

PROFESSIONAL TRAINING REPORT - II

entitled

DEVELOP A NETWORK INTRUSION DETECTION SYSTEM USING NEURAL NETWORKS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
specialization in Cyber Security

by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

CATEGORY -1 UNIVERSITY BY UGC

**Accredited with Grade "A++" by NAAC | 12B Status by UGC | Approved by AICTE
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MAY 2024



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BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Ms. Mahalakshmi. S (41614054), Ms. Barathi. K (41614010), Mr. Kusumanchi Abhinav Gupta (41614051), Mr. Makkena Balagopal Chowdary (41614055)** who carried out the project entitled **"DEVELOP A NETWORK INTRUSION DETECTION SYSTEM USING NEURAL NETWORKS"** under my supervision from January 2024 to May 2024.

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I, **MAHALAKSHMI.S (41614054)**, hereby declare that the Professional Training Report-II entitled **“DEVELOP A NETWORK INTRUSION DETECTION SYSTEM USING NEURAL NETWORKS”** done by me under the guidance of **Dr.VEENA.K,M.E.,Ph.D.**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Cyber Security.

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ABSTRACT

With the growth of network activities and data sharing, there is also increased risk of threats and malicious attacks. Network intrusion detection system (NIDS) refers to the process of detecting and preventing abnormal or suspicious activities over a given network. Different machine learning techniques have immense use in detecting dubious activities compromising the integrity, security, and confidentiality of the data. This paper introduces a pioneering approach to intrusion detection that leverages neural networks to monitor and identify unusual user activity. By employing a neural network, we aim to learn and characterize the individualized user behaviour and attack features, allowing for the identification of anomalies that may signify security breaches. Neural networks have already been used to solve many problems related to pattern recognition, data mining, data compression and research is still underway with regards to intrusion detection systems. Intrusion detection systems may be broadly classified as belonging to either misuse detection or anomaly detection. Misuse detection formulates a model from the known attacks, whereas anomaly detection searches for behavior that deviates from the normal patterns . Our proposed Neural Network Intrusion Detector (NNID) utilizes backpropagation neural networks trained to recognize the individual user behaviours for detecting the labelled attack. A backpropagation neural network called NNID (Neural Network Intrusion Detector) was trained in the identification task and tested experimentally . The system was 96% accurate in detecting unusual activity, with 7% false alarm rate. By harnessing the power of neural networks, our approach offers a robust and efficient solution for bolstering system security in the face of evolving threats. In this paper, the proposed system to detect network intrusion packets by using Neural Network for its relevance and efficiency, this algorithm gives suitable weight for all features in the input layer and used these weights in decision making.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The past few years have witnessed remarkable increase in the usage of advance computer networks, applications and sharing data . This led to the increase in unauthorized and malicious cyber-attacks. Cyber-attacks are more advanced, cagey, and targeted than ever before. Thus, security techniques must be continuously developed. Network intrusion detection system (NIDS) refers to the process of detecting and preventing abnormal or suspicious activities over a given network. Different machine learning techniques have immense use in detecting dubious activities compromising the integrity, security, and confidentiality of the data. Therefore, the role of Network Intrusion Detection Systems (NIDS), as special purpose devices to detect anomalies and attacks in the network, has become more and more important. A network intrusion detection system (NIDS) plays an important role in network security, where it detects the intrusions and communicates the appropriate authority. According to detection techniques, there are two kinds of IDS that we can classify: Anomaly detection and Misuse detection. one of the most important information security technologies is an Intrusion Detection System (IDS) that uses machine learning and deep learning techniques to detect anomalies in the network. The main idea of this project is to use an advanced intrusion detection system with high network performance to detect the unknown attack package, by using a deep neural network algorithm, also in this model, the attack detection is done by two ways (binary classification and multiclass classification). Anomaly Detection makes a normal activity database and any deviations from the normal activity are alerted that intrusion is possible in the network Whereas Misuse Detection defines the attacks activity in the database and If there are the same kind of possibilities in the network then they are defined as attacks . An anomaly IDS seeks deviations from the learned model of normal behaviour. The system assumes very little about the features of the future intrusion instances. It builds a representative model exclusively based on the previously collected normal behaviour. The system is capable of detecting novel and dynamically changing intrusion instances, when these are distinctively different from the model of normal behaviour. Unfortunately, any normal acceptable behaviour not

included in the training set will not match the model and will generate a false positive. The anomaly intrusion detection approach is adopted in this work. KDDCUP'99 dataset is widely used as one of the few publicly available data sets for network-based anomaly detection systems. It has been used as the main intrusion detection dataset for both training and testing different Intrusion Detection schemes. A specific combination of two neural network learning algorithms, the Error Back-Propagation and the Levenberg-Marquardt algorithm, is used to train an artificial neural network to model the boundaries of the clusters of recorded normal behaviour. It is shown that the training dataset, consisting of a combination of recorded normal instances and artificially generated intrusion instances, successfully guides the neural network towards learning the complex and irregular cluster boundary in a multidimensional space. The performance of the system is tested on unseen network data containing various intrusion attacks. This project uses the standard NSL_KDD dataset to validate the performance of twoneural network-based classifiers via multi-layer perceptron and radial basis function. NSL_KDD is a popular network intrusion detection dataset used to validate differentnetwork intrusion detection systems. It is actually a more refined version of the KDDCup 1999 intrusion dataset. One of the issues with the KDD Cup dataset is presence ofhuge amount of redundant records leading to the learning algorithm to become biasedtoward most frequent instances. In NSL_KDD, such redundant records are eliminated giving equal importance to minority classes as well. The NSL_KDD dataset contains separate files for training data and test data. Intrusions are quite a frequent scare especially with the exponential growth in improvement of technology. This project aims to detect such intrusions using certain algorithms in the domain of machine learning. Machine learning techniques are being widely used to develop an intrusion detection system (IDS) for detecting and classifying cyberattacks at the network-level and the host-level in a timely and automatic manner. Since there are many different types of intrusions happening on a large scale dynamically, this can be quite challenging. However, with the help of datasets and with constant updating, one can detect such intrusions. The one algorithm that stands out is the DNN (Deep Neural Network), which is a type of deep learning model, which helps to develop a flexible and effective Intrusion Detection System (IDS) to detect and classify unforeseen and unpredictable cyberattacks. Among the arsenal of cybersecurity tools, Network Intrusion Detection Systems (NIDS) play a crucial role in identifying and thwarting various forms of network attacks.Traditional NIDS solutions often rely on

handcrafted rules and signatures to detect known attacks, leaving them vulnerable to zero-day exploits and sophisticated evasion techniques. In contrast, the advent of machine learning, particularly neural networks, offers a promising avenue for building more robust and adaptive NIDS capable of learning complex patterns and behaviors inherent in network traffic data. In this project, we present a comprehensive approach to building a NIDS using neural networks, leveraging the power of deep learning to enhance the detection capabilities and resilience against evolving cyber threats. We delve into the key components of our proposed system, including data collection, preprocessing, feature engineering, model selection, training, evaluation, deployment, and ongoing monitoring. Furthermore, we discuss the challenges and considerations involved in designing an effective neural network-based NIDS, such as data privacy, model interpretability, scalability, and real-time performance. By addressing these challenges and leveraging the latest advancements in neural network architectures and training techniques, our goal is to contribute to the development of robust and adaptive NIDS capable of defending against the ever-evolving landscape of cyber threats possible by neural networks. Our project gives the details about the methodology and architecture of our proposed NIDS, including data preprocessing, model selection, and evaluation metrics. It presents experimental results demonstrating the effectiveness of our approach on benchmark datasets. It is shown that the training dataset, consisting of a combination of recorded normal instances and artificially generated intrusion instances, successfully guides the neural network towards learning the complex and irregular cluster boundary in a multidimensional space. The performance of the system is tested on unseen network data containing various intrusion attacks.

CHAPTER 2

LITERATURE REVIEW

2.1 SURVEY

Designing an IDS for mobile network teaching offers hands-on learning and critical thinking. It utilizes anomaly detection and machine learning for practical security knowledge. Challenges include updating for new threats and avoiding disruptions, but benefits prepare students for real-world cybersecurity [1].

The Dugat-LSTM system utilizes deep learning and chaotic optimization for accurate intrusion detection. It leverages LSTM networks and chaotic optimization techniques efficiently, despite challenges in training complexity and resource requirements. Overall, it offers robust detection capabilities, making it a promising approach for network security [2].

A data-driven IDS employing feature selection and deep learning improves accuracy in intrusion detection and adapts to evolving threats. It selects relevant features to enhance model performance and employs deep learning for efficient pattern recognition. Challenges include the need for large labeled data, computational complexity, and vulnerability to adversarial attacks. Still, its effectiveness against sophisticated intrusion attempts makes it valuable for network security [3].

Using deep learning-powered IDS enhances IoT security with improved accuracy and adaptability. Leveraging deep learning for pattern recognition enables effective identification of malicious activities, despite challenges such as data labelling, computational resources, and adversarial attacks. Nonetheless, its ability to quickly identify and mitigate threats makes it invaluable for safeguarding connected devices and networks [4].

A Blockchain-enabled intrusion detection model leveraging deep learning offers decentralized and immutable record-keeping, enhancing intrusion event integrity. Integrating deep learning for pattern recognition and Blockchain for secure storage ensures transparency. Challenges include Blockchain overhead, scalability, and potential latency. Nonetheless, the combined approach enhances security by effectively detecting and mitigating security attacks [5].

Deep learning enables adaptive IDS, reducing compromise risk, yet faces challenges such as resource needs and vulnerability to attacks. Methodology involves utilizing deep neural networks for flexible IDS, detecting evolving threats using real-world datasets like UNSW-NB15 [6].

Deep learning for cyber threat detection in IoT networks offers enhanced accuracy and adaptability, leveraging large datasets to learn malicious activity patterns. Challenges include resource demands, vulnerabilities to attacks, and the need for labelled data. Nonetheless, it holds promise in bolstering IoT network security by swiftly detecting and mitigating threats [7].

Anomaly employs GNNs for self-supervised intrusion detection, utilizing edge features and graph structure to enhance accuracy. Challenges include GNN complexity, scalability limits, and high computational demands. Despite these, Anomaly learns graph representations of network flows, showing promise for real-world intrusion detection [8].

distributed IDS in a blockchain-enabled IoT network offers decentralized monitoring and security via tamper-resistant record-keeping. Methodologies deploy IDS nodes to detect DDoS anomalies, utilizing blockchain for secure data sharing. Challenges include network overhead, consensus mechanisms, and risks of false detections, yet the system provides robust defense against DDoS attacks through combined IDS and blockchain strengths [9].

Using ensemble-based machine learning for intrusion detection ensures improved accuracy and resilience against cyber threats. While advantageous in adapting to evolving attacks and handling complex data, challenges include computational complexity and data preprocessing needs. Methodologies involve careful selection and tuning of ensemble algorithms, feature engineering, and monitoring ensemble performance for effective real-world security [10].

Federated Learning in intrusion detection systems balances data privacy and resource utilization, but grapples with communication overhead and data heterogeneity. Methodologies prioritize efficient algorithm development, security assurance, and addressing non-IID data distributions [11].

Unsupervised IDS for in-vehicle communication networks provides adaptability and real-time monitoring but faces challenges of high false positives and difficulty in distinguishing anomalies. Methodologies employ clustering or autoencoders for anomaly detection, yet further research is needed to improve accuracy and efficiency, especially in dynamic environments like in-vehicle networks [12].

SPIDER model integrates updated RNN variants with PCA for improved intrusion detection on NSL-KDD and UNSW-NB15 datasets. Challenges include complexity in implementing and tuning multiple RNNs and computational resource requirements. Methodologically, SPIDER combines Bi-LSTM, LSTM, Bi-GRU, and GRU variants, utilizing PCA for dimensionality reduction and evaluating against existing approaches [13].

The IDSGT-DNN framework integrates game theory and deep neural networks to enhance cloud security, improving accuracy, detection rate, and precision while addressing various attack environments. Challenges include implementing complex models in the cloud and potential resource requirements. Methodologically, IDSGT-DNN employs game theory and DNN with an attacker-defender mechanism, incorporating IWA for optimal solution identification and outperforming existing techniques on the CICIDS-2017 dataset in terms of multiple performance metric [14].

The study implements a Deep Neural Network for intrusion detection, addressing data imbalance using SMOTE and Random Sampling on the CICIDS 2017 dataset. Conducted on Google Collaboratory, it achieves high accuracy (99.68%) and low loss (0.0102) with relevant software libraries, showcasing deep learning's effectiveness in attack prediction. Challenges include the need for improved model performance and computational resources [15].

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

- **Reduced False Positives:** Minimize false positive alerts by fine-tuning neural network algorithms and optimizing detection thresholds, thereby reducing the burden on security analysts and preventing unnecessary investigations.
- **Real-time Detection:** Implement a NIDS capable of detecting intrusions in real-time, ensuring timely responses to potential threats as they occur.
- **Anomaly Detection:** Train neural networks to detect anomalous behavior within network traffic, allowing the system to identify novel threats or deviations from normal patterns.
- **Feature Extraction:** Develop neural network architectures capable of effectively extracting relevant features from network traffic data, enabling the system to distinguish between normal and malicious activities.
- **Traffic Monitoring:** Network-based IDSs typically monitor network packets for signs of reconnaissance, exploits, DoS attacks, and malware. They have strengths to complement host-based IDSs: Network-based IDSs can see traffic for a population of hosts; they can recognize patterns shared by multiple hosts; and they have the potential to see attacks before they reach the hosts.
- **Risk Mitigation:** Assist in the identification and mitigation of security risks within the network infrastructure, helping organizations to proactively protect their assets, data, and sensitive information from unauthorized access or manipulation.

3.2 REQUIREMENTS

- Windows Operating System
- Tensorflow
- Python installed on system
- Python and socket libraries
- Trained Dataset
- KDD Cup 1999 Dataset

3.2.1 HARDWARE REQUIREMENTS

- Computer with (intel core i5 or AMD Ryzen)
- RAM (Random Access Memory)
- CPU, GPU (Graphical Processing Unit)
- TPU (Tensor Processing Unit)
- Storage
- Network Interface Cards
- Operating system (includes Linux)

3.2.2 SOFTWARE REQUIREMENTS

- Operating System -Ubuntu, Cent OS, Debian
- Data Processing and Analysis Tools
- Deep learning frameworks-Keras, Tensorflow, Pytorch
- Packet Capture and Analysis Tools- Wireshark, Tcpdump
- System Monitoring and Management-Prometheus
- Real-Time Monitoring and Alerting-Elasticsearch, Grafana, Kibana
- Logging and Log Management -Syslog-ng, Fluentd
- Security Tools and Utilities -Snort
- Development Environment-Docker, Integrated Development Environment (IDE) such as PyCharm, Jupyter Notebook, or Visual Studio Code for code development and experimentation.
- Security and Compliance Tools- Encryption Libraries: OpenSSL, cryptography for implementing encryption and decryption algorithms to secure network traffic and sensitive data.
- Compliance Management Software: Tools for managing compliance with regulatory frameworks such as GDPR, HIPAA, and PCI-DSS.

Functional Requirements:

Traffic Monitoring:

The system should be capable of monitoring network traffic in real-time. It should support various network protocols such as TCP/IP, UDP, ICMP, etc.

Anomaly Detection:

Implement algorithms for detecting abnormal patterns and behaviors in network traffic. Identify deviations from normal network behavior that could indicate potential security threats.

Attack Classification:

Classify detected anomalies into different categories based on the type and severity of the attack. Provide meaningful labels or descriptions for each detected attack to aid in remediation efforts.

Alert Generation:

Generate timely alerts or notifications when suspicious activity or potential attacks are detected. Alerts should include relevant details such as the type of attack, source IP address, destination IP address, timestamp, etc. Support integration with existing incident response systems for automated or manual remediation actions.

Model Training and Updates:

Implement mechanisms for training and updating the neural network model using labeled training data. Support incremental learning to adapt to new attack patterns and evolving network behaviors over time.

CHAPTER 4

DESIGN DESCRIPTION OF PROPOSED PROJECT

4.1 PROPOSED METHODOLOGY

The proposed methodology for developing a Network Intrusion Detection System (NIDS) using neural networks involves several key steps. Firstly, a diverse dataset encompassing both normal and malicious network traffic is collected and preprocessed to remove noise and normalize features. Feature engineering follows, where relevant attributes like IP addresses, port numbers, and packet sizes are extracted. Next, an appropriate neural network architecture, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), is selected to capture spatial or sequential patterns in the data. Validation and testing phases evaluate the model's performance using metrics like accuracy, precision, and recall, ensuring its robustness.. A feedback loop is integrated to incorporate insights from detected intrusions and false alarms, refining the model's effectiveness over time. This comprehensive methodology aims to develop a resilient NIDS capable of accurately detecting network intrusions while minimizing false positives, thereby enhancing network security.. This encompasses identifying the types of intrusions to detect and specifying performance criteria like real-time detection and low false positive rates. Next comes the crucial phase of data collection and preprocessing. A diverse dataset comprising both normal and malicious network traffic is gathered and then refined through cleaning, filtering, and transformation to ready it for model training. Feature selection plays a pivotal role in distinguishing between benign and malicious activities. Various techniques such as correlation analysis and PCA help identify the most relevant features for effective detection. The choice of neural network architecture is equally critical and depends on the complexity of the intrusion detection task. Options range from traditional feedforward networks to more specialized architectures like convolutional or recurrent neural networks tailored to spatial or temporal data analysis, respectively. Once the architecture is selected, model training commences using the preprocessed dataset. This involves partitioning the data into training, validation, and test sets, followed by iterative training sessions where model parameters are optimized using techniques like gradient descent and adaptive learning rates.

4.1.1 Ideation Map/System Architecture

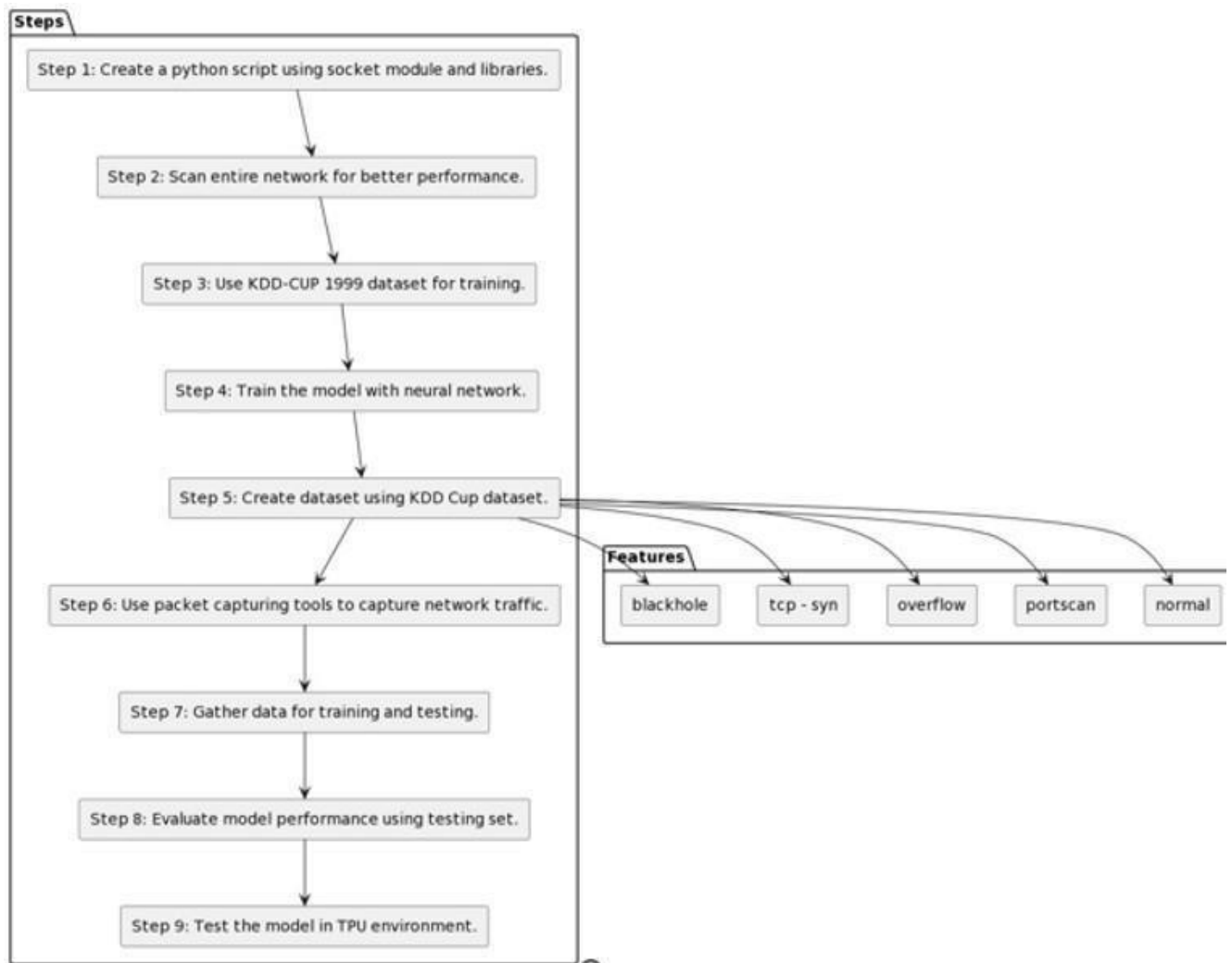


Fig 1 -Block diagram of NIDS Using neural networks



Fig 2 – Workflow of neural networks in NIDS

4.1.2 Various Stages

Packet Capture: In this initial stage, the NIDS captures packets traversing the network. This involves copying data packets from the network traffic for analysis.

Preprocessing: Once the packets are captured, they undergo preprocessing. During this stage, the packets may be normalized to ensure consistency in analysis. Normalization can involve tasks such as converting data to a common format or removing redundant information.

Traffic Analysis: This stage involves analyzing the traffic patterns and behavior to identify potential anomalies or threats. Statistical analysis, pattern recognition, and machine learning techniques may be employed to detect deviations from normal behavior.

Signature Detection: Signature-based detection involves comparing network traffic patterns against a database of known attack signatures. If a match is found, it indicates a potential intrusion.

Anomaly Detection: Anomaly-based detection involves identifying deviations from normal behavior that may indicate an intrusion. This can include unusual traffic patterns, unexpected network connections, or abnormal resource usage.

Alert Generation: When suspicious activity is detected, the NIDS generates alerts to notify system administrators or security personnel. Alerts may include details about the detected threat, such as the type of intrusion, the affected system, and the severity of the threat.

Response: In some cases, the NIDS may take automated actions to mitigate the threat, such as blocking traffic from a suspicious IP address or terminating a suspicious connection. Additionally, the NIDS may provide recommendations for manual intervention by security personnel.

Logging and Reporting: The NIDS logs all detected events and activities for further analysis and reporting. This information is valuable for understanding the nature of attacks, identifying trends, and improving the overall security posture of the network.

4.1.3 Internal or Component design structure

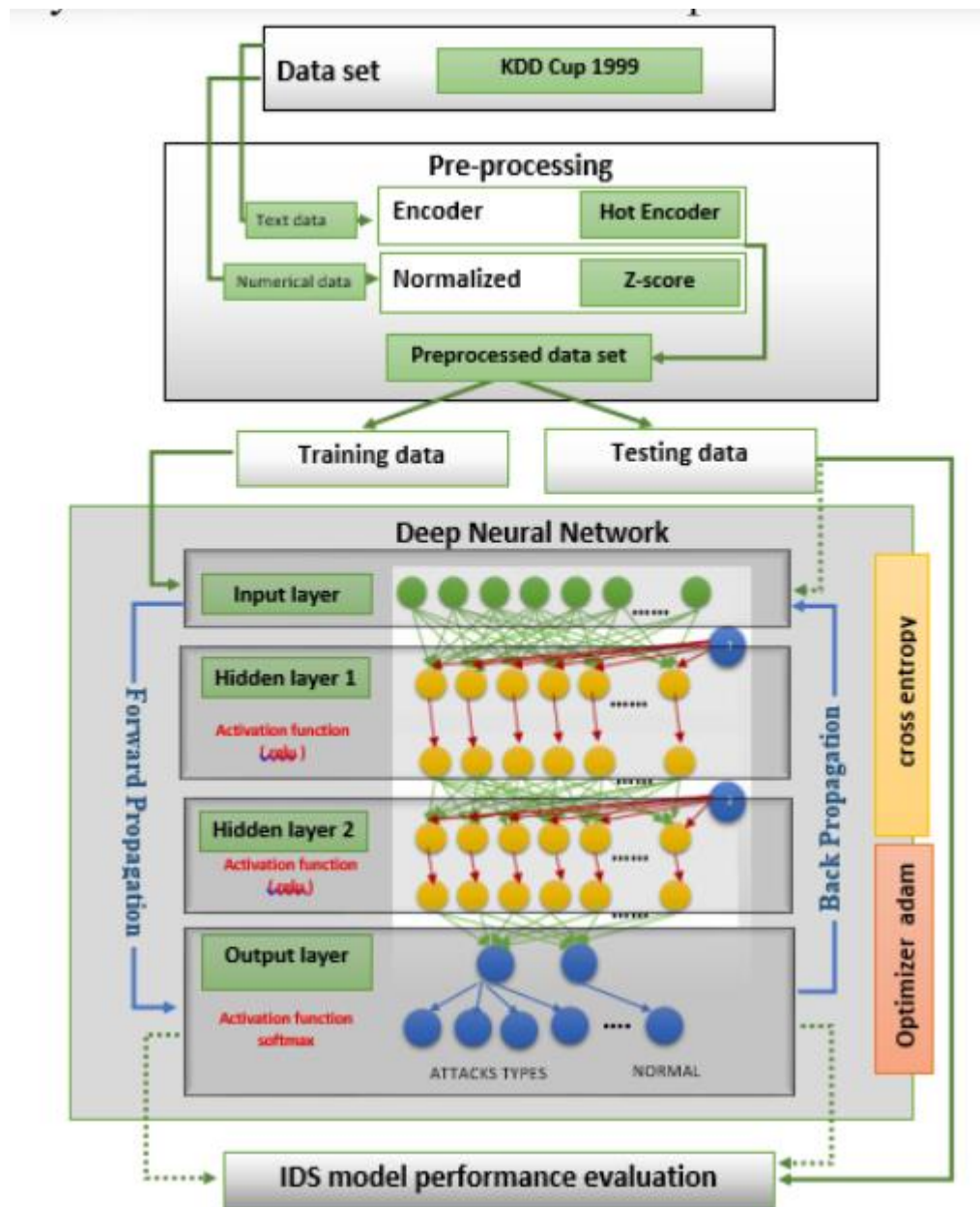


Fig 3 -Structure of NIDS

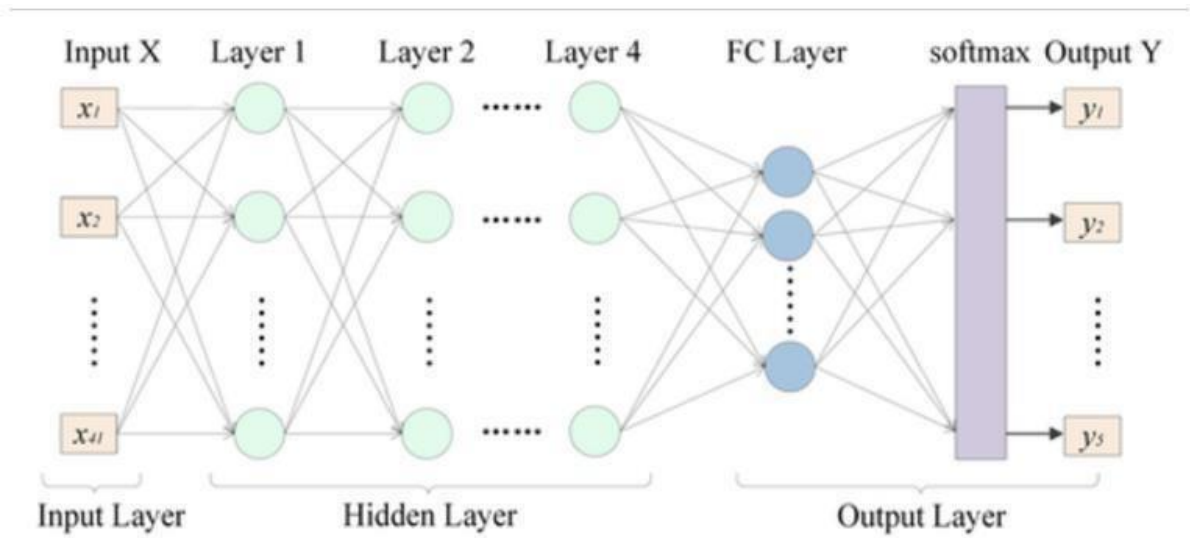


Fig 4 – Neural network architecture

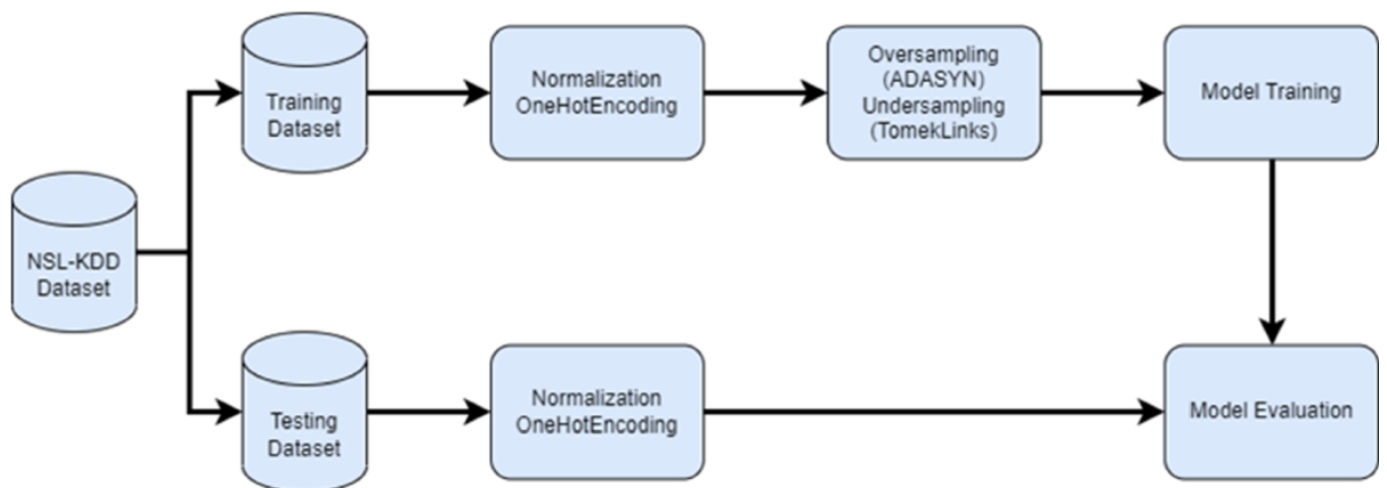


Fig 5 – Workflow of KDD CUP Dataset

4.1.4 Working Principles

- A Network Intrusion Detection System (NIDS) utilizing neural network algorithms operates by scrutinizing patterns within network traffic data to discern potential intrusions or security breaches.
- Initially, the NIDS gathers data from diverse network sources, such as taps or routers, encompassing packet headers, payloads, and other pertinent network attributes. Following data collection, preprocessing steps ensue to clean, normalize, and transform the data into an analyzable format, including feature extraction and dimensionality reduction. These processed data are then represented as feature vectors, encapsulating crucial network characteristics, like IP addresses, protocol types, and packet sizes.
- These vectors serve as inputs to the neural network model, which could be a convolutional neural network (CNN) or a recurrent neural network (RNN), adept at analyzing spatial or sequential data, respectively.
- During the training phase, the neural network learns from labeled datasets, discerning normal network behavior from various intrusion types.
- Once trained, the NIDS employs the neural network model in real-time inference, assessing incoming traffic and generating alerts upon detecting anomalies or potential threats.
- The data was being gathered for 9 weeks, 7 for training and 2 for testing set.
- Now, evaluate the trained model performance using testing set ,metrics used such as accuracy,F-score,precision.
- Finally, now test the model by running in tpu environment whether it is detecting the attackers.
- Continuous refinement through feedback loops ensures the NIDS adapts to evolving threats, enhancing its detection capabilities over time.
- Through this methodology, NIDS effectively scrutinizes network traffic, identifies potential security risks, and bolsters proactive protection against diverse intrusion attempts.

4.1.6.Implementation Screenshots

Step 1 – Create trained dataset using KDD Cup 1999 dataset for detecting the attacks.

Port Num	Received F	Received E	Sent Bytes	Sent Pack	Port alive	Delta Rec	Delta Rec	Delta Sent	Delta Sent	Delta Port	Connectio	Total Loac	Total Loac	Unknown	Unknown	Latest byt	Active Flo	Packets Lo	Packets M	Label
Port#:1	240	16586	12622603	467	126	0	0	280	2	5	1	0	0	0	0	0	4	819	757	TCP-SYN
Port#:2	158	20530	35464	376	171	4	556	3407	43	5	2	0	0	0	0	0	5	1018	918	TCP-SYN
Port#:3	1930	37881404	67857371	414333	1297	0	0	556	4	5	2	0	0	0	0	0	8	987400	987276	Normal
Port#:4	903	18946410	17900326	98088	176	3	320	270280	5002	4	3	0	0	0	0	0	8	195879	195780	PortScan
Port#:1	423	29020	19138042	1562	1451	0	0	560	4	5	1	0	0	0	0	0	4	4524	4411	Overflow
Port#:1	468	32234	42399682	408529	1097	0	0	560	4	5	1	0	0	0	0	0	4	645351	645228	Normal
Port#:2	134	18714	19008	141	161	2	278	278	2	5	1	0	0	0	0	0	7	3269	3159	TCP-SYN
Port#:3	5060	82203513	12769997	1678	1602	4	556	556	4	5	4	0	0	0	0	0	4	13477	13256	Diversior
Port#:3	252	6313946	18440	192	71	2	278	278	2	5	1	0	0	0	0	0	6	880	774	TCP-SYN
Port#:1	1058	18960201	34004	311	236	4	560	556	4	5	3	0	0	0	0	0	4	2846	2732	PortScan
Port#:2	187	6304507	27172	256	166	62	2232607	3278	41	5	1	0	0	0	0	0	6	1023	930	PortScan
Port#:4	7392	1.26E+08	94877805	5745	2427	2	278	560	4	5	4	-728	0	-728	0	-728	6	17819	17687	Blackhole
Port#:2	188716	64806726	61981473	122140	3030	4	560	560	4	5	2	0	0	0	0	0	4	522300	522212	Normal
Port#:3	180613	1.59E+08	1.95E+08	291184	2527	4	556	280	2	4	3	0	0	0	0	0	4	668392	668256	Normal
Port#:1	79722	16893358	4316282	79701	121	15588	841752	842382	15593	5	1	0	0	0	0	0	6	160226	160131	PortScan
Port#:4	8093	1.33E+08	1.14E+08	6486	3306	4	556	560	4	5	5	0	0	0	0	0	205	26638	26405	Diversior
Port#:4	4912	75947734	38116538	3656	2606	3	320	322	3	4	5	0	0	0	0	0	12	17822	17596	Diversior
Port#:2	5928	1.07E+08	75977370	5384	2567	3	320	278	2	5	5	0	0	0	0	0	4	16424	16201	Diversior
Port#:3	1564	19026292	97386	760	1012	4	556	556	4	4	4	0	0	0	0	0	6	4181	4014	Diversior
Port#:4	2299	25407600	12816219	2166	1857	2	278	278	2	5	1	0	0	0	0	0	504	9387	9262	Blackhole
Port#:2	535	18911291	40669	466	146	0	0	556	4	5	2	0	0	0	0	0	4	2397	2307	TCP-SYN
Port#:2	136	18022	17560	125	146	4	556	556	4	5	2	0	0	0	0	0	5	1104	996	PortScan

Fig 6 -Trained Dataset

Step 2 – Insert a values for detecting the labelled and unlabelled attacks.

Switch ID	Port Num	Received F	Received E	Sent Bytes	Sent Pack	Port alive	Delta Rec	Delta Rec	Delta Sent	Delta Sent	Delta Port	Connectio	Total Load	Total Load	Unknown	Unknown	Latest byte	Active Flo	Packets Lo	Packets M	Label
of:000000	Port#:1	2594	7.6E+07	3.2E+07	3308	1672	0	0	560	4	5	2	0	0	0	0	0	6	12271	12057	Diversior
of:000000	Port#:1	10	856	9732	74	61	0	0	348	3	4	2	0	0	0	0	0	8	778	697	TCP-SYN
of:000000	Port#:3	2192	1.3E+07	3.2E+07	2412	1566	57	1839337	2615	31	5	2	0	0	0	0	0	6	6233	6156	Blackhole
of:000000	Port#:1	401	6327186	24401	240	131	85	6316	759	5	4	4	0	0	0	0	0	6	1228	1134	PortScan
of:000000	Port#:1	3799	8.2E+07	8.9E+07	5526	2547	0	0	556	4	5	1	0	0	0	0	0	4	10977	10896	Blackhole
of:000000	Port#:3	477	6336128	1.9E+07	914	221	4	556	4661	62	5	1	0	0	0	0	0	5	2292	2190	PortScan
of:000000	Port#:1	96	12855	12855	96	96	2	278	278	2	4	3	0	0	0	0	0	4	483	386	PortScan
of:000000	Port#:1	308	112943	6309282	516	221	4	556	556	4	5	4	0	0	0	0	0	10	2190	2093	Overflow
of:000000	Port#:3	50	3672	45779	377	447	0	0	280	2	5	1	0	0	0	0	0	5	2097	1987	Blackhole
of:000000	Port#:3	3274	3.8E+07	1.3E+07	1799	1776	2	278	278	2	5	4	0	0	0	0	0	4	11611	11486	Blackhole
of:000000	Port#:3	578	37361	9823	70	66	104	6105	829	6	5	1	0	0	0	0	0	6	1070	970	TCP-SYN
of:000000	Port#:1	1473	3.2E+07	3.2E+07	2339	1296	0	0	556	4	5	1	0	0	0	0	0	5	8997	8877	Blackhole
of:000000	Port#:1	86	11715	1.5E+07	35963	81	4	560	598	5	5	4	0	0	0	0	0	6	36206	36097	PortScan
of:000000	Port#:2	6847	1.4E+08	7.6E+07	5979	2697	3	320	278	2	5	5	0	0	0	0	0	6	18547	18324	Diversior
of:000000	Port#:1	344	23746	1.9E+07	757	281	0	0	278	2	5	1	0	0	0	0	0	4	1594	1527	PortScan
of:000000	Port#:2	468	32234	4.2E+07	408523	1087	0	0	560	4	4	1	0	0	0	0	0	6	645327	645204	Normal

Fig 7 - Value Dataset

Step 3 – Test the dataset for labelling the attack

Port Num	Received F	Received E	Sent Bytes	Sent Packe	Port alive	Delta Rece	Delta Rece	Delta Sent	Delta Sent	Delta Port	Connectio	Total Loac	Total Loac	Unknown	Unknown	Latest bytr	Active Flo	Packets Lo	Packets M	Label
Port#2	117	15705	15537	113	126	2	278	348	3	4	3	0	0	0	0	0	6	2350	2265	TCP-SYN
Port#4	349224	14743367	38139845	156153	1430	4	556	560	4	4	4	0	0	0	0	0	4	649491	649367	Normal
Port#2	127	8855	6316408	271	96	0	0	280	2	5	2	0	0	0	0	0	6	3933	3848	TCP-SYN
Port#3	1396	25241475	31751210	2853	2172	178	4992757	7565	106	5	1	0	0	0	0	0	8	10237	10113	Blackhole
Port#1	12	1016	13549	101	101	0	0	556	4	5	2	0	0	0	0	0	10	6269	6181	TCP-SYN
Port#1	860	6367739	47182	437	366	4	556	556	4	5	4	0	0	0	0	0	4	2144	2040	Blackhole
Port#3	518	6327171	18937664	783	166	110	4332927	4797	64	5	1	0	0	0	0	0	6	1445	1379	TCP-SYN
Port#3	83	11339	11617	85	81	4	556	556	4	5	2	0	0	0	0	0	5	497	408	TCP-SYN
Port#3	1834	19063965	135477	1037	1412	4	556	556	4	5	4	0	0	0	0	0	4	7137	6929	Diversior
Port#2	13649	737406	744098	13692	41	1	42	602	5	5	2	0	0	0	0	0	6	27447	27357	PortScan
Port#3	3125	50625537	6470951	1478	1737	154	6170967	278	2	5	3	0	0	0	0	0	6	8948	8823	Blackhole
Port#1	40202	2172889	8231716	35749	86	0	0	322	3	5	1	0	0	0	0	0	10	76672	76579	PortScan
Port#3	3206	50649489	38086284	3489	2162	4	556	556	4	4	4	0	0	0	0	0	4	14358	14225	Blackhole
Port#1	172811	31828754	75547871	177986	246	49	3779	2495726	73	4	1	0	0	0	0	0	9	246502	246398	PortScan

Fig 8 -Test Dataset

Step 4 – Plot the values in program in order to obtain the packets and ports duration in graphical representation.

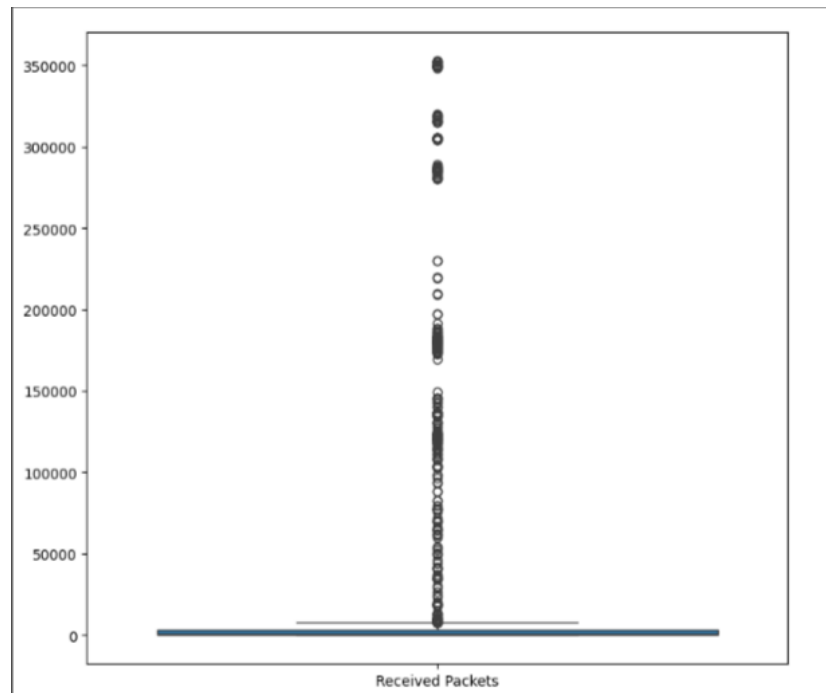


Fig 9 – Received Packets

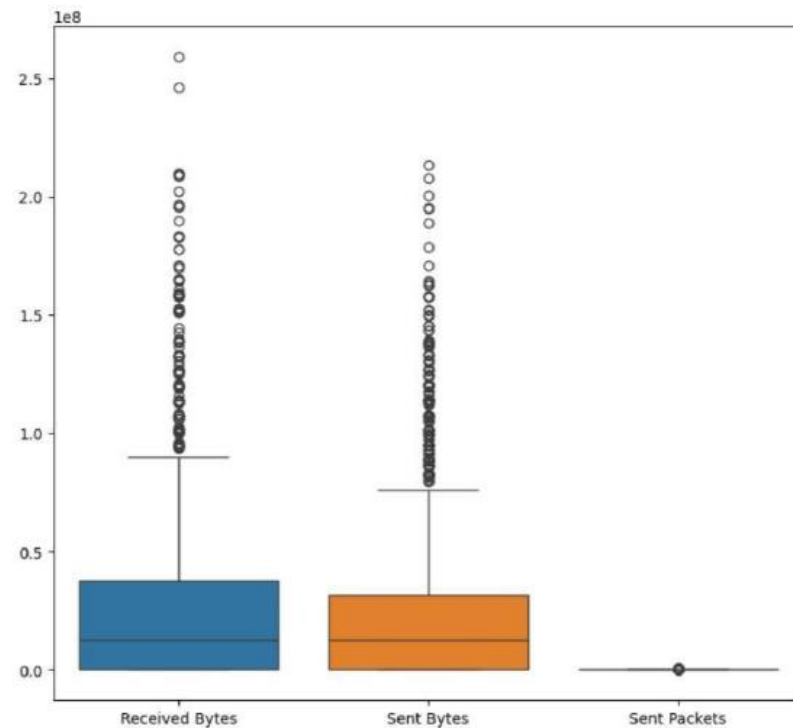


Fig 10 - Received and sent bytes and packets

Step 5 – Filter the number of outliers based on features.

```
Feature name Received Packets --> number of outliers is 312
Feature name Received Bytes --> number of outliers is 186
Feature name Sent Bytes --> number of outliers is 222
Feature name Sent Packets --> number of outliers is 379
Feature name Port alive Duration (S) --> number of outliers is 0
Feature name Delta Received Packets --> number of outliers is 649
Feature name Delta Received Bytes --> number of outliers is 648
Feature name Delta Sent Bytes --> number of outliers is 604
Feature name Delta Sent Packets --> number of outliers is 604
Feature name Delta Port alive Duration (S) --> number of outliers is 441
Feature name Connection Point --> number of outliers is 0
Feature name Total Load/Rate --> number of outliers is 396
Feature name Total Load/Latest --> number of outliers is 501
Feature name Unknown Load/Rate --> number of outliers is 396
Feature name Unknown Load/Latest --> number of outliers is 501
Feature name Latest bytes counter --> number of outliers is 396
Feature name Active Flow Entries --> number of outliers is 152
Feature name Packets Looked Up --> number of outliers is 536
Feature name Packets Matched --> number of outliers is 536
```

Fig 11 – Number of outliers based on feature

Step 6 -Train the dataset numerically to label the attack

	Received Packets	Received Bytes	Sent Bytes	Sent Packets	Port alive Duration (S)	Delta Received Packets	Delta Received Bytes	Delta Sent Bytes	Delta Sent Packets	Delta Port alive Duration (S)
count	2619.000000	2.619000e+03	2.619000e+03	2619.000000	2619.000000	2619.000000	2.619000e+03	2.619000e+03	2619.000000	2619.000000
mean	19929.095074	2.606639e+07	2.372645e+07	33676.567774	890.539137	174.948835	3.254661e+05	2.957171e+05	160.607866	4.831615
std	61817.860816	3.670801e+07	3.309908e+07	90565.150583	970.916789	1028.907797	1.166624e+06	1.107859e+06	972.484039	0.374279
min	10.000000	8.560000e+02	6.025000e+03	44.000000	26.000000	0.000000	0.000000e+00	2.780000e+02	2.000000	4.000000
25%	321.500000	8.464900e+04	5.360900e+04	333.500000	136.000000	2.000000	2.780000e+02	2.800000e+02	2.000000	5.000000
50%	1108.000000	1.262083e+07	1.262176e+07	1243.000000	254.000000	4.000000	5.560000e+02	5.560000e+02	4.000000	5.000000
75%	3268.500000	3.736785e+07	3.170219e+07	3727.000000	1721.000000	6.000000	8.310000e+02	7.590000e+02	5.000000	5.000000
max	352584.000000	2.589422e+08	2.130728e+08	420806.000000	3317.000000	15588.000000	6.171714e+06	6.302910e+06	15593.000000	5.000000

Fig 12 -Numeric trained dataset

Step 7 – Display the model accuracy per epoch in graphical representation.

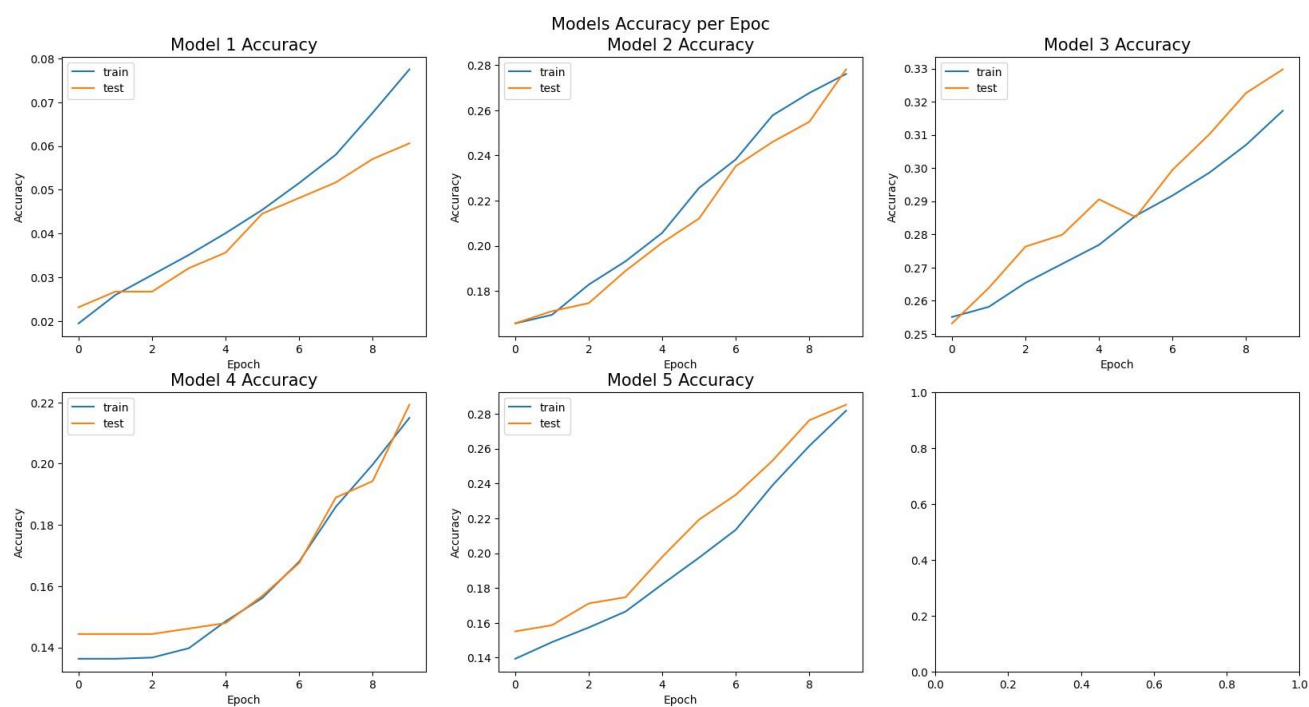


Fig 13 – Accuracy of the model

Step 8 -Display the model loss per epoch in graphical representation.

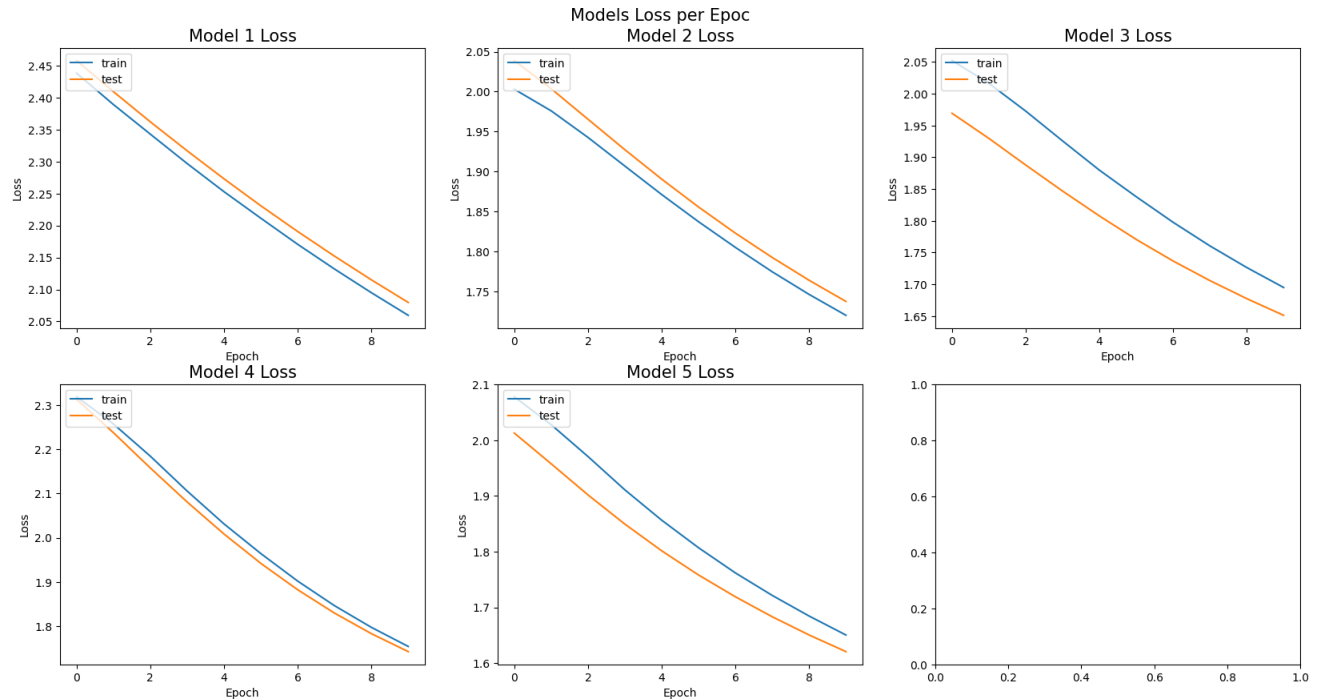


Fig 14 - Loss of the model

Step 9 – Predict the confusion matrix for detecting the attack.

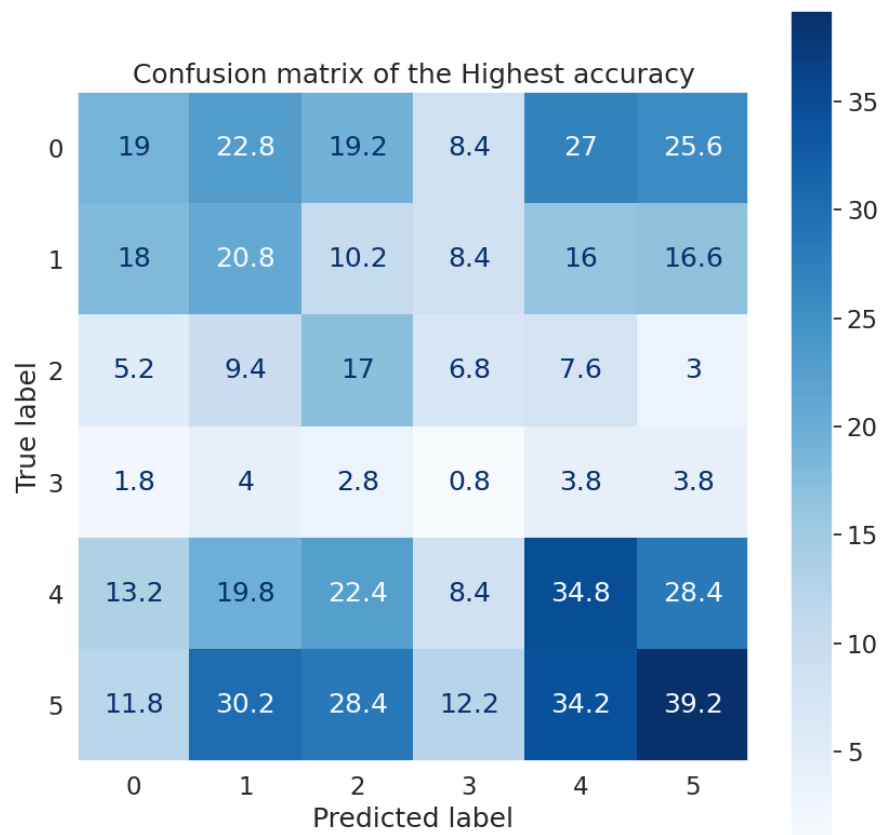


Fig 15 – Confusion matrix of highest accuracy

Step 10– Display the train,value and test datasets are defined using a T-SNE Projection (T-distributed Stochastic Neighbor Embedding)

Dataset T-SNE Projection

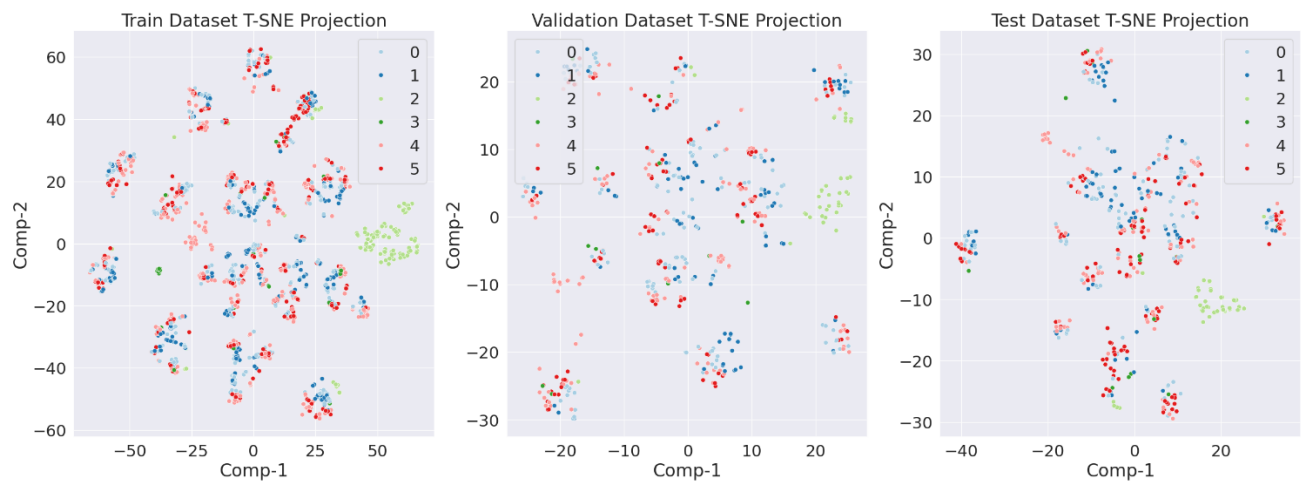


Fig 16 - Dataset T-SNE Projection(T-distributed Stochastic Neighbour Embedding)

Step 11 – Finally,display the testing accuracy of components or features used .

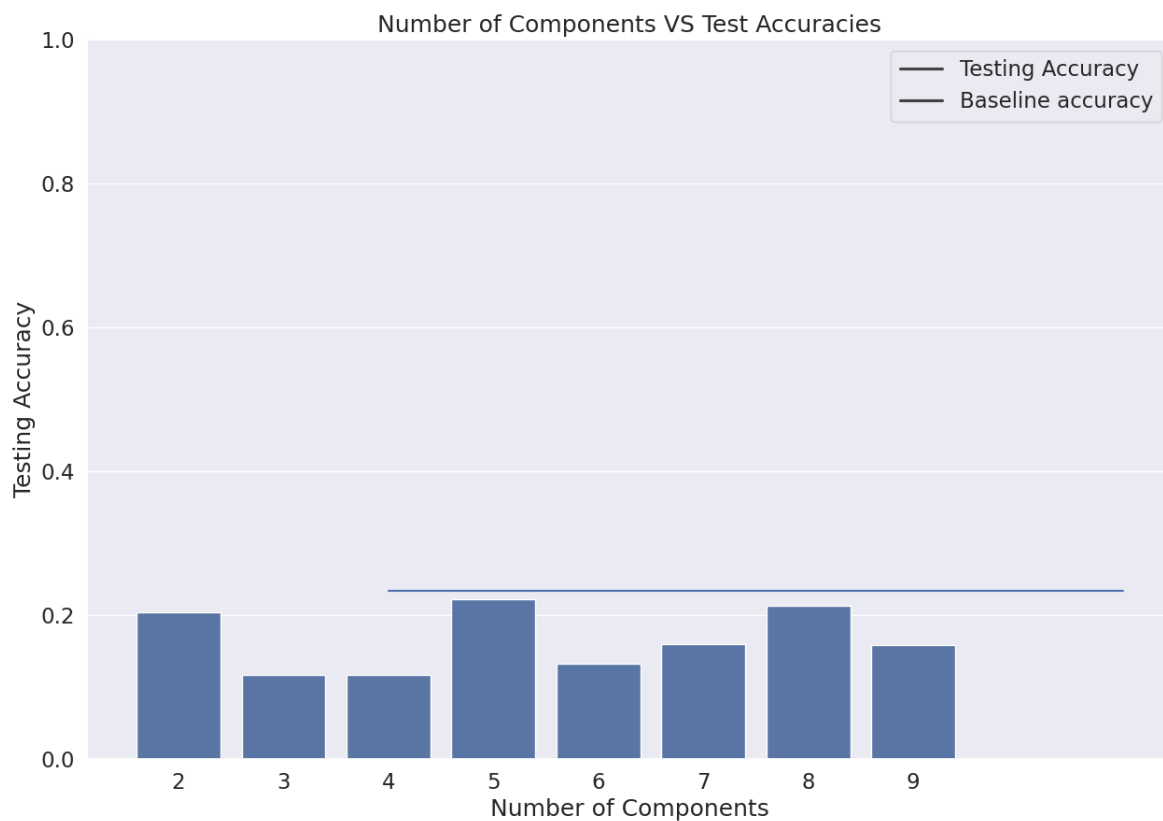


Fig 17 – Testing Accuracy and Baseline Accuracy

4.2 FEATURES

Feature Learning: Neural networks can automatically learn relevant features from raw network data without the need for manual feature engineering. This allows the NIDS to adapt to changing network environments and detect new types of intrusions.

Non-linearity: Neural networks are inherently non-linear models, allowing them to capture complex relationships and patterns in network traffic that may be difficult to detect using traditional linear methods.

Scalability: Neural networks can be scaled to handle large volumes of network traffic, making them suitable for deployment in high-speed networks with millions of packets per second.

Anomaly Detection: Neural networks excel at anomaly detection, making them well-suited for identifying unusual or suspicious patterns in network traffic that may indicate a potential intrusion.

Behavioral Profiling: Neural networks can learn the normal behavior of network traffic over time and detect deviations from this baseline. This enables the NIDS to detect insider threats or zero-day attacks that do not match known attack signatures.

Adaptability: Neural networks can adapt to changes in network traffic patterns and adapt their detection capabilities accordingly. This adaptability is crucial for handling dynamic network environments and emerging threats.

Deep Learning Architectures: NIDS based on neural networks often utilize deep learning architectures such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) to capture spatial and temporal dependencies in network traffic data.

Real-time Detection: Neural network-based NIDS can perform real-time intrusion detection, allowing them to quickly respond to threats as they occur and minimize the impact of attacks on the network.

False Positive Reduction: By learning from labeled data, neural network-based NIDS can reduce false positives compared to traditional signature-based approaches, leading to more accurate intrusion detection.

Transfer Learning: Neural network-based NIDS can leverage transfer learning techniques to transfer knowledge from related tasks or datasets, improving detection accuracy even with limited labeled data.

Deep Packet Inspection (DPI): NIDS performs in-depth analysis of packet contents beyond header information, examining payload data for signs of malicious activity, including malware signatures or command-and-control communications.

Traffic Monitoring and Logging: NIDS continuously monitors network traffic and logs relevant information such as source and destination IP addresses, ports, protocols, and timestamps for forensic analysis and incident response.

Integration with Security Information and Event Management (SIEM) Systems: NIDS integrates with SIEM systems to correlate alerts from multiple sources, providing a comprehensive view of security events across the network and facilitating centralized management and analysis.

Customization and Tuning: NIDS allows administrators to customize detection rules, fine-tune sensitivity levels, and adjust thresholds to minimize false positives and optimize detection accuracy for specific network environments.

Compliance and Reporting: NIDS supports compliance requirements by generating reports and audit trails of security events, demonstrating adherence to regulatory standards and facilitating compliance audits.

4.2.1 Novelty of the Project

The proposed Network Intrusion Detection System (NIDS) employing neural networks introduces a novel approach to enhancing cybersecurity. By leveraging the advanced learning capabilities of deep neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the system autonomously learns intricate patterns and anomalies within network traffic data. Unlike conventional NIDS that rely on predefined rules or signatures, this approach allows for automatic feature extraction from raw data, enabling deeper analysis and detection of subtle threats that may evade traditional methods. Operating in real-time, the NIDS continuously monitors network traffic, swiftly identifying and responding to potential intrusions. Furthermore, its adaptability to new threats ensures resilience against emerging attack vectors, as the system can continuously update and refine its detection mechanisms based on the latest threat intelligence. This project propose a hierarchical approach where multiple GANs are employed to model different aspects of network traffic, such as packet headers, payloads, and session-level behavior. This hierarchical architecture allows for fine-grained analysis and detection of anomalies at various levels of abstraction, enhancing the NIDS's sensitivity to subtle deviations indicative of malicious activity .Scalable and efficient, the proposed NIDS can handle increasing volumes of network traffic while maintaining optimal performance, making it a powerful tool for safeguarding against a diverse range of cyber threats in today's dynamic and evolving digital landscape. To evaluate the efficacy of our proposed approach, we will conduct extensive experiments using benchmark datasets such as NSL_KDD and evaluate the system's performance in detecting both known and unknown attacks. Additionally, we will compare our approach against traditional NIDS techniques to demonstrate its superiority in terms of detection accuracy, false positive rate, and adaptability to evolving threats.

CHAPTER 5

CONCLUSION

This paper addressed network intrusion detection systems(NIDS) using the latest simulated network traffic dataset, incorporating relevant features and common cybersecurity vulnerabilities and exposures. In our project, we trained model for features of labelled attack for training and testing the attack for the benefit of cybersecurity professionals. The models showed that our proposed approach obtained an overall accuracy of 95.4% and 95.6% for the pre-partitioned and user- defined multiclass classification. Although the proposed models have achieved promising results, we acknowledge that there is room for improvements, mainly using feature reduction methods. Future work calls for transfer learning with relevant existing datasets to serve as a baseline for model classification improvements with the KDD CUP 1999 dataset and extend our models' capability to handle zero-day attacks. In addition to transfer learning, bootstrapping techniques to produce a well-balanced dataset to train a multiclass classification model will be investigated. Deep learning anomaly detection models will amend cybersecurity architectures to develop adaptive and resilient network intrusion detection systems to detect common vulnerabilities and exposures correctly and zero-day network behavioural features reducing the risk of compromise. There is also a long-lasting challenge with available data-sets for performing experiments for IDSs. There are several public datasets described in these articles, but all of them have their drawbacks, like age or record redundancy. They are also not always representative for real-life data. This project explores the performance of two neural network algorithms based on multi-layer perceptron and radial basis function. Both the approaches have been implemented using IBM SPSS Statistics version 24.0 on the NSL_KDD dataset for network intrusion detection. It is observed that multi-layer perceptron returned better results when compared with radial basis function. Further work must be carried out to identify suitable techniques to handle class imbalance in the dataset .All the experiments were executed on Intel Core i5 3.10 GHz CPU with 4 GB RAM running on 32-bit Windows operating system. The results have been obtained from IBM SPSS Statistics version 24.0. Experiments were conducted on the benchmark NSL_KDD intrusion detection dataset which is a refined and condensed version of KDD Cup 1999 dataset. The performance of two neural

networks' classifiers based on multi-layer perceptron and radial basis function is presented. The efficiency of the two classifiers is evaluated in terms of accuracy and area under the curve (AUC) performance metrics. To address the issue of data imbalance in network data and low detection accuracy, we proposed an ADASYN oversampling algorithm as the data augmentation method to tackle the network intrusion data imbalance problem, the stacked autoencoder with increased dropout structure as the data downscaling method, to improve the generalization ability of the model, and the network structure by combining the channel attention mechanism with the bidirectional LSTM network. The accuracy and F1 score of the proposed network model reached 90.73% and 89.65% on the KDDTest+ test set, respectively. Compared with other reference network models, the proposed DLNID model offered a better classification performance. The proposed network model is considered useful for the current development of network intrusion detection. In the future, we plan to apply the DLNID model to an actual, combined network capture module to implement an online intrusion detection model. But on other hand, due to be publicly available, they enable researchers to perform comparable benchmarking. Some experiments are being executed based on self-generated datasets. They may be more suitable for particular researchers groups need, but they are subject to privacy concerns. Network Intrusion detection systems are now applied to the areas like internet of things, clouds, Blockchain technology, auto-motive, smart grids and mobile communication. Our model is used for training and testing the new features of attack categories such as TCP-SYN , Overflow, Blackhole, Diversion, Normal, Probe. We hope that all the solutions and datasets enlisted in this paper will enable researchers for more efficient and influential work regarding new NIDS based proposals. It can capture real-time network traffic and identify destructive intrusions and it is hosted in a web server to provide accessibility for personal and corporate sector networks to employ it to their networks via a RESTful API. Since the real-time feature extraction module is containerized, it is effortless to integrate into any system. The proposed system's usability and efficacy have been boosted by its ease of implementation and remote accessibility. The proposed system is extremely advantageous for instantly detecting intrusions by analysing inbound and outbound network traffic. This system outputs descriptive information regarding intrusion data packets, easing network administrators' decision-making for appropriate measures. Furthermore, because sufficient API documentation is available, even users with limited programming skills can utilize the proposed

system. The construction of the DNN, which is trained using the NSL-KDD dataset is systematically discussed together with the technical implementation and the simulation results on both training and testing aspects. Moreover, the techniques and procedures employed for real-time feature extraction from the inbound and outbound network traffic are clearly mentioned. In addition, how the ML prediction pipeline is hosted in a web server is descriptively discussed in this paper. The observed results of the DNN training and testing have showed exceptional training results and satisfactory results in the testing stage with a precision of 96%. Finally, our project work has contributed by presenting a fully functional RT-IDS which can be practically implemented as an extra layer of the network protection.

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Develop a Network Intrusion Detection System using Neural Networks

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Abstract - With the growth of network activities and data sharing, there is also increased risk of threats and malicious attacks. Network intrusion detection system (NIDS) refers to the process of detecting and preventing abnormal or suspicious activities over a given network. Different machine learning techniques have immense use in detecting dubious activities compromising the integrity, security, and confidentiality of the data. This paper introduces a pioneering approach to intrusion detection that leverages neural networks to monitor and identify unusual user activity.

Keywords: Network Intrusion Detection System(NIDS), Neural networks, KDD Cup dataset, Anomaly detection, normal patterns

I. INTRODUCTION

The past few years have witnessed remarkable increase in the usage of advance computer networks, applications and sharing data . This led to the increase in unauthorized and malicious cyber-attacks. Cyber-attacks are more advanced, cagey, and targeted than ever before. Thus, security techniques must be continuously developed. Network intrusion detection system (NIDS) refers to

the process of detecting and preventing abnormal or suspicious activities over a given network.

II. LITERATURE SURVEY

Designing an IDS for mobile network teaching offers hands-on learning and critical thinking. It utilizes anomaly detection and machine learning for practical security knowledge. Challenges include updating for new threats and avoiding disruptions, but benefits prepare students for real-world cybersecurity [1].

The Dugat-LSTM system utilizes deep learning and chaotic optimization for accurate intrusion detection. It leverages LSTM networks and chaotic optimization techniques efficiently, despite challenges in training complexity and resource requirements. Overall, it offers robust detection capabilities, making it a promising approach for network security [2].

A data-driven IDS employing feature selection and deep learning improves accuracy in intrusion detection and adapts to evolving threats. It selects relevant features to enhance model

performance and employs deep learning for efficient pattern recognition. Challenges include the need for large labeled data, computational complexity, and vulnerability to adversarial attacks. Still, its effectiveness against sophisticated intrusion attempts makes it valuable for network security [3].

III. RESEARCH METHODOLOGY

In this model, the most common intrusion detection evaluation metrics (confusion matrix) is used to evaluate the CNN-IDS model performance.

The experiment studied the performance of the proposed network on normal ,TCP-SYN, overflow, blackhole for binary and multiclassification experiments, respectively. When the network parameters were chosen , the high accuracy and F1 score could be achieved on the KDD Test+ test set. The output shows the experimental results using the confusion matrix. The experimental results show that most samples were classified correctly, which appear on the diagonal, indicating a better classification performance .The accuracy and F1 score of the proposed network model reached 90.73% and 89.65% on the KDD cup1999 test set, respectively. Compared with other reference network models, the proposed DLNID model offered a better classification performance. In the future, we plan to apply the DLNID model to an actual, combined network capture module to implement an online intrusion detection model. The proposed network model is considered useful for the current development of network intrusion detection.

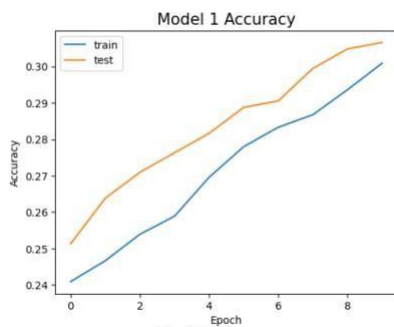


Fig – Model Accuracy

IV. CONCLUSION

This paper addressed network intrusion detection systems(NIDS) using the latest simulated network traffic dataset, incorporating relevant features and common cybersecurity vulnerabilities and exposures. In our project, we trained model for features of labelled attack for training and testing the attack for the benefit of cybersecurity professionals. The models showed that our proposed approach obtained an overall accuracy of 95.4% and 95.6% for the pre-partitioned and user-defined multiclass classification . Although the proposed models have achieved promising results, we acknowledge that there is room for improvements, mainly using feature reduction methods.

V. REFERENCE

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APPENDIX

B.Source Code

```
import keras

import numpy as np

import pandas as pd

import seaborn as sns

import tensorflow as tf

import matplotlib.pyplot as plt

seed = 0

tf.random.set_seed(seed)

train = pd.read_csv('train.csv')

val = pd.read_csv('val.csv')

test = pd.read_csv('test.csv')

X_train=train.drop('Label',axis=1)

y_train=train['Label']

X_test=test.drop('Label',axis=1)

y_test=test['Label']

X_val=val.drop('Label',axis=1)

y_val=val['Label']

X_train

X_train_numeric = pd.get_dummies(X_train, drop_first=True)

X_val_numeric = pd.get_dummies(X_val, drop_first=True)

X_test_numeric = pd.get_dummies(X_test, drop_first=True)

X_train_numeric

y_train.value_counts()
```

```

X_train_numeric.info()

for i in range(0,18,9):

    fig,axis =plt.subplots(1,3,figsize=(30,8))

    sns.boxplot(data=X_train.iloc[:,i:i+3],ax=axis[0])

    sns.boxplot(data=X_train.iloc[:,i+3:i+6],ax=axis[1])

    sns.boxplot(data=X_train.iloc[:,i+6:i+9],ax=axis[2])

    plt.show()

for i,col in enumerate(X_train_numeric.columns):

    if i > 18:

        break

    q_low = X_train[col].quantile(0.25)

    q_hi = X_train[col].quantile(0.75)

    IQR = (q_hi-q_low)

    df_filtered = X_train[(X_train[col] > (q_hi + 1.5 * IQR)) | (X_train[col] < (q_low - 1.5
* IQR))]

    print(f'Feature name {col} --> number of outliers is {len(df_filtered)}')

X_train_numeric.describe()

from sklearn.preprocessing import StandardScaler,MinMaxScaler

import tensorflow as tf

scaler = StandardScaler()

X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train_numeric), columns =
X_train_numeric.columns)

X_val_scaled= pd.DataFrame(scaler.transform(X_val_numeric), columns =
X_val_numeric.columns)

```

```

X_test_scaled= pd.DataFrame(scaler.transform(X_test_numeric), columns =
X_test_numeric.columns)

X_train_scaled

X_train_scaled.info()

X_train_scaled_tensor=tf.convert_to_tensor(X_train_scaled, dtype=np.float64)

X_val_scaled_tensor=tf.convert_to_tensor(X_val_scaled,dtype=np.float64)

X_test_scaled_tensor=tf.convert_to_tensor(X_test_scaled,dtype=np.float64)

X_train_scaled_tensor

from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

y_train_encoded = label_encoder.fit_transform(y_train)

y_val_encoded = label_encoder.transform(y_val)

y_test_encoded = label_encoder.transform(y_test)

y_train_encoded

import numpy as np

from statistics import mean

import matplotlib.pyplot as plt

import tensorflow as tf

from keras.layers import Dense

from tensorflow_addons.optimizers import AdamW

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

%matplotlib inline

def plot_history(dict_of_lists,type='loss'):

    axis_idx=[(0,0),(0,1),(0,2),(1,0),(1,1),(1,2)]

    fig, axes = plt.subplots(2, 3,figsize=(20,10))

```

```

for i in range(len(dict_of_lists)):

    ax=axes[axis_idx[i][0]][axis_idx[i][1]]

    ax.plot(dict_of_lists[i].history[type])

    ax.plot(dict_of_lists[i].history[f'val_{type}'])

    ax.set_title(f'Model {i+1} {type.title()}',size=15)

    ax.set_ylabel(f'{type.title()}',size=10)

    ax.set_xlabel('Epoch',size=10)

    ax.legend(['train', 'test'], loc='upper left')

plt.suptitle(f'Models {type.title()} per Epoc',size=15,y=.93)

plt.show()

def Build_model(X_train,y_train,X_val,y_val,X_test,y_test,optimizer,

                n_of_hidden_layers,n_neurons,activation='relu',epochs=500,batch_size=1

024,early_stopping=True):

    model = tf.keras.models.Sequential()

    model.add(tf.keras.Input(shape=(X_train.shape[1],)))

    for _ in range(n_of_hidden_layers):

        model.add(keras.layers.Dense(n_neurons, activation=activation))

    model.add(keras.layers.Dense(6, activation='softmax'))

    model.compile(optimizer=optimizer,

                  loss='sparse_categorical_crossentropy',

                  metrics=['accuracy'])

    es=tf.keras.callbacks.EarlyStopping(

        monitor="val_loss",

```

```

        patience=5,

        mode="auto",

        baseline=None,

        restore_best_weights=True,)

    if early_stopping :

        history=model.fit(X_train,y_train,validation_data=(X_val,y_val),e
            pochs=epochs,batch_size=batch_size,callbacks=[es],verbose=0)

    else:

        history=model.fit(X_train,y_train,validation_data=(X_test,y_test),epochs=
epochs,batch_size=batch_size,verbose=0)

    train_evaluation = model.evaluate(X_train, y_train)

    test_evaluation = model.evaluate(X_test, y_test)

    validation_evaluation = model.evaluate(X_val, y_val)

    return model, history, train_evaluation, validation_evaluation ,test_evaluation

def Build_experment(X_train,y_train,X_val,y_val,X_test,y_test,optimizer,

        n_of_hidden_layers,n_neurons,activation='relu',epochs=500,batch_size
=1024,n_of_models=5,early_stopping=True):

    models_dict = {'models':[], 'history': []}

    models_train_acc = []

    models_test_acc = []

    models_valid_acc = []

    for j in range(n_of_models):

        model,history,train_evaluation,valid_evaluation,test_evaluation=Build_model(X_train,
y_train,X_val,y_val,X_test,y_test,optimizer,

```

```

        n_of_hidden_layers,n_neurons,activation=activation,epochs=epochs,batch
_size=batch_size,early_stopping=early_stopping)

        models_train_acc.append(train_evaluation[1])

        models_test_acc.append(test_evaluation[1])

        models_valid_acc.append(valid_evaluation[1])


    models_dict['models'].append(model)

    models_dict['history'].append(history)


    accuracies_dict={}

    accuracies_dict["Min_train_acc"] =min(models_train_acc)

    accuracies_dict["Max_train_acc"] =max(models_train_acc)

    accuracies_dict["AVG_train_acc"] =mean(models_train_acc)


    accuracies_dict["Min_test_acc"] =min(models_test_acc)

    accuracies_dict["Max_test_acc"] =max(models_test_acc)

    accuracies_dict["AVG_test_acc"] =mean(models_test_acc)


    accuracies_dict["Min_valid_acc"] =min(models_valid_acc)

    accuracies_dict["Max_valid_acc"] =max(models_valid_acc)

    accuracies_dict["AVG_valid_acc"] =mean(models_valid_acc)


    return

    accuracies_dict,models_dict,models_train_acc,models_test_acc,models_valid_acc

    optimizer=AdamW(learning_rate=0.001, weight_decay=.00001)

```

```

base_line_accuracies_dict,base_line_models_dict,base_line_models_train_acc,base
_line_models_test_acc,base_line_models_valid_acc
Build_experiment(X_train_scaled_tensor, y_train_encoded, X_val_scaled_tensor,
y_val_encoded, X_test_scaled_tensor, y_test_encoded, optimizer,
n_of_hidden_layers=1, n_neurons=10, activation='relu', epochs=10,
batch_size=1024, n_of_models=5,early_stopping=False)

plot_history(base_line_models_dict['history'],type='accuracy')

plot_history(base_line_models_dict['history'],type='loss')

pd.DataFrame(pd.Series(base_line_accuracies_dict)).transpose()

cm = np.zeros(shape=(6,6))

for model in base_line_models_dict['models']:

    pred = model.predict(X_test_scaled).argmax(axis=1)

    cm += confusion_matrix(y_test_encoded, pred)

cm_avg = cm/ len(base_line_models_dict['models'])

colors = ["#FF0B04", "#4374B3"]

sns.set_palette(sns.color_palette(colors))

sns.set(font_scale = 1.5)


disp = ConfusionMatrixDisplay(confusion_matrix=cm_avg,)

disp = disp.plot(cmap=plt.cm.Blues,values_format='g',)


fig = disp.ax_.get_figure()

fig.set_figwidth(10)

fig.set_figheight(10)


plt.title('Confusion matrix of the Highest accuracy')

```

```

plt.grid(False)

plt.show()

from sklearn.manifold import TSNE

import matplotlib.pyplot as plt

import seaborn as sns

sns.set_context("notebook", font_scale=2)

def TSNE_visualizer(data_set):

    tsne = TSNE (n_components=2, random_state=0,init='pca',learning_rate='auto')

    z = tsne.fit_transform(data_set)

    return z

t_sne_plots = [TSNE_visualizer(np.array(X_train_scaled, dtype='float')),

                TSNE_visualizer(np.array(X_val_scaled, dtype='float')),

                TSNE_visualizer(np.array(X_test_scaled, dtype='float'))]

x_size , y_size =1,3

fig, axes = plt.subplots(1, 3,figsize=(30,10))

titles =["Train","Validation", "Test"]

c = [y_train_encoded, y_val_encoded, y_test_encoded]

for i in range(3):

    ax = axes[i]

    sns.scatterplot(x=t_sne_plots[i][:,0],

y=t_sne_plots[i][:,1],hue=c[i],ax=ax,palette="Paired")

    ax.set_title(f'{titles[i]} Dataset T-SNE Projection')

    ax.set_xlabel('Comp-1')

```

```

ax.set_ylabel('Comp-2')

plt.suptitle('Dataset T-SNE Projection',size=50,y=1.05)

plt.savefig("Dataset T-SNE Projection.png")

plt.show()

from sklearn.decomposition import PCA

n_comp = range (2,10)

PCA_test_accuracies=[]

PCA_val_accuracies=[]

for i in n_comp:

    pca = PCA(n_components=i,random_state=0)

    pca_train = tf.convert_to_tensor(pca.fit_transform(X_train_scaled))

    pca_val = tf.convert_to_tensor(pca.transform(X_val_scaled))

    pca_test = tf.convert_to_tensor(pca.transform(X_test_scaled))

    pca_accuracies_dict,pca_models_dict,pca_models_train_acc,pca_models_test_acc
    ,pca_models_valid_acc = Build_experiment(pca_train, y_train_encoded, pca_val,
    y_val_encoded, pca_test, y_test_encoded, optimizer, n_of_hidden_layers=1,
    n_neurons=4, activation='relu', epochs=1, batch_size=1024, n_of_models=5)

    PCA_test_accuracies.append(pca_accuracies_dict['AVG_test_acc'])

    PCA_val_accuracies.append(pca_accuracies_dict['AVG_valid_acc'])

import seaborn as sns

sns.set_context("talk")

sns.set(rc = {'figure.figsize':(15,10)})

```

```

sns.set(font_scale = 1.5)

sns.barplot(x=list(n_comp) , y = PCA_test_accuracies)

sns.lineplot(x=list(n_comp),y=[base_line_accuracies_dict["AVG_test_acc"]]*len(PCA
_test_accuracies),sizes=[10]).set(title='Number of Components VS Test Accuracies')

plt.xlabel('Number of Components')

plt.ylabel('Testing Accuracy')

plt.legend(['Testing Accuracy','Baseline accuracy'])

plt.ylim(0,1)

plt.show()

n_comp=list(n_comp)

best_n_com=n_comp[np.array(PCA_test_accuracies).argmax()]

best_n_com,max(PCA_test_accuracies)

pca = PCA(n_components=best_n_com)

pca_train = pca.fit_transform(X_train_scaled)

pca_val = pca.transform(X_val_scaled)

pca_test = pca.transform(X_test_scaled)

t_sne_plots = [TSNE_visualizer(np.array(pca_train, dtype='float')),
                TSNE_visualizer(np.array(pca_val, dtype='float')),
                TSNE_visualizer(np.array(pca_test, dtype='float'))]

x_size , y_size =1,3

fig, axes = plt.subplots(1, 3,figsize=(30,10))

titles =["Train","Validation", "Test"]

c = [y_train_encoded, y_val_encoded, y_test_encoded]

```

```

for i in range(3):

    ax = axes[i]

    sns.scatterplot(x=t_sne_plots[i][:,0],
y=t_sne_plots[i][:,1],hue=c[i],ax=ax,palette="Paired")

    # ax.scatter(x=t_sne_plots[i][:,0], y=t_sne_plots[i][:,1], c=
c[i]) ax.set_title(f'{titles[i]} Dataset T-SNE Projection')

    ax.set_xlabel('Comp-1')

    ax.set_ylabel('Comp-2')


plt.suptitle('Dataset T-SNE Projection',size=50,y=1.05)

plt.savefig("Dataset T-SNE Projection.png")

plt.show()

```