

FPGA IMPLEMENTATION OF NAIVE BAYES CLASSIFIER FOR NETWORK
SECURITY

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*To my beloved family members who always there for me,
my friends who assists, accompanying me now and then,
and also to my supervisor who guide me through the research's hardships*

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ABSTRACT

In the vast usage of internet nowadays, the rate of cybercrime such as fraud, hacking, identity theft, network intrusion, software piracy and espionage are becoming more critical. Malware code writers used this chance to create malware that able to breach the security and gain access to the information. Hence, the importance of malware detection system becoming more significant as the users need the protection from the malware threats. Most of malware detection systems implement signature based classification where only known malware can be detected. Nowadays, new malwares are able to change its signature sequence regularly in order to avoid detection. This polymorphic malware becomes the limitation for signature based detection approach. This project aim is to proposed signature-based detection approach that able to detect polymorphic malware by using Naïve Bayes algorithm. The integration of the classifier architecture onto FPGA board in order to measures the performances of the system. The feature from network traffic subset to Snort signature detection of known malware and benign samples are extracted using overlapping N-gram string format. The data set is then being used for training and testing for the classifier. The classifier for the malware detection used Naïve Bayes algorithm that using Bayesian Theorem probability for the features in the data set to determine types of the flow. The model is then being implemented into hardware FPGA architecture and being coded in RTL. The target FPGA that being used in Vivado software is Xilinx Virtex-7 VC709 that able to support the system requirements. The hardware performance of the model was analyzed and compared with the Naïve Bayes software classifier for the performance evaluation. The proposed hardware NB malware detection classifier has managed to achieve 96.3% accuracy and improved FPR rate of 3.1%. The hardware NB malware detection classifier on FPGA architecture also able to achieve better resource utilization and improved detection speed of 0.13 μs per flow.

ABSTRAK

Di zaman penggunaan internet yang meluas, jenayah siber turut juga menjadi jenayah utama yang mampu untuk meruntuhkan ekonomi negara. Melalui internet, transaksi-transaksi penting seperti pemindahan wang, transaksi bank, informasi peribadi, data sulit negara dan informasi-informasi penting dilakukan setaip hari. Pencipta virus komputer menggunakan peluang ini untuk mencuri data-data penting tersebut demi kepentingan mereka. Pengguna perlulah lebih peka terhadap jenayah siber ini. Kepentingan anti virus semakin meningkat bertujuan untuk memberikan perlindungan informasi kepada pengguna. Kaedah konvensional untuk mengesan virus ini hanya mampu mengesan virus yang mempunyai ciri-ciri program yang sudah dikenalpasti oleh pengesan virus. Di zaman sekarang, virus baru mampu untuk mengubah ciri-ciri lantas menyebabkan pengesan virus gagal mengasingkan virus. Projek ini bertujuan untuk mencipta model pengesan virus yang dilatih menggunakan contoh virus yang telah dikenalpasti dengan menggunakan ciri-ciri pengesanan Snort. Ciri-ciri tersebut akan melalui beberapa proses seperti pengurangan ciri dan dapatan informasi fasa sebelum berubah kepada format pertindanan n-gram. Algoritma yang digunakan oleh model tersebut ialah Naive Bayes (NB) yang berpandukan kepada teori Bayesian. Kebolehan mengadaptasikan algoritma tersebut kepada model tersebut adalah model itu mampu untuk diprogram untuk mempelajari ciri-ciri virus yang baru. Pengkalan data yang sudah dilatih dan mempunyai ciri-ciri penting virus akan melalui simulasi menggunakan perisian WEKA bagi mendapatkan prestasi ketepatan simulasi perisian. Selepas itu, model tersebut akan dibina menggunakan perkakasan FPGA. Prestasi yang dicapai oleh model perkakasan tersebut akan dibandingkan dengan prestasi model perisian. Kedua-dua model virus pengesan menggunakan NB algoritma tersebut akan dinilai dari segi ketepatan pengklasifikasian, masa pemrosesan dan beberapa aspek lain.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ASIC	-	Application-specific Integrated Circuit
API	-	Application Program Interface
CNG	-	Common n-gram
CPU	-	Central Processing Unit
DLL	-	Dynamic-link Library
FNR	-	False Negative Rate
FPGA	-	Field Programmable Gate Array
FPR	-	False Positive Rate
HDL	-	Hardware Description Language
IBK	-	Instance Based Learner
IG	-	Information Gain
LUT	-	Look-up Table
NB	-	Naïve Bayes
RTL	-	Register Transfer Level
SVM	-	Support Vector Machine
TCL	-	Tool Command Language
TCP	-	Transmission Control Protocol
TNR	-	True Negative Rate
TPR	-	True Positive Rate

CHAPTER 1

INTRODUCTION

1.1 Problem Background

Malware also known as malicious software is any computer program that bring harm to the computer hosts. Malware is the term used to represents viruses, Trojan horse, Backdoors, worms and etc. Most common actions from the malicious code is replicates rapidly by infecting any host files or any system inside the computer. It also capable of multiplying countless time to form new obfuscated virus code [1]. Besides, it is easier to learn on how to create malware as there are high resources of malware construction and attacking tools in the internet. Hackers also able to buy malware on the black market and learn on anti-detection techniques used to create undetectable malware. Resulting from that, anyone can learn easily to become hacker and not depending on programming skills anymore. In [2], it states that there are major malware attacked are being created by script-kiddies in the recent years.

The classification to identify malware is that any software or system that performing malicious action can be considered as malware. The crimes resulting from malware are espionage, identity stealing, information breach, and lots more. Anti-virus scanners are not able to scan and filter out most of malware as the increasing diversity and new malware are introduced every day that resulting in millions of users being hacked. Anti-viruses can't provide perfection protection towards malware and based on statistic, 6 563 145 were attacked and 4 000 000 malware objects are detected in 2015 only. The data provided by Kaspersky Labs (2016). By 2019, Jupiter Research (2016) predicts that the cost for the data breach resulting from malware will increases significantly to \$2.1 trillion globally.

Malware protection for computer system is significantly important in order to secure the data regardless for business purpose or single user. This cybersecurity is important to prevent data leaked and espionage. The need for accurate and reliable malware detection methods is high to overcome the frequent attacks. Conventional detection using static and dynamic methods does not able to provide efficient detection as the malware keep changing in time. Machine learning techniques is suitable to overcome the limitation of the malware detection.

This paper discussing the implementation of machine learning using Naïve Bayes classifier embedded in FPGA to increase the efficiency, reliability, accuracy, throughput and computational resources [3]. To generate the detection models for the malware, signatures from known malware samples are used in the algorithm for classic malware detection. The signatures are created by determining the unique fingerprint pattern for each malware family. It can produce accurate classifier with less low false rate. In spite of that, the detection method not able to detect new malicious samples as the code are more complicated and can slipped through the detection using packaging and obfuscated techniques. To prevent the malware undetected rate, the system can increase the malware database by keep updating the malware samples frequently. There is a draw back when increasing the database samples that resulting in increasing scanning time as the database increase in size [4]. Thus, the performance will reduce in term of throughput.

Data mining is used in this paper to overcome the limitation of the signature based classifier mention above. In this paper also, the implementation of Naïve Bayes classifier for the malware detection uses the concept of supervised classifier machine learning. Based on supervised classifier, the samples of known malware and benign program are used as the training set. Then, the feature of known malware and benign samples are extracted and used as classification model to classify types of malware and benign classes.

The samples are transform to n-gram sequences by using feature reduction process [5]. N-gram sequences are usually used in several types of classifier algorithm such as Naïve Bayes, Random Forest and Decision Tree classifier. In the purposed methodology, the n-grams sequences are extracted from the known benign and malware samples by using feature reduction method. The n-grams will assist as the class for the Naïve Bayes classifier to scan through unknown program samples. Classwise document frequency also being used in the flow to extract prominent features that able to differentiate malware from benign programs. Classwise document

frequency condense the huge feature size that will reduce the scanning time for that classifier during testing and training phase.

For finding the suitable number of n-grams, simulations using several types of classifier such as Naïve Bayes, Random Forest, J48, Instance Based Learner (IBK) and AdaBoost1 which are supported in WEKA tools [6]. The simulations are tested using the same training and testing data set. Based on the results, the proposed classifier NB produce high accuracy with slight false rate but the implementation will still use NB as the classifier due to advantages of using NB classifier that is more suitable to be used when the training and testing data set are small compared to other classifier that require bigger database for higher accuracy. The aim for this project is to focusing in the hardware implementation where hardware performance is more significant compared to reliability. Choosing NB classifier will slightly reduce the accuracy and reliability [7] of the classification but the hardware performances are believed to be better when implemented inside FPGA. The implementation of the classifier algorithm into FPGA will be done in the next phase. The target device is Xilinx Virtex-6 LX760 FPGA. The algorithm is transform into RTL code by using Verilog programming language [8]. The software used in the hardware design are Vivado that will virtually connect the algorithm in RTL code into the FPGA board while the software also used to create the testbench for the whole hardware system. The computational resources and performance of the system is observed and compared to other hardware classifier.

Simulation using Matlab [9] also being done onto the selected NB classifier algorithm to generate new results that will be compared with the results obtain from the hardware simulation. The results should be comparable relatively the same. This project will be focusing more on hardware simulation as the classifier algorithm already being set as NB classifier. Improvement and modification will be done in hardware parts to increase the performance, throughput, accuracy, reliability and processing time. Slight trade off in accuracy and hardware performance might be seen as only one of the aspect can be improve while the other will degrade.

1.2 Problem Statement

Most malware scanners employ signature based detection methods and these scanners fail to detect unseen and obfuscated malware samples. Malware has become harder to detect as new malware are being introduced frequently. The existing malware also has the capability to replicate and change its code in order to avoid anti-virus and detection. Exact pattern matching does not suit to detect new malware as the pattern matching uses limited sample databases. This disadvantage is the reason for the increasing data breach although new anti-viruses are being sold in the market.

Conventional malware detection is not suitable to implement deep machine learning technique due to restricted programmable ability of the normal system. The existing systems in market only implement several hardware accelerators such as pipelining, parallel classifications, fixed point data representation and look-up table. However, most of these hardware implementation works are designed for other application classification purpose instead of malware detection classification. The limited computational resources in normal malware detection system exhibit the throughput of the detection system. FPGAs are more suitable for implementing machine learning as they can handle different algorithms in computing, logic, and memory resources in the same device. Besides that, the performance of FPGAs is much faster compared to other chip as users can hard code the operations and algorithms into the hardware.

1.3 Objective

The aim of this project is to achieve the following objective:

1. To implement signature based approach for detecting malicious code by using n-grams which extracted from TCP traffic of benign and malware samples.
2. To obtain better performance on CPU usage by using Naive Bayes (NB) Classifier onto hardware (FPGA) based using machine learning to detect malware.

1.4 Scope

For this project, the scopes covered are as follows:

- The implementation of the malware detection using machine learning are done at the hardware based (middle box) where it is assumed the data packet (stateless) contains payload in hex in form of overlapping n-gram.
- Focusing on implementation of Naïve Bayes classifier to detect malware onto FPGA architecture.
- Using the existing Naïve Bayes classifier algorithm while the features are reduce based on Snort Signatures
- The system will function as malware detection system that implement NB in determining the class of malware either malware or benign.

1.5 Organization

The report is organized with 5 chapters. Chapter 1 provide the introduction of the project including background, problem statement, objective, and scope. Chapter 2 reviews the related literature review on state-of-the-art of N-gram text classification, malware types, malware signature, Naive Bayes algorithm, FPGA implementation using Naive Bayes classifier, limitation, research gap and other related works. Chapter 3 describe the research methodology for the overview of proposed work, research activities, techniques and tools used. Chapter 4 elaborates the design implementation onto FPGA hardware as hardware accelerator and the evaluation on proposed malware detection Naive Bayes classifier. Chapter 5 summarize the proposed works and discussed on the future works.

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