A Method for Robust and Explainable Image-based Network Traffic Classification with Deep Learning

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Abstract: In light of the growing reliance on digital technology, the security of digital devices and networks has become a critical concern in the information technology industry. Network analysis can be helpful for identifying and mitigating network-based attacks, as it enables the monitoring of network behavior and the detection of anomalous activity. Through the use of network analysis, organizations can better defend against potential security threats and protect their interconnected digital systems. In this paper, we investigate the use of deep learning techniques for network traffic classification. A robust and explainable deep learning-based approach for traffic classification is proposed starting from raw traffic data represented in PCAP format. This latter will be transformed into visualized images, which are then used as input for deep-learning models in order to discriminate malicious activities. We evaluate the effectiveness of the proposed method, by evaluating two datasets composed of 34389 network traces belonging to 35 categories: 25 related to different malware families and the remaining 10 categories belonging to trusted applications, reaching an accuracy equal to 96.8%. Moreover, we provide reasoning about model evaluation and the correctness of the models by taking into account a prediction explainability based on the visualization of the images generated from the network trace, of the areas symptomatic of a certain prediction.

1 INTRODUCTION AND RELATED WORK

An intrusion detection system (IDS) is a component used to detect and prevent unauthorized access to computer systems and networks. Many approaches to network traffic analysis have been introduced such as rule-based which relies on pre-defined signatures to identify malware and DPI-based which leverages the inherent properties of network traffic to detect malicious activity (Finsterbusch et al., 2013) which does not meet the requirements of the network analysis malware detection anymore. The challenge of classifying encrypted traffic presents a new issue for these approaches, as it requires proper feature design. This is particularly challenging due to the high computational cost of these algorithms, making it difficult to accurately classify encrypted traffic as benign or malicious.

Although machine learning algorithms have shown promising results in network analysis malware detection, they are not without their limitations (Dhote et al., 2015) which can be summarized in the need for feature engineering. This requires domain expertise and a good understanding of the dataset, which can be time-consuming and labor-intensive. Furthermore, these algorithms may not always be able to capture complex relationships in the data, leading to limitations in their performance (Casolare et al., 2021).

In recent years, image analysis has emerged as a powerful tool for intrusion detection, especially with the advent of deep learning models. Different deep learning models, such as Convolutional Neural Networks (CNNs) have been used in the literature for intrusion detection using image analysis (Li et al., 2017). These models have been trained on image datasets to identify patterns and anomalies that indicate a potential intrusion.

Deep learning models, particularly those that utilize complex architectures such as CNNs, have become increasingly popular in recent years for a

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wide range of tasks, including intrusion detection (Vinayakumar et al., 2017). However, the nature of these models, which are highly non-linear and data-driven, has led to them being considered black boxes. This lack of transparency in the decision-making process can make it difficult to understand how the model is making its predictions and why it is making certain decisions. This is particularly problematic in the context of intrusion detection, as it is important to understand why a model is identifying a certain image as potentially malicious and to be able to explain this decision to other interested parties.

To address this issue, in this paper, we propose the use of visualization techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) to make deep learning models more interpretable (Selvaraju et al., 2016). Grad-CAM works by computing the gradient of the class score with respect to the feature maps of the last convolutional layer in the model and generating a heatmap that highlights the regions of the image that are most important for the model's prediction. This allows researchers to understand how the model is making its predictions and identify the regions of the image that are most indicative of a potential intrusion. Moreover, the use of image comparison techniques such as SSIM (Structural Similarity Index) (Sara et al., 2019) can be employed to compare the heatmap images generated by different deep learning models for Network traffic classification based on image analysis. In recent studies, two novel metrics, IM-SSIM and IF-SSIM,(Iadarola et al., 2022) have been used to evaluate the performance of deep learning models in image-based malware detection. The IM-SSIM metric was used to compare the heatmaps generated by different models for the same malware family, providing information on how much the models differ in classifying the same samples. The IF-SSIM metric, on the other hand, focused on a single model and provided information on the variability of heatmaps generated for the same malware family. These two metrics, when used in conjunction with the traditional performance metrics, such as accuracy and precision, provide a more comprehensive analysis of the deep learning models and their robustness in detecting unknown malware patterns.

In general, the goal and the novelty of this step is to understand the difference in decision-making between the models, and if they agree on the same regions as important for the prediction. By comparing the heatmaps of two images generated by different models, we can identify any discrepancies and understand if there are any patterns or regions that the models consistently disagree on.

For these reasons, we consider the proposed method robust and explainable: as a matter of fact is explainable because we provide a kind of (visual) explanation behind the prediction through the adoption of Grad-CAM aimed to highlight the areas of interest in the image. Moreover, with the introduction of the two novel metrics (i.e., IM-SSIM and IF-SSIM) we provide also robustness: in fact, the metrics help to understand whether the area highlighted by the grad-cam is the same (for the same images) for different models, therefore allowing to increase the confidence in the use of deep learning. The main contribution regards the adoption of such novel metrics within image-based network traffic.

The paper proceeds as follows: in the next section, the proposed method is introduced; in Section 3 the experimental analysis is presented; and, finally, in the last section conclusion and future research directions are drawn.

2 THE METHOD

In this work, we propose a method for image-based network traffic classification using deep learning models. The proposed method is aimed to evidence the accuracy and robustness of intrusion detection systems by using image analysis techniques. It is centered on the explanations of individual input-output pairs and therefore employs local explanation techniques. However, we also suggest aggregating the input-output pairs into sets of output classes to provide explanations for decisions made by entire classes. This method can be applied to any deep learning (DL) model that has the capability to use Grad-CAM, as long as the model has convolutional layers. The majority of the steps, excluding data preprocessing, can be automated and do not require expertise or solid knowledge.

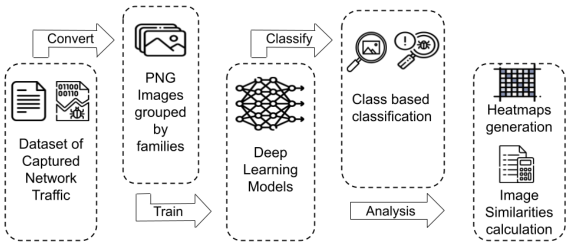
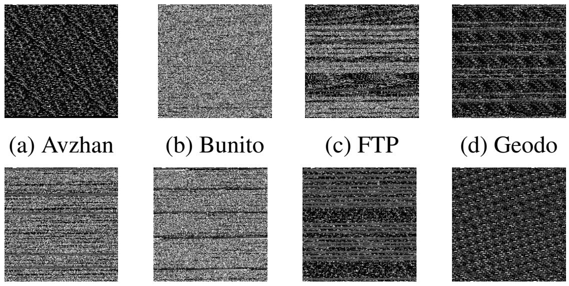


Figure 1: Overall schema of the method.

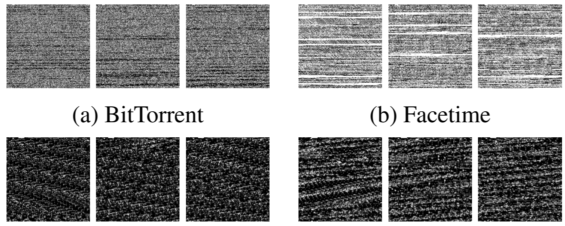
For a clearer comprehension of the proposed method, it can be broken down into several steps, as depicted in Figure 1. This figure illustrates the proposed approach for assessing the prediction of net-



(a) Avzhan (b) Bunito (c) FTP (d) Geodo

(e) Gmail (f) Htbot (g) Miuref (h) Shifu

Figure 2: A visualization analysis of some traffic classes.



(a) BitTorrent (b) Facetime

(c) Kelihos (d) Wannacry

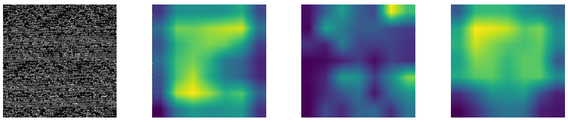
Figure 3: Similarities in the same traffic class.

work intrusion detection deep learning-based models. The initial step involves collecting samples including both "trusted" and "malware" network traffic to build the dataset. The latter shall encompass a wide range of network traffic, but it is crucial to label each sample and categorize them into families. This dataset will be used to train and test the deep learning models. In order to make the data usable for the deep learning models, we propose a transformation from RAW files which are presented in PCAP format to visualized images which represents the second step of the proposed method. This allows us to use the data as input for training and testing tasks. There are two modes for image generation either on grayscale or color (RGB). As a subsequent step, the deep learning (DL) models carry out resizing on the input images, which entails using images of similar size, but if the dimensions vary greatly, the loss of information can negatively impact the accuracy of the DL models. They will be also trained and tested on the dataset, and their performance will be evaluated based on the classification task. In the final phase of our method, for the purpose of gaining a comprehensive understanding of the decision-making process of these models, and identifying the regions of the image that are crucial for the models' decisions, we apply Grad-CAM to generate heatmaps. We also compute similarities between the heatmaps generated by different models. By using this method, we aim to manifest the performance and robustness of network intrusion detection systems based on image analysis techniques. On the other hand, we aim to understand the decision-making process of the models and identify the highlighted regions of the image that are important for the model's decision. Additionally, comparing the heatmaps generated by different models will help us identify any discrepancies between them and understand if they agree on the same regions as substantial, which is crucial for a robust network traffic classification.

Different network traffic will generate different images, based on this assumption we perform an examination of the visual representation of generated images shown in Figure 2 highlights the distinct differences between the various classes. These classes possess unique features that are easily noticeable through visual observation. A deeper understanding of this characteristic of samples within the same class possessing similar features while differing from those in other classes can help to correctly classify samples. This is because the model can leverage the similarities within each class to effectively learn and recognize the unique features associated with that class. For example, if we consider the visual representation of network traffic in Figure 3, it can be seen that samples within the same class tend to have similar textures and compositions, making it easier for the model to identify and distinguish that particular class. Conversely, the differences between classes can also provide crucial information to the model during the classification process, allowing it to accurately distinguish between classes and make informed decisions.

Observing the heatmaps generated by various deep-learning models in Figure 4 can reveal differences in the decision-making process of each model and highlight different areas within the same sample. By visualizing the regions where the model focuses its attention, we can gain insights into the features that are deemed most relevant for the model to make its prediction. This information can be used to better understand the strengths and weaknesses of different models and to refine them accordingly.

In general, when evaluating the performance of deep learning models for image classification tasks, it is important to ensure that the models are able to identify and agree on the key distinguishing features of the images. For example, when classifying images of dogs and cats, both models should be able to correctly identify the presence of a dog or a cat in the image and highlight the relevant features for classification. However, suppose one model is highlighting features that are not relevant to the task, such as highlighting the background of the image instead of the animal. In that case, it may indicate that the model is not properly trained or that there are issues with the dataset. In such cases, it may be necessary to re-evaluate the dataset and fine-tune the model's archi-



(a) Zeus (b) Dense (c) ResNet (d) MobNet

Figure 4: A plot of a malware sample which classified correctly belonging to Zeus including the heatmap of 3 models.

tecture or training parameters to improve its performance. Additionally, using visualization techniques such as grad-CAM can help to understand the model's decision and compare the important region generated by different models. This will help to check if the models agree on the same areas and if they are highlighting the important features. Furthermore, image similarity metrics like SSIM will be used to compare the heatmaps generated by different models. By calculating the similarity between the heatmaps. This can provide valuable insights into the performance of the models and help to identify any issues that may need to be addressed.

3 EXPERIMENTAL ANALYSIS

In this section, we describe the experiment we conducted in order to demonstrate the effectiveness of the proposed method. We first describe the (real-world) datasets we considered and then we present the experimental results.

3.1 Dataset

Having a decent dataset is of utmost importance in any machine learning research, especially in the field of network traffic classification. The quality and diversity of the dataset play a crucial role in the performance of the models and the results of the research. Finding a suitable dataset can be a challenging task, as network traffic samples are hard to come by, and it is not always possible to obtain real-world samples. Additionally, using self-made samples in a laboratory or private traffic of security companies can lead to bias and compromise the credibility of the results, which is why it is not recommended.

For these reasons, we employed a combination of two datasets to train and evaluate our proposed method. The first dataset is known in the state-of-the-art literature as the USTC-TFC2016 dataset and it is publicly available on a GitHub repository (Wei Wang, 2016). This dataset consists of a diverse set of network traffic samples, including a variety of protocols such as (FTP, P2P) used by several applications. The second dataset is a set of additional samples from The Stratosphere Laboratory at the CTU University of Prague in the Czech Republic (University, 2016) which includes only malware traffic belonging to other families. The combined datasets contain a total of 34,389 samples, belonging to 35 different classes: 25 to different malware families and the remaining 10 belonging to trusted applications. The samples are classified and presented in Tables 1 and 2, which present information regarding trusted and malware samples, specifying their families for better categorization. The samples are divided into three sets: training, validation, and test, with a split ratio of 80:10:10 respectively. There are 2,873 samples in the test set, while the training set consists of 25,589 samples, which are further split into 22,757 specifically for training and the remaining 2,832 for validation. The samples from each family are evenly distributed among the sets to ensure a balanced distribution.

3.1.1 Malware Traffic

The following provides a brief explanation of some malicious behavior per malware/family:

Avzhan: is a type of malware that encrypts the victim's files and demands payment in exchange for the decryption key. It typically spreads through phishing emails, malicious websites, and software vulnerabilities. Upon infection, the ransomware will scan the device for files to encrypt and display a ransom note with payment instructions.

Cridex: is a Trojan-Banker that is designed to steal financial information from the infected device. It typically spreads through phishing emails, malicious websites, or software vulnerabilities. Once installed, Cridex will monitor the victim's online activity and steal sensitive information, such as login credentials and credit card numbers.

Virut: is a type of worm that spreads by infecting executable files on the victim's device. It can also infect the Master Boot Record, making it difficult to remove. Virut spreads through phishing emails, malicious websites, and software vulnerabilities.

Htbot: is a type of backdoor that allows an attacker to remotely control the infected device. It spreads through phishing emails, malicious websites, and software vulnerabilities. Once installed, Htbot listens for commands from the attacker and can be used to steal sensitive information, install additional malware, or participate in a botnet.

3.1.2 Trusted Traffic

The following provides a brief explanation of the protocols used in three trusted traffic samples:

BitTorrent: is a popular peer-to-peer (P2P) file-sharing protocol that allows users to share large files by dividing them into smaller pieces and distributing them across multiple devices. BitTorrent relies on a decentralized network of users to share and distribute the data, reducing the load on a single server.

Facetime: is a voice and video calling application that is commonly used on Apple devices. It uses the Internet Protocol (IP) to transmit voice and video data, allowing for real-time communication between devices. Facetime also supports screen sharing and group video calls.

SMB: also known as Server Message Block, is a file and print sharing protocol that is commonly used on Microsoft Windows-based networks. SMB allows clients to access shared resources on a server, such as files, and printers, and provides a secure and reliable communication channel for transferring data. SMB supports various data transfer operations, including read, write, and execute operations.

3.2 Image Generation

The process of converting captured network data in PCAP format to an image is a method of visualizing network traffic data in a more intuitive and human-readable format, while also providing valuable input for training deep learning models. This approach allows for the analysis and interpretation of network traffic patterns in a more efficient and effective way by identifying trends and anomalies in network traffic that may not be immediately apparent in the raw data. The process typically involves first reading the binary data of the PCAP file, then calculating the size of the image, reshaping the data to create a 2D array, and finally, converting the data to an image using an image processing library. Depending on the requirement, the image can be in grayscale or RGB mode. The grayscale image is created by using the same data for all three channels (red, green, and blue) and reshaping it according to the image size. The RGB image is created by creating three separate arrays for red, green, and blue channels, and then stacking them together to create the final data array. This final data array is then used to create the RGB image.

The images generated through this process will be used as input for training various deep-learning models. The ability of deep learning models to automatically extract features and patterns from images makes them well-suited for analyzing network traffic data. Furthermore, the ability to create a large dataset of network traffic images will be used to train and evaluate different deep learning architectures, such as models that are known in the literature (DenseNet, AlexNet, MobileNet, etc.), to find the most suitable model for a specific task. Overall, the main idea behind the conversion of network traffic data to images is to provide valuable input for training deep learning models, which in turn can help to investigate which model will be the best for this task.

3.3 Deep learning Models

In this work, various deep learning (DL) models were utilized to assess their performance on Network Traffic represented as images. Well-known models in the literature used in this research, such as AlexNet, Inception, DenseNet, ResNet50, MobileNet, VGG16, and VGG19 are well-established models that have been widely reported in the literature and proven to be effective in different tasks such as image classification (Sharma et al., 2018), face recognition (Goel et al., 2021), etc. These models have been highly optimized and fine-tuned over the years, which has led to their widespread adoption in the field of DL. Our custom models, such as CNN (we refer to with the name Our-CNN), were designed and implemented with the specific requirements of the problem in mind. The results obtained from the experiments conducted with these different models were compared, and the most suitable model was selected based on their performance. This approach allowed us to leverage the advantages of pre-trained and custom-designed models to arrive at an optimal solution. The results obtained from these models will be compared with other predefined models to determine their performance and effectiveness. The goal of this comparison is to evaluate the proposed models against other state-of-the-art models and to gain a better understanding of their strengths and limitations. The table 3 shows the main hyper-parameters employed for training the deep learning models.

3.3.1 Our CNN

The CNN model used in this work is a feedforward deep neural network designed for image classification tasks. It consists of multiple layers of convolution, max-pooling, and fully-connected dense layers. The first three layers are Conv2D with 32, 64, and 128 filters respectively and each layer uses a 3x3 kernel size with ReLU activation. These are followed by MaxPooling2D layers with a 2x2 pool size, to reduce the spatial dimensions of the feature maps and retain the most important information. The feature maps are then flattened in the Flatten layer and regularized using Dropout layers with a rate of 0.5. The model also has three dense layers with 512, 256, and num_classes neurons, respectively, each followed by

Table 1: The list of trusted network traffic and their appropriate class.

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
Total trusted classes			**10**

Table 2: Malware network traffic and their corresponding families.

Name	Family	Name	Family	Name	Family
Andromeda	Botnet	Avzhan	Ransomware	Bunitu	Trojan
Caphaw	Banking trojan	Cedar	Trojan	CerberRansomeware	Ransomware
Cridex	Trojan-Banker	Dridex	Banking trojan	Emotet	Trojan
Geodo	Trojan-Banker	Htbot	Backdoor	Kazy	Trojan
Kelihos	Botnet	Miuref	Trojan-Downloader	Neris	Trojan-Banker
NjRat	RAT	Nsis-ay	Trojan	Shifu	Trojan-Banker
Stlrat	Trojan	Tinba	Trojan-Banker	Upatre	Downloader
Virut	Worm	Wannacry	Ransomware	Yakes	Trojan
Total malware families			**25**	Zeus	Trojan-Banker

a dropout layer. The final layer has num_classes neurons and uses softmax activation to produce the final probabilities for each class.

3.3.2 WangCNN

The WangCNN model was designed in a previous work (Wang et al., 2017) for Malware traffic classification using a Convolutional Neural Network (CNN) for representation learning. It is similar to the LeNet-5 model (LeCun et al., 1995). It has a two-layer convolution with 32 and 64 filters and two max pooling layers. It also has two fully connected layers with 1024 and 10 neurons. A softmax function is used for class probability output and dropout is applied to prevent overfitting. It was designed to perform well on the task of Malware traffic classification and has been named in this work as WangCNN. The model will be trained and evaluated on our proposed dataset, and its performance will be compared with other models based on metrics such as accuracy, precision, recall, and AUC. The goal is to determine the effectiveness of the WangCNN model for this particular task.

3.4 Results and Discussion

3.4.1 Results

The results in the table 5 present the performance comparison of various deep learning models on the test sets of Grayscale and RGB datasets. The models evaluated are OurCNN, WangCNN, AlexNet, DenseNet, MobileNet, ResNet50, VGG16, and VGG19. The metrics used to evaluate the models are Accuracy (Acc), Precision (Prec), Recall (Rec), F1-score (F1), and Area Under the Curve (AUC). This table is useful to evaluate the generalization of the models and it gives an idea of how well the models will perform on unseen data.

Upon analyzing the provided results, the top 4 models exhibiting strong performance across both Grayscale and RGB datasets can be identified. DenseNet consistently demonstrates exceptional performance in terms of accuracy, precision, recall, F1-score, and AUC for both datasets, making it the top performer with an accuracy equal to 0.982. MobileNet, the second strongest model, showcases commendable results in the Grayscale dataset and excels in the RGB dataset with high accuracy at 0.972 and outstanding precision, recall, F1-score, and AUC values. ResNet50, ranking third, delivers solid performance in both Grayscale and RGB datasets, featuring high accuracy equal to 0.982 in Grayscale images and competitive precision, recall, F1-score, and AUC values for both datasets. Finally, OurCNN holds the fourth position, displaying good performance in both Grayscale and RGB datasets with relatively high accuracy values. Although the performance metrics of OurCNN, such as precision, recall, F1-score, and AUC, are competitive, they are not as high as the top 3 models mentioned. These four models demonstrate superior overall performance in the classification task for Grayscale and RGB images compared to the other models listed in the tables. In contrast, VGG16 and VGG19 show relatively lower performance in

Table 3: The hyperparameters of different DL models.

Model	OurCNN	WangCNN	Alex	Dense	Mobile	ResNet	VGG16	VGG19
Input image/vector size	224x224x3							
Epochs and Batch size	30 and 32							
Number of layers	6	4	20	121	29	50	16	19

Grayscale images, particularly in terms of Recall and F1-score. In the RGB mode, VGG16 demonstrates a considerable drop in performance, with the lowest Recall and F1 score among all the models. Additionally, it can be observed that some models perform better on one type of dataset than the other, highlighting the importance of choosing the appropriate model for the data at hand. Overall, the table provides a comprehensive evaluation of the deep learning models' performance on the given classification task, revealing the effectiveness of each architecture in handling Grayscale and RGB datasets.

Table 4: Performance results on a subset of the dataset (Grayscale images).

Class	Model	IF-SSIM	IM-SSIM
Cedar	DenseNet	0.901	0.416
	ResNet50	0.592	
	MobileNet	0.810	0.232
	OurCNN	0.387	
Gmail	DenseNet	0.617	0.501
	ResNet50	0.514	
	MobileNet	0.497	0.271
	OurCNN	0.226	
NjRat	DenseNet	0.834	0.629
	ResNet50	0.646	
	MobileNet	0.894	0.200
	OurCNN	0.234	
SMB	DenseNet	0.644	0.461
	ResNet50	0.482	
	MobileNet	0.648	0.258
	OurCNN	0.305	
Wannacry	DenseNet	0.787	0.549
	ResNet50	0.499	
	MobileNet	0.605	0.265
	OurCNN	0.205	
Weibu	DenseNet	0.630	0.457
	ResNet50	0.498	
	MpbileNet	0.633	0.289
	OurCNN	0.285	

Table 4 shows the results of two performance metrics (IF-SSIM and IM-SSIM) applied to a subset of trusted (Gmail and SMB) and malware families (Cedar, NjRat, Wannacry, and Weibu) represented as grayscale. The grayscale images were chosen in this experiment due to their superior performance compared to RGB images. The metrics were computed for four different deep-learning models (DenseNet, ResNet, MobileNet, and OurCNN). Two performance metrics, IF-SSIM and IM-SSIM, were applied to evaluate the similarity of the heatmaps generated by the models for each sample. The IF-SSIM metric focuses on a single model and measures the difference in heatmaps generated for the same class using the same model. On the other hand, IM-SSIM compares heatmaps generated by a subset of models for a specific class. The results in the table show the average SSIM value for each combination of class and DL model.

A comprehensive analysis of the results in table 4 indicates that DenseNet consistently achieves the highest IF-SSIM values across all six classes, suggesting that it is the most effective model in capturing the relevant features in the heatmaps, moreover the model relies on a single, specific region of the input samples for accurate image classification. It utilizes the information contained within this restricted input area to perform the classification, as evidenced by the IF-SSIM values being close to 1, indicating high similarity among the heatmaps. MobileNet and ResNet50 exhibit competitive performance, with MobileNet slightly outperforming ResNet50 in most cases. However, OurCNN demonstrates the lowest IF-SSIM values among the four models for all classes, indicating room for improvement in its heatmap similarity capabilities.

The IM-SSIM values represent the overall similarity between heatmaps generated by the models, and the observed differences across classes indicate varying levels of heatmap similarity across the tested models. Regarding the IM-SSIM metric, the results show that NjRat class has the highest value, followed by Wannacry and Gmail, which means that the models do agree: the input area used by one model is similar to the area of the other one. while the Cedar class has the lowest value of 0232, this implies that the models (MobileNet and OurCNN) do not concur: the input region utilized by one model differs from the area employed by the other.

The image 5 reported the confusion matrix normalized. The confusion matrix serves as a visual representation of a classification model's performance, with predicted labels on the x-axis and true labels on the y-axis. This layout allows for a clear comparison between the model's predictions and the actual ground truth, highlighting areas of success and misclassification

In conclusion, DenseNet outperforms the other models in terms of heatmap similarity, as evidenced by its consistently high IF-SSIM values. MobileNet and ResNet50 show competitive performance, while OurCNN lags behind.

3.4.2 Discussion

In our method, we implemented a hybrid approach by combining well-known models in the literature with models designed by us. Furthermore, we provide versatility in image generation by allowing the choice between RGB and grayscale images. Our method involves evaluating several deep learning (DL) models on network traffic analysis using visualization techniques such as Grad-CAM and comparing the heatmaps generated using the Structural Similarity Index (SSIM). To further improve the analysis, we employed metrics IM-SSIM and IF-SSIM, which measure the similarity between the heatmaps of different DL models and of a single model respectively. These metrics provide a more comprehensive analysis of the DL models, particularly in the case of unknown target patterns in the dataset samples.

4 CONCLUSION AND FUTURE WORK

In this paper, we proposed an intrusion detection system aimed to automatically discriminate between legitimate and malicious network traces. In detail, we propose to represent network traces in terms of images to input several deep-learning models to detect the application that generated the specific network trace. We take into account also prediction explainability, by adopting the Grad-CAM, aimed to highlight with the heatmap the areas of the image symptomatic of a certain prediction. The deployment of two versions of SSIM metric to measure heatmap similarity. These metrics help assess the degree of resemblance between heatmaps, offering valuable insights into the effectiveness of various approaches or techniques. The limitations of the study include the use of a limited dataset and the need for further evaluation of the model's robustness with additional algorithms for heatmap generation. For this we plan as future work to consider more algorithms for heatmap generation, in order to evaluate the model's robustness. Moreover, different activation maps will be considered and we will explore the possibility to detect also malware in the IoT environment with the proposed method.

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Table 5: Comparison between the results of different models on the test sets of Grayscale and RGB datasets.

Mode	**Gray**					**RGB**				
Model	Acc	Prec	Rec	F1	Auc	Acc	Prec	Rec	F1	Auc
OurCNN	0.928	0.944	0.917	0.930	0.992	0.903	0.923	0.893	0.908	0.988
WangCNN	0.869	0.886	0.864	0.875	0.976	0.884	0.818	0.774	0.795	0.962
AlexNet	0.904	0.913	0.903	0.908	0.973	0.899	0.902	0.895	0.898	0.973
DenseNet	0.982	0.983	0.982	0.983	0.998	0.967	0.969	0.967	0.968	0.996
MobileNet	0.956	0.957	0.956	0.957	0.985	0.972	0.973	0.972	0.973	0.993
ResNet50	0.982	0.982	0.981	0.981	0.996	0.940	0.941	0.939	0.940	0.985
VGG16	0.978	0.738	0.452	0.561	0.941	0.976	0.952	0.230	0.371	0.747
VGG19	0.947	0.812	0.605	0.693	0.993	0.975	0.918	0.323	0.478	0.986

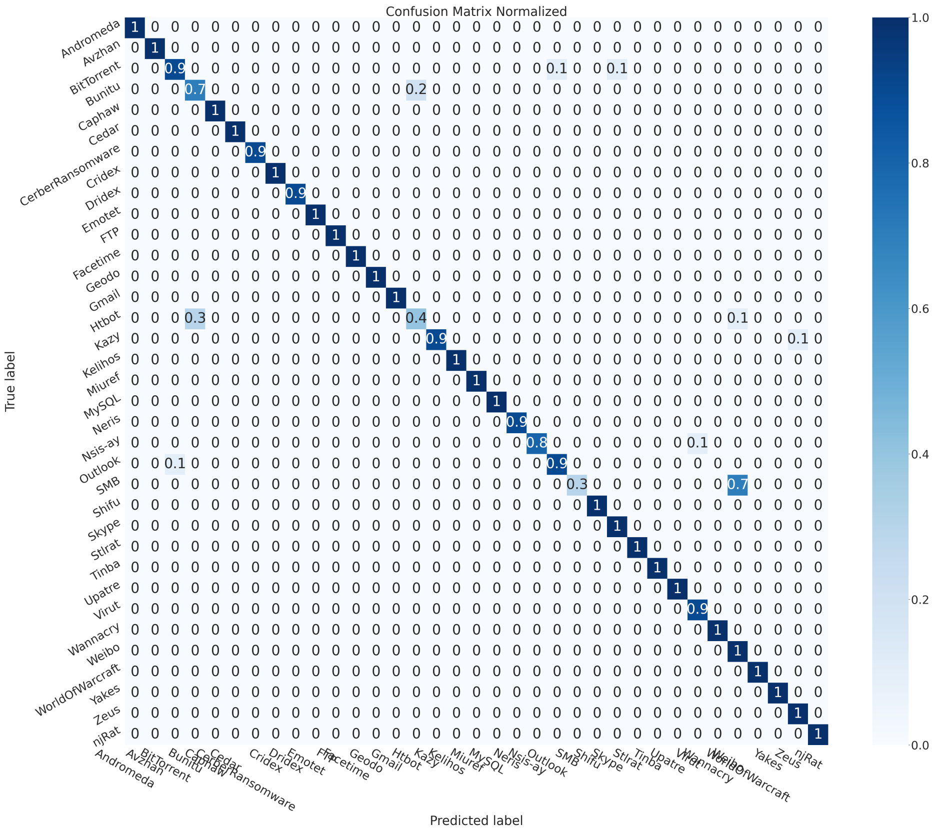

Figure 5: Plot of the confusion matrix normalized of the best-performing model (DenseNet) on the Grayscale dataset.

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