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Detection of Cyber Attack in Network Using Machine Learning Techniques

Supriya Sawwashere[1], Yuvraj Suryavanshi[2], Rahul Bambodkar[3], Kundan Kumar Rahangdale[4]

[1,2,3]Assistant Professor, Department Of CSE J D College of Engineering & Management, Nagpur
[4]Research Scholar, Department Of CSE J D College of Engineering & Management, Nagpur

ABSTRACT

In contrast to the past, advancements in personal computer and communication technologies have brought about significant changes. Although using new technology gives individuals, organisations, and governments enormous benefits, some people are messed up against them. For instance, the safeguarding of important data, the safety of information transfer channels, the availability of information, and so on. In light of these problems, digital oppression motivated by fear is one of the biggest problems we face today. Digital dread, which caused a lot of problems for individuals and organisations, has reached a point where it might compromise national and open security due to many groups, including the criminal underworld, professionals, and digital activists. As a result, Intrusion Detection Systems (IDS) were developed to keep a strategic distance from online attacks. Currently, learning the Support Vector Machine (SVM) computations were used to distinguish port sweep efforts based on the new CICIDS 2017 dataset with 97.80%, 69.79% accuracy rates were achieved separately. SVM may be replaced with alternative algorithms like random forest, convolutional neural network (CNN), and artificial neural network (ANN), which have higher accuracy than SVM (93.29, 63.52, 99.93, and 99.11, respectively).

1. INTRODUCTION

1.1 About the Projecct

In contrast to the past, advancements in personal computer and communication technologies have brought about significant changes. Although using new technology gives individuals, organisations, and governments enormous benefits, some people are messed up against them. For instance, the security of storage areas for sensitive information, information accessibility, and so on. In light of these problems, digital oppression motivated by fear is one of the biggest problems we face today. Digital dread, which caused a lot of problems for individuals and organisations, has reached a point where it might compromise national and open security due to many groups, including the criminal underworld, professionals, and digital activists. As a result, Intrusion Detection Systems (IDS) were developed to keep a strategic distance from online attacks. Currently, learning the support support vector machine (SVM) calculations were used to distinguish port sweep efforts based on the new CICIDS2017 dataset with 97.80%, 69.79% accuracy rates were achieved separately. We may use various algorithms in place of SVM, such as random forest, CNN, and ANN, which can achieve accuracy values of SVM 93.29, CNN 63.52, Random Forest 99.93, and ANN 99.11.

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1.2 Motivation

Although using new technology gives individuals, organisations, and governments enormous benefits, some people are messed up against them. For instance, the security of storage areas for sensitive information, information accessibility, and so on. In light of these problems, digital oppression motivated by fear is one of the biggest problems we face today. Digital dread, which caused a lot of problems for individuals and organisations, has reached a point where it might compromise national and open security due to many groups, including the criminal underworld, professionals, and digital activists. In light of this, intrusion detection systems (IDS) were developed to keep a safe distance from cyberattacks.

Literature Survey

2.1 R. Christopher, "Port scanning techniques and the defence against them," 2001, SANS Institute.

One of the most common methods used by attackers to find services they may use to access systems is port scanning. Services that listen to well-known and less well-known ports are executed on all computers that are linked to a LAN or the Internet through a modem. The following details about the targeted systems may be discovered by the attacker via port scanning: what services are active, whose users control those services, if anonymous logins are supported, and whether certain network services call for authentication. Sending a message to each port individually allows for port scanning. The kind of answer sent tells if the port is utilised and may be tested for other vulnerabilities. Network security specialists like port scanners because they can identify potential security flaws on the targeted system. Using the right tools, port scans can be detected, and the quantity of information about open services can be reduced, just as port scans can be run against your systems. Every system that is accessible to the general public has ports that are open and usable. The goal is to prevent access to locked ports and restrict authorised users' access to open ports.

2.2 "Practical automated detection of stealthy port scans," Journal of Computer Security, vol. 10, no. 1-2, pp. 105-136, 2002. S. Staniford, J. A. Hoagland, and J. M. McAlerney.

Port scanning is a typical task that is quite significant. Computer attackers often use it to describe sites or networks that they are contemplating engaging in hostile activities against. System administrators and other network defence personnel might therefore benefit from seeing port scans as potential precursors to more severe attacks. Network defenders also often utilise it to comprehend and identify vulnerabilities in their own networks. Thus, knowing whether or not a network's defences often do port scanning is of great relevance to attackers. Defenders, on the other hand, often do not want to conceal their port scanning, but attackers do. For the sake of clarity, we shall only refer to the attackers' scanning in the remaining sections of this work. defences attempting to find the scan on the network. On Internet mailing lists and newsgroups, discussions over port scanning's legality and morality often erupt. One wonders whether port scanning faraway networks without the owners' consent is a morally and legally acceptable practise. The majority of jurisdictions are now ambiguous on this. However, we have found that virtually all of the uninvited remote port scans we find in practise turn out to have originated from compromised hosts and are thus extremely likely to be hostile. The administrators of the remote network from which a port scan originated should be informed since in our opinion it is appropriate to consider it at least possibly

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hostile. The technical issues of how to detect port scans, which are unaffected by the importance that one gives them or by how one chooses to react to them, are the main subject of this study. Additionally, we are concentrating on the issue of using a network intrusion detection system (NIDS) to identify a port scan. We make an effort to consider some of the more blatant strategies an attacker would use to escape detection while maintaining a strategy that is feasible to utilise on busy networks. The rest of this section will describe port scanning, provide many in-depth examples, and go through several methods attackers might attempt to be inconspicuous. The discussion of several earlier port scan detection works is covered in the next section. Following that, we outline the algorithms we want to utilise and provide some very early evidence to support our strategy. Finally, we discuss future directions for this research as well as potential applications. We make the following assumptions about the reader: that they are acquainted with Internet protocols, fundamental concepts of network intrusion detection and scanning, and elementary concepts of probability, information theory, and linear algebra. An attacker may do a port scan for one of two broad reasons: either the primary or secondary goal. The main goal is to collect data on the status and reachability of certain IP address and port (either TCP or UDP) combinations. (While ICMP scans aren't specifically covered in this work, the concepts may obviously be applied to that scenario. The other goal is to overload intrusion detection systems with alarms in an effort to divert or stop network defenders from doing their duties. Since it is simple to identify flood port scans, the focus of this study will mostly be on identifying information collecting port scans. However, a significant concern will be the potential for malevolent information overload design of our algorithm into account. The group of port/IP combinations that the attacker is interested in characterising will be referred to as the scan footprint in this article. The script of the scan, which describes the order in which the attacker attempts to investigate the footprint, should be conceptually distinguished from the scan's footprint. The scan's speed, randomness, and other script-related features have no effect on the footprint. The attacker uses the footprint to represent the information collecting needs for her scan, and then she creates a scan script to satisfy those criteria as well as any possible additional non-information gathering requirements (such avoiding detection by an NIDS). At the moment, a horizontal scan is the most used kind of port scan footprint. By this, we imply that a hacker is searching for hosts that expose a certain service in order to use an exploit for it. She then checks all IP addresses within a certain range of interest on the port of interest. Additionally, at the moment, this is mostly carried out sequentially on TCP port 53 (DNS) 2.

Almansob and Lomte used Principal Component Analysis (PCA) and Blameless Bayes with the KDD99 dataset [9].Chithik and Rabbani also employed PCA, SVM, and KDD99 for IDS [10]. The NSL-KDD dataset was used by Aljawarneh et al. in their paper to express their evaluation and exams for their IDS model [11]. Composing inspects demonstrate that IDS [6]–[10] consistently uses the KDD99 dataset.KDD99 was made in 1999 and has 41 highlights. KDD99 is thus outdated and provides no information on modern, novel attack types, such as multiple-day abuses and so on. In this way, we conducted our research using the most recent and cutting-edge CICIDS2017 dataset [12].
Limitations of the current system include: tight regulations, difficulty for non-technical people to utilise, resource restrictions, a need for constant patching, and constant assault.

Proposed System
The algorithm's key stages are listed below.

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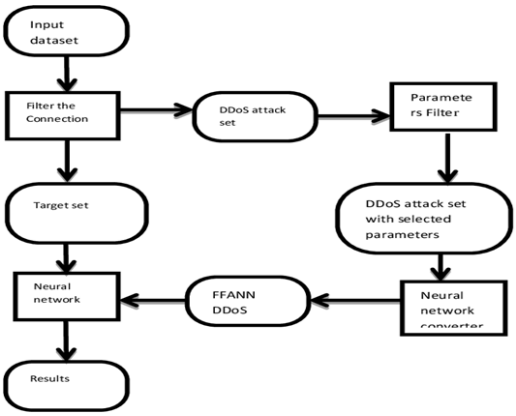
1) Every dataset should be normalised.
2) Create training and testing datasets using that dataset.
3) Use the RF, ANN, CNN, and SVM algorithms to create IDS models.
4) Assess the performances of each model.

Advantages

- Defence against harmful network assaults.
- Removal of harmful components from an already-existing network and/or their guarantee.
- Prevents people from accessing the network without authorization.
- Block programmes from accessing resources that could be contaminated.
- Protecting sensitive information

Block Diagram



2. SYSTEM ANALYSIS AND DESIGN

2.1. Software Requirements

• Python idel 3.7 version (or)
• Anaconda 3.7 (or)
• Jupiter (or) Google colab

2.2. Hardware Requirements

• Operating system : windows, linux
• Processor : minimum intel i3
• Ram : minimum 4 gb
• Hard disk : minimum 250gb

2.3. System Design

The technique or art of specifying a system's architecture, parts, modules, interfaces, and data in order to meet predetermined criteria is known as system design. It may be considered the application of systems theory to the process of product development. The fields of systems analysis, systems architecture, and systems engineering have some overlap and synergy.

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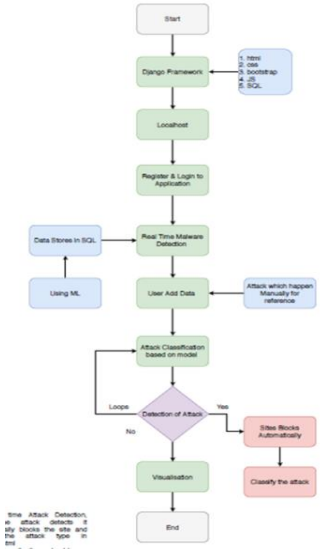
2.3.1 SYSTEM ARCHITECTURE



3. RESULTS AND DISCUSSIONS

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
import itertools
import seaborn as sns
import pandas_profiling
import statsmodels.formula.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from patsy import dmatrices
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

```
from sklearn import datasets
from sklearn.feature_selection import RFE
import sklearn.metrics as metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2, f_classif, mutual_info_classif
```

```
train=pd.read_csv('/content/drive/My Drive/kdd/NSL_Dataset/Train.txt',sep=',')
test=pd.read_csv('/content/drive/My Drive/kdd/NSL_Dataset/Test.txt',sep=',')
```

Data Preparation

```
columns=["duration","protocol_type","service","flag","src_bytes","dst_bytes","land",
"wrong_fragment","urgent","hot","num_failed_logins","logged_in",
"num_compromised","root_shell","su_attempted","num_root","num_file_creations",
"num_shells","num_access_files","num_outbound_cmds","is_host_login",
"is_guest_login","count","srv_count","serror_rate", "srv_serror_rate",
"rerror_rate","srv_rerror_rate","same_srv_rate", "diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv
"dst_host_diff_srv_rate","dst_host_same_src_port_rate",
"dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
"dst_host_rerror_rate","dst_host_srv_rerror_rate","attack", "last_flag"]
```

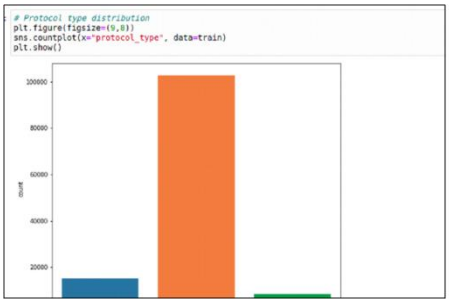
```
train.columns=columns
test.columns=columns
```

```
train.head()
```

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logged_in	num_compromised	root_
0	0	udp	other	SF	146	0	0	0	0	0	0	0	0	
1	0	tcp	private	S0	0	0	0	0	0	0	0	0	0	
2	0	tcp	http	SF	232	8153	0	0	0	0	0	1	0	
3	0	tcp	http	SF	199	420	0	0	0	0	0	1	0	
4	0	tcp	private	REJ	0	0	0	0	0	0	0	0	0	

```
test.head()
```

Data EDA



```
# Protocol type distribution
plt.figure(figsize=(9,8))
sns.countplot(x="protocol_type", data=train)
plt.show()
```

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Model Building

```
train_X=train_new[cols]
train_y=train_new['attack_class']
test_X=test_new[cols]
test_y=test_new['attack_class']
```

ML Deploy

Logistic Regression

```
# Building Models
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(random_state=0,solver='lbfgs',multi_class='multinomial')
logreg.fit( train_X, train_y)
logreg.predict(train_X)   #by default, it use cut-off as 0.5
```

```
list( zip( cols, logreg.coef_[0] ) )
```

```
logreg.intercept_
```

```
logreg.score(train_X,train_y)
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
pargrid_rf = {'n_estimators': [50,60,70,80,90,100],
              'max_features': [2,3,4,5,6,7]}
```

```
from sklearn.model_selection import GridSearchCV
gscv_rf = GridSearchCV(estimator=RandomForestClassifier(),
                       param_grid=pargrid_rf,
                       cv=10,
                       verbose=True, n_jobs=-1)

gscv_results = gscv_rf.fit(train_X, train_y)
```

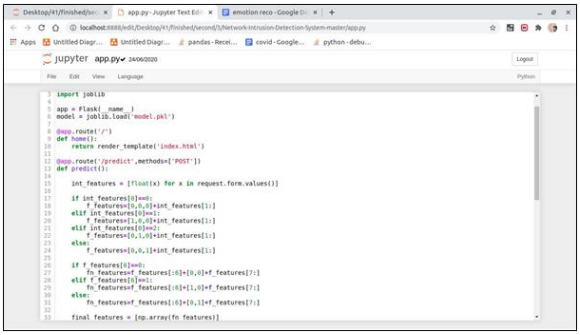
```
gscv_results.best_params_
```

```
gscv_rf.best_score_
```

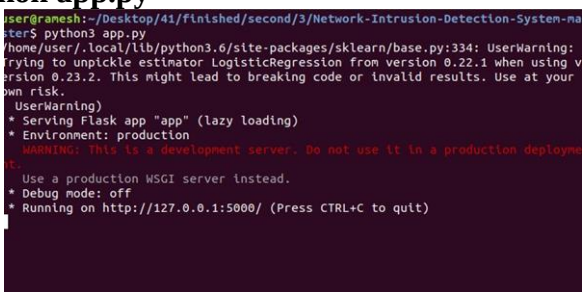
```
radm_clf = RandomForestClassifier(oob_score=True,n_estimators=80, max_features=5, n_jobs=-1)
radm_clf.fit( train_X, train_y )
```

```
radm_test_pred = pd.DataFrame( { 'actual':  test_y,
                                 'predicted': radm_clf.predict( test_X ) } )
```

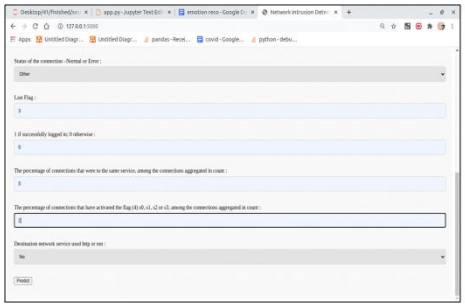
Application



Localhost - in cmd python app.py



Enter the input



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Predict attack -

4. CONCLUSION

Support vector machine, ANN, CNN, Random Forest, and deep learning calculations based on the latest CICIDS2017 dataset have all been released recently. The results reveal that when compared to SVM, ANN, RF, and CNN, the results from the deep learning computation are much superior. In the future, we want to use this dataset as the foundation for a variety of AI and deep learning-based computations, Apache Hadoop and sparkle-based attacks, including port sweeps. The results of these calculations aid in the identification of network-based cyberattacks. When looking back over many years, there may have been a large number of assaults, and after these attacks are identified, the characteristics at whose values they occurred will be recorded in various databases. So, we'll use these data sets to make predictions about whether or not a cyber-attack has already occurred. Four algorithms (SVM, ANN, RF, and CNN) are capable of making these forecasts. This study aids in determining which algorithm yields the most reliable results in determining whether or not cyber-attacks really occurred.

Future Scope

Future efforts to combat the ever-changing nature of cyber-attacks will centre on improving the accuracy of threat forecasts made using a combination of machine learning algorithms.

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