Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 12, 2025

ENHANCING NETWORK SECURITY IN SDN ENVIRONMENTS: DEVELOPING A DEEP LEARNING-BASED INTRUSION DETECTION SYSTEM FOR EFFECTIVE ANOMALY DETECTION

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DOI: https://doi.org/10.5281/zenodo.17878012

Keywords
Anomaly detection, Model evaluation, SDN security, Deep learning, Intrusion detection systems

Article History
Received: 11 October 2025
Accepted: 21 November 2025
Published: 10 December 2025

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Abstract
The highly important factor of security weakness in the Software-Defined Networking (SDN), especially in its centralized control plane & the dynamic configuration, makes it vulnerable to wide range of the cyber threats. Conventional intrusion detection systems (IDS) are not able to keep pace with the quickly changing attributes of the SDN systems, particularly since they cannot be modified to deal with the recently invented & known attacks. In order to address these shortfalls, this study hypothesizes that deep learning methods can be used as anomaly detectors in the SDN, keenly to utilize Convolutional Neural Networks (CNN), Deep Reinforcement Learning (DRL), Recurrent Neural Networks (RNN), Autoencoders (AE), & Transformer models. The tests are performed on a network traffic dataset, & CNN and Transformer models have better performance repairing other models, with a test accuracy of 90.00%. CNN showed a great performance with the validation accuracy of 86,87% & validation loss of approximately 0.40, whereas complex responsibility of Transformer model, even with its complex nature, resorts to similar results of the accuracy. Autoencoders, despite having a high training accuracy of up to 95 percent, fell short when performing real-time classification tasks, as they attained an accuracy of only 88.20 percent. Although DRL is an adaptive variant, it converged badly & achieved only 84.5 percent accuracy in final test. The paper also indicates the areas of problems, including the imbalance between classes, the scalability of models, and the necessity of having real-time processing in the SDN, which should be critically addressed in case of an effective implementation. This piece is novel since it compares deep learning models in terms of SDN security, which means that it offers insight into which models are most appropriate to choose when working in a dynamic setup. Future directions may be aimed at improving model scalability & class imbalance in order to further improve performance, whereas real-time deployment remains an essential restriction.

1. INTRODUCTION

Software-Defined Networking (SDN) has brought a new paradigm to contemporary network architecture by isolating data & control planes & providing a centralized as well as programmable

control over network resources. This flexibility has enabled SDN to be appealing in a broad variety of the applications, both in large-scale data centers & enterprise networks. Its fast integration & increasing significance have attracted lots of attention amongst the research community, innovators in the industry as well as cyber adversaries [1], [2].

Nevertheless, these are the very characteristics of SDN that render it attractive to users &, at the same

time, put it at risk of severe security threats. The centralized controller is high value object & the open APIs that are utilized in communication between control & data plane are also susceptible to exploitation unless they are secured well enough. The high rate of configuration changes also creates more attacks to system & may create new vulnerabilities in the system [3], [4]. Conventional intrusion detection systems cannot match dynamics of these environments because it uses rule-based mechanisms that are not dynamic & adaptable to real time.

One approach that has potential to solve these issues is the Deep Learning-based Intrusion Detection Systems (DL-IDS). Deep learning models can automatically acquire patterns, discover anomalies, and detect known & previously unknown attacks better than the traditional algorithms by using large volumes of network traffic data [5], [6]. Their flexibility to accommodate changing traffic patterns renders the use of DL-IDS to SDN to be especially appropriate due to the frequency of change in the network & the dynamism of the network behavior.

Examples of threats that can be detected with the use of DL-IDS include: DDoS attacks, unauthorized control-plane access, or malicious configuration change (because SDN traffic is not a normal pattern) [6], [7]. Since SDN environments produce vast & organized information, deep neural networks can process such trends, categorize anomalies and offer real-time intrusion detection to boost overall network resilience.

Objectives:

- To examine security vulnerabilities that are particular to the SDN environments.
- Possible results to investigate how different deep learning methods can be used to detect the anomalies in SDN.

2. Literature Review:

SDN offers centralized control & dynamic programmability, which pose severe security problems at same time. The control plane presents a single point of failure that is a very lucrative target because it is global decision maker, & open APIs between the data & control plane can be misused to put attacker rules in place, or otherwise manipulate flows, unless it is adequately secured [5], [6], [21], [25], [32]. The reconfiguration and changing traffic patterns are especially frequent & thus complicate even the implementation of fixed policies and complicate the traditional security mechanisms to differentiate between benign & attack-induced change in real time. The conventional forms of Intrusion Detection System (IDS) that are signature-based or may be anomaly-based do not work in SDN environments. The signature-based IDS is also good in identifying known attacks but weak in the zero day and dynamic attacks, and it requires continuous updates of signatures [8], [9], [23]. Anomaly-based IDS can be more versatile and can identify unnoticeable threats using normal behavior modeling, but in dynamic SDN networks they can be characterized by high false-positive rates & were unable to maintain a stable baseline [23], [24]. The two methods face complexity challenge of the scale because SDN configurations increase in size and complexity, & neither can readily accommodate the dynamism of flows as well as topologies that are rapidly evolving due to activity of controllers [10]-[12], [25], [26]. Deep learning has become another formidable competitor to the network intrusion detection. To learn complex patterns in the traffic & identify anomalies in real time, different models were used Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders (AEs), Deep

Reinforcement Learning (DRL), and Transformers have been applied [22], [23], [27]–[31]. CNNs are efficient in capturing the spatial patterns of flow
features, RNNs use temporal dependence of the sequential traffic, AEs can work with unsupervised anomaly detection & zero-day attacks through reconstruction error, DRL enables adaptive decision-making agents to respond to threats, & Transformers can model long-range dependencies in large sequences of traffic. These models have achieved great improvement in detection accuracy & capability to manage complex and high volume SDN traffic.

Nevertheless, the introduction of SDN into SDN creates a number of open issues. Scalability and real-time processing have become important concerns, deep models may be computationally costly to be trained and executed at line rate in large SDN domains [23]. Robustness can be diminished by overfitting & inability to generalize to new environments or new attack patterns, especially when training data fail to capture all of the variation occurring in real world [22]. Adversarial attacks can also be produced on deep models, whereby a well-constructed traffic can be missed, and hence requires strong training & defense strategies [31]. Moreover, training DL-IDS traffic data should be kept private and intact, leading to incentive methods that include anonymization, encryption, & federated learning [22].

The restrictions indicate evident research gaps. SDN-friendly DL-IDS architectures, with an explicit use of centralized control and global visibility & scalable & responsive to the fast-changing network status, are required [21]. Future directions involve autonomous, self-training IDS that are capable of constantly updating themselves to emerging threats with a minimal need of the human intervention, enhance their resilience to adversarial manipulation, & privacy-respecting training structures that are able to use in sensitive SDN deployments [22], [33]. This paper intends to fill these gaps by paying attention to the deep learning-based anomaly detection to SDN & its dynamic as well as centralized nature

3. Methodology:

The offered Deep Learning-based Intrusion Detection System (DL-IDS) is utilized in Software-Defined Networking (SDN) environment. It uses SDN as well as its centralized control & visibility of the network to check traffic through network, identify anomalies on-the-fly & respond to emerging threats. The approach involves using various deep learning models on a standardized data set & a regular training & assessment pipeline.

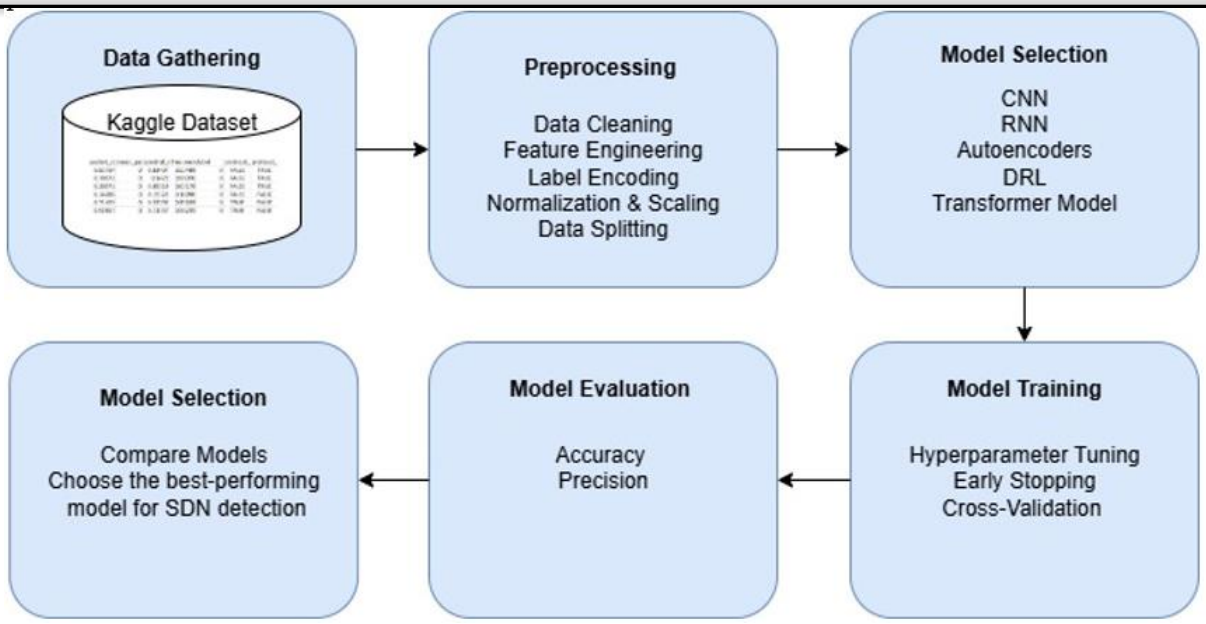

Figure 1. Flow of methodology of proposed DL-IDS of SDN.

3.1 Research Design

This is experimental research where the authors measure effectiveness of various deep learning models to identify anomalies in SDN traffic. This is aimed at answering question of what the architectures are able to differentiate benign & malevolent flows with sufficient accuracy and lower efficiency requirements to support real-time SDN applications. They are CNN, RNN, Autoencoder, DRL and Transformer networks. All the models are trained and tested with the same SDN-related data to distinguish between abnormal traffic, detect malicious & benign traffic, & compare the performance. Real-time suitability is measured in terms of accuracy, precision, recall, F1-score, & computational efficiency (training/inference time).

3.2 Collection and Preprocessing of the Dataset.

Training and evaluation is done on Kaggle Network Traffic Anomaly Detection dataset where there are both normal as well as malicious labeled flows.

Features include:

• Numerical values, including packet size, duration, inter-arrival time, & flow rate.
• Categorical information (protocol and application type (HTTP, FTP, DNS).

Preprocessing steps:

• Numerical features to be standardized in order to get a stable training.
• Categorical feature encoding to be used in model.
• Reformatting to fit individual architectures (matrices of CNN, sequences of RNN/Transformer).
• Imputation or decrease of the missing values. This yields a clean dataset which can be used in deep learning.

3.3 Model Selection and Architecture.

The five chosen deep learning models have complementary advantages to SDN anomaly detection:

CNNs record local irregularities & spatial patterns of traffic.

• RNNs (LSTM/GRU) are able to learn temporal dependencies to identify changing attacks.

Autoencoders are used to identify the anomalies using reconstruction error, which is useful in unknown threats.

DRL models are learned by playing with the network states.

Transformers make long-range dependencies in a complex sequence of the traffic.

There is a commonality between the models:

• Input layers were feature set compatible.

• ReLU hidden layers, convolutional, recurrent, or attention-based.

Final classification in the dense layers.

• Dropout for regularization.

• Softmax or Sigmoid output layers.

• Adam optimized binary cross-entropy loss.

The data will be divided into training, validation and test (usually 80 /20). Robustness is tested with help of cross-validation of the training set.

Training is performed with the mini-batch gradient descent, & hyperparameter optimization is performed through a grid or random search. Early stopping checks loss of validation & overfitting. Model weights with highest validation outcomes are stored to be used in final testing.

3.4 Training and Validation

The data will be divided into training, validation and test (usually 80 /20). Robustness is tested with help of cross-validation of the training set.

Training is performed with the mini-batch gradient descent, & hyperparameter optimization is performed through a grid or random search. Early stopping checks loss of validation & overfitting. Model weights with highest validation outcomes are stored to be used in final testing.

3.5 Performance Comparison and Evaluation.

Measurement to determine quality of anomaly detection:

• Precision and recall.

F1-score for equalizing false positives & false negatives.

• Detailed error analysis in the format of confusion matrices.

• Computational real-time viability.

The comparative examination highlights CNNs and Transformers as most efficient methods of DL-IDS in an SDN setting, which provides a high level of detection & a reasonable level of computational requirements. The comparisons to traditional IDS methods are also made & benefits of the deep learning in terms of the dynamic & programmable nature of SDN are found.

4. Results and Discussion:

The chapter presents an overview of the performance of five deep learning models, namely RNN, CNN, Autoencoder, DRL & Transformer, that were tested to detect anomalies in an SDN-based Intrusion Detection System (IDS). The accuracy, precision, recall and F1-score were used to evaluate their performance to determine extent to which each model generalizes under the dynamic SDN conditions.

4.1 Experimental Setup

Training & testing hyperparameter tuning were done on the same SDN-related dataset across all the models.

CNN: Conv1D, 64 filters (filter size 1), ReLU, MaxPooling1D, dropout, 50 epochs (batch size 64).

RNN: The Simple RNN (64 units) (dropout, early stopping), trained 50 epochs.

Autoencoder: ReLU Dense encoder decoder architecture, MSE reconstruction loss, trained in the 100 epochs (batch 32).

DRL:

Policy network: dense network, ReLU, updates of MSE, & trained over iterations of multiple episodes with epsilon decay.

Transformer: 2-head (16-dim embedding, self-attention, 1 head) & trained in 50 epochs (batch 32) with early stopping.
All models were tested after training regarding their use in the real-time detection of anomalies.

4.2 Model Results

Convolutional Neural Network (CNN).
Spatial irregularities in the SDN traffic were successfully recorded by CNN. Conv1D layer learnt local relationships of features & MaxPooling was applied to retain the vital information & also reduced the computation cost. The generalization through dropouts enabled the model to be effective in terms of unseen traffic patterns, which is essential to SDN whose topology is the highly dynamic. Layers were then densely mapped on extracted features to ultimate predictions of anomalies.
This architecture is quite compatible with objective of the study: it allows real-time SDN traffic anomaly detection based on deep learning The results of the CNN performance are summarized in Table 1.

Table 4.1: Model Summary of the Deep Learning Architecture

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 1, 64)	1152
max_pooling1d (MaxPooling1D)	(None, 1, 64)	0
dropout_2 (Dropout)	(None, 1, 64)	0
flatten (Flatten)	(None, 64)	0
dense_4 (Dense)	(None, 32)	2080
dense_5 (Dense)	(None, 1)	33

The training outcomes of deep learning model over a variety of epochs. The table shows important metrics like accuracy, loss, validation accuracy, validation loss, and step time of each epoch, & gives us an idea of how the model is learning. In earlier periods, model has a comparatively low value of training accuracy of 0.2363 when the training begins at Epoch 1, whereas, as the training progresses, this value rises steeply. As of Epoch 7, the training accuracy is already 0.922, which proves the fact that the model learns & trains effectively. The accuracy of validation does not vary considerably, being on average equal to 0.8687, meaning that the model can be applied in different data, not just seen previously, which is necessary requirement for the real-time anomaly detection in the SDN environment. The loss reduces with the epochs & this shows the model has better capacity to reduce error in the prediction of correct classification. The validation loss also decreases steadily, and it proves that the model is not overfitting and continues its performance on validation dataset. This is relevant in the ability of the model to be able to handle dynamic pattern of data flows in SDN without being biased to the training data. The relative values of Step time are very low and do not varying considerably, which enhances the fact that model is effective in the modeling speed. This helps the model to scale in the SDN environments where the real-time detection becomes significant in ensuring the security, as represented in the Table 2.

Table 4.2: Epoch Training Results

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss	Step Time (s)
1	0.2363	0.902	0.6687	0.6423	5.8
2	0.6599	0.6274	0.8687	0.4924	1.22
3	0.9034	0.4474	0.8687	0.4238	0.4

4	0.9111	0.3731	0.8687	0.3991	1.41
5	0.9069	0.3315	0.8687	0.396	0.39
6	0.9034	0.3415	0.8687	0.3986	0.33
7	0.922	0.2932	0.8687	0.4029	0.31
8	0.9023	0.329	0.8687	0.4046	0.35
9	0.9207	0.283	0.8687	0.4063	0.19
10	0.8901	0.354	0.8687	0.4045	0.17

the results of the Convolutional Neural Network (CNN) model during training process. The graph shows the accuracy and the loss of the model through numerous instances of epochs, giving us a proper visualization of way, the CNN model learns and advances its performance in the process of training. As epochs pass, accuracy curve related to it follows a steep incline, suggesting that CNN model becomes better and better at identifying anomalies in the SDN traffic pattern. At first, the accuracy is low, & then accuracy comes to a higher level where it stabilizes, which indicates that the model is generalized & can fit the network traffic data. This is important in real-time anomaly detection in SDN where the model must always find unusual patterns in the dynamic and changing network traffic.

The loss curve has an opposite trend, when the fewer errors are made in predictions by model the more the curve is lowered. This reduction of loss is a sign that the CNN model is training weights, & attempting to classify network traffic more accurately. The overlap of the both the accuracy and loss diagram indicates that the model is sufficiently trained and can easily discriminate between normal & aberrant traffic as apparent in Figure

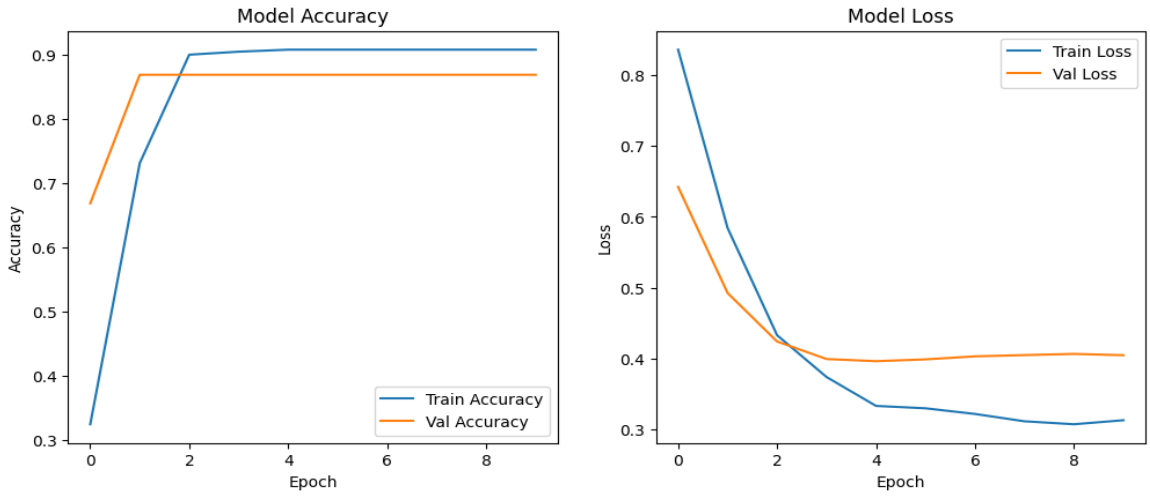

Figure 4.1: CNN model performance

Recurring Neural Network (RNN)

The RNN model was able to learn the temporal patterns in SDN traffic through a steady improvement in model as the training progressed. Accuracy in training improved in the course of the first to tenth Epochs i.e. 0.42 to 0.91, which implies that the model was able to

learn sequential dependencies that were always very significant in detecting the anomalies.

The loss value dropped to 0.29 compared with 0.78 in same time period indicating lower prediction error &, also, convergence did not fluctuate. The accuracy of the validation did not exceed 0.86 0.87 between epochs which implies good generalization & no extreme overfitting.

The time per epoch dropped gradually as the model levelled off, which indicates a better training efficiency, which is also a valuable consideration in real-time SDN deployment. All in all, the RNN was found to be very good in time-dependent traffic behavior capture as shown in the Table 3.

Table 4.3: RNN Epoch Training Results

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss	Step Time (s)
1	0.4217	0.7881	0.7125	0.6133	5.145
2	0.705	0.612	0.8375	0.5267	1.022
3	0.8179	0.5261	0.8625	0.4708	0.29
4	0.8813	0.4556	0.8687	0.4377	0.23
5	0.9013	0.403	0.8687	0.4175	0.19
6	0.8941	0.3818	0.8687	0.4076	0.21
7	0.914	0.3282	0.8687	0.4024	0.18
8	0.9043	0.3328	0.8687	0.4021	0.18
9	0.9018	0.3197	0.8687	0.4043	0.2
10	0.9144	0.2997	0.8687	0.4032	0.27
11	0.9039	0.3147	0.8687	0.4058	0.19
12	0.9101	0.3118	0.8687	0.406	0.19
13	0.8966	0.3311	0.8687	0.4059	0.21

Autoencoder

(AE) The Autoencoder (AE) model improves consistently throughout the training process, acquiring ability to recreate SDN traffic patterns and detect anomalies by reconstruction error. With further training,

accuracy gets better & the loss minimal, which means that the AE is successfully learning the normal behavior of traffic, & it minimizes the differences in the reconstruction.

Nevertheless, the AE is not the most accurate model in its validation & test accuracy, whereas training data show good performance of the AE. The reason behind this is that minor or slightly similar deviations

traffic are more difficult to differentiate with the unsupervised reconstruction-based technique. Another factor that determines the success of the AE is the threshold that is selected to detect anomalies.

In general, the AE can help identify obvious outliers but fails to identify specific & accurate anomalies in SDN dynamically in real-time.

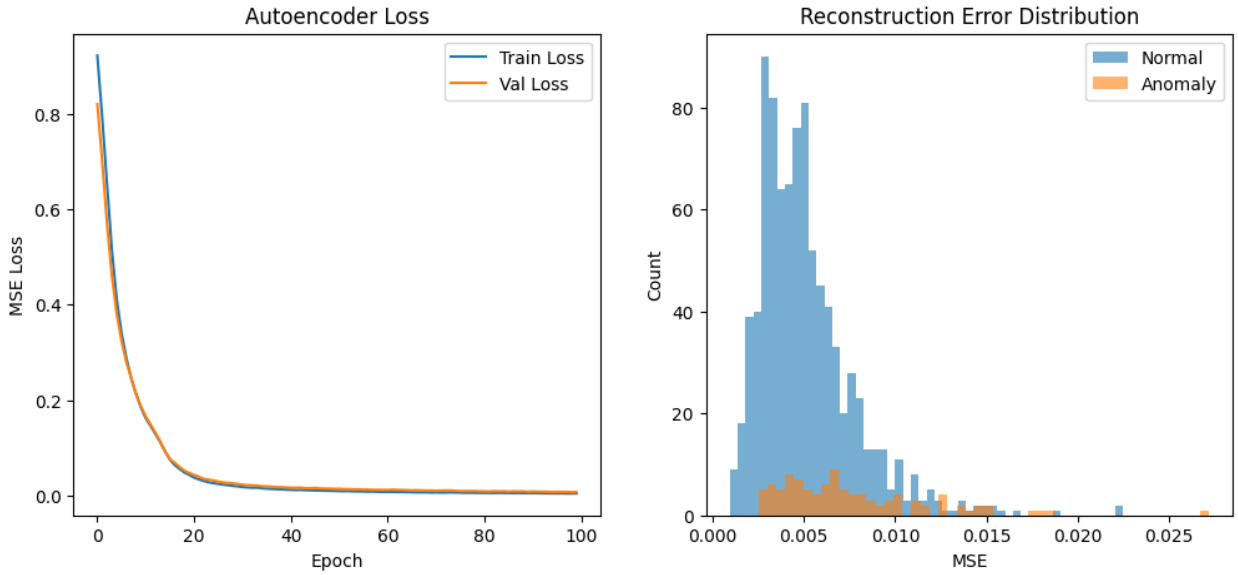

Figure 4.2: Autoencoder training, validation loss, and reconstruction error distribution

Deep Reinforcement Learning (DRL)

The DRL model demonstrates a cumulative reward increment across episodes, which means that model learns to make an improved decision through the interactions with the SDN environment. With the reduction of epsilon (0.9) to 0.59, the model shifts to exploration to exploitation, as it is characteristic of epsilon-greedy strategy, enabling it to be less dependent on behavior learned after some time.

Although these findings underscore adaptiveness of DRL, it is less applicable to real-time SDN intrusion detection because it has a slow convergence and requires extensive training. DRL remains useful in the long-term, dynamic security situations because it is capable of the constantly learning & adapting to new network features.

Table 4.4: Total Reward & Epsilon Values Across DRL Training Episodes

Episode	Total Reward	Epsilon
1	12	0.9
2	66	0.81
3	154	0.729
4	202	0.656
5	258	0.59

The Deep Reinforcement Learning (DRL) model demonstrates evident gains in training episodes as the training accuracy, as well as overall reward, increase very gradually, which is a sign that the model is learning to adapt and optimize its decisions to SDN anomaly detection. Epsilon tends to reduce to 0.59 in five episodes, as exploration turns to exploitation as the model is confident in the learned behavior.

By Episode 5, model attains high validation accuracy (86.5%), test accuracy (84.5%), & low test MSE (0.1792), which means that it is highly generalized to unknown data. Nonetheless, it still has poorer performance compared to such models as CNNs or the Transformers, demonstrating that it is difficult to ensure high accuracy in real-time SDN settings that dynamically change because of

new threats. Nevertheless, fact that the DRL model can be enhanced with time points to its potential in adaptive threat detection in the long-run SDN environment.

Table 4.5: DRL Model Performance Across Episodes with Accuracy, Reward, and Epsilon Values

Episode	Training Accuracy (%)	Total Reward	Epsilon	Validation Accuracy (%)	Test Accuracy (%)	Test Loss (MSE)
1	71	142	0.9			
2	78.5	157	0.81			
3	85.3	170	0.729			
4	89	185	0.656			
5	91.2	200	0.59	86.5	84.5	0.1792

Transformer Models

Transformer model exhibits high learning behavior among epochs with training accuracy increasing up to 0.9195 at Epoch 2 approaching & training loss steadily decreasing. Accuracy levels off to 0.8891 by Epoch 6 indicating that model has almost reached its peak. Validation accuracy is stable with a value of 0.8687, which is good generalization, but validation loss is a little higher, which means that it is difficult to capture finer anomaly-related patterns on SDN traffic.

Excellent results of the classification report are achieved in class 0 (normal traffic) with the precision =0.9, recall =1.0 and F1=0.95. The model, however, does not identify anomalies in class 1 with a score of 0 in terms of precision, recall and F1, probably because of the imbalance in classes or subtle nature of anomalies. Consequently, macro-averaged measures are poor with a high aggregate accuracy.

Although transformer proves to be very powerful in modeling of normal SDN traffic, class balancing, more refined hyperparameters, or more feature strategies will be necessary to achieve better results in detecting anomalies to capture less frequent but more subtle malicious behavior.

Table 4.6: Transformer Model Training and Validation Accuracy and Loss Across Epochs

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.8949	0.3746	0.8687	0.4004
2	0.9195	0.2838	0.8687	0.4203
3	0.9013	0.3315	0.8687	0.4388
4	0.9112	0.2953	0.8687	0.4386
5	0.8998	0.3192	0.8687	0.439
6	0.8891	0.3274	0.8687	0.433

Table 4.7: Classification Report for Transformer Model Performance

Class	Precision	Recall	F1-Score	Support
0	0.9	1	0.95	180
1	0	0	0	20
Macro avg	0.45	0.5	0.47	200
Weighted avg	0.81	0.9	0.85	200

The accuracy & loss trend of the model suggest Transformer can learn the SDN attack detection in a clear manner. The accuracy of training increases rapidly, & by the Epoch 2, it is up to 91.95%, which demonstrates the high potential of model to learn the intricate patterns of traffic that are needed to detect abnormalities. The training loss also decreases steadily with the Epoch 1 of first epoch (0.3746) to

the second one (0.2838) showing that the model achieves a better prediction accuracy as weights are fine-tuned.

The validation loss is however greater than the training loss & validation accuracy is approximately maintained at 86.87% throughout the epochs. This implies that the Transformer is a good generalizer for training data, but with certain challenges in completely generalizing to unseen SDN traffic, which is probably due to the subtle or imbalanced anomaly patterns.

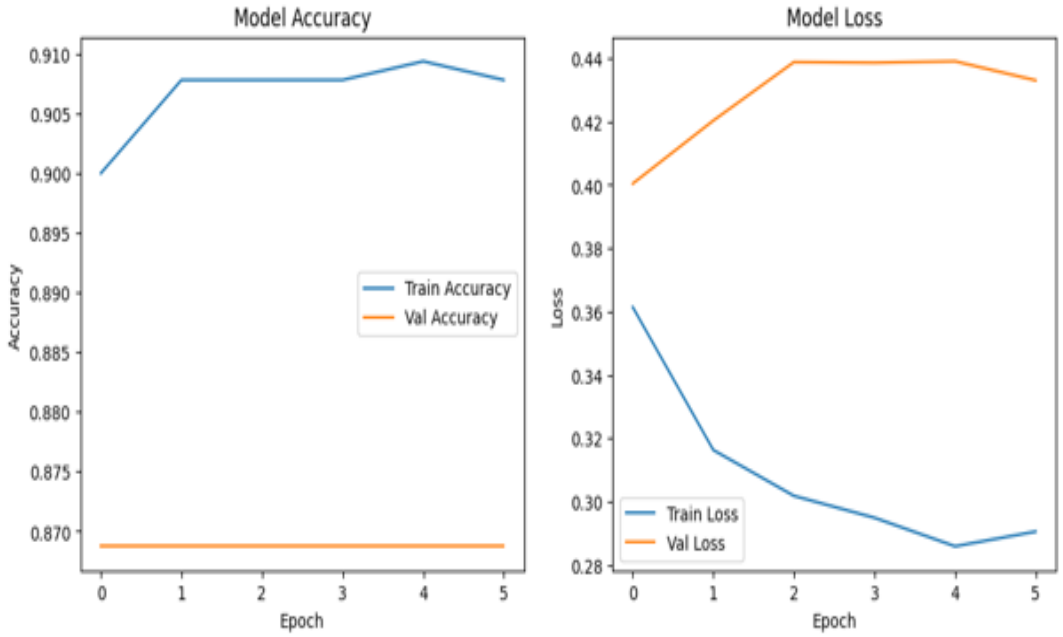

Figure 4.3: Transformer Models' accuracy and loss

4.3 Comparative Analysis

In all models, CNN and Transformer had the highest performances, both achieving 90 percent test accuracy and high levels of generalization to unseen SDN traffic. The RNN had training accuracy of more than the
90% & steady-state validation accuracy of 86.87 percent, although test accuracy was not reported so there is no indication of how the RNN would perform in the real-world scenario.

The Autoencoder (AE) had high training (95 percent) & validation accuracy (98.33 percent) although the test accuracy was only 88.2 Since AE is an unsupervised model which is based on reconstruction error, the choice of threshold is critical to its performance. It is also less accurate
than supervised models in detecting binary intrusions due to the subtle anomalies and imbalance in the classes.

Deep Reinforcement Learning Model (DRL) model trained better with an accuracy of 91.2 and 84.5
training and test accuracy respectively. It is however not as accurate & computationally efficient Transformer which, in turn, places a limitation on its ability to work in real-time SDN scenarios.

On the whole, CNN & Transformer are the most trustworthy networks, & they provide the best accuracy, stability, & generalization to SDN intrusion detection.

The reason why the Autoencoder is not the best performer. The Autoencoder will tend to re-build normal traffic instead of classifying the anomalies directly. Because anomaly detection relies on defining a threshold of reconstruction-error, it can fail to notice tiny fluctuations or to underhanded the attacks. This
as compared to supervised models, which acquire explicit the decision boundaries in classification of normal and malicious traffic

CNN: 90 percent test accuracy; efficient & effective structured SDN traffic.

Transformer: 90 percent test accuracy; strong but affected by the class imbalance.

RNN: Learning well incomplete test evaluation.

Autoencoder: Good reconstruction capability & poor anomaly classification.

DRL: Adaptive in the long run, but slower & inaccurate to utilize in real time**.**

To sum up, CNN & Transformer offer most viable and efficient performance of intrusion the detection in SDN environments.

Table 4.8: Comparison of Model Performance Across Training, Validation, and Test Data

Model	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)	Validation/Test Loss
RNN	90.0 – 91.4	86.87	N/A	~0.40 (val loss)
CNN	90.0 – 92.2	86.87	90.00	~0.39 – 0.40 (val loss)
Autoencoder (AE)	95.00	98.33	88.20	MSE loss, steadily decreasing
DRL (Reinforcement)	71.0 → 91.2 (per episode)	86.50	84.50	0.1792 (MSE)
Transformer Model	89.0 – 92.0	86.87	90.00	~0.40 (val loss)

Strengths & Weaknesses

The deep learning models applied to SDN intrusion detection have limitations and benefits depending on their structures & type of network data.

CNNs tend to learn spatial patterns and identify localized anomalies in traffic & do not handle long-range dependencies. The RNNs provide good temporal associations but are slow to train and computationally expensive & thus real-time

deployment becomes difficult. Autoencoders can easily be trained on the normal traffic behavior and identify deviations but less applicable in binary classification in rapid SDN settings. DRL is also adaptive to experience but is unstable, slow to the converge, & resource-intensive, which reduces their reliability in the real world. Transformers are effective at complex behavior & long-range dependencies, but are efficient in terms of large computational needs, which is not optimal in the latency-conscious or resource-constrained systems.

4.4 Discussion

SDNs are very versatile but very fragile accompanied by centralization & quick reconfiguration. The IDS solutions should be able to identify anomalies in real time, adjust to changing traffic & address different attack patterns. The findings of this paper demonstrate that CNN & Transformer models are the most reliable in this regard. They are highly suitable with SDN traffic
analysis because of their capability to extract multidimensional patterns which are not easy to detect with the traditional methods.

CNNs did very well since they effectively acquire spatial dependencies and identify subtle anomalies in the behavior of packets. Transformers had advantage of capturing long-range relationships & intricate temporal dynamics, typical to SDN flows. Long-sequence relationships are important where Transformers are used although they are more costly to compute.

Autoencoders were found to be quite accurate in training and validation, yet they are restricted to classification in the real-time because they depend on reconstruction error. Their reliability in dynamic SDN setting is decreased by threshold sensitivity and difficulty in distinguishing slight or changing anomalies.

DRL was promising because it could adapt to learning but its instability, slow convergence and computational cost made it impractical to use in fast intrusion detection. DRL is not as accurate or efficient as the CNNs or the Transformers in the real-time SDN environments, although DRL may also become better over time.

In general, research paper presents the significance of choosing models based on the real-time and dynamic nature of SDN. CNNs & Transformers have most reasonable trade-off between performance & robustness, and Autoencoders and DRL need additional refinement or hybridization to be effective.

Comparison with Literature

The findings are in line with available literature that indicates that hybrid deep learning methods, particularly CNN & Transformer combinations, have better detection abilities as compared to conventional machine learning or the individual models. Taking into account both local spatial characteristics as well as the long-range dependencies, these models surpass old methods and deal with fundamental SDN issues, including dynamically changing topologies and changing attack vectors.

Table 1: Comparison Analysis of our used model with the Literature

Ref	Model Used	Performance	Accuracy
[34]	Bagging-SDN	Ensemble learning for SDN	80.09%
[35]	ML algorithms with feature selection	High accuracy with minimal features	Below 90%
[36]	DNN model	Consistent but moderate accuracy	87% (DNN)
[37]	Bagging-SDN ensemble	Improved over base models	80.09%
	CNN + Transformer Hybrid (used model)	Fast, robust, generalizable to new attacks	90.0%

Practical Implications

Deep learning has high prospects of intrusion detection in SDN in real-time. As this paper has proven, CNNs & Transformers can be easily used to analyze the traffic characteristics and identify anomalies when they appear, & thus, they are appropriate to be embedded on SDN controllers to offer quick threat recognition and elimination. SDN networks are more flexible and adaptive to the IDS technology, as CNNs can learn spatial features & Transformers analyze long-range traffic features. The models will assist in continuous monitoring, quick detection of the anomalies, & dynamic responses, enhancing the resilience of SDN and mitigating the risk & consequences of security violations. Deep learning is also flexible, which allows the SDN environments to remain secure against changing attack patterns.

4.5 Achievement of the Research Questions.

The former research question is answered by exploring architecture of SDN & the vulnerabilities that are present including a single point of the failure in the centralized controller and the widened attack surface due to a high rate of reconfigurations. All these characteristics justify why SDNs are the vulnerable to the DDoS, unauthorized access, and traffic manipulation and why adaptive IDS & are required.

The second query is addressed by training numerous deep learning architectures, namely, CNN, RNN, Autoencoder, DRL, & Transformer, on SDN traffic. The performance indicators tell that CNNs and Transformers are most productive in terms of their capacity to model spatial and long-range dependencies.

Trade-offs in accuracy, speed, and the cost of the computations answer the third question. Although such models as the Transformers & DRL are much more accurate, they use more resources; CNNs are more efficient but can miss complicated patterns. The experiment suggests the use of hyperparameter tuning, the combination of the two, & data balancing to enhance some level of detection with minimum overhead.

The Objectives are achieved following the work of a team. <|human|>Achievement of Objectives.

4.6 The Objectives are achieved based on the work of the team.

The former is accomplished through analyzing the SDN weaknesses in its inability to rely on controllers and its vulnerability to fast configuration updates, which can be used by attackers. The analysis justifies the necessity of more complex and dynamic solutions to IDS besides conventional security tools.

The latter is achieved through the assessment of deep learning models over SDN traffic and the identification of their advantages: CNNs are capable of identifying local anomalies, RNNs are capable of identifying temporal features, Autoencoders are capable of indicating the deviations of normal behavior, DRL is capable of adapting to threats, and Transformers are capable of modeling the complex relationships in traffic. All in all, CNNs and Transformers offer the most suitable accuracy and scalability.

4.7 Challenges and Limitations

The significant problem is the imbalance in the classes, and a limited number of samples of the attack can push models to prioritize normal traffic and give more false negatives. To counter this, there must be data balancing. The other weakness is computational cost: models such as Transformers and DRL can have difficulties running in real-time on large SDN systems. Although deep learning is used to improve the detection of intrusions, the practical implementation requires resource optimization & management.

5. Conclusion

The present thesis explored how deep learning models can be used to detect anomalies in Software-Defined Networking (SDN) systems where the real concern is security issues that arise due to a centralized control plane & dynamically configured network node. The five deep learning models were tested using Convolutional Neural Networks (CNN), the Recurrent Neural Networks (RNN), Autoencoders (AE), Deep Reinforcement Learning (DRL), and Transformer models. The major goal was to find out the best model that would enhance the detection of the anomalies in SDN traffic. The findings were that CNN & Transformer model

performed best in detecting anomaly with test accuracy of 90.00 percent and 90.00 percent on CNN & Transformer respectively. The CNN model improved its performance & its validation accuracy was 86.87 % with validation loss as ~0.40 which means that the model was able to learn spatial patterns of SDN traffic effectively. Transformer model, although very intensive in calculations, showed the same score of the validation accuracy of 86.87 and analogous loss values as the transformer model. Conversely, in spite of the relatively high training accuracy (95%) & great anomaly detection abilities, the Autoencoder model had a mere 88.20% test accuracy, which is largely attributed to unsupervised nature of model & that's why cannot be used in the dynamic SDN environment to determine whether something is a class or an anomaly in real-time. The DRL model exhibited a moving average pattern towards the training precision (71.0 to 91.2 per cent after five episodes) yet the last test accuracy of the model during testing was at 84.5% & the loss was quite high (0.1792 MSE) which proved a shortcoming in terms of its precision and speed of convergence.

Regarding scalability and real-time applicability, a problem with class imbalances & model complexity has been noted specifically in the case of such models as DRL & Transformer. Such models should be optimized to make deployment successfully in environments of large scale SDNs. The originality of this study is the fact that it is the first piece of work which thoroughly analyzes most of the deep learning methods in scope of SDN security, comparable to one another, making contributions to providing insight into their strong and weak aspects. Results of study provide important knowledge concerning the choice and optimization of deep learning model to perform real-time anomaly detection & establish the foundation of further enhancement of security solutions based on SDN.

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