

CYBER THREAT DETECTION BASED ON ARTIFICIAL NEURAL NETWORK USING EVENT PROFILES

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ABSTRACT

One of the major challenges in cyber security is the provision of an automated and effective cyber-threats detection technique. In this paper, we present an AI technique for cyber-threats detection, based on artificial neural networks. The proposed technique converts multitude of collected security events to individual event profiles and use a deep learning-based detection method for enhanced cyber-threat detection. For

this work, we developed an AI-SIEM system based on a combination of event profiling for data preprocessing and different artificial neural network methods, including FCNN, CNN, and LSTM. The system focuses on discriminating between true positive and false positive alerts, thus helping security analysts to rapidly respond to cyber threats.

All experiments in this study are performed by authors using two benchmark datasets (NSLKDD and CICIDS2017) and two datasets

collected in the real world. To evaluate the performance comparison with existing methods, we conducted experiments using the five conventional machine-learning methods (SVM, k-NN, RF, NB, and DT). Consequently, the experimental results of this study ensure that our proposed methods are capable of being employed as learning-based models for network intrusion- detection, and show that although it is employed in the real world, the performance outperforms the conventional machine-learning methods.

1. INTRODUCTION

Contrasted with the past, improvements in PC and correspondence innovations have given broad and propelled changes. The use of new innovations gives incredible advantages to people, organizations, and governments, be that as it may, messes some up against them. For instance, the protection of significant data, security of put away information stages, accessibility of information and so forth. Contingent upon these issues, digital fear-based oppression is one of the most significant issues in this day and age. Digital fear, which made a great deal of issues people and establishments, has arrived at a level that could undermine open and nation security by different gatherings, for example, criminal association, proficient people and digital activists. Along these lines, Intrusion Detection Systems (IDS) has been created to maintain a strategic distance from digital assaults. Right now, learning the bolster support vector machine (SVM) calculations were utilized to recognize port sweep endeavors dependent on the new CICIDS2017 dataset with 97.80%, 69.79% precision rates were accomplished individually. Rather than SVM we can introduce some other algorithms like random forest, CNN, ANN where these algorithms can acquire accuracies like SVM – 93.29, CNN – 63.52, Random Forest – 99.93, ANN – 99.11.

1.1 MOTIVATION

The use of new innovations gives incredible advantages to people, organizations, and governments, be that as it may, messes some up against them. For instance, the protection of significant data, security of put away information stages, accessibility of information and so forth. Contingent upon these issues, digital fear-based oppression is one of the most significant issues in this day and age. Digital fear, which made a great deal of issues people and establishments, has arrived at a level that could undermine open and nation security by different gatherings, for example, criminal association, proficient people and digital activists. Along these lines, Intrusion Detection Systems (IDS) has been created to maintain a strategic distance from digital assaults.

1.2 OBJECTIVES

Objective of this project is to detect cyber-attacks by using machine learning algorithms like

1.2.1 CNN:

A Convolutional Neural Network (CNN) is a type of deep learning neural network that is well-suited for image and video analysis. Random forest: It is the tech industry's definitive destination for sharing compelling, first-person accounts of problem- solving on the road to innovation.

1.2.2 ANN:

ANN algorithm accepts only numeric and structured data. Convolutional Neural Networks (CNN) and Recursive Neural Networks (RNN) are used to accept unstructured and non-numeric data forms such as Image, Text, and Speech

1.3 OUTCOMES:

These predictions can be done by four algorithms like SVM, ANN, RF, CNN this paper helps to identify which algorithm predicts the best accuracy rates which helps to predict best results to identify the cyber-attacks happened or not.

1.4 APPLICATIONS:

This strategy used in Detection of Cyber Attack in Network using Machine Learning Techniques

2. LITERATURE SURVEY

Literature Survey Intrusion detection is very important for network situation awareness. While a few methods have been proposed to detect network intrusion, they cannot directly and effectively utilize semi-quantitative information consisting of expert knowledge and quantitative data.

Hence, this paper proposes a new detection model based on a directed acyclic graph (DAG) and a belief rule base (BRB). In the proposed model, called DAG-BRB, the DAG is employed to construct a multi-layered BRB model that can avoid explosion of combinations of rule number because of a large number of types of intrusion. To obtain the optimal parameters of the DAG-BRB model, an improved constraint covariance matrix adaption evolution strategy (CMA-ES) is developed that can effectively solve the constraint problem in the BRB. A case study was used to test the efficiency of the proposed DAG-BRB.

The results showed that compared with other detection models, the DAG-BRB model has a higher detection rate and can be used in real network.

Nowadays, IT organizations generate colossal amounts of data. Handling these chunks of data itself is critical in the IT world. Hence centralizing the log management system improves security thereby enhances data protection in an organization. Such enterprises require a high profiling tool that helps in managing the information and events data to improve the level of security.

Security Information and Event Management (SIEM) :

It is a procedure for security analysis that prominence an overview of security in an organization. SIEM tools collect, analyze,

normalize and correlates all files and analyze data coming from the various device and give a centralized view of logs. This paper articulates an abstraction of SIEM tools and event correlation engines, furnishing a description of their technical comparative study, focusing on most popular SIEM tools and open source rule-based correlation engines and profiles them.

Distributed computing has become an effective approach to enhance capabilities of an institution or organization and minimize requirements for additional resource. In this regard, the distributed computing helps in broadening institutes IT capabilities. One needs to note that distributed computing is now integral part of most expanding IT business sector. It is considered novel and efficient means for expanding business. As more organizations and individuals start to use the cloud

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itself is critical in the IT world. Hence centralizing the log management system improves security thereby enhances data protection in an organization. Such enterprises require a high profiling tool that helps in managing the information and events data to improve the level of security. Security Information and Event Management (SIEM) is a procedure for security analysis that prominence an overview of security in an organization. SIEM tools collect, analyze, normalize and correlates all files and analyze data coming from the various device and give a centralized view of logs.

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Due to security concern many clients hesitate in relocating their sensitive data on the clouds, despite significant interest in cloud-based computing. Security is a significant issue, since data much of an organizations data provides a tempting target for hackers and those concerns will continue to diminish the development of distributed computing if not addressed. Therefore, this study presents a new test and insight into a honeypot.

It is a device that can be classified into two types:

1. Handling
2. research honeypots.

Handling honeypots are used to mitigate real life dangers:

A research honeypot is utilized as an exploration instrument to study and distinguish the dangers on the internet. Therefore, the primary aim of this research project is to do an intensive network security analysis through a virtualized honeypot for cloud servers to tempt an attacker and provide a new means of monitoring.

3. EXISTING SYSTEM

1.1 EXISTING APPROACH:

Blameless Bayes and Principal Component Analysis (PCA) were been used with the KDD99 dataset by Almansob and Lomte. Similarly, PCA, SVM, and KDD99 were used Chithik and Rabbani for IDS. In Aljawarneh et Al's. Consequently, KDD99 is old and doesn't give any data about cutting edge new assault types, example, multi day misuses and so forth.

1.1.1 Drawbacks

- Strict Regulations
- Difficult to work with for non-technical users
- Restrictive to resources
- Constantly needs Patching
- Constantly being attacked

4. PROPOSED SYSTEM

4.1 Proposed System

Important steps of the algorithm are given in below.

- Normalization of every dataset.
- Convert that dataset into the testing and training.
- Form IDS models with the help of using RF, ANN, CNN and SVM algorithms.
- Evaluate every model's performance

4.2 ALGORITHMS

CNN:

A Convolutional Neural Network (CNN) is a type of deep learning neural network that is well-suited for image and video analysis.

Random forest:

It is the tech industry’s definitive destination for sharing compelling, first-person accounts of problem-solving on the road to innovation.

ANN:

ANN algorithm accepts only numeric and structured data. Convolutional Neural Networks (CNN) and Recursive Neural Networks (RNN) are used to accept unstructured and non-numeric data forms such as Image, Text, and Speech

4.3 USE CASE DIAGRAM

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

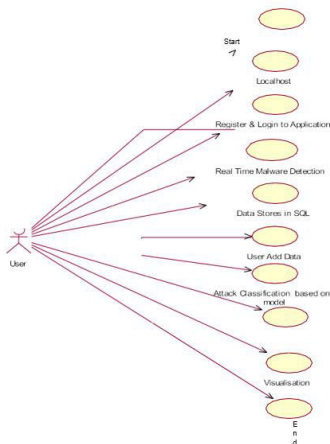


Fig 4.1: Use Case Diagram

4.4 CLASS DIAGRAM

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

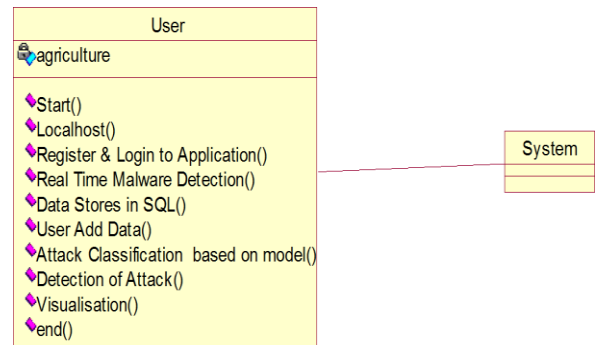


Fig 4.2: Class Diagram

4.5 SEQUENCE DIAGRAM

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

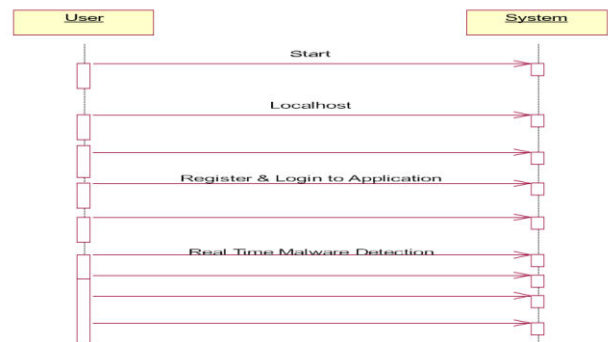


Fig 4.3: Sequence Diagram

4 RESULTS

```
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=',')
```

Fig 7.1:Input Data

```
n [6]: 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_error_rate',
'rerror_rate','srv_error_rate','same_srv_rate','diff_srv_rate','srv_diff_host_rate','dst_host_count','dst_host_sr',
'dst_host_diff_srv_rate','dst_host_same_src_port_rate',
'dst_host_srv_diff_host_rate','dst_host_serror_rate','dst_host_srv_error_rate',
'dst_host_rerror_rate','dst_host_srv_rerror_rate','attack','last_flag']

n [7]: train.columns=columns
test.columns=columns

n [8]: train.head()
Out[8]:
  duration  protocol_type  service  flag  src_bytes  dst_bytes  land  wrong_fragment  urgent  hot  num_failed_logins  logged_in  num_compromised  root_
0         0             0      udp     other  SF         146         0         0         0         0         0         0         0         0
1         0             0      tcp     private  SO         0         0         0         0         0         0         0         0         0
2         0             0      tcp     http     SF        232        8153         0         0         0         0         0         1         0
3         0             0      tcp     http     SF        199         420         0         0         0         0         0         1         0
4         0             0      tcp     private  REJ         0         0         0         0         0         0         0         0         0

n [9]: test.head()
```

Fig 7.2: Data Processing

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

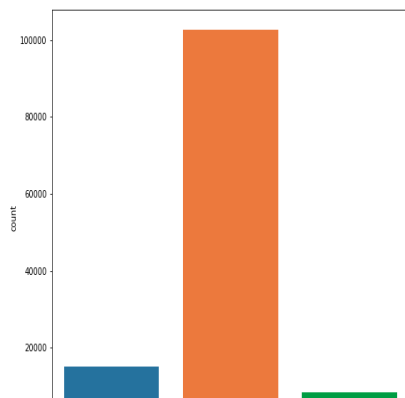


Fig 7.3: DATA EDA

```
Model Building

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

Fig 7.4: Model Building

```
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)
```

Fig 7.5: Logistic Regression

```
Decision Trees

train_X.shape

param_grid = {'max_depth': np.arange(2, 12),
              'max_features': np.arange(10,15)}

train_y.shape

from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier, export_graphviz, export
tree = GridSearchCV(DecisionTreeClassifier(), param_grid, cv = 10,verbose=1,n_jobs=-1)
tree.fit(train_X, train_y)

tree.best_score_

tree.best_estimator_
tree.best_params_

train_pred = tree.predict(train_X)

print(metrics.classification_report(train_y, train_pred))

test_pred = tree.oredict(test_X)
```

Fig 7.6: Decision Trees

```
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)})
```

Fig 7.7: Random forest

```
Support Vector Machine (SVM)

from sklearn.svm import LinearSVC
svm_clf = LinearSVC(random_state=0, tol=1e-5)
svm_clf.fit(train_X, train_y)

print(svm_clf.coef_)
print(svm_clf.intercept_)
print(svm_clf.predict(train_X))

from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
model = SVC(kernel='rbf', class_weight='balanced', gamma='scale')

model.fit(train_X, train_y)

from sklearn.model_selection import GridSearchCV
param_grid = {'C': [1, 10],
              'gamma': [0.0001, 0.001]}
grid = GridSearchCV(model, param_grid)
grid.fit(train_X, train_y)

print(grid.best_params_)
```

Fig 7.8: Support Vector machine (SVM)

```
user@ramesh:~/Desktop/41/finished/second/3/Network-Intrusion-Detection-System-master$ python3 app.py
/home/user/.local/lib/python3.6/site-packages/sklearn/base.py:334: UserWarning:
Trying to unpickle estimator LogisticRegression from version 0.22.1 when using version 0.23.2. This might lead to breaking code or invalid results. Use at your own risk.
UserWarning)
* Serving Flask app "app" (lazy loading)
* Environment: production
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
* Debug mode: off
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

Fig 7.9: LocalHost in cmd python app.py

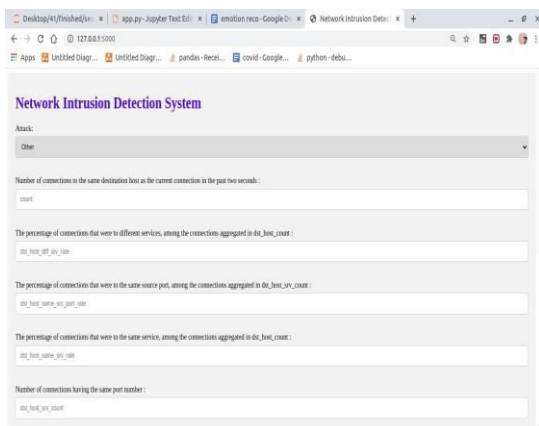


Fig 7.10: Network Intrusion Detection System



Fig 7.11: Entering the input data

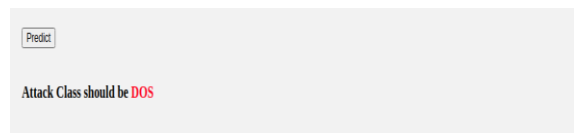


Fig 7.12: Predict attack

5. CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

Right now, estimations of help vector machine, ANN, CNN, Random Forest and profound learning calculations dependent on modern CICIDS2017 dataset were introduced relatively. Results show that the profound learning calculation performed fundamentally preferable outcomes over SVM, ANN, RF and CNN. We are going to utilize port sweep endeavors as well as other assault types with AI and profound learning calculations, Apache Hadoop and sparkle innovations together dependent on this dataset later on.

All these calculation helps us to detect the cyber-attack in network. It happens in the way that when we consider long back years there may be so many attacks happened so when these attacks are recognized then the features at which values these attacks are happening will be stored in some datasets. So by using these datasets we

are going to predict whether cyber-attack is done or not. These predictions can be done by four algorithms like SVM, ANN, RF, CNN this paper helps to identify which algorithm predicts the best accuracy rates which helps to predict best results to identify the cyber-attacks happened or not.

5.2 FUTURE SCOPE

The future scope of cyber threat detection using ANNs based on event profiles is promising, with potential benefits in terms of detection accuracy, real-time monitoring, adaptive learning, and scalability. However, organizations need to consider the challenges and invest in the necessary resources to implement and maintain these advanced systems effectively.

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