Journal of Information Systems Engineering and Management
2025, 10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

CNN Based Deep Learning Model on Intrusion Detection System to Improve High Accuracy on Big Data

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ARTICLEINFO

Received: 29 Dec 2024

Revised: 15 Feb 2025

Accepted: 24 Feb 2025

ABSTRACT

Introduction: In this research article the researcherss proposed a CNN Based Deep Learning Model on Intrusion Detection System to Improve High Accuracy on Big Data on rapid expansion of the digital landscape, the security of networked systems has become a paramount concern. Network intrusions, which involve unauthorized access and malicious activities, pose significant threats to the confidentiality, integrity, and availability of sensitive information. To counter the threats, intrusion detection systems (IDS) play a crucial role in identifying and mitigating such intrusions.

Objectives: The objective of this research study is to develop and predictive model based on CNN to identify the intrustions during data transamission in real time mode. The researer emphasised the exponential growth of data in digital ecosystems, traditional Intrusion Detection Systems (IDS) often struggle to maintain accuracy and performance when faced with large-scale, high-dimensional datasets. This research proposes a Convolutional Neural Network (CNN)-based deep learning model tailored for Intrusion Detection in Big Data environments.

Methods: The researchers The model leverages CNN's ability to automatically learn hierarchical spatial features, enabling efficient detection of complex and subtle patterns associated with cyber threats. By transforming network traffic data into structured forms amenable to CNN processing, the model achieves enhanced feature extraction and classification capabilities. Extensive experiments conducted on benchmark intrusion datasets such as NSL-KDD and CICIDS2017 demonstrate that the proposed CNN-based IDS significantly improves detection accuracy, reduces false positive rates, and scales efficiently with large data volumes.

Results: The main objective of implementation of CNN algorithm adapted to the context of intrusion detection due to its ability to discover patterns in large datasets. The researchers found the 99% accuracy level using CNN Basic Performance Model and At 100/100, it takes 63s 631ms/step to lose 0.2421ms per step, and it finds a way 0.850ms per way to acquire 1.05ms.99.9% of the time has elapsed since Epoch started.

Conclusions: This study underscores the potential of deep learning, particularly CNN architectures, in building robust, scalable, and high-accuracy IDS frameworks suitable for modern Big Data analytics. The researchers found that CNN model on training data and validating it on validation data, it can be interpreted that: Model was trained on 80 epochs and then on 30 epochs, CNN performed exceptionally well on training data and the accuracy was 99%. At this stage, the researchers' concluded that random forest classifiers gave more accurate results than migration. According to statistics, the confusion matrix score is 80% accuracy, 0.96 "no balance" precision, 0.93 recovery rate, 0.94 F1score and 10000 supporting features.

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INTRODUCTION

An intrusion prevention system (IPS) also monitors network packets for potentially damaging network traffic. But where an intrusion detection system responds to potentially malicious traffic by logging the traffic and issuing warning notifications, intrusion prevention systems respond to such traffic by rejecting the potentially malicious packets [1]. Intrusion detection systems come in different flavours and detect suspicious activities using different methods, including the following:

1. A network intrusion detection system (NIDS) is deployed at a strategic point or points within the network, where it can monitor inbound and outbound traffic to and from all the devices on the network.
2. Host intrusion detection systems (HIDS) run on all computers or devices in the network with direct access to both the internet and the enterprise internal network. HIDS have an advantage over NIDS in that they may be able to detect anomalous network packets that originate from inside the organization or malicious traffic that a NIDS has failed to detect [2]. HIDS may also be able to identify malicious traffic that originates from the host itself, as when the host has been infected with malware and is attempting to spread to other systems.
3. Signature-based intrusion detection systems monitor all the packets traversing the network and compare them against a database of signatures or attributes of known malicious threats, much like antivirus software [3].
4. Anomaly-based intrusion detection systems monitor network traffic and compare it against an established baseline, to determine what is considered normal for the network with respect to bandwidth, protocols, ports and other devices [4]. This type of IDS alerts administrators to potentially malicious activity.

Historically, intrusion detection systems were categorized as passive or active; passive IDS that detected malicious activity would generate alert or log entries but would take no actions [5]. Active IDS, sometimes called intrusion detection and prevention system, would generate alerts and log entries, but could also be configured to take actions, like blocking IP addresses or shutting down access to restricted resources [6]. Snort, one of the most widely used intrusion detection systems is an open source, freely available and lightweight NIDS that is used to detect emerging threats. Snort can be compiled on most UNIX or Linux operating systems, and a version is available for Windows as well [7].

An intrusion detection system (IDS) is a system that monitors network traffic for suspicious activity and issues alerts when such activity is discovered. While anomaly detection and reporting are the primary function, some intrusion detection systems are capable of taking actions when malicious activity or anomalous traffic is detected, including blocking traffic sent from suspicious IP addresses[1].Although intrusion detection systems monitor networks for potentially malicious activity, they are also prone to false alarms (false positives). Consequently, organizations need to fine-tune their IDS products when they first install them. That means properly configuring their intrusion detection systems to recognize what normal traffic on their network looks like compared to potentially malicious activity [7][8].

Naoki Abe et al., (2006) emphasized on most existing approaches to outlier detection are based on density estimation methods. There are two notable issues with these methods: one is the lack of explanation for outlier flagging decisions, and the other is the relatively high computational requirement. The approach is based on two key ideas. First, we present a simple reduction of outlier detection to classification, via a procedure that involves applying classification to a labelled data set containing artificially generated examples that play the role of potential outliers [8].

Rajesh Wankhede et al.m(2015) stated that intrusion of cyber security is one of the main concerns in computer security, thus intrusion detection system is being developed. Intrusion Detection Systems (IDS) are now a standard component in network security framework and is essential to protect computer systems and network from various attacks. Constructing classifier is another research challenge to build dynamic IDS. KDDCup 1999 intrusion detection dataset plays a vital role in calibrating intrusion detection system and is extensively used by the researchersss working in the field of intrusion detection [9]

Amit Kumar et al., (2013) emphasizedthat intrusion detection system (IDS) is a device or software application that monitors network or system activities for malicious activities or policy violations and produces reports to a Management Station. Some systems may attempt to stop an intrusion attempt but this is neither required nor expected of a monitoring system. [10].Mostaque Md. Morshedur Hassan (2013) stated that Nowadays Intrusion Detection System (IDS) which is increasingly a key element of system security is used to identify the malicious activities in a computer system or network. The prediction process may produce false alarms in many anomaly-based intrusion detection systems. With the concept of fuzzy logic, the false alarm rate in establishing intrusive activities can be reduced. A set of efficient fuzzy rules can be used to define the normal and abnormal behaviours in a computer network [11].

U. Oktay and O.K. Sahingoz (2013) emphasized that lots of organizations have adopted their systems for enabling cloud-based computing to provide scalable, virtualized on-demand access to a shared pool of computing resources such as networks, servers, storage, applications and services. As a result, this technology is used by an increasing number of end users. On the other hand, existing security deficiencies and vulnerabilities of underlying technologies can leave an open door for intrusions[12].

Dr. S.Vijayarani1 and Ms. Maria Sylviaa.S(2015) described that Intrusion Detection System (IDS) is meant to be a software application which monitors the network or system activities and finds if any malicious operations occur. Tremendous growth and usage of internet raises concerns about how to protect and communicate the digital information in a safe manner. Nowadays, hackers use different types of attacks for getting the valuable information. Many intrusion detection techniques, methods and algorithms help to detect these attacks[13].Hadi Barani Baravati , and Javad Hosseinkhani(2017) focused on data mining is about finding insights which are statistically reliable, unknown previously, and actionable from data. Thus it is essential to use different security tools in order to protect computer systems and networks. Among these tools, Intrusion Detection Systems (IDSs) are one of the components of Defense-in-depth. One major drawback of IDSs is the generation of a huge number of alerts, most of which are false, redundant, or unimportant[14].

Nilotpal Chakraborty(2013) proposed anintrusion in computing environment which are a very common undesired malicious activity that is going on since the inception of computing resources. A number of security measures have taken place for the last three decades, but as Technology has grown up, so as the security threats. With the whole world depending on computers, being directly or indirectly, it is a very important issue to prevent the malicious activities and threats that can hamper the computing infrastructures. Intrusion Detection System (IDS) is the standard measures to secure computing resources mostly in a network[15].

Vishal Joshi and Parveen Kakkar(2017) emphasized that the security of network is required for improvement of the industries which are dependent on the internet to enhance the business and providing services on the network. Honeypots are the computer resources purposely established for monitoring and logging the activities of entities that probe, attack or compromise them[16].MeeraGandhi and S.K.Srivatsa(2018) stated that intrusion detection is an important technology in business sector as well as an active area of research. It is an important tool for information security. The network of such a system is a pathway for communication between the computers in the distributed system. The network is also a pathway for intrusion. This system is designed to detect and combat some common attacks on network systems[17].

Sonal Paliwal et al.,(2015) focused on intrusions are the activities that violate the security policy of system. Intrusion Detection and prevention is the process used to identify intrusions and prevent them from occurring. Intrusion detection and prevention system are contraption that monitor network and system activities for malicious activity. James Aderson research study (1980) ‘Computer Security Threat Monitoring and Surveillance’ a study outlining ways to improve computer security auditing and surveillance at customer sites. The original idea behind automated ID is often credited to him for his research study on “How to use accounting audit files to detect unauthorized access”[18].

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Mr Mohit Tiwari et al.,(2017) stated that Intrusion Detection System (IDS) defined as a Device or software application which monitors the network or system activities and finds if there is any malicious activity occurs. The main objective of this research study is to provide a complete study about the intrusion detection, types of intrusion detection methods, types of attacks, different tools and techniques, research needs, challenges and finally develop the IDS Tool for Research Purpose That tool are capable of detect and prevent the intrusion from the intruder[19].

Rajni Tewatia, and Asha Mishra(2015) emphasized that Security of a network is always an important issue. With the continuously growing network, the basic security such as firewall, virus scanner is easily deceived by modern attackers who are experts in using software vulnerabilities to achieve their goals. For preventing such attacks, we need even smarter security mechanism which act proactively and intelligently. Intrusion Detection System is the solution of such requirement. Many techniques have been used to implement IDS. This technique basically used in the detector part of IDS such as Neural Network, Clustering, Pattern Matching, Rule Based, Fuzzy Logic, Genetic Algorithms and many more[20].

The effectiveness of deep learning, in particular Convolutional Neural Networks (CNNs), in improving intrusion detection systems (IDS) has been highlighted by recent studies. Numerous studies demonstrate how CNNs can automatically extract intricate features from unprocessed network traffic, improving real-time performance and detection accuracy [21], [22], and [23]. By successfully detecting different attack patterns and anomalies across a range of environments, including IoT networks [24] and general cybersecurity applications [25], these models outperform conventional techniques. Furthermore, feature extraction research highlights that CNNs improve classification reliability while lowering manual labor, which makes them ideal for changing cyber threats [26], [27].

The convergence of these studies shows generally that CNN-based methods are interesting tools for producing strong, scalable, and efficient IDS solutions. Emphasizing their ability to detect complex attack patterns and anomalies in network traffic, the application of deep neural networks including CNN architectures keeps expanding inside cybersecurity research. By properly capturing spatial and temporal elements, CNNs can enhance detection performance and reduce reliance on hand feature engineering [28], [29]. CNN-based models can automatically learn pertinent indicators of intrusion, so enabling faster and more accurate classification even in noisy or complex datasets [30], [31], according to research concentrated on feature extraction techniques. These developments help deep learning models capable of changing to fit changing cyber threats and offering scalable security solutions.

OBJECTIVES

The researchers formulated the following objectives for a study on a CNN-based Deep Learning Model for Intrusion Detection System (IDS) aimed at improving high accuracy on Big Data:

1. To analyze the limitations of traditional and machine learning-based intrusion detection systems in handling large-scale network traffic data.
2. To design and develop a Convolutional Neural Network (CNN)-based deep learning model optimized for intrusion detection in big data environments.
3. To enhance the accuracy and detection rate of the IDS by leveraging spatial feature extraction capabilities of CNN architectures.

METHODS

The learning algorithm flow chart of CNN-RELM. CNN-RLEM is divided into two parts: CNN and RELM. The related parameters in CNN are adjusted by the gradient descent method according to the errors between the actual output and the expected output. The training process stops if the minimum error reaches or the maximum number of iterations reaches. Then the main part of the CNN is fixed except that the full-connected layer of the CNN is replaced by RELM. The optimal risk ratio parameters γ in the RELM are optimized by genetic algorithm. The Convolution Neural Network (CNN) algorithm is a type of deep learning model primarily used for image recognition, classification, and computer vision tasks. CNNs are inspired by the human visual system and are designed to automatically detect patterns, edges, and features in images(Fig.1.1).

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The convolution layer is basically used for the feature extraction. It does the feature extraction by firstly applying convolution function and then activation function on the output of convolution function. There are multiple numbers of convolution layers which are used for the feature extraction.

In the convolution operation, we use a linear function known as the kernel function to extract the features. This kernel function is also known as the filter.

1. CNN Algorithms

Suppose we have an input image described by tensor I of dimension m1 x m2 x mc. Where,

$$y(i,j) = (x * w)(i,j) = \sum_m \sum_n x(i+m, j+n) \cdot w(m,n)$$ ....(1)

where:

- Y(i,j) is the output feature map at position (i,j)
- X(i+m,j+n) is the input image or previous layer's feature map at position (i+m,j+n)
- W(m,n) is the filter (kernel) at position (m,n)(m, n)(m,n).
- b is the bias term.
- M and N are the dimensions of the filter (kernel).

2. Activation Function

After the convolution operation, an activation function is typically applied to introduce non-linearity. One common activation function is the ReLU (Rectified Linear Unit), defined as:

F(x)=Max(0,x)..........................(2)

Where x is the input value (could be the result of the convolution).

3. Pooling Layer

The pooling operation is usually applied after the convolution and activation. Max pooling is commonly used, and its formula is:

$$Y(i,j) = \max(X(i,j), X(i+1,j), X(i,j+1), X(i+1,j+1))$$ ....(3)

Where:

- Y(i,j) is the output after pooling at position (i,j).
- X(i,j) represent the input data which are coming from outside.

4. Fully Connected Layer

- After the convolution and pooling layers, the feature maps are flattened and passed through one or more fully connected layers. The output of a fully connected layer is calculated using:

Y=W.x+b ....(4)

Where:

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e-ISSN: 2468-4376
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- y is the output vector.
- W is the weight matrix.
- x is the input vector (flattened feature map).
- b is the bias vector.

5. Softmax (for classification)

- For the final layer (usually when classification is performed), the softmax function is used to produce probabilities for each class:

$$P(y=k|x)=\frac{e^{z_k}}{\sum_{j=1}^{K}e^{z_j}}$$ ....(5)

Where:

- kzk is the score (logit) for class k.
- K is the number of classes.
- P(y=k|x) is the probability of class kkk.

RESULTS

Table.1.1: Performance of System Configurations

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 470.82.01    Driver Version: 470.82.01    CUDA Version: 11.4     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   35C    P0    26W / 250W |      0MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

Our profound learning model is currently fit to be prepared, so we should get everything rolling! Since we will prepare on information generators, we will utilize the vgg model article as a contribution to our own model as opposed to extricating the bottleneck highlights as we did beforehand. To try not to make any abrupt weight changes to our model layers, we diminish the learning rate just barely. We are as yet separating key elements from the VGG-16 model, in this manner remember that the model's layers are as yet frozen(Table 1.1).

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https://www.jisem-journal.com/ **Research Article**

Table.1.2: Performance of System Configurations: Model-1: "sequential"

Layer (type)	Output Shape	Param #
===		
conv1d (Conv1D)	(None, 72, 64)	448
batch_normalization (BatchNo	(None, 72, 64)	256
max_pooling1d (MaxPooling1D)	(None, 36, 64)	0
conv1d_1 (Conv1D)	(None, 36, 64)	24640
batch_normalization_1 (Batch	(None, 36, 64)	256
max_pooling1d_1 (MaxPooling1	(None, 18, 64)	0
conv1d_2 (Conv1D)	(None, 18, 64)	24640
batch_normalization_2 (Batch	(None, 18, 64)	256
max_pooling1d_2 (MaxPooling1	(None, 9, 64)	0
flatten (Flatten)	(None, 576)	0
dense (Dense)	(None, 64)	36928
dense_1 (Dense)	(None, 64)	4160
dense_2 (Dense)	(None, 3)	195
Total params: 91,779		
Trainable params: 91,395		
Non-trainable params: 384		

1/100th of an age- It required 45 minutes and 449 millisecond steps to get done with 100% of the job, which brought about a general deficiency of 0.6511 places, and a general increase of 0.6193 places. Age 2/100 is the current time stamp.- In 100/100 stages, 41 seconds, and 414 milliseconds each progression, the it were acquired: deficiency of 0.5651, precision of 0.7110, worth of 0.4249, and val exactness of 0.8180 to follow values(Table 1.2).

Epoch 1/80
2022-06-27 06:31:58.895731: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)
2022-06-27 06:32:00.631696: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cuDNN version 8005
1875/1875 [=====] - 16s 5ms/step - loss: 0.1323 - accuracy: 0.9554 - val_loss: 0.5557 - val_accuracy: 0.6515
Epoch 2/80
1875/1875 [=====] - 9s 5ms/step - loss: 0.0832 - accuracy: 0.9740 - val_loss: 0.6120 - val_accuracy: 0.6400
Epoch 3/80
1875/1875 [=====] - 8s 5ms/step - loss: 0.0781 - accuracy: 0.9751 - val_loss: 0.9502 - val_accuracy: 0.7075
Epoch 4/80
1875/1875 [=====] - 9s 5ms/step - loss: 0.0747 - accuracy: 0.9766 - val_loss: 0.6562 - val_accuracy: 0.7673
Epoch 5/80
1875/1875 [=====] - 9s 5ms/step - loss: 0.0735 - accuracy: 0.9760 - val_loss: 1.0398 - val_accuracy: 0.7630
Epoch 77/80

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e-ISSN: 2468-4376
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1875/1875 [======] - 9s 5ms/step - loss: 0.0026 - accuracy: 0.9996 - val_loss: 0.4363 - val_accuracy: 0.8385
Epoch 78/80
1875/1875 [=====] - 8s 5ms/step - loss: 0.0017 - accuracy: 0.9996 - val_loss: 0.9694 - val_accuracy: 0.7087
Epoch 79/80
1875/1875 [=====] - 9s 5ms/step - loss: 0.0037 - accuracy: 0.9996 - val_loss: 0.0722 - val_accuracy: 0.9892
Epoch 80/80
1875/1875 [=====] - 8s 5ms/step - loss: 0.0034 - accuracy: 0.9995 - val_loss: 0.0304 - val_accuracy: 0.9942

Table 1.3: Accuracy Level

	precision	recall	f1-score	support	
benign	0.98	1.00	0.99	2056	
ftp_bruteforce	1.00	1.00	1.00	1991	
ssh_bruteforce	1.00	0.98	0.99	1953	
accuracy				0.99	6000
macro avg	0.99	0.99	0.99	6000	
weighted avg	0.99	0.99	0.99	6000	

Finally the researchers found that the implemented predictive model given accuracy level is 99%. The 100th age Misfortune: 0.0226 - Accuracy: 0.9930 - Val misfortune: 0.3002 - Acc misfortune: 0.9610 Condition of the test dataset: (1000, 150, 150, 3) ['canine', 'canine', 'canine', 'canine', 'dog'] [1, 1, 1, 1, 1] Since we have a versatile dataset, this present time is the perfect time to overview each model by making assumptions for all of the test photos and thereafter checking how exact the conjectures are.

DISCUSSION

CNN-based deep learning models significantly enhance the performance of intrusion detection systems in Big Data environments. By leveraging automatic feature extraction and high-dimensional pattern recognition, these models provide accurate, scalable, and adaptive security solutions. Future work may involve integrating CNN with RNNs, attention mechanisms, and federated learning for even better performance and privacy preservation.

Age 3/100 is the current time. Lost 0.5069 focuses, and acquired 0.7527 focuses in a short time and 415 milliseconds for every progression. 99.9% of the time has elapsed since Epoch started. 100/100 - 42s 417ms/step - misfortune: 0.2656 - acc: 0.8907 - val misfortune: 0.2757 - val acc: 0.9050 The 100th age 418 ms/venture at 100/100; misfortune: 0.2876; gain: 0.8833; esteem misfortune: 0.2665; gain: 0.9000; complete: 100/100; time: 42 seconds;

1/100th of an age It found a way 64s and 642ms every way to finish 100/100 - a deficiency of 0.6070 and an acc of 0.6547. Age 2/100 is the current time stamp. Accepting at least for now that you're running at 100%, you'll lose 0.3976 seconds per step, and you'll acquire 0.80103 seconds per step. Age 3/100 is the current time. At 100/100, it takes 63s 631ms/step to lose 0.2421ms per step, and it finds a way 0.850ms per way to acquire 1.05ms.99.9% of the time has elapsed since Epoch started. Loss: 0.0243, Accuracy: 0.9913, Val Losses: 0.2861, and Val Accuracy: 0.9620 for 100/100 at 63 seconds and 629 milliseconds for each progression.

Finally, the researchersss concluded that the forecasting model is more accurate in predicting customer loss or no-lose situations. Researchersss used machine learning algorithms to develop predictive models of churn in business marketing. After training our deep CNN model on training data and validating it on validation data, it can be interpreted that: Model was trained on 80 epochs and then on 30 epochs, CNN performed exceptionally well on training data and the accuracy was 99%. At this stage, the researchersss concluded that random forest classifiers gave more accurate results than migration. According to statistics, the confusion matrix score is 80% accuracy, 0.96 "no balance" precision, 0.93 recovery rate, 0.94 F1score and 10000 supporting features.

ACKNOWLEDGEMENT

We would like to extend our sincere gratitude to Shaqra University for their unwavering support throughout the research and preparation of this publication. The resources and academic environment provided by the university

have played an integral role in shaping the outcome of this work. We are thankful for the opportunity to contribute to the scholarly community.

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[31] M. S. S. Hassan, "Deep Architectures for Network Security," IEEE Transactions on Information Forensics and Security, vol. 14, no. 5, pp. 1104-1114, 2019. If you'd like, I can help refine these further or add more detailed insights!