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Classification of Data Types Passing through the Network using Deep Learning

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ABSTRACT

Network traffic classification is crucial for network security and management. Traditional methods often struggle with accuracy and scalability. This paper proposes a deep learning-based approach to classify various data types traversing a network. By leveraging the powerful feature extraction capabilities of deep neural networks, we aim to improve classification accuracy and adaptability to evolving network traffic patterns. We explore the application of convolutional neural networks (CNNs) to capture both spatial and temporal dependencies within network packets. Experimental results demonstrate the effectiveness of our proposed method in accurately classifying different data types, surpassing traditional techniques in terms of precision, recall, and overall accuracy.

Our CNN model is designed to capture the underlying patterns and characteristics of network traffic. By processing raw traffic data as images, the model can learn to identify distinctive features that differentiate various traffic types.

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1. INTRODUCTION

Network traffic classification is a crucial component of network management and security. It involves categorizing network traffic based on the applications generating it. This categorization is fundamental to tasks like anomaly detection, which helps identify security breaches and unauthorized resource usage.[1]

Traffic classification primarily employs four techniques: port-based, deep packet inspection (DPI), statistical, and behavioral. Traditional methods like port-based and DPI-based rely on predefined rules. Statistical and behavioral methods, on the other hand, leverage machine learning to classify traffic by analyzing patterns within empirical data using selected features.[2]

While traditional machine learning methods offer advantages over rule-based approaches, such as handling encrypted traffic and reducing computational costs, they introduce a new challenge: the need for careful feature engineering. Recent research has extensively explored methods to address this challenge.[3]

Representation learning, a rapidly growing field within machine learning, has gained significant attention in recent years. This approach automatically extracts meaningful features from raw data, eliminating the need for

manual feature engineering. Deep learning, a prominent subset of representation learning, has demonstrated exceptional performance in various domains, including image classification and speech recognition.[5][6]

In this research, we aim to explore the potential of representation learning for accurate malicious network traffic classification.[2]

This research utilized a convolutional neural network (CNN), a widely used technique for learning representations. Instead of manually extracting features from traffic data, the raw data was directly treated as images and classified using the CNN. This research pioneered the applications of demonstration learning to classify malwares traffics by use raw traffics data. By treating traffic data as images and employing a CNN, we successfully categorized malicious traffic.[7]

To address the discrepancy between continuous traffic data and discrete image data, we explored various traffic representations and experimentally determined the most effective approach.

This paper is organized as follows:

- Section 2: Related Work provides a comprehensive overview of existing research and explains the rationale behind our proposed approach.
- Section 3: Methodology details the methodology of our convolutional neural network (CNN) model, outlining the steps involved in traffic classification.
- Section 4: Results and Analysis presents the results and analysis of our experiments, highlighting the performance and accuracy of our model.
- Section 5: Limitations and Future Work discusses the limitations of our current approach and identifies potential areas for future research and improvement.
- Section 6: Conclusion offers concluding remarks, summarizing our findings and contributions to the field.

2. RELATED WORK

The field of traffic classification has seen the development of mature rule-based approaches. Previous research has primarily focused on refining map rule and optimizing performances. The authors in [8] provide a comprehensive overview of the common DPI-based methods for traffic classification.

Academic research has extensively explored the application of classical machine learning techniques to traffic classification, particularly focusing on optimizing feature selection. Dhote et al. [3] conducted a comprehensive survey of various techniques employed in feature selection for internet traffic classification.

Existing research on traffic classification using representation learning is limited. While Gao et al. [9] and Javaid et al. [10] explored the application of deep belief networks and sparse autoencoders for malware traffic classification, both studies relied on handcrafted flow feature datasets like KDD CUP1999 and NSL-KDD.

Inspired by these previous studies, our research aims to classify malware traffic directly from raw traffic data. We employ a convolutional neural network (CNN) as our chosen representation learning method.

3. METHODOLOGY

A. As noted by Dainotti et al. [13], a significant challenge in traffic classification research is the scarcity of diverse and publicly accessible traffic trace datasets. Many studies investigating malware traffic classification rely on proprietary or self-collected traffic data, which can limit the generalizability of their findings. Traditional ML approach primarily effort on features collection technique [14], leading to publicly available datasets that primarily consist of pre-defined flow features rather than raw traffic data. Notable examples of such datasets include KDD CUP1999 and NSL-KDD, which offer a fixed set of 41 features [15].

Unfortunately, these datasets are insufficient for analyzing raw network traffic. There are only a few datasets that provide raw traffic data with enough samples of both normal and malicious activity, such as[16].

To address these challenges, the USTC-TFC2016 dataset was created. This dataset is divided into two main sections, as show in Tables 1 and Table 2. Segment 1 comprises ten diverse kinds of malwares traffics collected from open websites. This sample was gathered as of practical networks environments via CTUs researchers among 2011 to 2015.

Large traffics samples were shortened, while smaller ones were combined if they originated from similar applications. Segment 2 includes ten categories of typical traffics composed by use the IXIA BPS

[17], a proficient networks traffics simulations device. For more details on the simulation process, please visit the IXIA BPS website. To cover a variety of traffic types, the dataset includes ten different kinds of traffic representing eight common application classes. The USTC-TFC2016 dataset is 3.71GB in size and is stored in the pcap format.

Table 1: USTCs-TFC2016 segment 1 (MALWARES TRAFFICS)

Name	CTU num	Binary MD5	process
Cridex	108-1	25b8631afeea279ac00b2da70fffe18a	original
Geodo	119-2	306573e52008779a0801a25fafb18101	part
Htbot	110-1	e515267ba19417974a63b51e4f7dd9e9	original
Miuref	127-1	a41d395286deb113e17bd3f4b69ec182	original
Neris	42,43	bf08e6b02e00d2bc6dd493e93e69872f	merged
Nsis-ay	53	eaf85db9898d3c9101fd5fcfa4ac80e4	original
Shifu	142-1	b9bc3f1b2aace824482c10ffa422f78b	part
Tinba	150-1	e9718e38e35ca31c6bc0281cb4ecfae8	part
Virut	54	85f9a5247afbe51e64794193f1dd72eb	
Zeus	116-2	8df6603d7cbc2fd5862b14377582d46	original

Table 2: USTCs-TFC2016 segment 2 (TYPICAL TRAFFICS)

Name	Class	Name	Class
BitTorrent	P2P	Outlook	Email/WebMail
Facetime	Voice\Video	Skype	Chat/IM
FTP	Data Transfer	SMB	Data Transfer
Gmail	Email/WebMail	Weibo	Social NetWork
MySQL	Database	WorldOfWarcraft	Game

B. Networks Traffic Demonstration

In the initial stages of our ML-base traffics classifications approaches, it's necessary to divide continuous traffics into distinct unit depend on a specific level of granularity. Additionally, each packet can be selected from different OSI or TCP/IP layers. The following section introduces the process of selecting traffics granularities and packets layer within suggested method.

1) Traffics granularities

Networks traffics can be divided into different units based on various levels of granularity, such as TCPs connections, flows, sessions, services, and hosts [13]. Many granularities levels

result in distinct traffics unit. In proposed approach, we use flows and sessions as the chosen granularity, following the practices of many researchers in the field. A flow is defined as a group of packets with the same 5-tuple, including the source IP, source port, destination IP, destination port, and transport-level protocol. A session includes bidirectional flows, capturing traffic in both directions. The formal description of this distinction is as follow:

- Raw Traffics: Wholly packet is define as sets of $= \{p^1, \ldots., p^{|p|}\}$, with each packets are define as $p^i = (x^i, b^i, t^i)$, $i = 1,2, \ldots., |P|$. A first component x^i stand to 5-tuples, a second component stand to the size of packets $b^i \in [0, \infty\}$ in byte, and the latest component stand to started time of transmissions $t^i \in [0, \infty\}$ in second.
- Flows: is the sets of rows traffics P which could be divide to multiple subsets. Wholly packet in subsets is arrange in times orders, i.e. $\{p^1 = (x^1, b^1, t^1), \ldots., p^n = (x^n, b^n, t^n)\}$, $t^1 < t^2 < \cdots < t^n$. The subsets are define as a flows $f = (x, b, d, t)$. A first component is similar as 5-tuples , i.e. $x = x_1 = \cdots = x_n$. The second component is the total of sizes of entirely packet in flows. The third component is the flows period $d_1 = t^n - t^1$. A latest component is a started times of transmissions of first packets. A complete rows traffics could be converts to flow $F = \{f^1, \ldots., f^n\}$.
- Sessions: the sessions include all direction of flow, i.e. the sources and destinations IP/ports are substitutable.

Numerous flow or session might have several sizes, nonetheless the inputs data sizes of CNNs need to be unvarying. Therefore, just the 1st n byte (n = 784) of every flows or sessions is use. This choice could be intuitively explained. Generally, the noticeable part of a flow or session typically contains connections data with fewer contents data, which must be reflects the inherent characteristic of flows or sessions. These select align with other approaches such as [18, 19], that investigated malwares traffics identifications by use classical ML approaches. Additionally, by using only the first few hundred bytes, this technique could be higher lightweight than numerous rules-based approaches.

2) Packets layer

When analyzing packet layers, it's generally expected that the inherent characteristics of network traffic would be evident in the applications layers of the TCP/IPs models, specifically layers seven of OSI models. As instance, protocols like SMTP are associated with email traffic, while HTTP is linked to browsers traffics. Depend on these assumptions, the authors in [12] focuses exclusively on layers 7, referring to it as TCPs sessions payloads. However, it's important to consider that data from other layers can also provide valuable traffics features data. As instance, ports data in the transporting layers could recognize definite application or services.

Most applications use standard port numbers, and certain flags data could help identifying networks attacks such as SYN attacks and RSTs attacks. Hence, we considered two options for packet layer selection: including entirely layer and individual considering layer seven (L7). We can note that including IP and MACs data in sessions or flows can potentially interfere with the feature extraction process.

To address this issue, it's necessary to remove such information using randomization techniques, often referred to as traffics sanitizations. The study examines 4 different traffics representations types: Flows + All, Flows + L7, Sessions + All, and Sessions + L7. These representations were evaluated by testing their performance using the two traffic datasets introduced in Part A. Ultimately, the study identifies the most effective representation type based on the results obtained from eight experiments.

C. Preprocess of data

The preprocessing of data includes transform raw traffics data (in pcap format) into a suitable format for CNN input. This process consists of four steps: traffic splitting, traffic cleaning, image generation, and data augmentation. To facilitate these steps, a dedicated toolkit called USTC-TL2016 was developed. The overall data preprocessing workflow is illustrated in Figure 1.

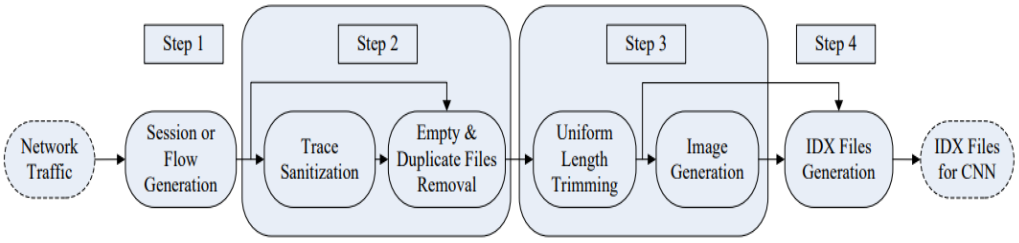


Figure 1: Preprocessing of data

1- **Step 1: Traffic Splitting:**

Traffic splitting involves dividing continuous rows traffics into multiple discrete traffics unit. The inputs data formatting is in (pcap). For representations type such as Flows + All or Sessions + All, the outputs data formatting remains as (pcap). However, for representations types like Flows + L7 or Sessions + L7, the outputs data formatting is in bin format.

2- **Step 2: Traffics Cleaning:**

Traffic cleaning involves two main actions. First, it includes the option to perform traffics anonymization/sanitizations that randomize the MACs addresses in the data links layers and the IP address in the IP layer. This step is not always necessary, such as when all traffic originates from the same network, where MAC and IP addresses may no longer be distinguishing factors. In such cases, this action can be skipped [9].

The 2nd actions in traffics cleaning are file cleaning. Certain packet may not has an applications layers, resulting in empty bin files. Additionally, identical content in packets can lead to the generation of duplicate files, which can introduce bias during CNN training. To address this, empty and duplicate files are removed. The data format remains unchanged in this step.

3- **Step 3 : Image Generation:**

Image generation involves two key steps. First, all files are trimmed to a uniform length. If the file is exceed 784 byte, which truncated to 784 byte. When the files are smaller than 784 byte, it is padded with 0x00 at the end to reach 784 byte. Then, the resulting file of the equal sizes is converts into gray scales image. Every byte in the origin files corresponds to pixels, where 0x00 represents blacks and 0xff represent whites.

The USTC-TFC2016 traffics datasets were processing by use the USTC-TK2016 toolkits, resulting in a total of 752,040 records. Table 3 displays the result. Since session contains bidirectional flow, the numbers of session is typically lower than the number of flow.

Table 3:SESSION & FLOW COUNT RESULTS

Dataset	Representation	Count Range	Count Total
Malware	Flow+ALL	6000~17178	134563
	Flow+L7	4569~13968	76716
	Session+ALL	6000~8629	71008
	Session+L7	4569~7592	63120
	Total	----------	406633
Benign	Flow+ALL	10051~17008	138145
	Flow+L7	8908~16391	126665
	Session+ALL	5134~9634	71692
	Session+L7	4952~9476	70131
	Total	----------	345407
Total	-----	------	752040

D. VISUALIZATION ANALYSIS

In this section, we analyze the images generated during the third step of the data preprocessing procedure. Each grayscale image is 784 bytes (28x28 pixels). The visualization results of the Session + All representation can be seen in Figures 2 and Figure 3. The results of another 3-representation type is in general same to these.

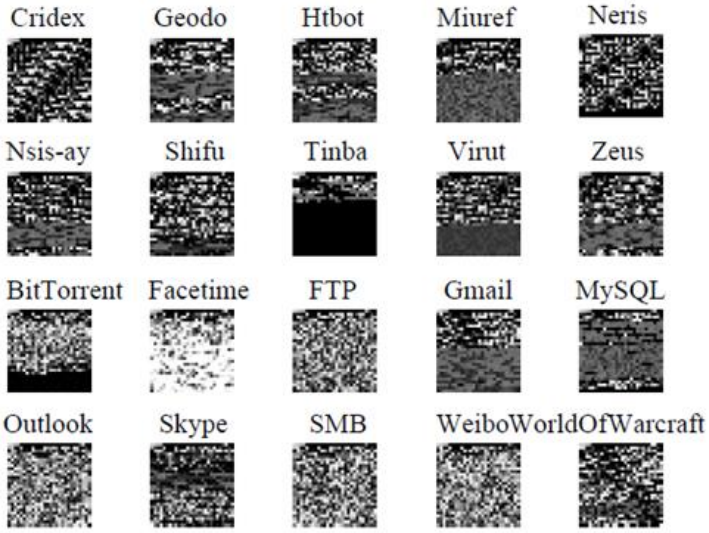


Figure 2: Data Preprocess Procedure

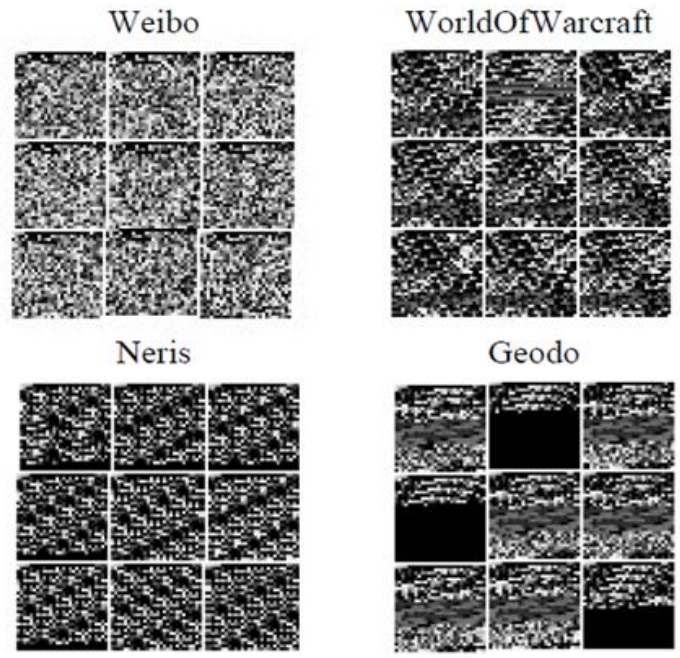


Figure 3: Visualization of All Classes of Traffic

Figure I shows the visualization results for all classes, clearly demonstrating their distinctness. While most images show significant differences, a few have similarities, such as between FTP and SMB. Figure II highlights the consistency within each traffics session.

The 9-random chosen image from a single session and 4-random selected class is displayed. Interestingly, the images from Weibo, WOW, and Neris have similar textures. Additionally, the Geodo class can be divided into two subclasses, with images in each subclass still showing significant similarities. Overall, the remaining sixteen classes exhibit a generally consistent pattern. Based on our visualization analysis, we can conclude that different traffic

classes are distinguishable, and each class has a high level of consistency. Therefore, we expect our approach to perform well [14].

E. CNN Architecture

The CNN image analysis process begins by reading a traffic image with dimensions of 128x128x3, extracted during the third stage of data preprocessing. The pixel values in the image are normalized to a range of [0, 1] from the original [0, 255]. Subsequently, the first convolutional layer, C1, applies a convolution operation to the image using 32 kernels with a size of 3x3. This generates 32 feature maps, each with a size of 128x128. A 2x2 max-pooling operation is then applied to the feature maps produced by the C1 layer.

Next, two additional convolution layers, C3 and C2, are employed, each using the same 3x3 kernel size as C1 but with 64 channels. This generates 64 distinct feature maps, each measuring 64x64 pixels. Subsequently, 64 distinct maps with dimensions of 32x32 are produced. Finally, three layers, C3, C4, and C5, are utilized, each with the same kernel size as before but with 128 channels. This process culminates in the generation of 128 distinct maps, each sized 16x16 pixels.

To calculate the probability of each class, a sigmoid function is applied, and dropout is implemented to mitigate overfitting. This CNN architecture is employed in the classifiers presented in this study [19].

F. Scalability Study

The proposed method was applied to two different scenarios using two types of CNN classifiers: a binary classifier and an 8-class classifier. In the first scenario, data was classified into two categories: malicious and normal, constituting a binary classification task. In the second scenario, the output from the binary classification was utilized as input for a subsequent classification task with 8 classes to identify each traffic class sequentially.

4. EVALUATION

A. EVALUATION METRICS

Four evaluation metrics were employed to assess the performance of the classifiers: accuracies (A), precisions (P), recalls (R), and F1-scores (F1). Accuracies were use to measure the complete performances of classifiers. Precisions, recalls, and F1-scores are use to calculate the performances of each individual traffic classes.

$$A = \frac{TP+TN}{TP+FP+TN+FN} \quad \text{.....(1)}$$

$$P = \frac{TP}{TP+FP} \quad \text{.....(2)}$$

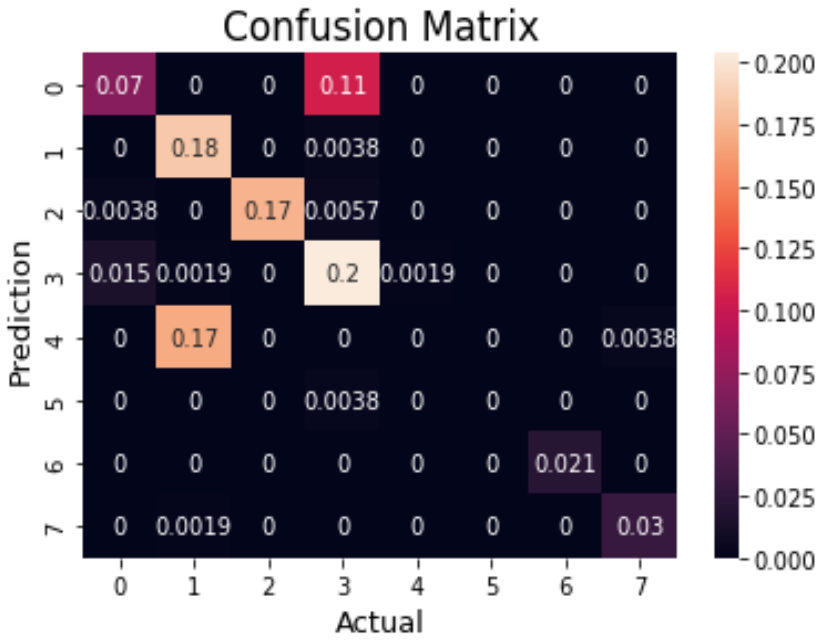
$$R = \frac{TP}{TP+TN} \quad \text{.....(3)}$$

$$F1 = \frac{2PR}{P+R} \quad \text{.....(4)}$$

In the evaluation process, the following terms are used: TP (true positives) represents the number of instances correctly classified as positive, TN (true negatives) represents the number of instances correctly classified as negative, FP (false positives) represents the number of instances incorrectly classified as positive, and FN (false negatives) represents the number of instances incorrectly classified as negative.

B. Representation Experiment Results and Analysis

A confusion matrix is a table that illustrates the difference between the actual and predicted outcomes of a machine learning model. In this context, the model is a web security system trained to detect web attacks. The matrix comprises six squares, each with a distinct color. Each square represents the proportion of correct or incorrect predictions for a specific case. For instance, the top-left square represents the proportion of correct predictions that a user is not wearing a mask.



Components of the confusion matrix:

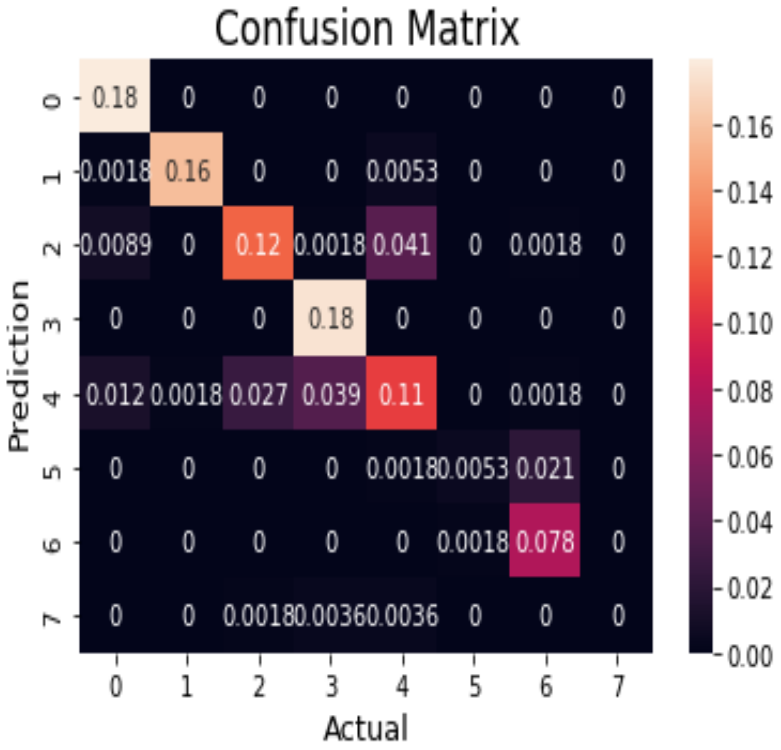
- Rows: represent the actual (true) classes.
- Columns: represent the predicted classes (predicted by the model).
- Values inside the matrix: represent the number of samples that were correctly or incorrectly classified into each class.

In the previous matrix, we have a multi-class classification model (8 classes) which are the types of non-malicious traffic, which are: BitTorrent, Facetime, FTP, Gmail, MySQL, Outlook, Skype , WorldOfWarcraft . Each number in the matrix represents a percentage of samples.

	precision	recall	f1-score	support
0	0.79	0.40	0.53	93
1	0.52	0.98	0.68	100
2	1.00	0.95	0.97	97
3	0.63	0.92	0.75	118
4	0.00	0.00	0.00	92
5	0.00	0.00	0.00	2
6	1.00	1.00	1.00	11
7	0.89	0.94	0.91	17
accuracy			0.68	530
macro avg	0.60	0.65	0.60	530
weighted avg	0.61	0.68	0.61	530

Accuracy : 0.6830188679245283

The model performed fairly well, obtaining relatively high values for precision, recall, and F1 score. and the overall accuracy is about 68%.



In the previous matrix, we have a multi-class classification model (8 classes) which are the types of non-malicious traffic, which are: Cridex, Geodo, Htbot, Miuref, Neris, Shifu, Tinba , Virut. Each number in the matrix represents a percentage of samples.

	precision	recall	f1-score	support
0	0.89	1.00	0.94	101
1	0.99	0.96	0.97	93
2	0.81	0.69	0.75	98
3	0.80	1.00	0.89	99
4	0.67	0.57	0.62	106
5	0.75	0.19	0.30	16
6	0.76	0.98	0.85	45
7	0.00	0.00	0.00	5
accuracy			0.82	563
macro avg	0.71	0.67	0.66	563
weighted avg	0.81	0.82	0.81	563

Accuracy : 0.8241563055062167

The model performed fairly well, obtaining relatively high values for precision, recall, and F1 score. and the overall accuracy is about 82%.

The results showed that there is a variation in the accuracy of the classes within the multi-classifier model due to the difference in the size of the training data for each class and the type of this data.

5. CONCLUSIONS

Traffics classifications are the first phase of networks anomalies detections or networks-base intrusions detections systems and play significant roles in the field of networks securities. Firstly, this work introduces innovative traffics classifications from the perspective of AI, and then proposes malwares traffics classifications technique of CNN by take traffics data as image. These techniques does not need hand-design features nevertheless direct take rows traffics data as inputs data for the classifiers. The technique is confirmed in two situations containing two categories of classifier, and experimental result shows that the suggested technique could meet the accuracies requirements of real-world applications.

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