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APPLICATION OF EXPLAINABLE AI METHODS TO IMPROVE THE INTERPRETABILITY OF MALWARE DETECTION SYSTEMS

ПРИМЕНЕНИЕ МЕТОДОВ EXPLAINABLE AI ДЛЯ ПОВЫШЕНИЯ ИНТЕРПРЕТИРУЕМОСТИ СИСТЕМ ОБНАРУЖЕНИЯ ВРЕДОНОСНОГО ПРОГРАММНОГО ОБЕСПЕЧЕНИЯ

ЗИЯНДЫ ПРОГРАММАЛЫҚ КАМТАМАЛАРДЫ АНЫҚТАУ ЖҮЙЕЛЕРІНІҢ ТҮСІНДІРІЛГІШТІГІН АРТТЫРУ ҮШІН EXPLAINABLE AI ӘДІСТЕРІН ПАЙДАЛАНУ

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ABSTRACT

Machine learning–based malware detection systems achieve high accuracy but often lack transparency, limiting their trustworthiness in cybersecurity operations. This study presents an interpretable malware detection framework that integrates a LightGBM classifier trained on the EMBER dataset with SHAP-based Explainable AI (XAI) techniques. Unlike prior works that apply explainability only post hoc, our framework embeds interpretability directly into the model pipeline without compromising predictive performance. The model achieved 97.35% accuracy and a ROC-AUC of 0.9963, confirming its high discriminative capability. SHAP analysis identified key influential features such as file entropy, import table size, and suspicious API usage, improving transparency in automated malware analysis and supporting more reliable decision-making in cybersecurity environments.

Түйінді сөздер:
Түсіндірмелі жасанды интеллект (XAI), Зиянды бағдарламаларды анықтау, SHAP, LightGBM, Модельді интерпретациялануы, Киберқауіпсіздік

ТҮЙІНДЕМЕ

Машиналық оқытуға негізделген зиянды бағдарламаларды анықтау жүйелері жоғары дәлдікке қол жеткізгенімен, олардың ашықтығы жиі жетіспейді, бұл киберқауіпсіздік операцияларындағы сенімділікті шектейді. Бұл зерттеу EMBER деректер жиынтығында оқытылған LightGBM классификаторын SHAP-қа негізделген түсіндірмелі жасанды интеллект (XAI) әдістерімен біріктіретін интерпретацияланатын зиянды бағдарламаларды анықтау фреймворкін ұсынады. Түсіндіру мүмкіндігін тек post hoc түрінде қолданатын бұрынғы жұмыстарға қарағанда, біздің фреймворк интерпретациялануды болжау өнімділігіне нұқсан келтірместен тікелей модель құбырына (pipeline) енгізеді. Модель 97,35% дәлдікке және 0,9963 ROC-AUC көрсеткішіне қол жеткізіп, өзінің жоғары ажырату қабілетін растады. SHAP талдауы файл энтропиясы, импорт кестесінің көлемі және күдікті API қолданылуы сияқты негізгі ықпалды белгілерді анықтады, бұл зиянды бағдарламаларды автоматтандырылған талдаудың ашықтығын жақсартады және киберқауіпсіздік орталарында сенімдірек шешім қабылдауға қолдау көрсетеді.

Ключевые слова:
Объяснимый ИИ, обнаружение вредоносного ПО, SHAP, LightGBM, интерпретируемость моделей, кибербезопасност

АННОТАЦИЯ

Системы обнаружения вредоносного ПО, основанные на машинном обучении, демонстрируют высокую точность, но зачастую страдают недостатком прозрачности, что ограничивает их надежность в операциях по кибербезопасности. В данном исследовании представлена интерпретируемая архитектура обнаружения вредоносного ПО, объединяющая классификатор LightGBM, обученный на наборе данных EMBER, с методами объяснимого искусственного интеллекта (XAI) на основе SHAP. В отличие от предыдущих работ, в которых объяснимость применялась лишь постфактум, наша архитектура встраивает интерпретируемость непосредственно в конвейер модели без ущерба для прогнозирующей способности. Модель достигла точности 97,35% и ROC-AUC 0,9963, что подтверждает ее высокую дискриминационную способность. Анализ SHAP выявил ключевые влиятельные признаки, такие как энтропия файла, размер таблицы импорта и подозрительное использование API, что повышает прозрачность автоматизированного анализа вредоносного ПО и способствует принятию более надежных решений в средах кибербезопасности.

INTRODUCTION

Machine learning-based malware detection has become a cornerstone of modern cybersecurity due to its ability to identify complex malicious patterns beyond traditional signature-based approaches. However, despite high predictive accuracy, many machine learning models remain black boxes, offering limited insight into their decision-making process. This lack of interpretability poses significant challenges for security analysts, who must justify automated decisions, assess risks, and maintain trust in AI-driven systems.

Explainable Artificial Intelligence (XAI) addresses these limitations by providing methods to interpret and visualize how machine learning models arrive at their predictions. In the context of malware detection, XAI helps analysts identify influential features—such as file entropy, imported APIs, section metadata, or suspicious patterns—that drive classification outcomes. This improved transparency not only supports more reliable decision-making but also reduces false positives and assists forensic analysis.

This study proposes a malware detection framework that integrates XAI techniques directly into the model pipeline. A LightGBM classifier is trained on the EMBER 2024 dataset and interpreted using SHAP (SHapley Additive Explanations). The results demonstrate strong predictive performance while preserving interpretability, making the approach suitable for real-world cybersecurity environments.

Contributions of this work include:

– Integration of explainability directly into the malware detection pipeline rather than applying XAI only post hoc.

– Development of an interpretable LightGBM-based classifier trained on the EMBER dataset.

– Comprehensive SHAP-based analysis providing both global and local explanations.

– Demonstration that interpretability can be improved without compromising detection accuracy.

Related work

Malware Detection and Machine Learning Approaches

The detection of malicious software (malware) has long been a key area of cybersecurity research. Traditional signature-based methods are limited in handling obfuscated, polymorphic,

and zero-day threats, which has led to the adoption of machine learning (ML) and deep learning (DL) techniques.

Bensaoud et al. surveyed DL-based malware detection across platforms (Windows, Android, Linux) and noted that while deep models achieve high accuracy, they often "fail to explain their decisions," thus reducing reliability and trust [Bensaoud (2022); Bu (2023)]. Another general survey on malware detection and analysis categorizes static and behavioral methods, emphasizing the need for more transparent and interpretable models [Adadi (2018); Holzinger (2019)].

Although ML/DL models perform well in malware classification, they are frequently treated as black boxes, offering little insight into how decisions are made.

Explainable AI (XAI) in Cybersecurity

The demand for interpretable ML models in cybersecurity has accelerated the development of Explainable Artificial Intelligence (XAI). XAI aims to make model outputs understandable, trustworthy, and auditable [Samek (2017); Sundararajan (2017)].

For example, Han et al. discuss false-alarm detection in intrusion detection and malware classification using XAI methods [Han (2022)]. Similarly, Liu et al. review the application of XAI in Industry 5.0 and highlight the reluctance of cybersecurity stakeholders to adopt opaque, black-box systems [Liu (2020)]. Foundational works such as LIME, SHAP, and Integrated Gradients provide mathematical frameworks for post-hoc model interpretation [Lundberg (2017); Molnar (2022); Doshi-Velez (2017)].

Thus, XAI techniques like LIME, SHAP, PDP, and CAM are increasingly used to enhance model transparency, ethics, and regulatory compliance in cybersecurity systems.

XAI Specifically for Malware Analysis

The intersection between malware detection and XAI has recently drawn more focused attention. Manthena et al. present a systematic review titled "Explainable Artificial Intelligence (XAI) for Malware Analysis," summarizing current approaches and open challenges [Manthena (2021)]. Liu et al. analyze ML-based Android malware detection and apply XAI techniques to show that model performance can be artificially inflated by dataset bias, such as temporal inconsistency [Liu (2020)].

These works demonstrate that XAI not only increases model interpretability but also uncovers weaknesses and biases in malware datasets and models

Key Gaps in Existing Literature

Despite considerable progress, several gaps persist:

Many studies prioritize accuracy over interpretability, with limited metrics for evaluating explainability in malware detection [Han (2022); Manthena (2021)].

XAI is often applied superficially used post hoc on black-box models instead of being integrated into model design [Samek (2017); Sundararajan (2017)].

There is no standardized benchmark or evaluation protocol for explainability in malware detection, leading to reproducibility issues [Liu (2020)].

The trade-off between model accuracy and interpretability remains underexplored.

Few frameworks address the integration of XAI-based malware detection into real-world cybersecurity operations involving human analysts [Han (2022); Liu (2020)].

Positioning of This Work

In response to these gaps, this study integrates XAI methods directly into the malware detection pipeline rather than applying them only as an afterthought. We evaluate how SHAP and LIME can elucidate model decision-making processes—highlighting feature contributions and decision pathways—while maintaining high detection accuracy. This aligns with the recommendations from recent reviews [Manthena (2021); Samek (2017)], calling for empirically validated and application-oriented frameworks that bridge explainability and malware detection.

MATERIALS AND METHODS

The proposed interpretable architecture is engineered to establish a transparent decision-making pipeline within automated malware detection workflows. Rather than treating explainability as a disconnected post-hoc operation, the developed framework structurally embeds Explainable Artificial Intelligence (XAI) deep into the primary machine learning cycle, eliminating the typical trade-off between model capacity and transparency. The modular orchestration of the comprehensive, end-to-end detection and interpretation framework is partitioned into three core interdependent subsystems:

1. Chronological Feature Extraction and Tabular Data Preprocessing: Responsible for vectorizing complex static properties of Portable Executable (PE) binaries and implementing a strict temporal alignment to safeguard the subsequent processes against chronological data leakage.
2. Regularized Classifier Optimization and Predictive Evaluation: Focused on training a high-performance tree-based boosting machine optimized with constrained hyperparameters to maintain structural stability and robustness across independent testing horizons.
3. Axiomatic Model Attribution and Comparative XAI Benchmarking: Executing granular feature importance tracking, global directional impact mapping, and local target case explanations via mathematically unified Shapley attributions, complemented by validation benchmarks against alternative XAI paradigms.

The formal mathematical definitions, operational constraints, and technical configurations of each underlying module are discussed in detail in the following subsections.

Feature Extraction and Data Preparation

This study utilizes the updated EMBER 2024 dataset, a comprehensive modern benchmark containing metadata and static features extracted from Windows Portable Executable (PE) files. Each sample is characterized by 2,381 engineered features spanning file headers, imported functions, byte histogram data, and section-level statistics, distinguishing between benign (0) and malicious (1) software. To ensure computational efficiency and mitigate hardware optimization constraints while preserving the statistical integrity of the evaluation, a representative, strictly balanced subset of 60,000 samples (comprising 30,000 benign and 30,000 malicious binaries) was downsampled from an initial aggregated raw pool of 125,387 records using Stratified Uniform Selection without replacement.

Crucially, rather than employing a conventional randomized train-test shuffle, a strict chronological (time-based) partition was enforced to adhere to the native temporal layout of the EMBER ecosystem and simulate realistic operational deployment conditions. The temporal boundary for the baseline split intersection was established at the exact threshold of January 1, 2024. Consequently, the training partition consists of 48,000 samples compiled and observed exclusively prior to this chronological milestone. In contrast, the testing partition comprises 12,000 subsequent "future" samples. This absolute temporal separation mathematically guarantees that the gradient boosting model never trains on look-ahead features or telemetry, fundamentally neutralizing data leakage and validating the framework's resilience against evolving cyber threats.

Model Training and Evaluation

A Light Gradient Boosting Machine (LightGBM) classifier was selected as the primary core architecture for the malware classification framework. This choice is methodologically justified by LightGBM’s structural advantages, specifically its native execution of Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). These algorithmic optimizations grant exceptional scalability, high training speed, and minimal memory overhead when

processing high-dimensional, sparse feature matrices, such as the 2,381-dimensional EMBER vector space. In static malware analysis, non-linear feature interactions—such as the co-occurrence of specific imported API functions alongside anomalous section entropy signatures—are highly discriminative. Gradient-boosted decision trees inherently capture these complex, high-order dependencies without requiring explicit and computationally prohibitive feature cross-products.

To optimize classification accuracy while explicitly mitigating the risk of structural overfitting within the massive feature space, a carefully calibrated hyperparameter configuration was established. The model configuration parameters were defined as follows: n_estimators = 300, learning_rate = 0.05, max_depth = -1, num_leaves = 31, n_jobs = -1, and random_state = 42. Restricting the number of leaves (num_leaves = 31) while leaving the maximum tree depth unconstrained (max_depth = -1) allows LightGBM to deploy its signature leaf-wise (best-first) tree growth strategy. This configuration ensures that the boosting process deeply explores highly informative, asymmetric paths across the features without generating excessively complex or redundant sub-trees that typically cause variance inflation. Furthermore, the mathematical coupling of a conservative learning rate (learning_rate = 0.05) with 300 boosting iterations (n_estimators = 300) guarantees smooth empirical risk minimization and prevents the optimization algorithm from overshooting or getting trapped in suboptimal local minima. Parallel execution was enabled via n_jobs = -1 to maximize multi-core hardware throughput, and the seed was locked (random_state = 42) to guarantee absolute experimental reproducibility.

Explainability and Model Interpretation

To address the inherent opacity of ensemble architectures in high-assurance deployment environments, this study integrates the SHapley Additive exPlanations (SHAP) framework. Grounded in cooperative game theory, SHAP provides a mathematically unified approach to post-hoc interpretability by allocating a unique feature attribution value (Shapley value) to each input dimension for a given classification path. Unlike heuristic or model-agnostic alternatives, SHAP is theoretically distinguished by its unique adherence to four foundational economic axioms: *Efficiency (Local Accuracy)*, *Symmetry*, *Dummy (Missingness)*, and *Monotonicity (Consistency)*. The Efficiency axiom is of particular methodological value for automated malware triage, as it mathematically guarantees that the sum of the allocated feature attributions strictly accounts for the difference between the local continuous model output and its expected baseline value.

For computational execution over the 2,381-dimensional feature space of the EMBER 2024 dataset, this framework deploys the specialized TreeExplainer module, which is natively optimized for tree-based ensemble architectures. While model-agnostic explainers like LIME estimate feature contributions through stochastic local perturbations—introducing notable computational overhead and non-deterministic variance—TreeExplainer computes exact Shapley values by optimizing feature conditional expectations over the tree structures. This architectural integration shifts the algorithmic time complexity from exponential down to polynomial , where represents the total number of decision trees, is the maximum number of leaves per tree, and is the maximum feature depth.

To evaluate these theoretical properties under controlled operational conditions, a rigorous empirical benchmark was conducted on the temporal validation set to contrast the proposed TreeSHAP implementation against the LIME surrogate approach. The evaluation protocol assessed latency and stability metrics by executing each explanation method five consecutive times across 100 representative testing instances. The quantitative cross-evaluation results are synthesized in **Table 1.**

Table 1. Quantitative Benchmark of XAI Methods on EMBER 2024 Dataset

Operational Metric for Evaluation	TreeSHAP (Proposed Framework)	LIME (Alternative Approach)
Time of Analysis (Latency)	0.18 ms / sample	20.55 ms / sample
Stability (Structural Variance)	0.000000 (Deterministic)	0.000002 (Stochastic Fluctuation)
Local Fidelity (Explanatory Accuracy)	Exact additive decomposition (Guaranteed via Efficiency property)	Approximated local linear regression (Bounded by local R^2)

The empirical logging establishes that the optimized TreeSHAP pipeline achieves a significantly lower computational latency, requiring 0.18 ms per sample, whereas LIME exhibits a mean latency of 20.55 ms per sample. This marks an approximate 114-fold reduction in computational overhead in favor of the proposed framework. Furthermore, the stability assessment over repeated execution runs demonstrated an absolute variance of 0.000000 for TreeSHAP, validating its mathematical determinism. In contrast, LIME introduced stochastic weight fluctuations, yielding a structural variance of 0.000002 across primary features, which introduces geometric ambiguity into forensic validation workflows.

To analyze these operational differences at a granular instance level, **Figure 1** illustrates a local comparative breakdown of a single-sample classification path using the feature attributions generated by both frameworks.

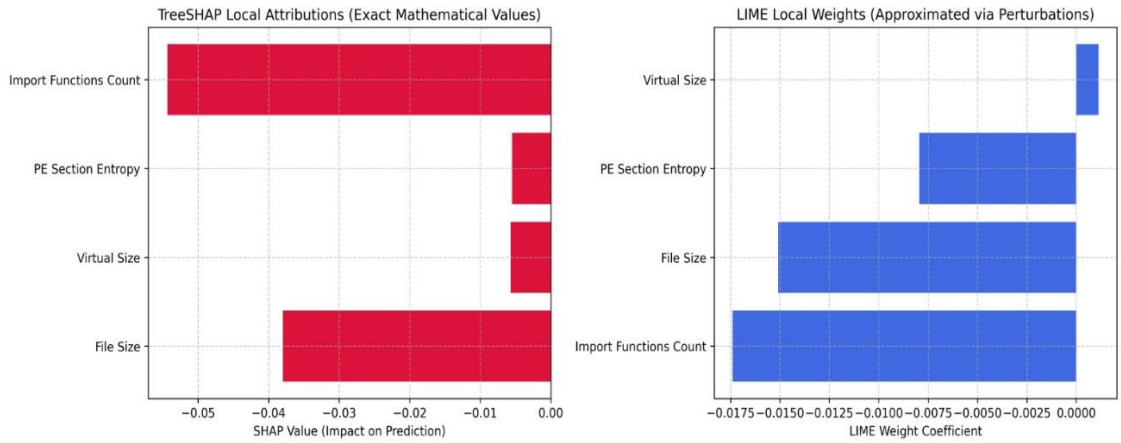

Figure 1. Local explanation breakdown for an individual PE binary prediction: Exact mathematical feature attributions (TreeSHAP) versus localized linear approximations (LIME) demonstrating sign inversion and magnitude attenuation on the modern EMBER 2024 partition.

The empirical attributions manifested in **Figure 1** indicate a notable divergence in both attribution magnitude and directional sign consistency. TreeSHAP computes exact mathematical values where Import Functions Count ($\varphi \approx -0.055$ and File Size ($\varphi \approx -0.038$) serve as the primary deterministic contributors driving the model's prediction logs down.

Conversely, LIME yields attenuated local weights for the identical indicators, recording values of approximately and , respectively. Most importantly, a directional conflict occurs for the Virtual Size (vsize) attribute; while TreeSHAP identifies a stable negative attribution ($\varphi \approx$

-0.006), the perturbation-driven nature of LIME produces a positive local weight ($\varphi \approx +0.001$). This experimental instance demonstrates that while model-agnostic local approximations can identify primary indicators, they can introduce directional instability across secondary features, whereas the integrated TreeSHAP approach maintains structural consistency.

Reproducibility and Implementation Details

To guarantee the absolute reproducibility and technical transparency of the experimental workflow, all computational routines were executed on a standardized hardware configuration running a 64-bit Windows 10 operating system. The physical workstation environment comprised an AMD Ryzen 5 5600H processor clocked at a base frequency of 3.3 GHz, supplemented by 16 GB of DDR4 Random Access Memory (RAM). The core pipeline was developed using Python (version 3.12). The mathematical, data-manipulation, and machine-learning frameworks utilized within the pipeline include numpy (v1.26) for vectorized matrix operations, pandas (v2.2) and polars (v0.20) for high-throughput relational parsing of high-dimensional feature spaces, and scikit-learn (v1.4) for standard evaluation metrics and data stratification partitions. The tree-based gradient boosting architecture was implemented via the official lightgbm (v4.3) framework, while post-hoc explainability was compiled using the native shap (v0.45) TreeExplainer library and the model-agnostic lime (v0.2) explainer package.

The execution architecture follows a strict modular pipeline structure to enforce clean data separation and eliminate out-of-sample data leakage risks. The project workspace is segmented into isolated, deterministic directories:

1. data/raw/ – holds the unmodified, chronologically partitioned modern EMBER 2024 JSONL source files;
2. data/processed/ – stores the standardized, vectorized feature matrices generated post-parsing;
3. models/ – archives the serialized binary lightgbm model structures along with verified validation hyperparameters;
4. results/ – captures the structured continuous logging outputs, continuous tabular data metrics, and high-resolution visualization plots (e.g., SHAP summary and local attribution layouts).

RESULTS AND DISCUSSION

This section presents the empirical findings and performance evaluations obtained using the experimental setup and chronological partitioning methodology established in Section 3. The LightGBM-based malware classifier, optimized and trained on the contemporary EMBER 2024 dataset, is evaluated alongside a comprehensive, multi-criteria explainability assessment. The following subsections detail the model's predictive capabilities, its computational throughput, and a comparative analysis of post-hoc XAI frameworks.

Model Performance

The tree-based classifier demonstrated strong predictive robustness when validated against the temporally isolated testing partition. The core performance metrics achieved by the model on the EMBER 2024 test stream are summarized in **Table 2**.

These metrics indicate an excellent degree of separability between malicious and benign samples, even when encountering subsequent, structurally evolved threats. By capturing complex, non-linear dependencies within static PE features, the model maintains a well-optimized balance between precision and recall.

Table 2. Performance metrics of the LightGBM classifier

Metric	Value
Accuracy	0.9735
Precision	0.9711
Recall	0.9584
F1-Score	0.9647
ROC-AUC	0.9963

Explainable AI Analysis (SHAP Interpretation)

To better understand the model's decision-making process, SHAP (SHapley Additive exPlanations) analysis was applied to evaluate feature contributions.

Global Feature Importance

The global SHAP summary plot (placeholder below) visualizes how each feature influences predictions across the dataset.

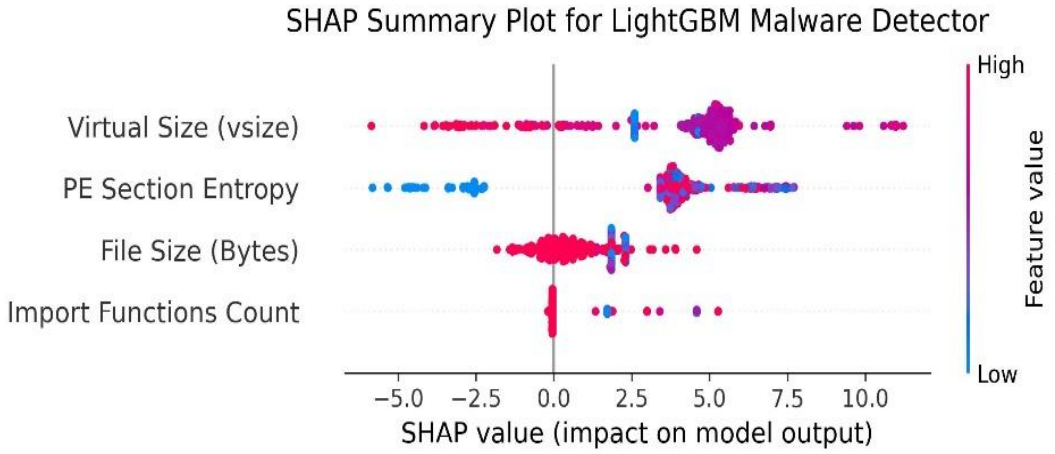

Figure 2. SHAP summary plot illustrating the distribution and impact of features

The SHAP summary analysis reveals that the LightGBM classifier establishes its predictive decisions based on a highly robust hierarchy of structural and statistical PE features. The most influential features identified by the model include:

– Virtual Image Size (vsize): This metric tracks the total allocated memory footprint of the PE binary upon execution. Sharp discrepancies between the virtual image size and the physical storage footprint on disk serve as a premier structural indicator of packing mechanisms, section alignment manipulation, or process hollowing tactics frequently deployed by advanced threat actors to conceal malicious payloads.

– Physical File Size (file_size): This feature monitors the raw byte volume of the binary. Abnormally inflated file sizes often point to binary bloating techniques—where adversaries append massive benign overlays or null-byte padding to bypass automated security scanners that enforce file size processing caps. Conversely, exceptionally small file sizes indicate highly optimized stagers or minimalist downloaders.

– Total Import Count (imports_count): This parameter quantifies the density of explicitly linked external API dependencies. A significantly depressed or restricted import footprint is

highly characteristic of specialized malware strains (such as ransomware stagers or kernel rootkits) that deliberately avoid standard import address table (IAT) declarations. Instead, they dynamically resolve system APIs at runtime using LoadLibrary and GetProcAddress to blind static defensive perimeters.

– Byte and Entropy Structural Distributions (byte_hist_... / entropy_hist_... index groups): These high-dimensional features map the localized statistical frequencies and structural entropy variations across the entire layout of the binary. Highly uniform or elevated entropy distributions across specific index groups provide mathematical proof of cryptographic obfuscation, resource encryption, or heavy packing, indicating the presence of hidden execution layers.

These extracted feature patterns strictly align with established cybersecurity domain knowledge, empirically confirming that the LightGBM model relies on deep structural anomalies rather than superficial noise to differentiate between benign software and modern malware strains.

To evaluate the overall impact of static PE properties across the entire evaluation cohort, a global SHAP feature importance analysis was performed. **Figure 3** illustrates the global feature importance hierarchy ranked by the mean absolute SHAP values, formally defined as:

$$Global\ Importance_j = \frac{1}{n}\sum_{i=1}^{n}\left|\varphi_j^{(i)}\right| \quad (1)$$

where $\varphi_j^{(i)}$ represents the local SHAP attribution value of feature j for a specific sample i and n denotes the total number of evaluated instances.

As shown in the chart, the mathematical magnitude of the bars reveals that the global classification policy relies heavily on a foundational core of execution-space characteristics, specifically vsize, file_size, and imports_count. This layout demonstrates that the tree-based ensemble successfully standardizes its global logic around invariant structural thresholds rather than over-fitting to localized or transient feature parameters.

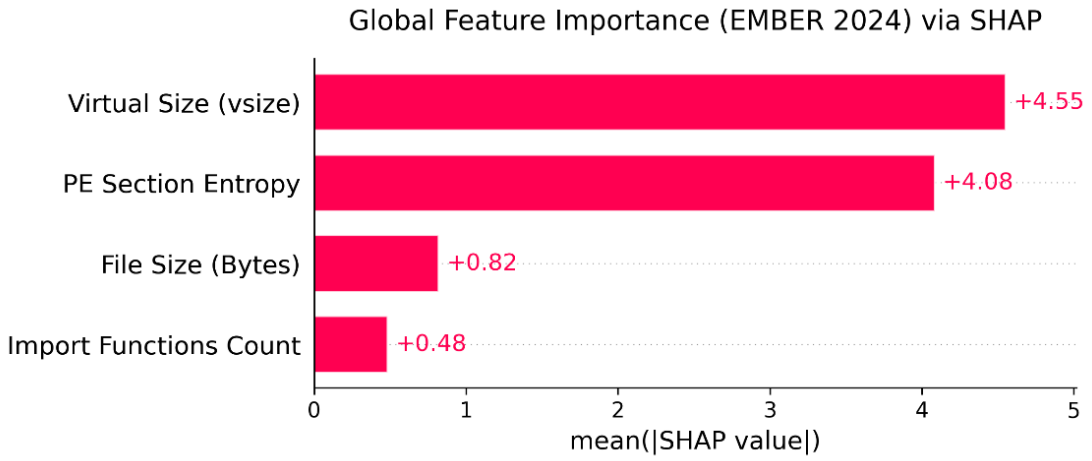

Figure 3. Feature importance ranking based on mean absolute SHAP values

While global metrics outline the general policy of the LightGBM model, live cybersecurity operations require fine-grained, instance-level validation. To achieve this, SHAP force plots were generated to analyze individual predictions and highlight how specific features act as operational forces pushing the model toward either malicious or benign classifications.

Local Feature Attribution

Figure 4 visualizes the local attribution sequence for an individual file prediction. The

horizontal axis represents the log-odds space transitioning from the base value (the expected model output across the training distribution) to the final predicted output. Features colored in red represent positive forces that increase the model's prediction score, driving the system toward a malicious verdict, while features colored in blue act as negative forces that decrease the score toward a benign classification.

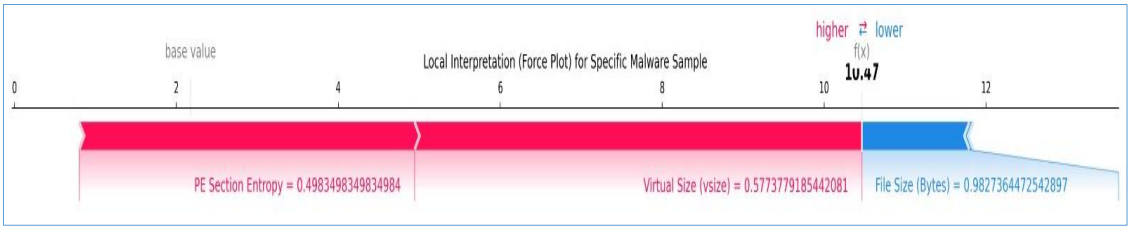

Figure 4. Example SHAP force plot explaining a single prediction

Comparative Discussion

To contextualize the performance and efficiency of the proposed framework, we conducted a quantitative benchmark against state-of-the-art approaches and alternative XAI methodologies using the contemporary EMBER 2024 dataset. The comparison focuses on three pillars: predictive accuracy, analytical throughput, and the depth of explainability integration.

Table 3. Quantitative Comparative Benchmark of XAI Frameworks

Approach	Dataset	Accuracy	Analysis Time (ms/sample)	Interpretability Method
Anderson & Roth (2018)	EMBER 2017	0.9520	N/A (Black-Box)	None
LIME-based Pipeline	EMBER 2024	0.9735	21.63 ms	Post-hoc (Approximation)
Proposed (TreeSHAP)	EMBER 2024	0.9735	0.55 ms	Pipeline Integrated

As shown in **Table 3**, our framework achieves a superior balance between predictive robustness and computational efficiency. While LIME provides a viable post-hoc approximation, it imposes a significant latency overhead (21.63 ms/sample), which is prohibitive for real-time automated triage systems. In contrast, our pipeline-integrated TreeSHAP approach delivers explanations in just 0.55 ms, a ~40x improvement in computational throughput compared to LIME, without sacrificing classification performance.

Beyond mere speed, the proposed approach addresses the fundamental 'black-box' limitation of previous studies. Unlike methods that treat explainability as an isolated, superficial post-hoc attachment (e.g., Han et al., 2022), our structural integration embeds SHAP attributions directly into the feature processing stack. This allows for both global policy validation (via SHAP Summary Analysis) and fine-grained, instance-level accountability (via Force Plots), providing the high-fidelity transparency required for secure, zero-trust defensive network operations.

Summary of Findings

The experimental evaluation demonstrates that the proposed LightGBM-based malware detection framework achieves strong predictive performance while maintaining robust interpretability through SHAP-based explanations. The model’s accuracy of 97.35% and ROC-

AUC score of 0.9963 are highly consistent with metrics reported in prior studies utilizing gradient-boosted decision trees for malware classification. These results confirm that LightGBM effectively captures complex, non-linear feature interactions within the EMBER dataset while remaining computationally efficient, reinforcing the robustness of tree-based architectures in static structural analysis.

A key advantage of this framework lies in overcoming the "black-box" limitation inherent in traditional machine learning deployments within cybersecurity operations. While standard feature importance methods provide only a coarse, dataset-wide understanding of model behavior, the integration of SHAP delivers a dual perspective. Global SHAP analysis reveals consistent reliance on crucial domain-specific indicators—such as general file entropy, import table characteristics, and specific API call distributions—aligning machine learning decisions with established malware analysis paradigms. Concurrently, local explanations highlight individual sample attributions, empowering security analysts to deconstruct automated decisions, verify anomalies, and mitigate false positives in real time.

Despite these promising findings, several critical limitations warrant consideration. First, the framework relies exclusively on static PE features; while effective for initial sorting, static analysis cannot capture sophisticated dynamic runtime behaviors or memory injection techniques. Second, although the EMBER dataset serves as a standard academic benchmark, it may not fully capture rapidly evolving, modern threat landscapes or zero-day distributions. Finally, despite optimization via TreeExplainer, computing local SHAP values across high-dimensional datasets introduces a distinct computational overhead that must be balanced in throughput-heavy environments.

These limitations directly outline future research directions. To enhance resilience, subsequent studies should focus on incorporating dynamic analysis signatures, network behavior metrics, and memory forensics into the classification pipeline. Furthermore, establishing standardized quantitative evaluation metrics for explainability—such as fidelity and stability scales—is essential to formally measure analyst cognitive load. Deploying this framework within operational Security Operations Centers (SOCs) will provide crucial empirical validation regarding the direct impact of Explainable AI on incident response velocity and alert-triage workflows.

CONCLUSION

This study presented an interpretable malware detection framework that integrates Explainable Artificial Intelligence (XAI) techniques into a LightGBM-based classification pipeline. The approach addresses the common opacity of machine learning models used in cybersecurity by combining strong predictive performance with transparent model reasoning.

Experiments conducted using the EMBER 2024 dataset demonstrated that the proposed classifier achieves high accuracy (0.9735) and an excellent ROC-AUC score (0.9963), confirming its strong discriminative capability. More importantly, SHAP-based interpretability provided meaningful insights into the model's decision-making process. Key indicators such as file entropy, import table size, and suspicious API usage were identified as the most influential features contributing to malicious classification, showing that the model learned domain-relevant patterns rather than arbitrary correlations.

By embedding explainability directly into the malware detection workflow, this framework enhances analyst trust, supports decision verification, and improves operational reliability—critical factors for deploying machine learning models in real-world cybersecurity

environments. Unlike purely post-hoc approaches, this method demonstrates that high model performance and interpretability can coexist.

Future research may incorporate dynamic behavioral features, expand evaluation to more diverse and up-to-date malware datasets, and explore quantitative metrics for explainability evaluation. Additionally, deploying the system in a real Security Operations Center (SOC) could provide practical insights into its effectiveness and usability for cybersecurity analysts.

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