future internet

Review

CNN for User Activity Detection Using Encrypted In-App Mobile Data

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Abstract: In this study, a simple yet effective framework is proposed to characterize fine-grained in-app user activities performed on mobile applications using a convolutional neural network (CNN). The proposed framework uses a time window-based approach to split the activity's encrypted traffic flow into segments, so that in-app activities can be identified just by observing only a part of the activity-related encrypted traffic. In this study, matrices were constructed for each encrypted traffic flow segment. These matrices acted as input into the CNN model, allowing it to learn to differentiate previously trained (known) and previously untrained (unknown) in-app activities as well as the known in-app activity type. The proposed method extracts and selects salient features for encrypted traffic classification. This is the first-known approach proposing to filter unknown traffic with an average accuracy of 88%. Once the unknown traffic is filtered, the classification accuracy of our model would be 92%.

Keywords: encrypted traffic classification; network analysis; mobile data; network traffic to image

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1. Introduction

In recent years, traffic classification has attracted increasing attention, as it is used in network management, security, advertising, network design, and engineering. Network traffic classification involves analyzing traffic flows and identifying the type of content within these flows. In network traffic analysis, a network trace of a device or a group of devices is taken as input and, as output, information about those devices, their users, their apps, or in-app activities is given. Network traffic classification has many possibilities to solve personal, business, internet service provider, and government network problems such as anomaly detection, quality of service control, application performance, capacity planning, traffic engineering, trend analysis, interception, and intrusion detection. To date, several traffic classifications approaches have been proposed and developed. These methods have evolved significantly over time from port-based, deep packet inspection (DPI) to machine learning (ML) methods [1]. The use of dynamic port-negotiation mechanisms by applications has made port-based methods no longer suitable. An increase in the use of encrypted internet traffic and privacy policies that prevent access to packet content have rendered relying on a packet's payload or DPI no longer effective. Most research activities that perform encrypted traffic classification rely on extracting statistical features from traffic flows, which is followed by performing feature selection to eliminate irrelevant and redundant features. They then use classical machine learning algorithms, such as random forest (RF) [2,3], Bayes net [4], K-nearest neighbors (KNNs), and support vector machine (SVM) [5] to perform the classification. These methods can handle both encrypted and unencrypted traffic. However, the performance of these methods greatly relies on human-engineered features, which limit their generalizability [1].

CNNs, an important model of deep learning (DL), were initially applied in the field of image recognition [6] and achieved remarkable results. With the advances in DL, the use of CNNs has become prevalent in many fields such as speech recognition, audio processing, visual document analysis, genomics, and in medical use [7]. Yet, it has not been sufficiently utilized in network traffic classification [6]. This paper proposes an image-based method that represents network traffic as images and utilizes DL architecture based on CNNs to learn the traffic features in these images and perform traffic classification. This research focused on conducting network traffic classification to identify user activities performed on mobile applications (known as in-app activities) from a sniffed encrypted internet traffic stream. Figure 1 shows the generated images using encrypted in-app activity data for three different in-app activities. The main advantage of using a CNN in image classification is that there is no need to extract features beforehand, because the CNN model can learn features by itself.

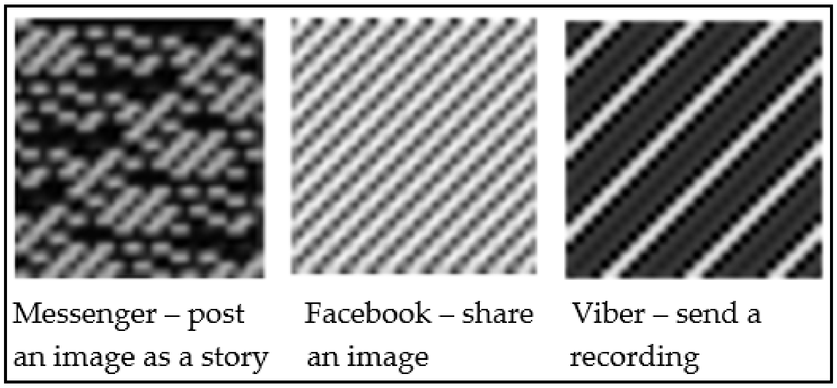

Messenger – post an image as a story
Facebook – share an image
Viber – send a recording

Figure 1. Grayscale images generated from the encrypted in-app activity data.

In this research, sensitive information related to online users, such as the activities performed with their mobile apps, are inferred by passively sniffing encrypted wireless network traffic. Even though encryption protocols are used to encrypt data, it protects only the packet's payload, but it does not hide *side channel data* such as frame length, data length, inter arrival time, and direction (incoming/outgoing). Therefore, in this research, the side channel data were used to reveal private information related to the user's online behavior. Users perform different activities using the apps installed on their mobile devices. Each in-app activity has a distinct network behavior [8] and, thus, generates different traffic flows. Traffic flow data are converted into images and image classification deep learning techniques are used to detect in-app activities.

The contributions of this paper are summarized as follows:

(a) Unknown app data detection: A wide range of apps are available in app stores. It is not practical to train a machine learning model for such a wide variety of apps and for every in-app activity that can be performed using those apps. When deploying an in-app activity detection model in a real network, the model needs to correctly detect applications and in-app activities while earmarking previously untrained activities as unknown traffic. Most existing works in the literature involve model training and testing on the same set of apps, which renders them unfit for detecting previously unknown traffic. The proposed model in our work was designed to conduct network traffic analyses effectively, even in the presence of noise generated by unknown traffic;

(b) Activity detection using minimal data: When network traffic is captured to detect in-app activities, there can be instances when an eavesdropper captures only part of the activity-related traffic instead of the entire transaction, as the target user's activity may have been underway already. The proposed model was designed to identify in-app activities even by observing a subset of an activity's traffic;

(c) Fine-grain in-app activity detection: Works in the literature have considered coarse-grained activities such as uploading, chatting, downloading, or generic activities, including sending an email, messaging on Messenger, and posting on Instagram. Our work advances this existing body of work by designing the model to identify fine-grained in-app activities. For example, when a generic Facebook activity "posting on wall" is considered, the model can determine whether the post is an image, a long text, a short text, a video, or a check-in. This level of fine-grained analysis is challenging, as classification is performed in an encrypted domain using only side channel data;

(d) Novel data set for future research: A comprehensive data set was created by performing a series of actions on eight apps, namely, Facebook, Instagram, WhatsApp, Viber, Messenger, Gmail, Skype, and YouTube. This data set will be shared openly with the research community to foster new studies and allow reproduction of the results presented. (https://www.drop-box.com/s/9tihcj9wx2sia1t/Data set.7z?dl=0 (accessed on 4 October 2021))

The rest of this paper is organized as follows: In Section 2, the related work is reviewed. Section 3 describes the methodology of the proposed classification system. Section 4 presents the experimental results and discussions. Section 5 provides concluding remarks.

2. Related Work

In the literature, two types of research methods have dominated traffic classification: statistical methods and neural networks.

Statistical classification is a technique that exploits the statistical characteristics of network traffic flow to perform traffic classification. Features, such as packet length, packet duration, packet inter-arrival time, and traffic flow idle time, are used in this method. To perform an actual classification based on statistical features, classifiers, specifically ML algorithms, are used. Conti et al. [9] performed mobile user actions classification based on packet sizes and their order. Saltaformaggio et al. [5] developed NetScope to detect user activities based on inspecting statistical features obtained from internet protocol (IP) headers. Taylor et al. [2,10] used features, such as packet lengths and statistical properties of flows, to train support vector classifier (SVCs) and random forest classifiers to perform mobile app classification. Pathmaperuma et al. [4] identified user activities performed on mobile apps using statistical features generated from frame length, inter-arrival time, and direction leaked from encrypted traffic. Wang et al. [3] computed 20 statistical features from frame size and inter-arrival time to train an RF classifier to perform app identification. Zhang et al. [11] proposed a scheme by combining supervised and unsupervised machine learning techniques to classify apps. Twenty unidirectional flow statistical features related to packet size, packets, inter-packet time, and bytes were extracted and used to train the proposed classifier. A classification method was proposed by Draper-Gil et al. [12] with only time-related flow features on both regular encrypted traffic and protocol encapsulated traffic.

Many works have applied neural networks in network traffic analysis such as malware classification [13], anomaly detection [14], DDoS attacks detection [15], and intrusion detection [16,17]. In [18], Wang et al. proposed an end-to-end encrypted traffic classification approach with 1D CNN to detect traffic types such as streaming, VoIP, and file transfer. Lopez-Martin et al. [19] proposed using a recurrent neural network (RNN) combined with a CNN for IoT traffic classification. In [20], Aceto et al. performed traffic classification in encrypted network flow using DL techniques. Wang [21] proposed a stacked auto encoder (SAE)-based method to detect network protocols. The results showed that Wang's approach worked well on the applications of feature learning, protocol classification, anomalous protocol detection, and unknown protocol identification. In [22], Lotfollahi et al. proposed a framework to perform traffic characterization and application identification using DL, embedding an SAE and CNN to classify network traffic.

Recent studies have explored the use of CNNs to perform classification by converting network traffic flows into images. Wang et al. [13] converted traffic to 2D images and then applied 2D CNN to classify the traffic images achieving the goal of malware classification. Ma et al. [8] proposed a CNN model that predicts large-scale, network-wide traffic speed. In this work, spatiotemporal traffic dynamics were converted to images describing the time and space relations of traffic flow via a 2D time–space matrix. Zhou et al. [6] proposed a classification algorithm Min–Max Normalization (MMN) CNN that processes traffic data and maps them into gray images that are input into a CNN to detect 12 types of traffic categories such as mail, game, and multimedia. Tavakoli [23] presented the Seq2Image method to perform human genomic sequence classification converting genome sequences to images and then using a 2D CNN to classify the created images of sequences. Shapira et al. [7] presented the FlowPic approach to transform flow data into an image and then used image classification DL techniques, a CNN, to identify the flow category and application in use. Kim et al. [24–26] presented the NetViewer approach that detects and visualizes attacks and anomalous traffic by passively monitoring packet headers. In these works, multiple pieces of traffic data are represented as different colors of an image. Image processing techniques are applied to generated images to analyze the network traffic. He et al. [27] proposed an image-based method that converts the first few non-zero payload sizes of session to gray images and uses a 1D CNN to perform the classification.

The works in the literature primarily focus on classifying previously trained traffic, while none has considered performing network traffic analysis accurately in the presence of noise generated by unknown traffic, even though this would be a typical situation in a real-world scenario. Thus, this work aimed to advance the state-of-the-art by identifying previously trained fine-grained in-app activities accurately as well as by detecting and classifying previously untrained in-app activities as unknown data.

To detect unknown in-app activities, the function needs to reject the classification label for those inputs belonging to classes never exposed during training. An output-based rejection technique is proposed in this work that leverages additional information from the deep learning model output such as the SoftMax probabilities of each class. Usually in classification tasks, the neuron with the highest probability will be chosen and the corresponding class label is assigned. In this work, a two-stage approach was used to check if the neuron with the highest probability satisfied a pre-set threshold value. Based on this, the known and unknown instances were classified. However, setting this threshold is challenging, as setting it too high increases false negatives, whereas setting it too low increases false positives. To test the impact of the threshold value on the model's performance, a range of threshold values were selected, and tests were performed.

3. Proposed Methodology

This paper proposes a CNN-based method that transfers network traffic flows into images to identify in-app activities while detecting unknown data. The method contains two main procedures. The first is to convert network traffic into images that represent side channel data of a network flow as a 2D image. The second is to apply image classification DL techniques to the generated images and perform traffic classification of previously trained and untrained apps' traffic flows.

3.1. Data Collection

For this research, a data set was created that consisted of network traffic from in-app activities of eight popular mobile apps, namely, Facebook, Instagram, YouTube, Viber, WhatsApp, Gmail, Skype, and Messenger. To obtain the ground truth, network traffic generated after executing each activity was collected separately, and the network trace was labeled with the name of the activity performed. Each app was run separately, thus limiting the presence of background traffic. To generate a sufficient number of traffic flows for inference, each activity was repeated four times and captured traffic was saved as .pcap files. The number of in-app activities considered in each app and number of samples obtained after segmenting the traffic into 1, 0.5, 0.2, and 0.1 s time intervals are presented in Table 1. The 92 in-app activities considered in this research are given in Appendix A.

Table 1. Features of the collected data set.

App	Category	No. of in-App Activities	Number of Samples			
			1 s	0.5 s	0.2 s	0.1 s
Facebook	Social networking	22	9477	19,944	55,283	110,588
Instagram	Photo and video	20	2907	6818	25,529	81,505
Gmail	Productivity	5	561	1036	2361	5514
Messenger	Social networking	10	2199	6061	18,514	43,113
Skype	Social networking	8	5436	15,703	69,884	211,981
Viber	Social networking	9	434	690	1207	1875
WhatsApp	Social networking	9	273	436	873	1458
YouTube	Photo and video	9	5161	14,501	58,173	207,013
Total 8 apps		92	26,448	65,189	231,824	663,047

We monitored the network passively and traffic was captured without connecting to the wireless network to which the target user's mobile device was connected. The traffic transmitting within the wireless network was sniffed using Airmon-ng and Airodump-ng sniffing tools from the Aircrack-ng suite [28]. Default setting of network adapters allow only to capture packets that are sent to them. To capture all traffic, we set the network adapter to its monitor mode. The experimental testbed used to sniff traffic is shown in Figure 2. The internet access to the smartphone was provided over a wireless connection via a router. The smartphone was connected to the wireless network exclusively to avoid interference from other sources. The network adapter (Alfa AWUS036NHA) was plugged to the laptop (Toshiba PORTEGE Z30-C), which was used to capture the network traffic.

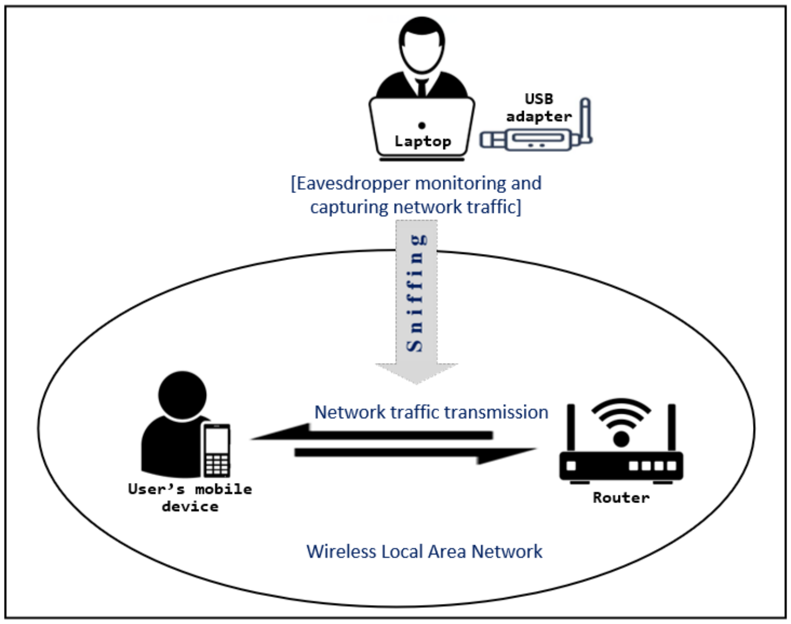

Laptop
USB adapter
[Eavesdropper monitoring and capturing network traffic]
Sniffing
Network traffic transmission
User's mobile device
Router
Wireless Local Area Network

Figure 2. Experimental testbed for data collection.

3.2. Network Traffic to Image

Pre-processing needed to be applied on the captured traffic flows prior to mapping traffic data into images. The following pre-processing steps were performed on the obtained data set in this work.

(a) Sanitization

The three main frame types used in WLAN (IEEE 802.11) are data, control, and management frames. Only the data frames are used for data transmission. The presence of the other two types may hinder the process of analysis; therefore, the control and management frames were eliminated, and only data frames were processed further. There were data frames that did not carry data. Keeping these frames would cause bias in training the CNN [29]. Therefore, null data frames were also eliminated at this stage.

(b) Normalization

Normalization is an important step in data pre-processing to avoid having different scales of feature vectors and, thus, improves integrity of data. The data set contained feature values in different scales that may lead to obtaining biased results. To normalize the feature values, the standard scaler [30] was used, which normalizes each feature by removing its mean and scaling to unit variance. This equalizes the importance of all features and allows DL methods to converge faster. For each original value X with a mean μ and standard deviation σ, its normalized value X′ can be determined from (1):

$$X' = (X - \mu)/\sigma \quad (1)$$

(c) Segmentation

During in-app activity detection, it is not possible to guarantee that the entire transaction of an activity can be observed. There can be situations where the eavesdropper starts to capture the traffic while the user is already performing an activity. In these instances, the eavesdropper can capture only a part of the traffic flow instead of the entire flow transaction. To perform in-app activity detection even by observing only a part of an activity related traffic, time windows are used to divide the traffic flows into segments. A thorough analysis of the sensitivity of this approach was performed by conducting experiments with different time window sizes: 1, 0.5, 0.2, and 0.1 s as discussed in Section 4.1.

Following network traffic pre-processing, each segmented traffic sample was converted into an image, where features and corresponding feature values were represented by pixels and pixel intensities, respectively. In this work two sets of data images were generated that used different color schemes. These were grayscale and red, green, and blue (RGB). If the segmented traffic sample, *S*, has *n* number of frames and *m* number of data values, then the value of *m*th data at *n*th frame can be represented as A_{nm}. The segment *S* is represented as matrix (2):

$$S = \begin{bmatrix} A_{11} & \cdots & A_{1m} \\ \vdots & \ddots & \vdots \\ A_{n1} & \cdots & A_{nm} \end{bmatrix} \quad (2)$$

The three main side channel data considered in this work were frame length, data length, and inter arrival time. Segment S comprised values of these side channel data. Based on these data, individual vectors were created. The division can be expressed as matrix (3):

$$X_i = [A_{1i}, A_{2i}, \ldots A_{ni}] \quad (3)$$

where n is the number of frames and X_i represents all data values of the ith side channel data. The number of vectors that are created depends on the number of side channel data. In this research, three side channel data were considered; thus, three vectors were created. When employing a grayscale model, these three vectors combined to form one vector. Whereas in the RGB model, these were passed together as three separate vectors.

If the image size is very small, then it cannot be sent through the required number of convolutional layers, because after each layer, the size is reduced. Therefore, resizing was applied to match with the respective pre-defined input image size.

Each element in the matrix is treated as a pixel with the grayscale value of the pixel, where the color intensity is proportional to the matrix value. Figure 1 shows three in-app activities' traffic flows in grayscale format. The input image dimensions were h × w × c, where h × w were the dimensions of the image, and c was the number of channels. The image dimension wass constructed according to the number of features in the data set. The dimensions of the images were set to 28 × 28 following empirical tests. Grayscale images had one channel. Hence, the input image size of grayscale images was resized to 28 × 28 × 1 (784). Data fed into CNN must be uniform. The data that were less than these pre-defined image sizes were zero-padded, and data that were more than the pre-defined image sizes were truncated to match the respective pre-defined size.

3.3. Image Classification Using CNN

The CNN architecture proposed to identify in-app activities was composed of four main parts: model input, traffic feature extraction, prediction, and model output as shown in Figure 3.

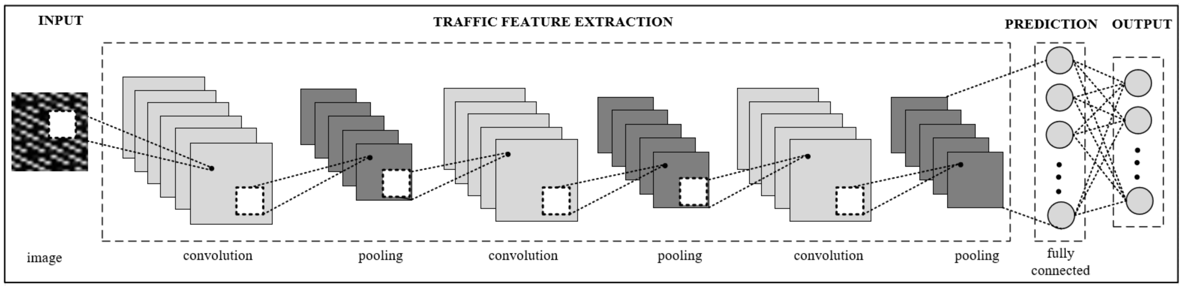


Figure 3. Proposed CNN architecture to identify in-app activities. The traffic flow data transferred into pixelized images are used as the input to the CNN model with input dimension of 28 × 28.

The input layer was then connected to a combination of convolution and pooling layers to learn image features. In this proposed architecture, three convolutional layers were used, where each convolution layer was followed by a pooling layer that selects the most important features from its receptive region and reduces the number of parameters required to train the model. Pooling layers reduce the size of the output through the convolutional process and cancel noise. In our model, the max-pooling function was used, which outputs the maximum value in a rectangular neighborhood of the previous layer.

The fully connected layers at the end of CNN concatenated the output of the convolution layer into a dense vector. This was passed to the model prediction phase.

The dense vector was then transformed into model outputs through a fully connected layer, which had 92 outputs indicating the number of classes (in-app activities) used to classify the input images. This output layer was a SoftMax layer, which output a K-dimensional probability distribution vector of values in the range of 0–1, where K is the number of classes (K = 92). Each node value represents a class score. The class with the highest score was selected and the corresponding class label was assigned.

The hyperparameters, such as the number of convolutional layers, number of fully connected layers, number of filters for each hidden layer, filter and stride size, and activation functions, were selected through comprehensive tests involving numerous parameter combinations. The depth of the CNN should be neither too large nor too small [31], and thus it is able to learn complex relations while maintaining model's convergence. To determine the suitable value for the model's depth, different values from small to large were assigned to test the CNN model until the best model was found. The rationale behind using this architecture was based on the experiments we conducted in which we discovered that this architecture was the best fit model for our problem.

3.4. Unknown In-App Data Detection

In a real-world setting, data traffic captured contains both previously known and unknown traffic flows. Previously known traffic is related to the in-app activities considered during model training whereas unknown traffic relates to the in-app activities not considered during model training. A major challenge to the robustness of the classifier's performance comes from previously unknown/unseen traffic. Identifying previously untrained in-app activities using the proposed method is one of the key contributions of this work.

When the traffic flows are converted into images and input to the CNN model, they pass through hidden layers and reach the output layer. A SoftMax layer is added to the end of the CNN, which converts the output values into a probability distribution. Model's output layer has nodes that is equal to the number of classes. The SoftMax layer provides probabilities for each class label in the interval (0, 1). Usually for a given input sample, one of the classes will have a higher probability value than the rest of the classes. In normal traffic classification tasks, a class is assigned to a data point based on the highest probability. However, in this work instead of making the class with the highest probability be the final classification, a threshold approach is used to determine if the test sample is a known or unknown instance. Figure 4 shows the technique used to detect noise (unknown in-app data) generated by previously unknown traffic. *Pmax* denotes the node with the highest predicted class probability. The decision for converting the predicted probability into a class label is dominated by a parameter known as the *threshold*. If *Pmax* < *threshold*, then the test sample is labeled as an unknown instance. Threshold set on a positive class determines whether the test sample belongs to one of the trained classes, which translates into a pre-trained in-app activity or not.

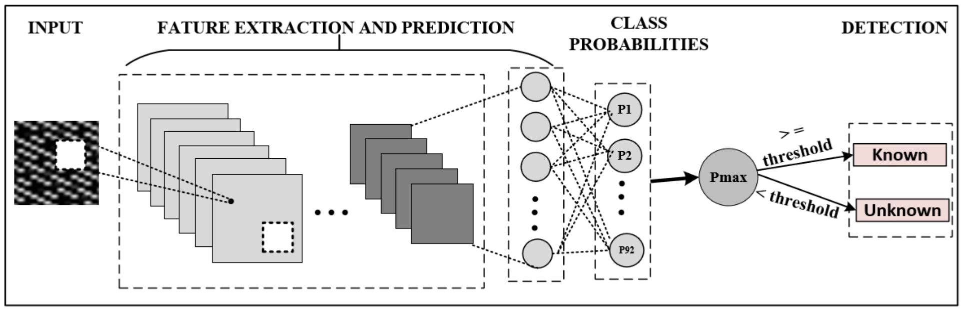


Figure 4. Framework to detect unknown in-app activity data.

To examine the impact of the threshold on model's performance, a range of threshold values were selected and tested. Setting a threshold too high results in an increase in false negatives, while setting it too low leads to an increase in false positive. Therefore, setting a balanced threshold value is challenging. In this work, a threshold value that contributes to achieving the highest classification accuracy was utilized, which was obtained empirically as 0.97.

4. Experimental Results and Discussion

The performance evaluation of the proposed model is presented in this section. When evaluating the proposed model, the following two factors are considered to measure the performance.

- Ability to detect previously trained in-app activities correctly;
- Ability to detect previously untrained/unknown in-app activities as noise data.

The CNN models were constructed, trained, and tested by Keras 2.5.0 with TensorFlow 2.5.0 running at the back end. Experiments were conducted using 92 in-app activities from the Facebook, Instagram, YouTube, Viber, WhatsApp, Gmail, Skype and Messenger apps (see Table 1). Eighty percent of the total samples were dedicated for training, and remaining 20% for validation.

Accuracy was used to evaluate the model performance, which is computed as follows:

$$\text{Accuracy of known data} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total no.of known instances}} \tag{4}$$

$$\text{Accuracy of unknown data} = \frac{\text{True Negatives}}{\text{Total no.of unknown instances}} \tag{5}$$

4.1. Model Analysis

The proposed CNN architecture comprises of seven layers excluding the input and output layers (as depicted in Figure 3). The three convolutional layers had 256, 128, and 64 numbers of filters in each layer, respectively. The fully connected layer had 128 nodes. Tanh activation function is applied to the output of every convolutional and fully connected layer. To reduce overfitting, the dropout technique is used to prevent complex co-adaptations on the training data [7]. In this architecture, the Adam optimizer and categorical cross entropy loss function were used.

The model performance varied with different image sizes as inputs according to our tests. When the image size was too small, there was a sign of learning degradation. When the image size was too large, then the extraction phase took much longer time. Thus, we selected 28 × 28 pixel image size, which helped to reduce the run-time and memory consumption while improving detection rate in all our experiments.

In addition to grayscale images, RGB images were also created from the collected network traffic data set. This was done to observe the performance of in-app activity classification when in-app data is converted to 3D images. Instead of considering the entire flow of an activity, we used the segment-based approach to perform the classification. Four different time windows were used to divide the traffic flows into segments: 1 s, 0.5 s, 0.2 s, and 0.1 s. Table 2 presents the training and validation accuracies, and time needed to train and test the models.

Table 2. Classification performance of grayscale and RGB models.

	Window Sizes							
	1 s		**0.5 s**		**0.2 s**		**0.1 s**	
	Gray	**RGB**	**Gray**	**RGB**	**Gray**	**RGB**	**Gray**	**RGB**
Training accuracy (%)	97	84	98	84	96	83	95	81
Validation accuracy (%)	83	71	88	76	92	80	86	74
Training and testing time	8 min	15 min	19 min	27 min	1 h 9 min	1 h 20 min	2 h 30 min	2 h 48 min

From the experimental results, it can be observed that the accuracy values obtained for the grayscale models are higher than those recorded for the RGB models for all time windows tested. This is because RGB models suffer from overfitting due to the presence of large number of features resulting from the three color channels. Therefore, grayscale images are selected as inputs to avoid false classification and complexities for the rest of the experiments.

Validation accuracy was highest when the time window size was 0.2 s. The reason is when traffic traces are segmented into a smaller window size, we were able to obtain plenty of samples. Training the model with large of samples contributed positively towards the classification accuracy. However, this was not true when the window size was further reduced. Even though the sample size increased when traffic traces were segmented into a smaller window size such as 0.1 s, the classification accuracy decreased. This was because the number of frames contained in such smaller window segments is less. When frames were considered individually or when the number of frames was insignificant, they contained very little information to perform the classification.

With the decrease in window size, leading to an increase in the number of samples, the results present that long times are needed to pre-process, train, and test the models. From the Table 2 data, it can be observed that all grayscale models achieved an average accuracy of 87%. This shows that the proposed model can identify fine-grained in-app activities even by observing only a small subset of an activity's traffic.

4.2. Unknown In-App Data (Noise) Detection

In noise detection tests we use leave-one-out approach where two data sets were created, namely training and noise data sets. From the eight apps considered in the experiments, each time an app was singled out and used to create the noise data set. The remaining seven apps were used to create the train data set. While the training data set was used to train the model, the noise data set (with in-app activities unknown to the trained model) was input to the trained model to determine its ability to detect unknown data. The result of this experiment is shown in Figure 5.

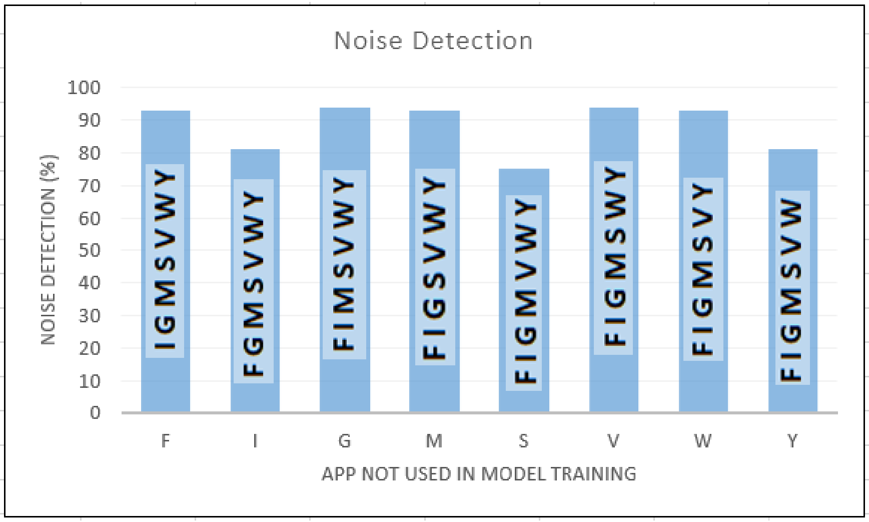


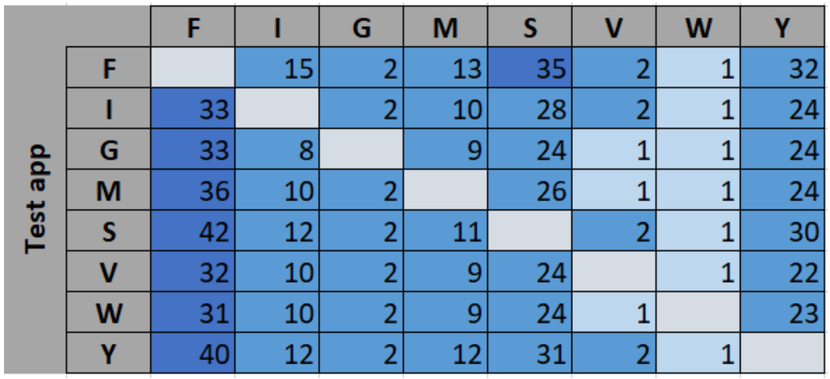
Figure 5. Noise detection rates of unknown apps.

In Figure 5, F, I, G, M, S, V, W, and Y denote Facebook, Instagram, Gmail, Messenger, Skype, Viber, WhatsApp, and YouTube, respectively. On each vertical bar in Figure 5, the apps used to train the model at each instance are denoted. The app labelled on the X axis is the app in the noise data set.

Let's us explain how to interpret Figure 5. The first vertical bar in Figure 5 shows that a CNN model is trained with the in-app activity data from the following 7 apps: I, G, M, S, V, W and Y. The in-app activity data from F is kept away from the training process. During the testing, the in-app activity data from F is used to determine the robustness of trained CNN model. As shown in the first bar in Figure 5, the trained CNN model successfully identified more than 90% of the in-app data from F as unknown data.

As shown in Figure 5, the proposed method achieved 75% or more in detecting noise with average accuracy of 88%. Data from Gmail and Viber applications were detected with 94% accuracy. However, the proposed model couldn't distinguish data from Skype with the trained data only 75% of the Skype traffic got correctly detected as unknown traffic. The remining 25% was misclassified as in-app activities that belong to the training data set.

To understand the nature of the misclassified traffic, further analysis was performed on the apps to which the unknown traffic got classified. The results are presented in Figure 6 in percentage values (%). For example, only 8% of the data from F is classified as known data (see first bar in Figure 5). The distribution of this 8% of the misclassified data from F is shown in the first row in Figure 6. Majority of this data (35%) are assigned to S (Skype).



Test app		F	I	G	M	S	V	W	Y
	F		15	2	13	35	2	1	32
	I	33		2	10	28	2	1	24
	G	33	8		9	24	1	1	24
	M	36	10	2		26	1	1	24
	S	42	12	2	11		2	1	30
	V	32	10	2	9	24		1	22
	W	31	10	2	9	24	1		23
	Y	40	12	2	12	31	2	1	

Figure 6. Confusion matrix (% values).

Looking at Figure 6, the majority of the misclassified data was assigned to Facebook. We observed that there was a high correlation among all the considered apps with Facebook, which contributed to the misclassification. For Instagram, Gmail, Messenger, Viber, and WhatsApp, the second and third highest misclassifications came from Skype and YouTube, respectively. This can also be seen by plotting the correlation between these apps (see Figure 7).

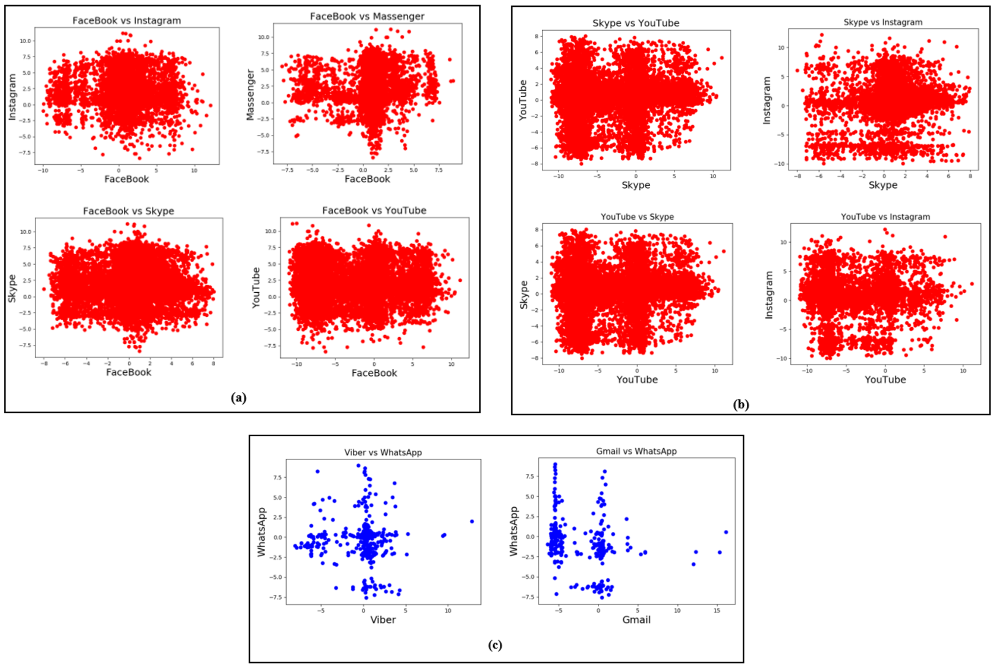


Figure 7. Correlations among different apps. (**a**) correlation of Facebook with Instagram, Messenger, Skype and YouTube. (**b**) correlation of Skype vs YouTube and Instagram with YouTube and Skype. (**c**) correlation of WhatsApp with Viber and Gmail.

Figure 7a shows the correlation plots of Facebook with four different apps. Figure 7b shows the correlation plots of Skype and YouTube with two different apps. In Figure 7a,b the points are closely packed, which means the strength of the correlation was high. Apps that are highly correlated with each other have similar in-app activities with similar behavior.

Looking at the W column in Figure 5, the least amount of misclassification resulted from WhatsApp, which was 1% for all the test apps. This was due to the least correlation between W and other apps as shown in Figure 7c. It can be observed that the points are distributed loosely which means the considered apps are only slightly correlated to each other. The behavior of Facebook, Instagram, Gmail, Messenger, Skype, Viber, and YouTube in-app activities was not similar to WhatsApp's in-app activities, which makes them less correlated to each other.

To obtain a better insight into the misclassifications occurred, further analysis of the in-app activities to which the test apps got misclassified was conducted. Table 3 lists the six in-app activities with the highest misclassification percentage against each of the test apps, where the in-app activities were coded as follows:

Utuv—uploading a video on YouTube;
Skvc—having a video call on Skype;
Msgac—having an audio call on Messenger;
Skv—sending a video on Skype;
Indvc—having a video chat on Instagram Direct;
Fblive—uploading a live video on Facebook;
Skac—having an audio call on Skype;
Fbpv—posting a video on Facebook wall
Utwv—watching a video on YouTube.

Table 3. Misclassified in-app activities with misclassification percentage (%) values.

F	I	G	M	S	V	W	Y
Utuv—27	Utuv—21	Utuv—21	Utuv—21	Utuv—26	Utuv—19	Utuv—19	Fblive—20
Skvc—13	Fblive—15	Fblive—16	Fblive—17	Fblive—22	Fblive—15	Fblive—14	Skvc—11
Msgac—9	Skvc—9	Skvc—8	Skac—9	Msgac—8	Skvc—7	Skvc—8	Msgac—8
Skv—9	Skac—8	Skac—7	Skvc—7	Fbpv—6	Skac—7	Skac—7	Skac—8
Skac—8	Msgac—7	Msgac—6	Fbpv—6	Indvc—6	Msgac—6	Msgac—6	Skv—8
Indvc—6	Skv—7	Fbpv—6	Skv—5	Utwv—4	Skv—6	Skv—5	Fbpv—7

The highest percentage of misclassification was recorded from Utuv on Facebook and Skype. When Facebook was input to the model as the unknown/noise app, 27% of its traffic was misclassified as Utuv. When creating the Facebook data set, activities such as posting a video on wall, uploading a live video were considered, which are very similar to Utuv on YouTube. Therefore, having such similarity in the in-app activities caused the misclassification. When Skype was considered as the unknown app, 26% of its traffic was also misclassified as Utuv. Similarly, when creating the Skype data set activities such as sending a video message, engaging in a video call were considered. Again, having such similar in-app activities to Utuv has caused the reported misclassification.

While most of the Facebook traffic was misclassified as Utuv, which is in fact an activity from YouTube; most of the YouTube traffic got misclassified as Fblive, an activity from Facebook. Both Utuv and Fblive activities are related to video uploading and thus have a high correlation between each other due to their similarity in behaviour, resulting in the misclassification.

4.3. Performance Comparison

Even though in this work a CNN model was used to perform the traffic classifications, other types of neural networks could also be employed for this purpose, such as a

Deep Neural Network (DNN). This section reports on the performance comparison between the DNN and CNN models when they are used in our tests.

In both models, the output types were in-app activities. But the format of the input was different: in CNN, images were provided as the input whereas in DNN, statistical features related to the traffic flows constituted the input. Although the same data set was used for both DNN and CNN models to perform tests, we employed the network architecture that resulted in the highest accuracy for each model instead of using the same network architecture across the board for a fair comparison. This was needed as the input format was different in both cases, which had a direct influence on accuracy performance. For CNN, the network architecture proposed in Section 4.1 was used. For the DNN model, four hidden layers were used with 1024, 512, 256 and 128 nodes in each layer. Tanh activation function was used for all layers expect for the output layer which used the SoftMax layer. The 48 statistical features used in [4] were utilized as the input of DNN. Figure 8 shows the training and validation accuracies obtained at 0.5 s and 0.2 s time window sizes when both models were used to perform in-app activity classification.

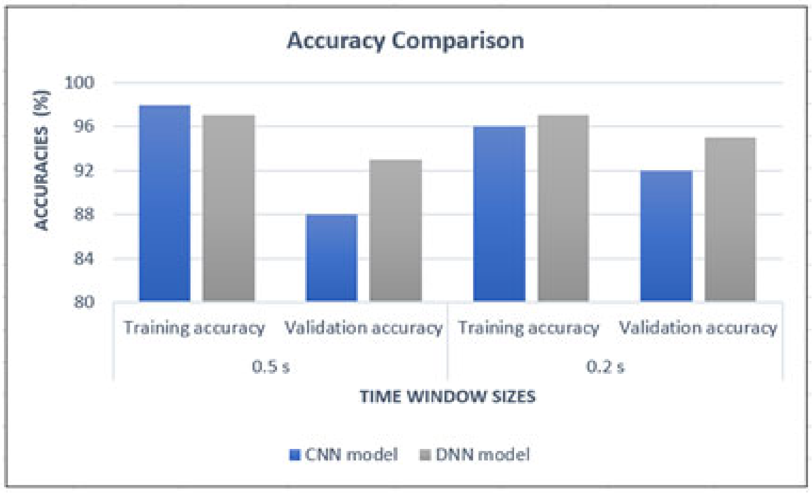


Figure 8. Accuracy comparison of the CNN and DNN models.

From Figure 8, it is noted that the DNN model has recorded the highest accuracy values compared to the CNN model in all categories. But when looked closely at the comparison at each time window size, the difference in accuracy values is maximum 5%. Significantly, all the accuracies of the CNN model are at 88% or above. Therefore, it can be concluded that both models can accurately detect previously trained in-app activities.

To compare the detection of unknown in-app data, it can be observed from Figure 9 that the CNN model has outperformed the DNN model at all the instances when different noise test traffic data sets (Test app) were applied. In both models, Gmail and Viber reported the highest noise detection rates. Compared to the DNN model, when the CNN model is employed, there is an increment of 19%, 18%, and 12% noise detection rates when YouTube, Messenger, and Skype are input as test app, respectively.

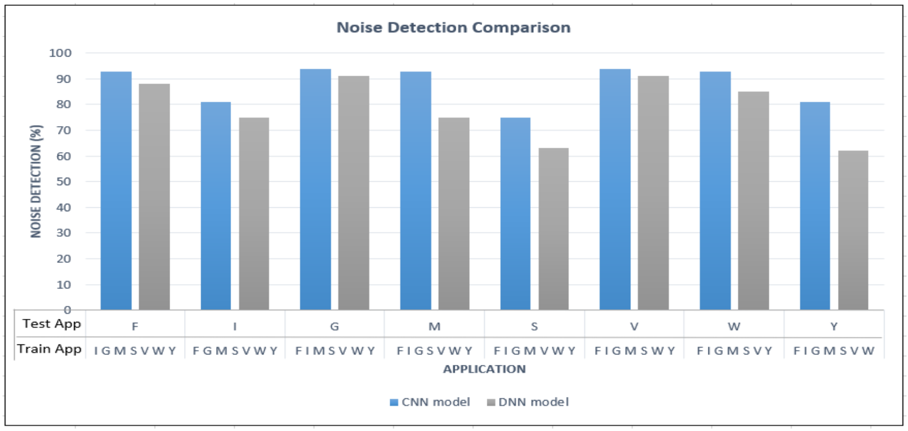


Figure 9. Noise detection comparison of the CNN and DNN models.

Even though the ability to detect previously trained in-app activities correctly by the CNN model is slightly weaker than that of DNN, its ability to detect previously untrained/unknown in-app activities as noise data is much stronger than that of DNN. Therefore, when the overall performance is considered, the proposed CNN model outperforms DNN. This is because when traffic flows are converted to images, the model can apply image processing techniques to reveal interesting properties of the traffic. As such, applying the proposed CNN model on the input traffic images allows for extracting and selecting salient features that enable the model to learn to differentiate trained and unknown traffic.

5. Conclusions

In this paper, a novel approach was introduced for encrypted Internet traffic classification, both for identifying known and unknown traffic and categorizing in-app activity type, based only on frame's size and time related information. User actions identified through analysing network traffic can be used in forensic investigations and security incident analysis, to improve correlation of events. Profiling users based on their in-app activities is also useful for marketing or intelligence purposes. Deep Learning obviates the need to select features by a domain expert as it automatically selects features through training, making it a desirable approach when new classes constantly emerge, and patterns of old classes evolve. Performance of the proposed CNN based method that learns traffic as images was compared with DNN that uses statistical features. The results demonstrate that the proposed CNN model has outperformed DNN when overall performance is considered. Moreover, a windowing approach was used to perform classification by observing a short time window of a flow instead of the entire session. Even though this is significantly a harder task as there is less information in partial encrypted traffic flow compared to the entire flow, our model was able to identify in-app activities with an accuracy of 92% even by observing the traffic only for 0.2 s. The novel approach of using a threshold on the confidence values exploits the model's output layer to identify in-app activities while removing noise traffic generated by untrained in-app activities with an average accuracy of 88%.

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Appendix A

Table A1. The 92 in-app activities considered in this research.

Application	Category	Fine Grained Activity
Facebook	Social networking	Post an image on wall
		Post a video on wall
		Post a long text on wall
		Post a short text on wall
		Post a feeling on wall
		Post a check in on wall
		Post a live video on wall
		Comment a short text on a post
		Comment a long text on a post
		Comment a post with a sticker
		Comment a post with an image
		Add an image to a story
		Add a video to a story
		Add a text to a story
		Share an image to the wall
		Share a video to the wall
		Share a text to the wall
		Like an image
		Like a video
		Like a comment
		Send a friend request
		Watch Facebook video
Instagram Instagram- Direct	Photo and Video	Add an image to a story
		Add a video to a story
		Add a text to a story
		Like an image
		Like a video
		Like a comment
		Comment a short text on a post
		Comment a long text on a post
		Post an image on feed

		Post a video on feed
		Follow a friend
		Follow back a friend
		Send a message to a story
		Watch Instagram video
		Send a long text message
		Send a short text message
		Send a voice recording message
		Send an image
		Like a message
		Video chat
YouTube	Photo and Video	Watch a video
		Like a video
		Dislike a video
		Comment a long text on a video
		Comment a short text on a video
		Like a comment
		Dislike a comment
		Upload a video
		Subscribe a channel
Skype	Social networking	Video call
		Audio call
		Send a long text message
		Send a short text message
		Send voice recording
		Send an image
		Send a video
		Send a file
Gmail	Productivity	Send short text email
		Send long text email
		Send an image
		Send a video
		Send a file attachment
Messenger	Social networking	Video call
		Audio call
		Send a ling text message
		Send a short text message
		Send a voice recording
		Send an image
		Send a video
		Add an image to a story

		Add a video to a story
		Add a text to a story
WhatsApp	Social networking	Send long text message
		Send short text message
		Video call
		Audio call
		Send voice recording
		Send an image
		Send a video
		Send location
		Send contact
Viber	Social networking	Send long text message
		Send short text message
		Video call
		Audio call
		Send voice recording
		Send an image
		Send a video
		Send location
		Send contact

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