Host Based Intrusion Detection Systems : Techiniques, Datasets & Challenges

Introduction

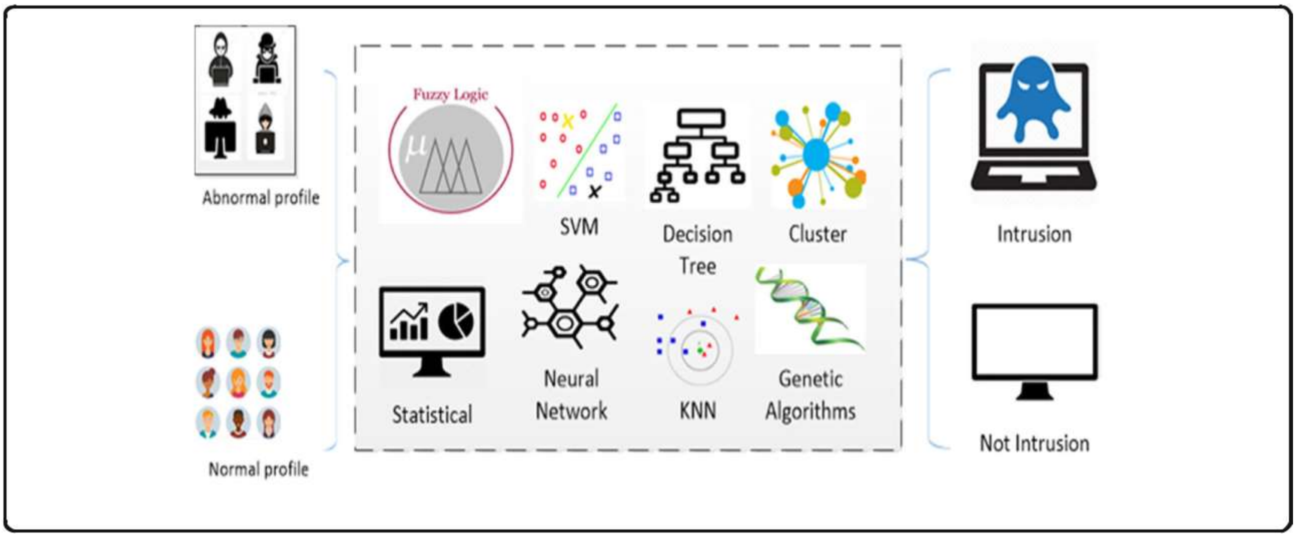
The aim of an IDS is to identify different kinds of malware as early as possible, which cannot be achieved by a traditional firewall. With the increasing volume of computer malware, the development of improved IDSs has become extremely important.

Table -1 Comparison of IDS technology types based on their positioning within the computer system

		Advantages	Disadvantages	Data source
Technology	HIDS	• HIDS can check end-to-end encrypted communications behaviour. • No extra hardware required. • Detects intrusions by checking hosts file system, system calls or network events. • Every packet is reassembled • Looks at the entire item, not streams only	• Delays in reporting attacks • Consumes host resources • Needs to be installed on each host. • It can monitor attacks only on the machine where it is installed.	• Audits records, log files, Application Program Interface (API), rule patterns, system calls.
	NIDS	•Detects attacks by checking network packets. •Not required to install on each host. •Can check various hosts at the same period. •Capable of detecting the broadest ranges of network protocols	•Challenge is to identify attacks from encrypted traffic. •Dedicated hardware is required. •It supports only identification of network attacks. •Difficult to analysis high-speed network. •The most serious threat is the insider attack.	•Simple Network Management Protocol (SNMP) •Network packets (TCP/UDP/ICMP), •Management Information Base (MIB) •Router NetFlow records

The focus of our analysis will be to build an **HIDS system using systemcall data** and machine learning techniques.

We will explore Supervised learning-based IDS techniques to detect intrusions by using labeled training data. A supervised learning approach usually consists of two stages, namely training and testing. In the training stage, relevant fea-tures and classes are identified and then the algorithm learns from these data samples. In supervised learning IDS, each record is a pair, containing a network or host data source and an associated output value (i.e., label), namely intrusion or normal. Next, feature selection can be applied for eliminating unnecessary features. Using the training data for selected features, a supervised learning technique is then used to train a classifier to learn the inherent relationship that exists between the input data and the labelled output value. The resultant classifier then becomes a model which, given a set of feature values, predicts the class to which the input data might belong.



Performance metrics for HIDS

HIDS are typically evaluated based on the following standard performance measures for a two-class classifier:

Table-2 Confusion Matrix for IDS System

Actual Class	Predicted Class		
	Class	Normal	Attack
	Normal	True negative (TN)	False Positive (FP)
	Attack	False Negative (FN)	True positive (TP)

True Positive Rate (TPR): It is calculated as the ratio between the number of correctly predicted attacks and the total number of attacks. If all intrusions are detected then the TPR is 1 which is extremely rare for an IDS. TPR is also called a Detection Rate (DR) or the Sensitivity. The TPR can be expressed mathematically as

$$TPR = TP / TP + FN$$

False Positive Rate (FPR): It is calculated as the ratio between the number of normal instances incorrectly classified as an attack and the total number of normal instances.

$$FPR = FP/FP+TN$$

False Negative Rate (FNR): False negative means when a detector fails to identify an anomaly and classifies it as normal. The FNR can be expressed mathematically as:

$$FNR = FN/FN + TP$$

Classification rate (CR) or Accuracy: The CR measures how accurate the IDS is in detecting normal or anomalous traffic behavior. It is described as the percentage of all those correctly predicted instances to all instances:

$$Accuracy = TP+TN / TP+TN + FP+FN$$

Receiver Operating Characteristic (ROC) curve: ROC has FPR on the x-axis and TPR on the y-axis. A test with perfect discrimination (no overlap in the two distributions) has a ROC curve that passes through the upper left corner (100% sensitivity, 100% specificity).

Dataset Details

ADFA-LD dataset created by Australian Defence Force Academy created for evaluation of system-call-based HIDS

https://www.unsw.adfa.edu.au/unsw-canberra-cyber/cybersecurity/ADFA-IDS-Datasets/

Table-3 Number of system calls traces in different categories of AFDA-LD and AFDA-WD

ADFA- LD

Dataset	Traces	System Calls
Training data	833	308,077
Validation data	4372	2,122,085
Attack data	746	317,388
Total	5951	2,747,550

Table-4 ADFA-LD attack class

Attack	Payload	Vector	Count
Hydra-FTP	Password brute force	FTP by Hydra	162
Hydra-SSH	Password brute force	SSH Hydra	176
Adduser	Add new super user	Client-side poisoned executable	91
Java-Meterpreter	Java based Meterpreter	TIkiWiki vulnerability exploit	124
Meterpreter	Linux Meterpreter Payload	Client side poisoned executable	75
Webshell	C100 Webshell	PHP remote file inclusion vulnerability	118

Machine Learning Techinques Applied

Data Preprocessing

1) Split the Attack data of each category (Hydra-FTP, Hydra-SSH, Adduser, Java-Meterpreter, Meterpreter and Webshell) into 70% training data and 30 % test data. For instance there are are 10 folders in “Adduser” attack. Therefore, 7 of these folders are to be used for training and 3 folders are to be used for testing.

2) For the Normal data, files in “Training_Data_Master” folder are to be used as training data and files in “Validation_Data_Master” folder are to be used as test data.

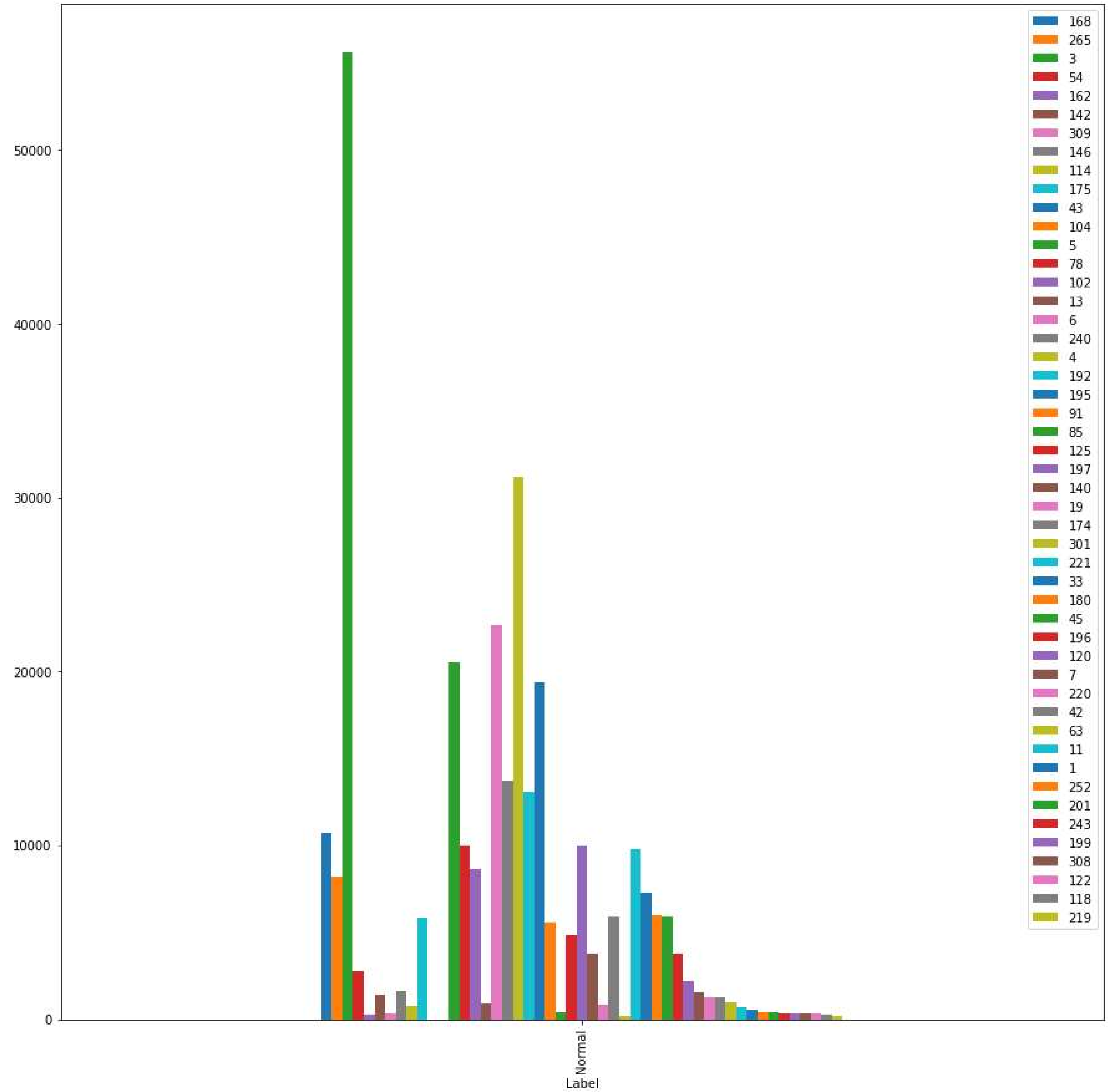
3) Write a python script to find the frequency of occurences of all unique 1-grams, 2-grams and 3-grams system call sequences in the training data for both Attack data (across all categories of attack) and Normal data.

4) Perform the same task on files in the “Training_Data_Master” to obtain all the unique 1- grams, 2-grams and 3-grams.

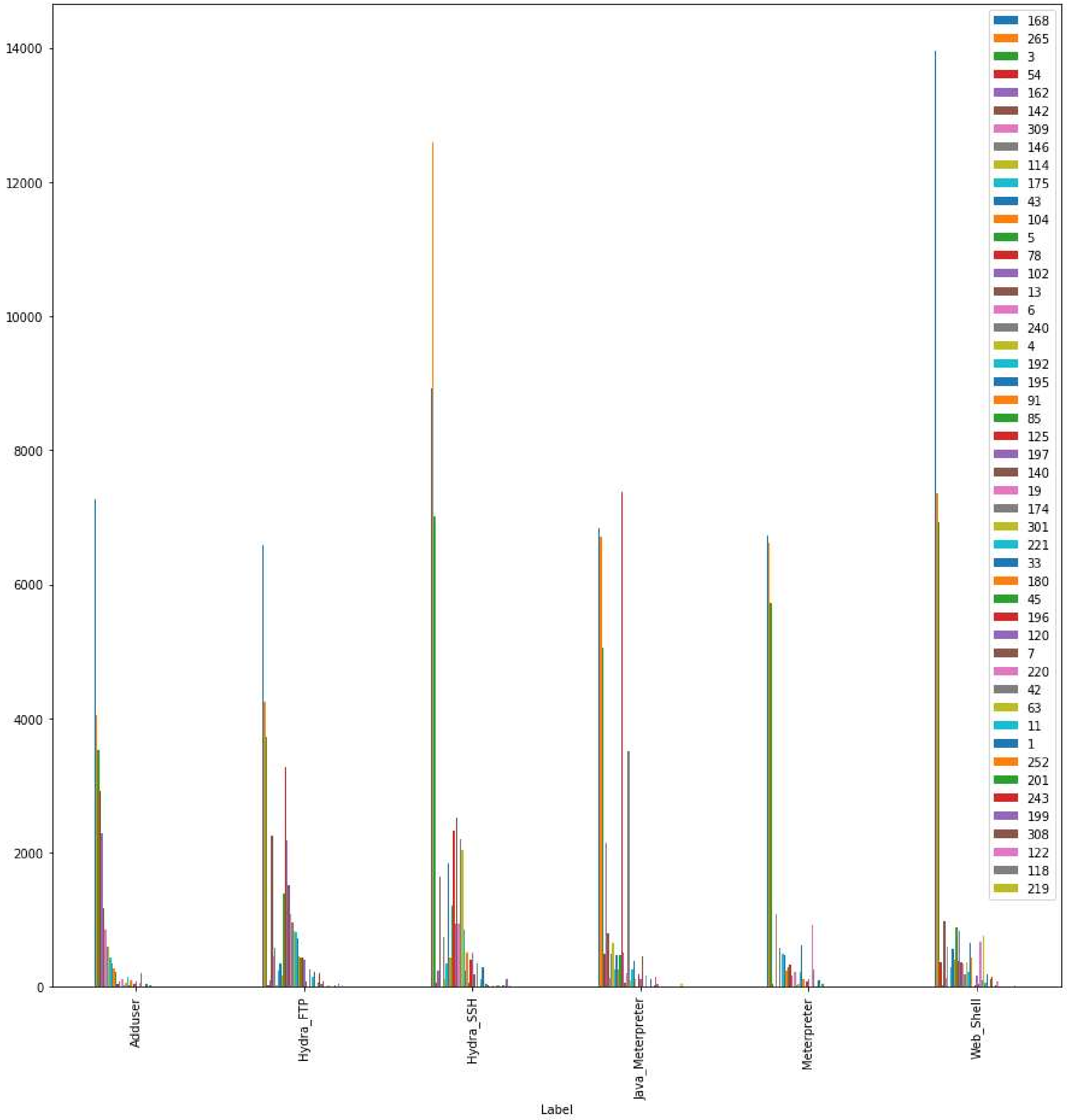
5) Once we have obtained the frequencies of all the unique n-grams terms in the training data, use the top 30% n-grams terms with the highest frequency to create a data set.

6) Apply the same procedure to generate the test dataset from the test files of the attack data (for all attack types) and the normal files in the “Validation_Data_Master” using the top 30% 3-grams terms with highest frequencies obtained during the training phase. The classifier model developed during the training phase will finally be validated on the Test dataset.

EDA : Top 50 n-grams for 1/2/3 were plotted



For Normal System Call 1-gram distribution is seen in this graph



For Attacks System Call 1-gram distribution is seen in this graph

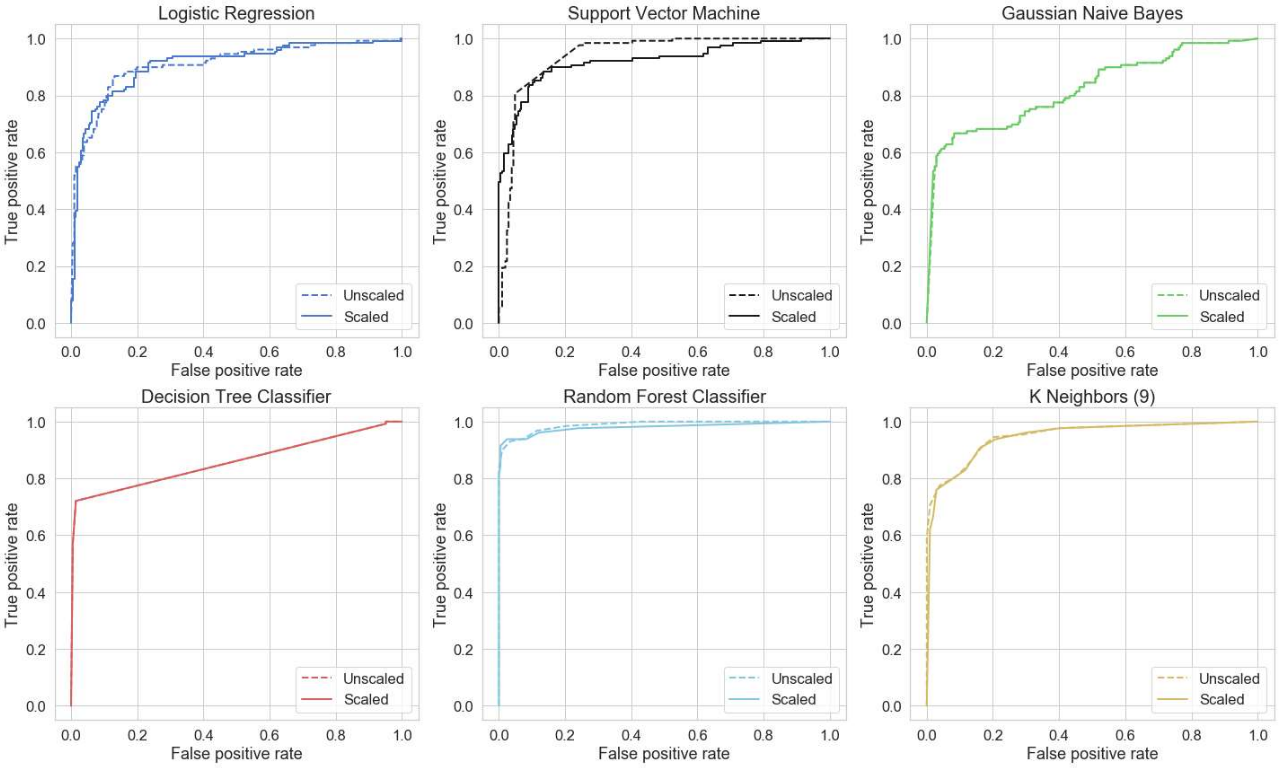
Model Comparison

Supervised Models

On the preprossed data supervised learning modelling was done the results observed are as follows:

	Accuracy	**Precision**	**Recall**	**F1**
LogisticReg	0.844776	0.834783	0.744186	0.786885
SVMC	0.683582	0.925926	0.193798	0.320513
GaussNB	0.811940	0.934211	0.550388	0.692683

DecisionTree	0.886567	0.978947	0.720930	0.826667
RandomForest	0.958209	0.983193	0.875969	0.930041
kNN9	0.865672	0.818182	0.837209	0.827586



We further improved Random Forest Model using Grid Search validation & obtained following results:

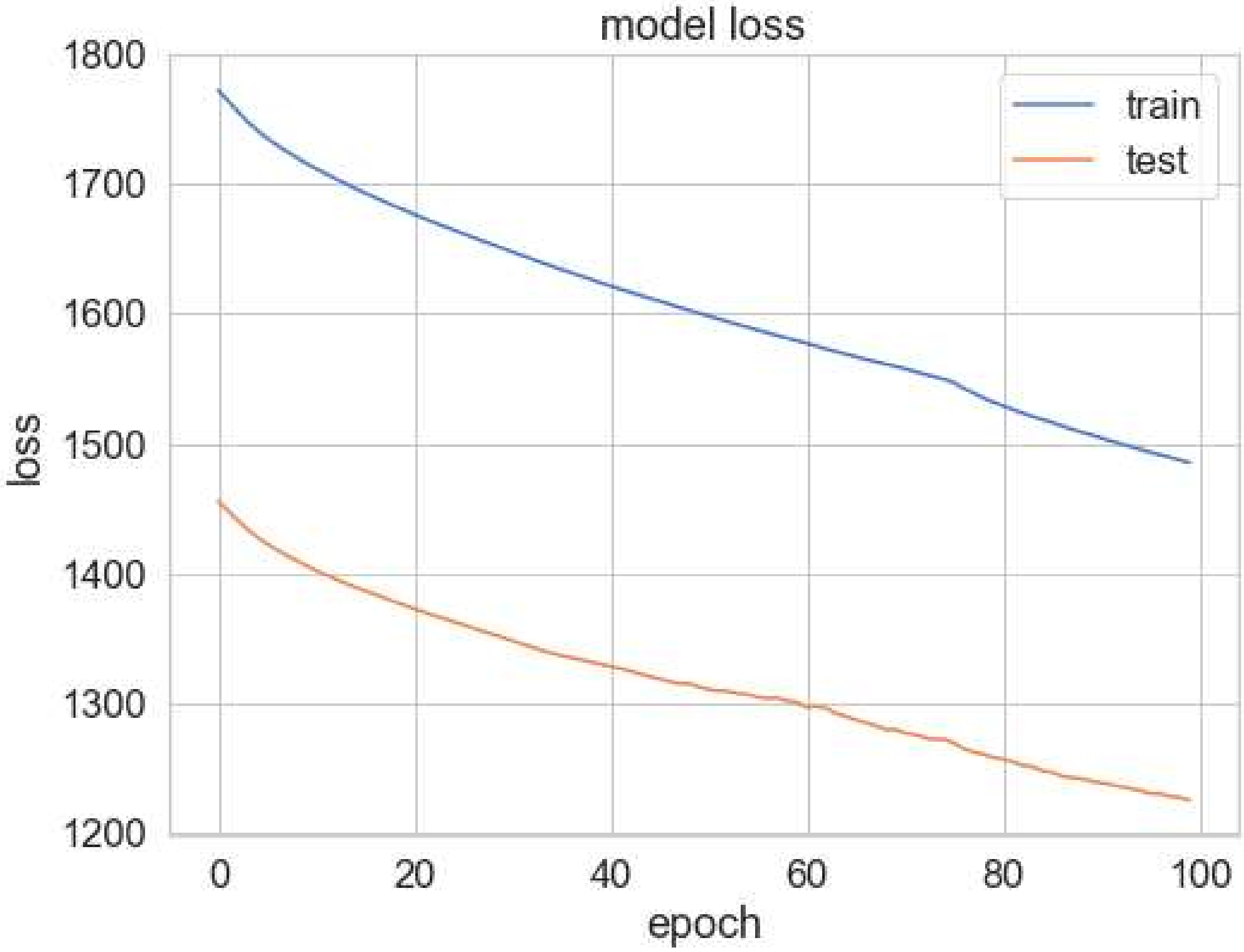
```
Final Model Parameters:

{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 80,
 'max_features': 3,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 3,
 'min_samples_split': 8,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 300,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}


Accuracy: 0.91
```

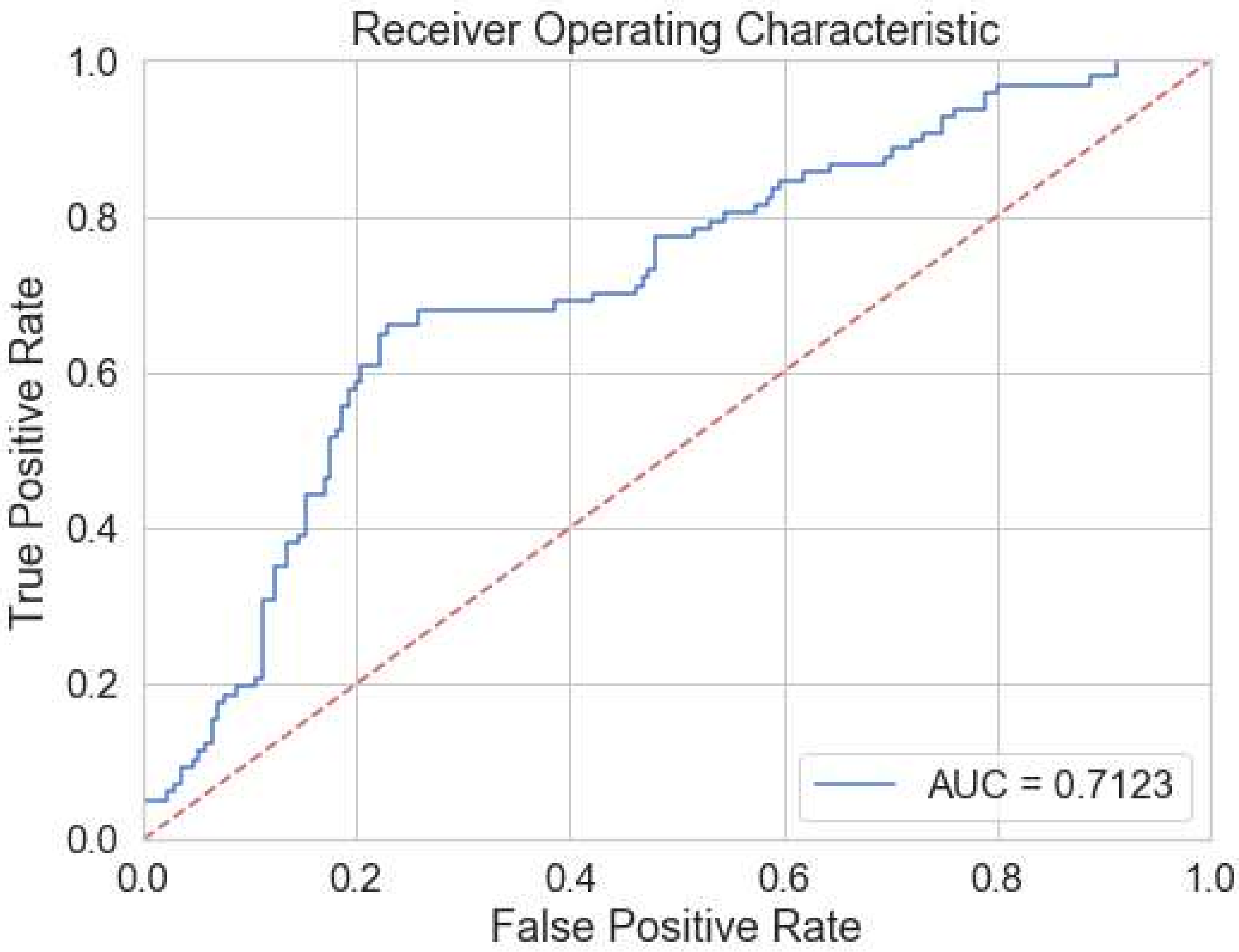
Deep Learning Models - Deep Autoencoder

We used Deep Autoencoder model to evaluate how Deep Learning techiques will perform on this dataset.

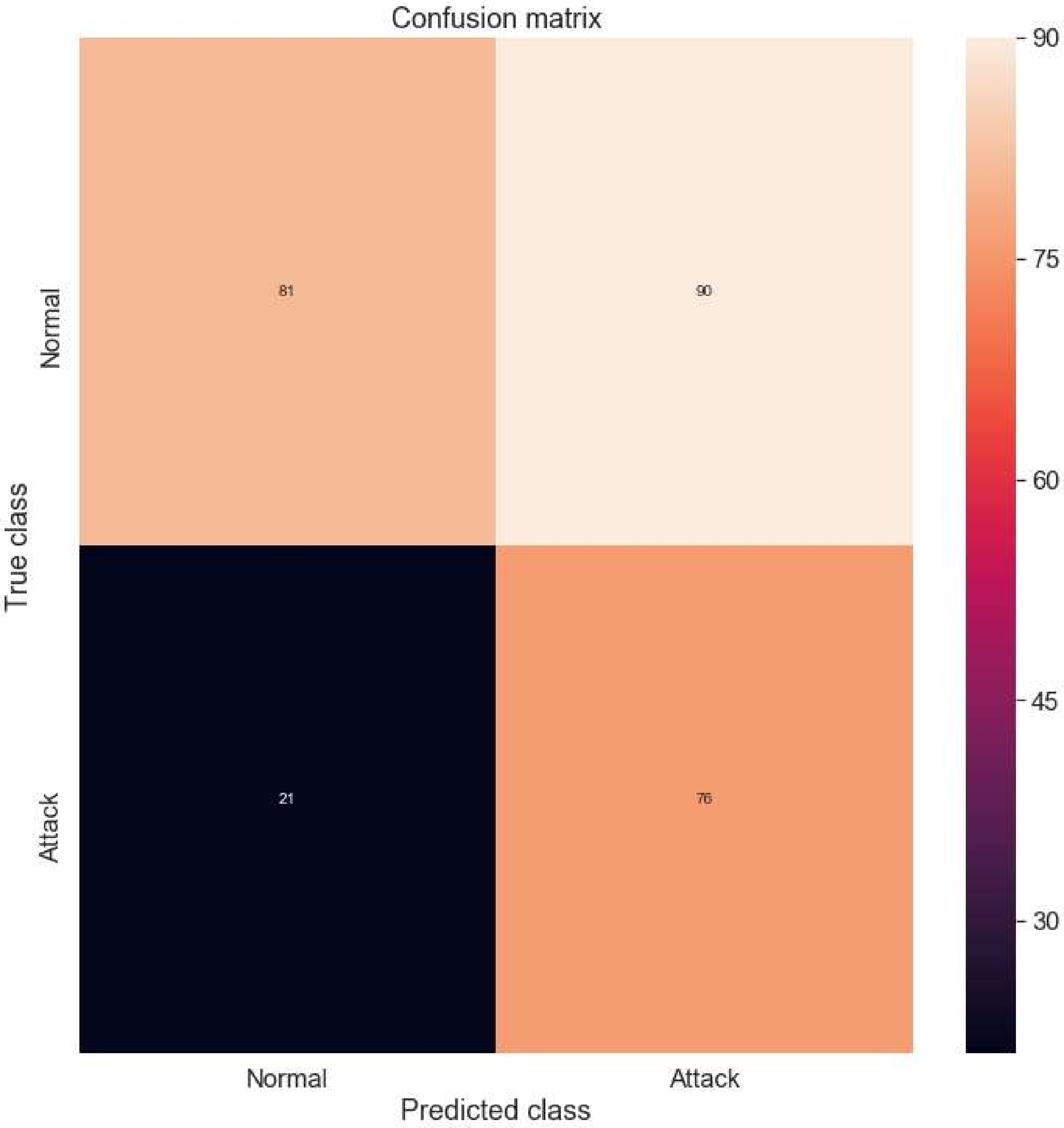
Building the model Our Autoencoder uses 4 fully connected layers with 14, 7, 7 and 29 neurons respectively. The first two layers are used for our encoder, the last two go for the decoder. Additionally, L1 regularization will be used during training :

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_6 (InputLayer)         (None, 87)                0
_________________________________________________________________
dense_22 (Dense)             (None, 87)                7656
_________________________________________________________________
dense_23 (Dense)             (None, 43)                3784
_________________________________________________________________
dense_24 (Dense)             (None, 43)                1892
_________________________________________________________________
dense_25 (Dense)             (None, 87)                3828
=================================================================
Total params: 17,160
Trainable params: 17,160
Non-trainable params: 0


Epoch 100/100
662/662 [==============================] - 0s 115us/step - loss: 1485.2451 -
acc: 0.6360 - val_loss: 1225.0467 - val_acc: 0.6157


_________________________________________________________________
```


model loss
train
test
loss
1800
1700
1600
1500
1400
1300
1200
0
20
40
60
80
100
epoch



threshold = 0.2



Obtained accuracy with Deep Autoencoder **63%.**

We've created a very simple Deep Autoencoder in Keras that can reconstruct what normal system call looks like. Initially we gave a lot of one-class examples (normal systemcalls) to a model and it learned (somewhat) how to discriminate whether or not new examples belong to that same class. Our model seems to catch a lot of the attack cases.

LSTM For SystemCall Prediction

We also attempted to use simple LSTM for system call predictions, the results are summarized below.

Data dimention : (20450(n_samples), 19 (time-step), 341(unique calls))

ADFA Dataset Preprocessing:
1) The system call language model estimates the probability distribution of the next call in a sequence given the sequence of previous calls.

2) We assume that the host system generates a finite number of system calls.

3) We index each system call by using an integer starting from 1 and denote the fixed set of all possible system calls in the system as S = {1, · · · , K}. Let x = x1x2 · · · xl(xi ∈ S) denote a sequence of l system calls.

LSTM Based Model :
1) At the Input Layer, the call at each time step xi is fed into the model in the form of one-hot encoding,
in other words, a K dimensional vector with all elements zero except position xi.

2) At the Embedding Layer*, incoming calls are embedded to continuous space by multiplying embedding matrix W,
which should be learned.

3) At the Hidden Layer*, the LSTM unit has an internal state, and this state is updated recurrently at each time step.

4) At the Output Layer, a softmax activation function is used to produce the estimation of normalized probability values of possible calls coming next in the sequence.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_28 (LSTM)               (None, 100)               176800    
_________________________________________________________________
dense_16 (Dense)             (None, 341)               34441     
_________________________________________________________________
activation_10 (Activation)   (None, 341)               0         
=================================================================
Total params: 211,241
Trainable params: 211,241
Non-trainable params: 0

Epoch 10/10
20298/20298 [==============================] - 19s 928us/step - loss: 0.0049 
- acc: 0.9983 - val_loss: 0.0083 - val_acc: 0.9978

_________________________________________________________________
```

LSTM Binary Classifier

Model Summary

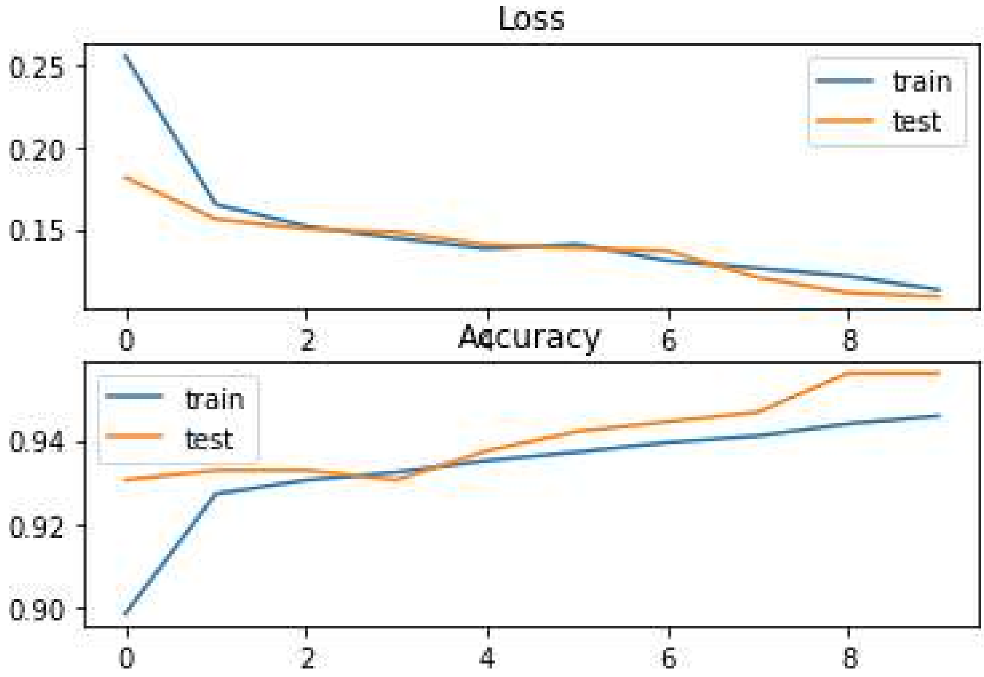
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_41 (LSTM)               (None, 13)                780       
_________________________________________________________________
dense_59 (Dense)             (None, 1)                 14        
_________________________________________________________________
dense_60 (Dense)             (None, 1)                 2         
=================================================================
Total params: 796
Trainable params: 796
Non-trainable params: 0
```

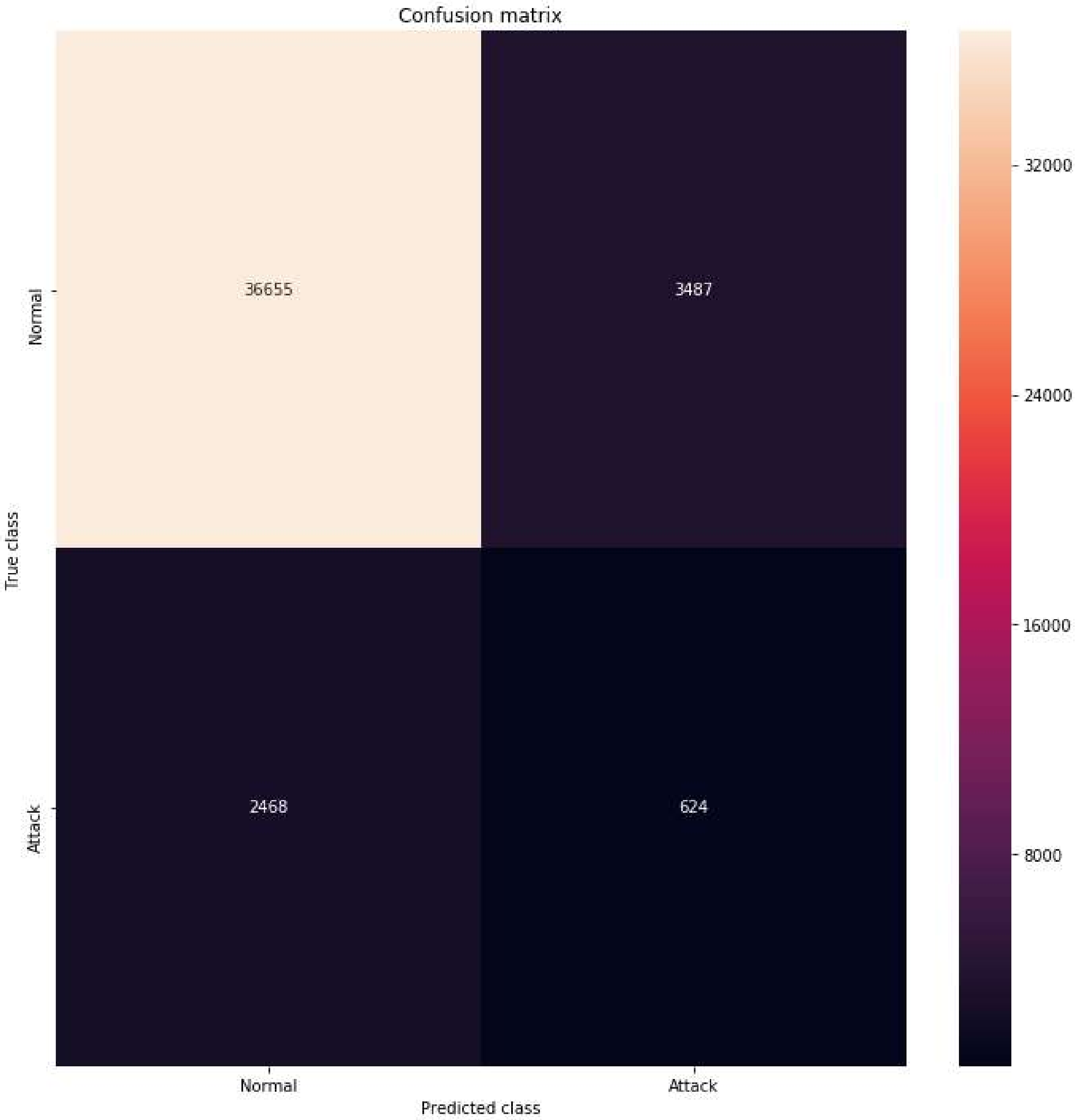
Model Performance Summary/Plots

```
                 precision    recall  f1-score support

           0       0.91      0.94      0.92     39123
           1       0.20      0.15      0.17      4111

   micro avg       0.86      0.86      0.86     43234
   macro avg       0.56      0.54      0.55     43234
weighted avg       0.85      0.86      0.85     43234
```

Test Data performace

```
Accuracy    : 0.862261
Precision   : 0.880766
Recall      : 0.862261
F1 score    : 0.871119
ROC AUC     : 0.601735
```


Loss
0.25
0.20
0.15
train
test
0
2
4
6
8
Accuracy
0.94
0.92
0.90
train
test
0
2
4
6
8



Conclusion

HIDS is complex dataset ,pre-processing step is crucial to understand and then use various ML & DL to build models for same. DL techniques Though ADFA-LD dataset contains many new attacks, it is not adequate.As normal activities are frequently changing and may not remain effective over time, there exists a need for newer and more comprehensive datasets that contain wide-spectrum of malware activities.

References

LSTM-BASED SYSTEM-CALL LANGUAGE MODELING AND ROBUST ENSEMBLE METHOD FOR DESIGNING HOST-BASED INTRUSION DETECTION SYSTEMS https://arxiv.org/pdf/1611.01726.pdf

Idea: char-based system call

https://github.com/karpathy/char-rnn -char NN

padding the sequence

https://stackoverflow.com/questions/42002717/how-should-we-pad-text-sequence-in-keras-using-pad-sequences

https://github.com/fchollet/keras/issues/1641

loss functions : https://keras.io/losses/#categorical_crossentropy