# A Deep Learning Approach for Network Intrusion Detection System

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## ABSTRACT

A Network Intrusion Detection System (NIDS) helps system administrators to detect network security breaches in their organization. However, many challenges arise while developing a flexible and effective NIDS for unforeseen and unpredictable attacks. In this work, we propose a deep learning based approach to implement such an effective and flexible NIDS. We use Self-taught Learning (STL), a deep learning based technique, on NSL-KDD - a benchmark dataset for network intrusion. We present the performance of our approach and compare it with a few previous work. Compared metrics include the accuracy, precision, recall, and f-measure values.

## 1. INTRODUCTION

Network Intrusion Detection Systems (NIDSs) are important tools for the network system administrators to detect various security breaches inside an organization's network. An NIDS monitors, analyzes, and raises alarms for the network traffic entering into or exiting from the network devices of an organization. Based on the methods of intrusion detection, the NIDSs are categorized into two classes: i) signature (misuse) based NIDS (SNIDS), and ii) anomaly detection based NIDS (ADNIDS). In SNIDS, e.g., Snort [1], rules for the attacks are pre-installed in the NIDS. A pattern matching is performed for the traffic against the installed rules to detect an intrusion in the network. In contrast, an ADNIDS classifies network traffic as an intrusion whenever a deviation from the normal traffic pattern is observed. SNIDS is

effective in the detection of known attacks and shows high detection accuracy and less false-alarm rates. However, its performance suffers during detection of unknown or new attacks due to the limitation of rules that can be installed beforehand in an IDS. ADNIDS, on the other hand, is well-suited for the detection of unknown and new attacks. Although ADNIDS produces high false-positive rates, its theoretical potential in the identification of novel attacks has caused its wide acceptance among the research community.

There are primarily two challenges that arise while developing an effective and flexible NIDS for the unknown future attacks. First, proper feature selections from the network traffic dataset for anomaly detection is difficult. As attack scenarios are continuously changing and evolving, the features selected for one class of attack may not work well for other classes of attacks. Second, unavailability of labeled traffic dataset from real networks for developing an NIDS. Immense efforts are required to produce such a labeled dataset from the raw network traffic traces collected over a period or in real-time and this serves as the reason behind the second challenge. Additionally, to preserve the confidentiality of the internal organizational network structures as well as the privacy of various users, network administrators are reluctant towards reporting any intrusion that might have occurred in their networks [2].

Various machine learning techniques have been used to develop ADNIDSs, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Naive-Bayesian (NB), Random Forests (RF), Self-Organized Maps (SOM), etc. The NIDSs are developed as classifiers to differentiate the normal traffic from the anomalous traffic. Many NIDSs perform a feature selection task to extract a subset of relevant features from the traffic dataset to enhance classification results. Feature selection helps in the elimination of the possibility of incorrect training through the removal of redundant features and noises [3]. Recently, deep learning based methods have been successfully applied in audio, image, and speech processing applications. These methods aim to learn a good feature representation from a large amount of unlabeled data and subsequently apply these learned features on a limited amount of labeled data in the supervised classification. The labeled and unlabeled data may come from different distributions, however, they must be relevant to each other.

of these datasets using deep learning techniques can be obtained. These features can, then, be applied for supervised classification to a small, but labeled traffic dataset consisting of normal as well as anomalous traffic records. The traffic data for labeled dataset can be collected in a confined, isolated and private network environment. With this motivation, we use self-taught learning, a deep learning technique based on sparse auto-encoder and soft-max regression, to develop an NIDS. We verify the usability of the self-taught learning based NIDS by applying it on NSL-KDD intrusion dataset, an improved version of the benchmark dataset for various NIDS evaluations - KDD Cup 99. We also provide a comparison of our current work with other techniques.

Towards this end, our paper is organized in four sections. In Section 2, we discuss a few closely related work. Section 3 presents an overview of self-taught learning and the NSL-KDD dataset. We discuss our results and comparative analysis in Section 4 and finally conclude our paper with future work direction in Section 5.

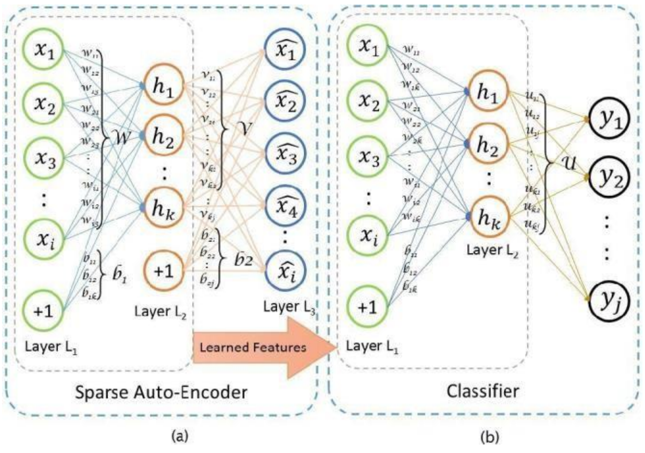
## 2. RELATED WORK

This section presents various recent accomplishments in this area. It should be noted that we discuss only the work which have used the NSL-KDD dataset for their performance benchmarking, therefore, any dataset referred from this point forward should be considered as NSL-KDD. This allows a more accurate comparison of our work with other found in literature. Another limitation is the use of training data for both training and testing by most work. Finally, we discuss a few deep learning based approaches that have been tried so far in this area.

One of the earliest work found in literature used ANN with enhanced resilient backpropogation for the design of such an IDS [6]. This work used only the training dataset for both training (70%), validation (15%) and testing (15%). As expected, use of unlabeled data for testing resulted in a reduction of performance. A more recent work used J48 decision tree classifier, and again only the training dataset with 10-fold cross validation for testing was used [7]. This work used a reduced feature set of 22 features instead of the full set of 41 features. A similar work evaluated various popular supervised tree-based classifiers and found that Random Tree model performed best with highest degree of accuracy along with reduced false alarm rate [8].

Many 2-level classification approach have also been proposed. One such work uses Discriminative Multinomial Naive Bayes (DMNB) as base classifier and Nominal to Binary supervised filtering at the second level, along with 10-fold cross validation for testing [9]. This work was further extended to use END (Ensembles of Balanced Nested Dichotomies) at the first level and Random Forest at the second [10]. As expected, this enhancement resulted in an improved detection rate and a lower false positive rate. Another 2-level implementation using PCA (principal component analysis) for feature set reduction and then SVM (using Radial Basis Function) for final classification, resulted in a high detection accuracy with only the training dataset and full 41 feature set. A reduction in feature set to 23 resulted in even better detection accuracy in some of the attack classes but the overall performance was reduced [11]. The authors improved their work by using information gain to rank the features and then a behavior-based

feature selection to reduce the feature set to 20. This resulted in an improvement in reported ac-



The second category to look at, used both the training and testing dataset. An initial attempt in this category used fuzzy classification with genetic algorithm and resulted in a detection accuracy of 80%+ with a low false positive rate [13]. Another important work in used unsupervised clustering algorithms and found that the performance using only the training data was reduced drastically when testing data was also used [14]. A similar implementation using the k-point algorithm resulted in a slightly better detection accuracy and false positive rate, using both training and test datasets [15]. Another less popular technique, OPF (optimum-path forest) which uses graph partitioning for feature classification, was used for IDS and was found to demonstrate a high detection accuracy [16] within one-third of the time compared to SVM-RBF method.

We observed a deep learning approach with Deep Belief Network (DBN) as a feature selector and SVM as a classifier in [5]. This approach resulted in an accuracy of 92.84% when applied on training data. Our current work could be easily compared to this work due to the enhancement in approach over this work and use of both the training and testing dataset in our work. A similar, however, semi-supervised learning approach has been used in [2]. The authors used real-world trace for training, and evaluated their approach on real-world and KDD Cup 99 traces. Our approach is different from them in the sense that we use NSL-KDD dataset to find deep learning applicability in NIDS implementation. Moreover, the feature learning task is completely unsupervised and based on sparse auto-encoder in our approach. We recently observed an sparse auto-encoder based deep learning approach for network traffic identification in [17]. The authors performed TCP based unknown protocols identification in their work instead of network intrusion detection.

## 3. LITERATURE REVIEW

Certainly, let's structure the literature review of Network Intrusion Detection Systems (NIDS) in paragraph form:

Network Intrusion Detection Systems (NIDS) are a critical component of modern cybersecurity, designed to identify and respond to unauthorized access, attacks, and abnormal network behavior. These systems can be broadly categorized into two main types: signature-based and anomaly-based. Signature-based NIDS rely on predefined attack signatures to detect known patterns of intrusion, while anomaly-based NIDS establish a baseline of normal network behavior and flag any deviations from this baseline. The ongoing challenge in the field has been the high rate of false positives generated by NIDS, which can overwhelm security personnel with an excessive number of alerts. Researchers have continually worked to improve the accuracy of NIDS to reduce these false positives, enhancing their effectiveness.

Machine learning, particularly deep learning techniques, has gained prominence in the NIDS landscape. These methods offer the potential to enhance intrusion detection accuracy by learning and adapting to new attack patterns. Additionally, the surge in network traffic data, driven by the digital transformation, has led to the application of big data technologies and analytics in NIDS. These technologies enable the efficient processing and analysis of large datasets, which can be instrumental in identifying subtle attack patterns that might go unnoticed using traditional methods.

The advent of cloud computing and IoT has brought forth new challenges for NIDS. Researchers have shifted their focus towards developing NIDS that are capable of monitoring and protecting cloud-based networks. For IoT environments, constrained resources and diverse communication protocols necessitate the development of lightweight NIDS solutions that can cater to the unique needs of IoT devices. This includes addressing device vulnerabilities, data integrity, and privacy concerns specific to IoT.

An emerging trend in NIDS research involves behavioral analysis. This falls under the umbrella of anomaly-based detection and revolves around the continuous monitoring and learning from user and network behavior. Advanced behavioral analysis techniques aim to adapt to changing network dynamics and detect sophisticated attacks that might lack known signatures. Furthermore, hybrid NIDS approaches have been explored, combining both signature-based and anomaly-based methods to improve detection accuracy by leveraging the strengths of each approach.

As network sizes and complexities continue to grow, scalability and performance become crucial aspects of NIDS development. These systems must efficiently process large volumes of data while maintaining low latency, especially in high-traffic environments. Moreover, the integration of threat intelligence feeds into NIDS has become a common practice, enhancing their ability to detect and respond to emerging threats by staying updated with the latest threat information.
Certainly, let's expand on the literature review of Network Intrusion Detection Systems (NIDS):

Network Intrusion Detection Systems (NIDS) serve as a vital component in the realm of network security. They are designed to monitor network traffic and identify any suspicious or malicious activity that may compromise the security and integrity of a network. NIDS can be broadly classified into two main categories: signature-based and anomaly-based. Signature-based NIDS, also known as rule-based NIDS, rely on predefined patterns or signatures of known attacks. They compare network traffic against these signatures and generate alerts when a match is found. Anomaly-based NIDS, on the other hand, establish a baseline of normal network behavior and raise alarms when deviations from this baseline occur. This approach is particularly useful for identifying previously unknown or novel attacks.

## 4. SELF-TAUGHT LEARNING & NSL-KDDDATASET OVERVIEW

### 4.1 Self-Taught Learning

Self-taught Learning (STL) is a deep learning approach that consists of two stages for the classification. First, a good feature representation is learnt from a large collection of unlabeled data, $x_u$, termed as Unsupervised Feature Learning (UFL). In the second stage, this learnt representation is applied to labeled data, xl, and used for the classification task. Although the unlabeled and labeled data may come from different distributions, there must be relevance among them. Figure 1 shows the architecture diagram of STL. There are different approaches used for UFL, such as Sparse Auto-Encoder, Restricted Boltzmann Machine (RBM), K-Means Clustering, and Gaussian Mixtures [19]. We use sparse auto-encoder based feature learning for our work due to its easy implementation and good performance [4]. An sparse auto-encoder is a neural network consists of an input, a hidden, and an output layers. The input and output layers contain N nodes and the hidden layer contains K nodes. The target values in the output layer set to the input values, i.e., ˆxi

= xi as shown in Figure 1(a). The sparse auto-encoder network finds the optimal values for weight matrices, W ∈ KXN and V

∈ $R^{NXK}$, and bias vectors, b1 ∈ KX1 and b2 ∈ $\sim^{NX1}$, using back-propagation algorithm while trying to learn the approximation of the identity function, i.e., output xˆ simi lar

to x [18]. Sigmoid function, g(z) = 1

The cost function to be minimized in sparse auto-encoder using back-propagation is represented by Eqn. 2. The first term is the average of sum-of-square errors term for the all m input data. The second term is a weight decay term, with A as weight decay parameter, to avoid the over-fitting in training. The last term in the equation is sparsity penalty term that puts a constraint into the hidden layer to maintain a low average activation values, and expressed as KullbackLeibler (KL) divergence shown in Eqn. 3:

Where p is a sparsity constraint parameter ranges from 0 to 1 and β controls the sparsity penalty term. The KL(p~ˆpj) attains a minimum value when p = ˆpj, where ˆpj denotes the average activation value of hidden unit j over the all training inputs, x. Once, we learn optimal values for W and b1 by applying the sparse auto-encoder on unlabeled data, $x_u$, thereafter, we evaluate the feature representation a = hW,b1(xl) for the labeled data, (xl, y). We use this new features representation, a, with the labels vector, y, for the classification task in the second stage. We use soft-max regression for the classification task, shown in Figure 1(b) [21].

### 4.2 NSL-KDD Dataset

As discussed earlier, we use NSL-KDD dataset in our work. The dataset is an improved and reduced version of the KDD Cup 99 dataset [20]. The KDD Cup dataset was

prepared using the network traffic captured by 1998 DARPA IDS evaluation program [22]. The network traffic includes normal and different kinds of attack traffic, such as DoS, Probing. The network traffic for training was collected for seven weeks followed by the two weeks collection of traffic for testing purpose in the form of raw tcpdump format. The test data contains many attacks that were not injected during the training data collection phase to make the intrusion detection task realistic. It is believed that most of the novel attacks can be derived from the known attacks. Thereafter, the training and test data were processed into the datasets of five million and two million TCP/IP connection records, respectively.

the KDD Cup dataset has been widely used as a benchmark dataset for many years in the evaluation of NIDS. One of the major drawback with the dataset is that it contains an enormous amount of redundant records both in the training and test data. It was observed that almost 78% and 75% records are redundant in the training and test data, respectively [20]. This redundancy makes the learning algorithms biased towards the frequent attack records and leads to poor classification results for the infrequent, but harmful records. The training and test data were classified with the minimum accuracy of 98% and 86% respectively using a very simple machine learning algorithm. It made the comparison task difficult for various IDSs based on different learning algorithms. NSL-KDD was proposed to overcome the limitation of KDD Cup dataset. The dataset is derived from the KDD Cup dataset. It improved the previous dataset in two ways. First, it eliminated all the redundant records from the training and test data. Second, it partitioned all the records in the KDD Cup dataset into various difficulty levels based on the number of learning algorithms that can correctly classify the records. After that, it selected the records by random sampling of the distinct records from each difficulty level in a fraction that is inversely proportional to their fraction in the distinct records. These multi-steps processing of KDD Cup dataset made the number of records in NSL-KDD dataset reasonable for the training of any learning algorithm and realistic as well.

Each record in the NSL-KDD dataset consists of 41 features and is labeled with either normal or a particular kind of attack. These features include basic features derived directly from a TCP/IP connection, traffic features accumulated in a window interval, either time, e.g. two seconds or number of connections, and content features extracted from the application layer data of connections. Out of 41 features, three are nominal, four are binary, and remaining 34 features are continuous. The training data contains 23 traffic classes that include 22 classes of attack and one normal class. The test data contains 38 traffic classes that include 21 attacks .The NSL-KDD dataset is a widely recognized and utilized resource within the field of network intrusion detection and cybersecurity. It serves as an improved version of the original KDD Cup 1999 dataset, which was initially created for the DARPA Intrusion Detection Evaluation Program. The primary motivation behind the development of the NSL-KDD dataset was to rectify certain shortcomings of its predecessor, including issues like data redundancy and unrealistic data distribution. Essentially, the NSL-KDD dataset was curated to provide a more robust and representative collection of data for the assessment and development of network intrusion detection systems (NIDS). This dataset encapsulates a wealth of information, encompassing both network traffic data and labels denoting intrusion instances. It incorporates a diverse mix of both normal and malicious network traffic, with the data itself comprising a range of features associated with network connections, such as protocol types, services, connection duration, source and destination IP addresses, and more.One of the distinguishing characteristics of the NSL-KDD dataset is its categorization of attacks into four primary classes: "Normal," "DoS" (Denial of Service), "Probe," and "R2L" (Remote to Local). Each class represents a distinct type of network intrusion, thus allowing for a comprehensive evaluation of intrusion detection systems across various threat scenarios.The NSL-KDD dataset has been instrumental in addressing the deficiencies of the original KDD Cup 1999 dataset, offering a more balanced and realistic representation of network traffic. Researchers predominantly divide this dataset into training and testing subsets, enabling the development and evaluation of intrusion detection algorithms. As a result, it has become a pivotal resource for researchers and cybersecurity practitioners seeking to benchmark, compare, and advance the performance of different intrusion detection systems.

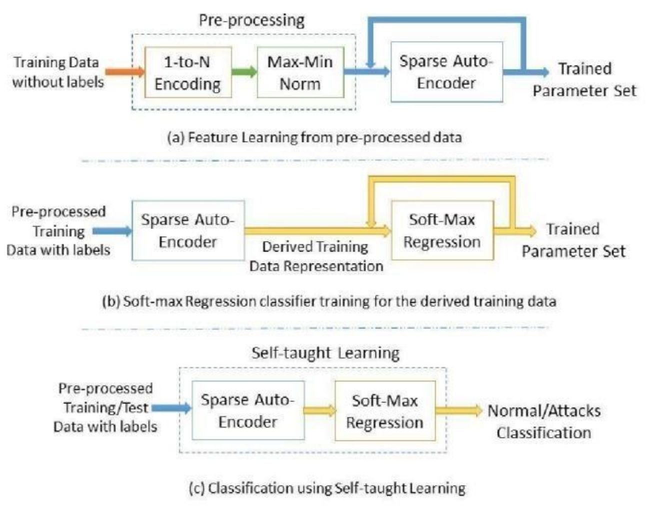

Pre-processing
Training Data without labels
1-to-N Encoding
Max-Min Norm
Sparse Auto-Encoder
Trained Parameter Set
(a) Feature Learning from pre-processed data
Pre-processed Training Data with labels
Sparse Auto-Encoder
Derived Training Data Representation
Soft-Max Regression
Trained Parameter Set
(b) Soft-max Regression classifier training for the derived training data
Self-taught Learning
Pre-processed Training/Test Data with labels
Sparse Auto-Encoder
Soft-Max Regression
Normal/Attacks Classification
(c) Classification using Self-taught Learning

Figure 2: Various steps involved in our NIDS implementation

## 5. RESULTS AND DISCUSSION

As discussed in Section 2, there are two approaches applied for the evaluation of NIDSs. In the most widely used approach, the training data is used for both training and testing either using n-fold cross-validation or splitting the training data into training, cross-validation, and test sets. NIDSs based on this approach achieved very high-accuracy and less false-alarm rates. On the other hand, the second approach uses the training and test data seperately for the training and testing. Since the training and test data were collected in different environments, the accuracy obtained using the second approach is not as high as in the first approach. Therefore, we emphasize on the results for the second approach in our work for the accurate evaluation of NIDS. However, for the sake of completeness, we present the results for the first approach as well. We describe our NIDS implementation before discussing the results.

### 5.1 NIDS Implementation

As discussed in the previous section, the dataset contains different kinds of attributes with different values. We preprocess the dataset before applying self-taught learning on it. Nominal attributes are converted into discrete attributes using 1-to-n encoding. In addition, there is one attribute in the dataset whose value is always 0 for all the records in the training and test data. We eliminated this attribute from the dataset. The total number of attributes become 121 after performing the above mentioned steps. The values in the output layer during the feature learning phase, shown in Figure 1(a), is computed by the sigmoid function which gives values from 0 to 1. Since, the output layer values are identical to the input layer values in this phase, causes to normalize the values in the input layer from 0 to 1. Training the deep learning model involves using the preprocessed data to teach the model to distinguish between benign and malicious traffic patterns. This process may involve hyperparameter tuning, cross-validation, and fine-tuning to achieve the best performance. Validation and testing follow model training to ensure its effectiveness and generalization. The NIDS must be capable of accurately identifying network intrusions while minimizing false positives. Fine-tuning and retraining may be necessary based on the performance evaluation results. Finally, the deployed NIDS continually monitors network traffic, classifying it in real-time. When malicious activity is detected, appropriate actions are taken, such as alerting administrators or implementing automatic mitigation measures.

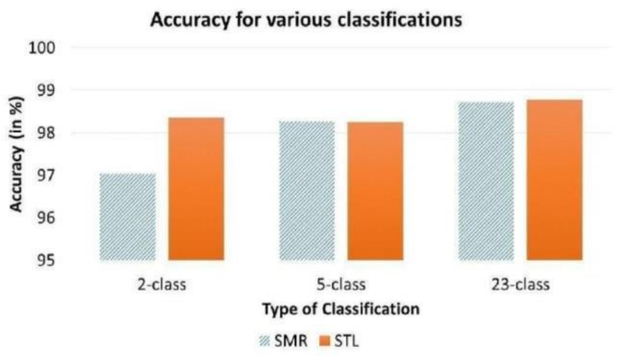


Figure 3: Classification accuracy using self-taught learning (STL) and soft-max regression (SMR) for 2-Class, 5-Class, and 23-Class when applied on training data

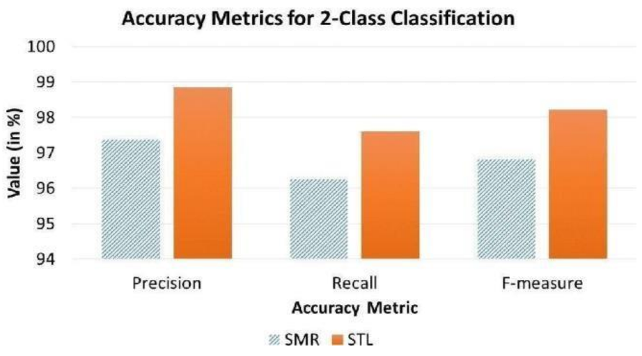


Figure 4: Precision, Recall, and F-Measure values using self-taught learning (STL) and soft-max regression (SMR) for 2-Class when applied on training data

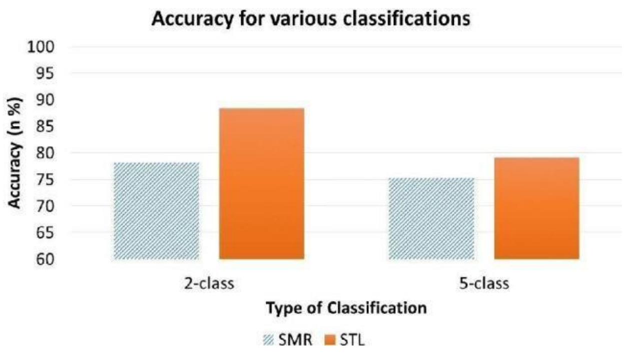
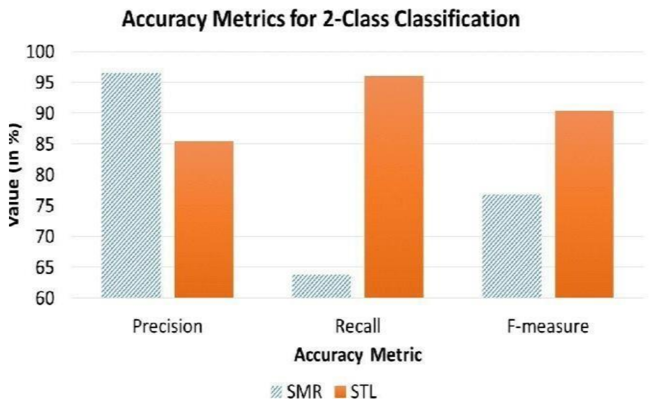


Figure 5: Classification accuracy using self-taught learning (STL) and soft-max regression (SMR) for 2-class and 5-class when applied on test data

Implementing a Network Intrusion Detection System (NIDS) through a deep learning approach involves several critical steps. Initially, data collection is imperative, where a substantial dataset of network traffic is a massed, encompassing both normal and malicious traffic. It's vital to accurately label the data, distinguishing benign from malicious network flows. Data preprocessing follows suit. This stage encompasses leaning and preparing the raw network data, often in the form of packet capture files (PCAPs) or network flow records (NetFlow data).Relevant features, such as source and destination IP addresses, ports, packet sizes, protocols, and timestamps, need to be extracted. Normalization and scaling are also applied to standardize the data, ensuring that it's suitable for deep learning model training. Next, the heart of the NIDS is the deep learning model. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are popular choices for this task. CNNs are adeptat capturing spatial patterns in data, making them suitable for detecting irregularities in network traffic, while RNNs excel at handling sequential data, which is crucial fornetwork traffic analysis.



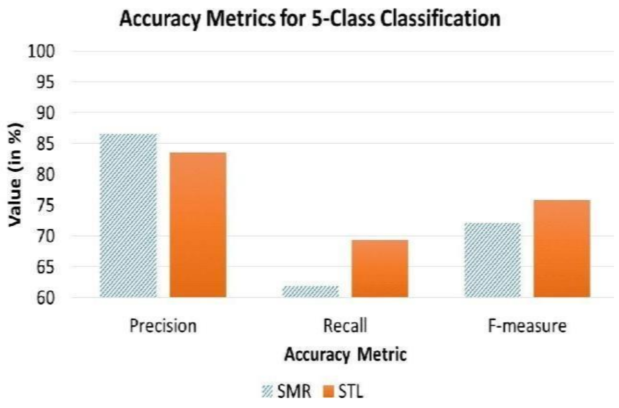


Figure 6 &7: Precision, Recall, and F-Measure values using self-taught learning (STL) and soft-max re- gression (SMR) for 5-class when applied on test data

To obtain this, we perform max-min normalization on the new attributes list.

With the new attributes, we use the NSL-KDD training data without labels for the feature learning using sparse auto-encoder for the first stage of self-taught learning. In the second stage, we apply the new learned features representation on the training data itself for the classification using soft-max regression. In our implementation, both the unlabeled and labeled data for feature learning and classifier training come from the same source, i.e, NSL-KDD training data. Figure 2 shows the steps involved in our NIDS implementation.

## 5.2 Accuracy Metrics

We evaluate the performance of self-taught learning based on the following metrics:

- Accuracy: Defined as the percentage of correctly classified records over the total number of records.
- Precision (P): Defined as the % ratio of the number of true positives (TP) records divided by the number of true positives (TP) and false positives (FP) classified records.

$$P = \frac{TP}{(TP + FP)} \times 100\% \quad (4)$$

- Recall (R): Defined as the % ratio of number of true positives records divided by the number of true positives and false negatives (FN) classified records.

$$R = \frac{TP}{(TP + FN)} \times 100\% \quad (5)$$

## 6. CONCLUSION AND FUTURE WORK

We proposed a deep learning based approach to build an effective and flexible NIDS. An sparse auto-encoder and softmax regression based NIDS was implemented. We used the benchmark network intrusion dataset - NSL-KDD to evaluate anomaly detection accuracy. We observed that the NIDS performed very well compared to previously implemented NIDSs for the normal/anomaly detection when evaluated on the test data. The performance can be further enhanced by applying techniques such as Stacked Auto-Encoder, an extension of sparse auto-encoder in deep belief nets, for unsupervised feature learning and NB-Tree, Random Tree, or J48 for further classification. It was noted that the latter techniques performed well when applied directly on the dataset [20]. In future, we plan to implement a real-time NIDS for real networks using deep learning technique. Additionally, on-the-go feature learning on raw network traffic headers instead of derived features using raw headers can be another

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