Evaluating Adversarial Learning Resilience on Various Encrypted Traffic Classifications

by

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Abstract

Machine learning and deep learning algorithms are applied to reduce false alarm rates, improve accuracy in classifying encrypted network applications, and improve resilience against multiple types of network attacks. Due to the fast growth of learning techniques, various types of adversarial attacks are increased to reveal ML and DL vulnerabilities and add more challenges in classifying encrypted traffic. In this research, we focus on investigating and evaluating the effectiveness of different adversarial attacks and see how resilient ML and DL algorithms are in classifying encrypted traffic applications, i.e., C4.5 Decision Tree, K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). We train our models in the adversarial-free environment on ISCX VPN-NonVPN and NIMS encrypted traffic datasets using the same top features generated from the feature selection method. Then, we use adversarial samples to attack the trained models and check their resilience in classifying the encrypted applications. Finally, we repeat the experiments and retrain the models using the top nine features per each dataset in the adversarial-free and adversarial environment to compare the effect of the adversarial samples in both scenarios. With our experiments on multiple learning algorithms and two benchmark datasets, we demonstrate that DL shows better resilience against the adversarial samples in encrypted traffic classifications in comparison to ML. We also indicate that the ML and DL model's performance in

an adversarial-free environment and their resilience against adversarial samples was improved when using more top selected features. However, the impact of the attack varies depending on the type of attack.

To my Parents: Mohamed and Amira

To my Lovely Wife: Fatma

To my Mother-in-law: Hana

To my Kids: Layla and Ramsey

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List of Abbreviations

ADAM Adaptive Learning Rate Algorithm

AI Artificial Intelligence

ANN Recurrent Neural Network

CNN Convolutional Neural Network

DL Deep Learning

F1 F1-Score

FGSM Fast Gradient Sign Method

FNN Feed-Forward Neural Network

IDS Intrusion Detection System

KNN K-Nearest Neighbor

LSTM Long Short-Term Memory networks

ML Machine Learning

PGD Projected Gradient Descent

PR Precision Rate

<i>RC</i>	Recall Rate
<i>ReLU</i>	Rectified Linear Unit(s)
<i>RNN</i>	Recurrent Neural Network
<i>SVM</i>	Support Vector Machine
<i>TPR</i>	True Positive Rate
<i>VPN</i>	Virtual Private Network
<i>ZOO</i>	Zeroth Order Optimization

Chapter 1

Introduction

This chapter covers an overview of the research in adversarial attacks in encrypted traffic classifications and the techniques used to carry out the research questions and contributions. Lastly, a summary of the thesis structure.

The characteristics of network topologies and Internet traffic vary depending on network environments and locations [5]. So, the Internet traffic supported in a simple home environment considerably differs from the enterprise network and we can consider the same for traffic applications being used and their critically too.

Network encrypted traffic classification is a key tool to monitor network activity and detect early threats that could threaten both regular and secured communications in any network. Network encrypted traffic can not be regarded as static as it changes over time and between networks [6]. Service providers, and more generally network administrators, have expressed their deep interest in being able to identify encrypted traffic for several reasons, such as, monitoring application trends, and applying policies depending on the traffic class. So, it became a challenge trying to classify encrypted traffic due to the evolution and fast emergence of applications. Artificial Intelligence (AI) techniques, such as Machine Learning and Deep Learning, can be applied to detect and characterize the encrypted traffic in the network. In

this direction, ML and DL learning algorithms are used, where they can learn from the information contained in training data samples and process big data. Due to the rapid increase of using these algorithms and the volume of data generated and used through systems, the attack is becoming more sophisticated. According to the literature [7] [8] [9], there are various growing types of attacks targeting vulnerable ML and DL architecture designs.

The fact that the training of these algorithms is based on data, classification tasks can be carefully manipulated by crafted perturbations called adversarial samples, which can mislead any model towards inaccurate classification [10] [11]. Adversarial attacks are the method of adding noise to the original sample in such a way as to make the decision boundary between the regular and the crafted data shift and inaccurate. There are many types of adversarial attacks and algorithms to generate adversarial samples [10] [12] [13] [14] [15] [16] [17].

In this research, our primary goal is to study the effectiveness of the adversarial attacks against various state-of-the-art ML and DL models and their accuracy in classifying encrypted traffic. We achieve our goal by using multiple ML (C4.5 and KNN) and DL (ANN, CNN, and RNN) models and investigate their resilience against different state-of-the-art adversarial attacks (PGD, ZOO, and DeepFool) that have been recognized in different classification domains, such as in image classification and intrusion detection systems.

1.1 Research Questions

The thorough study of related work in adversarial attack and defence helped to derive several research questions:

1. How to build and train resistant ML and DL models in the adversarial-free

environment to evaluate their resilience against adversarial attacks in classifying encrypted traffic?

2. Does use the top feature selection in each dataset improve our model's resilience against adversarial samples or not?
3. Which is more resilient in correctly classifying encrypted traffic against adversarial attacks, machine learning or deep learning?

1.2 Thesis Contributions

After reviewing the literature in the field of adversarial attack against encrypted traffic classifications, none of the current studies elaborated a comprehensive comparison between machine learning and deep learning in classifying encrypted multilabel traffic applications at adversarial-free and adversarial attack environments.

This research aims to study the resilience of using different learning techniques: Machine Learning (C4.5 and KNN) and Deep Learning (ANN, CNN, and RNN) in the encrypted traffic classification field through the aspect of resilient attack in an adversarial environment.

Several existing adversarial attack methods were proposed in the literature. We utilize three common state-of-the-art evasion attack methods, including Zeroth Order Optimization (ZOO), Projected Gradient Descent (PGD), and the DeepFool to generate adversarial samples. The results are discussed in Chapter 6 and 7.

To the best of our knowledge, we are the first to demonstrate a comprehensive comparison between machine learning and deep learning in classifying encrypted multilabel traffic applications in an adversarial-free environment and under the risk of adversaries from multiple state-of-the-art attack methods.

Our major contributions are elaborated below:

- Firstly, to the best of our knowledge, this is the first research elaborates comprehensive comparison between machine learning (C4.5, KNN) and deep learning (ANN, CNN, RNN) accuracy in classifying encrypted multilabel traffic applications on two benchmark datasets (ISCX VPN-NonVPN, NIMS) in an adversarial-free environment. The results show that on average, deep learning models perform better than machine learning models in terms of encrypted classification. Details in Chapter 5.
- Secondly, we investigate and evaluate each model’s resilience against three state-of-the-art adversarial attacks (PGD, ZOO, and DeepFool) using the same top features. The result provides evidence that deep learning shows better resilience against adversarial samples classifying encrypted traffic in comparison to machine learning. Whereas, the impact of the attack varies depending on the type of attack. Evaluation of the model’s resilience against multiple adversarial attacks is discussed in Chapter 6.
- Finally, we repeated the last two experiments using the top nine features generated from the feature selection technique. The results show that the model’s resilience is substantially improved and attaining higher resilience compared to the results when using the same top features from Chapter 6. Details in Chapter 7.

1.3 Research Papers

This research produced the following research paper:

Evaluating Resilience of Encrypted Traffic Classification against Adversarial Evasion Attacks

This paper [18] is published in IEEE ISCC 2021. This paper is a result of collaborations with Dr. Danish Sattar and Dr. Ashraf Matrawy. This paper is part of this thesis: Chapter 5 and 6. The main purpose of this study is to investigate the effectiveness of different evasion attacks on two different benchmark datasets: ISCX VPN-NonVPN and NIMS and see how resilient machine and deep learning algorithms are, including C4.5, KNN, ANN, CNN, and RNN.

1.4 Thesis Organization

We structure the remainder of the thesis as follows. Chapter 2 begins with a background about Network Security, Machine and Deep learning models, and finally, an overview of the classification of adversarial samples, adversarial crafting methods, and adversarial threat models. That is followed by a literature review on machine learning, deep learning, in particular in encrypted traffic classification, and a summary of some related work on adversarial attacks. Chapter 3 states our research problem and our used methodology to carry out the research. In chapter 4, we describe the selected datasets and how we preprocess them using the feature selection techniques, followed by the architecture characteristics, learning setup, and evaluation criteria. Chapter 5 describes the performance of adversarial-free Machine learning and Deep learning models using the same top feature selection and performance comparison between the two learning models. Chapter 6 presents the experimental results and impact of using multiple adversarial attacks, followed by a performance comparison between machine and deep learning. In Chapter 7, we repeated the experiments done in the last two chapters (5 and 6) but using the top nine features selected for each dataset, and a quick comparison between the output and chapter's 5 and 6 results. Finally, in chapter 8, we summarize our work, contributions, and the conclusion of our experiment

results. Also, we present some recommendations on how we can strengthen our work in future research.

Chapter 2

Background

2.1 Network Security

The Internet of Things, or IoT, is billions of physical devices that are now embedded in every part of our lives, connected to the internet, collecting and sharing data. IoT devices add so much to the home comforts. But all those appliances and devices that connect to the internet and each other on the home network have created new opportunities and offer new points of entry for cyberattacks [19]. A cyberattack is an attack launched by cybercriminals using different ways and techniques against single or multiple networks or computers. There are two types of cyberattacks, passive and active [20]. Passive cyberattack's purpose is to gain access to the computer system or network and to collect data without detection. Active cyberattack is often an aggressive attack where the attacker attempts to modify the data they have compromised to gain greater access to more restricted and valuable data. That makes an active attack more likely to be discovered compared to passive attacks.

Network security has become essential against cybercriminals in designing data protection and network integrity and usability. It takes preventative measures to protect the underlying networking infrastructure from unauthorized access, misuse,

malfunction, modification, destruction, or improper disclosure [21]. Implementing these measures allows IoT devices, users and programs to perform their permitted critical functions within a secure environment.

2.2 Machine Learning Models

Machine Learning can be defined as an application of AI that gives computers the power to automatically extract information and enhance their performance from sample data or experience without any explicit programming [22]. It is a set of algorithms that can define data, learn from it, and then apply this gained knowledge to form smart decisions.

There is various type of learning paradigms derived from the type and volume of data. One of them is supervised learning, which begins with an established set of data and a certain understanding of how that data is classified. It is responsible for searching for patterns in data with labeled features that can be applied to an analytic process [22].

There are different types of machine learning networks, such as the C4.5 Decision Tree and K-Nearest Neighbor (KNN) algorithms, and all of them are supervised learning models. The following section focuses on machine learning architectures and algorithms.

2.2.1 Decision Tree (C4.5)

Decision trees are one of the most widely used classification techniques. A decision tree is a classifier expressed as a recursive partition of the training instances. It is constructed in a top-down manner, in each iteration, the instance space is partitioned by choosing the best attribute to split them [23].

The C4.5 algorithm is a machine learning algorithm that constructs a single decision tree, in which each internal node represents a test on features, each branch representing an outcome of the test, and each leaf node representing a class label [24]. Its accuracy level is high enough, independently of the data volume to be processed. Various studies identify the C4.5 algorithm as one of the top classifiers in data mining [25]. The C4.5 algorithm has the ability to handle an incomplete training dataset and to prune the resulting decision tree in order to reduce its size and optimize the decision path. C4.5 also has the ability to deal with continuous attributes.

2.2.2 K-Nearest Neighbor (KNN)

The KNN classifier is one of the simplest and basic machine learning algorithms based on the distance between data points in the vector space. It uses lazy learning for classification and is commonly referred to as a lazy classifier [26]. It can be used for both classifications as well as regression predictive problems. KNN works on a principle assuming every data point falling in near to each other is falling in the same class. In other words, it classifies a new data point based on similarity.

The advantage of using KNN is that it is robust to the noisy training data, as the amount of training data increases, the KNN becomes more effective and easy to implement in a multi-class problem. Its drawback is that the computation cost is high because of calculating the distance between the data points for all the training samples. Also, the KNN algorithm is very sensitive to outliers as it simply chose the neighbors based on distance criteria [27].

2.3 Deep Learning Models

On the other hand, one of the machine learning's members that carry out massive amounts of data and has significant learning flexibility by dividing its work as a nested hierarchy of concepts and each concept is defined with simpler concepts and so on, is the deep learning [28]. Unlike machine learning, it defeats the need for domain expertise as it works on learning high-level features from data in an incremental manner. Deep learning strength depends on some criteria starts with; How complex is the problem? What type of prediction is needed? How important is the accuracy to work vs. the interpretability? Will there be enough quality labelled data? How many resources will allocate for work?

Most deep learning models are built on neural networks and divided into three linear models of different layers [29]. The first layer is the input layer that provides the information from the outside world and passes on this information to the next layer called the hidden layer. This layer performs the needed computations and transfers the generated information to the output layer, which is responsible for showing the predicted results. The neural network structure is the same as a human brain, which is made up of cells called neurons, responsible for transmitting electrical signals to each other based on the received signals from other neurons [30].

There are different types of deep learning networks, such as Feed-forward (or Artificial) Neural Networks (ANN), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), and all of them are supervised learning models. The following section focuses on deep learning architectures and algorithms.

2.3.1 Artificial Neural Network (ANN)

ANN or known as a Feed-Forward Neural Network (FNN) processes input in a forwarding direction bypassing the input layer first, then the hidden layers, to the output layer, as shown in Figure 2.1. The ANN architecture consists of many neurons connected to other neurons, where each neuron connection is associated with weights to multiply with input variables (features). Weights are adjusted based on the input, the prediction output, and the activation function. The activation function has different selections, such as Sigmoid, Softmax, Tanh, and ReLU. In our work, we will use Softmax and ReLU as the activation functions in the hidden layers. The Softmax function is a combination of multiple Sigmoid functions that returns values in the range 0 to 1 [31]. While ReLU linear function is easy to compute and gives fast learning. It is widely used in the neural network because all the neurons are not activated at the same time, so when the output of linear transformation is zero, it deactivates a neuron [32].

The main advantage of using ANN is that it can map and learn any input to any output by using the activation function, where the system can approximate any function, regardless of its linearity. Due to additional hierarchy needs, it learns only one step at a time, therefore the learning time increases (almost) linearly in the number of levels in the model hierarchy, which is one of the ANN drawbacks [33].

2.3.2 Convolutional Neural Networks (CNN)

CNN is a subdomain for neural networks that are inspired by human brain neural networks. It is a technique inspired by the visual mechanisms of living organs and

Figure 2.1: The Layered Architecture of ANN System

used with dimensional inputs. CNNs reduce the number of learning parameters significantly by using a set of convolution filters (kernels) in convolutional layers [34]. CNN is suitable for the following kinds of data: data in the form of multiple arrays; data that have strong local correlations; data whose features can appear anywhere; data in which objects are invariant to translations and distortions [35].

CNN architecture has various components, including convolution, pooling, and fully connected layers for sharing weight and pooling. The first layer is the convolution layer which emulates the behavior of the human eye, is connected to the input neurons in the first hidden layer. This layer applies a linear operation to extract input features and activation functions on 3D vectors. The pooling layer collects and concise the information received from the convolution layer. Since this layer reduces the dimension of the layer and parameter in training time, so it reduces the computational time accordingly. It is often added after a convolutional layer. The main pooling function used in the pooling layers is the Max Pooling. The final layer of the CNN is a Softmax layer, where the CNN layer flattens the output and passes it to the output layer for label prediction using the Softmax layer to emulate a probability distribution.

Figure 2.2: RNN Architecture

The main advantage of using CNN is learning the spatial pattern, which leads to learning complex patterns. CNN learns simple features at the first layers, and by the time it recognizes more complex features, and at the final layer, it recognizes objects. Another crucial point of this architecture is that neighboring neurons share portions of the receptive field combining percepts allows the extraction of general patterns.

2.3.3 Recurrent Neural Networks (RNN) and LSTM

RNN is are a class of neural networks that are used to classify series of data. It has both feed-forward and feed-back connections to the previous layers. Feed-back connections add a memory of past inputs where each unit receives the current and previous state where it feed-back the out to itself. RNN has a different learning phase from other neural network architectures, as it was designed to capture such correlation via a hidden layer, which keeps track of the context determined by the previous samples. RNN works similar to human brains where it does not start from scratch every time as it has a loop in its network that allows persisting information and share weight over time, as shown in Figure 2.2.

Figure 2.3: LSTM Unit Illustration

One of RNN's drawbacks is that its performance is poor when dealing with long-term dependencies as it does not learn how to successfully link with these dependencies. Another drawback is that it suffers from the vanishing gradient problem, which leads to insufficient and inaccurate results. To solve this problem, Long Short-Term Memory cells were introduced as RNN variation [36]. It can learn long-term dependencies and maintains the information for long-term periods. Several applications used it, such as speech recognition in smartphones, translation, image classification. LSTM has different layers as shown in Figure 2.3. Input Gate layer is the first layer where i_t decides what information we are going to update. The second layer is the Forget Gate layer where f_t decides what information to keep and which information to forget. The Output Gate is the final layer where o_t decides how much the internal state to transfer to the unit output. Outputs and cell memories (c_t) from last time step are connected to the three gates. With those layers, LSTM remembers all information through time.

2.4 Adversarial Attack Classification and Threat Model

In this section, we focus on adversarial samples in the machine and deep learning algorithms and how they are designed to deceive these models to make a mistake. We will review the adversarial threat model and classification and explore the methodology of the state-of-art attack methods used to generate adversarial samples. At last, we will review some related work in adversarial attacks and encrypted traffic classification using machine learning and deep learning.

An adversarial attack is a purposeful attempt to deceive various machine learning algorithms [37] [38] [39]. At the same time, deep learning algorithms also have been proved to be vulnerable to adversarial samples causing deep learning to make predictions different from the ground truth with high confidence [15] [16] [40]. It employs the use of malicious samples that are crafted by an attacker to force a model to misclassify input data and fool the model by adding noisy perturbations to the original sample in such a way to make the decision boundary between the regular and the crafted data shift and inaccurate. It has become a real threat to modern technologies that rely on trained learning models to automate certain tasks. Identifying adversarial attacks remains a challenging problem due to the craftiness of adversarial samples generated by the attackers.

2.4.1 Adversarial Samples

We study adversarial samples used for classification, with final layers as Softmax activation functions. Adversarial samples were originally introduced by [7] as data points fed to a machine learning algorithm that is visually indistinguishable from

”normal” examples but are specifically tuned to fool or mislead the machine learning system. These earliest forms of adversarial examples were framed as an intriguing property of neural networks where even a single, small gradient step was sufficient to harm the performance of deep learning classifiers [10] [11]. Adversarial samples can often be generated not only with access to the model’s architecture and parameters but also without it, where such attacks would be called white-box and black-box attacks, respectively [41]. Therefore, it is important to understand the weaknesses of our models and come up with ways to defend them against potential adversaries.

2.4.2 Adversarial Threat Model

In this section, we focus on the adversarial machine threat model in terms of capabilities, knowledge, goal, timing, and limitations of an adversary [42] [43] [44].

Adversarial Attack Surface

An attacker can tamper with either the data inputs or the processing of data to confuse the target model, where the attack can be identified by the attack surface/time. We can classify adversarial attacks depending on the surface into two attacks: Evasion and Poisoning attack [41].

- **Evasion Attack:** Evasion is a most common attack on machine learning model performed during production. It exploits misclassifications but does not affect training. This type occurs at the decision time and alters the test set during the testing or prediction time [45] [46].
- **Poisoning Attack:** Poisoning is another category of attacks and can be considered as one of the most widespread. Poisoning can be different from evasion, where the adversary can poison the training dataset. To achieve this, the

adversary derives and injects a point to decrease the classification accuracy. Poisoning attacks alter the training process through influence over the training data [46] [47].

Adversarial Attack Capabilities

Adversarial attack capabilities are determined by the amount of information available to an adversary about the system, which indicates the attack vector they may use on the threat surface. Adversarial capabilities in machine learning can be determined in different phases: training and testing phase [43].

While training the data, the attacker attempt to influence or corrupt the model directly by altering the dataset used for training by accessing partial or full training data considered the weakest attack on the training phase. Altering the model or input based on the adversarial capabilities depends on three broad attack strategies [43]:

- **Data Injection:** The adversary does not have any access to the training data or the learning algorithm but can insert adversarial samples to the training set and corrupt the target model.
- **Data Modification:** The adversary has full access to the training data only and not to the learning algorithm, where he can modify the data before used for training the target model.
- **Logic Corruption:** The adversary has to interfere with the learning algorithm, so it becomes very difficult to design a counter-strategy against these adversaries who can alter the learning logic.

Adversarial Attack Goal

- **Targeted Attack:** The attacker aims to misclassify the predicted class of a benign input to a targeted class by crafting the benign input via adversarial perturbation [48].
- **Misclassification Attack:** The attacker aims to misclassify the benign input by adding adversarial perturbation so that the input predicted class is changed without a specific target class [49].

Adversarial Attack Knowledge

Adversarial attack efficiency and limitation are specified by the degree of information available to the attacker about the model at the attack time. It can be classified into White-box or Black-box attacks [50].

- **White-box Attack:** The adversary has total knowledge about the model, the algorithm used in training and can access the training data distribution.
- **Black-box Attack:** In this type of attack, the attacker does not know the model and uses information about the settings or past inputs to analyze the model vulnerability.

2.4.3 Adversarial Samples Generation

In this section, we present a state-of-the-art attack method used to generate adversarial samples in our research experiments, so that a classification model yields an adversarial output. The adversarial sample modification can be performed both in the training and testing phase. The robustness of the adversarial sample depends on the attacker's ability to find a sample relative to the original input.

Zeroth Order Optimization (ZOO)

In [17], authors proposed this method to directly estimate the gradients of the targeted models for generating adversarial samples. The main goal of this method is to provide improved attacks to the targeted models, avoid the loss in attack transferability, and spare the need for training substitute models. Instead of training a substitute model, it directly approximates the gradient of the target model just based on the input data and output scores using stochastic gradient coordinate. Using this method proves the same effectiveness as the state-of-the-art white-box different attacks and exceeds other black-box attack methods. One of the advantages of this method that it can be applied to non-DL classifiers admitting the same input and output relationship as DL [17]. The ZOO attack decreases the probability of the original class and increases the probability of the target class, successfully attacking the model.

Given that x denotes the adversarial example with a targeted class label t toward misclassification, and $f(x, t)$ is the loss function that reflects the level of unsuccessful adversarial attacks. The loss function based on the output F of a model is defined as:

$$f(x, t) = \max\{\max_i \log[F(x)]_i - \log[F(x)]_t, -k\} \quad (2.1)$$

Where k is a tuning parameter for attack transferability and is set to zero for attacking a targeted model, and suggested large k when performing transfer attacks. A well-trained model yields a skewed probability distribution on its output $F(x)$ such that the confidence score of one class significantly dominates the confidence scores of the other classes. The use of the log operator lessens the dominance effect while preserving the order of confidence scores due to monotonicity [17].

Projected Gradient Descent (PGD)

This type of adversarial attack attempts to find the perturbation that maximizes the loss of a model on a particular input while keeping the size of the perturbation smaller than a specified amount. Since it is a multi-step with a negative loss function, it overcomes the network overfit problem and became more robust than the Fast Gradient Sign Method (FGSM) adversarial samples, which comes from it [16]. In ℓ_∞ -ball, PGD iterate to explore the maximum loss. The Resistance against PGD samples grants resistance against any first-order adversaries.

DeepFool

Moosavi et al. proposed [13] an algorithm that can compute adversarial examples and defeat state-of-art classifiers to change output prediction labels. It searches for the minimal perturbation to fool a classifier and uses concepts from geometry to direct the search. DeepFool attack is considered an efficient method to evaluate the robustness of classifiers. DeepFool was used in both models, binary and multi-class classifiers.

2.5 Literature Review of Traffic Classification using ML

Significant works have been surveyed in the field of machine learning-based IP traffic classification using anomaly detection techniques that do not rely on well-known port numbers, but statistical traffic characteristics [51].

One of the surveyed papers [52] presented a technique for clustering network flows without using packet payloads, but by taking few representative features from each

flow, such as the total number of bytes, the number of exchanges between the end-points, and the connection duration. They investigated a way to identify traffic with similar observable properties, applying an untrained machine learning classifier to this problem, where this classifier has the advantage of identifying groups/classes of Internet traffic using only transport layer characteristics. That was done without any direct assist in understanding what or why applications have been grouped this way. And, they did not evaluate the accuracy of the classification or explore which flow attributes produce the best results.

Erman et al. [53] addressed the challenge of traffic classification at the core of the network, where the network flows information and their contributors were limited at this period. They proposed a machine learning algorithm that uses the packets of a unidirectional TCP flow to estimate the flow statistics of the unobserved opposite direction. K-means algorithm was used for clustering, and they studied web, P2P and FTP traffic. The mapping method they used can merge the traffic clusters of known applications based on the payload of flows, but they cannot merge the traffic clusters of unknown applications. Their results demonstrated that with a sufficient set of labelled flows, the mapping method can achieve high accuracy.

Haffner et al. [54] proposed an approach for automated construction of application signatures (ACAS) by applying the supervised machine learning algorithms to automatically identify signatures for a range of applications. This technique uses features, such as flow duration, bytes per flow, packets per flow, and average packet size, for encrypted traffic, such as SSH and HTTPS, by extracting features from the unencrypted handshake that negotiate the encryption parameters of the TCP connection. The algorithms used to classify network traffic into different applications were AdaBoost, Hidden Markov, Naive Bayesian and Maximum Entropy models. Their results showed AdaBoost outperforms Naive Bayesian and Maximum Entropy with

an SSH detection rate of 86% and a false positive rate of 0.0%. The error rate is shown to be below 1%. A major limitation of ACAS is that it assumes that the first 64 bytes of a flow completely describes the structure of the application protocol carried by the flow.

Moore et al. [55] proposed using a supervised machine learning technique to categorize Internet traffic by application. They used a Naive Bayes classifier with 248 full-flow-based features for training to classify network traffic based on flow statistical features. Selected traffic for Internet applications was grouped into different categories for classification, e.g. bulk data transfer, database, interactive, mail, services, WWW, P2P, attack, games and multimedia. The authors used Recall as evaluation metrics to evaluate the classifier's performance. The results showed that the Naive Bayes technique got high accuracy in network classifications where the Recall for the individual class of application ranged, for instance, from 98% for WWW to 90% for bulk data transfer, to approximately 44% for services traffic and 55% for P2P.

2.6 Literature Review of Traffic Classification using DL

A comprehensive review of applications of deep learning methodologies has been done. And, the employed techniques for network traffic classification were investigated, besides discussing the advantages/disadvantages of the deep learning techniques used for network traffic monitoring applications [56].

Lotfollahi et al. [57] proposed a deep learning architecture that learns new features for each application from the packet content. The proposed architecture is called Deep Packet, which can handle both traffic characterization in the network traffic by categorizing it into major classes, such as email, chat, FTP, Skype, torrent, and P2P

and application identification for recognizing end-user applications, such as Spotify, BitTorrent and Skype. They used a combination of a one-dimensional CNN and Stacked Auto-Encoders (SAE) for automatic feature extraction and classification of network traffic, for both application identification and traffic characterization, which is either encrypted or unencrypted traffic. Their framework reduces the amount of hand-crafted feature engineering and achieves great accuracy. The only drawback is that they extracted the first 1500 bytes only in the packets that may lead to uncertain results because there are some similar attributes in the same services.

Iliyasu et al. [58] introduced a deep learning technique for classifying on an enormous scale for encrypted communication of semi-supervised encrypted traffic to overcome the challenges associated with establishing ground truth labels of large encrypted traffic datasets. This technique was deep convolutional generative adversarial networks (DCGAN), where GAN is the technology that deploys the high machine speed for traffic encryption and imitates network traffic to solve problems and performs enormous amounts of calculations with encryption. Their work proposal was to use the samples generated by the DCGAN generator and the labeled data to improve the performance of the trained classifier on a small number of labeled samples, where their approach achieved good accuracy with these small labeled samples.

Wang et al. [35] proposed a one-dimensional convolutional neural network for the end-to-end encrypted traffic classification method. The method integrates feature extraction, feature selection and classifies the end-to-end framework by learning the nonlinear relationship between the original input and the expected output. They used a public ISCX VPN-nonVPN traffic dataset for verification. The proposed model has two convolutional, two pooling, and two fully connected layers. The bytes in each packet were normalized and the first 784 bytes were used by the model. In terms of classifying Non-VPN versus VPN, it achieved 100% and 99% Precision, and 99%

and 100% Recall, respectively. This method shows outstanding performance on both Non-VPN and VPN traffic, about 10% higher than the C4.5 machine learning model that uses time series and statistical features. The authors' achievement using this method in VPN classification was due to the usage of training data and test data that are based on the same encryption method and encryption keys.

Alom et al. [59] proposed a deep learning model called Deep belief neural (DBN), which was based on Stack Restricted Boltzmann Machines (RBMs) for feature extraction and dimensionality reduction and based on SVM for the classification of network intrusion detection. The approach was implemented on merely 40% of the NSL-KDD training dataset and did not use all the training datasets, where it explored the intrusion detection capabilities through a series of experiments. The trained DBN network can effectively identify unknown attacks provided to it, and the proposed system achieves 97.5% accuracy after 50 iterations. The authors report on the classification accuracy based on the test set comparing their approach with Support Vector Machines (SVM) and a hybrid version of DBN with SVM.

2.7 Literature Review of Adversarial Attacks

An adversarial attack is considered an attempt to deceive machine learning algorithms. It employs the use of malignant samples crafted by an attacker to force a model to misclassify a particular input or fool the model by adding noisy perturbations. Various studies were performed regarding adversarial attack samples and how they can mislead machine learning systems. Other researches focused on adversarial attack classes and their effectiveness on machine learning systems either as resilience or robustness.

Adversarial attacks and defences in images, graphs and text: A review

Xu et al. [60] defined each type of adversarial attack and divided them into three categories: robust optimization techniques, gradient obfuscation methods, or adversarial example detection algorithms. Robust optimization techniques aim to improve the robustness of a classifier by learning model parameters by incorporating adversarial examples from a given attack into the training process. On the other hand, obfuscation methods rely on masking the input gradient needed by an attacker to construct adversarial examples. They focused on the adversarial examples of deep learning models and evaluated most research efforts on attacking various deep neural networks in different applications [60].

Adversarial Examples: Attacks and Defences for Deep Learning

Yuan et al. [12] focused on the adversarial examples on deep-learning models. They reviewed current research efforts on attacking various deep neural networks in different applications. They focused on explaining a single prediction in contrast to adversarial examples where the emphasis is on reversing the prediction. They also reviewed the robustness analysis of proposed schemes against noisy and maliciously generated inputs using adversarial attack algorithms. The defence methods are also extensively surveyed, where they proposed several detection and defence methods to mitigate the vulnerability induced by adversarial perturbation.

Adversarial attacks against intrusion detection systems: Taxonomy, solutions and open issues

Corona et al. [61] presented an overview of adversarial attacks against intrusion detection systems (IDS). They provided a general taxonomy of attacks, IDS implementation weaknesses, and solutions for each mentioned attack. They highlighted the most promising research directions for the design of adversary-aware, harder to defeat IDS solutions. A high-level categorization of attack schemes through security event reconstruction for protecting against defence mechanism violations was discussed.

Deep learning-based intrusion detection with adversaries

Other researchers [9] proved that adversarial attacks are equally effective against deep learning models in network security applications on the NSL-KDD dataset. They also studied the impact of feature selection in generating adversarial examples and illustrated the vulnerability of deep learning algorithms against adversarial samples. They performed four white-box inference integrity feature vector attacks against trained classifiers on the NSL-KDD dataset: FGSM, JSMA, Deepfool, and CW, where the most effective attack was targeted FGSM and the least efficient was CW.

Chapter 3

Problem Statement and Methodology

This chapter covers our research problem statement that carried out the purpose, scope, and thesis direction. We also present our methodology, including the encrypted traffic classification architecture and algorithm.

3.1 Problem Statement

A network encrypted traffic classification is a key tool to monitor the network activity and detect threats in a specific network [62]. Artificial Intelligence (AI) techniques, such as Machine Learning and Deep Learning, are increasingly used to detect and characterize the type of encrypted traffic in the network. The high volume of encrypted traffic increases the number and type of attacks and the challenges to label and classify the network traffic data. Adversarial samples have intentionally been designed to target a model to degrade performance and mislead any model towards inaccurate classification with high confidence [11] [10]. The linear nature of ML and DL is the main reason for its vulnerability against adversarial perturbation. The fact that adversarial samples can simply be generated using different algorithms can be used to perform attacks against various models that lead to misclassifying the input.

Several types of research have been done in studying the effect of adversarial attacks in image classification [16], and Intrusion Detection Systems [9]. That served as a potential and motivation to explore machine learning and deep learning models, including C4.5, KNN, ANN, CNN, and RNN, on different benchmark datasets and train them in an adversarial-free environment. After that, we can study the effectiveness of various well-known and state-of-the-art adversarial attacks to evaluate machine and deep learning algorithms' resilience.

Our primary goal is to explore and study several ML and DL architectures on two benchmark datasets: ISCX VPN-NonVPN and NIMS in the adversarial environment. To do that, we needed to concentrate on two main points: how to generate capable adversarial samples that can attack and deceive a model with small perturbation and how to train a model to be resilient against adversarial samples.

3.2 Research Methodology

We use the following methodology to carry out the research. We describe the details and justify our approach with our experimental results. In this research, we have conducted three main experiments, as this allows us to do a comprehensive analysis and comparison between these results. The experiments that we perform are presented in this research to analyze and compare different ML and DL model's effect in classifying encrypted traffic in an adversarial-free environment and their resilience against adversarial attacks on two benchmark datasets: ISCX VPN-NonVPN and NIMS. And also, compare the model's resilience against adversarial samples when using the same top features of both datasets and when using the top nine features for each dataset. In chapters 5, 6, and 7, we present our experimental results to validate our selected approach.

We start with a brief of our experiment methodology. We then describe the two datasets and how we preprocess them. The following section is about our model's architecture and learning setup for each set of experiments. Then we illustrate our experiment process.

1. We first split ISCX VPN-NonVPN and NIMS into training, testing, and validation sets.
2. We then preprocess the datasets: i) convert the non-numerical features, ii) normalize the datasets, apply feature selection using the Mutual Information technique, which we will use with the entire experiments in Chapters 5, 6 and 7.
3. We train the five models, two of ML (C4.5 and KNN) and three of DL (ANN, CNN, and RNN), on the two adversarial-free datasets: ISCX VPN-NonVPN and NIMS using the same top features, as in Chapter 5.
4. We then used the three adversarial attack methods: PGD, ZOO, and DeepFool, to generate a collection of adversarial samples to analyze and compare the performance of machine learning and deep learning in an adversarial-free and adversarial attack environment for each dataset, respectively, as in Chapter 6.
5. In Chapter 7, we retrained the models by conducting the same sets of experiments using the top nine feature selections per each dataset, to evaluate the effectiveness of the generated adversarial samples from three evasion adversarial attack methods, and compare the model's resilient with the results from using the same top features in Chapter 6.

We denote the evasion attack methods as PGD, ZOO, and DeepFool. All experiments were performed on two encrypted traffic flow datasets and evaluated based on

Precision, Recall, and F1-Score accuracy. All our evaluations performed using test data: 18,758 and 14,681 traffic flow on ISCX VPN-NonVPN and NIMS, respectively. In this work, we consider some assumptions about our attack threat model. The details of C4.5, KNN, ANN, CNN, and RNN, experiments are described in the sections below. The training process and evaluation work the same way across all our models. We will specify the training configuration in each experiment in terms of the selected optimizer, loss function, parameters, and metrics in Chapter 5.

The attacks are evasion attacks, where an attacker has access to our model during prediction time that leads to misclassify the model decision, taking into considerations that a complete knowledge of the targeted models are known to perform a white-box attack with multi iterations. The adversarial threat model, including goal, capabilities, and knowledge of all the adversarial attacks are the same across all experiments. We use a sufficient number of samples in both datasets for training, validation and test. We split the training dataset into training and validation set to evaluate and assess the performance of the models during training time with 80% and 20%.

Chapter 4

Experimental Approach

We start with the platform we used to conduct the experiments. Then, we illustrate the two datasets: ISCX VPN-NonVPN and NIMS, and how we preprocess them to be suitable for our experiments. After that, we will discuss our proposed model's architecture and how we set them up for the experiment operation.

In the next phase, we evaluated the effectiveness of using the adversarial evasion attack techniques to generate adversarial samples by performing several sets of experiments. That was done by retraining our models using the achieved feature selection data.

We use a sufficient number of samples in both datasets, and we split the dataset into training and validation set to evaluate the performance of the models with 80% and 20%, respectively. We tried several data splitting such as 70% - 30%, 75% - 25%, and also, 85% - 20%. But, 80% - 20% approach allows us to find the model's best hyper-parameter and also estimate the model's best performance and accuracy. We state the training design used in each experiment in terms of the selected optimizer, loss function, parameters, and metrics.

4.1 Development Platform and Tools

Machine learning models were implemented using Scikit-learn, and deep learning models were executed using TensorFlow and Keras [63]. The experiments were performed on a 64-bit Windows machine with 16 GB memory and eight Intel core processors 3.00 GHz. We used the Scientific Python Development Environment (Spyder) [64], included with the Anaconda platform, to write and run our code from there. We used the open-source IBM Robustness Toolbox (ART) framework for generating the adversarial samples [65]. ART is a Python library that provides algorithms to build defences against several machine learning models and test them against adversarial threats.

Each evasion attack algorithm found in the ART framework has its own parameters, i.e., type of classifier used, the maximum number of iterations, the batch size on which the samples are generated, and the number of class gradients to compute, where each parameter in every attack are modified according to the attacked model and the number of classes in each dataset. Several experiments and trials have been done on each attack's parameter to get the best adversarial attack results, to accurately test the trained model's performance. After splitting the dataset, we provided the attack algorithm with the 20% test data to add noisy perturbations to these original samples and then push it to our trained models to check their accuracy and resilience against those adversarial samples in accurately classifying the encrypted traffic applications.

4.2 Traffic Classification Datasets

Since the performance of machine learning and deep learning algorithms depends on the dataset to some extent, classifier accuracy differs between various datasets.

Therefore, it is significant to study the dataset carefully as part of the learning approach. Generally, the dataset used for encrypted traffic classifications is flow-based. In our research, we use two datasets: ISCX VPN-NonVPN and NIMS.

4.2.1 ISCX VPN-NonVPN Traffic Dataset

ISCX VPN-NonVPN traffic Dataset [1] is a captured network encrypted traffic set consisting of different types of traffic and applications. There are two data formats in this encrypted traffic dataset, labeled flow features (ARFF format) and unlabeled raw traffic (PCAP format). It contains packets captured over Virtual Private Network (VPN) sessions and regular encrypted sessions (Non-VPN). The dataset objective was to identify different types of applications using VPN and Non-VPN sessions. The flow-based classification method (such as flow bytes per second, duration per flow, etc.) was used to characterize Non-VPN and VPN encrypted traffic using only time-related features. Each row in the dataset has 24 features, including class labels, and has more than eighteen thousand records.

The ISCX dataset has fourteen application labels (or classes), where seven of them were collected using VPN sessions, and the same seven were collected using regular Non-VPN encrypted sessions, as shown in Table 4.1. We use in our experiments 15,005 records for training and 3,752 for testing. The ISCX VPN-NonVPN dataset is a combination of both VPN and Non-VPN encrypted sessions. Table A.1 in the Appendix provides a summary of dataset features.

4.2.2 NIMS Multi-Class Dataset

NIMS Dataset [2] [3] [4] is a captured network encrypted traffic set consisting of packets collected internally at the authors' research testbed network. The dataset is

Table 4.1: List of ISCX Encrypted Traffic

Traffic Type	Content
Browsing	Firefox, Chrome
Chat	ICQ, AIM, Skype, Facebook, Hangouts
Streaming	Vimeo, Youtube, Netflix, Spotify
Mail	Email, Gmail (SMPT, POP3, IMAP)
VoIP	Facebook, Skype, Hangouts, VoipBuster
P2P	uTorrent, Bittorrent
File Transfer	Skype, FTPS, SFTP

Table 4.2: List of NIMS Encrypted Traffic

Traffic Type
Local Tunneling
Remote Tunneling
SCP
SFTP
X11
Shell

available in two data formats, ARFF format and CSV format. The dataset is labeled. Different network scenarios are emulated using one or more computers to capture the resulting traffic. SSH connections are generated by connecting a client computer to four SSH servers outside the testbed via the Internet. Each row in the dataset has 23 features, including class labels, and has more than fourteen thousand records. It has six classes of encrypted SSH labels, as shown in Table 4.2. In our experiments, we use 11,408 records for training and 2,936 for testing. Table A.2 in the Appendix provides a summary of dataset features.

4.3 Data Preprocessing

Data preprocessing is a necessary step before building a model and feeding it with the data. Our datasets have different scales and significant deviations that resulted in a weak performance model and slow training time. To prevent that, we normalized the dataset to change the values of the numeric features that have a different range to increase classifier performance and accuracy using StandardScaler [66]. It helped in scaling the data within a range to avoid building incorrect models while training and/or executing data analysis. After that, we reshaped the train and test input for CNN and RNN models into three dimensions (3D) using reshape() function [67]. In our experiment, we reshaped the input for the ISCX VPN-NonVPN dataset into a matrix of size (15005 x 5 x 1) for the training set and size of (3752 x 5 x 1) for the testing set. For the NIMS dataset, we reshaped the input into a matrix of size (11408 x 5 x 1) for the training set and size (2936 x 5 x 1) for the testing set.

4.3.1 Feature Selection

ISCX VPN-NonVPN and NIMS datasets have a large number of features, and many of them are insignificant and redundant, which may lead to prediction process inefficiency due to their low availability in prediction time compared to other essential features. Sometimes they lead to high training time consumption and overfitting. That is why it is mandatory to select essential features and enhance the model performance in respect of prediction accuracy and a faster prediction process. So, we used the feature selection methods to reduce the model complexity as shown in Figure 4.1.

There are different types of feature selection methods, such as wrapper, intrinsic, and filter methods [68]. Wrapper feature selection methods generate many models

Figure 4.1: Feature Selection Process

with different subsets of input features and get the best-performing model by selecting those features. While intrinsic feature selection methods are machine learning algorithms that perform automatic feature selection during training as part of learning the model. Regularization and tree-based methods are good examples of an intrinsic feature selection method. Finally, filter feature selection methods use statistical measures to score the correlation and evaluate the relationship between the input variable and the target variable that can be filtered to choose those input variables that will be used in the model. A good example of a filter feature selection method is the correlation filter method. In our experiment, we focus on exploring the best feature selection methods that can achieve high accuracy and better performance for our models. We use a multilabel classification technique called mutual information [69]. Mutual information is a measure of statistical independence with two main properties: it can measure any relationship between random variables, including nonlinear relationships, and is invariant under transformations in the feature space invertible and differentiable [70]. In Chapter 5, we analyzed the experimental details and results of feature selection techniques.

4.4 Architecture Characteristics & Learning Setup

In the section, we explore the selected parameters for building two machine learning, i.e., C4.5 and KNN, and three deep learning models, i.e., ANN, CNN, and RNN, in consideration of selecting the best hyper-parameters that have a significant impact on model performance. We use different parameters in building our neural network architecture, such as the number of hidden layers, learning rates, flatten, and dropout. The number of hidden layers is selected usually depending on the dataset size and dimensions. So, increasing the number of neurons in hidden layers will guarantee strong neural networks but at the expense of longer model training time. Also, since the learning rate manages the number of weights alteration, so it should be small to reach acceptable results.

4.4.1 C4.5 Architecture

It generates a decision tree for classification. It can accept data with categorical or numerical values as it uses information gain as splitting criteria [71]. The algorithm uses a training set containing interpreted and classified instances with any number of features and a class attribute. The algorithm selects the feature from the remaining feature set at every step, that splits the instances in the best way based on the statistical measure information gain. After determining the best feature, all instances get split into two or more smaller subsets using the selected feature as the splitting criterion. This split is represented by a single node in the decision tree that branches out for every resulting split set. The instances that cannot be split again by the used feature, are removed from the corresponding feature set. That is the case with binary

features, where this procedure is repeated over and over for every subset, until only a single instance is left in a subset or another stopping criterion is met, thus creating a leaf node containing the remaining instances. This creates a decision tree with nodes and leafs. The multi-classification of new instances with the resulting decision tree is very easy. Starting with the first root node, the instance is tested for the feature that was used in the corresponding decision node, and the appropriate branch is selected. There, the following node determines the next test. This is repeated until a final leaf node is reached, and each leaf node determines the classification result of the prompted instance depending on the class attribute of the instances that remained there in the training process. This class attribute is predicted for the new instance.

4.4.2 KNN Architecture

It is an algorithm based on a distance function that measures the difference or similarity between two instances [72] by storing all the available data. In other words, KNN works on a principle assuming every data point falling in near to each other is falling in the same class. In the case of classification, the algorithm starts to find the distances between a query and all the examples in the data, selecting the specified number of examples (K) closest to the query, then votes for the most frequent label. To identify and select the closest neighbors to the input instance, the Euclidean method is the standard measure used in the KNN algorithm to determine the distance between instances. It uses lazy learning for classification and is sometimes referred to as a lazy classifier. It can perform both binary and multiclass classification.

Table 4.3: Training Parameters and Architecture in ANN Experiments

Parameter	Value
No. of hidden layers	2
Layer 1	180 neurons
Layer 2	160 neurons
Dropout	0.2
Optimizer	ADAM
Activation function	ReLU and Softmax
Learning rate	0.01
Epoch	20
Batch Size	64

4.4.3 ANN Architecture

In ANN experiments, we use the same architecture on both ISCX VPN-NonVPN and NIMS datasets. We slice the data into batches with a batch size of 64 and repeatedly over the entire dataset over twenty epochs to train the model. We use ADAM optimizer for its computational efficiency since it works well on problems with noisy and large datasets, and over that, it requires little memory space only. Our network parameters and architecture listed in Table 4.3.

We use these parameters to run our ANN experiments for classifying the encrypted traffic on the two datasets. First, we train the model using the original dataset to built an adversarial-free ANN model. Then, we attack the adversarial-free ANN models using the adversarial evasion attacks.

4.4.4 CNN Architecture

We use the same CNN architecture and the same hyper-parameters on both ISCX VPN-NonVPN and NIMS datasets. We use two types of one-dimensional layers in our CNN architecture: Convolution and Max Pooling layers. Our CNN architecture has two Conv1D that extract features from the packet flow. It also has two MaxPooling1D that apply dimensionality reduction to reduce the size of the inputs and decrease computation time. We use three fully connected layers with the ReLU activation function and one output layer with a softmax activation layer to classify the input according to each dataset category. We use a flatten layer to flatten the input shapes and Dropout layers to prevent overfitting in the model during training time. We then use the ADAM optimizer in our CNN model, and we slice the data into batches with a size of 64 and repeatedly over the entire dataset over twenty epochs to train the model. Our network parameters and architecture listed in Table 4.4.

We use these parameters to run our CNN experiments for classifying the encrypted traffic on the two datasets: ISCX VPN-NonVPN and NIMS. First, we train the model using the original dataset to build an adversarial-free ANN model. Then, we attack the adversarial-free CNN models using the adversarial evasion attacks.

4.4.5 RNN Architecture

We use the same RNN architecture with LSTM for long-term learning and the same LSTM architecture on both ISCX VPN-NonVPN and NIMS datasets. Our RNN network architecture uses two LSTM layers with a sigmoid activation function and one fully connected layer with a ReLU activation function. And one output layer with a sigmoid activation layer to classify input according to each dataset category.

Table 4.4: Training Parameters and Architecture in CNN Experiments

Parameter	Value
Convolution layer	2
Layer 1	84 neurons
Layer 2	64 neurons
Max Pooling layer	2
Dropout	0.2
Optimizer	ADAM
Activation function	ReLU and Softmax
Learning rate	0.01
Epoch	20
Batch Size	64

We use Dropout layers to prevent overfitting in the model during training time. We then use the ADAM optimizer in our RNN model, and we slice the data into batches with a size of 64 and repeatedly over the entire dataset over twenty epochs to train the model. Our network parameters and architecture listed in Table 4.5.

We use these parameters to run our RNN experiments for classifying the encrypted traffic on the two datasets: ISCX VPN-NonVPN and NIMS. First, we train the model using the original dataset to built an adversarial-free ANN model. Then, we attack the adversarial-free RNN models using the adversarial evasion attacks.

4.5 Evaluation Criteria

To help evaluate and compare the effectiveness of using different classifiers in the adversarial-free environment and examine their resilience against adversarial attacks,

Table 4.5: Training Parameters and Architecture in RNN Experiments

Parameter	Value
LSTM layer	2
Layer 1	84 neurons
Layer 2	64 neurons
Dropout	0.25
Optimizer	ADAM
Activation function	ReLU and Sigmoid
Learning rate	0.01
Epoch	20
Batch Size	64

we will present the evaluation metrics we use in all experimental phases. To evaluate the model performance, various metrics can be used, including model Precision Rate (PR), Recall Rate (RC), and F1-Score (F1), which are commonly used in the literature.

Now, we give an example of what we mean by TP, FP, and FN as commonly used in the literature. If we are talking about Browsing, TP is the number of instances correctly classified as Browsing. FP is the number of instances incorrectly classified as Browsing, and FN will be the case where Browsing be incorrectly classified as something else (e.g. Chat) [9].

The following metrics formulas are based on True/False-positive and False-negative [9].

- **Precision:** The ratio of real positive samples over the total predicted positive samples [9].

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

- **Recall:** It is also called True Positive Rate (TPR) or detection rate. It is the total number of True Positives (TP) among all actual positive samples [9].

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

- **F1-Score:** It is a measure of the model's accuracy on a dataset. It evaluates the binary classification systems, which classify examples as positive or negative. The F1-score is a way of combining the Precision and Recall of the model and is defined as the harmonic mean of the model's Precision and Recall [9].

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The F1-Score metric was used to weigh the two ratios (Precision and Recall) in a balanced way since we have uneven class distribution. If the cost of false positives and false negatives are very different, it is better to look at both Precision and Recall.

Chapter 5

ML vs DL in Adversarial-Free Environment

In this chapter, we build a highly accurate model on ISCX VPN-NonVPN and NIMS for each architecture model, i.e., C4.5, KNN, ANN, CNN, and RNN. The experimental setup was repeated several times to obtain the finest accuracy using the feature selection technique: Mutual Information. We compare the accuracy of ML and DL models using the same top features from both datasets. We will discuss the accuracy results generated when the classifiers were applied on the two selected datasets: ISCX VPN-NonVPN and NIMS. We train each model on the same 80% of the dataset and conduct the validation on the remaining 20%, respectively. The performance of each architecture is described in the following sections.

5.1 Evaluation of Feature Selection Experiment

We focus on using a multi-classification feature selection method that can be applied to achieve high Precision and Recall accuracy and better performance. We used the Mutual Information technique.

We train the C4.5, KNN, ANN, CNN, and RNN using Mutual Information for

ISCX VPN-NonVPN and NIMS. The Experiment was executed six times for each algorithm with different batches and epoch values to obtain the best accuracy. After various tries and observations, we improve our model performance by selecting the same top five features for each dataset listed in Table 5.1.

Table 5.1: The 5 features selected from ISCX VPN-NonVPN and NIMS Datasets

ID	ISCX	ID	NIMS
0	duration	16	duration
5	max-fiat	10	max-fiat
6	max-biat	14	max-biat
7	mean-fiat	9	mean-fiat
8	mean-biat	13	mean-biat

5.2 Evaluating the Performance of ML Algorithms

5.2.1 Performance of C4.5

We report C4.5 models' performance and discuss their capability to learn encrypted traffic flow characterization and application identification on ISCX VPN-NonVPN and NIMS datasets. Table 5.2 and Table 5.3 shows the performance metrics results for the ISCX VPN-NonVPN and NIMS categorical classification in an adversarial-free environment to assist in understanding and comparing the model performance. The result values are rounded to the nearest integer. Figure 5.1 and 5.2 show the F1-Score performance metrics results for each application that was calculated from the Precision and Recall results in Table 5.2 and Table 5.3.

In ISCX VPN-NonVPN, Figure 5.1 illustrates that VoIP has the highest and

almost the same F1-Score accuracy of 98% in both VPN and Non-VPN over the other applications. Also, we can see that Chat is getting the lower F1-Score results of 42% in both VPN and Non-VPN classification.

Regarding the NIMS in Figure 5.2, we can see that RT and X11 prediction have the highest F1-Score results of 98.5% and 97.5%, respectively, compared to LT and SFTP where their prediction was 85.5% and 91.5%, respectively.

Table 5.2: Evaluation Metric Results (%) of C4.5 models in adversarial-free environment for ISCX VPN-NonVPN

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Browsing	64	65
Chat	43	40
Streaming	53	53
Mail	50	50
VoIP	99	98
P2P	68	71
File Transfer	69	54
VPN-Browsing	62	61
VPN-Chat	42	42
VPN-Streaming	76	82
VPN-Mail	55	60
VPN-VoIP	99	97
VPN-P2P	48	61
VPN-File Transfer	58	57
Average	63	64

Table 5.3: Evaluation Metric Results (%) of C4.5 models in adversarial-free environment for NIMS dataset

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Local Tunneling	99	85
Remote Tunneling	99	98
SCP	88	98
SFTP	89	82
X11	97	98
Shell	98	89
Average	95	92

Figure 5.1: C4.5 models trained by Adversarial-free ISCX VPN-NonVPN dataset

5.2.2 Performance of KNN

In this section, we evaluate the performance and capabilities of the KNN models to learn encrypted traffic flow characterization and application identification on ISCX

Figure 5.2: C4.5 models trained by Adversarial-free NIMS dataset

VPN-NonVPN and NIMS datasets. Table 5.4 and Table 5.5 presents the generated metrics results in classifying the applications of ISCX VPN-NonVPN and NIMS datasets to help in evaluating the KNN model's performance. The result values are rounded to the nearest integer. We can see the F1-Score accuracy results for each application in Figure 5.3 and 5.4.

Similar to C4.5 results in ISCX VPN-NonVPN, Figure 5.3 indicates that KNN models lead to high F1-Score accuracy prediction for VoIP application in both VPN and Non-VPN traffic of almost 95%. But, Browsing and Streaming accuracy prediction was improved in VPN traffic from 68% and 80%, respectively, compared to Non-VPN traffic, which was 64% and 52%, respectively.

In NIMS, the F1-Score of LT and RT was accurately predicted by 98.5% and 99% compared to SCP where its accuracy was less by 15%, as shown in Figure 5.4.

Table 5.4: Evaluation Metric Results (%) of KNN models in adversarial-free environment for ISCX VPN-NonVPN

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Browsing	64	65
Chat	54	51
Streaming	53	52
Mail	55	46
VoIP	96	97
P2P	71	70
File Transfer	67	52
VPN-Browsing	69	67
VPN-Chat	46	48
VPN-Streaming	74	86
VPN-Mail	52	60
VPN-VoIP	96	94
VPN-P2P	55	40
VPN-File Transfer	49	60
Average	64	63

5.3 Evaluating the Performance of DL Algorithms

5.3.1 Performance of ANN

In this section, we study and report the ANN model’s effectiveness in learning encrypted traffic flow characterization and application identification on ISCX VPN-NonVPN and NIMS datasets. From Table 5.6 and Table 5.7, we can see the Precision and Recall results for the ANN accuracy performance in ISCX VPN-NonVPN and

Table 5.5: Evaluation Metric Results (%) of KNN models in adversarial-free environment for NIMS dataset

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Local Tunneling	99	99
Remote Tunneling	97	100
SCP	84	83
SFTP	90	88
X11	89	82
Shell	79	91
Average	90	91

Figure 5.3: KNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

NIMS categorical classification to help in comparing with the other model's performance. The result values are rounded to the nearest integer. The F1-Score accuracy for each application are stated in Figure 5.5 and 5.6.

For ISCX VPN-NonVPN, the ANN models prediction accuracy of Browsing,

Figure 5.4: KNN models trained by Adversarial-free NIMS dataset

Streaming, and Mail in Non-VPN traffic was significantly improved in VPN traffic from 64%, 52%, and 2% to 72%, 78% and 43%, respectively, as shown in Figure 5.5.

As shown in Figure 5.6, the F1-Score prediction of ANN models in NIMS was 97.5% and 98% for RT and X11, respectively. Unlike SFTP, which was lower in prediction by almost 7%.

5.3.2 Performance of CNN

Table 5.8 and 5.9 illustrate the Precision and Recall metrics results initiated from the ISCX VPN-NonVPN and NIMS datasets in an adversarial-free environment to report CNN models' performance in acquiring encrypted traffic flow characterization and application identification. The result values are rounded to the nearest integer. The F1-Score accuracy for each application are presented in Figure 5.7 and 5.8.

Figure 5.7 propose the F1-Score prediction accuracy of CNN models in ISCX

Table 5.6: Evaluation Metric Results (%) of ANN models in adversarial-free environment for ISCX VPN-NonVPN

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Browsing	60	69
Chat	53	61
Streaming	50	55
Mail	100	1
VoIP	71	83
P2P	50	68
File Transfer	87	80
VPN-Browsing	69	76
VPN-Chat	60	37
VPN-Streaming	67	92
VPN-Mail	60	33
VPN-VoIP	73	86
VPN-P2P	59	57
VPN-File Transfer	75	61
Average	67	61

VPN-NonVPN, where VoIP and P2P show high accuracy in Non-VPN traffic of 90% and 92% compared to VPN traffic which was 64% and 74%, respectively. While, Mail shows a diversity in the accuracy prediction, which was low in Non-VPN traffic of 2% in contrast to VPN traffic of 73%.

The prediction accuracy of CNN in NIMS for all applications was exceeding 95% where the lowest predicted application was SFTP of 95.5% and the highest predicted

Table 5.7: Evaluation Metric Results (%) of ANN models in adversarial-free environment for NIMS dataset

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Local Tunneling	96	98
Remote Tunneling	98	97
SCP	87	96
SFTP	99	84
X11	99	97
Shell	89	99
Average	95	95

Figure 5.5: ANN models trained by Adversarial-free ISCX VPN-NonVPN dataset

applications with the same results of 97.5% are LT and SCP, as shown in Figure 5.8.

Figure 5.6: ANN models trained by Adversarial-free NIMS dataset

5.3.3 Performance of RNN

In this experiment, we will discuss the RNN model's abilities in identifying applications and learning encrypted traffic flow characterization on ISCX VPN-NonVPN and NIMS datasets. Table 5.10 and 5.11 analyze the performance metrics results in an adversarial-free for ISCX VPN-NonVPN and NIMS datasets. The result values are rounded to the nearest integer. Figure 5.9 and 5.10 show the F1-Score performance metrics results for each application.

As we can see in Figure 5.9, the Browsing, Mail, and FT got low F1-Score predicted accuracy in Non-VPN traffic of 44%, 1%, and 53% in comparison to VPN traffic of 75%, 70%, and 67% respectively.

Similar to CNN results in NIMS, Figure 5.10 shows that all application's prediction exceeds 95% and the top two applications have the same predicted results of 97.5% was X11 and Shell.

Table 5.8: Evaluation Metric Results (%) of CNN models in adversarial-free environment for ISCX VPN-NonVPN

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Browsing	52	40
Chat	38	69
Streaming	71	68
Mail	12	1
VoIP	91	89
P2P	95	90
File Transfer	40	83
VPN-Browsing	81	73
VPN-Chat	54	79
VPN-Streaming	84	65
VPN-Mail	81	67
VPN-VoIP	82	53
VPN-P2P	70	79
VPN-File Transfer	83	80
Average	67	67

5.4 Performance Comparison of ML and DL

We train two machine learning, i.e., C4.5 and KNN, and three deep learning models, i.e., ANN, CNN, and RNN, on two adversarial-free datasets. Figure 5.11 shows the performance metrics of all models in the adversarial-free environment using the same top five selected features in Table 5.1.

If we look closer to each model in Figure 5.11 and evaluate its F1-Score accuracy in the ISCX VPN-NonVPN dataset, we can find that there is a slight improvement

Table 5.9: Evaluation Metric Results (%) of CNN models in adversarial-free environment for NIMS dataset

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Local Tunneling	97	98
Remote Tunneling	98	95
SCP	99	96
SFTP	94	97
X11	98	96
Shell	94	97
Average	97	97

in deep learning models performance in classifying encrypted traffic by 2-3%, on average, in comparison to machine learning models. While in NIMS dataset, the deep learning performance was significantly better in classifying encrypted traffic by 5-7%, on average, compared to machine learning models in the adversarial-free environment.

Figure 5.7: CNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 5.8: CNN models trained by Adversarial-free NIMS dataset

Table 5.10: Evaluation Metric Results (%) of RNN models in adversarial-free environment for ISCX VPN-NonVPN

Class	Clean Data	
	<i>Precision</i>	<i>Recall</i>
-		
Browsing	41	47
Chat	48	71
Streaming	62	64
Mail	1	1
VoIP	95	98
P2P	92	86
File Transfer	38	85
VPN-Browsing	77	73
VPN-Chat	55	67
VPN-Streaming	89	68
VPN-Mail	80	63
VPN-VoIP	87	57
VPN-P2P	71	63
VPN-File Transfer	84	83
Average	66	66

Table 5.11: Evaluation Metric Results (%) of RNN models in adversarial-free environment for NIMS dataset

Class	Clean Data	
-	<i>Precision</i>	<i>Recall</i>
Local Tunneling	100	94
Remote Tunneling	97	96
SCP	94	100
SFTP	94	97
X11	99	96
Shell	96	99
Average	97	97

Figure 5.9: RNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 5.10: RNN models trained by Adversarial-free NIMS dataset

Figure 5.11: Evaluation Metric Results (%) of five models in adversarial-free environment. DL algorithms are shown in different shades of Blue. ML algorithms are shown in different shades of Red.

Chapter 6

ML and DL Resilience against Adversarial Evasion Attacks

This chapter reports and evaluates the learning model’s resilience against adversarial evasion attacks. Our experiment results illustrate the effectiveness of using different evasion attacks, i.e., PGD, ZOO, and DeepFool, against the machine and deep learning models: C4.5, KNN, ANN, CNN, and RNN on test data: ISCX VPN-NonVPN and NIMS. First, we start finding adversarial samples from the state-of-the-art adversarial attack methods with high perturbation to maximize the loss. Second, we evaluate the quality of the adversarial samples found on ISCX VPN-NonVPN and NIMS datasets against our five learning models. Finally, we evaluate the resilience of the adversarially trained models against adversarial samples generated from the evasion attacks.

As we mentioned earlier, the proposed attacks are evasion attacks, where the attacker has access to our network and tries to predict the type of encrypted traffic and identify the application used, which misclassifies the model decision and targets the positive sample to be classified as a negative sample. We used the same adversarial threat models across all experiments done. We will notice sharp prediction

accuracy fall among all learning models compared to that of the adversarial-free environments, which is expected due to the different ways of training these models with clean datasets or adversarial samples. Evaluation results are discussed in detail in the following sections.

6.1 Evaluating ML Algorithms Resilience against Adversarial Attacks

6.1.1 Performance of C4.5

We are exploring the C4.5 model's resilience against adversarial attacks on ISCX VPN-NonVPN and NIMS datasets. We can see that the C4.5 predicted accuracy was degraded by the adversarial samples generated from the two datasets using PGD, ZOO, and DeepFool adversarial evasion attacks in misleading encrypted traffic classifications.

For ISCX VPN-NonVPN and NIMS datasets, we show the C4.5 model's resilience per each application against the three adversarial attacks, as shown in Table 6.1 and 6.2. We calculate F1-Score using an average Precision and Recall to evaluate the model's performance and compare the results of the adversarial samples to that from the adversarial-free environment, as shown in Figure 6.1 and 6.2. As a reminder, we achieve F1-Score accuracy of 63% and 93% with no attack in Chapter 5 for ISCX VPN-NonVPN and NIMS, respectively.

The F1-Score accuracy of ISCX VPN-NonVPN is reduced from 53%, 50%, 98%, and 57% to 0% for Streaming, Mail, VoIP, and VPN-Mail using PGD adversarial samples, respectively. Similarly, as illustrated in Figure 6.1 with ZOO and DeepFool adversarial samples, the accuracy of VoIP and VPN-Mail degraded to 0%.

For NIMS, the F1-Score accuracy is significantly reduced from 98%, 85%, and 97% to 3%, 5%, and 6% for RT, SFTP, and X11 using DeepFool adversarial samples, respectively. At the same time, in Figure 6.2, accuracy decreased to 52%, 16%, and 43% using PGD adversarial samples, respectively.

We can conclude that the performance of C4.5 in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks compared to ISCX VPN-NonVPN. We also find that the DeepFool attack has the most influence on C4.5 models on NIMS dataset. Unlike the ISCX VPN-NonVPN dataset, where C4.5 models are less resilient to PGD evasion attacks. The ZOO attack achieves 12% and 23% as an average F1-Score accuracy on both datasets compared to the other two evasion attacks.

Figure 6.1: Effect of Adversarial Samples generated on C4.5 models trained by Adversarial-free ISCX VPN-NonVPN dataset

Table 6.1: Evaluation Metric Results (%) of C4.5 models in adversarial attack environment for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	38	24	27	26	26	12
Chat	4	4	22	16	19	5
Streaming	0	0	5	16	13	15
Mail	0	0	13	14	32	4
VoIP	0	0	0	0	0	0
P2P	4	1	13	4	3	3
File Transfer	3	3	9	28	3	6
VPN-Browsing	9	17	19	16	12	11
VPN-Chat	18	4	16	22	27	13
VPN-Streaming	1	4	10	15	15	10
VPN-Mail	0	0	8	8	0	0
VPN-VoIP	2	0	1	0	13	0
VPN-P2P	14	15	8	8	10	9
VPN-File Transfer	10	36	13	13	14	16
Average	7	8	12	13	13	7

6.1.2 Performance of KNN

As shown in Figure 6.3 and 6.4, the accuracy of the KNN model was degraded by the adversarial samples generated from ISCX VPN-NonVPN and NIMS datasets using the PGD, ZOO, and DeepFool adversarial evasion attacks in misleading encrypted traffic classifications.

For ISCX VPN-NonVPN and NIMS datasets, we show the KNN model's resilience per application against the adversarial attacks, as shown in Table 6.3 and 6.4. We

Table 6.2: Evaluation Metric Results (%) of C4.5 models in adversarial attack environment for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	25	9	9	6	16	28
Remote Tunneling	49	55	41	28	10	2
SCP	33	51	5	8	14	36
SFTP	19	14	2	2	11	3
X11	40	46	40	47	8	5
Shell	41	38	45	38	3	2
Average	35	36	24	22	10	13

calculate F1-Score using an average Precision and Recall to evaluate the model's performance and compare the results of the adversarial samples to that from the adversarial-free environment, as shown in Figure 6.3 and 6.4. As a reminder, we achieve F1-Score accuracy of 64% and 90% with no attack in Chapter 5 for ISCX VPN-NonVPN and NIMS, respectively.

The F1-Score accuracy of ISCX VPN-NonVPN is reduced from 50%, 59%, 68%, and 80% to 3%, 5%, 4%, and 2% for Mail, FT, VPN-Browsing, and VPN-Streaming using PGD adversarial samples, respectively. As shown in Figure 6.3 with ZOO and DeepFool adversarial samples, the F1-Score accuracy is degraded to 13%, 11%, 9%, 11% and 7%, 9%, 16%, 15%, respectively. We also noticed that ZOO and DeepFool strength are equal compared to PGD.

For NIMS, the F1-Score accuracy is reduced significantly from 98% and 85% to 6% and 2% for RT and X11 using DeepFool adversarial samples, respectively. F1 accuracy decreased to 34%, 34% and 20%, 36% using PGD and ZOO adversarial

Figure 6.2: Effect of Adversarial Samples generated on C4.5 models trained by Adversarial-free NIMS dataset

samples, respectively, as illustrated in Figure 6.4.

Adversarial-free KNN trained on NIMS was more resilient to the three adversarial attacks than trained on ISCX VPN-NonVPN. We observe that KNN models on NIMS were less resilient to DeepFool attack and more resilient to PGD attack. In ISCX VPN-NonVPN, PGD has a higher impact comparing to ZOO and DeepFool attacks.

6.2 Evaluating DL Algorithms Resilience against Adversarial Attacks

6.2.1 Performance of ANN

It can be seen from Figure 6.5 and 6.6 that the ANN model accuracy was degraded by the adversarial samples generated from ISCX VPN-NonVPN and NIMS datasets using the PGD, ZOO, and DeepFool adversarial evasion attacks in misleading encrypted

Table 6.3: Evaluation Metric Results (%) of KNN models in adversarial attack environment for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	18	20	36	27	19	21
Chat	23	16	27	14	27	16
Streaming	40	8	36	11	12	11
Mail	4	2	17	10	37	4
VoIP	0	1	0	2	0	0
P2P	41	12	21	12	8	7
File Transfer	4	8	7	26	7	13
VPN-Browsing	15	2	19	6	13	20
VPN-Chat	7	6	12	25	16	11
VPN-Streaming	11	1	8	17	13	18
VPN-Mail	0	0	8	4	0	0
VPN-VoIP	0	0	0	0	18	2
VPN-P2P	14	5	7	4	9	4
VPN-File Transfer	9	22	6	5	9	14
Average	13	7	15	12	13	10

traffic classifications.

For ISCX VPN-NonVPN and NIMS datasets, we show the ANN model’s resilience per each application against the three adversarial attack’s Precision and Recall, as shown in Table 6.5 and 6.6. We calculate F1-Score using an average Precision and Recall to evaluate the model’s performance and compare the results of the adversarial samples to that from the adversarial-free environment, as shown in Figure 6.5 and 6.6. As a reminder, we achieve F1-Score accuracy of 64% and 95% with no attack in Chapter 5 for ISCX VPN-NonVPN and NIMS, respectively.

Table 6.4: Evaluation Metric Results (%) of KNN models in adversarial attack environment for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	37	15	15	18	19	7
Remote Tunneling	37	31	22	19	4	12
SCP	32	53	17	23	31	20
SFTP	28	15	23	26	16	11
X11	26	50	39	33	13	1
Shell	23	14	15	9	19	17
Average	31	30	22	21	17	11

Figure 6.3: Effect of Adversarial Samples generated on KNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 6.4: Effect of Adversarial Samples generated on KNN models trained by Adversarial-free NIMS dataset

As shown in Figure 6.5, the F1-Score accuracy of ANN in ISCX VPN-NonVPN is reduced by almost 70% from the original accuracy. We also noticed that PGD, ZOO, and DeepFool consider having the same effect on ANN. DeepFool attack has the most considerable influence on the ANN on ISCX VPN-NonVPN.

For NIMS, the F1-Score accuracy is outstandingly reduced from 97%, 91%, and 98% to 0%, 3%, and 2% for RT, SFTP, and X11 using DeepFool adversarial attack, respectively. We can notice that the PGD and ZOO attacks decreased the F1- Score accuracy to 49%, 22%, 35% and 23%, 20%, 52%, respectively, as illustrated in Figure 6.6.

We can conclude that the performance of ANN in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks compared to ISCX VPN-NonVPN. We also find that the DeepFool attack has the most influence on ANN models on both datasets.

Table 6.5: Evaluation Metric Results (%) of ANN models in adversarial attack environment for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	34	8	17	20	14	6
Chat	6	10	28	1	11	1
Streaming	30	54	0	0	5	2
Mail	0	0	0	0	0	0
VoIP	1	1	41	13	2	0
P2P	0	0	25	15	0	0
File Transfer	14	15	5	30	3	17
VPN-Browsing	15	5	47	3	3	4
VPN-Chat	11	0	0	0	14	0
VPN-Streaming	40	2	79	20	10	4
VPN-Mail	0	0	0	0	4	1
VPN-VoIP	25	19	0	0	19	22
VPN-P2P	0	0	42	0	25	31
VPN-File Transfer	3	2	20	21	19	16
Average	13	8	22	9	9	7

Table 6.6: Evaluation Metric Results (%) of ANN models in adversarial attack environment for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	33	15	47	20	15	23
Remote Tunneling	49	49	31	18	7	0
SCP	39	45	9	13	9	23
SFTP	27	19	23	17	3	3
X11	39	32	51	53	3	1
Shell	42	47	21	6	2	10
Average	38	35	30	21	7	10

Figure 6.5: Effect of Adversarial Samples generated on ANN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 6.6: Effect of Adversarial Samples generated on ANN models trained by Adversarial-free NIMS dataset

6.2.2 Performance of CNN

We can demonstrate that the CNN model accuracy on Figure 6.7 and Figure 6.8 were also degraded by the adversarial samples generated from ISCX VPN-NonVPN and NIMS datasets using the PGD, ZOO, and DeepFool adversarial evasion attacks in misleading encrypted traffic classifications.

For ISCX VPN-NonVPN and NIMS datasets, we show the CNN model’s resilience per each application against the three adversarial attack’s Precision and Recall, as shown in Table 6.7 and 6.8. We calculate F1-Score using an average Precision and Recall to evaluate the model’s performance and compare the results of the adversarial samples to that from the adversarial-free environment, as shown in Figure 6.7 and 6.8. As a reminder, we achieve F1-Score accuracy of 67% and 97% with no attack in Chapter 5 for ISCX VPN-NonVPN and NIMS, respectively.

The F1-Score accuracy of ISCX VPN-NonVPN is reduced from 69%, 92%, 64%, and 81% to 0% for Streaming, P2P, VPN-VoIP, and VPN-FT using DeepFool adversarial samples, respectively. Similarly, as illustrated in Figure 6.7 with PGD and ZOO adversarial samples, the accuracy of CNN degraded to 23%, 30%, 7% and 40%,

8%, 10%, respectively.

For NIMS, the F1-Score accuracy is significantly reduced from 96% and 97% to 5% and 0% for RT and X11, using DeepFool adversarial samples, respectively. At the same time, in Figure 6.8, accuracy decreased to 42%, 36% and 20%, 50% using PGD and ZOO adversarial samples, respectively.

We can conclude that the performance of CNN in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks compared to ISCX VPN-NonVPN. We also find that the CNN models are less resilient to the DeepFool attack on both datasets. The resilience of CNN against PGD and ZOO was almost the same on both datasets compared to the DeepFool evasion attack.

Figure 6.7: Effect of Adversarial Samples generated on CNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Table 6.7: Evaluation Metric Results (%) of CNN models in adversarial attack environment for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	6	10	31	20	10	9
Chat	18	27	19	11	28	15
Streaming	16	38	0	0	0	0
Mail	0	0	0	0	0	0
VoIP	0	9	40	31	34	10
P2P	0	0	26	87	20	0
File Transfer	15	19	0	0	0	0
VPN-Browsing	27	17	42	9	27	10
VPN-Chat	15	10	22	39	11	17
VPN-Streaming	19	8	0	0	18	9
VPN-Mail	0	0	0	0	0	0
VPN-VoIP	32	29	0	8	0	0
VPN-P2P	0	0	35	0	18	16
VPN-File Transfer	14	5	15	7	0	24
Average	12	12	16	15	12	8

Table 6.8: Evaluation Metric Results (%) of CNN models in adversarial attack environment for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	32	40	40	51	10	16
Remote Tunneling	51	35	23	17	4	8
SCP	31	18	22	18	19	9
SFTP	30	40	10	9	12	21
X11	35	38	51	50	0	0
Shell	73	45	28	26	18	21
Average	42	36	29	29	11	13

Figure 6.8: Effect of Adversarial Samples generated on CNN models trained by Adversarial-free NIMS dataset

6.2.3 Performance of RNN

Consistently with the result of the ISCX VPN-NonVPN and NIMS on CNN and ANN experiments, it can be seen from Figure 6.9 and Figure 6.10 that the RNN models was degraded by the adversarial samples generated from ISCX VPN-NonVPN and

NIMS datasets using the PGD, ZOO, and DeepFool adversarial evasion attacks in misleading encrypted traffic classifications.

For ISCX VPN-NonVPN and NIMS datasets, we show the RNN model’s resilience per each application against the three adversarial attack’s Precision and Recall, as shown in Table 6.9 and 6.10. We use an average Precision and Recall to calculate F1-Score to evaluate the model’s performance and compare the results of the adversarial samples to that from the adversarial-free environment, as shown in Figure 6.9 and 6.10. As a reminder, we achieve F1-Score accuracy of 66% and 97% with no attack in Chapter 5 for ISCX VPN-NonVPN and NIMS, respectively.

As shown in Figure 6.9, the F1-Score accuracy of RNN in ISCX VPN-NonVPN is reduced by almost 80% from the original accuracy. We also noticed that PGD, ZOO, and DeepFool consider having the same effect on RNN. DeepFool attack has the most considerable influence on the RNN on ISCX VPN-NonVPN.

For NIMS, the F1-Score accuracy is reduced from 97%, 96%, and 97% to 8%, 4%, and 3% for LT, RT, and X11 using DeepFool adversarial samples, respectively. At the same time, in Figure 6.10, accuracy decreased significantly to 32%, 41%, 35% and 20%, 28%, 51% using PGD and ZOO adversarial samples, respectively.

We can conclude that the performance of RNN in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks compared to ISCX VPN-NonVPN. We also find that the DeepFool attack has the most influence on RNN models on both datasets. The resilience of RNN was less against ZOO in NIMS compared to PGD attacks. The effect of the PGD and ZOO attacks was equal, on average, on ISCX VPN-NonVPN.

Table 6.9: Evaluation Metric Results (%) of RNN models in adversarial attack environment for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	7	16	24	19	12	6
Chat	27	17	23	10	23	5
Streaming	19	43	0	0	0	0
Mail	0	0	0	0	0	0
VoIP	0	1	52	10	53	12
P2P	0	0	16	79	25	1
File Transfer	10	11	0	0	0	10
VPN-Browsing	18	14	21	18	35	13
VPN-Chat	18	13	24	28	17	7
VPN-Streaming	20	8	0	0	16	14
VPN-Mail	0	0	0	0	0	0
VPN-VoIP	33	31	9	0	0	1
VPN-P2P	0	0	32	4	10	4
VPN-File Transfer	11	6	25	18	15	25
Average	12	11	16	13	15	7

6.3 Performance Comparison of ML and DL in Adversarial Environment

We evaluate the resilience of the trained models in classifying encrypted traffic against the crafted adversarial samples (using PGD, ZOO, and DeepFool evasion attacks). In this experiment, we build the learning models with different architecture, and we preprocess the benchmark datasets: ISCX VPN-NonVPN and NIMS using the

Table 6.10: Evaluation Metric Results (%) of RNN models in adversarial attack environment for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	27	40	25	17	17	5
Remote Tunneling	43	40	49	20	14	2
SCP	23	12	12	22	23	7
SFTP	35	42	18	15	10	28
X11	35	35	46	57	4	3
Shell	64	56	31	18	9	11
Average	38	38	30	25	13	9

same top features. Figure 6.11 and 6.12 compare the effect of the adversarial attack methods against the learning algorithms. From Figure 6.11 and 6.12, we can see that machine learning and deep learning model accuracy were degraded significantly by the adversarial samples generated from the two datasets using the PGD, ZOO, and DeepFool evasion attacks.

In the ISCX VPN-NonVPN dataset in Figure 6.11, we can conclude that, on average, deep learning models were more resilient in classifying encrypted traffic to ZOO and PGD attacks compared to machine learning models. We also find that the resilience of deep learning was lower against the DeepFool attack than other attacks.

In NIMS dataset, deep learning performance shows more resilience in classifying encrypted traffic against ZOO and PGD adversarial samples compared to machine learning, as shown in Figure 6.12. Unlike DeepFool attack where deep learning was

Figure 6.9: Effect of Adversarial Samples generated on RNN models trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 6.10: Effect of Adversarial Samples generated on RNN models trained by Adversarial-free NIMS dataset

less resilient to this type of attack compared to machine learning. We can also conclude that the DeepFool attack method has the highest effect on NIMS dataset, similar to the ISCX VPN-NonVPN dataset.

Figure 6.11: Effect of Adversarial Samples generated on five models trained by Adversarial-free ISCX VPN-NonVPN dataset. DL algorithms are shown in different shades of Blue. ML algorithms are shown in different shades of Red.

Figure 6.12: Effect of Adversarial Samples generated on five models trained by Adversarial-free NIMS dataset. DL algorithms are shown in different shades of Blue. ML algorithms are shown in different shades of Red.

Chapter 7

ML and DL Resilience against Adversarial Evasion Attacks: Experiments with Top Feature Selection

This chapter reports and evaluates the learning model’s resilience against the three adversarial evasion attacks: PGD, ZOO, and DeepFool, using the top nine features generated from the Mutual Information algorithm, as listed in Table 7.1. Our objective is to find if we can improve the model’s performance in an adversarial-free environment and their resilience against adversarial attacks when using more top selected features. We will compare our results with the experimental results generated using the same top five features in Chapters 5 and 6. First, we retrain the five models: C4.5, KNN, ANN, CNN, and RNN using Mutual Information for ISCX VPN-NonVPN and NIMS in an adversarial-free environment with the same experimental setup in Chapter 5. Then, we evaluate the adversarially trained models’ resilience in classifying encrypted traffic against adversarial samples generated from the same adversarial methods used in Chapter 6.

Table 7.1: The Top 9 features selected from ISCX VPN-NonVPN and NIMS Datasets

ID	ISCX	ID	NIMS
4	min-fiat	8	min-fiat
5	max-fiat	10	max-fiat
6	max-biat	14	max-biat
0	duration	1	mean-fpctl
9	flowPktsPerSecond	3	std-fpctl
10	flowBytesPerSecond	5	mean-bpctl
12	max-flowiat	7	std-bpctl
13	mean-flowiat	9	mean-fiat
14	std-flowiat	15	std-biat

7.1 Evaluating ML Algorithms against Adversarial Attacks: Top Feature Selection

7.1.1 Performance on C4.5

We will evaluate the C4.5 model’s resilience in adversarial-free and adversarial attack environments on the same datasets: ISCX VPN-NonVPN and NIMS, using the same evasion attacks: PGD, ZOO, and DeepFool. Table 7.2 and 7.3 indicate the Precision and Recall of the model’s resilience in classifying each encrypted application against the three adversarial attacks.

We noticed that PGD, ZOO, and DeepFool consider having the same effect on C4.5. In ISCX VPN-NonVPN, the F1-Score accuracy is reduced from 64% and 69% to 0% for Chat and VPN-FT using PGD adversarial samples, respectively. Similarly, as illustrated in Figure 7.1 with DeepFool adversarial samples, the accuracy of Mail

and VoIP degraded to 0%, respectively.

In Figure 7.2, we can see an accuracy degradation in NIMS from 99% and 99% to 17% and 6% for RT and Shell using DeepFool adversarial samples, respectively. We also can see that the F1-Score decreased to 95% and 49% using ZOO adversarial samples, respectively.

We can conclude that the performance of C4.5 in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks in classifying encrypted traffic compared to ISCX VPN-NonVPN. We also find that the DeepFool attack has the most influence on C4.5 models on NIMS dataset. Unlike the ISCX VPN-NonVPN dataset, where C4.5 models are less resilient to PGD evasion attacks. The effect of the ZOO attack is on average on both datasets compared to the other two evasion attacks.

Table 7.2: Evaluation Metric Results (%) of C4.5 models in attack environment using Top FS for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	7	11	21	15	36	29
Chat	0	0	11	7	26	5
Streaming	3	20	4	9	7	1
Mail	0	0	6	8	0	0
VoIP	1	0	4	1	0	0
P2P	5	10	9	6	28	4
File Transfer	4	8	3	6	1	7
VPN-Browsing	3	0	1	0	1	1
VPN-Chat	20	5	9	16	24	5
VPN-Streaming	2	3	1	1	12	43
VPN-Mail	11	10	9	10	17	12
VPN-VoIP	20	2	14	13	12	3
VPN-P2P	13	45	6	9	20	7
VPN-File Transfer	0	0	9	8	10	11
Average	6	8	8	8	14	9

Table 7.3: Evaluation Metric Results (%) of C4.5 models in attack environment using Top FS for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	0	0	1	0	17	59
Remote Tunneling	92	99	91	100	11	38
SCP	5	9	1	2	10	1
SFTP	0	0	0	0	15	16
X11	91	97	1	1	31	50
Shell	90	63	45	53	7	5
Average	46	45	23	26	15	28

Figure 7.2: Effect of Adv. Samples generated on C4.5 models using Top FS trained by Adversarial-free NIMS dataset

7.1.2 Performance on KNN

For ISCX VPN-NonVPN and NIMS datasets, we illustrate the KNN model's resilience in classifying encrypted traffic against the PGD, ZOO, and DeepFool adversarial

evasion attacks by presenting each application's Precision and Recall, as shown in Table 7.4 and 7.5. Figure 7.3 and 7.4 show the F1-Score calculations used to evaluate the model's performance and compare the results to that from the adversarial-free environment.

We observe in ISCX VPN-NonVPN, as shown in Figure 7.3, an F1-Score accuracy reduction from 82%, 40%, 81%, and 51% to 0% for P2P, VPN-Chat, VPN-Streaming, and VPN-P2P using PGD adversarial attack, respectively. Similarly, as illustrated in Figure 7.3 with ZOO and Deepfool adversarial samples, the accuracy of KNN degraded to 8%, 22%, 16%, 32% and 17%, 11%, 10%, 12% respectively.

The F1-Score accuracy is tremendously reduced from 94% and 99% to 16% and 15% for RT, and Shell using DeepFool adversarial attack in NIMS, respectively. We can notice a slight drop in the F1-Score accuracy when using PGD and ZOO attacks to 88%, 84% and 92%, 71%, respectively, as illustrated in Figure 7.4.

We can conclude that the resilience of KNN in classifying encrypted traffic was less against PGD attacks in ISCX VPN-NonVPN compared to ZOO and DeepFool attacks where KNN models were more resilient to them. While in NIMS, KNN was more resilient to PGD attacks compared to DeepFool that has more influence on KNN models.

Table 7.4: Evaluation Metric Results (%) of KNN models in attack environment using Top FS for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	4	12	23	36	29	31
Chat	21	3	50	2	11	8
Streaming	100	1	4	12	5	10
Mail	0	0	0	0	10	28
VoIP	0	0	0	0	5	1
P2P	0	0	10	7	25	13
File Transfer	15	7	26	26	3	14
VPN-Browsing	13	37	11	1	1	0
VPN-Chat	0	0	18	29	8	17
VPN-Streaming	0	0	10	37	15	7
VPN-Mail	10	3	13	22	15	27
VPN-VoIP	30	6	23	14	23	8
VPN-P2P	0	0	23	53	12	13
VPN-File Transfer	22	5	43	3	14	8
Average	15	5	18	17	13	13

7.2 Evaluating DL Algorithms against Adversarial Attacks: Top Feature Selection

7.2.1 Performance on ANN

As shown in Table 7.6 and 7.7, we calculate the Precision and Recall of each encrypted application in ISCX VPN-NonVPN and NIMS datasets against the three adversarial

Table 7.5: Evaluation Metric Results (%) of KNN models in attack environment using Top FS for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	0	0	1	2	19	64
Remote Tunneling	80	98	97	99	14	18
SCP	12	10	2	9	3	5
SFTP	20	19	0	0	95	17
X11	95	94	0	4	28	36
Shell	93	77	63	81	17	14
Average	50	50	27	33	29	26

Figure 7.3: Effect of Adv. Samples generated on KNN models using Top FS trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 7.4: Effect of Adv. Samples generated on KNN models using Top FS trained by Adversarial-free NIMS dataset

attacks. We also used these results to determine the F1-Score accuracy to evaluate the model's performance and resilience, as shown in Figure 7.5 and 7.6.

If we take a closer look at ANN in ISCX VPN-NonVPN, we find that PGD, ZOO, and DeepFool consider having the same effect and the overall accuracy is reduced by almost 85%, as shown in Figure 7.5. PGD attack has the most considerable influence on the ANN on ISCX VPN-NonVPN.

We can see from Figure 7.6 that the F1-Score accuracy is reduced from 97%, 91%, and 98% to 0%, 3%, and 2% for RT, SFTP, and X11 using DeepFool adversarial attack, respectively. We can notice that the PGD and ZOO attacks decreased the F1-Score accuracy to 49%, 22%, 35% and 23%, 20%, 52%, respectively, as illustrated in Figure 7.6.

We can conclude that the performance of ANN in the adversarial-free environment in NIMS was more resilient to the three adversarial attacks in classifying encrypted traffic compared to ISCX VPN-NonVPN. We also find that the DeepFool attack has

Table 7.6: Evaluation Metric Results (%) of ANN models in attack environment using Top FS for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	19	10	10	18	9	16
Chat	4	4	41	1	17	10
Streaming	31	39	9	1	2	8
Mail	0	0	1	1	0	0
VoIP	1	1	0	0	0	0
P2P	2	3	0	0	7	1
File Transfer	33	26	14	1	8	15
VPN-Browsing	0	0	15	28	40	32
VPN-Chat	27	8	23	20	29	18
VPN-Streaming	44	11	37	19	6	18
VPN-Mail	7	12	29	20	18	12
VPN-VoIP	3	0	25	15	18	20
VPN-P2P	0	0	27	39	20	17
VPN-File Transfer	10	9	16	40	10	11
Average	13	9	18	15	13	13

the most influence on ANN models on both datasets.

7.2.2 Performance on CNN

In this experiment, we show the CNN model's resilience per each encrypted application against the three adversarial attack's Precision and Recall, as shown in Table 7.8 and 7.9. We calculate the F1-Score and present the results in Figure 7.7 and 7.8, to evaluate the model's performance and compare the results of the adversarial samples

Table 7.7: Evaluation Metric Results (%) of ANN models in attack environment using Top FS for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	40	36	0	0	0	0
Remote Tunneling	82	99	91	98	87	99
SCP	29	41	4	5	2	4
SFTP	12	2	0	0	0	0
X11	63	99	95	90	48	51
Shell	95	69	86	72	13	2
Average	54	58	46	44	25	26

Figure 7.5: Effect of Adv. Samples generated on ANN models using Top FS trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 7.6: Effect of Adv. Samples generated on ANN models using Top FS trained by Adversarial-free NIMS dataset

to that from the adversarial-free environment.

In general, we noticed that the F1-Score accuracy of CNN in ISCX VPN-NonVPN is reduced from 81%, 86%, 83%, and 85% to 9%, 0%, 8%, and 6% for Chat, VPN-Browsing, VPN-Streaming, and VPN-VoIP using PGD adversarial attack, respectively, as illustrated in Figure 7.7. We also noticed that with ZOO and Deepfool adversarial samples, the accuracy of RNN degraded to 33%, 14%, 20%, 20% and 13%, 10%, 14%, 22%, respectively.

We find that the accuracy in NIMS was roughly reduced from 100%, and 99% to 56%, and 3% for RT, and Shell, using DeepFool adversarial samples, respectively. At the same time, in Figure 7.8, accuracy decreased to 93%, 98%, and 99%, 53% using PGD and ZOO adversarial samples, respectively.

We can conclude that the resilience of CNN in classifying encrypted traffic was less against PGD attacks in ISCX VPN-NonVPN compared to ZOO and DeepFool attacks where CNN models were more resilient to them. While in NIMS, CNN was more resilient to PGD attacks compared to DeepFool that has more impact on RNN

Table 7.8: Evaluation Metric Results (%) of CNN models in attack environment using Top FS for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	19	27	34	19	27	11
Chat	6	19	43	27	16	11
Streaming	18	7	40	11	21	36
Mail	20	1	17	9	0	0
VoIP	0	0	21	3	0	0
P2P	17	21	30	27	20	10
File Transfer	30	27	22	41	24	16
VPN-Browsing	0	0	21	11	11	10
VPN-Chat	1	8	19	19	20	1
VPN-Streaming	17	5	21	20	18	12
VPN-Mail	19	23	48	50	5	4
VPN-VoIP	4	9	21	19	29	18
VPN-P2P	24	12	13	22	24	38
VPN-File Transfer	9	10	14	24	10	21
Average	13	12	26	22	16	13

models.

7.2.3 Performance on RNN

Consistently with the Precision and Recall results of the ISCX VPN-NonVPN and NIMS datasets, as shown in Table 7.10 and 7.11, we can calculate the F1-Score to evaluate the model's performance and compare the results of the adversarial samples

Table 7.9: Evaluation Metric Results (%) of CNN models in attack environment using Top FS for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	19	25	0	1	69	58
Remote Tunneling	88	99	99	99	39	99
SCP	27	20	4	8	8	2
SFTP	50	53	0	0	0	0
X11	100	98	90	98	38	56
Shell	99	97	49	58	4	3
Average	64	65	40	44	26	36

Figure 7.7: Effect of Adv. Samples generated on CNN models using Top FS trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 7.8: Effect of Adv. Samples generated on CNN models using Top FS trained by Adversarial-free NIMS dataset

to that from the adversarial-free environment, as shown in Figure 7.9 and 7.10.

The RNN performance in ISCX VPN-NonVPN when using the F1-Score results shows a degradation from 89%, 77%, and 87% to 0%, 7%, and 7% for VPN-Browsing, VPN-Streaming, and VPN-VoIP using PGD adversarial attack, respectively. Same with ZOO and Deepfool adversarial samples, the accuracy of RNN degraded to 12%, 29%, 18% and 25%, 17%, 20%, respectively, as illustrated in Figure 7.9.

While we observe in Figure 7.10 that the F1-Score accuracy in NIMS is significantly reduced from 100%, 99%, and 99% to 50%, 57%, and 18% for RT, X11, and Shell using DeepFool adversarial samples, respectively. Also, the accuracy decreased to 98%, 97%, 96% and 98%, 86%, 68% using PGD and ZOO adversarial samples, respectively.

We can conclude that the resilience of RNN in classifying encrypted traffic was less against PGD attack in ISCX VPN-NonVPN compared to ZOO attack where RNN models were more resilient to it. While in NIMS, RNN was more resilient to PGD

Table 7.10: Evaluation Metric Results (%) of RNN models in attack environment using Top FS for ISCX VPN-NonVPN

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Browsing	21	14	20	22	14	7
Chat	8	7	23	46	8	11
Streaming	7	15	30	39	18	29
Mail	23	10	14	12	0	0
VoIP	0	0	14	46	0	0
P2P	9	9	37	21	3	1
File Transfer	22	32	12	35	9	19
VPN-Browsing	0	0	15	10	30	21
VPN-Chat	11	10	19	31	14	3
VPN-Streaming	8	6	26	33	33	11
VPN-Mail	7	27	33	52	30	24
VPN-VoIP	14	5	24	15	18	22
VPN-P2P	27	34	13	27	21	43
VPN-File Transfer	16	9	22	39	20	35
Average	12	13	22	31	16	16

attacks compared to DeepFool that has more impact on RNN models.

7.3 Performance Comparison of ML and DL in Adv. Environment using Top FS

In this experiment, we build the learning models with different architecture, and we preprocess the benchmark datasets: ISCX VPN-NonVPN and NIMS using Mutual

Table 7.11: Evaluation Metric Results (%) of RNN models in attack environment using Top FS for NIMS dataset

Class	Attack Methods					
-	PGD		ZOO		DeepFool	
-	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>
Local Tunneling	26	20	0	0	39	73
Remote Tunneling	97	100	100	97	44	58
SCP	19	28	2	3	13	15
SFTP	59	45	0	0	0	0
X11	95	99	80	92	57	58
Shell	100	92	74	63	30	13
Average	66	64	43	43	31	36

Figure 7.9: Effect of Adv. Samples generated on RNN models using Top FS trained by Adversarial-free ISCX VPN-NonVPN dataset

Figure 7.10: Effect of Adv. Samples generated on RNN models using Top FS trained by Adversarial-free NIMS dataset

Information. We evaluate and compare the resilience of the trained models in classifying encrypted traffic to that in Chapters 5 and 6 against the same adversarial attacks. From Figure 7.11 and 7.12, we can observe that both ML and DL model's accuracy in the adversarial-free environment and their resilience in classifying encrypted traffic against the generated adversarial samples were improved compared in Chapters 5 and 6.

In the ISCX VPN-NonVPN dataset in Figure 7.11, we can conclude that, on average, deep learning models were more resilient in classifying encrypted traffic to ZOO and DeepFool attacks compared to machine learning models. We also find that the resilience of machine learning was lower against the PGD attack than deep learning. We can conclude that the PGD attack has the most impact on the ISCX VPN-NonVPN dataset.

In NIMS dataset, on average, deep learning performance shows more resilience in classifying encrypted traffic against ZOO and PGD adversarial samples, compared to machine learning, as shown in Figure 6.12. Unlike DeepFool attack, where machine

Figure 7.11: Effect of Adversarial Samples generated on five models using Top FS trained by Adversarial-free ISCX VPN-NonVPN dataset. DL algorithms are shown in different shades of Blue. ML algorithms are shown in different shades of Red.

learning was less resilient to this type of attack compared to deep learning. We can also conclude that the DeepFool attack method has the highest effect on NIMS dataset.

Figure 7.12: Effect of Adversarial Samples generated on five models using Top FS trained by Adversarial-free NIMS dataset. DL algorithms are shown in different shades of Blue. ML algorithms are shown in different shades of Red.

Chapter 8

Conclusions

8.1 Summary

In this research, we attempt to study the resilience of trained models in classifying encrypted traffic against adversarial perturbations techniques in an adversarial environment. The Novelty of this research derives from the fact that it is the first experiment that implements and compares machine learning, e.g., C4.5 and KNN, and deep learning, e.g., ANN, CNN, and RNN, architectures in encrypted traffic classifications in an adversarial environment, and evaluated on two benchmark datasets: ISCX VPN-NonVPN and NIMS using various adversarial attack methods. Most of the literature in the adversarial domain demonstrated the concept of using either machine or deep learning architecture [73] with different adversarial attacks [74] [38].

Sufficient research was also provided that confirms the high accuracy and fast processing speed of our chosen classifiers in classifying network traffic applications [57] [75]. One of the reasons we chose those datasets is that we were looking for encrypted datasets that are publicly available, and used for classification of different types of encrypted applications, as it contains encrypted traffic data collected from normal encryption traffic (i.e., HTTPS, SSL, SFTP), VPN sessions, and SSH sessions.

This research took the path further in investigating and evaluating the resilience of different types of ML and DL models against three state-of-the-art adversarial attack methods: PGD, ZOO, and DeepFool. Part of the experiments that we conducted was to study and analyze the effect of feature selection on two public benchmark datasets: ISCX VPN-NonVPN and NIMS. We applied feature selection using the Mutual Information technique that is used for multilabel classification. We moved forward with the entire experiments using this technique by selecting the same top five features in Chapters 5 and 6 and selecting the top nine features per each dataset in Chapter 7.

Finally, we can summarize the results and findings in this work.

1. On average, the performance of deep learning models was better than machine learning models in an adversarial-free environment in terms of encrypted traffic classification on both datasets: ISCX VPN-NonVPN and NIMS, using the same top five features.
2. Our results in adversarial attack environment demonstrate that:
  - On average, deep learning models show better resilience in classifying encrypted traffic against the adversarial samples in comparison to machine learning.
  - DeepFool Attack has more impact on almost all the models in both datasets.
  - PGD and ZOO attack effectiveness in ISCX VPN-NonVPN and NIMS experiments in most of the models are nearly similar, and the difference is minimal and difficult to observe.

3. When we retrained the models using the top nine selected features, our results demonstrate that:

- On average, all the model's accuracy in classifying encrypted traffic in an adversarial-free environment and their resilience against adversarial attacks were better than the results obtained in the initial training using the same top features.
- On average, deep learning models show better resilience against the adversarial samples in comparison to machine learning, using the top nine features.
- PGD Attack has more influence on almost all the models in ISCX VPN-NonVPN, unlike NIMS, where DeepFool was more effective than the other attacks.
- We can conclude that as more top selected features are applied, the model's performance is enhanced in both adversarial-free and adversarial attack environments.

8.2 Future Work

Although ML and DL models showed some resilience against state-of-art adversarial attacks in classifying one level of encrypted traffic applications (VPN or SSH), we believe the exploration of classifying two encrypted traffic levels, i.e., one level encryption from HTTPS or SSL, and using VPN on top of it as the second encryption level, might leads to optimal learning model's resilience in an adversarial environment.

Bibliography

- [1] G. Draper-Gil, A. H. Lashkari, M. S. I. Mamun, and A. A. Ghorbani, “Characterization of encrypted and vpn traffic using time-related,” in *Proceedings of the 2nd international conference on information systems security and privacy (ICISSP)*, pp. 407–414, 2016.
- [2] R. Alshammari and A. N. Zincir-Heywood, “Can encrypted traffic be identified without port numbers, ip addresses and payload inspection?,” *Computer networks*, vol. 55, no. 6, pp. 1326–1350, 2011.
- [3] R. Alshammari and A. N. Zincir-Heywood, “Investigating two different approaches for encrypted traffic classification,” in *2008 Sixth Annual Conference on Privacy, Security and Trust*, pp. 156–166, IEEE, 2008.
- [4] R. Alshammari and A. N. Zincir-Heywood, “A flow based approach for ssh traffic detection,” in *2007 IEEE international conference on systems, man and cybernetics*, pp. 296–301, IEEE, 2007.
- [5] A. Huet, A. Saverimoutou, Z. B. Houidi, H. Shi, S. Cai, J. Xu, B. Mathieu, and D. Rossi, “Revealing qoe of web users from encrypted network traffic,” in *2020 IFIP Networking Conference (Networking)*, pp. 28–36, IEEE, 2020.

- [6] R. Sommer and V. Paxson, “Outside the closed world: On using machine learning for network intrusion detection,” in *2010 IEEE symposium on security and privacy*, pp. 305–316, IEEE, 2010.
- [7] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, “Intriguing properties of neural networks,” *arXiv preprint arXiv:1312.6199*, 2013.
- [8] S. Gu and L. Rigazio, “Towards deep neural network architectures robust to adversarial examples,” *arXiv preprint arXiv:1412.5068*, 2014.
- [9] Z. Wang, “Deep learning-based intrusion detection with adversaries,” *IEEE Access*, vol. 6, pp. 38367–38384, 2018.
- [10] I. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and harnessing adversarial examples,” in *International Conference on Learning Representations*, 2015.
- [11] A. Kurakin, I. Goodfellow, and S. Bengio, “Adversarial examples in the physical world,” *ICLR Workshop*, 2017.
- [12] X. Yuan, P. He, Q. Zhu, and X. Li, “Adversarial examples: Attacks and defenses for deep learning,” *IEEE transactions on neural networks and learning systems*, vol. 30, no. 9, pp. 2805–2824, 2019.
- [13] S.-M. Moosavi-Dezfooli, A. Fawzi, and P. Frossard, “Deepfool: a simple and accurate method to fool deep neural networks,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2574–2582, 2016.
- [14] U. Jang, X. Wu, and S. Jha, “Objective metrics and gradient descent algorithms for adversarial examples in machine learning,” in *Proceedings of the 33rd Annual Computer Security Applications Conference*, pp. 262–277, 2017.

- [15] N. Papernot, P. McDaniel, S. Jha, M. Fredrikson, Z. B. Celik, and A. Swami, “The limitations of deep learning in adversarial settings,” in *2016 IEEE European symposium on security and privacy (EuroSecP)*, pp. 372–387, IEEE, 2016.
- [16] A. Madry, A. Makelov, L. Schmidt, D. Tsipras, and A. Vladu, “Towards deep learning models resistant to adversarial attacks,” in *International Conference on Learning Representations*, 2018.
- [17] P.-Y. Chen, H. Zhang, Y. Sharma, J. Yi, and C.-J. Hsieh, “Zoo: Zeroth order optimization based black-box attacks to deep neural networks without training substitute models,” in *Proceedings of the 10th ACM workshop on artificial intelligence and security*, pp. 15–26, 2017.
- [18] R. Maarouf, D. Sattar, and A. Matrawy, “Evaluating resilience of encrypted traffic classification against adversarial evasion attacks,” *arXiv preprint arXiv:2105.14564*, 2021.
- [19] T. Rid and B. Buchanan, “Attributing cyber attacks,” *Journal of Strategic Studies*, vol. 38, no. 1-2, pp. 4–37, 2015.
- [20] M. Uma and G. Padmavathi, “A survey on various cyber attacks and their classification,” *Int. J. Netw. Secur.*, vol. 15, no. 5, pp. 390–396, 2013.
- [21] C. LaBounty, “What is network security and why is it important?.”
- [22] A. Singh, N. Thakur, and A. Sharma, “A review of supervised machine learning algorithms,” in *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 1310–1315, Ieee, 2016.

- [23] G. L. Agrawal and H. Gupta, "Optimization of c4. 5 decision tree algorithm for data mining application," *International Journal of Emerging Technology and Advanced Engineering*, vol. 3, no. 3, pp. 341–345, 2013.
- [24] J. R. Quinlan, *C4. 5: programs for machine learning*. Elsevier, 2014.
- [25] X. Wu, V. Kumar, J. R. Quinlan, J. Ghosh, Q. Yang, H. Motoda, G. J. McLachlan, A. Ng, B. Liu, S. Y. Philip, *et al.*, "Top 10 algorithms in data mining," *Knowledge and information systems*, vol. 14, no. 1, pp. 1–37, 2008.
- [26] J. M. Keller, M. R. Gray, and J. A. Givens, "A fuzzy k-nearest neighbor algorithm," *IEEE transactions on systems, man, and cybernetics*, no. 4, pp. 580–585, 1985.
- [27] K. Gayathri and A. Marimuthu, "Text document pre-processing with the knn for classification using the svm," in *2013 7th International Conference on Intelligent Systems and Control (ISCO)*, pp. 453–457, IEEE, 2013.
- [28] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A survey of deep learning and its applications: A new paradigm to machine learning," *Archives of Computational Methods in Engineering*, pp. 1–22, 2019.
- [29] R. Vinayakumar, K. Soman, and P. Poornachandran, "Applying deep learning approaches for network traffic prediction," in *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pp. 2353–2358, IEEE, 2017.
- [30] R. E. Uhrig, "Introduction to artificial neural networks," in *Proceedings of IECON'95-21st Annual Conference on IEEE Industrial Electronics*, vol. 1, pp. 33–37, IEEE, 1995.

- [31] S. Sharma, “Activation functions in neural networks,” *towards data science*, vol. 6, 2017.
- [32] X. Glorot, A. Bordes, and Y. Bengio, “Deep sparse rectifier neural networks,” in *Proceedings of the fourteenth international conference on artificial intelligence and statistics*, pp. 315–323, JMLR Workshop and Conference Proceedings, 2011.
- [33] H. U. Dike, Y. Zhou, K. K. Deveerasetty, and Q. Wu, “Unsupervised learning based on artificial neural network: A review,” in *2018 IEEE International Conference on Cyborg and Bionic Systems (CBS)*, pp. 322–327, IEEE, 2018.
- [34] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5455–5516, 2020.
- [35] W. Wang, M. Zhu, J. Wang, X. Zeng, and Z. Yang, “End-to-end encrypted traffic classification with one-dimensional convolution neural networks,” in *2017 IEEE International Conference on Intelligence and Security Informatics (ISI)*, pp. 43–48, IEEE, 2017.
- [36] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [37] P. Laskov and R. Lippmann, “Machine learning in adversarial environments,” 2010.
- [38] J. Li, W. Monroe, T. Shi, S. Jean, A. Ritter, and D. Jurafsky, “Adversarial learning for neural dialogue generation,” in *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, (Copenhagen, Denmark), pp. 2157–2169, Association for Computational Linguistics, Sept. 2017.

- [39] P. Russu, A. Demontis, B. Biggio, G. Fumera, and F. Roli, “Secure kernel machines against evasion attacks,” in *Proceedings of the 2016 ACM workshop on artificial intelligence and security*, pp. 59–69, 2016.
- [40] V. Zantedeschi, M.-I. Nicolae, and A. Rawat, “Efficient defenses against adversarial attacks,” in *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pp. 39–49, 2017.
- [41] O. Ibitoye, R. Abou-Khamis, A. Matrawy, and M. O. Shafiq, “The threat of adversarial attacks on machine learning in network security—a survey,” *arXiv preprint arXiv:1911.02621*, 2019.
- [42] N. Akhtar and A. Mian, “Threat of adversarial attacks on deep learning in computer vision: A survey,” *Ieee Access*, vol. 6, pp. 14410–14430, 2018.
- [43] A. Chakraborty, M. Alam, V. Dey, A. Chattopadhyay, and D. Mukhopadhyay, “Adversarial attacks and defences: A survey,” *arXiv preprint arXiv:1810.00069*, 2018.
- [44] N. Papernot, P. McDaniel, X. Wu, S. Jha, and A. Swami, “Distillation as a defense to adversarial perturbations against deep neural networks,” in *2016 IEEE symposium on security and privacy (SP)*, pp. 582–597, IEEE, 2016.
- [45] F. Zhang, P. P. Chan, B. Biggio, D. S. Yeung, and F. Roli, “Adversarial feature selection against evasion attacks,” *IEEE transactions on cybernetics*, vol. 46, no. 3, pp. 766–777, 2015.
- [46] N. Pitropakis, E. Panaousis, T. Giannetsos, E. Anastasiadis, and G. Loukas, “A taxonomy and survey of attacks against machine learning,” *Computer Science Review*, vol. 34, p. 100199, 2019.

- [47] B. Biggio, B. Nelson, and P. Laskov, “Poisoning attacks against support vector machines,” in *Proceedings of the 29th International Conference on International Conference on Machine Learning*, ICML’12, (Madison, WI, USA), p. 1467–1474, Omnipress, 2012.
- [48] W. Wei, L. Liu, M. Loper, S. Truex, L. Yu, M. E. Gurney, and Y. Wu, “Adversarial examples in deep learning: Characterization and divergence,” *arXiv preprint arXiv:1807.00051*, 2018.
- [49] S. Chen, M. Xue, L. Fan, S. Hao, L. Xu, H. Zhu, and B. Li, “Automated poisoning attacks and defenses in malware detection systems: An adversarial machine learning approach,” *computers & security*, vol. 73, pp. 326–344, 2018.
- [50] B. Wu, S. Wang, X. Yuan, C. Wang, C. Rudolph, and X. Yang, “Towards defeating misclassification attacks against transfer learning,” *arXiv preprint arXiv:1908.11230*, 2019.
- [51] T. T. Nguyen and G. Armitage, “A survey of techniques for internet traffic classification using machine learning,” *IEEE communications surveys & tutorials*, vol. 10, no. 4, pp. 56–76, 2008.
- [52] A. McGregor, M. Hall, P. Lorier, and J. Brunskill, “Flow clustering using machine learning techniques,” in *International workshop on passive and active network measurement*, pp. 205–214, Springer, 2004.
- [53] J. Erman, A. Mahanti, M. Arlitt, and C. Williamson, “Identifying and discriminating between web and peer-to-peer traffic in the network core,” in *Proceedings of the 16th international conference on World Wide Web*, pp. 883–892, 2007.

- [54] P. Haffner, S. Sen, O. Spatscheck, and D. Wang, “Acas: automated construction of application signatures,” in *Proceedings of the 2005 ACM SIGCOMM workshop on Mining network data*, pp. 197–202, 2005.
- [55] A. W. Moore and D. Zuev, “Internet traffic classification using bayesian analysis techniques,” in *Proceedings of the 2005 ACM SIGMETRICS international conference on Measurement and modeling of computer systems*, pp. 50–60, 2005.
- [56] M. Abbasi, A. Shahraki, and A. Taherkordi, “Deep learning for network traffic monitoring and analysis (ntma): A survey,” *Computer Communications*, 2021.
- [57] M. Lotfollahi, M. J. Siavoshani, R. S. H. Zade, and M. Saberian, “Deep packet: A novel approach for encrypted traffic classification using deep learning,” *Soft Computing*, vol. 24, no. 3, pp. 1999–2012, 2020.
- [58] A. S. Iliyasu and H. Deng, “Semi-supervised encrypted traffic classification with deep convolutional generative adversarial networks,” *IEEE Access*, vol. 8, pp. 118–126, 2019.
- [59] M. Z. Alom, V. Bontupalli, and T. M. Taha, “Intrusion detection using deep belief networks,” in *2015 National Aerospace and Electronics Conference (NAECON)*, pp. 339–344, IEEE, 2015.
- [60] H. Xu, Y. Ma, H.-C. Liu, D. Deb, H. Liu, J.-L. Tang, and A. K. Jain, “Adversarial attacks and defenses in images, graphs and text: A review,” *International Journal of Automation and Computing*, vol. 17, no. 2, pp. 151–178, 2020.
- [61] I. Corona, G. Giacinto, and F. Roli, “Adversarial attacks against intrusion detection systems: Taxonomy, solutions and open issues,” *Information Sciences*, vol. 239, pp. 201–225, 2013.

- [62] A. Dainotti, A. Pescapè, and K. C. Claffy, “Issues and future directions in traffic classification,” *IEEE network*, vol. 26, no. 1, pp. 35–40, 2012.
- [63] J. Brownlee, *Deep learning with Python: develop deep learning models on Theano and TensorFlow using Keras*. Machine Learning Mastery, 2016.
- [64] P. Raybaut, “Spyder-documentation,” *Available online at: pythonhosted.org*, 2009.
- [65] M.-I. Nicolae, M. Sinn, T. N. Minh, A. Rawat, M. Wistuba, V. Zantedeschi, I. M. Molloy, and B. Edwards, “Adversarial robustness toolbox v0. 2.2,” 2018.
- [66] J. Brownlee, “Machine learning mastery with python,” *Machine Learning Mastery Pty Ltd*, vol. 527, pp. 100–120, 2016.
- [67] J. Brownlee, “How to index, slice and reshape numpy arrays for machine learning.”
- [68] G. Chandrashekar and F. Sahin, “A survey on feature selection methods,” *Computers & Electrical Engineering*, vol. 40, no. 1, pp. 16–28, 2014.
- [69] A. Kraskov, H. Stögbauer, and P. Grassberger, “Estimating mutual information,” *Physical review E*, vol. 69, no. 6, p. 066138, 2004.
- [70] J. R. Vergara and P. A. Estévez, “A review of feature selection methods based on mutual information,” *Neural computing and applications*, vol. 24, no. 1, pp. 175–186, 2014.
- [71] H. Sharma and S. Kumar, “A survey on decision tree algorithms of classification in data mining,” *International Journal of Science and Research (IJSR)*, vol. 5, no. 4, pp. 2094–2097, 2016.

- [72] L. Jiang, Z. Cai, D. Wang, and S. Jiang, “Survey of improving k-nearest-neighbor for classification,” in *Fourth international conference on fuzzy systems and knowledge discovery (FSKD 2007)*, vol. 1, pp. 679–683, IEEE, 2007.
- [73] B. Biggio, I. Corona, G. Fumera, G. Giacinto, and F. Roli, “Bagging classifiers for fighting poisoning attacks in adversarial classification tasks,” in *International workshop on multiple classifier systems*, pp. 350–359, Springer, 2011.
- [74] R. Abou Khamis and A. Matrawy, “Evaluation of adversarial training on different types of neural networks in deep learning-based idss,” in *2020 International Symposium on Networks, Computers and Communications (ISNCC)*, pp. 1–6, IEEE, 2020.
- [75] M. Shafiq, X. Yu, A. A. Laghari, L. Yao, N. K. Karn, and F. Abdessamia, “Network traffic classification techniques and comparative analysis using machine learning algorithms,” in *2016 2nd IEEE International Conference on Computer and Communications (ICCC)*, pp. 2451–2455, IEEE, 2016.

Appendix A

Table A.1: ISCX VPN-NonVPN dataset Features based on the description in [1]

ID	Name	Description
1	duration	Record total duration
2	total-fiat	Total Forward Inter Arrival Time
3	total-biat	Total Backward Inter Arrival Time
4	min-fiat	Minumim Forward Inter Arrival Time
5	min-biat	Minumim Backward Inter Arrival Time
6	max-fiat	Maxumim Forward Inter Arrival Time
7	max-biat	Maxumim Backward Inter Arrival Time
8	mean-fiat	Mean Forward Inter Arrival Time
9	mean-biat	Mean Backward Inter Arrival Time
10	flowPktsPerSecond	Flow packets per second
11	flowBytesPerSecond	Flow Bytes per second
12	min-flowiat	Minumim Flow Inter Arrival Time
13	max-flowiat	Maxumim Flow Inter Arrival Time
14	mean-flowiat	Mean Flow Inter Arrival Time
15	std-flowiat	Standard Deviation of Flow Inter Arrival Time
16	min-active	Minumim amount of time a flow was active
17	mean-active	Mean amount of time a flow was active
18	max-active	Maxumim amount of time a flow was active
19	std-active	Standard Deviation of the amount of time a flow was active
20	min-idle	Minumim amount of time a flow was idle
21	mean-idle	Mean amount of time a flow was idle
22	max-idle	Maxumim amount of time a flow was idle
23	std-idle	Standard Deviation of the amount of time a flow was idle

Table A.2: NIMS dataset Features based on the description in [2] [3] [4]

ID	Name	Description
1	min-fpktl	Minumim forward packet length
2	mean-fpktl	Mean forward packet length
3	max-fpktl	Maximum forward packet length
4	std-fpktl	Standard Deviation of forward packet length
5	min-bpktl	Minumim backward packet length
6	mean-bpktl	Mean backward packet length
7	max-bpktl	Maximum backward packet length
8	std-bpktl	Standard Deviation of backward packet length
9	min-fiat	Minumim forward Inter Arrival Time
10	mean-fiat	Mean forward Inter Arrival Time
11	max-fiat	Maxumim forward Inter Arrival Time
12	std-fiat	Standard Deviation of forward Inter Arrival Time
13	min-biat	Minumim backward Inter Arrival Time
14	mean-biat	Mean backward Inter Arrival Time
15	max-biat	Maxumim backward Inter Arrival Time
16	std-biat	Standard Deviation of backward Inter Arrival Time
17	duration	Record total duration
18	proto	Protocol
19	total-fpackets	Total Packets in forward direction
20	total-fvolume	Total Bytes in forward direction
21	total-bpackets	Total Packets in backward direction
22	total-bvolume	Total Bytes in backward direction