A New Fully Convolutional Neural Network Strategy For Detecting And Categorizing Assaults On Industrial IoT Devices in Smart Manufacturing Systems

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Abstract - *Internet of Things (IoT) devices have recently become widely used and technologically advanced in manufacturing settings to monitor, gather, exchange, analyze, and send data. However, this transformation has dramatically raised the risk of cyberattacks. As a result, establishing effective intrusion detection systems based on deep learning algorithms has shown to be a dependable intelligence tool for protecting Industrial IoT devices from cyber attacks. This paper describes the implementation of two different classifiers and detection methods using the long short-term memory (LSTM) architecture to address cybersecurity concerns on three benchmark industrial IoT datasets (BoT-IoT, UNSW-NB15, and TON-IoT) that employ a variety of deep learning algorithms. An overview of the proposed models' performance is provided. Augmenting the LSTM with convolutional neural networks (CNN) and fully convolutional neural networks (FCN) results in state-of-the-art performance in detecting cybersecurity threats.*

Key Words: IOT, DL, Attacks, dataset, LSTM

1.INTRODUCTION

The tenacious blend of computerized genuine structures (CPS) into the Internet has provoked an impact in clever IoT contraptions and the ascent of various purposes of Industry 4.0 [1, 2] like keen gathering. A savvy gathering structure is strongly contained perplexing associations of immense degree CPS that are prosperity essential and rely upon coordinated and conveyed control models [3]. The decreasing cost of sensors and significant level single board laptops got together with better permission to high exchange speed distant associations (by and by in its fifth age — 5G) have upheld the development of the Trap of Things (IoT) structures into collecting systems [4]. Regardless, individuals who choose to reap the benefits of IoT structures need to moreover defy the continuously creating risk of receptiveness to attacks. Thus, the security of IoT structures has transformed into an incredibly fundamental issue for individuals and associations. IoT systems have been assigned by harmful third social events and the example has been growing emphatically in numbers and filling in multifaceted design and assortment after the advancement of Mirai in 2016 [5]. As per reports, from 2013 to 2017, not a solitary month went by without insight about a web-based break including a particular business that brought about the revelation of delicate client data information [6]. According to the Advanced Control Structures Monito Flyer gave by the U.S. Division of Nation Security, it is surveyed that 33% of these advanced attacks centre around the gathering region making manufacturing structures at the centre of such follows [7, 8]. Moreover, based to the Public Foundation of Standards and Advancement (NIST) — part of the U.S. Part of Exchange , these attacks through the web, centre around an endeavor's usage of the web to upset, weaken, wreck, or harmfully controlling a handling environment establishment; then again destroy the genuineness of the data or take controlled information [9]. To address the extended risks and hardships of the creating number and capacity of advanced attacks, pragmatic protection and assessment countermeasures, for instance, network interference revelation and association criminological structures ought to be made effectively [10, 11]. Yet, a couple of investigation have been done to settle and lessen the bet of computerized attacks with different man-made intelligence models and algorithms [10, 11], it is critical to execute novel and efficient strategies to keep protections revived. In this paper, for the first time, we propose and break down the usage of two novel models, trustworthy, and effective data assessment estimations for time series classification on three different and remarkable datasets. The first approach is long transient memory totally convolutional network (LSTM-FCN) and the resulting strategy is convolutional mind network with long flitting memory (CNN-LSTM). The results of the continuous audit show the way that such strategies can be utilized to further develop the counteraction level of noxious attacks in present day IoT contraptions

2. LITERATURE SURVEY

The most recent thirty years have been set apart by a significant expansion in accessible information and figuring power. These days, information examination is at the very front of the conflict against cyberattacks. Online protection specialists have been using information examination not exclusively to further develop the network safety checking levels over their organization streams yet additionally to increment ongoing location of danger designs and to direct observation of constant organization streams [12-14]. Both regulated learning and solo learning strategies in information examination have been utilized in the discovery cycle of malevolent assaults [12, 15]. One of the extraordinary elements of brain organizations (NN) is that they can be utilized in both administered and solo growing experiences. NN were enlivened by the manner in which the human mind works. NN is made out of different information layers which makes them the most appropriate calculations to be utilized in different artificial knowledge (man-made intelligence) and AI (ML) applications. Repetitive brain organizations (RNNs) spread information forward and furthermore in reverse from later handling stages to prior stages (networks with cyclic information flows that can be utilized for applications in regular language handling and discourse acknowledgment) [16]. RNN was utilized to accomplish a genuine positive pace of 98.3% at a bogus positive pace of 0.1% in identifying malware [17]. In another as of late distributed paper, Shibahara et al. [18] utilized RNN to distinguish malware in view of organization conduct with high accuracy. Additionally, Loukas et al. [19] have utilized RNN on a vehicle's constant information [19] to foster a numerical model to distinguish digital actual interruption for vehicles utilizing a profound learning (DL) approach. Regardless of many benefits, one issue with RNN is that it can retain part of the time series which brings about lower exactness while managing long arrangements (evaporating data issue). To take care of this issue, the RNN design is joined with long momentary memory (LSTM) [20]. A RNN-LSTM approach has been utilized in interruption location frameworks to recognize botnet movement inside shopper IoT gadgets and organizations [21, 22]. LSTM [20] alludes to brain networks that are fit for learning request reliance in succession expectation and ready to recollect a great deal of past data utilizing back engendering (BP) or past neuron flags and remember it for the ongoing handling. LSTM can be utilized with different structures of NN. The most observable application for such organization constructs is found in text expectation, machine interpretation, discourse acknowledgment, and more [16, 23]. LSTM proposes an improvement to the RNN model by supplanting the secret layer hubs with three entryways structure (neglecting, input, yield) that follows up on memory cells through the Sigmoid capability. These memory cells are liable for exchanging of data by putting away, recording, and refreshing past information [24]. Convolutional brain organization (CNN) utilizes a feed-forward geography to proliferate signals, CNN is all the more frequently utilized in classification and PC vision acknowledgment errands [16, 25]. Kim et al. [26] utilized KDD CUP 1999 and CSE-CICIDS2018 informational indexes to foster a CNN model to distinguish denial of-administration classification interruption assaults, early outcomes showed a high precision recognition that went between 89-close to 100%. CNN was likewise utilized by Wang et al. [27], McLaughlin et al. [28], and Gibert et al. [29] to distinguish malware. The last option assessed their strategy utilizing a Microsoft Malware Classification Challenge dataset and figured out how to beat different techniques as far as precision and classification time. Wang et al. [27] proposed a malware traffic classification strategy utilizing a CNN by taking traffic information like pictures and afterward introduced his technique as another scientific categorization of traffic classification from an artificial insight point of view. In a novel report, Yu et al. [30] proposed a brain network design that joins CNN with autoencoders to assess network interruption discovery models. Additionally, Kolosnjaji et al. [31] proposed brain network design that comprised of CNN joined with RNN to all the more likely recognize malware from a VirusShare dataset showing that this recently evolved engineering had the option to accomplish a typical accuracy of 85.6%. A similar methodology was likewise used by Macintosh et al. [32] and Yu et al. [33], to recognize area creating calculations codes that furnish malware with new requests on the fy to keep their servers from being distinguished and fagged. All in all, CNN is a DL network engineering that advances straightforwardly from information without the need of manual component extraction. It is significant that CNN can likewise be exceptionally effective for characterizing time series, and sign information. A completely convolutional brain organization (FCN) is a CNN without completely associated layers [34]. A significant benefit of utilizing FCN models is that it doesn't need weighty preprocessing or include designing since their' neuron layers are not thick (completely associated) [35]. FCN has been utilized [36] to distinguish counterfeit fingerprints and it was shown that FCN gives high recognition exactness as well as less handling times and less memory necessities contrasted with other NN. In this paper, LSTM will be joined with FCN and CNN to demonstrate the way that these two models can be utilized to precisely recognize network protection dangers with three different datasets. LSTM empowers any NN to nearly flawlessly show issues with numerous info highlights.

Reference	Title	Authors	Year	Methodology/Approach	Key Findings
[1]	"Deep learning-based intrusion detection system for industrial Internet of Things in Industry 4.0"	Kim, S. et al.	2021	Deep learning (Convolutional Neural Networks)	Proposed system achieved high detection rates for various attacks on IIoT devices.
[2]	"IoT-SAS: A Scalable Security Assurance Scheme for Industrial IoT Systems"	Liu, Y. et al.	2020	Hybrid approach combining blockchain and machine learning	Developed a scalable security assurance scheme to protect IIoT systems from attacks, including detection and categorization.
[3]	"Real-time intrusion detection in Industrial IoT using deep learning approaches"	Zhao, Y. et al.	2019	Deep learning (Recurrent Neural Networks)	Demonstrated the effectiveness of recurrent neural networks for real-time intrusion detection in IIoT environments.
[4]	"An Intelligent Intrusion Detection System for IoT-Based Smart Grids Using Machine Learning Classifiers"	Samanta, S. et al.	2018	Machine learning classifiers (Random Forest, K-Nearest Neighbors)	Developed an intelligent intrusion detection system tailored for IoT-based smart grids, applicable to industrial IoT systems.

3. PROPOSED SYSTEM

The goal of this project is to create a sophisticated intrusion detection system specifically for Internet of Things devices. When it comes to identifying complex cyber threats in these networked devices, traditional methods frequently fall short. Novel deep learning models that combine Long Short-Term Memory (LSTM) with Convolutional Neural Network (CNN) and Fully Convolutional Neural Network (FCN) architectures are presented as a solution to this gap. The goal of this fusion is to obtain cutting-edge cybersecurity threat detection and classification capabilities.

3.1 IMPLEMENTATION

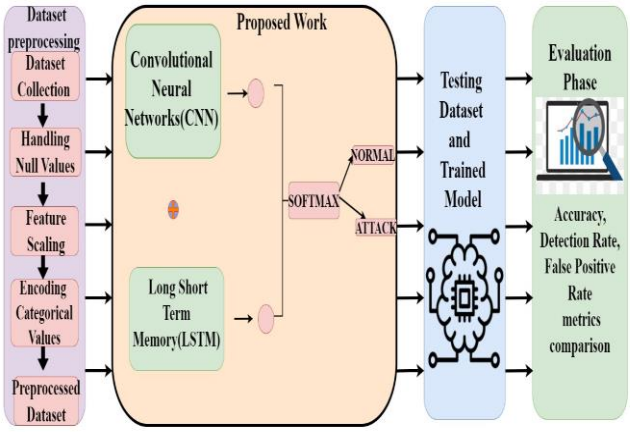
Dataset preprocessing
Dataset Collection
Handling Null Values
Feature Scaling
Encoding Categorical Values
Preprocessed Dataset
Proposed Work
Convolutional Neural Networks(CNN)
Long Short Term Memory(LSTM)
SOFTMAX
NORMAL
ATTACK
Testing Dataset and Trained Model
Evaluation Phase
Accuracy, Detection Rate, False Positive Rate metrics comparison

Fig 1: Architecture

One epoch represents one complete pass through the entire training data set. At each time point, the model computes predictions for all training samples, estimates loss (error), and updates its parameters using optimization algorithms (e.g., stochastic gradient descent). Several years allow the model to refine its parameters and learn more effectively from the data. One epoch represents one complete pass through the entire training data set. At each time point, the model computes predictions for all training samples, estimates loss (error), and updates its parameters using optimization algorithms (e.g., stochastic gradient descent). Several years allow the model to refine its parameters and learn more effectively from the data.

Specifically measure how often the machine learning model correctly predicts outcomes across classes. You can calculate accuracy by dividing the number of predictions correct by the total number of predictions recalled.

It ranges from 0 to 1 (or percentage), with higher values indicating better performance. The accuracy focuses on correct prediction when the model predicts the target class. Accuracy is calculated as the coefficient of the true positive. Recall is considered as the ratio of both true positivity and actual positive information.

4. RESULTS AND DISCUSSION

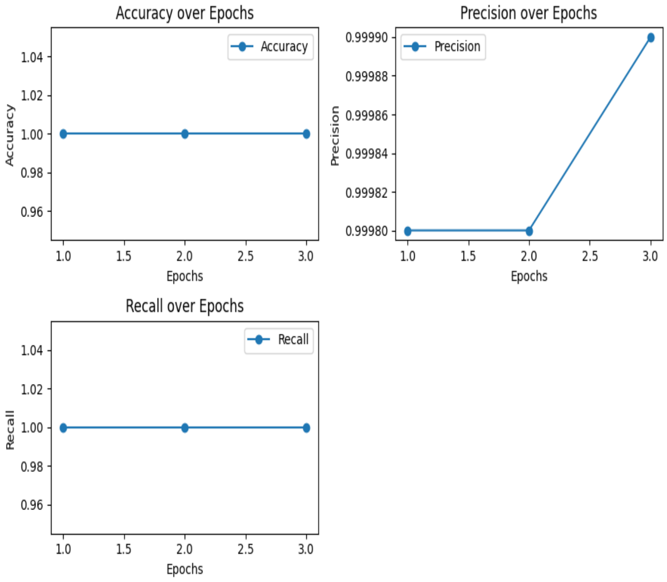

Chart 1: CNN-LSTM evaluation metrics results for BoT-IoT dataset.

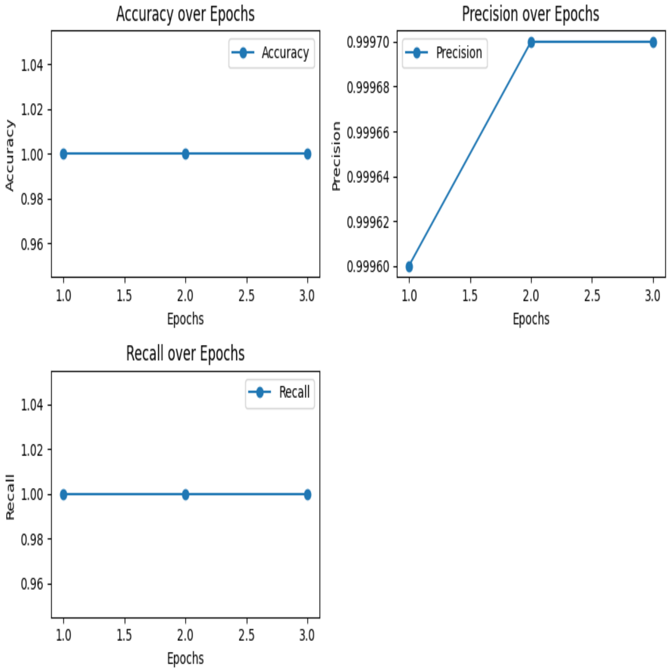

Chart 2: LSTM-FCN evaluation metrics results for BoT-IoT dataset

CNN-LSTM			LSTM-FCN		
BoT-IoT	UNSWNB15	TON-IoT	BoT-IoT	UNSWNB15	TON-IoT
2	3	3	3	3	3

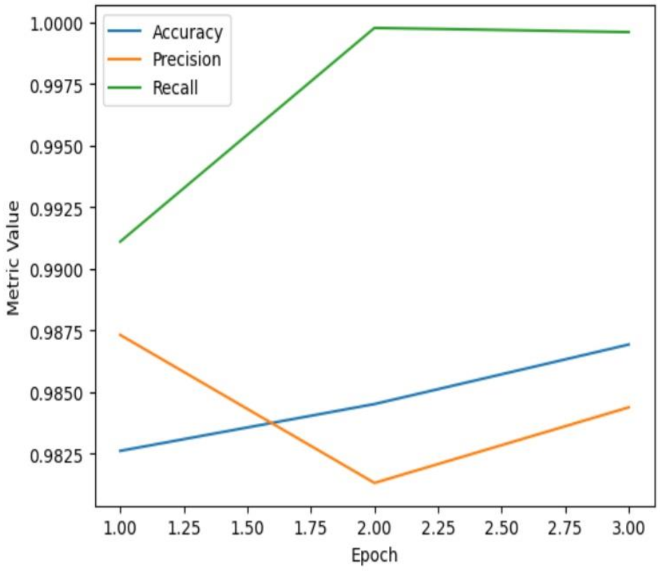

Chart 3: CNN-LSTM evaluation metrics results for TON-IoT dataset

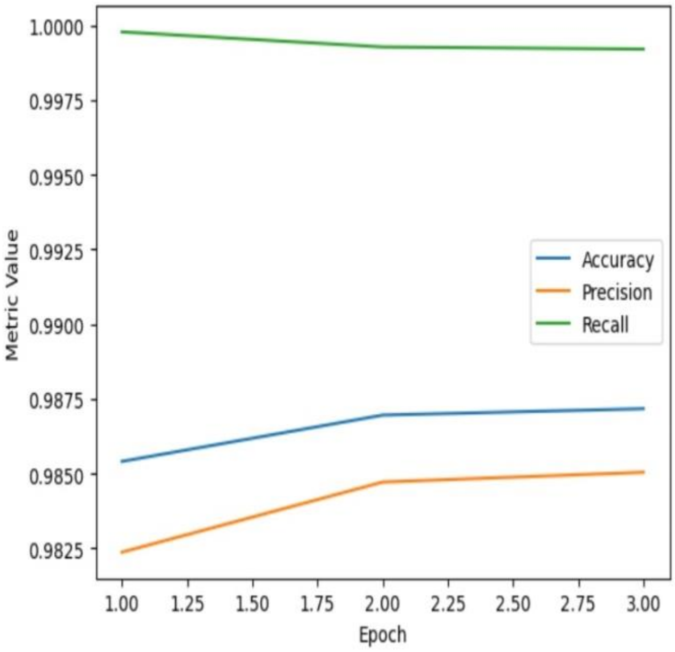

Chart 4: LSTM-FCN evaluation metrics results for TON-IoT dataset

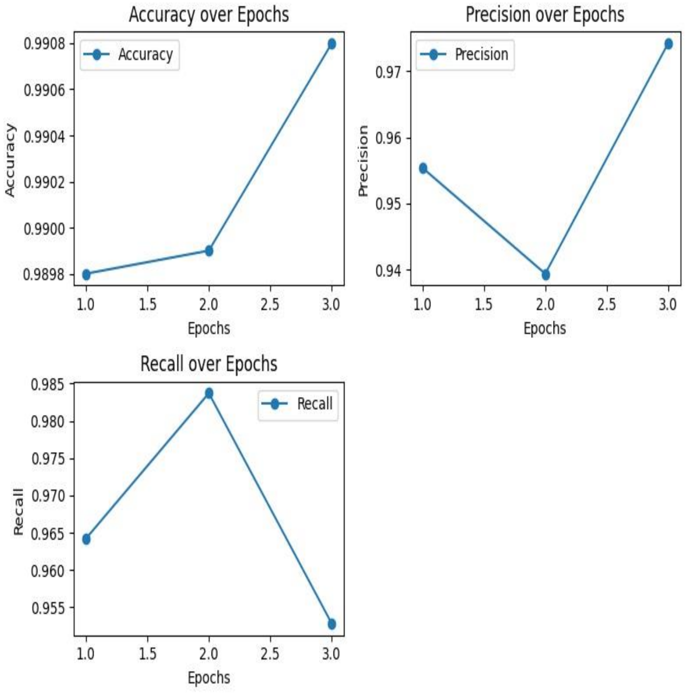

Chart 3: CNN-LSTM evaluation metrics results for UNSW-NB15 dataset

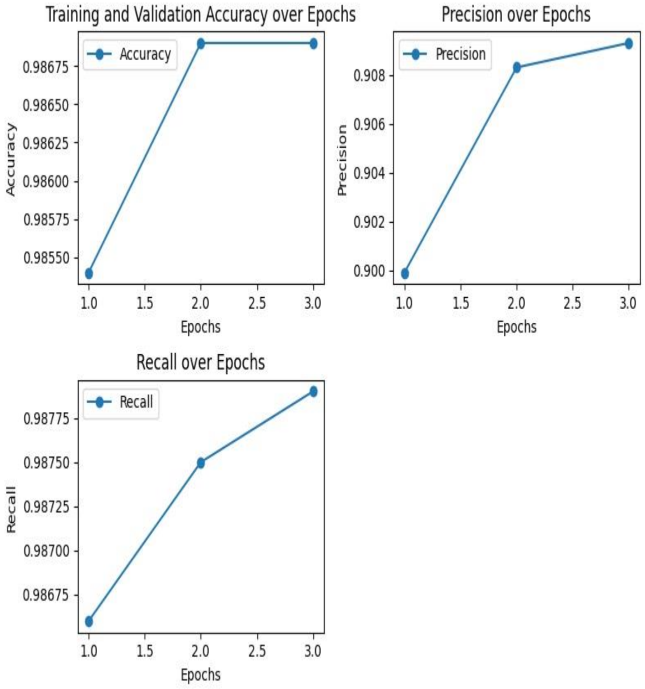

Chart 4: LSTM-FCN evaluation metrics results for UNSW-NB15 dataset

5.CONCLUSION

Novel deep learning models for attack detection and classification were suggested using Industrial IoT datasets. Certain protective concepts, like variants, unique forms, encryption, and packed malware, can be difficult to recognise when discovering IoT malware. This proposed system provided a new way to classify malware that is compatible with Internet of Things devices and a way to combine static and dynamic analysis to analyse malware that is not yet classified.

REFERENCES

1. Zheng Y, Pal A, Abuadbba S, Pokhrel SR, Nepal S, Janicke H (2020) Towards IoT security automation and orchestration, 2020 Second IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA), Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA), TPS-ISA 55–63. https://doi.org/10.1109/TPSISA50397.2020.00018

2. Shahin M, Chen FF, Bouzary H, Krishnaiyer K (2020) Integration of Lean practices and Industry 4.0 technologies: smart manufacturing for next-generation enterprises. Int J Adv Manuf Technol 107(5):2927–2936. ttps://doi.org/10.1007/s00170-020-05124-0

3. Baumann D, Mager F, Wetzker U, Thiele L, Zimmerling M, Trimpe S (2021) Wireless control for smart manufacturing: recent approaches and open challenges. Proc IEEE

109(4):441– 467. https://doi.org/10.1109/JPROC.2020.3032633

4. Donnal J, McDowell R, Kutzer M (2020) Decentralized IoT with Wattsworth. 2020 IEEE 6th World Forum on Internet of Things (WFIoT), Internet of Things (WF-IoT), 2020 IEEE 6th World Forum on 1–6. https://doi.org/10.1109/WF-IoT48130.2020.9221350

5. Sungwon LEE, Hyeonkyu JEON, Gihyun PARK, Jonghee YOUN (2021) Design of automation environment for analyzing various IoT malware. Tehnicki vjesnik / Technical Gazette 28(4):827–835. https://doi.org/10.17559/TV-20210202131602

6. Elhabashy AE, Wells LJ, Camelio JA, Woodall WH (2019) A cyber-physical attack taxonomy for production systems: a quality control perspective. J Intell Manuf 30(6):2489–2504. https://doi. org/10.1007/s10845-018-1408-9

7. Elhabashy AE, Wells LJ, Camelio JA, Woodall WH (2019) A cyber-physical attack taxonomy for production systems: a quality control perspective. J Intell Manuf 30(6):2489–2504. https://doi. org/10.1007/s10845-018-1408-9

8. ICS Monitor Newsletters | CISA. https://www.us-cert.gov/ics/ monitors Accessed 20 Oct 2019.