**Exploration of Machine Learning Approaches for**

**Intelligent Network Intrusion Detection System**

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Instruction: the total number of pages should not be more than 5 pages in total (including graphs and references). Please use the text with Arial 11-point font and single spacing.

**Introduction**

***Keywords***: Network Intrusion Detection System, Machine Learning.

In modern society, information and communication technology systems and networks has become one of the most important parts of the human life. The risk of cyber security also continues to rise as the networks becomes more popular, which enlarges the attack surface for malicious attempts. The landscape of cyber threats encompasses both manual and machine-generated attacks that are increasingly sophisticated, diverse, and adept at obfuscation, often leading to undetected breaches. For example, the loss of some enterprises, like Yahoo and Bitcoin, caused from sensitive data breach was over $100M [1].

These challenges pose an urgent need for powreful and efficient network intrusion detection systems (NIDS) [2]. An NIDS is a proactive tool that can detect and identify invasive activity, such as attacks, violations of the security policies, and so on. In recent decades, machine learning methods have been used and designed as intelligent NIDS to detect malicious intrusion, which can learn from passing attacks to conclude some attacking patterns.

Different machine learning methods have been discussed by researchers, which mainly includes Support Vector Machine (SVM) based systems and deep learning (CNN, DNN) based approaches [3]. In 2013, Jayshree developed a SVM-based NIDS incoperating Gain Ratio (IGR) and K-means algorithm [4]. After 2016, the most high-cited papers are typically deep learning based NIDS. Nathan Shone proposed onsymmetric deep autoencoder (NDAE) for unsupervised feature learning and deep learning classification model constructed using stacked NDAEs [5]. Deep neural network (DNN), a type of deep learning model, is also used to develop a flexible and effective IDS to detect and classify unforeseen and unpredictable cyberattacks [6]. Since NIDS is real-time system, it is natural to develop sequential algorithms like Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN). For example, researchers (Muhammad Ashfaq Khan and Yangwoo Kim) utilized LSTM to detect temporal features and an Auto Encoder (AE) to more effciently detect global features [7].

Machine learning methods require large amounts of data for training. Also, intelligent intrusion detection systems can only be built if there is availability of an effective data set. Among the datasets used for NIDS research, ‘KDD Cup 99’ and ‘NSL-KDD’ datasets [8] are most typical datasets to evaluate the proposed methods. ‘NSL-KDD’ is the improved version of ‘KDD Cup 99’, and so the expriments in thie report are all conducted on ‘KDD Cup 99’

These novel research works trigger me to develop and compare different machine learning methods in NIDS. Therefore, in this report, I implement some classical algorithms, such as SVM and K-Nearest Neighbor (KNN), and some deep learning methods, such as DNN, LSTM, and AE to compare their performance on NSL-KDD dataset. My source code runs on Google colab and it is available from my github repository (66Tracy/SE6011-assignment) <https://github.com/66Tracy/SE6011-assignment/tree/main>.

**Background**

The aforemetioned novel methods combine different algorithms to construct the complicated detection systems. Therefore, in this paper, I try to implement different machine learning methods to explore the feasibility of intelligent NIDS. In this section, I would simply introduce the methods (SVM, KNN, LSTM, AE, DNN) I developed and the common dataset ‘NSL-KDD’ used for NIDS research. The pictures showed are all made by myself.

***A. NSL-KDD dataset***

NSL-KDD is a data set suggested to solve some of the inherent problems of the KDD'99 data set, which becomes the benchmark dataset for NIDS research [8]. This data set is comprised of four sub data sets: KDDTest+, KDDTest-21, KDDTrain+, KDDTrain+\_20Percent. And KDDTrain+ will be referred to as train and KDDTest+ will be referred to as test. In my experiments, only KDDTrain+ is used.

KDDTrain+ contains 125973 samples with 42 features. The features are ‘duration time’, ‘protocol type’, ‘servie’, and so on, which recored the states of the network system when it is attacked or normal. And the labels classify these samples into 23 different classes according to attacks they faced. Considering the classification effectiveness, researchers generally re-category the labels items into 5 major kinds of attacks or normal state: ‘normal’, ‘DoS’, ‘Probe’, ‘R2L’, and ‘U2R’. The numbers of these different categories are imbalanced and their ratio relationship is showed below (Fig.1):

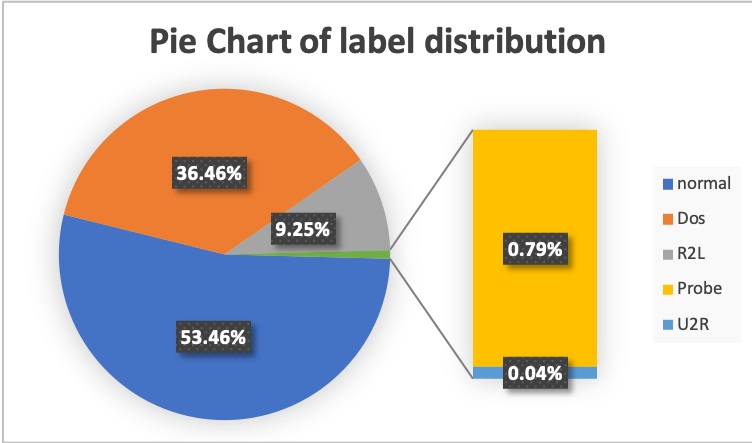


Fig.1 Pie Chart of distribution of labels (made from Excel)

***B. SVM and KNN***

To save the space, this part would simply introduce what is SVM and KNN. SVM is an effective classifier, which aims to learn the largest classificaiton margin [9]. And KNN is a naïve classifier to match and assign label to the target sample based on the k-nearest samples’ labels. The mechanisms of SVM and KNN are showed as Fig.2 below. Seeing the Fig.2 (right), KNN method would classify the target sample in the centre to be ‘red’ since its 5 nearest neighbors are all ‘red’.

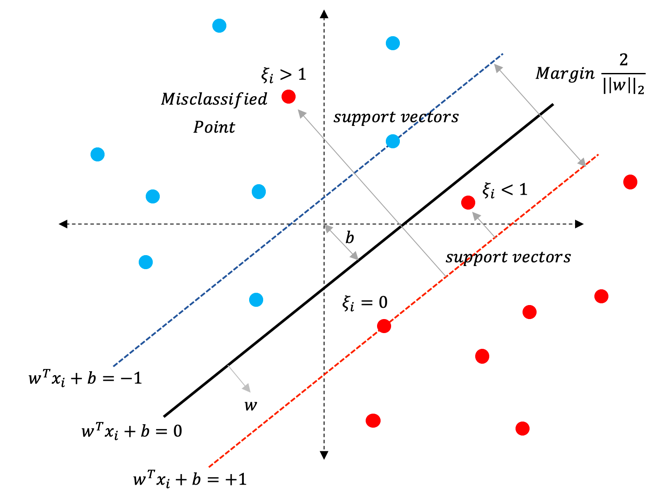
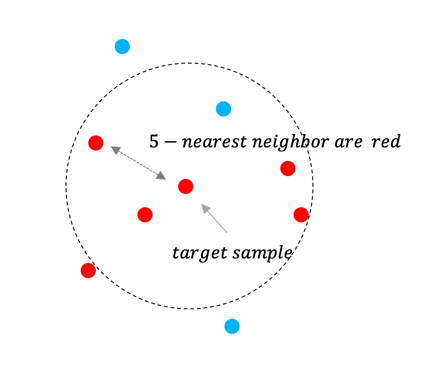
 

Fig.2 (left) SVM’s mechanism, (right) KNN’s mechanism

***C. DNN, AE, and LSTM***

Deep Neural Network(DNN), Auto Encoder(AE), and LSTM are all deep learning algorithms, so I introduce them together. DNN is actually a multi-layer perceptron model which is composed of several fully-conntected layers. The first layer is Input Layer. There are three or four Hidden Layers in the middle, and the last layer is Output Layer, in which each layer has several neurons. The computation between each two layers is mathematically defined as: , where is the non-linear activation function. The output layer of DNN uses softmax function to give the prediction possibility of each class, and generally the class with largest output possibility is assigned as prediction label.

AE is a variant of DNN for unsupervised learning, which can be used as a feature extractor. The learning purpose of AE is to learn the best parameters required to reconstruct its output as close to its input vector as possible. Researchers (Nathan Shone .et al) [5] expect to utilize AE as a non-linear generalization of Principle Component Analysis (PCA) [10]. However, AE is not strictly a complete NIDS since it cannot classify the input by itself. So in [5], Nonsymmetric Deep Autoencoder (NDAE) is proposed to be stacked by two AE and followed by a Random Forest [11] to predict the output.

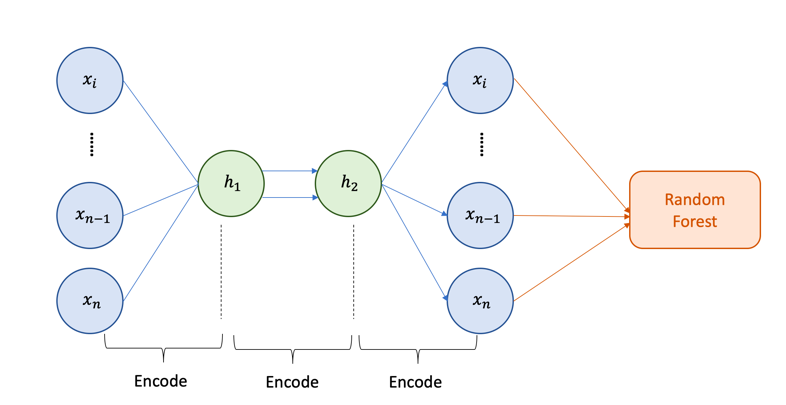


Fig.3 The architecture of NDAE

Long Short-Term Memory (LSTM) network is a recurrent neural network (RNN), aimed to deal with the vanishing gradient problem present in traditional RNNs. LSTM is network with loop in its architecture so that it can handle sequential information like words or timing actions that are related to its previous units and afterward units. That is why LSTM can model network traffic information in time series to detect attacks.

**Technical Details**

(A more detailed explanation of the project and derailed explanation of the solutions.)

A. Environment Setting

The experiments are runned on Google Colab using python language.

B. Experiments

The …

**Conclusion**

**Reference**

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[12]