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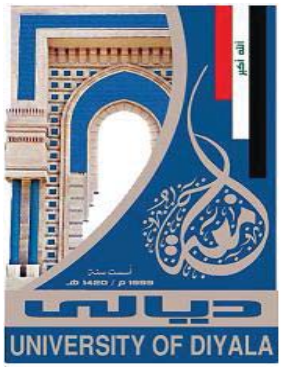

Classification Method of Advanced Persistent Threat (APT) Malware Using Advanced Machine Learning

A Thesis

Submitted to the Department of Computer Science\ College of Science\ University of Diyala in a Partial Fulfillment of the Requirements for the Degree of Master in Computer Science

By

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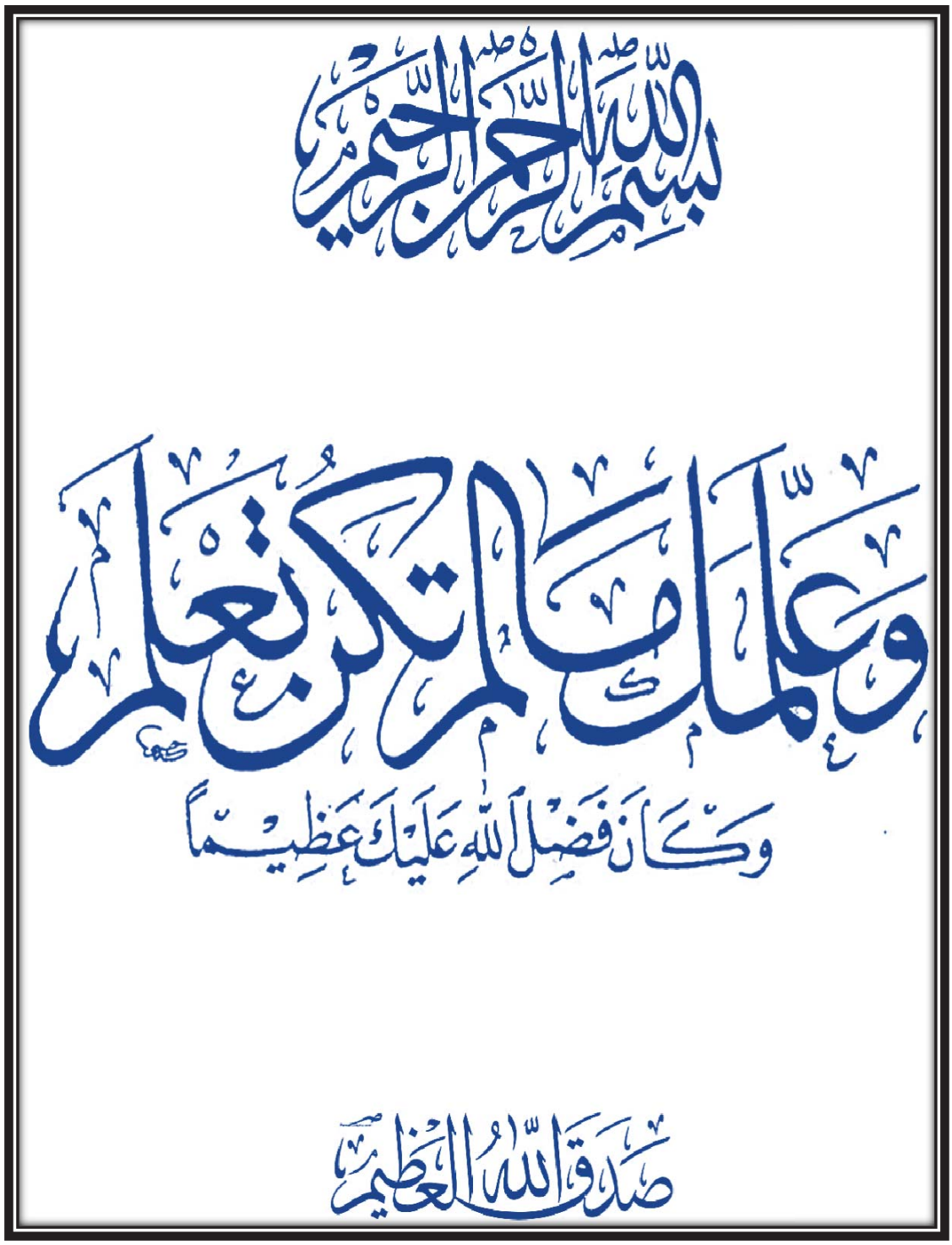

سورة النساء

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Dedication

I would like to dedicate this work to

To the one who honored me by bearing his name

To the one who gave the most precious things to reach this degree (my beloved father), may God prolong his life.

To her prayers and words were companions of brilliance and excellence (my beloved mother); may God prolong his life.

To my brother, the martyr (Mustafa), may God have mercy on him; thanks to him, I was accepted into the Master's degree.

To my brother and sisters, the ones who gave me unstopped support, help, and encouragement when I was disappointed,

To my soul, my life, and my happiness, my daughter, Rawnaq.

Emaan Jalal Khalifa

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Finally, I am sincere gratitude thanks to my family for their unlimited love, encouragement, patience, and support during all stages of my study which helped me in achieving my goals.

Thank you all!

Emaan Jalal Khalifa

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ABSTRACT

Advanced Persistent Threat (APT) is a complex type of attack that steals personal data by staying in the infected system for a long time. APT represents sophisticated attacks that are executed in multiple steps. Recently, detecting and classifying APT attacks using Machine Learning (ML) or Deep Learning (DL) algorithms has become a common approach for analyzing network traffic for signals and anomalous behaviors. APT attack detection approach that uses behavior analysis and evaluation approaches encounter many issues. Network traffic analysis to detect a common APT attack is one of the solutions for dealing with this situation.

In this thesis, we propose two systems for classifying APT malware using advanced machine learning. The first, binary-class classification identifies two-class APT malware and normal malware; the second, multi-class classification identifies 15 APT malware and normal malware. Moreover, each system has two classification subsystems: ML based on Random Forest Classifier (RFC), Light Gradient Boosting Machine (LightGBM), and DL using a hybrid Convolution Neural Network (CNN) with Long Short-Term Memory networks (LSTM).

The main methods used are Exploratory Data Analysis (EDA) for detecting and removing outlier data, Extra Tree Classifier (ETC) for selecting essential features, and Synthetic Minority Oversampling Technique (SMOTE) for solving the unbalance data problem.

A reliable APT Malware dataset with 11,107 samples spread over 16 unique malware classes. Each proposed system is studied separately, and the performance results of the machine and deep learning algorithms are compared based on the accuracy value. At the same time, four case studies were conducted

to evaluate the performance of ML algorithms and the impact of using Feature Selection (FS) and SMOTE technology on their results.

The machine learning results demonstrated the significant impact of feature selection and SMOTE technology on the performance of both proposed systems. The binary class classification system results show that machine learning has better performance than deep learning, with the random forest accuracy being around 0.999723 and LightGBM accuracy being 0.999480, while the CNN-LSTM hybrid has an accuracy of around 0.914798. The results of the multi-class classification system illustrated that machine learning has the best performance than deep learning; the LightGBM accuracy is about 0.999727, the random forest has an accuracy of about 0.999632, while hybrid CNN-LSTM achieved an accuracy of about 0.798206.

Furthermore, the comparison of the results of the proposed systems with the results corresponding to the previous works proved that the two proposed systems have the highest classification accuracy, and this indicates the effectiveness of the proposed system for detecting and classifying the attack with a high determination and avoiding the significant risks that it causes.

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List of Abbreviations

Abbreviations	***Full Form***
1D CNN	1-Dimensional Convolutional Neural Network
AI	Artificial Intelligent
APT	Advanced Persistent Threat
BN	Batch Normalization
C&C	Command And Control
CL	Convolutional Layer
CNN	Convolutional Neural Network
CV	Cross Validation
DL	Deep Learning
DNS	Domain Name System
DT	Decision Tree
EDA	Exploratory Data Analysis
EFB	Exclusive Feature Bundling
ET	Extra Tree
ETC	Extra Tree Classifier
FN	False Negatives
FP	False Positive
FS	Feature Selection
F_t	Forget Gate
GBDT	Gradient Boosting Decision Tree
GOSS	Gradient-Based One-Side Sampling
GRU	Gated Recurrent Unit
IDS	Intrusion Detection System

I_t	Input Gate
KNN	K-Nearest Neighbors
LightGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron
NIST	National Institute of Standards and Technology
OHE	One-Hot Encoder
Organization	Computer Network Used
O_t	Output Gate
OTP	One-Time Password
ReLU	The Rectified Linear Unit
RF	Random Forest
RFC	Random Forest Classifier
SMOTE	Synthetic Minatory Oversampling Tree Technique
TN	Tue Negatives
TP	True Positives
XGBoost	eXtreme Gradient Boosting
σ	Standard Deviation
μ	Mean

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Chapter One
General Introduction

Chapter one
General Introduction

1.1 Overview

In recent years, Advanced Persistent Threats (APTs) have become a new security danger for companies and governments, which is a new type of network attack that can freely use multiple attack techniques. APT attackers use small companies as stepping-stones to gain access to large organizations by avoiding all detection [1]. The most dangerous malware is that developed by APTs, since it applies a high level of sophistication, and targets important victims [2].

APT attacks are a form of attack that uses advanced attack methods to carry out long-term persistent cyber-attacks on specific targets. APT attacks are becoming more frequent. Advanced attack methods, long duration, and a high degree of threat are three main characteristics of APT attacks [3]. APT attacks have two main objectives: one is to steal critical data and the second is to destroy system infrastructure [4].

Advanced Persistent Threat (APT) attack is a persistent, targeted attack on a aparticular organization and is performed through several steps. The primary goals of APT are data exfiltration and espionage. APT is therefore viewed as a newer and more sophisticated type of multi-step attack [5]. APTs are long-term network attacks on specific targets with attackers using advanced attack methods. APTs are more advanced than other forms of attacks. APT is advanced because it uses advanced attack tools and methods [6].

Advanced persistent threat attacks threaten both public and private institutions worldwide and will continue to do so. These attacks offer a severe threat that is hard to see in their early stages because the attackers use various ategies to remain unnoticed as long as possible and to dodge effectively [7].

APT attacks have become the most massive threat to companies and governments as they are increasingly becoming the target of these attacks. APT attacks target the victim's network to gain useful information or to compromise the network to destroy the victim's systems or to steal the target's data without getting caught [8].

In this thesis, a classification method of APT Malware is proposed which uses Machine and Deep learning algorithms. The proposed system divided into two branches and follow same procedure for training and testing the APT Malware dataset with 11,107 samples spread over 16 different unique malware classes: binary, multi class classification systems and each of them include two branches for classification ***Machine learning branch*** based on Random Forest (RF) and Light Gradient Boosting Machine algorithms (LightGBM); ***Deep learning branch*** based on proposed combing hybrid Convolutional Neural Networks (CNN) algorithm and Long Term-Short Memory algorithm (LSTM) are used as a classifier to classify the attack APT malware or normal malware.

The proposed binary–class system obtains an optimal accuracy value of **0.999723** with random forest,**0.99948** with LightGBM, and **0.914798** with hybrid CNN-LSTM. The proposed multi-class system obtains optimal accuracy values of **0.999727** with LightGBM, **0.999632** with random forest, and **0.798208** with hybrid CNN-LSTM.

1.2 Related Work

Several efforts have tried identifying and categorizing the APT problem with increased cyberattacks. This section reviews related work in APT detection and compares with them as shown below:

- ***Ghaffir et al.(2018) [9]:*** The system is composed of three-layers detection, i.e., threat detection, alert correlation, and attack prediction which provided an accuracy of 84.4%. The system needs to be tested for real-time APT signature covering all seven phases of the APT life cycle.

- ***Yan, et al. (2020) [10]:*** This study introduces a new feature that shows the relationship between a DNS request and the response message using deep learning to evaluate DNS request records. Based on the suspicious value, the system assesses DNS activity for threats. This study uses 4, 907, 147, 146 DNS request records (376, 605, 606 after DNS Data Pre-processing) from a large university network to test the system's authenticity and correctness. Experiments reveal that our technique detects suspicious DNS behavior with 97.6% accuracy, 2.3% false positives, and 96.8% recall. The suggested approach detects unusual DNS activities in APT.
- ***Chen, W. et al. ,in (2020) [11]***: In this paper, a new gene model combining malware behavior knowledge graph is proposed. Researchers use malware information to create the APT gene pool. The gene pool should contain APT genetics. Theoretically, genetic traits can help us identify IoT malware and APT. Genetic similarity algorithms can't be employed directly. Instead, a genetic similarity algorithm will identify APT malware.. The experiment is 85% accurate. The model can recognize APT gene organization properties. The program compares sample genes to the gene pool and outputs gene similarity to identify APT.

- ***Laurenza ,G. et al., in (2020) [2]:*** In the paper, the authors offer malware triage for early APT detection. The proposed solution necessitates a significant training time and must be retrained if new APT samples or classes are found. In this paper, they go from multi-class to one-class classification, which reduces run time and increases modularity while maintaining over 90% precision and accuracy.

- ***Zimba ,A., et al. ,in (2020) [7]:*** This article proposes a new APT detection technique based on semi-supervised learning and complex network properties to overcome attack network dynamics. The goal of APT-AN is small-world networking. APT uses finite state machines. The method is supported by information from Los Alamos' 17,684-host enterprise network. The method analyzes huge datasets for C&C and victim APT attack features. APT hosts are ranked. In our framework, three-stage APT detection is 90.5% accurate. Results show model can identify APT hosts.

- ***Zhang, et al. (2021)[12]***. proposed an attribution classification method of APT malware in IoT using the ML approach. The method analyzes samples, pre-processes the acquired behavioral data, constructs a behavioral data set of malware samples, then uses the TF-IDF method to perform the feature representation forming a vector matrix and calculates the chi-square value of the high latitude feature vector to perform feature selection. SMOTE-RF model is used in the multi-class model to train and test sets for predicted output with accuracy of 80%.

- ***C. Do Xuan and M. H. Dao(2021) [13]***.The proposal of a combined deep learning model to detect APT attacks based on network traffic is a new approach, and there is no research proposed and applied yet. In the

experimental section, combined deep learning models proved their superior abilities to ensure accuracy on all measurements from 93 to 98%.

- ***F. J. Abdullayeva (2021)[14]:*** In this study, a deep neural network model built by adding layers was evaluated on a public database and compared to existing methods; the new method showed superior results in detecting APT attacks. This approach uses a machine learning dataset that includes APT1, Crypto, and other attacks. The architect's accuracy was 98.32%.

1.3 Problem Statement

APT attacks are challenging to detect and allow hackers to hide within the network for months. While the hackers remain in the system, the company experiences data loss and outages regularly without knowing the cause of the problems; Traditional detection technologies cannot identify them efficiently.

For the reasons mentioned above, therefore, the ***main problem*** that depends on this work is that detecting and classifying APT malware attack systems, which depend on deep and machine learning, still need an analytical study of the data and improved accuracy in identifying APT malware organizations.

1.4 The aim of the Thesis

The main aim of this work is to design and implement a system for **detection and classification** of the Advanced persistent threat (APT) malware accurately and rapidly based on machine learning and deep learning algorithms, which that help security analysts in government institutions, organizations, and large companies to discover and identify APTs early and accurately to avoid losses caused by APTs attackers as well as develop strategies to counter this type of attack.

1.5 Layout of Thesis

Chapter One (General Introduction)

The first chapter (General Introduction), the other chapters in this thesis are follows as:

Chapter Two (Theoretical Background)

This chapter provides a background and overview about malware, advanced persistent threat (APT), basic characteristics, and APT life cycle, theoretical background and techniques that are used in this thesis.

Chapter Three (Proposed System Design)

This chapter describes the proposed APT malware classification system with its design and implementation.

Chapter Four (Experimental Test Results)

This chapter explains the results and evaluation that have been getting from the proposed system.

Chapter Five (Conclusions and Suggestions for Future Work)

This chapter presents the conclusions of this work. Furthermore, it provides suggestions for future work.