Encrypted Internet traffic classification using a supervised Spiking Neural Network

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Abstract

Internet traffic recognition is an essential tool for access providers since recognizing traffic categories related to different data packets transmitted on a network help them define adapted priorities. That means, for instance, high priority requirements for an audio conference and low ones for a file transfer, to enhance user experience. As internet traffic becomes increasingly encrypted, the mainstream classic traffic recognition technique, payload inspection, is rendered ineffective. This paper uses machine learning techniques for encrypted traffic classification, looking only at packet size and time of arrival. Spiking neural networks (SNN), largely inspired by how biological neurons operate, were used for two reasons. Firstly, they are able to recognize time-related data packet features. Secondly, they can be implemented efficiently on neuromorphic hardware with a low energy footprint. Here we used a very simple feedforward SNN, with only one fully-connected hidden layer, and trained in a supervised manner using the newly introduced method known as Surrogate Gradient Learning. Surprisingly, such a simple SNN reached an accuracy of 95.9% on ISCX datasets, outperforming previous approaches. Besides better accuracy, there is also a very significant improvement on simplicity: input size, number of neurons, trainable parameters are all reduced by one to four orders of magnitude. Next, we analyzed the reasons for this good accuracy. It turns out that, beyond spatial (i.e. packet size) features, the SNN also exploits temporal ones, mostly the nearly synchronous (i.e.,

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within a 200ms range) arrival times of packets with certain sizes. Taken together, these results show that SNNs are an excellent fit for encrypted internet traffic classification: they can be more accurate than conventional artificial neural networks (ANN), and they could be implemented efficiently on low power embedded systems.

1 Introduction

Today, more than half of the global population uses the Internet network. The amount of data exchanged through it increases endlessly each year giving people ever more access to information. Whether it be sending emails, downloading or uploading files, watching videos on streaming platforms, chatting on social media, etc. all these operations involve devices interacting with computer servers located around the world. To improve the integrity of traffic flows, a protocol stack named TCP-IP is used (see e.g. [20] chap. 5). When data are exchanged via this protocol stack, they are broken down into different packets. Traffic classification consists of associating traffic flows, comprised of data packets, with the categories corresponding to different use cases (e.g. email, chat, file transfer, etc.).

Increasing demands to protect privacy have led to the development of methods to encrypt traffic and of different ways to navigate on the Internet anonymously, such as The Onion Router (Tor)[5] or Virtual Private Networks (VPN) (see e.g. [24]). These techniques encrypt the original whole packets (payload and headers) into a new encrypted payload to which is added a new header to ensure traffic handling in the VPN or Tor network. Thus neither the original payload nor header are available for inspection and the only features that can be used for classification are the encrypted size of the original packet and the time at which the packet is captured. With only these features, packet inspection is not possible any more, and statistical or machine learning techniques must be used for traffic classification. The state of the art results for such an approach to traffic classification are based on ANNs.

There are different types of neural networks that are used in different contexts:

- Convolutional Neural Networks (CNNs) [10] are mainly employed for image recognition, and have a structure inspired by the primate's visual cortex.
- Recurrent Neural Networks (RNNs) [23] are used for automatic speech or text recognition, and take into account the temporal dimension by interconnecting neurons to form cycles in the networks.
- Spiking Neural Networks (SNNs) [15] are aimed at imitating biological neural networks. A neuron fires an electrical impulse called "spike" when its membrane potential reaches a specific value, leading to a signal composed of spikes that propagates on to next neurons. They are very interesting for recognizing time-related patterns.

The main challenge of SNNs is that their binary nature prevents the use of classic training methods like back-propagating gradient descent [18]. To solve this, most current methods are rate-based, meaning that they only consider the number of spikes inside a temporal window, ignoring their times. This is a severe limitation as different spike trains can have the same number of spikes but present distinct temporal patterns. To solve this problem, different alternatives have been developed. For instance, Neftci et al. 2019 [18] proposed a surrogate gradient algorithm trying to use a more local approach. It consists of approximating the true gradient of the loss function while keeping good optimization properties.

1.1 Contributions

In this paper we show that SNNs lead to very promising results for traffic recognition of encrypted traffic. We beat the state of the art [25] for almost every metric on accuracy, precision or recall. The average accuracy for Tor traffic rises from 67.8% to 98.6%, and for unencrypted traffic from 85% to 99.4%. For VPN traffic it rises from 98.4% to 99.8%. The number of errors is thus divided by a factor 8 for VPN traffic and by a factor 20 for Tor and unencrypted traffic.

It is important to note that for VPN traffic the hardest situation (browsing versus chat traffic) is not present as the dataset used by [25] has no VPN browsing data. One versus all experiments show that SNNs lead to a very significant improvement with all the problematic categorizations such as File Transfer for Tor (increased from 55.8% to 99.7%), Browsing for Tor (from 90.6% to 99.0%), Browsing for unencrypted (90.6% to 99.4%) and Chat for Tor (89% to 99.1%).

These results are obtained with: simpler inputs (300x300 images versus 1500x1500 images), a simpler network (one hidden layer of 100 neurons versus a six hidden layer LeNet-5 CNN with one million neurons), less training parameters (31.5k versus 300k) and a higher testing data over training data ratio (20/80 versus 10/90).

Our approach is all but fancy, the merit is due to the superior capabilities of SNNs to detect and exploit time related features. In Section 5 we study this with some experiments that highlight that short-term synchronicity detection seems to be an important feature for traffic categorization, and SNNs naturally excel at this.

1.2 Outline

The rest of this paper is organized as follows. Section 2 gives a brief introduction to related works in the field of internet traffic classification. Section 3 gives a complete review on the proposed model for classification of internet traffic using a SNN and with the help of supervised surrogate gradient method. In section 4 and 5 some experiments and corresponding results are given to investigate the power of the proposed model to classify internet traffic data. Conclusions and future work are presented in Section 6.

2 Related works

Mainstream techniques for classifying unencrypted traffic, port-based classification and deep packet inspection [4], and part of the alternative statistical and machine learning techniques, are unusable for encrypted traffic as they use features that are only available before encryption. Such related work will therefore not be described here.

There are two usual classification problems: traffic categorization (or characterization) which considers types of traffic such as VoIP, File Transfer, Video, Browsing, Chat, P2P, etc.; and application identification which considers given applications such as Kazaa, BitTorrent, Google Hangouts Chat, AIM, WhatsApp Web, etc. In this work we focus on traffic categorization and leave application categorization for future work.

There is a rich literature on traffic categorization through machine learning methods (statistics based or neural network based). Multiple statistical approaches using features compatible with encryption (such as packet times and sizes) have led to scientific publications: fingerprinting [3, 29, 21], Bayes [16, 17, 7, 1], k-nearest neighbor [6, 31], decision trees [6, 34], bag of words [34, 33] and cross-entropy similarity [21]. Similarly multiple approaches have been studied using different types of neural networks such as: convolutional neural networks [30, 28, 13, 12, 2], recurrent neural networks [12], probabilistic neural networks [27] and stacked auto-encoders [30, 13].

Regarding accuracy and precision over encrypted traffic, the state-of-the-art results are the Deep Packet approach [14] from 2018 (published in [13]) and the Flowpic approach [25] from 2019. Both build up over the works of Draper-Gil et al. [6] and Lashkari et al. [9] which set up datasets for traffic categorization, the former containing both VPN and unencrypted traffic, and the latter containing both Tor and unencrypted traffic.

In [13] each packet (header and payload) is converted to a normalized byte sequence, and used as an input for a 1-D convolutional neural network and for a set of stacked auto-encoders. Both are trained with unencrypted and VPN-encrypted traffic and, surprisingly, the resulting networks are able to do traffic categorization for both unencrypted and VPN traffic without using time-related features (but using size). Performance is quite good with 94% average recall and 93% average recall but, unfortunately, for the unencrypted vs Tor dataset there is an important drop on both average recall (down to 57%) and average precision (down to 44%).

The Flowpic approach [25] uses all spatial and temporal information contained in a traffic flow without looking at its content. Flow packets, encrypted or not, are represented with a 2D-histogram, in the form of a square picture, with packet size in ordinate and normalized arrival times in abscissa. The main idea of Flowpic is that with this approach the traffic category can be derived from image recognition techniques. The images are thus fed to a LeNet-5 [11] convolutional neural network and categorization is done in a class vs all game with 97% average accuracy for unencrypted traffic, 99.7% for VPN traffic, and 85.7% for Tor traffic. Given their nice results over all three sorts of traffic,

Flowpic will be our main point of comparison.

3 Proposed model

3.1 Prospects

The approach used in this paper is very similar to the one employed in [25]. Histograms represent flow packets grouped by size and feed the neural network. The difference relies on the use of a SNN to operate such classification, instead of a CNN. No previous research with that method has been reported and the results will be mainly compared to the study presented in [25]. To ensure that this comparison is fair, we follow the same dataset generation and processing as in [25].

3.2 Dataset generation

To generate the data, we used two public datasets from University of New Brunswick (UNB) called "2016 ISCX VPN-nonVPN traffic dataset" from [6] and "2017 ISCX Tor-nonTor dataset" from [9], both used in the closely related works [13, 25]. They comprise a range of packet captures (pcap) format files corresponding to traffic flow captures of five main classes (Video, VoIP, Chat, File Transfer and Browsing) using three different types of encryption (unencrypted, VPN and Tor). We converted them into comma separated values (CSV) files containing arrival times and sizes in order to exploit the data. We have not considered any restriction about the amount of packets or their size. Again it is important to note that there is no Browsing-VPN data in the ISCX dataset, so we have not used this type of data for training or testing our model (as neither did the authors of [6, 9, 13, 25]). Introducing such a traffic and doing a fair comparison with other approaches when it is included is left as future work.

3.3 Data processing methodology

The first step is to extract the suitable features from these flow packets. A traffic flow can be seen as a sequence of packets that have the same source and destination IP. They are bidirectional: forward when a message is sent from source to destination, and backward when a message or acknowledgment (ACK) is sent back from destination to source. Thus, we consider, for each exchange, data from both directions of the flow. We pick, as in [25], packet size and time of arrival as features, since they are always available, whether the traffic is encrypted or not. Then, we split each flow every 15s into equal sequences lasting 60s. We have therefore csv files representing one minute chunks of a communication session and containing packet sizes and times of arrival. As a result, we generate 2D-histograms of packet sizes as a function of the time of arrival from each csv file as shown in Figure 1. For one flow, we have two series of histograms, each corresponding to one direction (forward and backward), that were concatenated along the v (size) dimension. The histogram values

correspond to the number of packets with the same (time size) coordinates. In addition, the resolution of the histograms can be adjusted by increasing or decreasing the number of bins it contains. If the number of bins is too high, the memory and computation requirements for the classification training become prohibitive. Moreover, as we will associate one input line to each size bin, overfitting can become an issue. Indeed, adding one size bin increases the number of trainable weights by the number of hidden neurons, here 100. If the number of bins is too low, it degrades the histogram quality and therefore the network's ability to recognize the right traffic class. By trial and error we found that 300 time bins and 300 size bins is a good choice (whereas [25] used 1500x1500). Once implemented, the histograms can be classified according to their category. Some examples of images obtained are shown in Figure 2.

3.4 Labeling dataset

A label is attributed to each csv file according to its traffic category. A label is a number giving both the traffic class (Chat, Browsing, File Transfer, Video or VoIP) and the encryption method (Tor, VPN or Unencrypted). For instance, label 2 matches with Video over VPN traffic while label 7 matches with File Transfer over Tor traffic. Once created, the csv files containing the histograms are distributed between groups of equal size, called batches, that will be used as input data for the neural network training. Thus, the batch size, representing how many histograms each batch contains, is a parameter to be adjusted. Increasing it avoids scattering data whereas decreasing it introduces stochasticity which can be beneficial for gradient descent. Moreover, we use a weighted random sampler on our training dataset. For each class, a weight is attributed to each file, this weight being inversely proportional to the amount of files of in this class. This allows to balance the batches in the training dataset and therefore to improve the classification performance.

3.5 The model

3.5.1 Spiking Neural Network

A SNN can be seen as a type of biologically inspired deep learning model, whose state evolves in time, and in which information between neurons is transmitted by spikes [18]. In most SNNs, neurons are modeled using the leaky integrate-and-fire (LIF) model. It introduces a neuron dynamic able to capture temporal patterns. In discrete time, it can be described as follows:

$$V[n+1] = \beta(V[n] - Reset[n]) + (1-\beta) \sum_{j} w_{j} S_{j}^{in}[n]$$
 (1)

$$S^{out}[n+1] = \theta(V[n+1] - Threshold) \tag{2}$$

$$Reset[n+1] = Threshold.S^{out}[n]$$
(3)

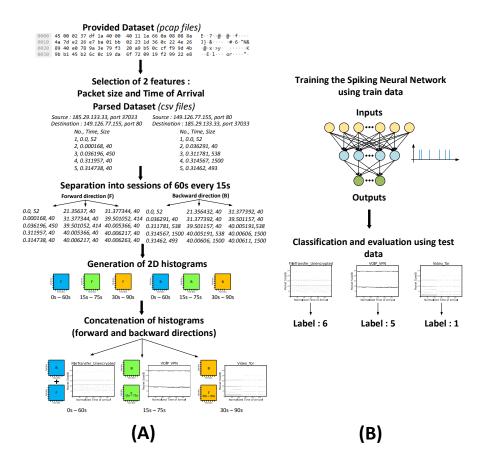


Figure 1: Architecture proposed for classifying Internet traffic using a SNN. Section (A). This section is the part which is similar to [25], At first from the original peap files in dataset, we generate csv files containing the time of arrival and the size of each packet in each flow (forward and backward direction), then we separate these sessions into sessions of 60s with 15s of gap between them. Next we generate two dimensional histograms using these sessions which the time bins are considered on X-axis and size bin on Y-axis and also we concatenate the forward and backward traffic histograms to generate the final histogram as the input of our network. Section (B). This section describes our model. The concatenated histograms are fed to the SNN and the network is trained using these histograms. Finally the evaluation of the model is done using test dataset histograms.

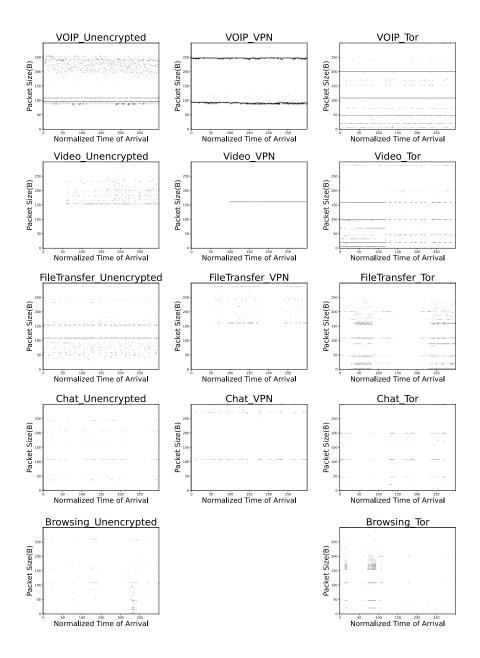


Figure 2: Examples of obtained two dimensional histograms for each traffic category. The X-axis and Y-axis show time and size bins respectively. For clarity, all non empty bins are represented in black, whatever the packet count. Note: there is no Browsing-VPN data in the ISCX dataset.

V represents the membrane potential, n the discrete time, $\beta=e^{-\frac{\Delta t}{\tau}}$ the leak coefficient (with τ the membrane time constant), $\sum_j w_j S_j^{in}$ the weighted input spikes, Reset the reset function due to the output spikes, S^{out} the output spike, and θ the Heaviside step function. Equation 2 implies that whenever the membrane potential reaches the threshold, an output spike is fired and the potential is reset. As for ANNs, a SNN can be described as a large number of neurons connected via synapses, that are represented by weights. A weight is a number that evaluates the way information, here spikes, is transmitted between two neurons. Thus, training a network means adjusting the weights so that data provided as an input leads to the activation of the correct output. The difference between the result provided by the network and the desired result is computed by a loss function and has to be minimized. Here, we use the cross entropy function H calculated as follows

$$H(p,q) = -\sum_{i} p_i log(q_i)$$
(4)

With $p_i = 1$ if the true label is i and 0 otherwise, and q_i the predicted value of the model. To adjust the weights and train the network, the mainly used method that has proved to be efficient is backpropagation. It consists in updating the weights from the output layer back to the input layer of the network in a way that minimizes the loss function. As SNN are recurrent (see Eq. 2), backpropagation through time (BPTT), which consists in unfolding through time the network before applying backpropagation, is employed (see Figure 3). Still, this method requires to calculate the gradient of the activation function. In the case of SNNs, it poses an issue because the Heaviside function gradient is 0 everywhere except in 0 which implies that no information can flow through the activation function during the backpropagation. Recent research has managed to solve this problem by switching the true gradient by a surrogate function [18]. Here we used the derivative of a sigmoid, since a sigmoid is continuous and can approximate the Heaviside function as seen in Figure 4.

One of the main assets of SNNs compared to other networks is that inference can be implemented at low power using event-driven computation on neuromorphic chips [22]. They are thus appealing for embedded systems such as satellites. Furthermore, SNNs are adapted to dynamic inputs: they detect synchronicity and other time related features. The proposed architecture for traffic classification consists of two fully connected layers: one Spiking Dense Layer made up with 100 neurons with 300 inputs, and one Read Out Layer with 14 neurons corresponding to the different categories to classify (Figure 5). We adapted the s2net code (available at https://github.com/romainzimmer/s2net), designed to train both fully connected and convolutional SNNs using surrogate gradient learning, and based on PyTorch. This code has already given excellent results on the Google speech commands dataset [35, 19], and for epileptic crisis detection from EEG signal [26]. In our case, the network receives histogram batches as inputs and then delivers a prediction vector over the 14 labels. The first layer is a dense spiking layer. The neurons' potentials (V) are calculated for the 300 time steps and spikes are generated according to equation 2. The second

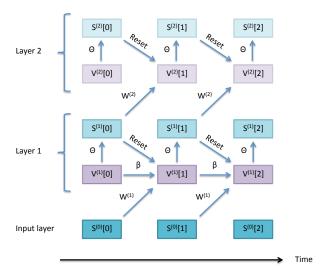


Figure 3: Backpropagation through time. This image shows the unfolded SNN demonstrating how the gradient is backpropagated through the network using BPTT.[18]

dense layer (called Readout layer) can be seen as a spiking layer with an infinite threshold. The potential of each neuron is calculated over the 300 times steps using equation 2 and then the neuron with highest mean potential is the winner and specifies the prediction of the network for the corresponding input.

4 Experiments

Our dataset has been split into three separated sets: 65% of samples used to train the model, 15% to validate it during the training phase, and 20% to evaluate it during the testing phase. The training phase consists of optimizing the network by adjusting its weights, but also the leak coefficients β (we had one trainable β per layer, as previous works suggested that training these coefficients can increase accuracy [8, 32]). The validation set is used to control model performances and tuning hyper-parameters, whereas the testing phase enables to evaluate final model performance. As a result, we have extracted from the dataset independent data used only for the test. Otherwise, there could be a risk of developing an over-fitted model. This would be an important issue since it would mean the model is biased, too specific and unable to classify new data correctly. For training, we set the batch size to 128 and used 30 epochs. Cross entropy loss was used as the loss function. We also used the Adam optimizer along with ReduceLROnPlateau as a scheduler which allows to

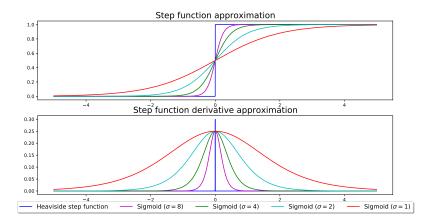


Figure 4: Surrogate gradient for activation function. Different Sigmoid functions can be a suitable approximation for Heaviside function. Because the step function is not differentiable and it hasn't gradient we need to use a surrogate gradient to use in back propagation algorithm of training the SNN, so the sigmoid function is assumed as a substitution of the main Heaviside function and its gradient is used as a surrogate gradient in back propagation algorithm. In the forward path we use the main Heaviside function but in the backward the surrogate gradient is used. [18]

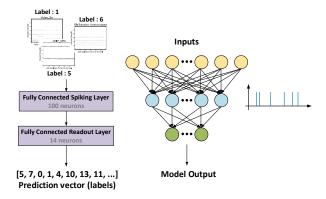


Figure 5: Architecture of the proposed network. In the proposed architecture there is just one hidden layer with 100 neurons and one Readout layer with 14 neurons. The size of input histograms which are fed to the network (in the input layer) is (300,300) which is 300 for time bins and 300 for size bins on the 2D-histogram, the time bins. The time bins dimension is used as the time steps of the spiking neurons while the size bins are considered as the size of input layer. At the Readout layer (with 14 neurons) each neuron is representative of one traffic category and the winner neuron is the neuron with highest mean potential during all time steps. The winner neuron tells which class is chosen by the network.

adjust the learning rate according to the epoch and thus to improve gradient descent for BPTT. To avoid over-fitting, we also introduce a regulatory loss coefficient which penalizes solutions using a large number of spikes. Thus, even if classification may be less efficient, the number of spikes remains quite low which saves energy. This could be very significant in embedded systems for instance.

5 Results

As explained in Section 3.4 our model predicts both the traffic category (e.g. VoIP) and the encryption technique (e.g. VPN) at the same time, and it was trained over the whole dataset. This is in contrast with [25], where the dataset was split in three according to the encryption techniques, and different classifiers were trained for each encryption technique and for each task ("one vs all" or multi-class categorization). The task in [25] is thus simpler as each of their three classifiers only needs to find one among 5 categories (or 4 in the VPN case), whereas in our case it must find one among 14. That being said, we can compute the accuracy of our network for all the tasks used in [25], because they are sub-tasks of the tasks we solved (i.e. all performance measures can be computed from the confusion matrix of Figure 8). It is however important to note that not only the proposed model outperforms Flowpic at its sub-tasks but it also solves a harder problem with a very small error rate.

We first evaluated our model in one vs all classification, meaning that each class is compared to the rest of the dataset. We have used three different performance metrics. For one class, recall (Re) measures the capacity of the model to successfully retrieve the class and not to miss it. Precision (Pr) measures the ability of the model to specifically retrieve the class and ensure the class returned is the good one. Accuracy (Ac) represents a global score quantifying if the model is often right or not.

$$Pr = \frac{TP}{TP + FP} \ Re = \frac{TP}{TP + FN} \ Ac = \frac{TP + TN}{TP + TN + FP + FN}$$

TP, FP, TN, FN stand for True Positive, False Positive, True Negative and False Negative respectively. For the sake of brevity, in this section we just report the accuracy measure but the other measures can be found in A. Table 1 shows the results for each category and encryption technique. It extends Table 4 in [25] with our results (we kept the same form to simplify the comparison). Note however that in [25] they also provide accuracy when using a classifier (e.g. VPN-trained) on another setting (e.g. Tor). As we only have one classifier for all the categories, we only kept for the comparison the best figures of the original table (which correspond to using the right classifier in its own setting, e.g. the VPN-trained classifier to classify VPN traffic). We have reached at least 99.0% of accuracy in all categories and even 100% for some categories. Moreover, our model outperforms [25]'s model for all categories except File transfer-VPN which Flowpic sightly performs better (99.9% vs 99.8% for us). Figures 6 and

7 compare again the results of our network with [25] in categorization tasks on different traffic classes and different encryption techniques using error rates instead of success rates. As the accuracy rates are all very close to 100% it is hard to compare the relative improvements and these graphs are probably a better indicator on the relative multiplicative drop obtained on the amount of errors when using our strategy. The proposed model also reached an accuracy of 96.7% on multi-class categorization of different encryption techniques which is better than the 88.4% reported by [25] (see their Table 3, row 7).

Finally, we reached an overall accuracy of 95.9% and average precision of 96.9% (full precision measures are available in A). Note that [25] could not report this global accuracy, because they always separated the encryption techniques. Figure 8 shows the confusion matrix. We observe that there are some confusions between for instance Chat Tor and Browsing Tor or between VoIP Unencrypted or VoIP VPN. When analyzing the instances that failed, we observed that most of them contained too few packets to be classified correctly.

Class		Accuracy (%)	
	Work/Data	Unencrypted	VPN	Tor
VoIP	Flowpic	99.6	99.9	93.3
	This paper	100.0	100.0	99.4
	Work/Data	Unencrypted	VPN	Tor
Video	Flowpic	99.9	99.9	99.9
	This paper 100.0		100.0	100.0
	Work/Data	Unencrypted	VPN	Tor
File Transfer	Flowpic	98.8	99.9	55.8
	This paper	100.0	99.8	99.7
	Work/Data	Unencrypted	VPN	Tor
Chat	Flowpic	96.2	99.2	89.0
	This paper	99.4	99.8	99.1
	Work/Data	Unencrypted	VPN	Tor
Browsing	Flowpic	90.6	-	90.6
	This paper	99.4	_	99.0

Table 1: Comparison between results of this paper and Flowpic [25] in one vs all categorization of different traffic classes. It is noteworthy that the unencrypted traffic is named Non-VPN in Flowpic [25]. As the table depicts, the results are improved in all traffic classes and encryption methods except File transfer-VPN for which Flowpic performs slightly better.

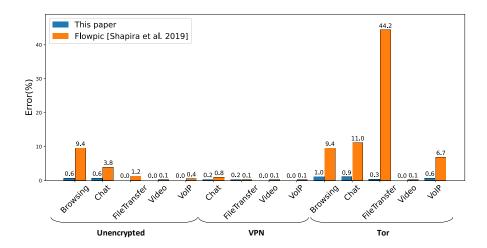


Figure 6: Comparison of one vs all errors on categorization of different traffic classes and encryption methods between this work and Flowpic [25]. Note that in Flowpic the unencrypted traffic is named Non-VPN. The task was one versus all classification of different traffic categories with the data from just one encryption method (Unencrypted, VPN, Tor). We have used the error rate on classification (100-accuracy) of the data instead of the accuracy to highlight the relative multiplicative gap between the performance of the proposed network in comparison to Flowpic [25]. As the Figure depicts this paper is better in all traffic classes and encryption methods except File transfer-VPN which Flowpic performs slightly better.

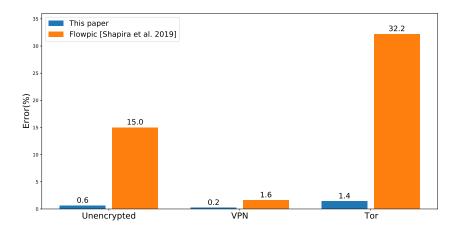


Figure 7: Comparison of error rates on categorization of different encryption techniques between this work and Flowpic [25]. The task was multi-class categorization between different traffic classes of each encryption method. We outperformed Flowpic for all encryption methods.

Predicted\Label	Vid. nonVPN	Vid. Tor	Vid. VPN	VoIP nonVPN	VoIP Tor	VoIP VPN	F.T. nonVPN	F.T. Tor	F.T. VPN	Chat nonVPN	Chat Tor	Chat VPN	Brow. nonVPN	Brow. Tor
Vid. nonVPN	99.50%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Vid. Tor	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Vid. VPN	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
VoIP nonVPN	0.50%	0.00%	0.00%	84.20%	0.00%	0.30%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
VoIP Tor	0.00%	0.00%	0.00%	0.00%	98.30%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
VoIP VPN	0.00%	0.00%	0.00%	15.80%	0.00%	99.70%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
F.T. nonVPN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
F.T. Tor	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	98.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
F.T. VPN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	97.90%	0.00%	0.00%	0.00%	0.00%	0.00%
Chat nonVPN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	92.50%	0.00%	0.00%	0.80%	0.00%
Chat Tor	0.00%	0.00%	0.00%	0.00%	0.70%	0.00%	0.00%	1.00%	0.00%	0.00%	92.10%	0.00%	0.00%	0.50%
Chat VPN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.10%	0.00%	0.00%	100.00%	0.00%	0.00%
Brow. nonVPN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.50%	0.00%	0.00%	99.20%	0.00%
Brow. Tor	0.00%	0.00%	0.00%	0.00%	1.00%	0.00%	0.00%	1.00%	0.00%	0.00%	7.90%	0.00%	0.00%	99.50%

Figure 8: Confusion matrix of the proposed model on categorization of the all classes simultaneously (including all the data from different traffic classes and encryption methods and 14 classes as depicted in the matrix). The classes on the lines are the predicted labels while the classes on the columns are the true labels

The results highlight that our SNN is able to classify with very good performance different types of traffic classes according to three encryption techniques. This is even more noticeable considering the limited amount of data needed for training and the simplicity of our network. It is fully connected with only

one hidden layer compared to the two convolutional layers plus one fully connected layer used in [25]. This can be very useful for embedded systems such as satellites for instance due to their low energy requirements.

Finally, we performed some additional analyses to get more insight on the reasons why our SNN reaches such a good accuracy despite its simplicity. Firstly, we tried to destroy all the temporal features, at inference time (after normal training). This was done by shuffling the histograms along the temporal dimension. More specifically, we randomly permuted the elements of each row of the histograms, using a different permutation for each row. This completely destroys the temporal features, but not the spatial ones (for example if a certain sort of traffic tends to use larger packets than another, it can still be used for discrimination). Such an approach led to an total accuracy of only 90.6%, and the comparison to the accuracy in normal mode (95.9%) indicates that our SNN does exploit temporal features.

Secondly, we tried to destroy all the temporal features but the synchronous ones (still at inference time, after normal training). This was done by shuffling again the histograms along the temporal dimension, but this time the same permutation was used for all the rows of a given histogram. This means that if multiple packets with different sizes arrived in the same time bin before the shuffling, they still arrived in the same time bin after it. Conversely, any intertime-bins temporal information, i.e. long range temporal correlations, was lost. Of course, this second shuffling method also conserved the spatial features. This second experiment led to an accuracy of 95.1%, almost as good as the baseline one (95.9%). This means that our SNNs mostly exploits synchronous features (with a 200 ms resolution), largely ignoring longer range correlations. Of course, this second sort of shuffling is more harmful when increasing the resolution (e.g. with 40ms time bins the accuracy drop is about 2%, indicating that cross-correlations with a 40-200 ms lag matter).

To confirm the range of useful correlations, we went back to a 200 ms resolution, and we analyzed the final values of the leak coefficients β (recall that it is trainable). It turns out that, whatever the initial values, the β of the hidden layer converges towards ~ 0.42 . With such a fast decay, neurons quickly forget any packet that arrived before the current time bin. In other words, neurons mostly care about synchrony (with a 200ms resolution). In a last experiment, we forced $\beta=0$. In this extreme case, the neurons become stateless: they only care about current inputs. This led to an accuracy of 95.2%. This consistent with the second shuffling experiment, and confirms that inter-time-bins correlations are not very informative when the time-bin size is large enough to capture short-term synchronicity.

All together, these additional experiments confirm that the dataset contains temporal features, mostly synchrony patterns (with a 200ms resolution), that are highly diagnostic, and that are efficiently exploited by a SNN with a fast decay.

6 Conclusion

In this paper, we proposed an approach to use a SNN in order to classify different traffic classes encrypted with different techniques (via VPN or Tor). We only considered packet size and time of arrival of flow traffic. The input data were therefore 2D-histograms representing a session of 60s in both forward and backward directions. We reached an overall accuracy of 95.93% and an average precision of 96.9% on test dataset with a simple network made up with only one hidden layer and trained on only 65% of the dataset. Thus, we have shown that SNN can be very relevant for Internet traffic classification, with applications in the industry since SNN can run on neuromorphic hardware with low energy consumption [22]. Finally, progress can be made and the model performance can be enhanced by considering spiking convolutional layers that are very promising.

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A Complete results

In this section we bring complete performance results, while in Section 5 we just mentioned the accuracy. Complete results of one vs all categorization are presented in Table 2 for different traffic classes, and in Table 3 for all different traffic classes and encryption methods. The accuracy and average precision of the network are respectively 95.93% and 96.9% in multi-class categorization of all types of traffic (traffic classes and encryption methods simultaneously with 14 output neurons). Finally, the average accuracies for one vs all categorization of different traffic classes with the data of each encryption technique are reported in Table 4.

Traffic class	$\operatorname{Recall}(\%)$	$\operatorname{Precision}(\%)$	Accuracy(%)
Browsing	99.3	99.0	99.4
Chat	96.4	94.3	99.4
File Transfer	98.9	100.0	99.9
Video	99.8	100.0	100.0
VoIP	99.6	99.9	99.8

Table 2: Complete performance results on one vs all categorization of different traffic classes. The task was to classify each traffic class versus all other classes with all the data from the test dataset.

Traffic class	$\operatorname{Recall}(\%)$	$\operatorname{Precision}(\%)$	Accuracy(%)
Browsing-Unencrypted	99.2	99.5	99.6
Browsing-Tor	99.5	96.6	99.8
Chat-Unencrypted	92.5	88.6	99.6
Chat-Tor	92.1	89.7	99.8
Chat-VPN	100.0	99.2	100.0
File Transfer–Unencrypted	100.0	100.0	100.0
File Transfer–Tor	98.0	100.0	99.9
File Transfer-VPN	97.9	100.0	100.0
Video-Unencrypted	99.5	100.0	100.0
Video-Tor	100.0	100.0	100.0
Video-VPN	100.0	100.0	100.0
VoIP-Unencrypted	84.2	99.7	96.6
VoIP-Tor	98.3	100.0	99.9
VoIP-VPN	99.7	72.1	96.7

Table 3: Complete performance results on one vs all categorization of different traffic classes and encryption techniques. The tasks was to classify each class versus all other classes on the test dataset.

Traffic class	Our accuracy(%)	Flowpic's accuracy(%)
Unencrypted	99.7	97.0
Tor	99.4	85.7
VPN	99.9	99.7

Table 4: Average accuracies for on one vs all categorization of different traffic classes for each encryption technique. The reported results are the averages of results in Table 1 for each encryption technique. The corresponding Flowpic accuracies, from Table 3 (rows 4-6) in [25], are always lower.

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