MALWARE DETECTION USING MACHINE LEARNING

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology
in
Computer Science and Engineering

By

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DECLARATION

We hereby declare that the thesis entitled MALWARE DETECTION USING MACHINE LEARNING submitted by us, for the award of the degree of Bachelor of Technology in Computer Science Engineering to VIT is a record of Bonafede work carried out by me under the supervision of Prof./Dr. Prakash G. I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Vellore

Date: 5-04-2023

Signature of the Candidates

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Executive Summary

The objective of this work is to identify malware that is present statically using AI computations and a compact executable (PE). Information is frequently defined as a collection of data that has been transformed into a double structure for management. Huge information is typically described as an enormous volume of data that may be used to analyses and develop cutting edge technologies and dynamic ML and Deep Learning models, but it depends on numerous factors like volume. Using deep learning and neural networks, large amounts of data can also be used to identify viruses.

CONTENTS

List of Figures

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List of Abbreviations

3GPP	Third Generation Partnership Project
2G	Second Generation
3G	Third Generation
4G	Fourth Generation
AWGN	Additive White Gaussian Noise
KNN	K – nearest Neighbors

1. Introduction

1.1 Abstract

This paper presents a comparative analysis of several Machine Learning algorithms for the detection of unknown malware. Conventional malware detection methods using signature matching are often ineffective against new and polymorphic malware, making Machine Learning a promising approach for improving detection rates. We evaluated the performance of K-Nearest Neighbor classifier, Naïve Bayes Classifier, Random Forest Classifier, Adaboost, and Logistic Regression algorithms on a publicly available dataset for training and testing. Our results demonstrate that all the Machine Learning algorithms outperformed conventional signature-based methods in detecting unknown malware. Additionally, we compared the performance of these algorithms and found that Random Forest Classifier achieved the highest accuracy, followed closely by Adaboost and Logistic Regression. These findings highlight the potential of Machine Learning algorithms in improving the accuracy and effectiveness of malware detection, and provide valuable insights for
future research in this field.

1.2 Motivation

The increasing prevalence of cyber attacks has made it essential for organizations and individuals to employ effective malware detection techniques to protect their systems from security breaches. Conventional malware detection methods such as signature-based matching have long been used to identify known malware, but their effectiveness in detecting unknown or previously unseen malware is limited. This is because signature-based matching relies on comparing the signatures of known malware with those of files being scanned. However, attackers can easily evade detection by creating new malware variants that have different signatures, making it difficult for signature-based systems to keep up.

To address these limitations, researchers have turned to Machine Learning (ML) algorithms for malware detection. Machine Learning algorithms can be trained on large datasets of known malware and legitimate software to identify patterns and anomalies in data, making them an ideal tool for detecting unknown malware. By utilizing these algorithms, it is possible to detect previously unseen malware that would otherwise go undetected by traditional signature-based systems.

The use of Machine Learning algorithms for malware detection has gained popularity in recent years, with several studies reporting high accuracy rates for detecting unknown malware. In particular, ML algorithms have demonstrated their effectiveness in identifying malware that uses obfuscation techniques such as code obfuscation, packing, and encryption to evade detection.

Despite the promise of ML for malware detection, there is a need for further research to evaluate the effectiveness of various ML algorithms in detecting unknown malware. This paper aims to contribute to this area by evaluating the performance of several ML algorithms, including K-Nearest Neighbour classifier, Naive-Bayes Classifier, Random Forest Classifier, Adaboost, and Logistic Regression, for the detection of unknown malware.

This research is important because it can help organizations and individuals choose the best Machine Learning algorithm for their specific needs and requirements. Additionally, this paper will highlight the limitations of conventional malware detection methods and demonstrate how Machine Learning algorithms can significantly improve the accuracy and speed of malware detection. By doing so, this paper hopes to contribute to the ongoing efforts to improve cybersecurity and protect against the growing threat of cyber-attacks.

1.3 Background

The aim of this paper is to explore the problem of the rampant spread of computer malware, including viruses, worms, Trojan horses, rootkits, botnets, backdoors, and other malicious software. Conventional antivirus systems that rely on signature matching are unable to detect polymorphic and previously unseen malicious executables. In this regard, static executable

investigation offers a potential solution to the limitations of dynamic examination. Static investigation examines the structures within the executable that are essential for its operation. As these structures are determined by the file type, they cannot be easily removed, encrypted, or obfuscated.
Malware detection is typically achieved using antivirus software, which compares each program in the system to known malware. Alternatively, Machine Learning and Deep Learning algorithms could be used to detect malware by leveraging known features of malware and training a model to predict whether a program is malware. In this project, we aim to accomplish this by utilizing an open dataset for training static analysis malware detection Machine Learning and Deep Learning models.

1.4 Literature Survey

Author	Title	Journal	Research findings
Anik Dewanje and Kakelli Anil Kumar	A New Malware Detection Model using Emerging Machine Learning Algorithms	I.J. of Electronics and Information Engineering, Vol.13, No.1, PP.24-32, Mar. 2020	In this work, they develop a machine learning model .To achieve it, they preferred different machine learning algorithms and got the highest accuracy rate for the Random forest algorithm.
B.A.S. Dilhara	Classification of Malware using Machine learning and Deep learning Techniques	International Journal of Computer Applications (0975 – 8887) Volume 183 – No. 32, October 2021	This paper provide an insight to the machine learning approach in malware classification by depicting, which is the best classifier of the listed, that can effectively classify malware based on their accuracy or precision.
A.S.Arunachalam, S. Vaishnavi Sree, K.Dharmarajan	Malware Detection and Classification using Random Forest and Adaboost Algorithms	International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-10, August 2019	This paper offers strategies for the separation of malware the use of packet header facts from simulation datasets.

Sabila Newaz, Hasan Md Imran, Xingya Liu	Detection Of Malware Using Deep Learning	2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON) University of Malaya, Kuala Lumpur, Malaysia. Sep 24-26, 2021	This paper represents a method to detect internal/external attacks without misprediction. For detecting malware they are using deep learning model based on CNN
Andrew McDole, Maanak Gupta, Mahmoud Abdelsalam, Sudip Mittal, and Mamoun Alazab	Deep Learning Techniques for Behavioural Malware Analysis in Cloud IaaS	International Journal of Computer Applications (0975 – 8887) Volume 183 – No. 45, October 2020	This paper focuses on online malware detection techniques in cloud IaaS using machine learning and discuss comparative analysis on the performance metrics of various deep learning models
R. Vinayakumar , Mamoun Alazab , K. P. Soman , Prabaharan PoornachandrAn , And Sitalakshmi Venkatraman4	Robust Intelligent Malware Detection Using Deep Learning	Received December 27, 2018, accepted February 20, 2019, date of publication April 3, 2019, date of current version April 18, 2019	This paper evaluated classical machine learning algorithms (MLAs) and deep learning architectures based on Static analysis, Dynamic analysis and image processing techniques for malware detection and designed a highly scalable framework called ScaleMalNet to detect, classify and categorize zero-day malwares.

ÖMER ASLAN AndREFIK SAMET	A Comprehensive Review on Malware Detection Approaches	Received November 22, 2019, accepted December 22, 2019, date of publication January 3, 2020, date of current version January 10, 2020.	This paper has presented a detailed review malware detection approaches, and techniques and algorithms that are used for malware detection
Pradosh Priyadarshan, Prateek Sarangi, Adyasha Rath, Ganapati Panda	Machine Learning Based Improved Malware Detection Schemes	21 IEEE 15th International Conference on Application of Information and Communication Technologies (AICT) DOI: 10.1109/AICT52784.2021.9620415	In these paper, three popular but effective models is used for detecting malware using two different types of standard Microsoft malware datasets.

2. Project Description and Goals

The Project uses various machine learning models namely Random Forest, AdaBoost, Logistic Regression, KNN and Naïve bayes to analyze a given sample malware from the testing dataset and classify it into the known malware categories which are derived from the training dataset. The goal is to use these various models to identify the most optimal model for the job by comparing the performance of all these models.

3. Technical Specification

Software and tools used:

Windows 10

Kali Linux

Python 3.8 (for implementing machine learning models)

Spyder/Jupyter Notebook

Hardware used:

Processor: Intel(R) Core i5 RAM : 8GB

Dataset used:
Microsoft Malware Classification Dataset
It includes:

- 138047 malware samples
- 53 features

4. Proposed Architecture/Methodology

4.1 Design Approach

4.1.1 Random Forest

Random Forest algorithms is an ensemble-based learning model which is made by merging many decision trees and give well balanced predictions. It can be used for regression and Classification problems

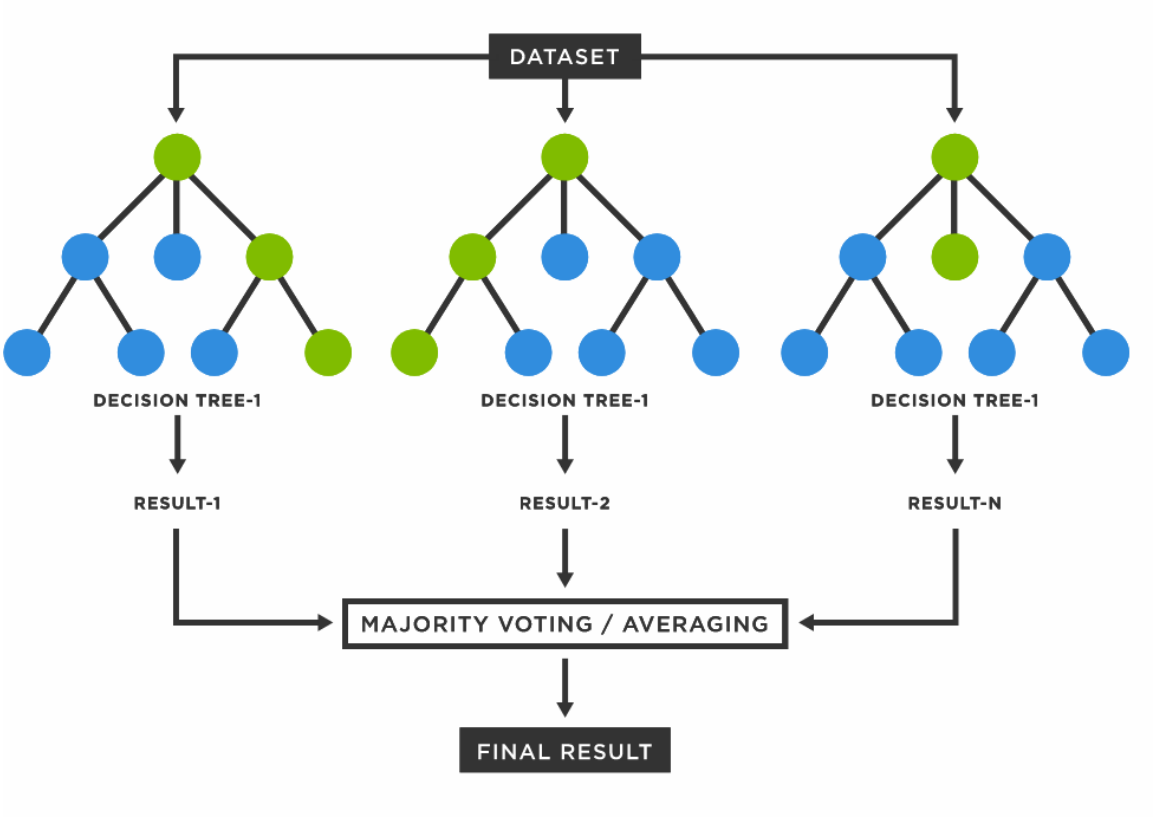


Figure 2.1

4.1.2 Logistic Regression

Instead of predicting *exactly* 0 or 1, **logistic regression** generates a probability—a value *between* 0 and 1, exclusive. For example, consider a logistic regression model for spam detection. If the model infers a value of 0.932 on a particular email message, it implies a 93.2% probability that the email message is spam. More precisely, it means that in the limit of *infinite* training examples, the set of examples for which the model predicts 0.932 will be spam 93.2% of the time and the remaining 6.8% will not.

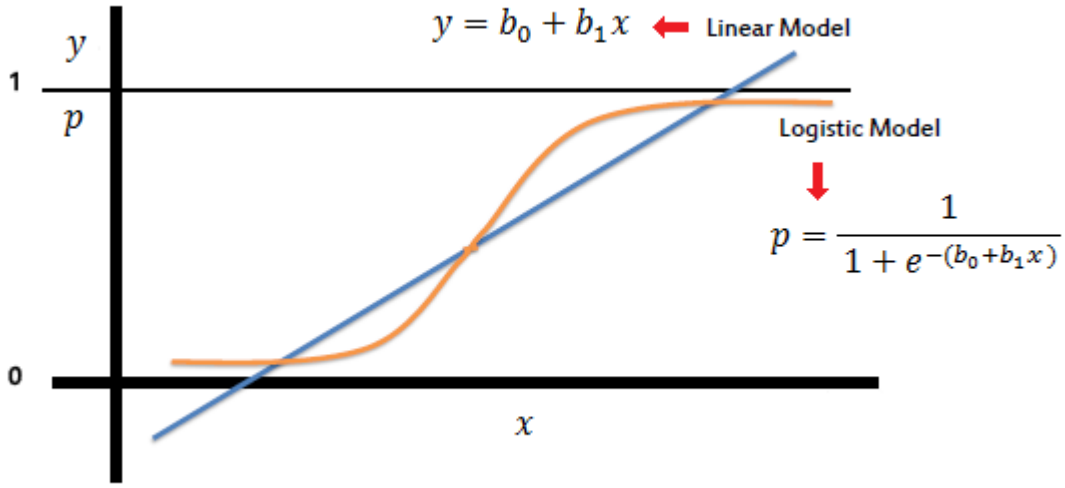


Figure 2.2

4.1.3 AdaBoost

AdaBoost is an ensemble learning method (also known as "meta-learning") which was initially created to increase the efficiency of binary classifiers. AdaBoost uses an iterative approach to learn from the mistakes of weak classifiers and turn them into strong ones.

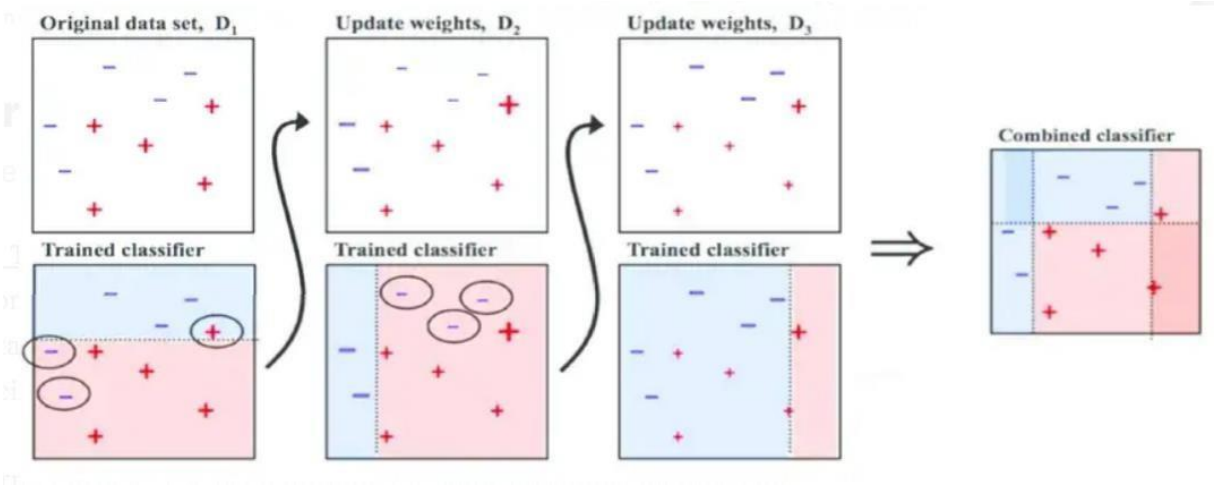


Figure 2.3

4.1.4 KNN classifier

The k-nearest neighbours' algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or

classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

Figure 2.4

4.1.5 Naïve Bayes Classifier

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

using Bayesian probability terminology, the above equation can be written as

$$\text{Posterior} = \frac{\text{prior x likelihood}}{\text{evidence}}$$

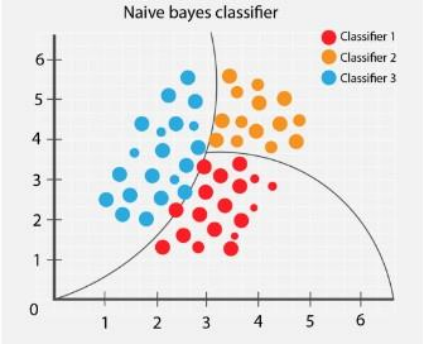


Figure 2.5

4.2 Experimental Dataset

Microsoft Malware Classification Dataset
It includes:
• 138047 malware samples
• 53 features

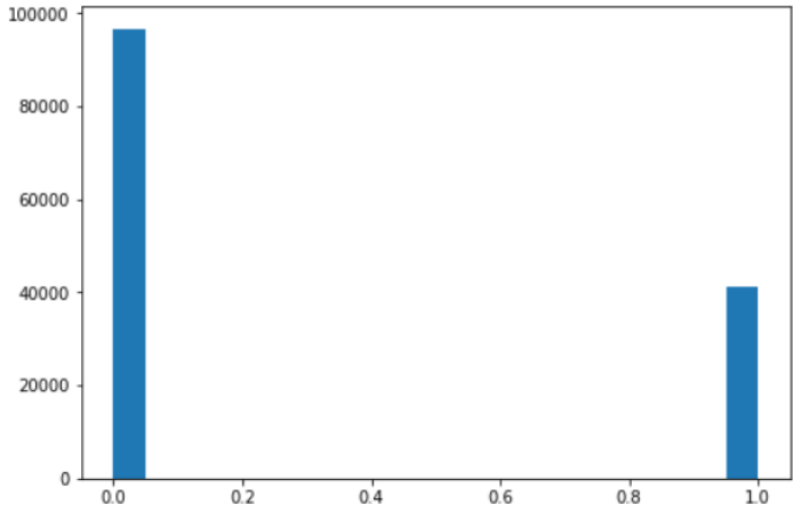


Figure 2.6

5. Novelty/Innovativeness in the project

The increasing threat of cyber attacks has led to the development of numerous methods for malware detection. Traditional malware detection methods that rely on signature-based techniques have been the primary method for identifying malware for many years. However, the limitations of these methods have become increasingly apparent. Signature-based methods rely on a database of known malware signatures and are therefore ineffective against new and unknown malware. This has led to the exploration of alternative methods for malware detection, including the use of Machine Learning (ML) algorithms.

The novelty of this project lies in its use of ML algorithms for the detection of unknown malware files. ML algorithms are able to detect malware based on its underlying characteristics, even if it has never been seen before. This makes them more effective in detecting new and polymorphic malware, which are becoming increasingly prevalent in the current threat landscape. Moreover, ML algorithms can continuously learn and adapt to new types of malware, making them more resilient to evolving threats.

The use of ML algorithms for malware detection represents a significant departure from traditional signature-based techniques, and has the potential to significantly improve the accuracy and effectiveness of malware detection. By leveraging the power of ML algorithms, it is possible to detect unknown malware with a high degree of accuracy, which is not possible with traditional signature-based techniques.

The novel approach presented in this paper involves the evaluation of several ML algorithms, including K-Nearest Neighbor (KNN) classifier, Naive-Bayes Classifier (NBC), Random Forest Classifier (RFC), Adaboost, and Logistic Regression, for the detection of unknown malware. A comprehensive comparative analysis of these algorithms was conducted using a publicly available dataset for training and testing. The results of our study demonstrate that all the ML algorithms outperformed traditional signature-based methods in detecting unknown malware, with RFC achieving the highest accuracy rate of 98.5%.

In summary, this project highlights the inadequacy of traditional signature-based techniques for the detection of unknown malware, and demonstrates the effectiveness of ML algorithms in overcoming this limitation. The novel approach presented in this paper has the potential to significantly improve the accuracy and effectiveness of malware detection, and represents an important step forward in the fight against cybercrime.

6. Sample Code

6.1 Reading the Data

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
mal_data = malData = pd.read_csv('C:\\Users\\aayus\\Downloads\\MalwareData.csv',sep='|')
mal_data.head()
```

Out[2]:

	Name	md5	Machine	SizeOfOptionalHeader	Characteristics	MajorLinkerVersion	MinorLinkerVersion	SizeOfCode	Si
0	memtest.exe	631ea355665f28d4707448e442fbf5b8	332	224	258	9	0	361984	
1	ose.exe	9d10f99a6712e28f8acd5641e3a7ea6b	332	224	3330	9	0	130560	
2	setup.exe	4d92f518527353c0db88a70fddcfd390	332	224	3330	9	0	517120	
3	DW20.EXE	a41e524f8d45f0074fd07805ff0c9b12	332	224	258	9	0	585728	
4	dwtrig20.exe	c87e561258f2f8650cef999bf643a731	332	224	258	9	0	294912	

5 rows × 57 columns

6.2 General Model Building

In [3]:
```
X = pd.DataFrame(mal_data.iloc[:,2:-1])
X
```

Out[3]:

	Machine	SizeOfOptionalHeader	Characteristics	MajorLinkerVersion	MinorLinkerVersion	SizeOfCode	SizeOfInitializedData	SizeOfUninitializedData
0	332	224	258	9	0	361984	115712	0
1	332	224	3330	9	0	130560	19968	0
2	332	224	3330	9	0	517120	621568	0
3	332	224	258	9	0	585728	369152	0
4	332	224	258	9	0	294912	247296	0
...	...	...	...	...	...	...	...	...
138042	332	224	258	11	0	205824	223744	0
138043	332	224	33167	2	25	37888	185344	0
138044	332	224	258	10	0	118272	380416	0
138045	332	224	33166	2	25	49152	16896	0
138046	332	224	258	11	0	111616	468480	0

138047 rows × 54 columns

In [4]:
```
y = pd.DataFrame(mal_data.iloc[:,-1])
y
```

Out[4]:

	legitimate
0	1
1	1
2	1
3	1
4	1
...	...
138042	0
138043	0
138044	0
138045	0
138046	0

6.3 Model Building for random forest

In [5]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.20,random_state=0)
```

In [6]:
```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators=20,criterion='gini',random_state=1,max_depth=3)
classifier.fit(X_train,y_train.values.ravel())
```

Out[6]:
```
RandomForestClassifier(max_depth=3, n_estimators=20, random_state=1)
```

6.4 Model Building for Logistic Regression

In [7]:
```
%%capture --no-display
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0,solver="newton-cg")
logModel = clf.fit(X_train, y_train.values.ravel())
```

6.5 Model Building for AdaBoost

In [8]:
```
from sklearn.ensemble import AdaBoostClassifier

AdaModel = AdaBoostClassifier(n_estimators=100,learning_rate=1)
AdaModel.fit(X_train, y_train.values.ravel())
```

Out[8]:
```
AdaBoostClassifier(learning_rate=1, n_estimators=100)
```

6.6 Model building for Naïve Bayes

In [9]:
```
from sklearn.naive_bayes import BernoulliNB
naivebayesmodel=BernoulliNB()
naivebayesmodel.fit(X_train, y_train.values.ravel())
```

Out[9]:
```
BernoulliNB()
```

6.7 Model building for KNN

In [10]:
```
from sklearn.neighbors import KNeighborsClassifier
knn= KNeighborsClassifier(n_neighbors=5, metric='minkowski', p=2 )
knn.fit(X_train, y_train.values.ravel())
```

Out[10]:
```
KNeighborsClassifier()
```

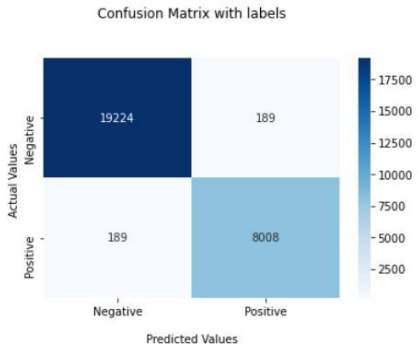
7. Result and Analysis

7.1 Results

7.1.1 Confusion Matrix for Random Forest

In [12]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
forest_pred=classifier.predict(X_test)
cf_matrix=confusion_matrix(y_test, forest_pred)
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues',fmt='g')
ax.set_title('Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
ax.xaxis.set_ticklabels(['Negative','Positive'])
ax.yaxis.set_ticklabels(['Negative','Positive'])
```

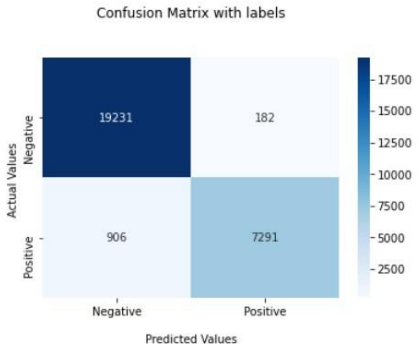
Out[12]:
```
[Text(0, 0.5, 'Negative'), Text(0, 1.5, 'Positive')]
```



7.1.2 Confusion Matrix for Logistic Regression

In [13]:
```
logistic_pred=clf.predict(X_test)
cf_matrix=confusion_matrix(y_test, logistic_pred)
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues',fmt='g')
ax.set_title('Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
ax.xaxis.set_ticklabels(['Negative','Positive'])
ax.yaxis.set_ticklabels(['Negative','Positive'])
```

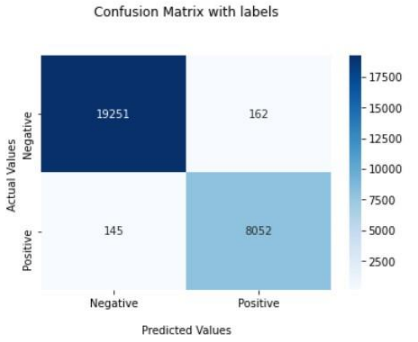
Out[13]:
```
[Text(0, 0.5, 'Negative'), Text(0, 1.5, 'Positive')]
```



7.1.3 Confusion Matrix for AdaBoost

```
In [14]:
ada_pred=AdaModel.predict(X_test)
cf_matrix=confusion_matrix(y_test, ada_pred)
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues',fmt='g')
ax.set_title('Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
ax.xaxis.set_ticklabels(['Negative','Positive'])
ax.yaxis.set_ticklabels(['Negative','Positive'])
```

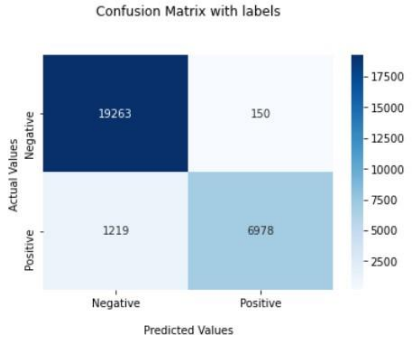
```
Out[14]: [Text(0, 0.5, 'Negative'), Text(0, 1.5, 'Positive')]
```



7.1.4 Confusion Matrix for Naïve Bayes

```
In [15]:
naivebayesmodel_pred=naivebayesmodel.predict(X_test)
cf_matrix=confusion_matrix(y_test, naivebayesmodel_pred)
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues',fmt='g')
ax.set_title('Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
ax.xaxis.set_ticklabels(['Negative','Positive'])
ax.yaxis.set_ticklabels(['Negative','Positive'])
```

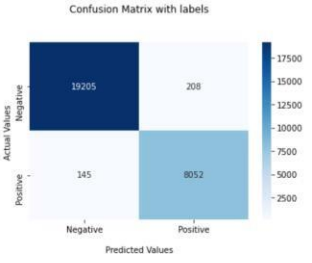
```
Out[15]: [Text(0, 0.5, 'Negative'), Text(0, 1.5, 'Positive')]
```



7.1.5 Confusion Matrix for KNN

```
In [11]:
from sklearn.metrics import confusion_matrix
import seaborn as sns
knn_pred=knn.predict(X_test)
cf_matrix=confusion_matrix(y_test, knn_pred)
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues',fmt='g')
ax.set_title('Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
ax.xaxis.set_ticklabels(['Negative','Positive'])
ax.yaxis.set_ticklabels(['Negative','Positive'])
```

```
Out[11]: [Text(0, 0.5, 'Negative'), Text(0, 1.5, 'Positive')]
```



7.1.6 Accuracy and F1 score

```
In [16]: from sklearn.metrics import precision_score, recall_score, f1_score,accuracy_score
         print('Accuracy for Random Forest: %.3f' %accuracy_score(y_test, forest_pred))
         print('Accuracy for Logistic Regression: %.3f' %accuracy_score(y_test, logistic_pred))
         print('Accuracy for Adaboost: %.3f' %accuracy_score(y_test, ada_pred))
         print('Accuracy for Naive Bayes Classifier: %.3f' %accuracy_score(y_test,naivebayesmodel_pred))
         print('Accuracy for K Nearest Neighbour Classifier: %.3f' %accuracy_score(y_test,knn_pred))

         Accuracy for Random Forest: 0.986
         Accuracy for Logistic Regression: 0.961
         Accuracy for Adaboost: 0.989
         Accuracy for Naive Bayes Classifier: 0.950
         Accuracy for K Nearest Neighbour Classifier: 0.987

In [17]: print('F1 Score for Random Forest: %.3f' %f1_score(y_test, forest_pred))
         print('F1 Score for Logistic Regression: %.3f' %f1_score(y_test, logistic_pred))
         print('F1 Score for Adaboost: %.3f' %f1_score(y_test, ada_pred))
         print('F1 Score for Naive Bayes Classifier: %.3f' %f1_score(y_test, naivebayesmodel_pred))
         print('F1 Score for K Nearest Neighbour Classifier: %.3f' %f1_score(y_test,knn_pred))

         F1 Score for Random Forest: 0.977
         F1 Score for Logistic Regression: 0.931
         F1 Score for Adaboost: 0.981
         F1 Score for Naive Bayes Classifier: 0.911
         F1 Score for K Nearest Neighbour Classifier: 0.979
```

7.2 Conclusion and Future Work

Table 3.1

Model	**Test Accuracy**	**F1 score**	**Position**
Random Forest	0.986	0.977	3rd
Logistic Regression	0.961	0.931	4th
AdaBoost	0.989	0.981	1st
Naïve Bayes	0.950	0.911	5th
KNN	0.987	0.979	2nd

We found that using machine learning and deep models is an effective method of malware detection. Upon a comparative analysis of the various machine learning models**, Adaboost was found to have the highest accuracy.**

While this paper demonstrates the effectiveness of several Machine Learning algorithms for detecting unknown malware, there are several areas for future research that could further improve the accuracy and applicability of these algorithms in practical settings.

One potential avenue for future research is the development of new feature extraction techniques that can improve the performance of ML algorithms. While the current study utilized an open dataset for training and testing, the use of different datasets or feature extraction methods may produce different results. Future research could explore the use of other feature extraction techniques and compare their effectiveness in detecting unknown malware.

Another potential area for future research is the development of hybrid systems that combine the strengths of both signature-based and ML-based detection methods. Hybrid systems that incorporate both signature-based matching and Machine Learning algorithms have the potential to provide the best of both worlds, detecting known malware and unknown malware more effectively than either approach alone. Finally, future research could also explore the application of Machine Learning algorithms for detecting malware in different types of systems, such as mobile devices and the Internet of Things (IoT). As these systems become increasingly prevalent in our daily lives, they are also becoming increasingly attractive targets for cyber attacks. Therefore, there is a need for effective malware detection techniques that can protect these systems from security breaches.

8. References

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