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# Predicting Anomalies in Network Traffic

Phase-1 : Data Analysis and Preparation
Phase-2 : Build a model to overfit the dataset
Phase-3 : Model selection and evaluation
Phase-4: Interative Feature Reduction and Selection

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# Contents

# 1 Introduction

## 1.1 Intrusion Detection Systems (IDS)

Intrusion Detection Systems (IDS) provide network security software applications by continuously monitoring network traffic and classifying the connections as normal or malicious. IDS are categorized into two types based on the responsive nature - Passive IDS and Active IDS. A passive IDS is designed to identify and block the malicious and malware attacks manually by human experts whereas active IDS is designed to identify and block the malware attacks using a software automatically.

IDS are also categorized into Signature based IDS and Anomaly Based IDS. In the Signature based IDS, there exists a database which contains details about all known malware attacks against which each network traffic connection is validated to identify the malicious nature if it exists. This type of IDS is costly and has to keep updating new types of attacks frequently. Anomaly based IDS is a behavior-based system where any deviation from the normal network traffic patterns will be reported using pattern-recognition techniques. In this research paper, a proof-of-concept for a machine learning based Anomaly based intrusion detection will be evaluated on a benchmark intrusion detection dataset.

## 1.2 Motivation

The Internet of Things (IoT) has changed the way devices communicate across a network. There are over 30 billion devices connected to each other in today's world where their communication happens over the network. Due to the variety, velocity and vast nature of this traffic, the traditional intrusion detection systems are not sufficient to identify the malware patterns [1]. With the help of data science, machine learning and neural network techniques, one can leverage the historic network traffic patterns and can build an intelligent artificial intelligence model to solve this intrusion detection problem. This project exactly tries to provide a proof-of-concept for this problem by applying machine learning and neural network techniques on a benchmark network intrusion detection dataset.

## 1.3 Problem Statement

In this research, KDD Cup 1999 dataset will be used to build a machine learning based intrusion detection problem to predict (classify) whether a network connection is "normal" or "abnormal". As this is a categorical prediction, this is a binary classification problem

Github Link to this project:click here
Jupyter notebook html: click here

# 2 Dataset Description and Exploration

In this research, the KDD Cup 1999 dataset has been chosen for the data analysis and model building. This dataset was used in the fifth international conference for the data mining and knowledge discovery competition and contains a huge variety of network intrusion data that is simulated in an environment equipped with a military network setting.

The original source of the dataset is from the official KDD website [2] and can also be found in the kaggle website [3]. The dataset contains about 494,000 records and 41 features (columns) which contains network traffic details like source bytes, destination connection information, type of attacks and so on. Below are the list of features (columns) and their data types in the dataset.

## 2.1 Target Variable ”label” distribution

The target variable ”label” contains all different types of malware attacks and also the value ”normal” (i.e., not an attack) as shown below.

’normal’, ’buffer overflow’, ’loadmodule’, ’perl’, ’neptune’, ’smurf’, ’guess passwd’, ’pod’, ’teardrop’, ’portsweep’, ’ipsweep’, ’land’, ’ftp write’, ’back’, ’imap’, ’satan’, ’phf’, ’nmap’, ’multihop’, ’warezmaster’, ’warezclient’, ’spy’, ’rootkit’

All malware attacks are grouped (transformed) to the value ”abnormal” to make this problem a binary classification problem instead of a multi-class classification. The target variable distribution can be found below (see **Figure 1**).

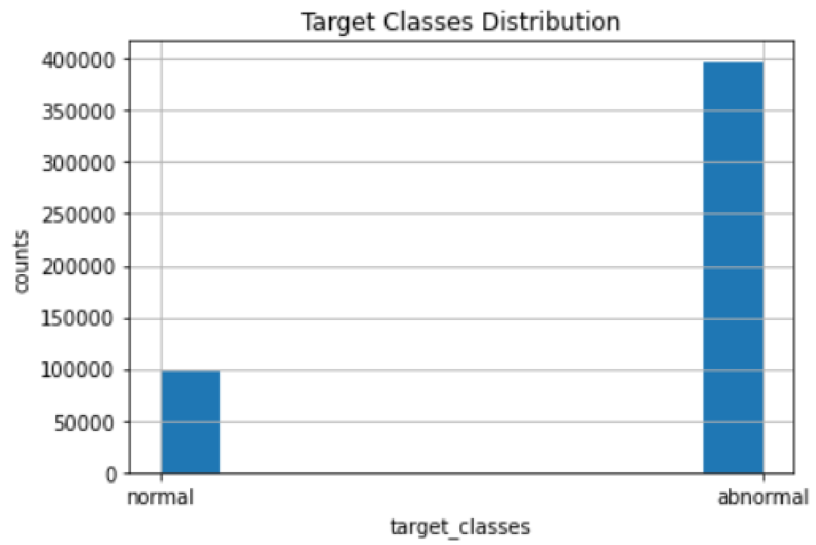


Figure 1: Target Variable ”label” Distribution.

## 2.2 Categorical Columns Distributions

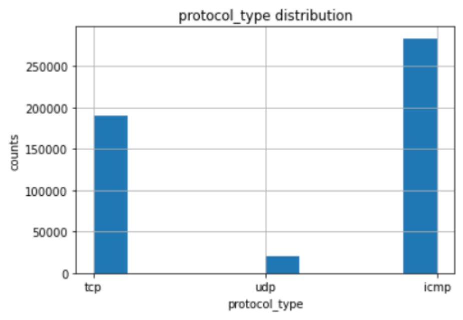
Below are the categorical columns in this dataset and their corresponding distribution plots.

’protocol type’, ’service’, ’flag’, ’land’, ’logged in’, ’is host login’, ’is guest login’

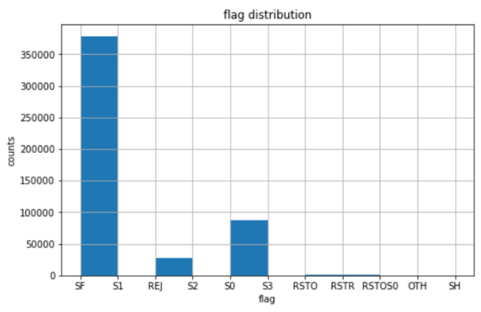
Categorical variables statistics can be found in the below table:

Table 1: Categorical Variables Statistics.

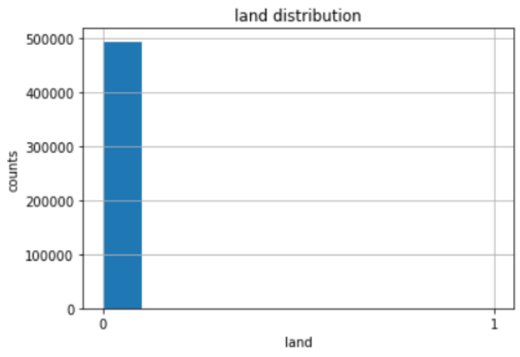
| Stats | protocol_type | service | flag | land | logged_in | is_host_login | is_guest_login |
|---|---|---|---|---|---|---|---|
| count | 494020 | 494020 | 494020 | 494020 | 494020 | 494020 | 494020 |
| unique | 3 | 66 | 11 | 2 | 2 | 1 | 2 |
| top | icmp | ecr_i | SF | 0 | 0 | 0 | 0 |
| freq | 283602 | 281400 | 378439 | 493998 | 420784 | 494020 | 493335 |



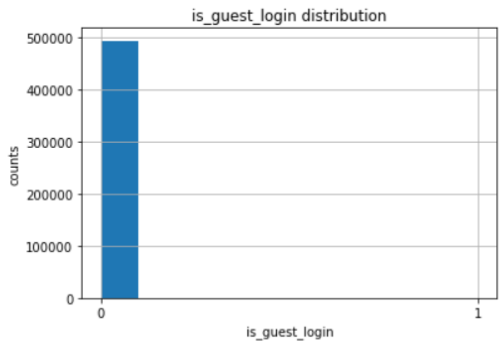
(a) protocol type



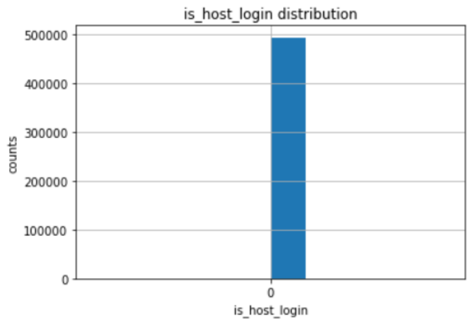
(b) Flag



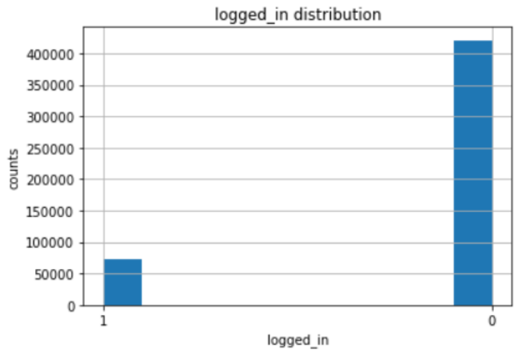
(c) Land



(d) Is Guest Login



(e) Is Host Login



(f) Logged In

Figure 2: Categorical Columns Distributions

## 2.3 Continuous Columns

Below are the continuous columns in this dataset and their corresponding distribution plots.

'duration', 'src bytes', 'dst bytes', 'wrong fragment', 'urgent', 'hot', 'num failed logins', 'num compromised', 'root shell', 'su attempted', 'num root', 'num file creations', 'num shells', 'num access files', 'num outbound cmds', '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 count', 'dst host same srv rate', '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'

Continuous variables statistics can be found in the below table:

Table 2: Categorical Variables Statistics.

| Stats | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| duration | 494020 | 47.9794 | 707.7472 | 0 | 0 | 0 | 0 | 58329 |
| src_bytes | 494020 | 3025.616 | 988219.1 | 0 | 45 | 520 | 1032 | 6.93E+08 |
| dst_bytes | 494020 | 868.5308 | 33040.03 | 0 | 0 | 0 | 0 | 5155468 |
| wrong_fragment | 494020 | 0.006433 | 0.134805 | 0 | 0 | 0 | 0 | 3 |
| urgent | 494020 | 1.42E-05 | 0.00551 | 0 | 0 | 0 | 0 | 3 |
| hot | 494020 | 0.034519 | 0.782103 | 0 | 0 | 0 | 0 | 30 |
| num_failed_logins | 494020 | 0.000152 | 0.01552 | 0 | 0 | 0 | 0 | 5 |
| num_compromised | 494020 | 0.010212 | 1.798328 | 0 | 0 | 0 | 0 | 884 |
| root_shell | 494020 | 0.000111 | 0.010551 | 0 | 0 | 0 | 0 | 1 |
| su_attempted | 494020 | 3.64E-05 | 0.007793 | 0 | 0 | 0 | 0 | 2 |
| num_root | 494020 | 0.011352 | 2.01272 | 0 | 0 | 0 | 0 | 993 |
| num_file_creations | 494020 | 0.001083 | 0.096416 | 0 | 0 | 0 | 0 | 28 |
| num_shells | 494020 | 0.000109 | 0.01102 | 0 | 0 | 0 | 0 | 2 |
| num_access_files | 494020 | 0.001008 | 0.036482 | 0 | 0 | 0 | 0 | 8 |
| num_outbound_cmds | 494020 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| count | 494020 | 332.2864 | 213.1471 | 0 | 117 | 510 | 511 | 511 |
| srv_count | 494020 | 292.9071 | 246.3227 | 0 | 10 | 510 | 511 | 511 |
| serror_rate | 494020 | 0.176687 | 0.380717 | 0 | 0 | 0 | 0 | 1 |
| srv_serror_rate | 494020 | 0.176609 | 0.381017 | 0 | 0 | 0 | 0 | 1 |
| rerror_rate | 494020 | 0.057434 | 0.231624 | 0 | 0 | 0 | 0 | 1 |
| srv_rerror_rate | 494020 | 0.057719 | 0.232147 | 0 | 0 | 0 | 0 | 1 |
| same_srv_rate | 494020 | 0.791547 | 0.38819 | 0 | 1 | 1 | 1 | 1 |
| diff_srv_rate | 494020 | 0.020982 | 0.082206 | 0 | 0 | 0 | 0 | 1 |
| srv_diff_host_rate | 494020 | 0.028996 | 0.142397 | 0 | 0 | 0 | 0 | 1 |
| dst_host_count | 494020 | 232.4712 | 64.7446 | 0 | 255 | 255 | 255 | 255 |
| dst_host_srv_count | 494020 | 188.6661 | 106.0402 | 0 | 46 | 255 | 255 | 255 |
| dst_host_same_srv_rate | 494020 | 0.753781 | 0.41078 | 0 | 0.41 | 1 | 1 | 1 |
| dst_host_diff_srv_rate | 494020 | 0.030906 | 0.109259 | 0 | 0 | 0 | 0.04 | 1 |
| dst_host_same_src_port_rate | 494020 | 0.601936 | 0.481309 | 0 | 0 | 1 | 1 | 1 |
| dst_host_srv_diff_host_rate | 494020 | 0.006684 | 0.042133 | 0 | 0 | 0 | 0 | 1 |
| dst_host_serror_rate | 494020 | 0.176754 | 0.380593 | 0 | 0 | 0 | 0 | 1 |
| dst_host_srv_serror_rate | 494020 | 0.176443 | 0.38092 | 0 | 0 | 0 | 0 | 1 |
| dst_host_rerror_rate | 494020 | 0.058118 | 0.23059 | 0 | 0 | 0 | 0 | 1 |
| dst_host_srv_rerror_rate | 494020 | 0.057412 | 0.230141 | 0 | 0 | 0 | 0 | 1 |

## 3 Data Normalization

As seen from the above continuous variables distribution in the above section the scale of some of the features (columns) values are not in same range as others. This irregularity will make the machine learning model train poorly. Hence the features need to be normalized so that the optimization during model training will happen in a better way and the model will not be sensitive to the features. This research paper uses the existing normalization function that exists in python's scikit-learn library which can be found here

After applying normalization transformation to each continuous feature, below are the new distribution plots.

## 4 Modeling

### 4.1 Model that over-fits the entire dataset

To understand the dataset and to estimate the model size (architecture and hyper-parameters) , we decided to build a model that over-fits the entire dataset. This is an experiment step to understand what model size would be required to overfit entire data. We performed below steps:

- Step-1: Using ENTIRE dataset to "OVERFIT" the model using vannila (single neuron) logistic regression model to reach accuracy 100 percent or close to 100 percent

- Step-2: If the accuracy did not reach 100 percent, then a bigger architecture model will be designed and modeled to achieve accuracy of 100 percent or close to 100 percent.

#### 4.1.1 Model-1 Architecture Summary Diagram

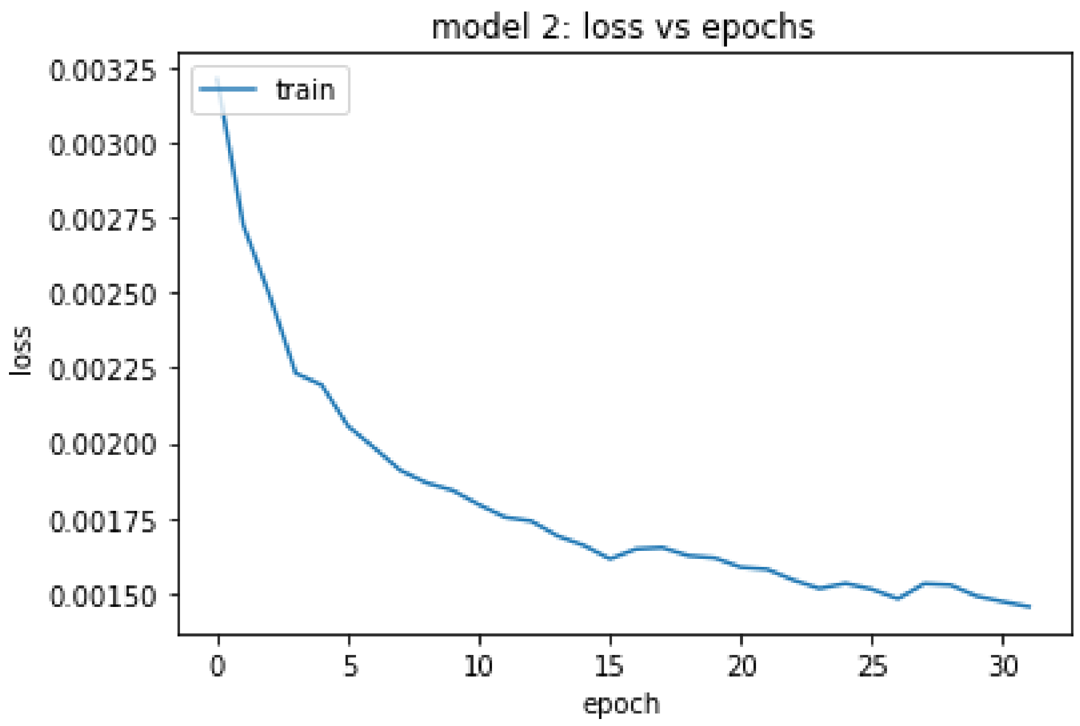
#### 4.1.2 Inference

As seen from the above model, the basic logistic regression model has achieved an accuracy of 99.81 with 256 epochs.A seen from the model-2 performance we have achieved 99.96 percent accuracy (close to 100 percent) which means this model did over-fit the dataset. Therefore, a 4-layer neural network model architecture with 8 neurons, 4 neurons and 2 neurons in internal layers is sufficient enough to overfit the entire dataset.

## 5 Generalized Model building, selection and evaluation

In the previous section, after exploring the architectures that would result in an over-fitting model, in this section, the focus will be on using a feed-forward neural network (and its architecture variants) to build a best model that would perform well on the validation dataset. The data has been shuffled before performing the experiments and the same dataset has been used for all the models for fair comparison. The code did not implement seeding (which is used for ability to reproduce the model), hence a new run might result in a slight difference in the performances of the models.

The path towards building the best models involves performing experiments with different hyper-parameter settings from a baseline model configuration to the best model (iterations of



experiments). The notebooks/code related to this section can be found in the below github link.

Github Link to this project:click here

### 5.1 Iteration-0: Baseline Modeling

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

### 5.2 Iteration-1: Modifying activation functions

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

### 5.3 Iteration-2: Modifying Optimizer functions

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

### 5.4 Iteration-3: Modifying Batch Size

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

### 5.5 Iteration-4: Modifying Number of Neurons

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

## 5.6 Iteration-5: Modifying Number of Epochs

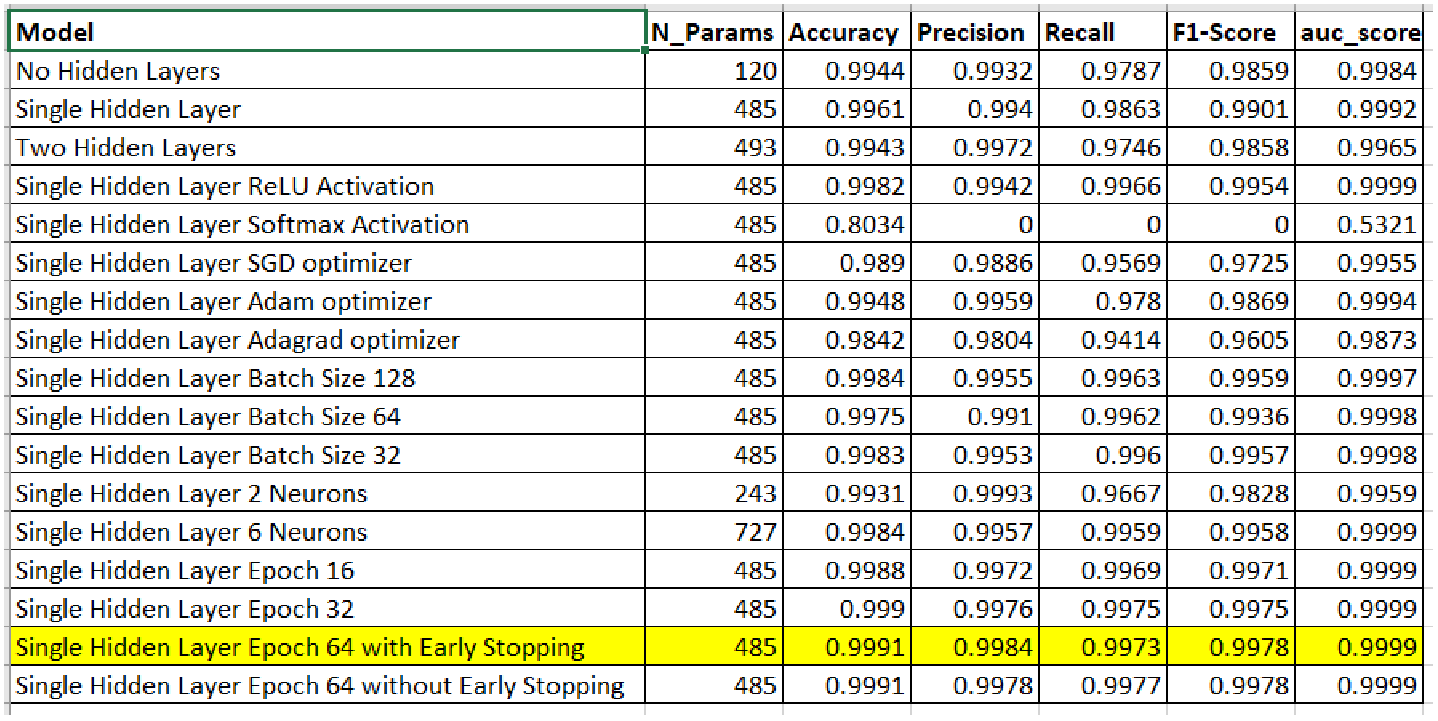
The baseline architecture used 8 epochs for the computations. We will be trying out different epoch sizes (16,32 and 64) to find out the best epoch number for this model architecture

### 5.6.1 Iteration-5 Model Performances

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

## 5.7 Model Selection

We have obtained various metrics like precision, recall, F1, and Area-Under-Curve (AOC) for each model to select the best model.



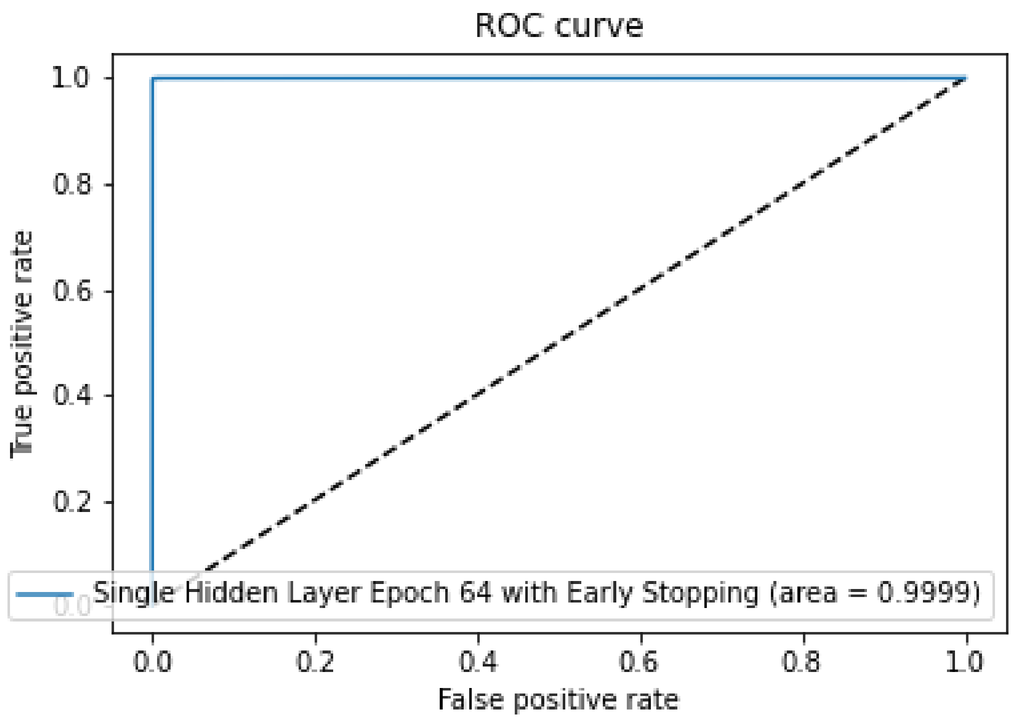
| Model | N_Params | Accuracy | Precision | Recall | F1-Score | auc_score |
|---|---|---|---|---|---|---|
| No Hidden Layers | 120 | 0.9944 | 0.9932 | 0.9787 | 0.9859 | 0.9984 |
| Single Hidden Layer | 485 | 0.9961 | 0.994 | 0.9863 | 0.9901 | 0.9992 |
| Two Hidden Layers | 493 | 0.9943 | 0.9972 | 0.9746 | 0.9858 | 0.9965 |
| Single Hidden Layer ReLU Activation | 485 | 0.9982 | 0.9942 | 0.9966 | 0.9954 | 0.9999 |
| Single Hidden Layer Softmax Activation | 485 | 0.8034 | 0 | 0 | 0 | 0.5321 |
| Single Hidden Layer SGD optimizer | 485 | 0.989 | 0.9886 | 0.9569 | 0.9725 | 0.9955 |
| Single Hidden Layer Adam optimizer | 485 | 0.9948 | 0.9959 | 0.978 | 0.9869 | 0.9994 |
| Single Hidden Layer Adagrad optimizer | 485 | 0.9842 | 0.9804 | 0.9414 | 0.9605 | 0.9873 |
| Single Hidden Layer Batch Size 128 | 485 | 0.9984 | 0.9955 | 0.9963 | 0.9959 | 0.9997 |
| Single Hidden Layer Batch Size 64 | 485 | 0.9975 | 0.991 | 0.9962 | 0.9936 | 0.9998 |
| Single Hidden Layer Batch Size 32 | 485 | 0.9983 | 0.9953 | 0.996 | 0.9957 | 0.9998 |
| Single Hidden Layer 2 Neurons | 243 | 0.9931 | 0.9993 | 0.9667 | 0.9828 | 0.9959 |
| Single Hidden Layer 6 Neurons | 727 | 0.9984 | 0.9957 | 0.9959 | 0.9958 | 0.9999 |
| Single Hidden Layer Epoch 16 | 485 | 0.9988 | 0.9972 | 0.9969 | 0.9971 | 0.9999 |
| Single Hidden Layer Epoch 32 | 485 | 0.999 | 0.9976 | 0.9975 | 0.9975 | 0.9999 |
| Single Hidden Layer Epoch 64 with Early Stopping | 485 | 0.9991 | 0.9984 | 0.9973 | 0.9978 | 0.9999 |
| Single Hidden Layer Epoch 64 without Early Stopping | 485 | 0.9991 | 0.9978 | 0.9977 | 0.9978 | 0.9999 |

### 5.7.1 ROC Curves for all Models

Below is the ROC curve for the best model with epoch size = 25 along with best parameters. ROC curves for all models can be found in this notebook

## 5.8 Model Selection Inference

As seen from the classification metrics and ROC curves, the single layer model with 4 neurons, rmsprop optimizer and ReLU activation function along with batch-size=128, epochs=25 achieved higher accuracy, precision, recall, f1-score and auc values. This proves that this model is more generalized across both the target classes. Hence, the above highlightened model is being selected.



## 6 Overfitting with target variable

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

## 7 Custom predict function

Refer to phase-3 report. Removed this section to avoid overleaf loading Issues

## 8 Iterative Feature Reduction  Selection

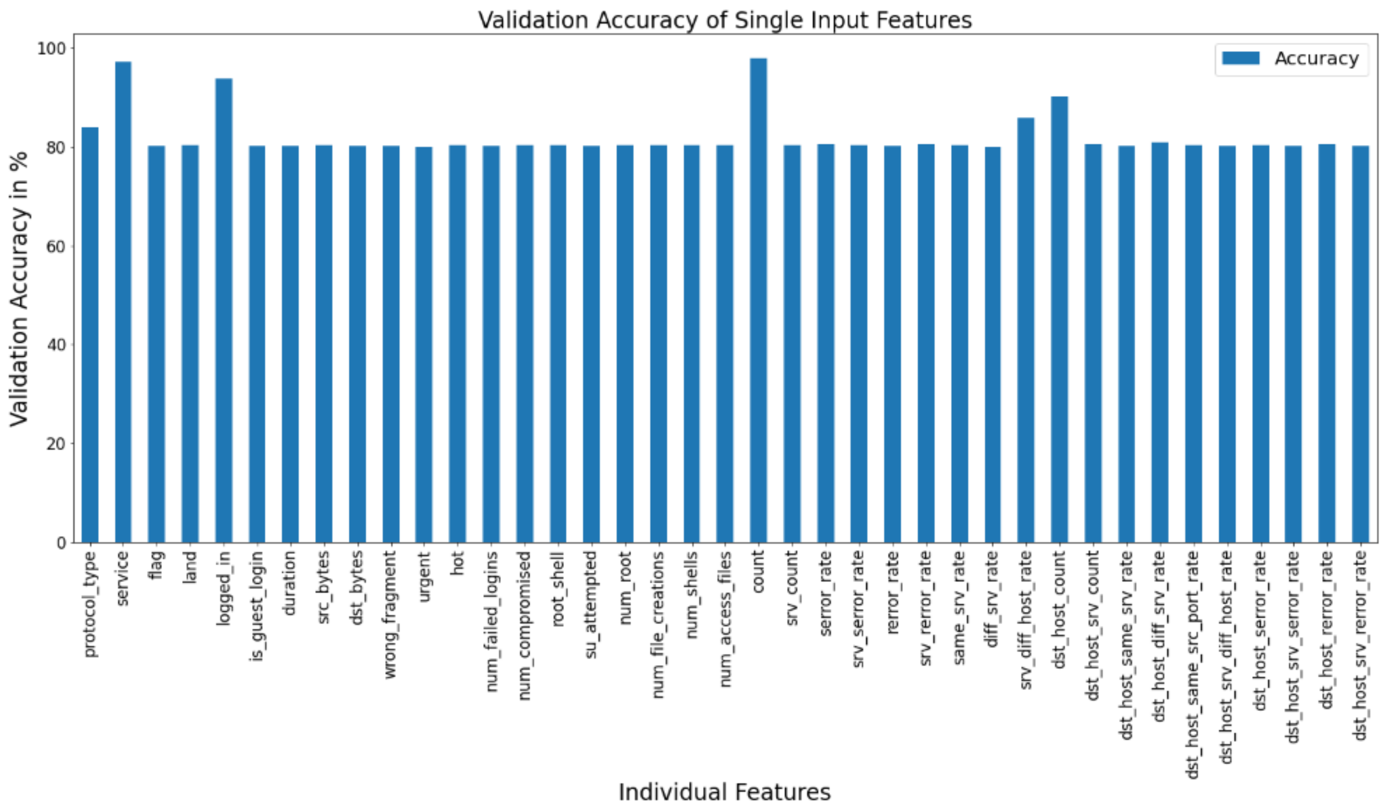
### 8.1 Feature Importance

We ran all 39 features through the best model architecture individually and obtained the accuracy of each model on the validation set. We then ranked the model performances based on the validation accuracy. Our assumption is that feature with lowest validation accuracy has less feature importance compared to others.

As seen in the below table and the picture, the feature "count" has the highest importance and the feature "diff-srv-rate" has the least importance.

Table 3: Feature Importance Ranking

| Rank | Accuracy | feature_name |
|---|---|---|
| 0 | 79.959315 | diff_srv_rate |
| 1 | 80.054450 | urgent |
| 2 | 80.109107 | dst_host_srv_diff_host_rate |
| 3 | 80.175906 | dst_host_same_srv_rate |
| 4 | 80.178940 | su_attempted |
| 5 | 80.182987 | duration |
| 6 | 80.184001 | is_guest_login |
| 7 | 80.204242 | flag |
| 8 | 80.215377 | dst_host_srv_serror_rate |
| 9 | 80.223471 | num_failed_logins |
| 10 | 80.252826 | wrong_fragment |
| 11 | 80.259907 | dst_bytes |
| 12 | 80.271041 | rerror_rate |
| 13 | 80.271041 | dst_host_srv_rerror_rate |
| 14 | 80.283189 | dst_host_serror_rate |
| 15 | 80.285209 | same_srv_rate |
| 16 | 80.288249 | land |
| 17 | 80.299383 | srv_count |
| 18 | 80.302417 | srv_serror_rate |
| 19 | 80.305451 | num_root |
| 20 | 80.330753 | root_shell |
| 21 | 80.340874 | num_shells |
| 22 | 80.341887 | num_file_creations |
| 23 | 80.378324 | num_access_files |
| 24 | 80.385411 | src_bytes |
| 25 | 80.407673 | num_compromised |
| 26 | 80.437028 | dst_host_same_src_port_rate |
| 27 | 80.444109 | hot |
| 28 | 80.465364 | srv_rerror_rate |
| 29 | 80.479532 | dst_host_srv_count |
| 30 | 80.494720 | serror_rate |
| 31 | 80.529130 | dst_host_rerror_rate |
| 32 | 80.915755 | dst_host_diff_srv_rate |
| 33 | 83.928788 | protocol_type |
| 34 | 85.939842 | srv_diff_host_rate |
| 35 | 90.297961 | dst_host_count |
| 36 | 93.734062 | logged_in |
| 37 | 97.144854 | service |
| 38 | 97.977817 | count |


Validation Accuracy of Single Input Features
Accuracy
Validation Accuracy in %
0
20
40
60
80
100
protocol_type
service
flag
land
logged_in
is_guest_login
duration
src_bytes
dst_bytes
wrong_fragment
urgent
hot
num_failed_logins
num_compromised
root_shell
su_attempted
num_root
num_file_creations
num_shells
num_access_files
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_count
dst_host_same_srv_rate
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
Individual Features

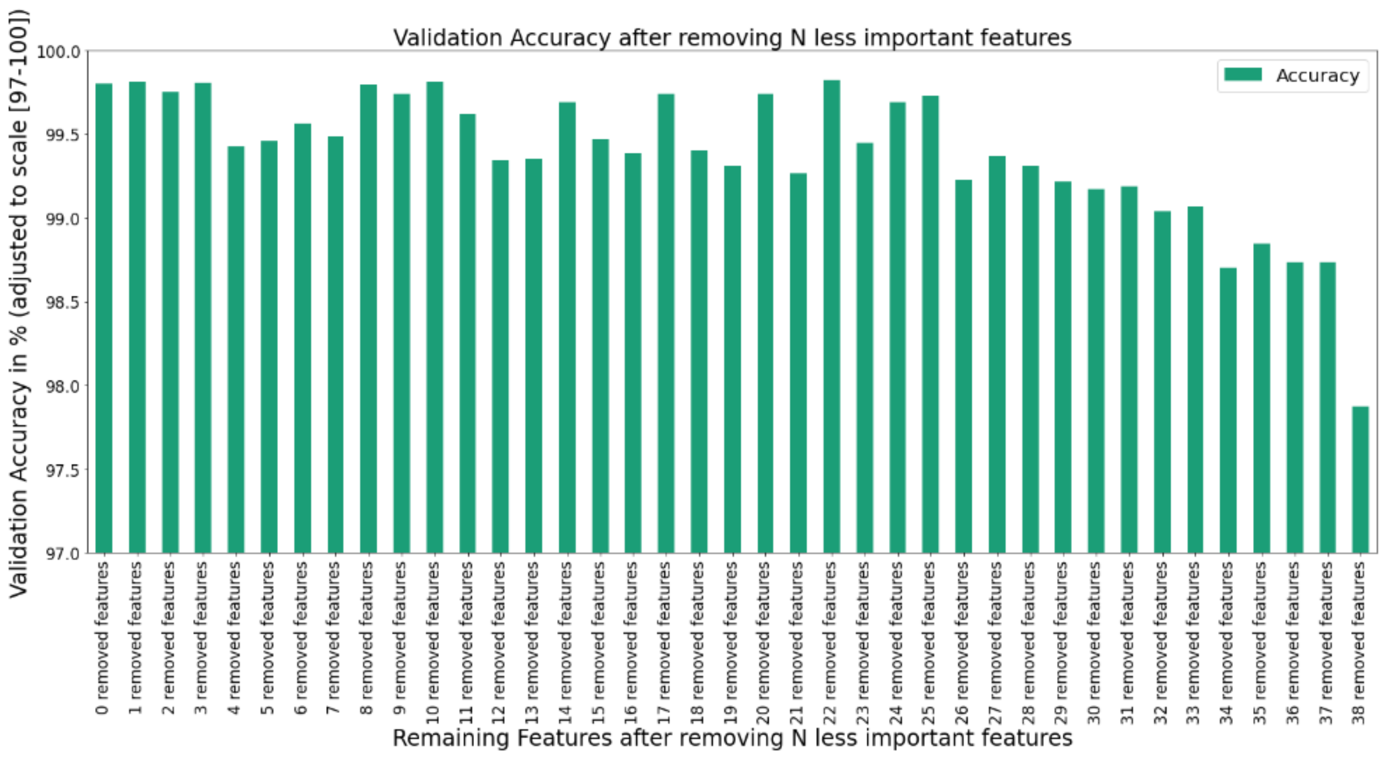
## 8.2 Performance After Removal

The list of features used for this data set can be categorized into three categories - 1) Basic features of individual TCP connections.2) Content features within a connection suggested by domain knowledge. 3) Traffic features computed using a two-second time window.

We observed if there is a correlation between above three categories and the feature importance values of the individual features. We did not find any strong correlation between this domain specific categorization. However, it is evident that the mostly traffic related features ended up having high feature importance values. Therefore, we strongly believe that the actual values in each feature contributed to the model performance which made sense.

Based on the above feature importance values, we started building the models by removing the unimportant features (importance based on the validation accuracy, the higher the better) an iterative way. As seen in the below plot, all models' validation accuracy values are obtained and are plotted below.

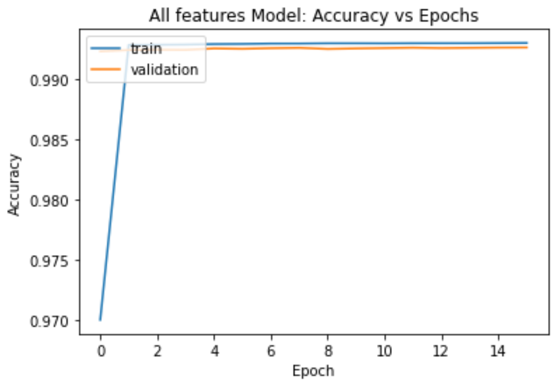
The main motive of this experiment is to find out the ideal subset of features that would yield best results with less computation power consumption and modeling time. From the below plot, we concluded that the model built after removing 22 less important features showed higher validation accuracy. We thus select the features used for this model as the best features for this data set. The features used for this model are:
['num_access_files', 'src_bytes', 'num_compromised', 'dst_host_same_src_port_rate', 'hot', 'srv_rerror_rate', 'dst_host_srv_count', 'serror_rate', 'dst_host_error_rate', 'dst-host-diff-srv-rate', 'protocol-type', 'srv-diff-host-rate', 'dst-host-count', 'logged-in', 'service', 'count']

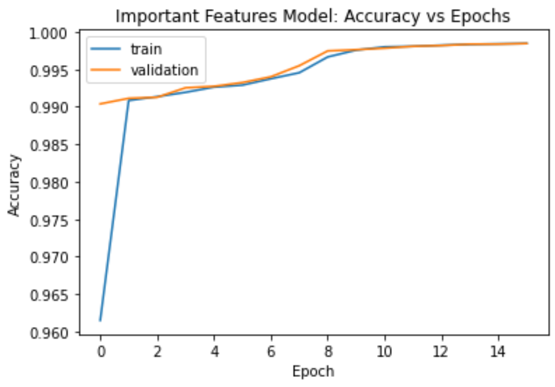


## 8.3 Performance Comparison: All-Features-Model vs Important-Features-Model

We performed comparison analysis on the model that was built with all features and on the model that was built with important features. As seen in the below plots, the learning rate of the model that was built with all features is not increasing and saturated right after first epoch. Whereas, the learning rate of the model built with subset of importance features (taken from previous step), increased per each epoch (loss reduced for every epoch). Therefore, it is evident that the model built with subset of important features showed more generalization which will be helpful when the data set sizes are varied.

Moreover, building the model with less number of features requires less computations thus less computing power. The model built with the above subset of important features is evidently better in terms of modeling times, model performance and computation cost.





## 9 Conclusion

Will be updated in next phase

## References

[1] Manoj Kumar Putchala. Deep learning approach for intrusion detection system (ids) in the internet of things (iot) network using gated recurrent neural networks (gru). 2017.

[2] Mahbod Tavallaee, Ebrahim Bagheri, Wei Lu, and Ali A Ghorbani. A detailed analysis of the kdd cup 99 data set. In *2009 IEEE symposium on computational intelligence for security and defense applications*, pages 1–6. IEEE, 2009.

[3] Steven Huang. Kdd cup 1999 data, computer network intrusion detection (version 1). 2018. Available from https://www.kaggle.com/galaxyh/kdd-cup-1999-data.