
- [4] Mustapha Belouch, Salah El Hadaj, and Mohamed Idhammad. Performance evaluation of intrusion detection based on machine learning using apache spark. *Procedia Computer Science*, 127:1–6, 2018.
- [5] Anna L Buczak and Erhan Guven. A survey of data mining and machine learning methods for cyber security intrusion detection. *IEEE Communications surveys & tutorials*, 18(2):1153–1176, 2015.
- [6] Sudipta Chowdhury, Mojtaba Khanzadeh, Ravi Akula, Fangyan Zhang, Song Zhang, Hugh Medal, Mohammad Marufuzzaman, and Linkan Bian. Botnet detection using graph-based feature clustering. *Journal of Big Data*, 4:1–23, 2017.
- [7] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20:273–297, 1995.

- [8] Gints Engelen, Vera Rimmer, and Wouter Joosen. Troubleshooting an intrusion detection dataset: the cids2017 case study. In *2021 IEEE Security and Privacy Workshops (SPW)*, pages 7–12. IEEE, 2021.
- [9] Nabila Farnaaz and MA Jabbar. Random forest modeling for network intrusion detection system. *Procedia Computer Science*, 89:213–217, 2016.
- [10] Sebastian Garcia, Martin Grill, Jan Stiborek, and Alejandro Zunino. An empirical comparison of botnet detection methods. *computers & security*, 45:100–123, 2014.
- [11] Arash Habibi Lashkari, Andi Fitriah Abdul kadir, Hugo Gonzalez, Kenneth Mbah, and Ali Ghorbani. Towards a network-based framework for android malware detection and characterization. In *Towards a Network-Based Framework for Android Malware Detection and Characterization*, pages 233–23309, 08 2017.
- [12] Trevor Hastie, Robert Tibshirani, Jerome Friedman, Trevor Hastie, Robert Tibshirani, and Jerome Friedman. Random forests. *The elements of statistical learning: Data mining, inference, and prediction*, pages 587–604, 2009.
- [13] Md Reazul Kabir, Abdur Rahman Onik, and Tanvir Samad. A network intrusion detection framework based on bayesian network using wrapper approach. *International Journal of Computer Applications*, 166(4):13–17, 2017.
- [14] Dong Seong Kim and Jong Sou Park. Network-based intrusion detection with support vector machines. In *Information Networking: International Conference, ICOIN 2003, Cheju Island, Korea, February 12-14, 2003. Revised Selected Papers*, pages 747–756. Springer, 2003.
- [15] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30, 2017.
- [16] Shraddha Mane and Dattaraj Rao. Explaining network intrusion detection system using explainable ai framework. *arXiv preprint arXiv:2103.07110*, 2021.
- [17] Mirco Marchetti, Fabio Pierazzi, Michele Colajanni, and Alessandro Guido. Analysis of high volumes of network traffic for advanced persistent threat detection. *Computer Networks*, 109:127–141, 2016.
- [18] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg,

- et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.
- [19] Abdurrahman Pektaş and Tankut Acarman. A deep learning method to detect network intrusion through flow-based features. *International Journal of Network Management*, 29(3):e2050, 2019.
- [20] Bernhard Schölkopf and Alexander J Smola. *Learning with kernels: support vector machines, regularization, optimization, and beyond*. MIT press, 2002.
- [21] Iman Sharafaldin, Arash Habibi Lashkari, Ali A Ghorbani, et al. Toward generating a new intrusion detection dataset and intrusion traffic characterization. *ICISSp*, 1:108–116, 2018.
- [22] Robin Sommer and Vern Paxson. Outside the closed world: On using machine learning for network intrusion detection. In *2010 IEEE symposium on security and privacy*, pages 305–316. IEEE, 2010.
- [23] Shaohua Teng, Naiqi Wu, Haibin Zhu, Luyao Teng, and Wei Zhang. Svm-dt-based adaptive and collaborative intrusion detection. *IEEE/CAA Journal of Automatica Sinica*, 5(1):108–118, 2017.
- [24] Serpil Ustebay, Zeynep Turgut, and Muhammed Ali Aydin. Intrusion detection system with recursive feature elimination by using random forest and deep learning classifier. In *2018 international congress on big data, deep learning and fighting cyber terrorism (IBIGDELFT)*, pages 71–76. IEEE, 2018.
- [25] Alexander Warnecke, Daniel Arp, Christian Wressnegger, and Konrad Rieck. Evaluating explanation methods for deep learning in security. In *2020 IEEE european symposium on security and privacy (EuroS&P)*, pages 158–174. IEEE, 2020.