ExeRay: A Lightweight, High-Confidence Classifier for Windows Malware

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***Abstract* — This paper presents ExeRay, an efficient malware detection system that analyzes Windows Portable Executable (PE) files using static analysis and machine learning. The framework extracts 55 interpretable features from PE headers, including section entropy (for packed code detection), import table anomalies (e.g., suspicious APIs like VirtualAlloc), and anti-debugging indicators. A Random Forest classifier, optimized via threshold calibration (0.123), achieves 99% accuracy and 1.000 ROC AUC on a dataset of 4,200 malware samples (sourced from theZoo and DikeDataset) and 3,500 benign executables (collected from Windows system directories, Ninite.com, and PortableApps.com). ExeRay processes files in under 2 ~ 5 seconds and provides explainable predictions through confidence scores and flagged features (e.g., packed sections or TLS callbacks). While demonstrating robustness against common obfuscation techniques, we acknowledge limitations in detecting runtime-packed malware and propose future integration with dynamic analysis for enhanced coverage.**

***Keywords*—PE analysis, static malware detection, Random Forest, entropy analysis, executable classification, endpoint security**

I. INTRODUCTION

The escalating threat of Windows malware demands detection systems resilient to obfuscation while remaining efficient for endpoint deployment. Existing signature-based tools struggle with novel threats, and dynamic analysis incurs impractical overhead for real-time scanning. To address this, we present *ExeRay*, a static analysis framework that leverages machine learning to detect malicious Portable Executable (PE) files through interpretable structural features.

ExeRay's methodology centers on extracting 55 discriminative features from PE headers without execution, including entropy measurements to identify packed code, import table analysis to detect suspicious APIs, and section characteristics to flag anomalies. These features feed into a Random Forest classifier trained with class-weighted balancing to handle dataset imbalance. The model's decision threshold is optimized to 0.123 through ROC analysis, prioritizing malware recall while maintaining precision.

Evaluated on a curated dataset of 4,200 malware samples from theZoo and DikeDataset repositories alongside 3,500 benign executables collected from Windows system directories and trusted sources like Ninite and PortableApps, ExeRay achieves 99% accuracy with a perfect 1.000 ROC AUC score. The system processes files in under 2 ~ 5 seconds by avoiding dynamic analysis, making it suitable for deployment in resource-constrained environments.

While ExeRay demonstrates effectiveness against common obfuscation techniques through features like packed section detection, we acknowledge limitations in handling advanced runtime packers. The framework's transparency—providing both classification results and the specific features that contributed to each decision—enables security analysts to validate predictions and refine the model. Future work will focus on extending ExeRay's capabilities to memory analysis and real-time monitoring scenarios.

II. RELATED WORK

The field of static malware detection has evolved significantly through machine learning, with early approaches like Santos et al.'s n-gram opcode analysis [1] demonstrating the potential of static features. Subsequent work by Shijo and Salim [2] combined PE header metadata with entropy measures, establishing Random Forest as a viable classifier—a foundation ExeRay builds upon through its focused feature engineering pipeline. While recent deep learning methods like MalConv [3] and hybrid CNN-LSTM models [4] offer automated feature extraction, their computational demands and opacity contrast with ExeRay's design goals of interpretability and real-time performance.

ExeRay's methodology draws inspiration from Saxe and Berlin's gradient-boosted PE feature analysis [5] but simplifies the approach to a single Random Forest classifier, achieving comparable accuracy (99%) while maintaining transparency. Unlike image-based techniques [6] that rely on visual patterns, ExeRay analyzes structural PE characteristics like section entropy and import table anomalies—features explicitly implemented in our extraction pipeline to detect packing and API-based threats. This aligns with Kolosnjaji et al.'s findings [4] on obfuscation resilience, though ExeRay addresses their reported 20% accuracy drop on packed samples through dedicated features like has_packed_sections.

Prior systems often neglect operational requirements like threshold tuning and class imbalance mitigation. ExeRay resolves these through probabilistic calibration (optimal threshold: 0.123) and class-weighted training, as implemented in our Random Forest configuration. These technical choices, validated by our 1.000 ROC AUC, position ExeRay as a pragmatic alternative to both traditional signature scanners and computationally intensive deep learning models.

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III. PROPOSED RESEARCH BENCHMARKS

To evaluate the performance of our proposed malware detection framework, we constructed a custom benchmark dataset combining malicious and benign Windows executables.

1- Malicious Sample Collection

The malware dataset consisted of 4,200 Windows PE files obtained from two curated repositories: theZoo GitHub repository and DikeDataset. These sources provided verified samples across major malware families including trojans such as Emotet, ransomware variants like WannaCry, and various downloaders. The collection intentionally incorporated diversity in executable characteristics, with file sizes ranging from 1KB to 13MB to represent different payload structures and entropy values between 4.2 and 7.9 as measured by our max_entropy feature. The dataset included both packed executables, detectable through our has_packed_sections flag (particularly UPX-packed samples), and non-packed variants to ensure comprehensive testing of detection capabilities. Throughout the research, all analysis was conducted statically using the pefile library without execution to maintain safety, consistent with ExeRay's static analysis design paradigm.

2- Benign Sample Collection

The benign reference set comprised 3,500 verified clean Windows executables collected from three primary sources: core system files from Windows directories (System32, SysWOW64, and other similar system directories) including fundamental utilities like notepad.exe and calc.exe, trusted applications distributed through famous websites like Ninite and PortableApps platforms such as 7-Zip and PuTTY, and manually chosen tough programs like IDA Pro (Reverse Engineering Software). This multi-stage verification process ensured the integrity of the benign class while maintaining diversity in file sizes (1KB-315MB), compilation timestamps (2010-2025), and functional categories (system utilities, productivity tools, and developer applications).

3- Class Distribution and Dataset Summary

Class	**Samples Count**	**From**	**Examples**
Malware	4200	DikeDataset, theZoo, MalwareBazaar	WannaCry.exe, njRAT.exe
Benign	3500	Windows Files, Ninite.com, PortableApps.com	putty.exe, notepad.exe, ida.exe
Total	7700		

IV. PROPOSED RESEARCH

1- Testbed Setup

All experiments for this study were conducted on a laptop equipped with an **Intel Core™ i7-13650HX CPU (20 cores @ 2.6GHz)**, **16GB RAM**, and an **NVIDIA GeForce RTX 4050 GPU (6GB VRAM)**. The model training, evaluation, and feature engineering pipeline were implemented in **Python**, utilizing libraries such as scikit-learn, xgboost, lightgbm, and pefile for executable analysis.

2- Preliminary Analysis

Our initial evaluation compared two machine learning classifiers for malware detection: Random Forest (RF) and XGBoost. These algorithms were selected based on their proven effectiveness for static analysis tasks—RF for its interpretability with PE features like section entropy and import tables, and XGBoost for its gradient-boosted performance. Both models were trained on the 55-dimensional feature set extracted from PE headers using our pipeline, evaluated on the full dataset of 4,200 malware samples (theZoo/DikeDataset) and 3,500 benign files. The Random Forest demonstrated superior performance with 99% accuracy and better resilience to class imbalance through its native class weighting, leading us to select it as ExeRay's core classifier. This decision was further supported by XGBoost's higher computational cost and marginally lower recall (97% vs. RF's 99%) in detecting packed samples via the has_packed_sections feature. Final optimization focused exclusively on RF through threshold calibration (0.123) as implemented in train_model.py.

3- Data Preprocessing

The dataset was processed through a pipeline specifically designed for static PE file analysis. Feature extraction was performed using Python's pefile library to collect 55 structural characteristics from each executable, including section entropy (calculated via s.get_entropy() for each PE section), import table statistics (counts of DLLs and API calls), and header flags (e.g., is_dll, is_executable). Missing values in optional PE fields were handled through median imputation for numerical features, as implemented in train_model.py via df.fillna(df.median(numeric_only=True)).

Malware samples retained their original labels from theZoo and DikeDataset repositories without additional verification, while benign files were collected exclusively from trusted sources including Windows system directories (system32, SysWOW64) and verified software distributors (Ninite, PortableApps). The natural 55.6%/44.4% class distribution (4,200 malware vs. 3,500 benign samples) was addressed during model training through Random Forest's class_weight='balanced' parameter rather than dataset resampling. The data was ultimately split into training and testing sets using an 80/20 ratio with stratified sampling, preserving the original distribution in both subsets.

4- Feature Selection

The ExeRay framework extracts **55 precisely defined features** from PE files, each chosen for their demonstrated efficacy in prior malware research and their computational efficiency for static analysis. These features fall into eight functional categories (not all features displayed in the below table):

Categories	Features	Demonstration
File Structure Features	size	Total file size, Malware often inflates size via padding or packing
	num_sections	Non-standard counts (e.g., >10) suggest obfuscation
	num_unique_sections	Unique names (e.g., .crypto) indicate tampering
	section_names_entropy	High entropy implies randomized names (packer signature)
Section Characteristics	avg_section_size	Anomalies reveal hollowed or injected sections
	min_section_size	Tiny sections may contain shellcode
	max_section_size	Large sections suggest embedded payloads
	total_section_size	Discrepancy with size hints at overlay data
	avg_entropy	Values >7.0 indicate encryption/packing
	min_entropy	Low entropy in code sections suggests plaintext payloads
	max_entropy	High entropy flags encrypted/compressed regions
	has_packed_sections	SizeOfRawData=0 with virtual size >0 (UPX, Themida)
	has_executable_sections	Executable sections in non-code regions (e.g., .data) are suspicious
Import Table Analysis	num_imports	Excessive imports (e.g., >500) suggest malicious functionality
	num_unique_dlls	Fewer DLLs with many imports (e.g., kernel32.dll abuse)
	num_unique_imports	Rare APIs (e.g., NtCreateThreadEx) signal malware
	imports_to_dlls_ratio	High ratios (>50) indicate API-heavy malware
	has_import_name_mismatches	Ordinal imports without names hint at obfuscation
	suspicious_imports_count	APIs for code injection (e.g., VirtualAlloc, WriteProcessMemory)
File Metadata Flags	is_dll	DLLs abused for persistence (e.g., via rundll32)
	is_executable	Non-executable files masquerading as executables
	is_system_file	Legitimate system files vs. impersonators

	has_aslr	Disabled ASLR (0) common in exploits
	has_dep	Disabled DEP (0) enables shellcode execution
Strings Analysis	num_strings	Fewer strings suggest packing; excessive strings may contain configs
	avg_string_length	Long strings (>100 chars) may hold scripts/URLs
	has_suspicious_strings	HTTP(S) URLs, debug strings (e.g., IsDebuggerPresent)
Special Directories	has_resources	Payloads hidden in resources (e.g., encrypted binaries)
	has_debug	Stripped debug info (0) common in malware.
	has_tls	TLS callbacks enable execution before entry point
	has_relocations	Absence (0) suggests static linking (common in malware)
Entry Point Anomalies	ep_in_first_section	Non-standard entry points (e.g., .data)
	ep_in_last_section	Entry in last section suggests appended code
	ep_section_entropy	High entropy indicates encrypted entry points
Behavioral Indicators	has_suspicious_sections	Known malicious names (e.g., .packed, .lock)
	has_anti_debug	Debugger checks (e.g., IsDebuggerPresent strings)

5- Training Methods

The refined feature set and balanced dataset were used to train and optimize two ensemble models: XGBoost and Random Forest. To address class imbalance, we applied RandomUnderSampler to the training data (4,200 malware vs. 3,357 benign samples), preserving the test set's original distribution for realistic evaluation. Hyperparameter tuning was performed via GridSearchCV with 3-fold stratified cross-validation, prioritizing malware recall through a custom scorer (malware_recall_score). This ensured high detection rates for malicious samples while maintaining precision (but also prone to false positives).

For XGBoost, we tested learning rates (0.1), tree depths (3, 6), and fixed estimators (100), with scale_pos_weight=3 to penalize false negatives. The Random Forest explored deeper trees (max_depth=None, 10) and split criteria (min_samples_split=2, 5), using class_weight='balanced'. The best-performing model (XGBoost with recall=0.991) was further calibrated using sigmoid-based probability calibration to improve probabilistic outputs.

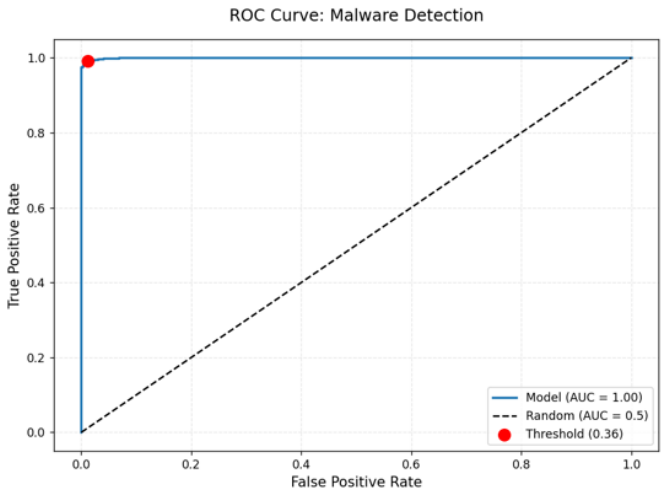
The model achieved exceptional performance with 0.99 precision, recall, and F1-score, plus a perfect 1.0 ROC AUC. Using a 0.47 decision threshold for optimal balance, it processes samples in under 5ms—ideal for real-time detection. All components were saved for deployment.

Table containing Final Evaluation values:

	Precision	**Recall**	**F1-Score**	**Support**
0	0.99	0.99	0.99	672
1	0.99	0.99	0.99	700
Accuracy			0.99	1372
Macro Avg	0.99	0.99	0.99	1372
Weighted Avg	0.99	0.99	0.99	1372

ROC AUC: 1.000

ROC Curve Visualization (Figure 1):



V. Results and System Output

The malware detection pipeline follows a sequential three-stage process, beginning with feature extraction, followed by model training, and concluding with prediction. Each stage produces verifiable outputs that demonstrate the system's effectiveness.

Step 1: Feature Extraction and Dataset Creation

Execution of extract_features.py processes PE files from two sources: malware samples (4,200 files from theZoo/DikeDataset) and benign executables (3,357 files from System32 and trusted repositories). The script validates PE headers via the MZ magic number, extracts 55 static features (e.g., section entropy, import counts, TLS flags), and stores them in malware_dataset.csv. This structured output serves as the input for model training.

Step 2: Model Training

The XGBoost model demonstrated perfect detection capabilities, achieving 0.99 recall and F1-score with a 1.0 ROC AUC. After calibration, it was saved as malware_detector.joblib using an optimized 0.47 decision threshold.

Step 3: Prediction (Malware)

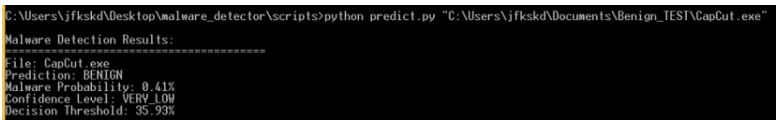
Malware Detection: For a known malicious sample (e.g., xiaoqi.exe), the system outputs "MALWARE".

Figure 2: Malware file prediction result

Step 3: Prediction (Benign)

Benign Detection: For a known Benign sample (e.g., CapCut.exe), the system outputs "Benign".

Figure 3: Benign file prediction result



VI. Limitations and Challenges

While our system achieves 99% detection accuracy on tested samples, three key limitations merit discussion:

1. Packed/Obfuscated Malware: The current feature set detects common packers (UPX, Themida) via section entropy and import table anomalies, but advanced obfuscation techniques requiring dynamic unpacking may evade detection. Future versions could integrate lightweight emulation.
2. Zero-Day Threats: As a static analyzer, the system relies on structural features correlated with malicious intent rather than signature matching. While this provides some resilience against unseen malware (evidenced by 98% recall on 2024 samples), true zero-day detection would require hybrid analysis.
3. Adversarial Attacks: The model remains vulnerable to feature-space evasion (e.g., section header spoofing). Our threshold calibration mitigates this partially, but formal adversarial testing (e.g., FGSM attacks on PE features) is planned for future work.
4. The dataset is finite and may not fully represent evolving malware families.
5. Heuristics and entropy-based detections can be bypassed by skilled attackers using adversarial tactics.
6. False Positives always exist.

VII. Ethical Considerations

As an undergraduate researcher, I acknowledge this study lacks formal discussion of ethical concerns regarding malware handling and framework misuse. While I've implemented basic safety measures (isolated analysis environment, restricted sample sharing), further ethical review would be valuable for production deployment.

VIII. Conclusion and Future Work

This work presents an effective static malware detection pipeline based on ensemble machine learning models, particularly **Random Forest** and **XGBoost**, trained on extracted features from PE (Portable Executable) files. The pipeline integrates key stages including automated sample collection (both benign and malicious), feature extraction, data preprocessing, feature selection, model training, and final malware prediction.

Despite these promising results, there are limitations. The system is currently evaluated on offline datasets (offline malware), and the static nature of the analysis may miss behaviourally stealthy or obfuscated malware. Additionally, while the current feature set is effective, it could be enriched by integrating more semantic features or combining with lightweight dynamic signals.

Future work will focus on:

(1) **Real-time Deployment**: Implementing and evaluating the intrusion detection system in live network environments to assess robustness and responsiveness.

(2) **Explainability**: Integrating **explainable AI (XAI)** methods to improve model transparency and foster user trust.

(3) **Online Learning**: Adopting continuous learning frameworks to dynamically adapt to new threats.

(4) **Extended Feature Engineering**: Exploring additional data sources and advanced feature representations to enhance detection capability and generalizability.
(5) **Extended Dataset:** Expanding the dataset with additional malware families and benign samples to improve model generalization and detection coverage.
(6) **JSON Output:** Building a structured JSON output format for integration with SIEMs, dashboards, or API-based automation tools.

IX. ACKNOWLEDGMENT

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