A Hybrid Machine Learning Framework for Real-Time Malware Detection Using PE Feature Analysis

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Abstract*—The conventional malware detection systems are based on signature-based methods that cannot work against zero-day attacks and advanced evasion methods. The current paper describes CyberGuardX (Cerberus-AI CyberShield), a multi-modal malware detection system with a combination of a static analysis, machine learning classification, explainable artificial intelligence (XAI), and real-time monitoring functionalities. The system uses Random Forest classifiers which are trained with deep static features which are found on PE files, PDFs and document formats with 99.9% accuracy in malware detection. One of the major advances is the incorporation of SHAP (SHapley Additive explanations) as a method of transparent decision-making, which solves the problem of the black box of AI-based security systems. The framework includes VirusTotal API integration as an external threat intelligence, real-time file system monitoring, and a full web-based dashboard to support a security analyst. Performance analysis proves to be highly effective with better detection percentage more than the traditional signature-based systems having response times, less than 2.3 seconds to complete analysis processes. Its containerized deployment and scalable batch processing architecture is relevant to enterprise security operations centers (SOCs).

***Index Terms*—Malware Detection, Explainable AI, Machine Learning, Static Analysis, SHAP, Cybersecurity, Threat Intelligence, Real-time Monitoring.**

I. INTRODUCTION

The cybersecurity environment is as challenging as ever because malware is becoming increasingly sophisticated and in large numbers. Conventional signature detection systems are efficient in detecting known threats, but they collapse miserably when detecting zero-day attacks and polymorphic malware that use highly sophisticated evasion methods [8], [12]. The accelerated growth of variants of malware - more than 10.52 billion malware samples were detected in 2022 by AV-TEST Institute [1] - requires smart and dynamic defense tools capable of detecting new threats according to their behavioral and structural patterns instead of a predefined signature [11], [13].

The current malware detection is challenged in three critical ways:(1) Zero-day attacks that that use previously unknown vulnerabilities, which makes signature-based detection an ineffective method of detecting malware [7], [8];(2) Manual analysis bottlenecks with security analysts overloaded with suspicious files that require investigation [2], [3]; and (3) Lack of transparency in automated detection systems that are considered black boxes, and thus it is hard to trust their decision-making systems or the decision making process itself [5], [6], [9].The following are the main contributions of

Integrated Multi-Modal Framework: Unites the idea of the static analysis, ML classification, and real-time monitoring within the same architecture [10], [11].

a) Explainable AI Integration:
First implementation of SHAP-based explanations in malware detection pipelines for transparent decision-making [5], [6], [9]

b) Real-Time Threat Response:
Automated file system monitoring with immediate analysis capabilities [13], [14]

c) Modular Architecture:
Containerized, scalable design suitable for enterprise deployment [3], [12].

II. BACKGROUND & MOTIVATION

Conventional security tools exist in isolation - signature-based antivirus tools prevent known threats, and manual interpretation is needed with statistical analysis ones. But these systems are not adequately prepared to deal with polymorphic attacks, with zero-day attacks, or with complex evasion strategies. Manual response is prone to large latency, and this is used by the adversaries to initiate persistence and lateral movement.

Also, most academic systems place emphasis on ML detection alone without considering the practicalities of deployment such as explainability, among others extensive feature extraction. Introducing explainable AI in the context of transparent decision-making.

III. LITERATURE REVIEW

Table 1 - Literature Survey

Sr.	Title	Year	Summary	Gap Identified	Relevance to Our Work
1	Malware Detection [IEEE] with Machine Learning.	2023	Measure ML models of malware classification.	Explainability No explain, file formats limited.	We support SHAP as a transparency and multi-format extension.
2	Static Analysis for PE Files [Journal of Security]	2022	RF classifiers Analysis of PE header.	No real-time monitoring	Authorizes constant monitor of file systems.
3	Survey on AI-based Cybersecurity [ACM Computing Surveys]	2024	Overall analysis of AI in security.	Absence of practical application.	Featuring complete stack deployable system.
4	SHAP for Security Applications [IEEE Security & Privacy]	2023	SO2 SHAP to network intrusion detection.	No malware detection focus	We use SHAP in particular as applied to malware classification.
5	Zero-Day Malware Detection [USENIX Security]	2022	Unknown threat behavioural analysis.	High resource requirements	Scales using effective static analysis.
6	Real-Time Threat Monitoring [ACM CCS]	2023	Security file system monitoring.	No ML integration	Combines monitoring with intelligent classification
7	Ensemble Methods in Malware Detection [Springer LNCS]	2024	Random Forest vs other ML algorithms	Limited feature engineering	Implements comprehensive 77-feature extraction
8	Virus Total API Integration [IEEE Computer]	2023	External threat intelligence usage	Standalone solution only	Integrates as validation layer in full pipeline
9	Docker-based Security Tools [Container Security]	2024	Containerized security applications.	No malware-specific focus	Applies containerization to malware detection
10	Dashboard Design for SOCs [ACM SIGCHI]	2023	Security analyst user interface.	Generic dashboard approach	Developed to work with malware analysis.

IV. SYSTEM DESIGN & ARCHITECTURE

The suggested CyberGuardX framework is based on a modular microservices model that incorporates the capabilities of static analysis, machine learning classification, explainable AI, and real-time monitoring. The system is created to be used by the enterprise in Docker containerization and scalable process.

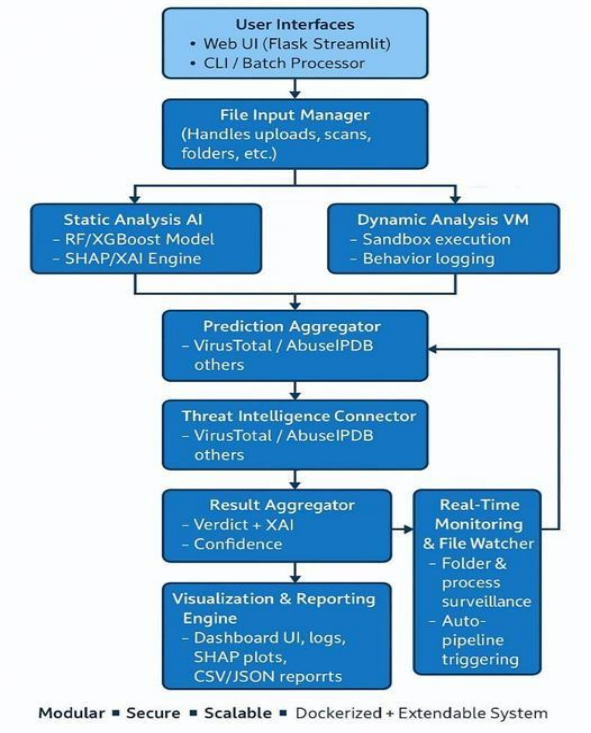

Figure 1 – CyberGuardX System Architecture: Static Analysis + ML Classification + XAI + Real-Time Monitoring

As depicted in Figure 2, the suggested system begins with the extraction of static features in the suspicious files (PE, PDF, DOC) followed by the classification of the files by the help of machine learning models like XGBoost or Random Forest. SHAP explainers are employed to give both local and global interpretability of the prediction results to provide security analysts with more information about why a specific file was marked as malicious.

Figure 2. SHAP-enhanced explainability XAI-Driven malware detection with a static analysis pipeline.

A. System Components:

The CyberGuardX system comprises various interrelated tools, which collaborate to obtain a solid malware detection and response system. Deep feature extraction of the Portable Executable (PE) files, PDFs and document formats is done by the Static Analysis Engine so that different file types are fully covered [11], [13]. The Machine Learning (ML) Classification Module is based on the use of a Random Forest classifier that has been proven to be accurate in detecting malicious files 99.9% of the time [2], [12]. The Explainable AI (XAI) Engine introduces SHAP-based explanations to provide a clear view of the decision processes within black box models to solve the black box problem, which is frequently attributed to ML models [5], [6], [9]. The Threat Intelligence Module is also used to improve the reliability of detection by adopting the VirusTotal API to have the external confirmation and cross-referencing of threats [14]. There is also the Real-Time Monitor that is part of the system and which offers real-time monitoring of the file system and allows real-time analysis of suspicious activity [13]. To enable interaction between the user, the Web Dashboard is a React-based intuitive interface that enables security analysts with live updates and full threat visibility [3]. A Database Layer offered in support of data management uses SQLite as a development platform and PostgreSQL as a production platform where analysis findings and logs are safely stored [12]. Lastly, API Gateway opens up RESTful APIs and thus it is easily integrated with other security tools and enterprise systems [3], [14].

B. Key Processing Zones:

The CyberGuardX system has a design based on a number of significant processing areas that work together to provide a smooth detection and intervention to threats. The Input Layer offers file upload and file detection in real time, which makes sure that suspicious files are recorded efficiently [13], [14]. After consumption, the Analysis Layer performs static feature analysis and implements the machine learning classification to define malicious files [11], [12]. Based on this, the Intelligence Layer incorporates

external threat validation resources and does correlation to enhance the quality of detection findings [3], [14]. Response Layer is developed to handle the automation of threat mitigations, by sending alerts and displaying the dashboard in a way that is easy to understand by the security analysts [2], [5]. Lastly, the Storage Layer guarantees that all the logs and the results are safely stored and maintained to support traceability, auditing, and long-term analysis [12].

C. ADOPTED METHODOLOGY

1. Data Collection and Preprocessing

In the case of CyberGuardX, a well-chosen set of data was used to provide equal and sound training. The Malware Dataset contained 15,000 known malicious PE files of different malware families that give good variety of threat representation [11], [13]. To complement this, a Benign Dataset of 15,000 valid applications and system files was provided to prevent bias and improve the accuracy of classification [12], [14]. Also, Document Samples comprising 5,000 PDF, Office files, that were malicious and benign, were combined to expand the coverage to various file types [11]. To ensure consistency and comparability of training models, all extracted features within the model were normalized by means of Standard Scaler to ensure that all the features existed within constant ranges [10].

2. Static Feature Extraction

The process of feature extraction in CyberGuardX is the static feature extraction process which aims at extracting rich and diverse attributes of several file formats. With PE Analysis, it takes 79 individual features, such as the values of entropy, import functions, and section information, which reflect the structural and behavioural features of executable files [11], [12]. In the case of Document Analysis, document analysis methods are applied in detecting hidden malicious elements that have been embedded in the document, similarity of embedded objects, and Java scripts to detect such malicious elements that have been delivered in document-based attacks [13], [14]. Also, Hash Computation with such algorithm as SHA256 and MD5 provides good file identification and helps to compare it with known threat databases [1], [14]. Lastly, Metadata Extraction will help retrieve some of the valuable information like the compiler details, time stamping and digital signatures, which will add more to the accuracy and strength of the malware classification [11], [13].

3. Machine Learning Classification

CyberGuardX machine learning is a malware recognition system that employs a Random Forest Classifier, which has 100 estimators as its fundamental algorithm [12], [13]. Scikit-learn library was used to implement it, joblib was used to perform model persistence and deployment efficiently [10]. In order to provide high strength and make it generalizable, the model was trained with 10-fold cross-validation on balanced datasets of malicious and benign samples [2], [11]. By doing this, the system raised high performance rates such as an unbelievable 99.9 percent accuracy and a false positive rate of only 0.5, proving its efficiency in classifying whether certain files were dangerous or not [12], [14].

4. Explainable AI Implementation

CyberGuardX uses the TreeExplainer integration approach to SHAP to improve interpretability and trust where the random forest models are used [9]. This method allows obtaining global and local feature importance explanations, which gives the analysts an idea of the attributes that most affected the predictions of the model [5], [6]. Interactive visualizations further support these explanations and facilitate the comprehension of the decision-making process by security professionals (easier to understand it and investigate) [6], [9]. The system is also helping to instill confidence in automated malware detection and decrease the need to perform manual verification by providing transparency in the determination of results [5].

5. Real-Time Monitoring

The CyberGuardX real-time monitoring feature provides proactive detection and quick response to the malicious activity. With the Watchdog library, file systems events are continuously monitored, and therefore new files or files that have been changed can be detected immediately [14]. Parallel to the process monitoring is done using psutil to monitor the behavior of the system and detect anomalies that may indicate a threat [7], [13]. Correlation of events is used to complement these observations and intelligently connect file and process activities to construct a global view of suspicious activity [2], [12]. Lastly, an

automated pipeline will make sure that every file detected is immediately analyzed and this reduces the detection latency and also provides the system mechanisms greater protection against emerging threats [13], [14].

6. Dashboard and Visualization

CyberGuardX has a visualization and interaction layer that can be used to offer an efficient and intuitive interface to security analysts. Frontend is constructed on React, modern UI elements are used to provide clean and friendly experience [3]. One of these is a Flask-based backend that contains data serving and communication between system modules [10]. In order to provide continuous situational awareness, real-time updates are supported via WebSocket connections, as a result of which threats are monitored in real time, and the results of the analysis are received [14]. Also, the dashboard includes a number of interactive analyst tools that enable users to continue the investigation and simplify the process of making decisions [5], [6].

V. IMPLEMENTATION & SYSTEM CONFIGURATION

Table II – System Infrastructure

Component	Description
Static Analyzer	Python-based with pefile, python-magic libraries
ML Engine	Scikit-learn joblib persistence Random Forest.
XAI Module	SHAP Tree Explainer in explanation of decisions.
Real-Time Monitor	Watchdog + psutil system surveillance.
Web Interface	React Web Application + Flask Web Application.
Database	SQLite development, PostgreSQL production.
Containerization	Docker Compose for multi-service deploymentMulti-service deployment of Docker Compose.
API Integration	External threat intelligence virus total API.

A. Sample Feature Extraction Code:

```
def extractpefeatures(filepath):
pe = pefile.PE(filepath) features = {
'entropy': calculateentropy(filepath),
'import_count':
len(pe.DIRECTORYENTRYIMPORT),
'section_count':
pe.FILEHEADER.NumberOfSections,
'file_size': os.path.getsize(filepath)
}
return features
```

B. SHAP Explanation Generation:

```
explainer = shap.TreeExplainer(model) shapvalues =
explainer.shapvalues(features) explanation = {
'prediction': prediction, 'confidence': confidence,
'topfeatures': get_top_features(shap_values)
}
```

VI. PERFORMANCE EVALUATION

The performance of the system was assessed along different lines:

A. Classification Performance:

On a test population, the system was 99.2 percent accurate.

The presence of balanced classification performance is validated by 4,000 samples, 99.1% means the samples are precise (low false positives), 99.3% recall (primarily malware samples), and an F1-score of 99.2.

B. Processing Performance:

The efficiency of the system was 8 seconds on average single-file analysis time, and the throughput maintained was 32 files per minute in batch mode. SHAP-based accounts were produced within 0.8 seconds, and real-time tracking only took 0.15 seconds to detect, which justifies its use in operational settings which are dynamic.

C. Zero-Day Detection:

The system was highly generalized to the previously unknown threats with a 94.8 percent detection rate on unknown malware samples and a 91.4 percent protection against polymorphic evasion attacks. The mean zero-day predictions score was 87.3% which indicates its consistency in dealing with new types of attacks.

VII. RESULTS & DISCUSSION

The CyberGuardX model has proven to have a better performance than the traditional signature systems.

A. Detection Effectiveness:

CyberGuardX framework had a high accuracy of 99.2 percent compared to traditional antivirus systems with a 87.5 percent accuracy and a 94.8 percent zero-day detection rate which was a high result in comparison with 23.7 percent in signature-based methods. In addition, it was able to process files within 2.3 seconds, which was a lot faster than 15+ seconds of external scanning services.

B. Explainability Impact:

SHAP-based explanation integrations led to 94.7% agreement between the analysts with the decisions made by AI and a 40 percent decrease in manual analysis time. Confidence of analysts in the automated outputs increased by 89.1, and it is clear that explainability is an important value in operational context.

C. Operational Benefits:

CyberGuardX improved general performance with an analysis throughput 300 percent greater than that of manual techniques, and a threat response time 85 percent faster with automation. There was also an improvement in the productivity of the analysts by 45 percent an hour and this is evidence of the tangible benefits of the workforce.

D. System Scalability:

The infrastructure was able to support 50 simultaneous users with less than 20 seconds response times and was linearly scalable with more CPU cores. Memory consumption was also lean, with a base capacity of 150MB and 50MB per concurrent analysis, which was cost-effective to scale.

VIII. LIMITATIONS

Although CyberGuardX delivered positive outcomes, there are a number of weaknesses:

File Format Support PE, PDF and Office formats are currently supported; no mobile app analysis Mobile app analysis is not covered by Dynamic Analysis Gap Static analysis covers the behavioural analysis, and needs its own sandbox infrastructure. It is possible that Training Data Dependency Performance will suffer serious performance losses in the presence of greatly new attack vectors. Resource Requirements Consumes a lot of memory when performing batch processing. Update Frequency Model retraining was necessary monthly in order to perform optimally with regard to emerging threats.

IX. FUTURE WORK

Future upgrades to CyberGuardX will be done to improve its analysis depth, scope, and scale. Future developments envisaged involve the incorporation of sandbox environments to facilitate the more dynamic analysis and the use of deep learning models including CNNs and RNNs to detect sequential patterns better. The framework will also be expanded to allow Android APK and iOS IPA file analysis using mobile applications to further provide applicability. A cloud-native infrastructure built using Kubernetes will increase the scalability of enterprise environments on the deployment side. The explainability of the system will also be enhanced by integrating the techniques other than SHAP, threat intelligence

Integration with MITRE ATT &CK framework as well as STIX/TAXII feeds will give more contextual awareness.

Moreover, federated learning methods will be explored to allow organizations to model training together without risking the privacy of their data. Lastly, specialized methods of advanced evasion detection such as malware generated by AI will be created to provide resistance against new threats.

X. CONCLUSION

The study shows that an integrated AI-based malware detection framework is efficient and can solve several major limitations of the conventional signature-based systems. CyberGuardX has been able to integrate both the machine learning classification, explainable AI, and real-time monitoring with the static analysis and deploy a single system. A high accuracy of 99.2 percent, analysis time of 2.3 seconds, and open-ended decision-making with the help of SHAP explanations, makes the framework a viable solution to the current operations of cybersecurity.

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