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Intrusion Detection of Imbalanced Network Traffic Based on Deep Learning

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Abstract: *In this work, include deep learning techniques for intrusion detection in imbalanced network traffic. A novel Difficult Set Sampling Technique (DSSTE) algorithm to tackle the class imbalance problem. First, use the Edited Nearest Neighbors (ENN) algorithm to divide the imbalanced training set into the difficult set and the easy set. Next, use the K Means algorithm to compress the majority samples in the difficult set to reduce the majority. Zoom in and out the minority samples' continuous attributes in the difficult set to synthesize new samples to increase the minority number. Finally, the easy set, the compressed set of majorities in the difficult, and the minority in the difficult set are combined with its augmentation samples to make up a new training set. The algorithm reduces the imbalance of the original training set and provides targeted data augmentation for the minority class that needs to learn. It enables the classifier to learn the differences in the training stage better and improve classification performance. For classification, convolution neural networks are used for model creation. In this study, the NSL-KDD dataset is used for the intrusion detection system.*

Keywords: Intrusion Detection, CNN, NSL-KDD, DSSTE, ENN, K-Means

I. INTRODUCTION

Relying on a firewall system alone is not sufficient to prevent a corporate network from all types of network attacks. This is because a firewall cannot defend the network against intrusion attempts on open ports required for network services. Hence, an intrusion detection system (IDS) is usually installed to complement the firewall. An IDS collects information from a network or computer system, and analyzes the information for symptoms of system breaches. A network IDS monitors network data and gives an alarm signal to the computer user or network administrator when it detects antagonistic activity on an open port. This signal allows the recipient to inspect the system for more symptoms of unauthorized network activities. In real cyberspace, normal activities occupy the dominant position, so most traffic data is normal traffic; only a few are malicious cyber-attacks, resulting in a high imbalance of categories. In the highly imbalanced and redundant network traffic data, intrusion detection is facing tremendous pressure

II. LITERATURE SURVEY

2.1 Network Intrusion Detection Using Naïve Bayes, With the tremendous growth of network-based services and sensitive information on networks,network security is getting more and more important than ever. Intrusion poses a serious security risk in a network environment. The ever-growing new intrusion types possess a serious problem for their detection. The human labeling of the available network audit data instances is usually tedious, time consuming and expensive. In this paper, we apply one of the efficient data mining algorithms called naïve bayes for anomaly-based network intrusion detection. Experimental results on the KDD cup'99 data set show the novelty of our approach in detecting network intrusion. It is observed that the proposed technique performs better in terms of false positive rate, cost, and computational time when applied to KDD'99 data sets compared to a back propagation neural network- based approach

2.2 A Deep Learning Approach to Network Intrusion Detection. Network intrusion detection systems (NIDSs) play a crucial role in defending computer networks. However, there are concerns regarding the feasibility and sustainability of current approaches when faced with the demands of modern networks. More specifically, these concerns relate to the increasing levels of required human interaction and the decreasing levels of detection accuracy. This paper presents a

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novel deep learning technique for intrusion detection, which addresses these concerns. We detail our proposed nonsymmetric deep autoencoder (NDAE) for unsupervised feature learning. Furthermore, we also propose our novel deep learning classification model constructed using stacked NDAEs. Our proposed classifier has been implemented in a graphics processing unit (GPU)-enabled TensorFlow and evaluated using the benchmark KDD Cup '99 and NSL-KDD datasets. Promising results have been obtained from our model thus far, demonstrating improvements over existing approaches and the strong potential for use in modern NIDSs.

III. PROPOSED SYSTEM

A network-based intrusion detection system that uses deep learning techniques to classify the type of network intrusion for the input network data. For the study, the dataset used is NSL-KDD dataset. It contains 5 classes of network class labels- DoS, PROBE, R2L, U2R, Normal. It considers 41 network features for the study. The dataset is imbalanced; thus, it is required to balance the dataset before classification. For that, this paper uses the DSSTE (Difficult Set Sampling Technique) algorithm to balance the imbalanced dataset. The algorithm reduces the imbalance of the original training set and provides targeted data augmentation for the minority class that needs to learn. For classification, this work proposed a deep learning algorithm called convolutional neural network.

IV. METHODOLOGY

CNN architecture is formed by a stack of distinct layers that transform the input volume into an output volume (e.g. holding the class scores) through a differentiable function. A few distinct types of layers are commonly used.

Three Layers of the Convolutional Neural Networks:

Convolution Layer (CNV): The convolutional layer is the core building block of CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot 16 product between the entries of the filter and the input and producing a 2- dimensional activation map of that filter. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input. Stacking the activation maps for all filters along the depth dimension forms the full output volume of the convolution layer. Every entry in the output volume can thus also be interpreted as an output of a neuron that looks at a small region in the input and shares parameters with neurons in the same activation map.

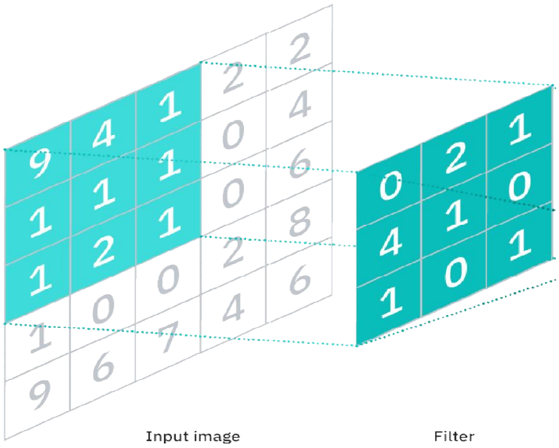

Fig. 1. Convolution layer

Pooling Layer(PL): Another important concept of CNNs is pooling, which is a form of nonlinear down- sampling. There are several nonlinear functions to implement pooling among which max pooling is the most common. It partitions the input image into a set of non overlapping rectangles and, for each such sub-region, outputs the maximum. The intuition is that the exact location of a feature is less important than its rough location relative to other features. The pooling layer serves to progressively reduce the spatial size of the representation, to reduce the number of parameters and amount of computation in the network, and hence to also control overfitting. It is common to periodically insert a pooling layer between successive convolutional layers in a CNN architecture.

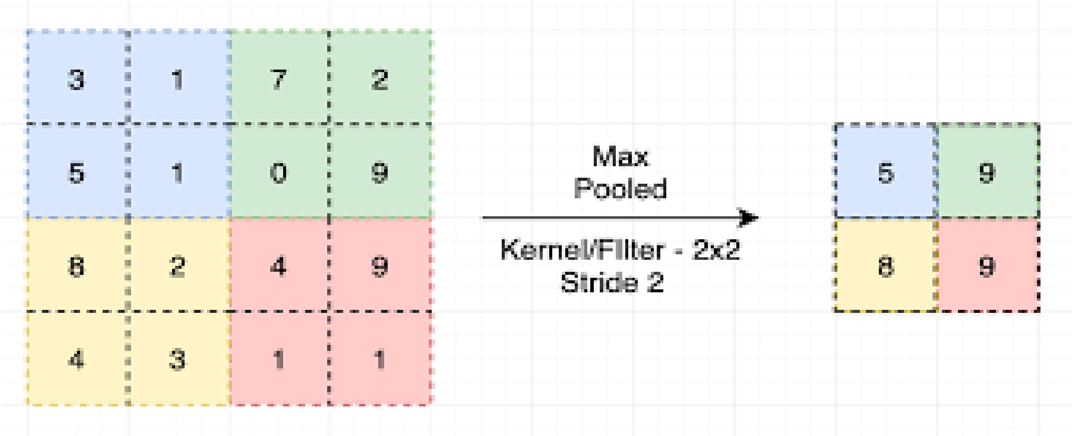

Fig. 2. Max pooling layer

Fully connected layer (FC): Finally, after several convolutional and max pooling layers, the high-level Reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular neural networks. Their activations can hence be computed with a matrix multiplication followed by a bias offset.

Classification Layer(CL): The classification layer specifies how training penalizes the deviation between the predicted and true labels and is normally the final layer. Various loss functions appropriate for different tasks may be used there. SoftMax loss is used for predicting a single class of K mutually exclusive classes. Sigmoid cross-entropy loss is used for predicting K independent probability values in [0,1] A typical CNN architecture is shown below A simple CNN (Convolutional Neural Net) is created as an initial step. This is then trained with training data.

CNN Classifier

A CNN (Convolutional Neural Network) classifier is a type of deep learning model used for image classification tasks. Here are the simple steps involved in building a CNN classifier:

a) Data preparation: The first step in building a CNN classifier is to gather and prepare the training data. This involves collecting a set of images with known labels, and splitting them into training and validation sets.

b) Network architecture design: Next, the network architecture needs to be designed. This involves specifying the number and types of layers in the network, such as convolutional layers, pooling layers, and fully connected layers.

c) Model training: The next step is to train the CNN classifier using the prepared data. This involves feeding the training data into the network and adjusting the weights of the network based on the errors between the predicted and actual labels.

d)Model evaluation: Once the training is complete, the model is evaluated on the validation set to measure its accuracy and performance.

e) Prediction: Finally, the trained model can be used to make predictions on new, unseen images. In summary, building a CNN classifier involves preparing the data, designing the network architecture, training the model, evaluating the performance, and using the trained model for making predictions. CNN in sign language classification Convolutional Neural Networks (CNNs) have shown excellent performance in various image classification tasks, including sign language classification. CNNs are particularly effective for recognizing patterns in images because of their ability to capture spatial dependencies and extract hierarchical features from images.

To use CNNs for sign language classification, we can follow these steps:

a) Data preprocessing: The Sign MNIST dataset, for example, can be preprocessed by normalizing pixel values and applying data augmentation techniques to increase the size of the training set.

b) Model architecture: We can design a CNN architecture with convolutional layers, pooling layers, and fully connected layers. The number of layers and their hyperparameters can be chosen through experimentation or using standard architectures like VGG or ResNet.

c) Training: The model is trained on the training set using an appropriate optimizer (such as Adam) and a suitable loss function (such as categorical cross-entropy). The training process involves updating the model's parameters to minimize the loss function.

d) Evaluation: Once trained, the model can be evaluated on the test set to determine its accuracy and performance.

e) Fine-tuning: We can fine-tune the model by adjusting its hyperparameters, or we can use transfer learning by fine-tuning pre-trained models like VGG, ResNet, or Inception. Overall, CNNs can achieve high accuracy in sign language classification tasks, making them an excellent choice for this application.

V. SYSTEM ARCHITECTURE

This includes identifying the purpose and scope of the system, the expected usage patterns, and any technical constraints or limitations. The next step is to create a high-level architecture that outlines the components of the system and how they will interact with each other. Once the high-level architecture is established, the system design process moves on to the detailed design phase. This involves defining the specific modules and components that make up the system, as well as their individual interfaces and data structures.

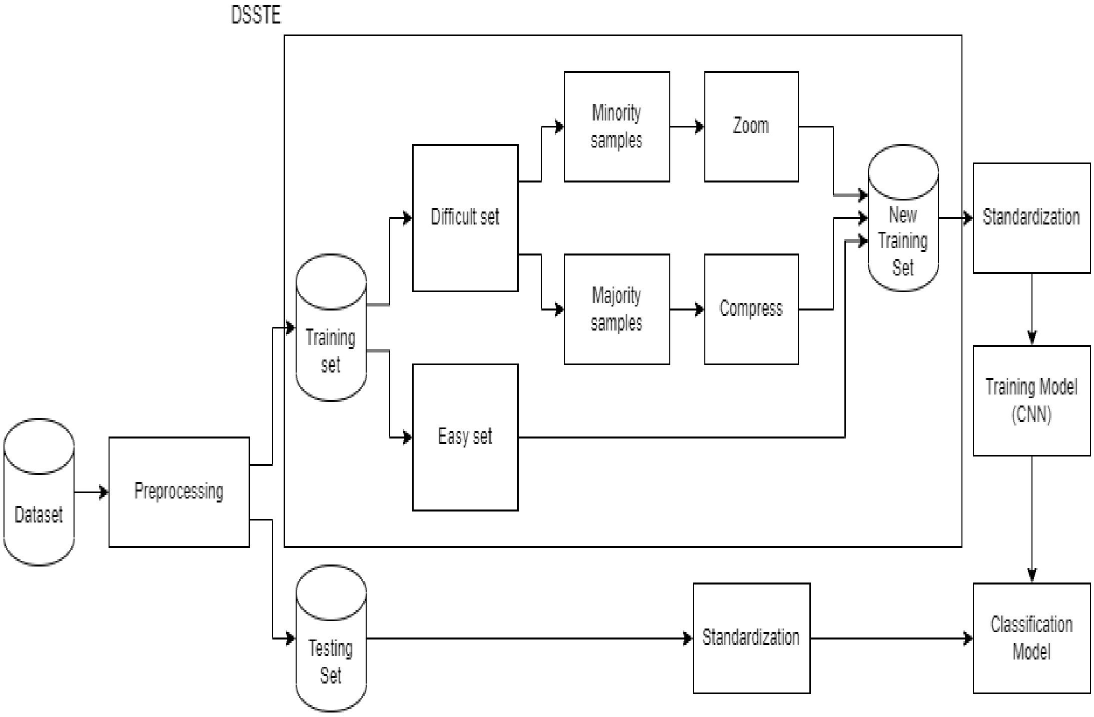

Fig. 3. Architecture

VI. CONCLUSION

In conclusion, the paper "Intrusion Detection of Imbalanced Network Traffic Based on Deep Learning" presents a novel approach to address the problem of imbalanced network traffic in intrusion detection systems (IDS). The proposed method employs a deep learning-based approach using an Autoencoder and a Convolutional Neural Network (CNN) to detect network anomalies and intrusions accurately. The results obtained in the experiments demonstrate that the proposed method outperforms other state-of-the-art techniques in terms of precision, recall, and F1-score. The paper highlights the importance of addressing the problem of imbalanced network traffic, which is a common issue in IDS. The proposed method uses an Autoencoder to balance the data distribution and a CNN to detect anomalies in the network traffic. The combination of these two techniques enables the system to identify network attacks and anomalies with a high degree of accuracy. Overall, the proposed method has shown promising results in detecting network intrusions accurately. The approach can be applied in various fields such as cybersecurity, network traffic monitoring, and intrusion detection

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systems. Further research can be conducted to improve the efficiency and effectiveness of the method by exploring other deep learning-based models and techniques.

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