An Intrusion Detection System for Multi-Class Classification based on Deep Neural Networks

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***Abstract*—Intrusion Detection Systems (IDSs) are considered as one of the fundamental elements in the network security of an organisation since they form the first line of defence against cyber threats, and they are responsible to effectively a potential intrusion in the network. Many IDS implementations use flow-based network traffic analysis to detect potential threats. Network security research is an ever-evolving field and IDSs in particular have been the focus of recent years with many innovative methods proposed and developed. In this paper, we propose a deep learning model, more specifically a neural network consisting of multiple stacked Fully-Connected layers, in order to implement a flow-based anomaly detection IDS for multi-class classification. We used the updated CICIDS2017 dataset for training and evaluation purposes. The experimental outcome using MLP for intrusion detection system, showed that the proposed model can achieve promising results on multi-class classification with respect to accuracy, recall (detection rate), and false positive rate (false alarm rate) on this specific dataset.**

***Index Terms*—Cybersecurity, Intrusion Detection System, Deep Neural Networks, CICIDS2017, Flow Feature-Based, Multi-Class Classification**

I. Introduction

During the past few years, the rising exposure of many organisations to sophisticated cyber-attacks have led to a rapid development of innovative IDSs. The development of IDSs concerns both the academic and the industrial community worldwide, due to the impact that each cyber attack has, as economic cost, reputational damage, and legal sequences. Therefore, it is a matter of great importance to secure networks from unauthorized access and protect the user communication and their data, [1], as well as to reveal new security issues that arise.

A. Intrusion Detection System

Intrusion Detection System (IDS) is an efficient security reinforcement tool for the detection and the protection of cyber-attacks in any network or host. The IDSs‘ responsibility is to detect suspicious behaviors and act appropriately to protect the network from the onset of attacks and reduce functionally and financial losses, [2].

In literature, IDSs can be categorized as, [3], either signature-based, [4], anomaly-based, [5], or a hybrid combination of both.

Signature-based intrusion detection systems (SIDS), also known as Rule-based or Misuse IDS, conducts ongoing monitoring of network traffic and seeks out sequences or patterns of inbound network traffic that matches an attack signature. An attack signature can be identified based on network packet headers, destination or source network addresses; sequences of data that correspond to known malware or other patterns, sequences of data or series of packets that are known to be associated with a particular attack. They work with high accuracy rates in identifying possible known invasions, by keeping error rates low. However, the system s database should be updated manually by the administrator and SIDS can detect only intrusions that exist in the system s database, excluding new attacks detection (zero-day-attack), as there is no relevant attack signature pattern in the system s database.

The anomaly-based intrusion detection systems (AIDS), or behavior-based detection, analyzes the normal networks behavior, by monitoring network traffic to detect abnormal activity. AIDS have the ability to be trained with anomaly detection algorithms or to be self-trained with self-learning algorithms, so they can detect new types of intrusions. Compared to signature-based, anomaly-based shows a significant difference in identifying novel attacks. Moreover, the configuration profile of each system can be customized, so it is difficult for the attackers to figure out which intrusion activities will be undetected, [6].

Hybrid Intrusion Detection System (HIDS) can combine the advantages of both signature-based and anomaly-based system and increase the detection of known intrusion attacks, while eliminating the error rates of unknown attacks. Most of the latest hybrid IDSs are based on machine and deep learning methods.

Due to the advantages of the anomaly-based intrusion detection systems in the field of zero-day attacks, the proposed model develop an anomaly-based Intrusion Detection System which is based on deep learning.

B. Flow feature-based Classification

One of the main methods of intrusion detection is the network traffic analysis and the extraction of the desired statistical features in order to detect abnormal network traffic, in near-real time. Thus, traffic classification is a core component in

an Intrusion Detection System, which since analyze network packets, can determine whether the network behavior violates the systems security, by continuously monitoring the network. IDSs, in order to work properly and detect abnormal activities effectively, use divided traffic packets into network flows, according to source/ destination IP, source/ destination port, protocol, and timestamp, [7], [8]. A useful flow definition is mentioned bellow. *A flow is a group of IP packets with some common properties passing a monitoring point in a specified time interval*, [9].

Cisco, [10], referred that *A complete flow is a unidirectional exchange of consecutive packets on the network between a port at an IP address and another port at a different IP address, using a particular application protocol*.

Therefore, traffic classification is necessary for the efficient flow management, processing and machine learning exploitation, [11]. In general, the most widespread and broad traffic classification categories are using different flow features and are divided to port-based methods, payload-based methods, host-based and flow feature-based methods.

Intrusion detection systems apply different anomaly detection methods, depending on each case study, the available resources and the accessible technologies. The current work focuses on the flow feature-based technique, since it can overcome numerous limitations of other techniques, such as unregistered port numbers, encrypted packet payload etc. Flow-based method uses flow features as discriminators to exploit the diversity of the traffic packets and map flows to classes, [11]. Moreover, concerning the privacy issues, flow-based method is preferable instead of payload method, because of the absence of payload.

Flow-based traffic classification is conducted with a high degree of accuracy, using machine-learning techniques, and occupies a large area of research. Boutaba et al., [11] referred that discriminative MLP-NN classifier can achieve over 99% of accuracy for traffic classification with flows. Furthermore, Sperotto et al., [12] provide a comprehensive flow-based intrusion detection survey.

C. Machine Learning and Deep Learning techniques for IDS

Machine learning and deep learning techniques have been used to develop IDSs in the field of cybersecurity. In order to increase effectiveness of IDSs, the research has been focused on novel learning technologies and algorithms of Artificial Neural Networks (ANN), Support Vector Machines (SVM), Naive-Bayesian (NB), Random Forests (RF), self-organizing map (SOM) etc. In fact, machine learning consists of a set of algorithms to draw conclusions using mathematical and statistical methods. The widespread use of machine learning extends to the fields of prediction, classification and estimation, especially in the field of network security.

The need for a complete, rich, up-to-date, and well-formed dataset with various criteria and features, is a key concern of researchers for experiments conduction, testing, and evaluation of the models, [13], [14] on modern networks. A dataset is appropriate when it:

- is updated in time due to the high malware mutation and evolution
- represents real world network traffic
- has traffic diversity and volume
- is desirable to be publicly available

In literature, there are numerous datasets available for experimentation, but only a few fulfil all the desired features. It is advisable to refer to some of the most well-known, nominally, with few details.

KDD-99, [15], CAIDA, [16], ISCX2012, [17], Kyoto, [18] are datasets that represent real world network traffic, but nowadays, are considered outdated due to the continuous evolution of network's attacks and threats. On the other hand, a quite popular in the field of research is the CICIDS2017 dataset, which was released recently and contains many traffic types, fulfils the criteria of the real world network traffic, and was created to overcome some issues of existing datasets. Based on Gharib et al., [19], CICIDS2017 meets all the criteria of an accurate and complete dataset. Although, an issue that need to be addressed in this dataset is that there is a high-class imbalance that can mislead the classifier, [13]. Currently, a new dataset appeared named CIC AWS 2018, [20], similar to its previous version, CICIDS2017, however has not yet been much reported.

Based on the CICIDS2017 dataset our goal was to implement an anomaly network intrusion system using flow-based statistical data that detects and classifies with high accuracy each type of attack into multi classification. Flow classification achieved with the use of deep learning methods in the field of machine learning. We used supervised learning and a Multi-Layer Perceptron (MLP). We designed an improved deep neural network model to classify the network traffic. Therefore, this paper propose a flow based anomaly detection system using Deep learning approach.

The structure of this paper is as follows. Section II describes some of the related work of network intrusion detection using machine learning and deep learning techniques, mostly in CICIDS2017 dataset. Section III explains the dataset used for the analysis and describes the pre-processing procedure. In Section IV, we provide a brief description of the architecture of the Deep neural network, the algorithms and our proposed MLP flow-based anomaly detection system. In Section V, we analyze the experimental results of MLP and discuss the proposed solutions. Finally, Section VI gives a conclusion of this paper and presents future work.

II. Related Work

In recent literature, most of the studies in flow-based Intrusion Detection Systems based on machine-learning technologies are using the CICIDS2017 dataset, for the training and the evaluation. However, due to the new entrant dataset in the field of cyber security, there are limited published studies yet.

Ullah and Mahmou, [21], proposed a hybrid model anomaly detection model, using technologies of flow-based anomaly detection for the classification at CICIDS2017 and UNSW-15 datasets. They used Recursive Feature Elimination (RFE)

for the selection of significant features, Synthetic Minority Over-Sampling Technique (SMOTE) for the oversampling and Edited Nearest Neighbors (ENN) for the cleaning the CICIDS2017 and UNSW-15 datasets, in order to be balanced. At level-1 the network flows were classified with decision tree classifier, as normal or abnormal (binary classification) and then, were forwarded to the level-2 in order to determine the type of the attack (multi-classification). The results of specificity, precision, recall and F-score for level-1 were measured 100% for the CICIDS2017 dataset and 99% for the UNSW-15 dataset, while the level-2 model precision, recall, and F-score were measured at 100 % for the CICIDS2017 dataset and 97 % for the UNSW-15 dataset, respectively.

Vijayanand, Devaraj and Kannapiran, [22], proposed a novel IDS with genetic-algorithm-based feature selection and multiple support vector machine classifiers for wireless mesh networks. In order to succeed better accuracy, they select specific features exploiting the Genetic Algorithm-based feature selection and SVM classifier. The evaluation of the system is done using an intrusion dataset, generated from a WMN, and simulated in Network Simulator 3 (NS3) tool by using the standard intrusion dataset. Moreover, they validate the system using ADFA-LD and CICIDS2017 intrusion datasets. A comparative analysis is performed, between the proposed system and MI-based feature selection, suggesting that GA-based feature selection with SVN classifier exhibit better performance metrics, with higher accuracy, about 99%, and less computational complexity.

Zhang, et al., [2], presented a anomaly detection model based on neural network. They designed an IDS using LeNet-5 convolutional neural network and LSTM network for feature extraction. The experiments were conducted using the CICIDS2017 and CTU datasets for both binary and multi-classification. They performed CNN, LSTM and the hybrid combination of both, which achieved good classification results in both binary-classification and multi-classification experiments. The accuracy succeeded was about 99%. They, also analyzed the flows which were important for the classification and for the efficient abnormal detection.

Ferrag and Maglaras, [23], presented the DeepCoin which is a novel deep learning and blockchain-based energy framework to protect the smart grid against cyber attacks. The used the practical Byzantine fault tolerance algorithm recurrent neural network algorithm for the block-based network using deep learning. They worked in three different datasets for evaluation reasons and performance testing, including CICIDS2017, a power system dataset, and a web robot (Bot)-Internet of Things dataset. The accuracy rate by using recurrent neural networks, with backpropagation through time was 98.23%.

Binbusayyis and Vaiyapuri, [24], mainly focused on creating an ensemble for feature selection using different evaluation measures, that can implement an intrusion detection system. Particularly, they proposed a set of feature selection and feature extraction and developed an IDS model by using the learning algorithm, Random Forest. The evaluation was done on various evaluation datasets, namely, KDDCup'99, NSL-KDD, UNSW-NB15 and CICIDS2017, in order to demonstrate the effectiveness of the proposed model. The results revealed that the specific subset of features is promising due to the final high performance metrics, achieving 99.88% accuracy, compared to other approaches.

Radford, Richardson and Davis, [25], presented an anomaly detection sequence model based on Long Short-term Memory (LSTM) recurrent neural network (RNN). They used embedded sequences passed through two bidirectional LSTM models in order to implement the proposed system. The testing experiments were conducted with the use of CICIDS2017 and the model results aimed at multi-classification.

Ahmim et al., [26], proposed a novel IDS using three different machine learning classifiers. They used REP Tree and JRip algorithm for binary classification and the output of them used as input to the Forest PA for multi-classification of cyber-threats. The experiments conducted in CICIDS2017 dataset and were compared with some well known classifiers (J48, Jrip, Naive Bayes, MLP, REP Tree, Random Forest, FURIA, LIBSVM, J48 Consolidated, Forest PA, WISARD). The performance metrics showed that they achieved accuracy rate of 96.66%, detection rate of 94.47% and false alarm rate of 1.14%, where it turned out that their model had a better and improved performance than the rest of the classifiers.

Idhammad, Afdel and Belouch, [27], implemented a distributed intrusion detection system for Cloud environments. At first, they used the Naive Bayes model for anomaly detection and data preprocessing and then, for the multi-classification, they used a classifier based on Random Forest, that detects the type of each attack. The experiments were conducted in CICDDS-001 dataset with high performance metrics, like overall accuracy rate of 97.05% and False Positive Rate of 0.21%.

III. Pre-Processing and Data Analysis

A. CICIDS2017 Dataset Description

This work is relying on a public intrusion detection dataset namely CICIDS2017, [14], created by the University of New Brunswick (UNB) in cooperation with the Canadian Institute for Cybersecurity (CIC). The CICIDS2017 dataset not only contains the most up to date network attack scenarios but also fulfills all the criteria of real-world cyber attacks.

The dataset contains benign (normal) and abnormal (different types of attacks) network traffic from five consecutive days of capturing, and it is divided into 8 different files. For each day a different type of attack was deployed as show in Table I. We merged the 8 files into one single file containing the whole dataset, and our work was based on this file. The number of instances/examples in the merged file is equal to 2830743, and the distribution of all the 15 classes is shown in Table II.

Each row in the dataset contains 83 features which have been extracted from the network traffic using the CICFlowMeter tool, [28], [29]. The CICFlowMeter generates Bidirectional Flows (Biflow), where the first packet determines the forward (source to destination) and backward (destination to source)

TABLE I
DAILY TRAFFIC OF CICIDS2017 DATASET

Day	Type of Traffic
Monday	Benign (Normal)
Tuesday	Benign, FTP-Patator, SSH-Patator
Wednesday	Benign, Dos GoldenEye, Dos Hulk, DoS Slowhttptest, Dos slowloris, Heartbleed
Thursday	Benign, Web Attack - Brute Force, Web Attack - SQL Injection, Web Attack - XSS, Infiltration
Friday	Benign, Bot, PortScan, DDoS

directions, hence the 83 statistical features include data that derive from both the forward and reverse direction. We used a subset of the original 83 features, ommiting some features like source and destination IPs, the ID of the Biflow, timestamp etc., and we ended up with a dataset of 79 features where the 79^{th} is the label, denoting what kind of traffic is described in the current Biflow.

TABLE II
CLASS DISTRIBUTION OF CICIDS2017 DATASET
(BEFORE PRE-PROCESSING)

ID	Label	Number of Instances	% w.r.t. the number of total instances
1	BENIGN	2273097	80.3
2	DoS Hulk	231073	8.16
3	PortScan	158930	5.61
4	DDoS	128027	4.52
5	Dos GoldenEye	10293	0.36
6	FTP-Patator	7938	0.28
7	SSH-Patator	5897	0.21
8	DoS slowloris	5796	0.20
9	DoS Slowhttptest	5499	0.19
10	Bot	1966	0.07
11	Web Attack - Brute Force	1507	0.05
12	Web Attack - XSS	652	0.02
13	Infiltration	36	0.0012
14	Web Attack - Sql Injection	21	0.0007
15	Heartbleed	11	0.0004

B. Data Cleansing

Machine learning algorithms are directly related to data, and in order to be as accurate as possible, this data needs to be refined. Firstly we identified rows/Biflows in the dataset having missing values, infinity values, and values that did not make sense (i.e. negative time duration of a communication, etc.). There are many ways to deal with missing/wrong values in a dataset such as, replacing with mean/median/mode of the column (feature), using a regression model to predict and replace these values, omitting the whole row/example which contains the missing values, and even more. This step is crucial in order to maintain the reliability of the dataset and not to add noise, so the choice of method has to be done with caution. In our case, most of the rows with missing/wrong values were on classes with many examples (BENIGN, DoS Hulk, PortScan, DDoS) so we decided to remove them, since we already had enough examples to work with.

Moreover, we analyzed and extracted some statistics (standard deviation, variance, mean, etc.) for each one of the features independently. We discarded the features with zero variance (i.e. features with a constant value for all the examples), since they could not provide additional statistical information, [30], for our ML algorithm to be able to "learn" from these features.

We also performed Pearson, [31]–[33] correlation test on the remaining features in order to evaluate the associations between them. If two or more features are highly correlated, this implies that they are measuring the same underlying information, so removing one should not compromise the performance of the model and may even lead to better results. Pearson correlation coefficient or Pearson's **r** is the metric which measures the linear correlation between two variables and it's value lays in $[-1, 1]$. We have removed features where this metric was above or below the threshold of 0.95 or -0.95 respectively.

Finally, we checked and deleted all the duplicate rows/Biflows. As a result of the above cleaning and feature extraction methods we end up with a dataset of 2515416 examples and 45 features where the 45^{th} column is the label.

C. Data Transformation

We have decided to merge three of the dataset classes into one larger common class. These classes are Web Attack-Brute Force, Web Attack-XSS, and Web attack Sql Injection. We merged them as their behavior in network traffic level is almost identical (something that was also confirmed by the results of several different ML models during the evaluation phase). The final distribution of the classes on the cleansed dataset is show in Table III.

Before start feeding the cleansed data into our ML algorithm we did some more statistical analysis by plotting and visually inspecting the distribution of each feature. We were able to do this since we had a relatively small number of features and we were able to inspect them one by one. During this process we noticed that many of the features were highly skewed (mostly on the left). Skewness is the asymmetry in a statistical distribution, in which the curve appears skewed either to the left (negatively skewed), or to the right (positively skewed). There are many ways to deal with data skewness such as cube root, square root, logarithm transformation, or square, cube, or a higher power transformation. Although these methods work on many cases, in our case we used the Yeo-Johnson, [34] transformation because it worked better for our ML algorithm.

Yeo-Johnson is a family of transformations which is appropriate for reducing skewness and to approximate normality. It extends in some way the functionality of the original Box

TABLE III
CLASS DISTRIBUTION OF CICIDS2017 DATASET
(AFTER PRE-PROCESSESING)

ID	Label	Number of Instances	% w.r.t. the number of total instances
1	BENIGN	2089692	83.07
2	DoS Hulk	172838	6.87
3	PortScan	128008	5.08
4	DDoS	90694	3.6
5	Dos GoldenEye	10283	0.41
6	FTP-Patator	5931	0.23
7	SSH-Patator	5385	0.21
8	DoS slowloris	5228	0.20
9	DoS Slowhttptest	3219	0.12
10	Web Attacks	2143	0.085
11	Bot	1948	0.08
12	Infiltration	36	0.0014
13	Heartbleed	11	0.0004

& Cox, [35] transformations, which is valid only for positive values, to be able to use both negative and positive values. The Yeo-Johnson transformations are defined as follows:

$$\psi(\lambda, x) = \begin{cases} ((y+1)^{\lambda} - 1)/\lambda & \text{if } \lambda \neq 0, y \geq 0 \\ \log(y+1) & \text{if } \lambda = 0, y \geq 0 \\ -[(-y+1)^{2-\lambda} - 1)]/(2-\lambda) & \text{if } \lambda \neq 2, y < 0 \\ -\log(-y+1) & \text{if } \lambda = 0, y < 0 \end{cases} \quad (1)$$

In Figure 1 we present the effect of the Yeo-Johnson transformation on the distributions of some of the features in the CICIDS2017 dataset. The Yeo-Johnson transformation also normalizes the data, so we did not have to do this step explicitly.

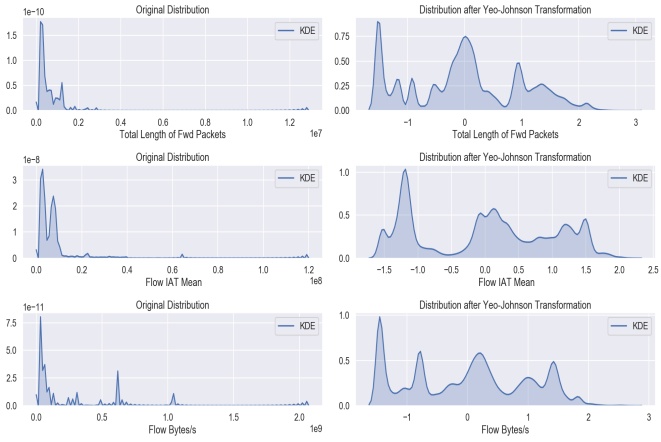


Fig. 1. Yeo-Johnson Transformation

By looking at the Table III, someone can notice the high class imbalance in the dataset. There are some classes (i.e. Heartbleed, Infiltration, and Bot) with very few examples. It can be very difficult for a ML algorithm to be able to "learn" how to map the input features of such classes to their corresponding labels since there are not many data to learn from. One of the most direct ways for dealing with class imbalance is to alter the class distributions toward a more balanced distribution. There are two basic methods for balancing class distributions. Under-sampling, i.e. eliminating examples of the majority class, and Over-sampling, i.e. replicating examples of the minority class.

There are many ways to under-sample and over-sample an imbalanced dataset, where some of the most common are described by Gustavo Batista et al. in their works, [36] and, [37]. In our case we have used the SMOTEENN method, which is a combination of the well known Synthetic Minority Over-Sampling Technique (SMOTE), [38] method for over-sampling the minority class (in our case there were more than one minority classes), followed by the Edited Nearest Neighbor (EEN), [39] method for under-sampling not only the majority class but all of the classes as a data cleaning method.

When using over-sampling methods, someone must be very careful with the evaluation process. If the over-sampling is performed before the splitting of the dataset in training, development, and test sets, then the evaluation will not be reliable since the test set has been merged with new artificially created data and its distribution will be different from the original. The proper way to proceed, is to split the dataset and then use the over-sampling method only on the training set. This way the ML algorithm gets more data for training, but the development and test sets remain untouched and reliable for fine-tuning and evaluating the model.

IV. DEEP NEURAL NETWORK ARCHITECTURE

As a step prior to neural network implementation we have splitted the data into 3 parts. The 80% of the data has been used for the training (known as training set), 10% has been used on the development process and hyperparameter tuning (known as dev or validation set), and the last part which is also 10% has been used for testing purposes (test set).

After a lot of experimentation and having tried many different architectures we came up with the architecture as shown in Figure 2. In the proposed architecture for the deep neural network, the model consists of one input layer which has 44 features passed as input to the neural network as those emerged from the feature engineering described in chapter III. The input layer is followed by 8 hidden layers with 140, 120, 100, 80, 60, 40, 20, and 120 nodes respectively. The final layer is the output layer or softmax layer, which produces the probabilities for the 13 classes where the prediction takes place.

For the initialization of the weights in all of the Dense (Fully Connected) layers we used the lecun-uniform initialization, [40], while for the output / softmax layer we used the glorot-uniform initialization, [41]. We came up using the ReLU, [42] as activation function for all of the Dense layers, after testing different activation functions like tanh, sigmoid, selu etc., since it produced the best results in comparison with the previously noted activation functions. In order to train the neural network we tested many optimizers like stochastic gradient descent, RMSProp, Adagrad but we finally used Adam optimizer, [43]

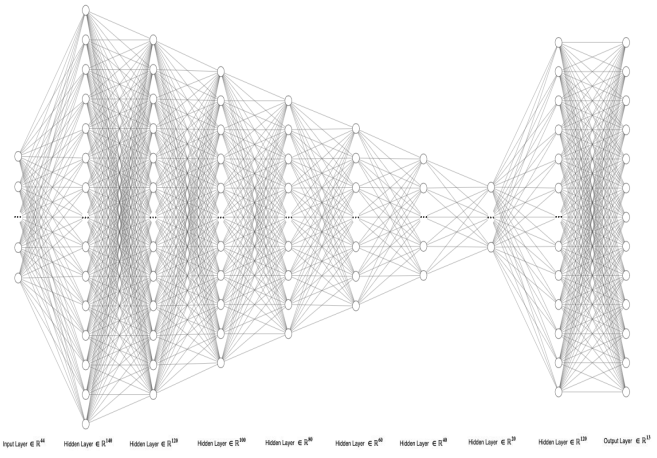


Fig. 2. Neural Network Architecture

since it produced a more robust model with better results during the evaluation. Although regularization techniques like L1, L2 regularization, dropout are used quite often to address overfitting in neural networks, in our case it made no different to the final results so we decide not to add any kind of regularization to our model.

V. Numerical Results

In this chapter we present the results of the proposed architecture in terms of recall, precision, and F1 score for each one of the 13 different classes that our model is able to detect. The evaluation of the model was based on a 10 fold cross validation. In each one of the 10 splits we choose 90% of the data as the training set and 10% as the test set, while the test set in each of the 10 splits is unique and never overlaps with any other test set in any other split. In order to produce a single final value for each specific metric on each class we average the results from each of the 10 splits on that metric, to finally get the evaluation results for our model.

The metrics we used to evaluate our model in each one of the 10 splits of cross validation are all based on the confusion matrix that each of the splits produced. The metrics are the following:

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

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 * TP}{2 * TP + FP + FN}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

For each one of the metrics we have calculated the (macro) average over the 10 splits of the cross validation in order to be as much robust and precise as possible in the evaluation of our model.

The results (average of 10 splits) of Precision, Recall, F1 are presented in Figure 3. Based on the results in Figure 3 we have also calculated the averages over all of the classes of the model. The overall accuracy of our model is 99.95%, precision equals to 94.31%, recall or detection rate is 95.62%, and F1 Score is 94.1%. Beside that we have also calculated the False Positive Rate or False Alarm Rate, which is equal to 0.0005, as an average of the FPR of all classes and all the splits.

Finally, we have calculated the ROC Curves for each class that our model detects as long as the micro and macro averages of these curves. This can be shown in Figure 4 alongside with the Area Under Curve (AUC) metric for each class and the average for all of the classes. The (macro) average AUC value of all the classes is equal to 0.99.

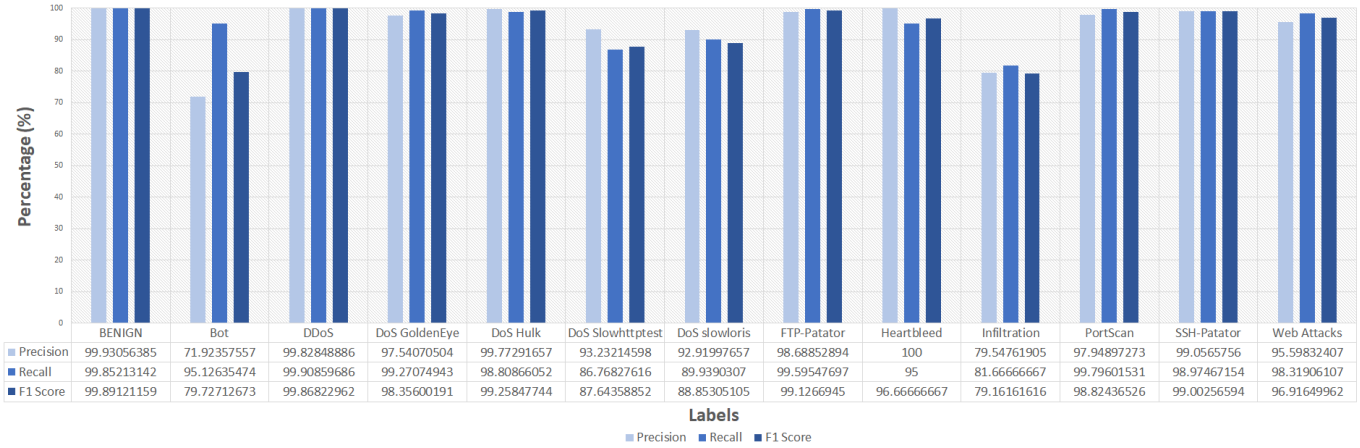
Comparison with relevant literature based on CICIDS2017 dataset, can not be performed directly, especially in the case of multi-class classification. Although, in most of the cases the evaluation details are not defined explicitly, a qualitative comparison can be performed. For example, Vijayanand et al., [22], used an SVM classifier resulting in a multi-class classification accuracy equal to 99.85% and FPR equal to 0.0009, but it is not stated if this was a result of a cross validation evaluation or if it was a random split of the dataset. The same occurs in some more cases, like in, [23], where Ferrag et. al. using an RNN classifier came up with the following results: accuracy of 99.81%, FPR of 0.009, and detection rate of 94.09%. Similarly, in, [24] and, [25] the authors using random forest and LSTM respectively came up evaluating their models using the AUC metric reporting 0.96 and 0.87 values as an average of all classes used. In, [2], Zhang et al., using CNN and LSTM models report accuracy equal to 99.77%, precision equal to 99.94%, recall equal to 99.95%, and F1 Score equal to 99.94%, classifying only 10 classes (dropping the ones with the fewer instances in the dataset) and without reporting the use of cross validation or not.

Even though the comparison with related work is not a straight forward process, the proposed work performs efficiently even though the relatively small model used for the classification.

VI. Conclusions and Future Work

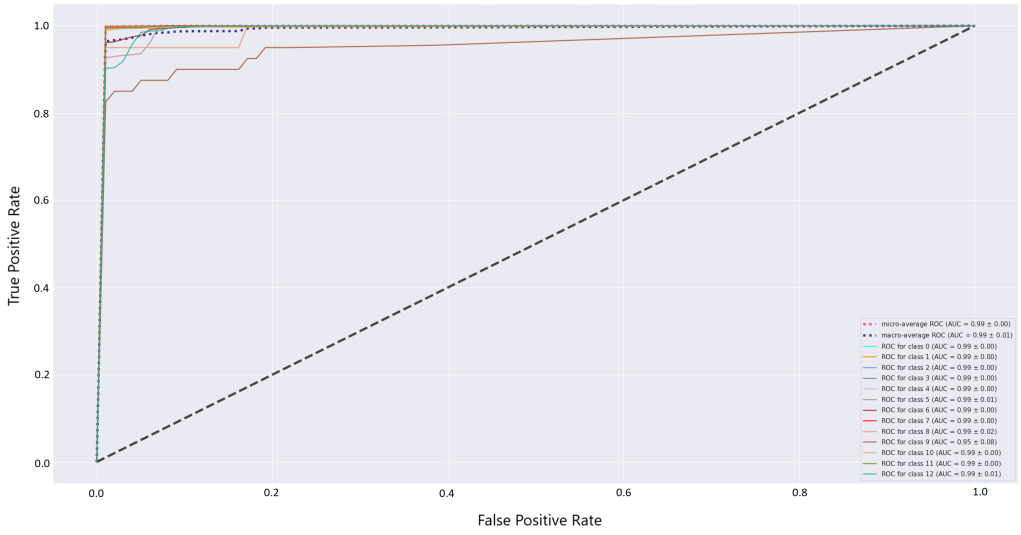
In this work we implemented a deep neural network model which is able to detect abnormal or malicious behavior (a potential cyber-attack) in the network traffic of an enterprise, and to classify the type of traffic between 13 different cases. During the data analysis and pre-processing of the dataset we were able to significantly reduce the number of input features to the model without reducing its performance at all. By using over-sampling and down-smapling techniques we were able to detect even minority classes with very few examples in the original dataset with high values of recall and precision. The proposed model achieves very promising results in a multi-class classification problem, while being at the same time a very simple and relatively small model.

Fig. 3. Model Evaluation on 10 Fold Cross Validation



	BENIGN	Bot	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator	Heartbleed	Infiltration	PortScan	SSH-Patator	Web Attacks
Precision	99.93056385	71.92357557	99.82848886	97.54070504	99.77291657	93.23214598	92.91997657	98.68852894	100	79.54761905	97.94897273	99.0565756	95.59832407
Recall	99.85213142	95.12635474	99.90859686	99.27074943	98.80866052	86.76827616	89.9390307	99.59547697	95	81.66666667	99.79601531	98.97467154	98.31906107
F1 Score	99.89121159	79.72712673	99.86822962	98.35600191	99.25847744	87.64358852	88.85305105	99.1266945	96.66666667	79.16161616	98.82436526	99.00256594	96.91649962

Fig. 4. ROC Curves on 10 Fold Cross Validation



As future work we plan to perform an analysis on reducing even further the input features, by testing various techniques such as Principal Component Analysis (PCA), Autoencoders, Independent Component Analysis (ICA), etc. so as not to reduce the performance of the model. One more thought is to improve and extend the current dataset with even more types of network based attacks and re-train the model to be able to detect them without reducing its performance on the original 13 classes. Finally, we plan on trying different types of architectures to approach this problem. More precisely, we consider the implementation of an RNN (LSTM, GRU, etc.) architecture for the model since the dataset contains sequential data.

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