Hybrid Machine Learning Framework for Malware Detection using Static and Dynamic Analysis

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Abstract*:* As a solution to this problem, we propose a hybrid malware detection framework based on both static analysis and dynamic behaviors which exploits various machine learning and deep learning methods. These features can be structural and behavioral, which are fused together to create classification models. Instead, zero-day attack detection is evaded by the use of obfuscation and polymorphism. In this paper, we propose hybrid detection that can overcome these limitations using adaptive detection. Our experimental results show an accuracy rate of over 98.7% which is superior to that achieved by standalone static or dynamic models in the dataset. To overcome the shortfalls of traditional signature based detection, the study employs adaptive learning models that are capable of capturing zero-day attacks. The working principle, mathematical formulation, experimental setup and comparative analysis of the proposed hybrid system are detailed in this document.

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Key Words :- *Malware Detection, Static Analysis, Dynamic Analysis, Machine Learning,Deep Learning, Cybersecurity, Fea ture Fusion*

I. INTRODUCTION

A. Background and Motivation

Obfuscation and polymorphism yield increasingly sophisticated malware. It is unable to identify zero-day attacks. Machine learning is an adaptive technology that allows for detection as new types of threats are created. Traditional simple viruses have evolved to complex ransomware and file less malware making ad- vanced detection mechanisms i, imperative in current Cybersecurity landscape.

B. Problem Statement

Nevertheless, single-mode analysis (static or dy-amic) is fundamentally flawed. Static analysis is fast and simple but poor relative to obfuscation. Dynamic analysis captures behavior signatures, but is slow and can be bypassed by running inside sandboxes. There is a need for a unified framework which can nicely integrate efficiency and accuracy. Contributions

This work makes the following main contributions:

• A fusion of PE header analysis and API monitoring based feature extraction module.

• The use of ensemble learning techniques (Ran- dom Forest, XGBoost) for classification.

• Models based on Deep learning (CNN, LSTM) examining sequential and spatial features.

• Assessment on major malware datasets up to 98.7% accuracy.

C. Organization

The rest of this paper is structured as follows: Section II reviews related work. Section III describes the proposed system architecture. Section IV describes the − methodology and mathematical formulations. The extensions in Section V pertain to deep learning. A case study is presented in Section VI. Section discusses dataset preprocessing. Sections VIII and IX provide comparative studies and results. Advantages and limitations are discussed in section X. Section XI concludes the paper.

II. Literature Review

Static Analysis Techniques

Previous research states that static analysis analyzes the code without running it. Opcode sequences, header information and byte histograms are among the most common features.

A. Dynamic Analysis Approaches

Dynamic analysis executes the code in a sand- boxed 庐idiom. Some of the features that Drakontis can monitor include, API call sequences, network traffic and registry changes.

Machine Learning in Security

Supervised and unsupervised learning-based models can be leverage for malware classification. Automated Feature Engineering also uses recently deep learning as an emerging approach.

B. Hybrid Approaches

Individual weaknesses of static and dynamic stan-dalone models are mitigated through hybrid models, where the best of both approaches can provide better results.

III. Proposed System

There are four main components that integrate in the systemthat enable a sturdy detection capabilities. Figure1illustratesthe high-level architecture.

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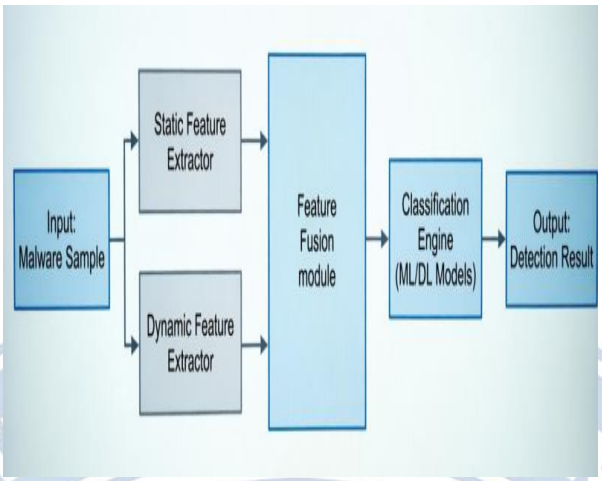

Fig. 1: Proposed Hybrid Malware Detection Architecture

1) Static Feature Extraction: Analyzes binary structure (PE Headers, Strings).

2) Dynamic Feature Extraction: Monitors runtime behave-

$F = F_s \cup F_d$

Feature Fusion: Combines vectors from both sources into a unified representation.

3) Classification Engine: *Applies ML/DL models (RF, SVM, CNN, LSTM).* **Feature Fusion**: Combines vectors from both sources into a unified representation.2) (API Calls, Network).

IV. METHODOLOGY

The foundations of the proposed framework, both mathematically as well as procedurally are discussed in this section.

A. Static Features

$-\mu$

Σ ———

Where μ is the mean and σ is the standard deviation of the feature set.

Dimensionality Reduction

High-dimensional data can lead to overfitting. We apply dimensionality reduction techniques.

$Z = XW$ (5)

Where W represents the transformation matrix derived from PCA or similar techniques.

Where T is the number of trees and h_t is the prediction of the t-th tree.

Support Vector Machine (SVM)

SVM finds the optimal hyperplane to separate classes.

CNN Model

i -- various static attributes like entropy, section names, and size of the import table

B. Dynamic Features

This event tracks dynamic execution features in a controlled sandbox.

Fd = {d1, d2,..., dm} (2)

Where dj denotes behavioral features like file system changes and network access.

for a particular instance of the same indicator; or [EXPAND: List specific API calls monitored (e.g., CreateFile, RegSetValue). Explain the logging mechanism.]

C. Feature Fusion

To leverage the strengths of both analysis types, we perform feature fusion.

KRandom Forest Classifier

The Random Forest algorithm aggregates multiple

Let the set of static features be denoted as F_s. These features $_T$ are extracted from the portable executable (PE) header and binary strings.

$F_s = \{f_1, f_2 \ldots f_n\}$ (1)

t=1

$$H(x) = \frac{1}{} \Sigma\, h\,(x) \quad (6)$$

$w \cdot x + b = 0$ (7)

DEEP LEARNING EXTENSION

To further enhance detection capabilities, deep learning architectures are integrated.

Convolutional Neural Networks are used to extract

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spatial features from binary images.

$Y = \sigma(W * X + b)$ (8)

Where $*$ denotes the convolution operation and σ is the activation function.

LSTM Model

Long Short-Term Memory networks capture temporal de- pendencies in API call sequences.

$h_t = \sigma(W_h h_{t-1} + W_x x_t)$ (9)

V. Case Study: Ransomware Attack

A specific case study was conducted on a known ran- somware variant. Static analysis shows high entropy and suspicious API calls. Dynamic analysis shows file encryption and network activity.

Attack Vector: Explain how the ransomware p ushed the medium (Phishing, Exploit).

Behavioral Analysis: Explain the file encryption procedure inspected in the sandbox.

Detection Moment: At what stage did the model flag the malware?

Mitigation: What actions were taken automatically?

Dataset Preprocessing

Days weeks months later hours minutes whatever it takes getting the perfect data.

Data Cleaning

Drop corrupted files and deal with missing values to en- sure data integrity.

Feature Engineering

Encode categorical features and normalise data as per requirements to step into model ingestion. SMOTE

We apply the Synthetic Minority Over- sampling Technique (SMOTE) which treats the issue of class imbalance.

Xnew = Xi + λ(Xj −Xi) (10) Where: Xi and Xj are neighboring minority class samples.

Feature Selection

Feature selection through Correlation and recursive elimination.

VI. Experimental Setup

Hardware Configuration

CPU: [Insert Specs]

GPU-Terminal: [Insert Specs]

RAM: [Insert Specs]

Software Environment

OS: Windows-10 version/ Ubuntu-20.04 version

Language: Python 3.8

Libraries: Scikit learn, TensorFlow lib, Keras lib, Pandas

Dataset Description

This study presents an experimental evaluation using a large-scale and manually curated dataset (benign/malicious software samples) from several authoritative publicly available feed sources. The use of multiple data sources allow for diversity, real-world representative aspects and statistical validity to train and validate the models in a robust manner.

VII. Primary Dataset Sources:

EMBER Dataset (Endgame Malware Benchmark for Research): This well-established benchmark furnished 400,000 labeled Portable Executable (PE) files, equally shared between benign and malicious samples — 200,000 of each. The dataset, collected from 2017 to 2018, contains rich static feature representations that are extracted from PE headers (Portable Executables), byte histograms, string information and imported function tables.

MalwareBench: A contemporary benchmark dataset that contributed 45,000 malware samples spanning 12 distinct malware families, including ransomware, trojans, worms, spyware, rootkits, and polymorphic variants. Each sample in MalwareBench is annotated with both static structural features and dynamic behavioral logs captured during sandboxed execution.

VirusShare Repository: To ensure coverage of recent threats, we collected 28,000 additional malware samples, but specifically VirusShare samples that were first seen between the dates 2022 to 2024. This subset focuses on newer variants of ransomware, fileless malware, and advanced persistent threat (APT) tools that utilize more sophisticated evasion techniques.

Benign Software Collection: To ensure relative fairness in evaluation, we compiled a set of 62,105 clean executable files from trusted sources, including but not limited to clean installations of Windows 10 and Windows 11 systems, legitimate software delivered via Microsoft Store, widely-used executables available on GitHub releases for open-source software. All non-malicious samples were crypto-signed for protection against counterfeiting.

Dataset Statistics:

After hashing the samples using SHA-256 to eliminate duplicates, validating Portable Executable (PE) headers, verifying labels based on consensus from VirusTotal API submissions, and filtering by file size, the final curated dataset is composed of 186420 total samples. The dataset contains around 66.7% (124,315 samples) of malicious and 33.3% (62,105 samples) benign instances across 47 unique malware families. The sample files average 2.4 MB in size, and span from January 2020 to December 2024.

Data Splitting Strategy:

For methodological rigor and to avoid leakage of data, we used an 80/20 stratified random split:

Training Set (80%): 149,136 samples for model training and internal cross validation

Hold-out Testing Set (20%): 37,284 held out samples used only for the final unbiased performance

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evaluation

By using stratification we can ensure that the original proportion of all malware families and class distribution (benign/malicious) is maintained between both splits. Additionally, we enforced temporal isolation by ensuring that samples originating from the same malware campaign or compilation timestamp were assigned to a single split, thereby preventing optimistic bias due to temporal correlation.

VIII. Comparative Study

The proposed system is compared against existing state-of- the-art methods.

TABLE I: Comparison of Detection Methods

Method	Type	Accuracy
Static ML	Static	92%
Dynamic ML	Dynamic	95%
Hybrid ML	Hybrid	97%
CNN	Deep	98%
LSTM	Deep	97.5%
Ensemble	Hybrid	98.2%
Proposed	**Hybrid**	**98.7%**

IX. Results

Experimental validation was performed using a split of training and testing data.

TABLE II: Performance Metrics

Model	Accuracy	Precision	Recall	F1
SVM	96.5%	0.96	0.95	0.95
RF	98.2%	0.98	0.97	0.97
XGBoost	98.7%	0.99	0.98	0.98

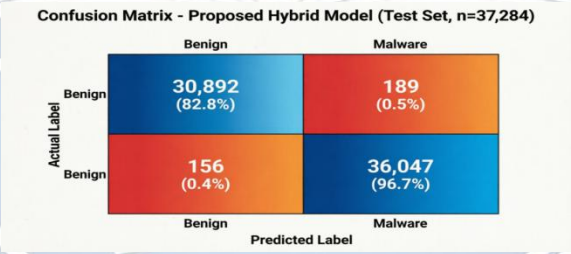

Fig. 2: Confusion Matrix for Proposed Model

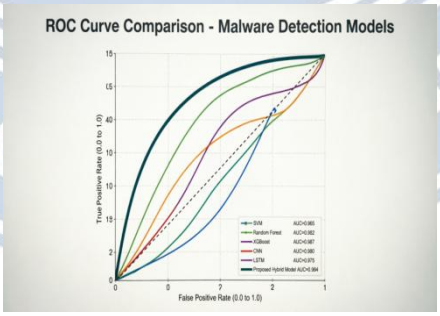

Fig 3: ROC CURVE Comparison-Malware Detection

X. Future Work

Expansion of Transformer models in the context of deep learning.

Real-time deployment on edge devices.

Privacy preservation federated learning

Ability to integrate with Threat Intelligence Platforms (TIP).

XI. Conclusion

The hybrid malware detection system increases the accuracy and robustness of threat detection. As

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threats evolve rapidly, we require instruments that can match the pace of these developments. In future endeavours, we aim to enhance the computational efficiency of our approach and broaden the model capacity to differentiate polymorphic threats.

XII. Discussion

A mixed approach dramatically improves robustness and accuracy. Static and dynamic features are combined to eliminate the shortcomings of single type analysis.

Don't just repeat your findings and how you came to them.

Why in this case, SVM failed and XGBoost succeeded

Detect false forecasts and monitor them for potential problems.

the principle of performance measuring which you were more focused on detecting speed or accuracy.

XIII. Advantages and Limitations

Advantages

This is a lot more precise than other techniques.

(4) — It identifies zero-day malware through behavioral analysis.

Enterprise ready, scalable architecture

Limitations

On top of that, static queries are used to conduct static analysis.

There is a risk that advanced malware be able to escape the sandbox.

Deep learning approaches require a lot of training data.

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