Cybersecurity Intrusion Detection with Image Classification Model Using Hilbert Curve

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Keywords: Machine Learning (ML), Deep Learning (DL), Cybersecurity, Security Operation Center (SOC), Intrusion Detection System (IDS), Hilbert Curve.

Abstract: Cybersecurity intrusion detection is crucial for protecting an online system from cyber-attacks. Traditional monitoring methods used in the Security Operation Center (SOC) are insufficient to handle the vast volume of traffic data, producing an overwhelming number of false alarms, and eventually resulting in the neglect of intrusion incidents. The recent integration of Machine Learning (ML) and Deep Learning (DL) into SOC monitoring systems has enhanced the intrusion detection capabilities by learning the patterns of network traffic data. Despite many ML methods implemented for intrusion detection, the Convolutional Neural Network (CNN), one of the most high-performing ML algorithms, has not been widely adopted for the intrusion detection systems. This research aims to explore the potentials of CNN implementation with the network data flows. Since the CNN was originally designed for image processing applications, it is necessary to convert the 1-dimensional network data flows into 2-dimensional image data. This research presents a novel approach to convert the network data flow into an image (flow-to-image) by the *Hilbert curve* mapping algorithm which can preserve the locality of the data. Then, we apply the converted images to the CNN-based intrusion detection system. Eventually, the proposed method and model can outperform the recent methods with 92.43% accuracy and 93.05% F1-score on the CIC-IDS2017 dataset, and 81.78% accuracy and 83.46% F1-score on the NSL-KDD dataset. In addition to the classification capability, the flow-to-image mapping algorithm can also visualize the characteristics of the network attack on the images visually, which can be an alternative monitoring approach for SOC.

1 INTRODUCTION

In the digital age, organizations are required to protect crucial and confidential data from malicious offenders who seek to exploit the system vulnerabilities to gain unauthorized access to sensitive information. Therefore, cybersecurity becomes vital for the prevention of unauthorized access. Currently, the Security Operations Center (SOC) is widely established to monitor the computer network and respond to network intrusion incidents according to the organization's cybersecurity policies.

Nevertheless, traditional intrusion detection methods typically implement rule-based filters to identify the potential threats and alert human operators monitoring the network system for intervention. These filters often yield a lot of alerts that can be overwhelming for the human operators (Feng et al., 2017), and this poses a challenge for the operators to identify the vulnerabilities in time, causing a significant loss to the organization. Therefore, many organizations have adopted automation tools based on Machine learning (ML) and Deep learning (DL) models to enhance the intrusion monitoring performance by learning the pattern of the network data under intrusion incidents. The models can range from simple algorithms such as logistic regression, to more sophisticated deep neural network architectures. As a result, there are a number of ML methods successfully implemented for intrusion detection applications. However, the Convolutional Neural Network (CNN) method, which is one of the pivotal methods in modern ML was rarely con-

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sidered for intrusion detection. Therefore, it is intriguing to explore the feasibility to applying CNN method with the network data and evaluate the performance of such a method.

Since the CNN algorithm was originally proposed for an image processing application requiring images as the input, it is essential to convert the 1-dimensional network data flows into 2-dimensional image data. Network data flow can be represented as images in various ways, such as the time-based mapping method found in (Ho et al., 2022). However, the existing methods to convert the network data flow into an image (flow-to-image) do not guarantee the locality preservation property. Locality preservation is especially crucial for analyzing network data flow by CNN, as it reflects the data interactions and dependencies among each sequential feature. To address the issue of locality preservation, the study of (Sun et al., 2019) presented a method using the Hilbert curve for this purpose. However, this method only targets its attacks on LAN systems, such as port scanning, which can be limited to the real-world attacks.

Our research adopted a similar implementation scheme of the Hilbert curve mapping algorithm in (Sun et al., 2019) to transform network data flows into images and extend its application to broader intrusion scenarios. The method is to map the values from the network data flow features over time and then align them to the image coordinate on the Hilbert curve. Finally, we obtain images of the network sequence in grayscale format. Note that we decided to use the grayscale format due to its simplicity and smaller size, ideal for large network datasets and avoiding RGB image padding, making them best suited for our study and perfectly complements the strengths of the CNN model in intrusion detection. Furthermore, such visualization of network data in an image form also allows human observers to better understand the representation of the network attacks visually, expanding the possible options for monitoring approaches for human operators in SOC.

Moreover, we have applied the mapping images with recent image classification models, including EfficientNetB0 (Tan and Le, 2019) and Vision Transformer (ViT) (Dosovitskiy et al., 2020). We also introduced our network architecture, HilxSEED (Hilbert curve x Squeeze-and-Excitation and Encoder-Decoder), integrated the concepts of Encoder-Decoder and SENet to capture the relationships within the mapped image from the Hilbert curve and decode them to produce an output in binary classification. Finally, the proposed method is trained on different schemes and evaluated by comparison with the previous methods on two datasets, the NSL-KDD dataset (Tavallaee et al., 2009) and the CIC-IDS2017 dataset (Sharafaldin et al., 2018).

2 RELATED WORKS

Internet connection could not be made entirely private, leading to confidential data leaks. Thus, the concept of an Intrusion Detection System (IDS) was invented. The work of (Anderson, 1980) proposed the concept of IDS by daily network batch analysis. Later, (Denning, 1987) introduced the first real-time IDS framework. The attack techniques were simpler at that time, allowing the administrator could manually detect and handle the common intrusions.

As time went by, network architectures have become more complex, along with increased difficulty in detecting cyber-attacks (Belej et al., 2020). For this reason, ML and DL were deployed to enhance the efficiency of IDS. (Saranya et al., 2020) presented the potential of the classical ML model. (Stolfo et al., 1999) performed experiments, and compared multiple ML methods. The study of (Belavagi and Muniyal, 2016) expressed the efficiency of classical binary classification ML, which was trained with the NSL-KDD dataset. (Liu and Lang, 2019) surveyed intrusion detection and found that ML and DL became increasingly crucial to the cybersecurity field in the IDS system.

In the field of DL, LSTM-RNN was used to assist in IDS for handling the sequential data. The study of (Muhuri et al., 2020) and (Kim et al., 2016) experimented LSTM-RNN model on the KDD99 dataset, which showed the highest accuracy with 96.93% accuracy with 100-time steps.

Additionally, DL has been employed for image classification and is rapidly growing with various applications. One of the essential growths is the CNN, inspired by the human brain's visual cortex, as discussed in (Zhang et al., 2016). Accordingly, many researchers have applied the CNN model to both image and non-image data for detecting cyber-attacks in the network system.

The capability of the CNN model shown in the study of (Kim et al., 2020) aimed to detect Denial-of-Service (DoS) attacks which outperform the Recurrent Neural Network (RNN). Meanwhile, (Vinayakumar et al., 2017) experimented with the hybrid CNN architecture, such as CNN-LSTM. For binary classification, a single CNN layer achieved 99.9% accuracy

The CNN models are highly performed in incident detection compared with the other DL models due to their advanced image processing capabilities. Many research studies are inspired by image recognition and converting network data flows into images for IDS applications. The work of (Khan et al., 2019) preprocessed the NSL-KDD dataset by transforming 464 dimensions of data into 8×8 grayscale images and using the CNN model to detect the attacks.

Similarly, (Ho et al., 2022) demonstrated the potential of the Vision Transformers (ViT) classifier with the CIC-IDS2017 dataset for multiclass classification. This paper selected 24 features and implemented the value mapping in RGB images. As a result, the experiment showed an accuracy of 88.92%, outperforming other methods. However, the relationships between the network data flow might not preserved due to the directly mapped data into the image.

One notable method for data transformation is the Hilbert curve that was introduced by (Hilbert, 1891), the fundamental principle is the traversal curve across the 2D space. The Hilbert curve can transform 1D data into 2D data while preserving the locality of information. Many researchers have applied this method in flow-to-image.

Various research studies have demonstrated the use of the Hilbert curve technique. The study of (Vu et al., 2020) implemented the Hybrid Image Transformation (HIT) to produce RGB images for malware classification. The HIT that uses the Hilbert curve technique and CNN model could outperform other methods, achieving a 93.01% accuracy. (Sun et al., 2019) implemented the CNN model to analyze the generated data from cyber-attack simulations within a LAN environment. The Hilbert curve maps the nine protocol features into a single image. Notably, the scope of their research was limited to the specific environment they established, which focused on port scans.

Despite the high potential of using the Hilbert curve for flow-to-image transformation and using an image classification model in real-world data, this application has not been widely adopted in cybersecurity. Hence, introduced a network data flow transformation for incident detection, improving attack detection precision by compressing multiple network packets into an image using the Hilbert curve's characteristics and leveraging CNN capabilities.

3 METHOD

To harness advanced image processing capabilities for incident detection, our method utilizes the locality preservation from the Hilbert curve for data transformation and employs a CNN model for network attack detection. This section is segmented into four distinct sections.

3.1 Preprocessing Network Data Flow

In preparing the network data flow, we transformed non-computable data into computable data by eliminating string-based or null values and applied One-Hot Encoding to transform categorical variables into unique binary numerical representation columns. After that, we focused on utilizing grayscale images. Therefore, the Min-Max normalization method was used to normalize the data to fit in [0, 1]. The equation is shown in Eq (1).

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

3.2 Data Transformation Using Hilbert Curve and Arrangement of the Features

The Hilbert curve will be used to transform network data flows into 2D images by mapping preprocessed values according to the Hilbert curve's coordinates. Consequently, the image will be formed, and the size will vary by the order of the Hilbert curve.

The order of the Hilbert curve is described as the number of iterations used to generate the space-filling curve and it indicates the data quantity mapped to an image by $2^{2\times order}$ where *order* is the order of the Hilbert curve.

3.2.1 Image Formation from Network Data Flows

Before mapping network data flow values, we selectively dropped features we dropped features with the least significant correlation to attack labels by considering the Pearson correlation coefficient (PCC). The PCC equation is shown in Eq (2).

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (2)$$

Where x_i and y_i are the individual data points. And $\bar{x}$ and $\bar{y}$ are the means of x and y respectively.

To ensure the generation of a rectangular image, the number of features should be factorizable into two integer components. Let f_1 and f_2 be the two closest factors. Furthermore, the height and width of the image should not be extremely different given the threshold difference between f_1 and f_2 is 5.

3.2.2 Mapping Network Data Flows into an Image by Hilbert Curve

To transform the network data flows into an image, the network data flow's values were mapped over time onto the coordinates of the Hilbert curve which is determined in Algorithm 1.

The Figure 1 is shown the Hilbert curve mapping procedure, when:

1. n represents the number of features.
2. v_n is the feature's value.
3. F_n is the layer of the mapped image.

Consequently, each coordinate of the result image contains data from a single network data flow. We obtain multi-layer image data in which each layer contains a single feature's value. Finally, we rearrange it into a single-layer grayscale image by f_1 as width and f_2 as height. The arrangement is shown in Figure 2.

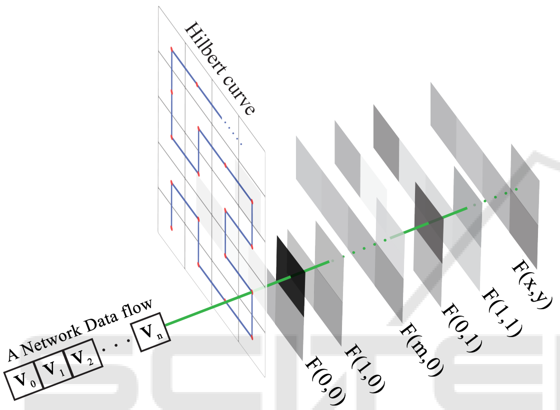


Figure 1: The visualization of mapping network data flow by Hilbert curve.

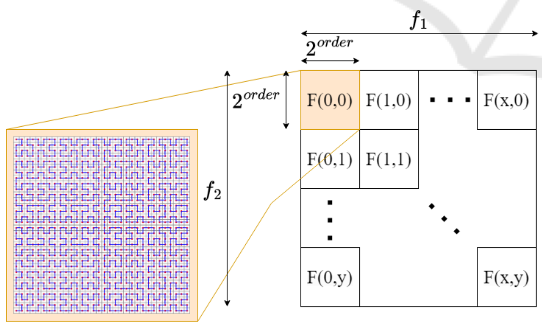


Figure 2: Features arrangement.

3.3 Training and Testing with CNN Classification Model

The experimental dataset was divided into three parts: training set, validation set, and testing set. We split the network dataset into two main halves by 50% of the total data. The first half is divided into a training set (70%) and a testing set (30%). The other half is used as the testing set. However, if the dataset is pre-partitioned, it can be used as the specific requirements.

Input: *network_flow* (DataFrame representing network data flow), *coordinates* (Hilbert curve coordinates), *order* (order of the Hilbert curve)
Output: A Image representing a sequence of the network data flow
Function `MakeImage`(*network_flow, coordinates, order*)**:**
 $size \leftarrow 2^{order}$;
 $image \leftarrow$ Array of zeros with dimensions $(size, size$, number of features in $network\_flow)$;
 for *each row index n in network_flow* **do**
  for *each feature F in network_flow* **do**
   $x, y \leftarrow coordinates[n]$;
   $image[x][y][F] \leftarrow v_n$;
   ; `// Map value to pixel`
  end
 end
 return *image*;
Function `ConcatImage`(*image, x, y, size*)**:**
 `// Rearrange the multi-layered image into a grid format for concatenation`
 $image \leftarrow$ rearrange and reshape *image* to prepare for concatenation;
 $size\_X \leftarrow x \times size$; $size\_Y \leftarrow y \times size$;
 `// Flatten the rearranged image into a single layer`
 $concat\_image \leftarrow image$.reshape($size\_X, size\_Y$);
 return *concat_image*;
Function `Main`**:**
 $image \leftarrow$ `MakeImage`$(network\_flow, coordinates, order)$;
 $network\_img \leftarrow$ `ConcatImage`$(image, x, y, order)$;

Algorithm 1: Mapping Network Data Flow Features to Image Layers and Concatenating into a Single Layer.

The HilxSEED model, which is based on the CNN network, integrated the concept of Encoder-Decoder with Squeeze-and-Excitation Networks (SENet) (Hu et al., 2020). The model aims to leverage enhanced convolutional feature representation by dynamically adjusting channel-wise responses and detecting the relationships between the channels of the CNN layers using SENet blocks. The Encoder compresses the important information within the image and the De-

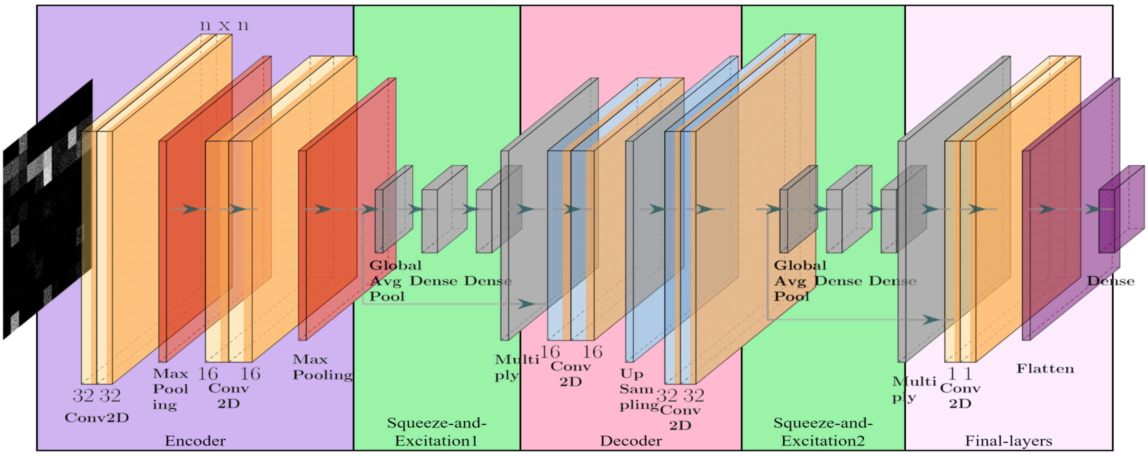


Figure 3: HilxSEED Model.

coder reconstructs to its original dimensions. The model configuration used Adam Optimizer with a 0.001 learning rate and Binary Cross entropy as a loss function. The model is shown in the Figure 3

3.4 Model Evaluation

In this research, the model evaluation was performed using the testing dataset. In the previous section, the separated Testing dataset is the former half of the network data flow. The evaluation metrics used were F1-score, Accuracy, Precision, and Recall.

The F1-score, is a harmonic mean of Precision and Recall, particularly in incident detection with low false alarms. Precision indicates prediction quality; high Precision means the model predicts a positive case. The Recall is defined as the completeness of detection; high Recall means the prediction does not miss a genuine incident.

The accuracy is determined as the true positive that the model predictions are corrected compared with all predictions. The equation is found in Eq. (3)

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

4 EXPERIMENTAL RESULTS

In this section, we explain the experimental settings and configuration, along with the outcomes observed from our proposed model in intrusion detection.

4.1 Experimental Setting

In this study, we used two datasets: the NSL-KDD as the baseline and the CIC-IDS2017 for real-world-like scenarios.

NSL-KDD Dataset: was prepared following these steps.

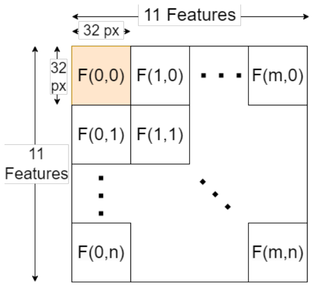
- Using One-hot encoding to convert the categorical variables into numerical data for further calculation, where each data category was mapped to a unique binary numerical vector representing the presence or absence of data. The categorical variables are in the following features: *protocol_type*, *service*, and *flag*.
- Using *Train+* as training and validation sets, dividing them into 70% and 30%, respectively. *Test+* was used to evaluate the proposed model.
- The dataset is originally sorted by time, so the sorting step can be omitted.
- The feature '*srv_count*' will be drop considered by the lowest PCC in equation (2). Arranging features into a full rectangle image by factorizing the number of features and selectively dropping the excess features by the lowest which was

CIC-IDS2017 Dataset: was prepared following these steps.

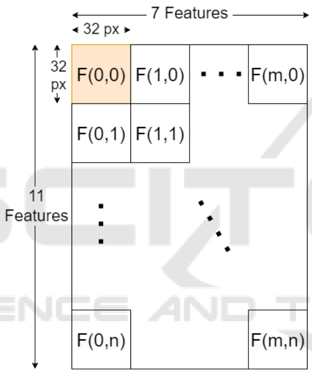
- Removing *NaN* and *infinity* values, these values are likely caused by division by zero in rate calculations, anomalies during data collection, or errors in data processing.
- Since this dataset does not provide a predefined data split, we divided it by 50%. The first half was the training set and the validation set with 70% and 30%, respectively, and the former half was the testing set.
- Sorted the dataset by timestamp feature to sequence the data, dropped some of the Non-numeric features, and randomly dropped *BENIGN* to ensure the balance between the attack.

- The feature '*bwd_avg_bulk_rate*.' will be drop considered by the lowest PCC in equation (2).

After dropping certain features, we mapped the data over time to image coordinates by the Hilbert curve. Then, we arranged the multi-layer image into a single grayscale image. The arrangement of each dataset is shown in Figure 4. Finally, we obtained the network images, which are shown in Figure 6 and 7.



(a) NSL-KDD features arrangement



(b) CIC-IDS2017 features arrangement

Figure 4: The arranging network data feature in each dataset.

4.2 Experimental Results

The experiments showed that the proposed Hilbert curve flow-to-image method could enhance the efficiency of intrusion detection. When comparing the use of regular network data flows with the LSTM-RNN model and the use of images converted from flow-to-image, testing with the proposed HilxSEED model resulted in higher accuracy and F1-Score in both datasets. Moreover, the HilxSEED model was competent and outperformed the classical ML and the recent models including EfficientNetB0 and Vision Transformer (ViT). The experimental results of using the Hilbert curve mapping image method are shown in table 1.

The HilxSEED model has shown satisfactory results in intrusion detection, demonstrated with two

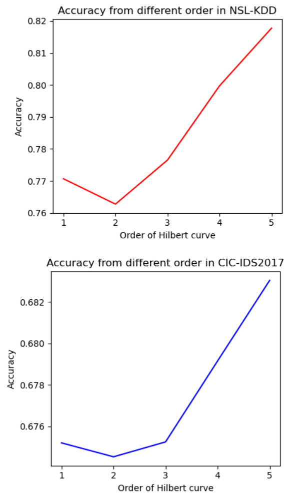
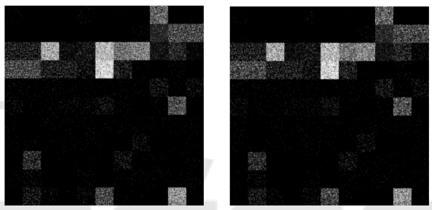


Figure 5: Order of Hilbert curve and the accuracy of the proposed model.

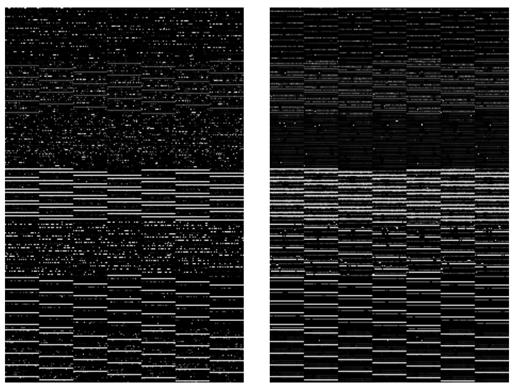


(a) Normal (b) Ipsweep

Figure 6: Example image from NSL-KDD dataset.

datasets. For the NSL-KDD dataset, it was capable of detecting with an accuracy of 0.818 and an F1-score of 0.835. In the case of the CIC-IDS2017 dataset, it achieved an accuracy of 0.924 and an F1-score of 0.931.

In addition, our study utilized the Hilbert curve with *order*=5 to map network data into images. This optimal order was determined through experiments by varying the order with the example training set using the proposed model. The result is shown in Figure



(a) Normal (b) DoS GoldenEye

Figure 7: Example image from CIC-IDS2017 dataset.

5. We hypothesized that a higher Hilbert curve order would enhance model efficiency, resulting in a single image encapsulating 1024 data points.

The experimental results of using the original network data flow to evaluate the classical ML are shown in table 2. We applied Classical ML such as logistic regression (LR), and decision tree (DT) to compare the single sample training on the network data flow.

In conclusion, the HilxSEED model might be one of the standards for using visualization in intrusion detection. It successfully addressed the key challenges in this field, the need for high accuracy, and the ability to process complex data patterns effectively. As cyber threats continued to evolve, approaches like the HilxSEED model were vital in developing robust and efficient systems to safeguard digital infrastructures.

5 CONCLUSION

In this study, we proposed the intrusion detection method. The Hilbert curve serves as a flow-to-image technique and utilizes an image classification model to detect the network attack. We map the network data flow following the coordinates of Hilbert's curve. Then, we train and evaluate the HilxSEED model, an integration of the Encoder-Decoder model and the SENet model comparing with previous methods on NSL-KDD and CIC-IDS2017. The result of the proposed HilxSEED model achieved higher performance than recent models, with 0.817 accuracy and 0.835 F1-score on the NSL-KDD, and 0.924 accuracy and 0.931 F1-score on the CIC-IDS2017.

Our results were influenced by our experiment's specific conditions. The Hilbert curve order was limited by our hardware's robustness, but future studies could use higher orders. Notably, as we increased the Hilbert curve's order, we generally observed enhanced efficiency. A limitation was the difficulty in visually detecting some attack types, though our method might indicate these patterns. Furthermore, exploring other filling curves could further enhance intrusion detection methodologies.

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APPENDIX

The table 2 shows the result of the classical ML model which is single network data flow sample training. This evaluation is the comparison with the proposed method in table 1.

Table 1: Result of Proposed method on both datasets.

Dataset and Model			Metrics			
Dataset	Data type	Model	Acc.	F1	Pre.	Rec.
NSL-KDD	Traditional Method	LSTM-RNN (Sherstinsky, 2020)	0.711	0.344	0.541	0.253
	Image Method	Hilbert + EfficientNetB0	0.807	0.810	0.922	0.722
		Hilbert + ViT	0.431	0.000	0.000	0.000
		HilxSEED	0.818	0.835	0.865	0.807
CIC-IDS2017	Traditional Method	LSTM-RNN (Sherstinsky, 2020)	0.807	0.804	0.957	0.692
	Image Method	Hilbert + EfficientNetB0	0.655	0.753	0.615	0.971
		Hilbert + ViT	0.760	0.299	0.541	0.206
		HilxSEED	0.924	0.931	0.923	0.938

Table 2: Result of Classical Machine Learning and Sequential model on both datasets.

Dataset and Model		Metrics			
Dataset	Model	Acc.	F1	Pre.	Rec.
NSL-KDD	Logistic Regression (LR)	0.755	0.744	0.918	0.625
	Decision Tree (DT)	0.789	0.789	0.914	0.695
	Random Forest (RF)	0.785	0.773	0.968	0.643
	Gradient Boost (GB)	0.778	0.775	0.920	0.669
	Support Vector Classifier (SVC)	0.760	0.750	0.919	0.633
CIC-IDS2017	Logistic Regression (LR)	0.694	0.632	0.900	0.486
	Decision Tree (DT)	0.517	0.201	0.929	0.112
	Random Forest (RF)	0.618	0.452	0.998	0.292
	Gradient Boost (GB)	0.469	0.041	0.800	0.021
	Support Vector Classifier (SVC)	0.652	0.547	0.920	0.389