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An Innovative Intrusion Detection Systems for smart Electronic Consumers

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Abstract: The advancement of Internet of Things (IoT) technologies has ushered in a new era for Consumer Electronics (CE), characterized by heightened connectivity and intelligence. This evolution enables enhanced data availability and automated control within CE networks, comprising sensors, actuators, and consumer devices. Cu-BLSTM offers advantages in processing sequential data and capturing long-term dependencies, making it a promising candidate for intrusion detection tasks. However, Cu-BLSTM also presents limitations, including high computational complexity and sensitivity to hyperparameters. To provide a comprehensive analysis, this study compares with Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and Recurrent Neural Networks (RNN) in the context of intrusion detection for smart CE networks. CNNs excel in extracting spatial features from data, making them suitable for certain types of intrusion patterns. DNNs offer scalability and ease of training, which can be advantageous for large-scale deployment scenarios. RNNs, on the other hand, are well-suited for processing sequential data with temporal dependencies. By understanding the strengths of CNN, DNN, and RNN, this research aims to inform the design and implementation of effective IDS solutions tailored to the unique requirements of smart CE networks.

Index terms: Consumer Electronics, Cyber Attacks, Deep Learning, Internet Of Things, Intrusion patterns

I. INTRODUCTION

The Internet of Things (IoT) represents a network of interconnected devices embedded with software programs and sensors, leveraging the Internet for data communication. Integration of IoT technology into traditional Consumer Electronics (CEs) has propelled them into the realm of next-generation CEs, characterized by enhanced connectivity and intelligence. This advancement facilitates improved data availability and automatic control within CE networks, driven by the seamless connectivity among sensors, actuators, appliances, and other consumer devices . However, the evolution of CE devices has expanded their connectivity to be remotely accessed from anywhere in the world, using various computing devices such as laptops, smartphones, and smartwatches, irrespective of the underlying network infrastructure. These smart devices find applications across diverse fields, including smart homes.

Additionally traditional static network infrastructure-based approaches require manual configuration and exclusive management of CE devices, potentially leading to inefficient resource utilization and leaving systems vulnerable to various cyber-attacks .Despite the advancements, smart CE networks are susceptible to a range of subtle cyber threats, including botnets, brute force attacks, Denial-of-Service (DoS), Distributed Denial of Service (DDoS), and web attacks . Among these, DDoS attacks are particularly concerning. In a DDoS attack, attackers utilize numerous compromised hosts to flood a target server with excessive traffic, overwhelming its resources and rendering it unreachable to legitimate users. Although DDoS attacks have been studied for over two decades, they remain a prevalent and impactful threat in contemporary times.

The research explores three distinct neural network architectures for enhancing cybersecurity measures in the context of IoT-based attack detection and intrusion detection in smart electronic consumer networks. Convolutional Neural Networks (CNNs) are leveraged for feature extraction and categorization, aiming to select critical features that aid in detecting IoT attacks. By prioritizing these features, CNNs enhance the accuracy and efficiency of attack detection systems, thereby contributing to advancing IoT security. Deep Neural Networks (DNNs) offer a promising alternative for intrusion detection in consumer networks by learning complex patterns from network traffic and device behaviours. Through empirical analysis, DNN-based IDS demonstrate effectiveness in detecting various cyber threats, compared to traditional methods. Recurrent Neural Networks (RNNs) handle sequential data by preserving information through recurrent connections, allowing them to identify subtle anomalies and emerging threats in consumer networks with high accuracy.

By harnessing the capabilities of these neural network architectures, the research aims to develop robust and adaptive intrusion detection solutions tailored to the unique challenges of IoT environments and smart electronic consumer networks, ultimately safeguarding the integrity and security of interconnected devices within modern households.

- The authors employed CNN,RNN,DNN to quickly and accurately identify threats in CE networks.
- We compared the performance of the proposed CNN, RNN and DNN to evaluate the proposed model thoroughly. For a fair comparison, all models have been trained and assessed in the same environment.
- A publicly accessible, intrusion dataset namely CICIDS-2017 dataset is employed for model training and evaluation. We also assessed the proposed model performance against the most recent detection models from the current literature and used 10-fold cross-validation technique to show balanced results.

II. RELATED WORK

The CE is characterized by the integration of physical things into a network in a way that makes them active participants in corporate operations. These objects might include everything from network gear to sensors to home and healthcare products. CE is made up of a range of devices that can be wireless or wired and can be used in several places and networks. According to a recent Juniper report, more than 46 billion IoT devices were in operation by 2021. This includes sensors, actuators, and gadgets and represents a 200% growth over 2016. In any changing computer and network paradigm, IoT becomes an integral part of it. IoT transformation is growing exponentially, leading to significant growth in terms of revenue and automation. Because these devices are created to satisfy the individual demands of users, it is difficult to find a solution that works for everyone.

TABLE 1: Literature review

S.No	Domain	Model	Dataset	Analysis
1	NIDS	LSTM-VAE	ToN-IoT, IOT-Botnet	The authors proposed a hybrid model to safeguard IoT environments and achieved efficient detection accuracy
2	IOT	SMO,SPDN	NSL-KDD	DL-based threat detection framework is proposed to counter DoS, U2R, R2L, and probe attacks. The model has shown 99.02%
3	IOT	CNN	BOT-IOT	An intrusion detection system for the vehicular network is presented to address frequently occurring IoT attacks and their proposed model has demonstrated 99.25% accuracy .
4	IOT	Auto Encoder With BiLSTM	CICIDS-2017 and ToN-IoT	The proposed methods obtained accuracy close to 99%.
5	NIDS	LSTM,GRU,CNN	CICIDS-2018	The proposed models gives the accuracy around 99.57%.

In a study referenced as the authors devised a threat intelligence method tailored for industrial environments. They employed Independent Component Analysis to reduce the size of both the UNSW-NB15 and power system datasets. Furthermore, researchers integrated Long Short-Term Memory (LSTM) with the Variational Auto Encoder (VAE) technique to craft an alternate attack detection scheme for IoT. The system underwent effective training utilizing ToN-IoT and IoT-Botnet datasets, thereby enhancing the learning process of the proposed system. Subsequently, the system demonstrated its efficacy across various analytical performance metrics, including attack detection accuracy and training duration. Another threat detection framework is proposed in that is composed of two renowned classifiers Spider Monkey optimization (SMO), and Stacked Deep Polynomial Network (SDPN). Along with DoS attacks, the designed model is capable to investigate major commonly occurring attacks such as User-to-Root (U2R) Attacks, Remote-to local(R2L) attacks etc.

The designed framework is trained on the NDL-KDD dataset, and its performance is compared with benchmarked schemes. The model has significantly achieved 99.02% accuracy. Authors have specifically designed an IDS to carefully detect DDoS attacks in large-scale IoT networks. The system is evaluated on comprehensive performance metrics where it remarkably achieves high attack detection accuracy.

In an additional intrusion detection strategy detailed in a Convolutional Neural Network (CNN) classifier forms the basis of the model, trained on the BoT-IoT dataset. Similarly, CNN is also utilized in a distinct threat detection framework proposed in targeting botnet, zero-day, and DDoS attacks. The initial model training is conducted on the MQTT-IoT-IDS2020 dataset, with runtime performance assessed in terms of accuracy, precision, and recall. Moreover, CNN integration is employed to devise yet another anomaly detection architecture dedicated to scrutinizing suspicious entities across the network. Performance evaluation of this model is conducted against pertinent security solutions, focusing on threat detection accuracy, as discussed. Other detection framework that is autoencoders with bidirectional. The hyperparameters governing the feature extraction process are crucial for transforming data into a novel format and extracting essential low-dimensional features, diverging from merely pinpointing threat observations. Consequently, the resultant datasets are primed for evaluating the efficacy of Bi-LSTM in threat detection.

Additionally, the hyperparameters dictating attack detection within the proposed IDS, coupled with the feature extraction technique, are pivotal. Through this method, the IDS attained an impressive validation accuracy of 99.03%, further emphasizing its robustness and reliability. Another detection framework which is an intelligent intrusion detection system based on software-defined networking-orchestrated deep learning approach. Specifically, software-defined networking architecture was integrated with consumer electronics network to handle its distributed architecture and heterogeneous consumer electronic devices. Then, an IDS based on Cuda-enabled bidirectional long short-term memory was proposed and deployed at control plane to enhance threat detection mechanism. We proved the effectiveness of the proposed IDS in terms of accuracy, precision and speed efficiency through experimental evaluation on the CICIDS-2018 dataset. We also compared the performance of the proposed IDS against some recent state-of-the art technique overall accuracy is 99.59%.

III. METHODOLOGY

Proposed RNN, CNN, and DNN-based framework

The proposed model employs a Recurrent Neural Network (RNN) architecture, specifically utilizing Simple RNN units, to effectively learn from sequential data. RNNs are well-suited for tasks involving time-series data, as they can process information from earlier time steps and utilize Back Propagation Through Time (BPTT) to learn from past states. However, traditional RNNs may face challenges with long sequences and suffer from issues such as vanishing gradients.

To address these limitations and enhance learning performance, researchers have explored Long Short-Term Memory (LSTM) networks. LSTMs are capable of capturing long-term dependencies in data, making them suitable for tasks where preserving information over extended sequences is crucial. Building upon the LSTM model, Bidirectional LSTMs (BLSTMs) have been introduced to further improve learning capabilities. BLSTMs traverse time steps in both forward and backward directions, enabling them to capture context from the entire sequence. The proposed RNN architecture, denoted as "rnn3," incorporates three layers of Simple RNN units.

The model begins with an input layer designed to process sequences of 78-dimensional vectors with a single feature. Three Simple RNN layers are subsequently added in sequence, each comprising 32 units and utilizing the Rectified Linear Unit (ReLU) activation function. Dropout regularization, with a dropout rate of 0.1, is applied to each RNN layer to mitigate overfitting.

Following the RNN layers, the model includes fully connected Dense layers for further feature extraction. The output from the last RNN layer is flattened into a single vector before being passed through two Dense layers with 32 and 16 units, respectively. The Leaky ReLU activation function, with an alpha value of 0.1, is applied to introduce non-linearity to these layers. Lastly, a Dense layer comprising 15 units and employing the softmax activation function is appended to generate class probabilities.

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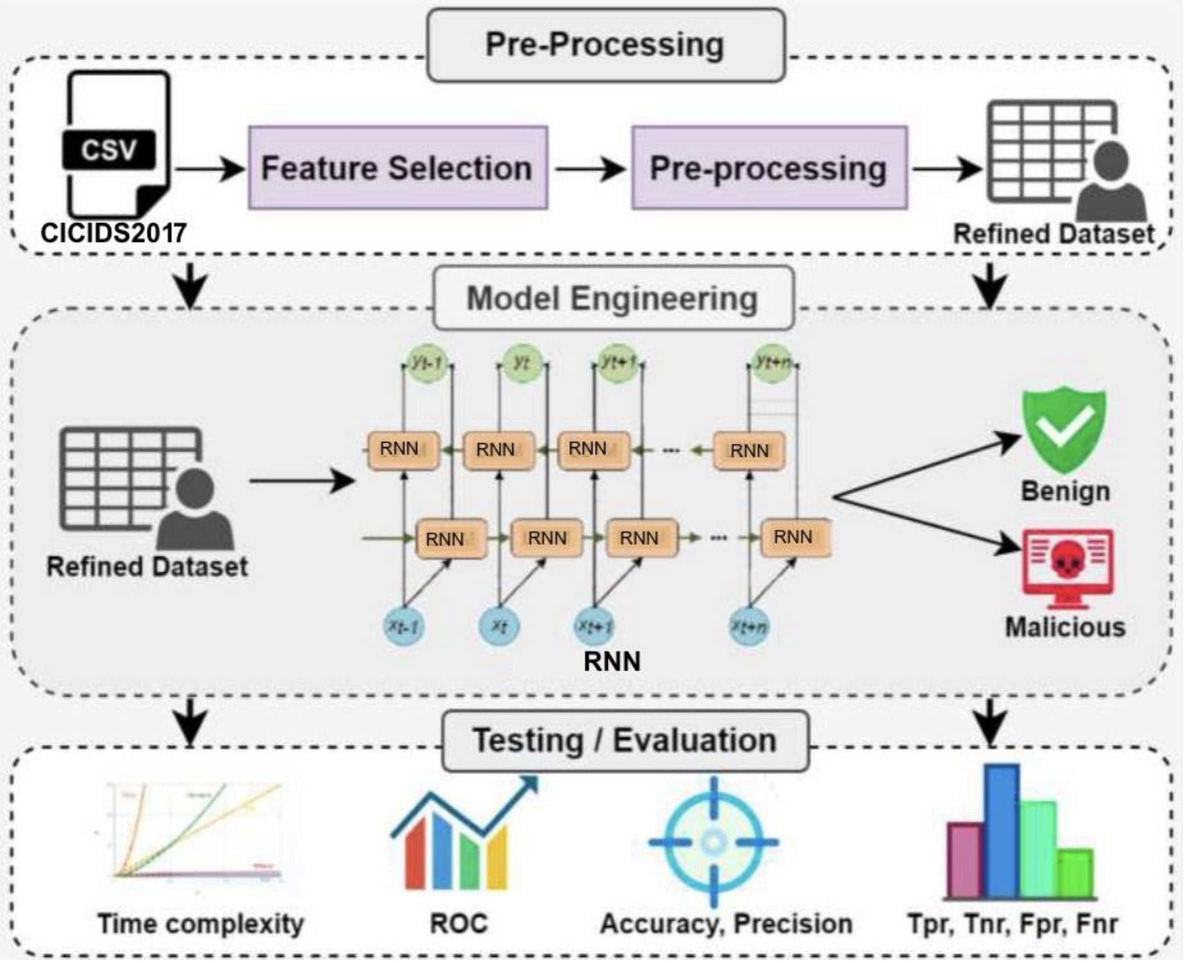

Fig1: Proposed Detection Scheme

During the training phase, the model is optimized using the Adam optimizer with categorical cross-entropy loss. Training involves iterating over the training data for 30 epochs, with a batch size of 512. The model's performance is evaluated using a validation set provided by `RNN features_val` and `y_val`, with callbacks such as TensorBoard and Early stopping utilized to monitor training progress and prevent overfitting.

In summary, the "rnn3" architecture leverages the capabilities of Simple RNN units and dropout regularization to effectively learn complex patterns from sequential data and perform multi-class classification tasks with high accuracy.

Algorithm 3 RNN3 Detection Framework

Input: Dataset DT

Output: Normal → 0, Attack1 → 1, Attack2 → 2, and so on.

```
1. Split DT into $DT_{train}$ and $DT_{test}$
2. Initialize RNN3 model
3. Train RNN3 model using $DT_{train}$
4. $DT'_{test}$ = Pre-process $DT_{test}$
5. while True do
6. Predict_attack_type → RNN3_model($DT'_{test}$)
7. if predicted value = 0 then
8. Return Normal
9. else
10. Return attack type
11. end if
12. end while
```

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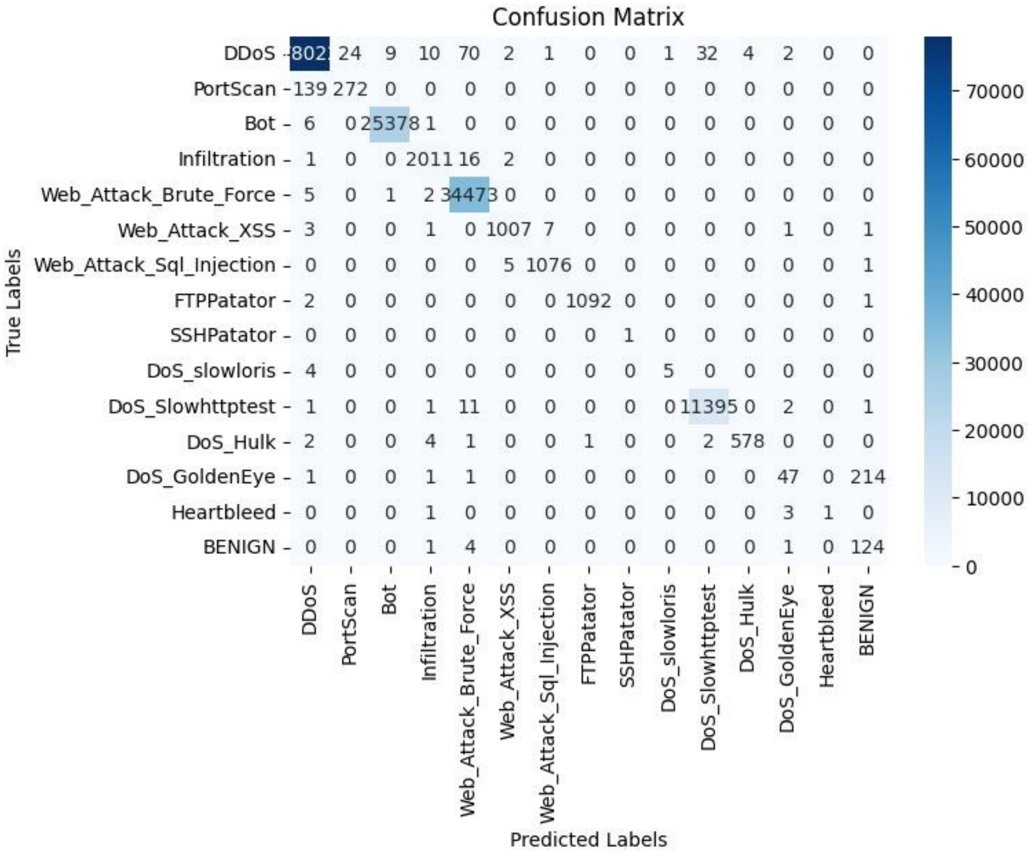
IV. EXPERIMENTAL SETUP AND EVALUATION METRICS

The proposed model, trained using Python version 3.8 and Keras coupled with TensorFlow and GPU-based processing, underwent evaluation using an Intel Core i7-7700 HQ CPU with a 2.80 GHz processor, 16GB RAM, and a 6GB, 1060 GPU. The evaluation utilized the CICIDS-2017 dataset, consisting of benign and various attack classes such as Brute-force, DDoS, DoS, SSH, etc., with seven classes used in this study. Pre-processing involved deleting lines with empty or non-numeric values to avoid impacting model performance, followed by label encoding using sklearn to transform non-numeric values into numeric ones. One-hot encoding was applied to output labels to mitigate any potential performance impacts due to segment order. Additionally, data normalization using the MinMax scalar function was performed to enhance model performance. The dataset was split into 70% training and 30% testing data. Model performance was assessed using standard evaluation metrics including accuracy (ACC), precision (PN), recall (RL), and F1-Score (FS), while the confusion matrix provided values for true positive (TP), true negative (TN), false positive (FP), false negative (FN), and Matthew's correlation coefficient (MCC). These metrics collectively provide a comprehensive assessment of the model's effectiveness in classifying benign traffic and various types of attacks, enabling informed decision-making regarding its deployment and optimization.



	DDoS	PortScan	Bot	Infiltration	Web_Attack_Brute_Force	Web_Attack_XSS	Web_Attack_Sql_Injection	FTPPatator	SSHPatator	DoS_slowloris	DoS_Slowhttptest	DoS_Hulk	DoS_GoldenEye	Heartbleed	BENIGN
DDoS	802	24	9	10	70	2	1	0	0	1	32	4	2	0	0
PortScan	139	272	0	0	0	0	0	0	0	0	0	0	0	0	0
Bot	6	0	25378	1	0	0	0	0	0	0	0	0	0	0	0
Infiltration	1	0	0	2011	16	2	0	0	0	0	0	0	0	0	0
Web_Attack_Brute_Force	5	0	1	2	34473	0	0	0	0	0	0	0	0	0	0
Web_Attack_XSS	3	0	0	1	0	1007	7	0	0	0	0	0	1	0	1
Web_Attack_Sql_Injection	0	0	0	0	0	5	1076	0	0	0	0	0	0	0	1
FTPPatator	2	0	0	0	0	0	0	1092	0	0	0	0	0	0	1
SSHPatator	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
DoS_slowloris	4	0	0	0	0	0	0	0	0	5	0	0	0	0	0
DoS_Slowhttptest	1	0	0	1	11	0	0	0	0	0	11395	0	2	0	1
DoS_Hulk	2	0	0	4	1	0	0	1	0	0	2	578	0	0	0
DoS_GoldenEye	1	0	0	1	1	0	0	0	0	0	0	0	47	0	214
Heartbleed	0	0	0	1	0	0	0	0	0	0	0	0	3	1	0
BENIGN	0	0	0	1	4	0	0	0	0	0	0	0	1	0	124

Fig 2: Confusion Matrix

The mathematical formulas are

Accuracy=(TP+TN)/(TP+TN+FP+FN)
Precision=(TP)/(TP+FP)
Recall=(TP)/(TP+FN)
F1 Score=2(TP)/2(TP+FP+FN)

A. Results and Discussion

The study employed 10-fold cross-validation, ensuring unbiased outcomes, with the results displayed in Table II to illustrate each fold's performance explicitly. Each fold's outcomes are presented in this section. The confusion matrix in Figure 2 showcases the model's performance on the test dataset.

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When dealing with binary or multi-category data, evaluating the receiver operating characteristic (ROC) curve provides valuable insights into the model's accuracy, precision, recall, and overall performance. The depicted confusion matrix illustrates the model's ability to correctly identify all five classes. Moreover, the ROC curve effectively visualizes the model's ability to distinguish between positive and negative instances, indicating the success of various class division tasks.

Table II 10-Fold Results

Parameters	Model	1	2	3	4	5	6	7	8	9	10
Accuracy%	DNN	86.94	91.79	93.03	93.48	94.06	94.30	94.11	94.30	94.17	94.29
	CNN	89.72	92.76	92.90	93.01	92.85	93.39	93.60	93.51	93.24	93.39
	RNN	96.15	97.34	98.31	98.67	98.92	99.07	99.13	99.61	99.63	99.64
Precision	DNN	88	99	100	99	99	91	98	100	100	99
	CNN	97	88	94	90	99	90	86	100	100	99
	RNN	100	91	100	100	100	99	99	100	99	100
Recall%	DNN	78	59	96	100	100	99	81	100	98	91
	CNN	66	100	91	97	99	99	95	91	96	91
	RNN	76	100	98	100	99	99	100	100	95	98
F1 Score%	DNN	93	56	88	72	97	100	100	98	95	90
	CNN	93	51	94	82	95	79	86	99	98	76
	RNN	100	77	100	99	100	99	99	100	100	99

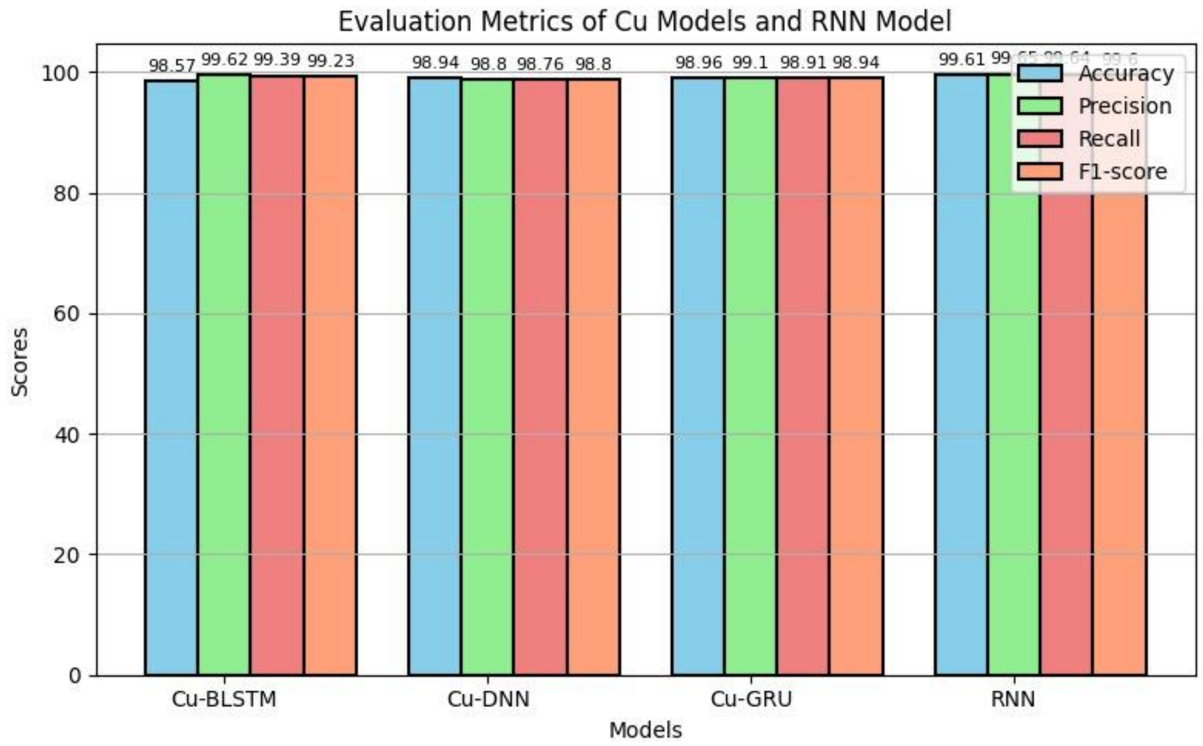

Fig3: Overall comparison Of RNN against Existing models.

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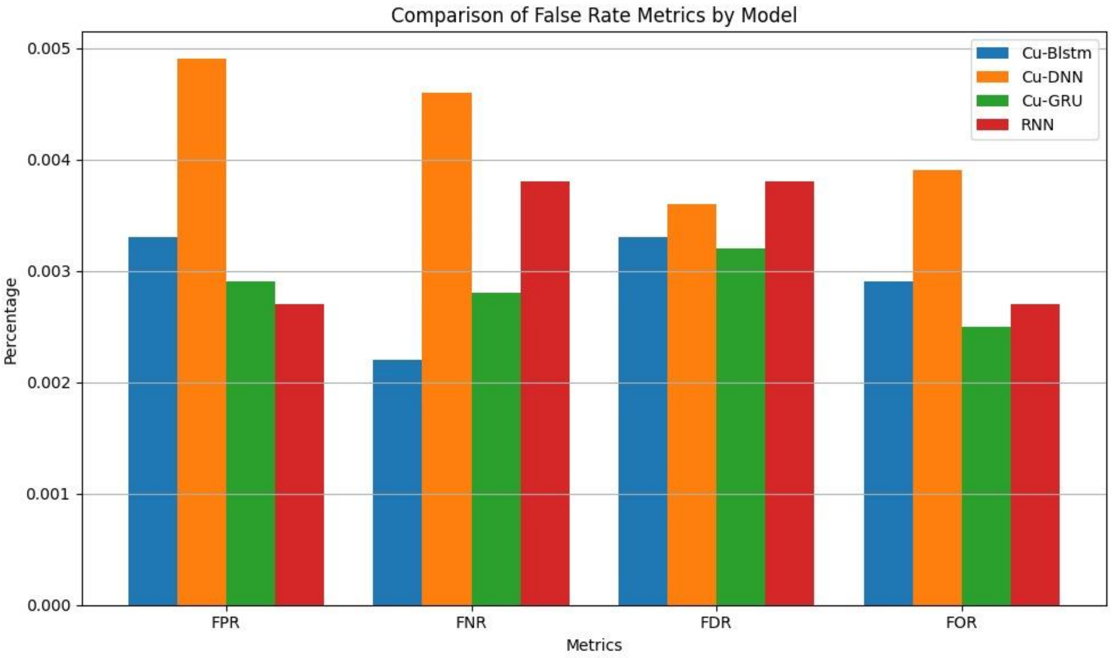

Fig4 : Overall comparison of False Rate Metrics with existing models

The proposed model, RNN, demonstrated better performance compared to DNN and RNN. The proposed models gives the accuracy values of 99.61%, 99.63%, and 99.64% respectively. These results clearly establish the effectiveness of the proposed model.

To validate the efficiency of the proposed RNN model, its performance is compared with recent threat detection techniques from existing literature in terms of accuracy (ACC). The comparison details are presented in Table 3. It is evident from the table that the proposed model outperforms the existing detection techniques, thereby proving its efficiency.

Table III : Comparison of RNN with existing Literature

YEAR	MODEL	DATASET	ACCURACY
2024	RNN	CICIDS-2017	99.64
2022	Cu-BLSTM	CICIDS-2018	99.57
2022	Ensembled model	CICIDS-2018	95.10
2022	SecFedNIDS	CICIDS-2018	97.03

V. CONCLUSION

In this article to protect consumer electronic network we proposed an innovative intrusion detection system, employing deep learning techniques such as RNN, DNN, CNN makes a significant advancement in cybersecurity for interconnected consumer electronics. This system leverages the capabilities of extract meaningful features from raw network data, enabling precise anomaly detection.

The technique provide a robust defense against evolving cyber threats and potential intrusions. We demonstrated the effectiveness of the proposed IDS by evaluating its accuracy, precision, and speed efficiency through experiments conducted on the CICIDS-2017 dataset. By harnessing the power of deep learning, this revived system not only safeguards the integrity and confidentiality of data within smart electronic consumer environments but also addresses the pressing need for adaptive and sophisticated intrusion detection methods in the era of interconnected consumer electronics

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