Deep Science Publishing
https://doi.org/10.70593/978-93-49307-51-3_4

Chapter 4

Evaluation and performance analysis of machine learning models for Identity and Access Management (IAM) attack detection

Esther Chinwe Eze

University of North Texas, United States

4.0 Implementation

This chapter documents how the experiment was implemented as well as a brief explanation of evaluation metrics.

4.1 Setup and Data Preparation

To begin, all libraries required to carry out the experiment and prepare the data are imported as shown in the figure below.

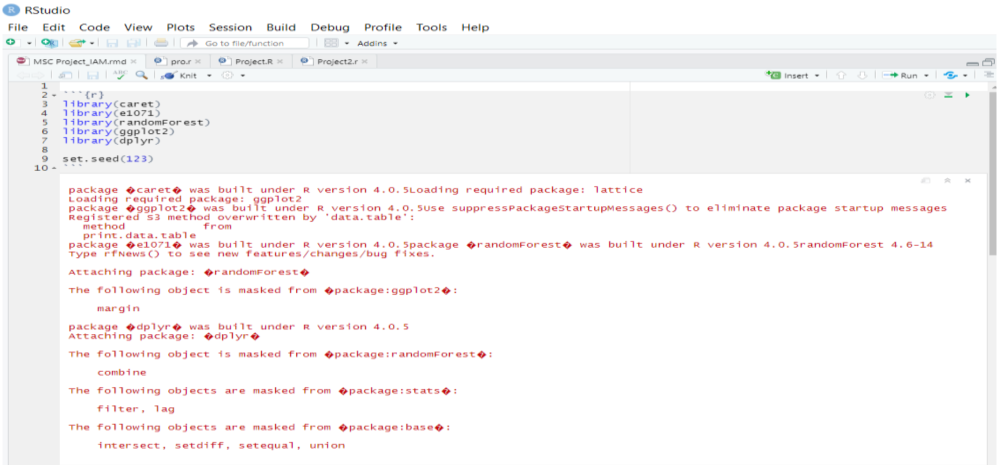


Figure 22: R Code: Importing Libraries

4.1.1 Loading the Data into r and Preprocessing

Here, the data generated from the server in the form of logs have been transformed into two datasets called ben_IAM and mal_IAM which are then loaded/imported into the R studio IDE for exploration.

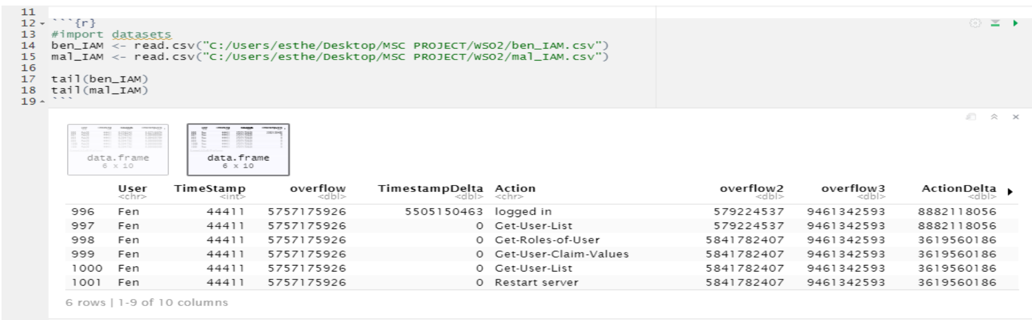


Figure 23: Loading Dataset

Although the datasets were already cleaned, some basic cleaning like checking for missing values was done. There was no need to remove any feature as relevant features had already been selected during the process of data transformation. Handling missing values is as important as training because it could determine the accuracy of results. The mathematics underlying most models assumes that data is numeric and so should be free of missing values. Missing values in R codes could trigger errors while training.

Before checking for missing values, the two datasets loaded were joined together using the rbind() function. Afterward, missing values were checked using the sum() function in R. The result shows no missing value was found as presented in figure 18 below.

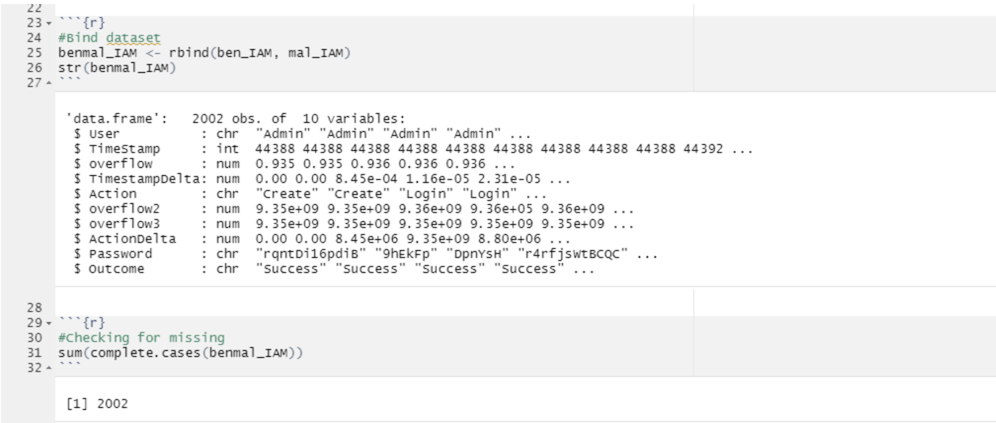


Figure 24: Handling missing values

4.1.2 Data Splitting

To split data, the CreateDataPartition () function in R was used as shown in the figure below. Before splitting, the classification label called 'Outcome' was converted to factor as data in numeric form while training. Data were split into the 80:20 ratio.

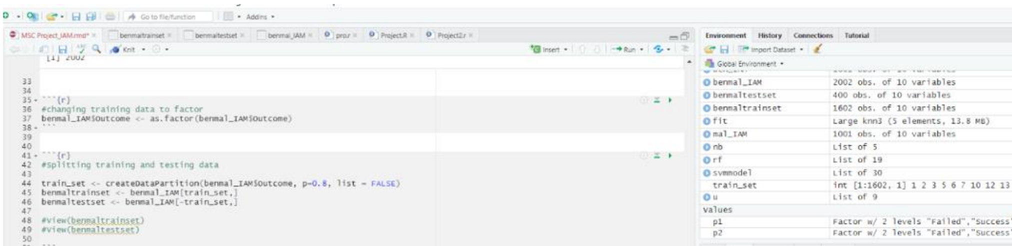


Figure 25: Data Splitting

4.1.3 Machine Learning Algorithms

During the process of training, the researcher encountered errors in the R codes and was unable to continue. The researcher intended to train with four (4) Machine Learning algorithms and select the one with the best performance. For this reason, the Weka GUI Machine Learning tool was selected as an alternative to continuing the experiment.

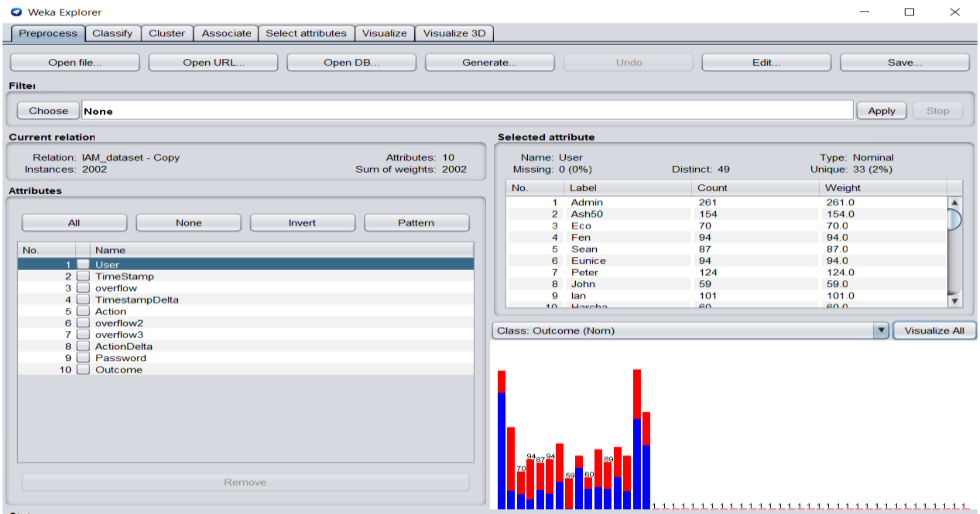


Figure 26: Loading of IAM_dataset to Weka

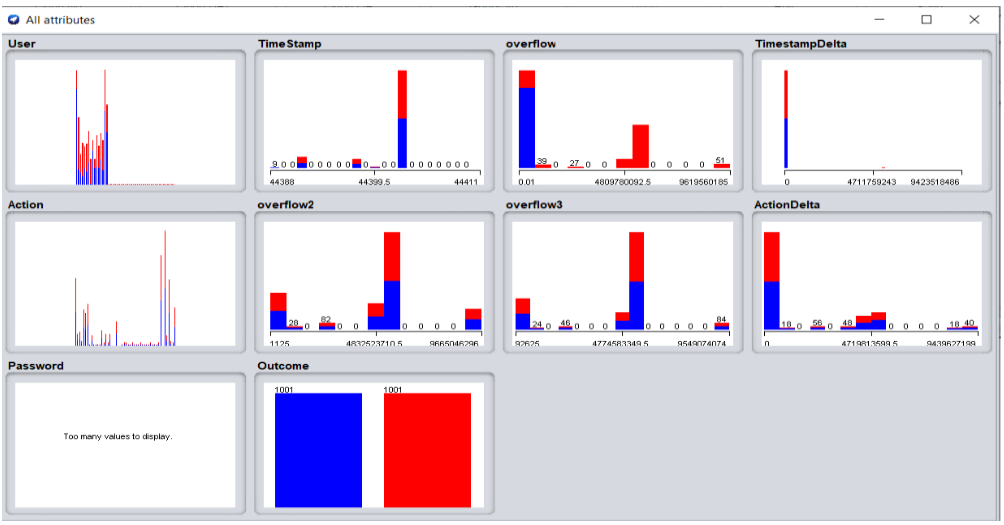


Figure 27: Visualisation of All attributes

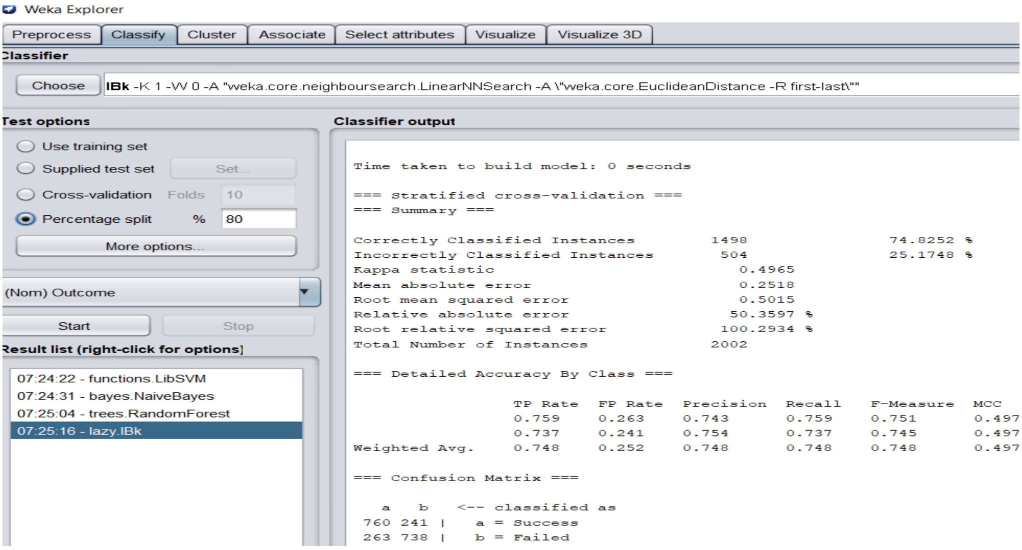


Figure 28: Selecting Algorithm for Testing

4.2 Evaluation Metrics: Confusion Matrix

In classification, many metrics are used for prediction and detection. Since the experiments for this project mainly distinguish normal activities from malicious activities, a confusion matrix will be used to determine the performance metrics. The confusion matrix is a table that describes in detail the results of the classification. The result from the confusion matrix be summated into four parts as shown below:

Confusion Matrix Component	Description
True Positive (TP)	This means that malicious instances are correctly classified to be malicious by the model.
True Negative (TN)	This means that benign instances are successfully identified to be benign by the model.
False Positive (FP)	This means that benign instances are wrongly classified to be malicious by the model.

False Negative (FN)	This means that malicious instances are wrongly identified as benign by the model.

Table 4a: Confusion Matrix Table

TRUE POSITIVE (TP)	FALSE NEGATIVE (FN)
FALSE POSITIVE (FP)	TRUE NEGATIVE (TN)

Table 4b: Confusion Matrix Table

The confusion matrix scenarios include classification indications such as accuracy, precision, recall, and F1-measure score (Porwal & Mukund, 2018). The result of the experiment follows

4.3 Performance of the Classifiers

Four (4) supervised Machine Learning algorithms were used for the experiment of this project – Random forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM), and K- Nearest Neighbor (KNN). These classifiers were chosen because they are good for classification and are employed for their good performance. The evaluation was based on the accuracy of the classifiers, their F1-measure score, recall, and precision. Additional challenges encountered were having errors with the R code and for this reason, the researcher had to utilize a GUI-based ML tool called WEKA to help produce the results.

4.3.1 Random Forest Classifier (RF)

To determine the RF classifier's performance, the model ran 100 iterations. Figure 29 below shows the result and performance of the RF classifier. The RF model had an accuracy of 100%.

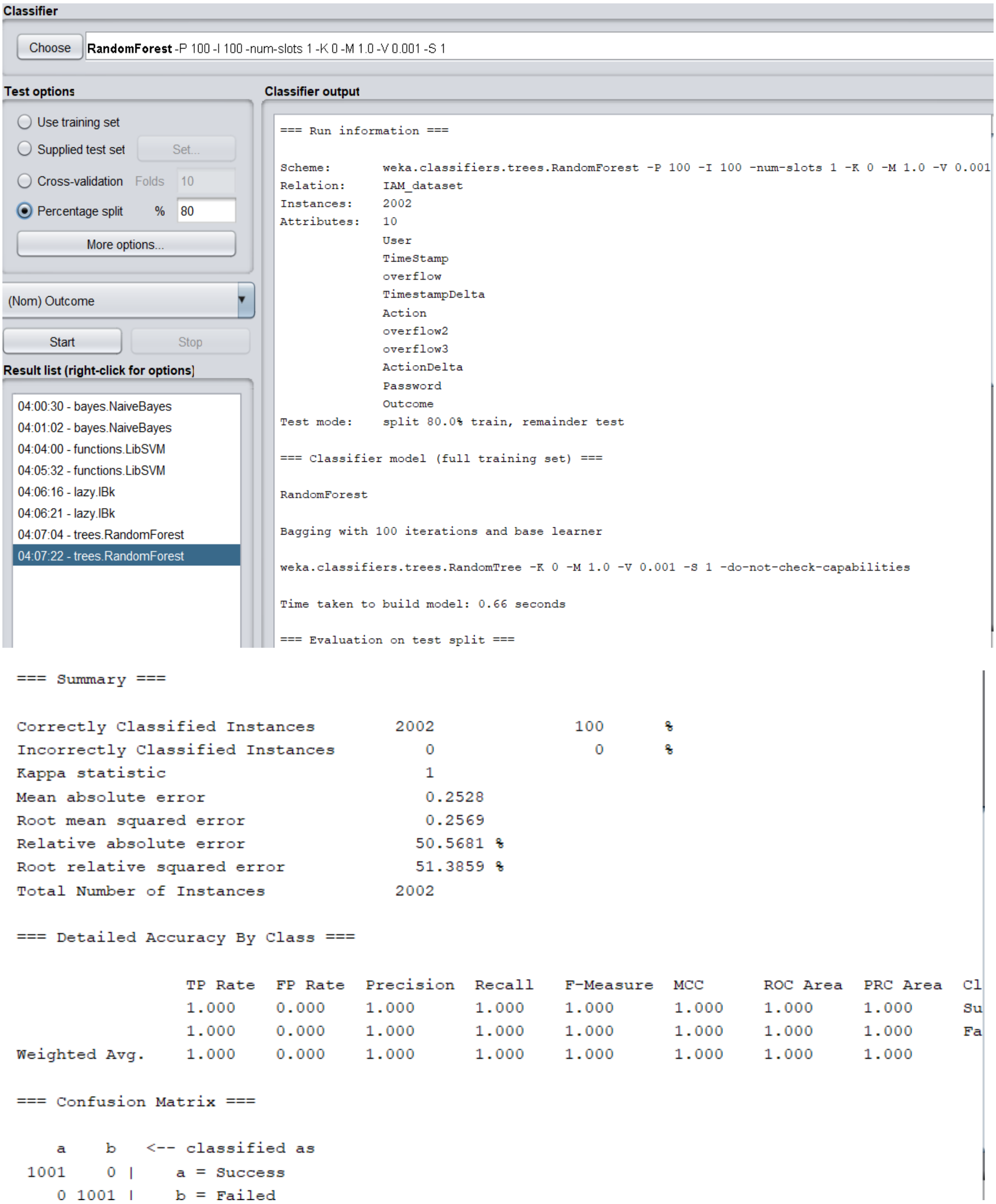


Figure 29: Performance Result of RF Classifier

Figure 30 below shows the confusion matrix of the classifier. The metrics for the evaluation have already been explained in Table 4.

True Positives (TP): The Random Forest model correctly classified 1001 malicious instances to be malicious.

True Negatives (TN): The model correctly classified 1001 benign instances to be benign.

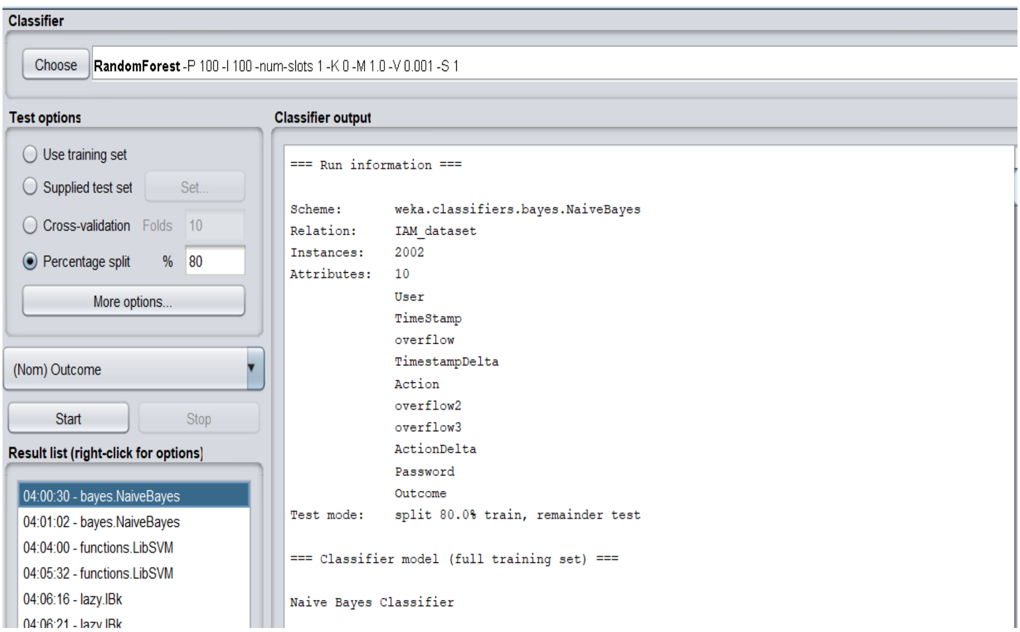
No False Positive (FP) and False Negative(FN).

1001	0
0	1001

Figure 30: Confusion Matrix showing the performance of the RF Classifier

4.3.2 Naïve Bayes Classifier (NB)

The NB classifier measured an accuracy of 91%.



```
:ime taken to build model: 0.02 seconds

=== Stratified cross-validation ===
=== Summary ===

:orrectly Classified Instances        1836               91.7083 %
:ncorrectly Classified Instances       166                8.2917 %
:appa statistic                          0.8342
lean absolute error                      0.083
loot mean squared error                  0.2879
lelative absolute error                 16.5914 %
loot relative squared error             57.5871 %
:otal Number of Instances             2002

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Cl
                1.000    0.166    0.858      1.000    0.923      0.846    0.883     0.761     Su
                0.834    0.000    1.000      0.834    0.910      0.846    0.883     0.932     Fa
leighted Avg.   0.917    0.083    0.929      0.917    0.917      0.846    0.883     0.847

=== Confusion Matrix ===

    a    b   <-- classified as
 1001    0 |    a = Success
  166  835 |    b = Failed
```

Figure 31: Performance result of Naïve Bayes Classifier

True Positives (TP): The NB classifier model correctly identified 1001 True Positives, this indicates that 1001 successful (malicious) instances were predicted correctly.

True Negatives (TN): As observed in the performance result of Figure 31, the number of true negatives obtained is 835 which indicates the number of benign instances correctly predicted.

False Positives (FP): The model identified 166 false positives which means that 166 benign instances were wrongly classified as malicious. The false positives are also known as type 1 errors. This type of error in a real-world situation may not appear critical but in the long run, it may lead to losses while attempting to resolve what does not happen.

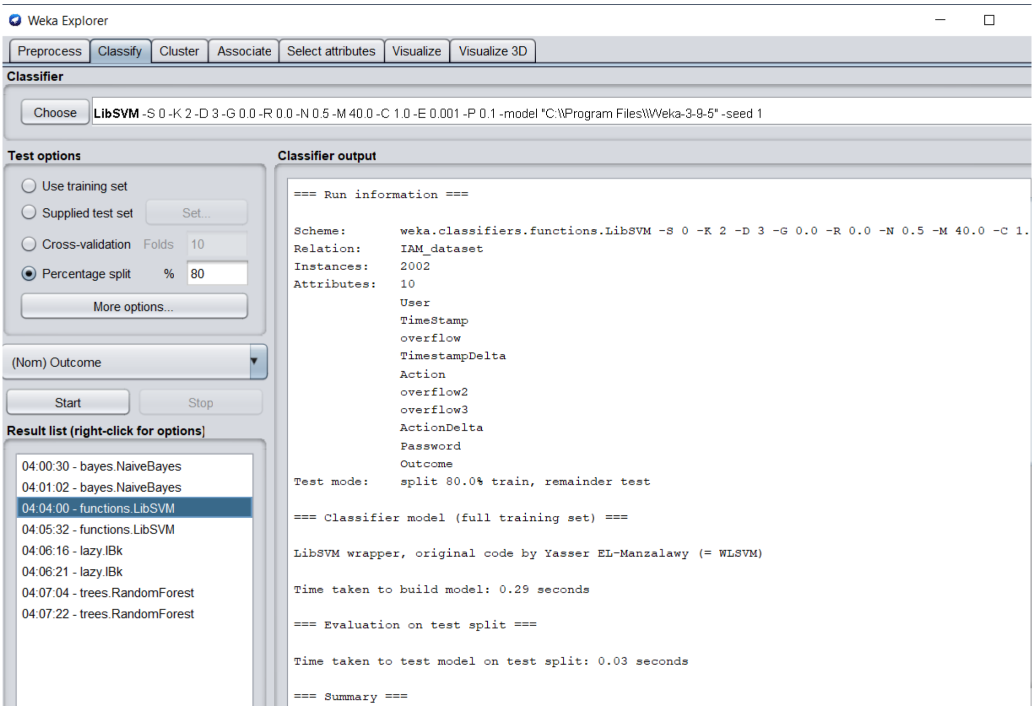
False Negatives (FN): As shown in the performance result, 0 false negatives were identified which indicates that no malicious instances were wrongly predicted as benign categories. False negatives are also known as type 2 errors, the implication of this type of error in an organization could result in serious damage.

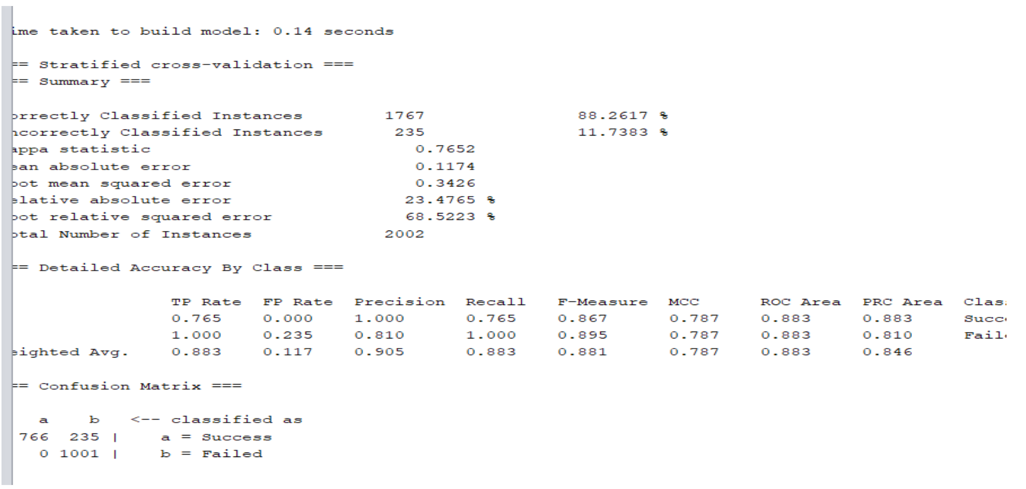
1001	0
166	835

Figure 32: Confusion Matrix showing the Naive Bayes Classifier

4.3.3 Support Vector Machine (SVM)

The SVM model had an accuracy of 88%.




```
ime taken to build model: 0.14 seconds

== Stratified cross-validation ===
== Summary ===

orrectly Classified Instances        1767               88.2617 %
ncorrectly Classified Instances       235               11.7383 %
appa statistic                          0.7652
ean absolute error                      0.1174
oot mean squared error                  0.3426
elative absolute error                 23.4765 %
oot relative squared error             68.5223 %
otal Number of Instances             2002

== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall  F-Measure  MCC    ROC Area  PRC Area  Clas
                0.765    0.000    1.000      0.765   0.867      0.787  0.883     0.883     Succ
                1.000    0.235    0.810      1.000   0.895      0.787  0.883     0.810     Fail
eighted Avg.    0.883    0.117    0.905      0.883   0.881      0.787  0.883     0.846

== Confusion Matrix ===

  a    b   <-- classified as
766  235 |    a = Success
  0 1001 |    b = Failed
```

Figure 33: Performance result of SVM Classifier

True Positives (TP): The model identified 766 true positives which means that 766 malicious instances were correctly predicted as malicious**.**

True Negatives (TN): As observed in the performance result in Figure 33, the number of true negatives obtained is 1001 which indicates the number of benign instances correctly predicted.

False Positives (FP): The model identified 0 benign instances that were wrongly classified as malicious categories.

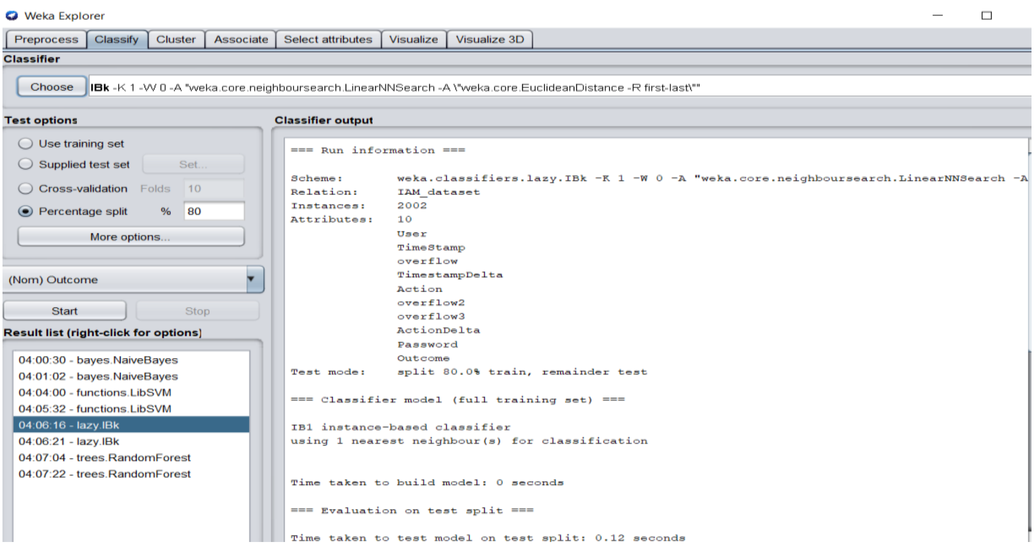
False Negatives (FN): The model identified 235 false negatives which means 235 malicious instances were wrongly classified as benign instances.

766	235
0	1001

Figure 34: Confusion Matrix of SVM Classifier

4.3.4 K-NEAREST NEIGHBOR (KNN)

KNN had an accuracy of 74% which is the lowest of all 4 algorithm



```
=== Summary ===

Correctly Classified Instances        1498               74.8252 %
Incorrectly Classified Instances       504               25.1748 %
Kappa statistic                          0.4965
Mean absolute error                      0.2518
Root mean squared error                  0.5015
Relative absolute error                 50.3597 %
Root relative squared error            100.2934 %
Total Number of Instances             2002

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  C
                 0.759    0.263    0.743      0.759    0.751      0.497    0.868     0.854     S
                 0.737    0.241    0.754      0.737    0.745      0.497    0.868     0.851     F
Weighted Avg.    0.748    0.252    0.748      0.748    0.748      0.497    0.868     0.853

=== Confusion Matrix ===

   a   b   <-- classified as
 760 241 |   a = Success
 263 738 |   b = Failed
```

Figure 35: Performance result of KNN Classifier

True Positives (TP): The KNN classifier correctly identified 760 True Positives, indicating the correct prediction of 760 malicious instances.

True Negatives (TN): As observed in the performance result of Figure 35, the number of true negatives obtained is 738 which indicates the number of benign instances correctly predicted.

False Positives (FP): The model identified 263 benign categories that were wrongly classified as malicious instances.

False Negatives (FN): As shown in the performance result, 241 false negatives were identified which indicates that 241 malicious categories were wrongly predicted as benign categories.

760	241
263	738

Figure 36: Confusion Matrix for KNN

4.4 Comparison of evaluation metrics

As shown in Table 5 below, four (4) supervised Machine Learning algorithms were experimented on to test the performance of each algorithm. The evaluation metrics included the Accuracy, Precision, Recall, and F1-measure scores of each model. As seen in almost all cases, the Random Forest (RF) algorithm gave better results as compared to other algorithms. The KNN records the lowest result across the four metrics. Based on the performance result, the Random Forest algorithm was selected for the project. This proves that In terms of IAM attack detection, the Random Forest algorithm has great potential to make the IAM process more secure, efficient, robust, and resilient in dealing with IAM attacks. Research shows that it has high performance for detection especially in areas of malicious detection. From the experiment, the result shows that Random Forest was able to correctly predict normal activities from malicious activities.

Model	Accuracy	Precision	Recall	F1-Measure
Random Forest	1	1.00	1.00	1.00
Naïve Baye	0.91	0.92	0.92	0.92
SVM	0.88	0.90	0.88	0.88
KNN	0.74	0.74	0.74	0.74

Table 5: Accuracy, Precision, Recall & F1-Measure Metrics

4.5 Result with compliance to project requirements and objectives

This sub-section compares the result achieved to the project's functional requirement to evaluate what has been achieved and what has not.

Table 6: Result comparison with Project Functional Requirement

S/N	REQUIREMENT DECLARATION	PRIORITIZATION	COMMENT	PASS/FAIL
1	The model must be able to detect IAM attacks.	Must	If properly implemented, the selected model will help detect attacks.	Pass
2	The model should be able to detect attacks based on the input dataset.	Should	The experiment shows that Random Forest was able to correctly predict normal activities from malicious activities based on the input dataset.	Pass
3	Achieve an accuracy above 75% in the testing phase	Should	The result from the experiment shows Random Forest with the highest accuracy of 100%.	Pass

Table 7: Non-Functional requirement

S/NO	REQUIREMENT	DESCRIPTION	PRIORITIZATION	COMMENT	PASS/FAIL
1	**Reproducible**	The result and code should be reproducible and accessible for reproducing the result. Therefore, the code will be written in R programming to ensure that it can be reusable.	Should	During the implementation stage, the R codes developed some errors and remained unsolved. The researcher opted to use an alternative to save time. The alternative tool used was WEKA (a GUI-based ML tool). However, the result is still reproducible.	Pass
2	**Adaptability**	The proposed detection model should be able to adjust to modifications in terms of features.	Could	The chosen algorithm is flexible and open for future improvement for optimum performance. Modifications can also be made to the	Pass

				dataset features.	
3	**Security Necessities**	The model should be able to detect unauthorized access	Must	The aspect of user authentication was focused on and the result showed that the algorithm was able to predict normal activities from malicious activities.	Pass
4	**Compatibility**	It should be compatible with either desktop or laptop Windows operating system.	should	Model is compatible	Pass
5	**Performance**	Should work as expected.	Must	Upon implementation, the model will work as intended i.e for the detection	Pass
6	**Efficiency**	The output is required to be more accurate and should have a low false-positives (FP)	Should	This was achieved as the RF algorithm had no false positives or	Pass

	rate and false negatives.	false negatives.

Table 8: Evaluation of Aim & Objectives

OBJECTIVES	**COMMENT**
Review various types of attacks targeted against IAM.	Achieved in the investigation report.
Review existing Machine Learning (ML) approaches, techniques, and tools in IAM attack detection.	Achieved in the investigation report.
Collect data by Setting up a testbed that mimics normal and malicious activities.	Achieved
Use data to train machine learning algorithms that distinguish normal activities from malicious activities.	Achieved
Select the best Machine Learning (ML) algorithm that predicts normal from malicious activities.	Achieved