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AI-Powered Malware Classification Using Static and Dynamic Feature Fusion

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Abstract:
The proliferation of sophisticated malware poses an escalating threat to cybersecurity, necessitating advanced detection mechanisms beyond traditional signature-based approaches. This research presents an AI-powered malware classification framework that leverages the fusion of static and dynamic features to enhance detection accuracy and adaptability. Static analysis extracts structural and code-based characteristics, while dynamic analysis captures behavioral patterns during execution, providing complementary insights into malware functionality. By integrating these heterogeneous features, the proposed model utilizes ensemble machine learning and deep learning techniques to achieve robust classification across diverse malware families. Experimental evaluation on benchmark datasets demonstrates the framework's high performance, achieving an average accuracy of 97.8%, with precision, recall, and F1-score consistently above 96%, outperforming conventional single-feature-based models. The fusion approach effectively mitigates limitations associated with obfuscation and polymorphic malware, ensuring resilience against evasive attacks. Significantly, the methodology reduces false positives and improves early threat detection, supporting proactive cybersecurity measures. The study highlights the potential of hybrid feature integration in enhancing AI-driven malware detection systems, providing a scalable, efficient, and adaptive solution for real-world cybersecurity applications. This work underscores the critical role of feature-level fusion in advancing automated malware classification and reinforces the importance of intelligent frameworks for robust digital threat mitigation.

1. Introduction

The rapid evolution of digital technologies has led to an unprecedented increase in the volume and sophistication of malicious software, commonly known as malware. Malware attacks, including viruses, worms, trojans, ransomware, and spyware, continue to pose significant threats to personal, corporate, and

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governmental cybersecurity infrastructures [1]. Traditional signature-based detection systems, which rely on known malware patterns, are increasingly inadequate due to the emergence of polymorphic and metamorphic malware capable of modifying their code to evade detection [2]. Consequently, the demand for intelligent, adaptive, and automated malware classification systems has become critical for enhancing cybersecurity resilience [3].

Artificial Intelligence (AI) and machine learning (ML) techniques have demonstrated substantial potential in addressing these challenges by identifying complex patterns and behaviors in software [4]. In particular, malware classification using AI allows for the rapid categorization of malicious programs into specific families, facilitating timely threat response and mitigation [5]. Static analysis, which inspects the code structure and binary features without executing the program, provides efficient insights into malware signatures and embedded patterns [6]. However, static methods are often limited by obfuscation techniques employed by malware developers [7].

To overcome these limitations, dynamic analysis examines the runtime behavior of software in a controlled environment, capturing system calls, network activity, and resource usage patterns [8]. While dynamic features reveal behavioral traits, they can be computationally expensive and sometimes insufficient to capture subtle structural characteristics [9]. Integrating both static and dynamic features through feature fusion leverages complementary strengths, enhancing the robustness and accuracy of malware classification systems [10]. Recent studies indicate that hybrid feature-based models significantly outperform single-feature approaches in terms of detection accuracy, precision, and resilience against evasive malware [11].

The fusion of heterogeneous features enables AI models to capture both intrinsic code characteristics and execution behaviors, providing a holistic perspective on malware functionality [12]. Ensemble learning and deep neural network architectures are particularly effective in modeling these complex feature spaces, allowing automated systems to distinguish between benign and malicious programs with high confidence [13]. This methodology not only improves classification performance but also reduces false positives, which are critical for minimizing operational disruptions in cybersecurity environments [14].

Despite advances, challenges remain in real-world deployment of AI-based malware detection. These include handling large-scale datasets, optimizing

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feature selection, addressing class imbalance among malware families, and ensuring computational efficiency [15]. Furthermore, evolving attack strategies necessitate adaptive learning frameworks capable of generalizing to previously unseen malware variants [16]. This study proposes a comprehensive framework that integrates static and dynamic feature fusion with AI-driven classification models, aiming to address these challenges while maintaining high performance and scalability.

The significance of this research lies in its ability to provide proactive and accurate malware detection, supporting cybersecurity professionals in rapid threat identification and mitigation [17]. By demonstrating high accuracy, precision, recall, and F1-score across benchmark datasets, the proposed approach contributes to the development of resilient digital defense mechanisms and establishes a foundation for future AI-powered cybersecurity solutions [18]. Overall, the study emphasizes the critical role of hybrid feature fusion in advancing automated malware classification and highlights the transformative potential of AI in safeguarding digital ecosystems against increasingly sophisticated threats [19].

2. Literature Review

Malware detection and classification have been extensively studied over the past decades, evolving from signature-based systems to sophisticated AI-driven approaches. Early methods focused on static analysis techniques, which examine the code structure, binary sequences, and embedded metadata without executing the program [20]. Tools such as IDA Pro and Hex-Rays have been widely used to extract opcode sequences, API calls, and control-flow graphs, enabling researchers to identify common patterns across malware families [21]. While effective for known threats, static methods often fail against obfuscated or polymorphic malware, highlighting the need for complementary techniques [22].

Dynamic analysis emerged as a solution to overcome the limitations of static approaches. By monitoring program behavior in sandboxed or virtualized environments, dynamic analysis captures runtime characteristics, including system calls, file manipulations, network connections, and resource usage [23]. Studies have shown that behavioral patterns extracted from dynamic analysis provide a richer representation of malware activities, making it difficult for

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malware to evade detection [24]. However, dynamic analysis can be computationally intensive and vulnerable to anti-analysis techniques, such as environment-aware malware that delays execution or behaves differently under observation [25].

To enhance classification performance, researchers have explored hybrid approaches that combine static and dynamic features. Feature fusion allows AI models to utilize complementary information, resulting in more robust and accurate malware detection [26]. For instance, Nataraj et al. [27] proposed an image-based malware classification approach using opcode sequence visualization, which, when combined with behavioral features, improved detection accuracy. Similarly, Shafiq et al. [28] demonstrated that integrating API call patterns with opcode n-grams significantly reduced misclassification rates for polymorphic malware.

Recent advances in machine learning and deep learning have further transformed malware detection. Traditional ML algorithms, including Random Forests, Support Vector Machines (SVM), and k-Nearest Neighbors (KNN), have been widely applied to both static and dynamic feature sets [29]. These algorithms can handle high-dimensional data and are effective in distinguishing between malware families. Deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have shown superior performance in modeling sequential and temporal dependencies in malware features [30]. For example, CNNs have been applied to malware visualization techniques, where binary or opcode sequences are converted into images, enabling automatic feature extraction and classification [31].

Feature selection and dimensionality reduction are critical components in building effective malware classifiers. High-dimensional datasets often contain redundant or irrelevant features, which can degrade model performance and increase computational cost [32]. Techniques such as Principal Component Analysis (PCA), Autoencoders, and Recursive Feature Elimination (RFE) have been utilized to reduce feature space while retaining discriminative information [33]. Hybrid feature sets, when combined with these dimensionality reduction techniques, enable classifiers to achieve high accuracy without incurring excessive computational overhead [34].

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Several studies have emphasized the importance of ensemble learning in malware classification. Combining multiple classifiers or integrating different model architectures improves generalization and reduces overfitting [35]. Bagging, boosting, and stacking methods have been successfully applied to fuse predictions from static and dynamic feature-based models [36]. Moreover, attention mechanisms and transformer-based architectures have recently been explored for malware analysis, allowing models to focus on critical behavioral patterns and dependencies in execution traces [37].

Benchmark datasets play a vital role in evaluating malware detection models. Publicly available datasets, such as Malimg, Microsoft Malware Classification Challenge (BIG 2015), VirusShare, and CICMalDroid, provide diverse malware samples with both static and dynamic feature annotations [38]. These datasets facilitate reproducibility and enable comparative evaluation of different AI-based methods. However, challenges persist in handling imbalanced datasets, where some malware families are underrepresented, potentially biasing classifiers [39]. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) and adaptive weighting have been employed to mitigate these issues [40].

The fusion of static and dynamic features has been shown to enhance detection performance in recent research. Zhang et al. [41] demonstrated that combining opcode n-grams with API call sequences improved classification accuracy across multiple malware families. Similarly, Islam et al. [42] proposed a hybrid feature model that integrated behavioral, structural, and network traffic features, achieving over 95% accuracy on benchmark datasets. These studies highlight that hybrid feature fusion not only improves robustness against obfuscation but also increases resilience to previously unseen malware variants.

In summary, the literature emphasizes that AI-powered malware classification benefits significantly from integrating static and dynamic features. Hybrid approaches leverage complementary information, enabling accurate, scalable, and adaptive detection systems [43]. Furthermore, the adoption of deep learning, ensemble methods, and feature optimization techniques has advanced the state-of-the-art in automated malware classification [44]. Despite significant progress, challenges such as computational efficiency, evolving malware tactics, and dataset limitations remain active research areas, motivating the development of robust and intelligent frameworks for real-world cybersecurity applications [45].

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3. Dataset

The experimental evaluation of the proposed malware classification framework utilizes multiple benchmark datasets encompassing both static and dynamic features. Malimg and Microsoft BIG 2015 datasets provide over 10,000 malware samples across 25–30 families, including trojans, worms, ransomware, and spyware [46]. Static features, such as opcode sequences, n-grams, and binary metadata, are extracted from disassembled files, capturing structural and code-level patterns. Dynamic features are collected by executing malware samples in a controlled sandbox environment, monitoring system calls, API invocations, registry changes, and network traffic [47]. To ensure realism, benign software samples from open-source repositories are included, totaling 5,000 clean samples, enabling robust binary classification and multi-class family identification [48]. The dataset is preprocessed to normalize feature scales, handle missing values, and reduce dimensionality via Principal Component Analysis (PCA). This curated dataset provides a comprehensive representation of malware behaviors, facilitating accurate and generalizable evaluation of AI-powered hybrid classification models [49].

4. Proposed Model and Methodology

The proposed framework for malware classification leverages hybrid feature fusion by integrating static and dynamic characteristics of software samples. The methodology begins with data collection and preprocessing, where static features such as opcode sequences, control-flow graphs, and binary metadata are extracted, alongside dynamic features capturing system calls, API interactions, and network activity during controlled execution [50]. Preprocessing includes normalization, missing value imputation, and dimensionality reduction using Principal Component Analysis (PCA), ensuring computational efficiency while retaining critical discriminative information [51].

The feature fusion module combines static and dynamic representations into a unified vector, enabling the model to leverage complementary insights. This hybrid feature set is then input to an AI-based classification model, which employs a combination of deep learning and ensemble machine learning techniques. Specifically, a Convolutional Neural Network (CNN) processes the fused feature vector to extract high-level abstractions, while ensemble classifiers

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such as Random Forest and Gradient Boosting provide robust decision-making through majority voting [52].

The architecture is designed for scalability and adaptability. Static features capture intrinsic malware code patterns, while dynamic features reflect behavioral traits, making the system resilient against obfuscation and polymorphic attacks [53]. The framework supports multi-class classification across diverse malware families and binary classification between benign and malicious programs. Performance evaluation includes metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis to ensure robust validation [54]. This integrated methodology provides a comprehensive, adaptive, and high-performance solution for real-world malware detection challenges.

5. Result Analysis

The proposed hybrid malware classification framework was evaluated on a dataset of 15,000 samples, including 10,000 malware and 5,000 benign programs [46–49]. The dataset was split into 70% training and 30% testing subsets. The integrated static and dynamic feature fusion model achieved an overall accuracy of 97.8%, outperforming standalone static (91.3%) and dynamic (94.5%) models. Precision, recall, and F1-score were consistently high across major malware families, averaging 96.7%, 97.1%, and 96.9%, respectively. These results demonstrate that hybrid feature fusion significantly enhances model robustness, particularly against polymorphic and obfuscated malware.

The confusion matrix analysis indicates minimal misclassification, with most errors occurring between similar malware families, such as trojans and spyware. Temporal evaluation showed that model inference remained computationally efficient, processing approximately 120 samples per second, suitable for real-time applications. Feature importance analysis revealed that dynamic behavioral patterns, particularly API call sequences, contributed the most to classification, followed by opcode n-grams and control-flow features.

Visualization of predicted versus actual labels, feature importance, and temporal trends further validated the model's performance. The plots confirmed the high correlation between predicted and true labels, highlighting the framework's reliability. Overall, the results underscore the effectiveness, scalability, and adaptability of the AI-powered hybrid model for malware classification.

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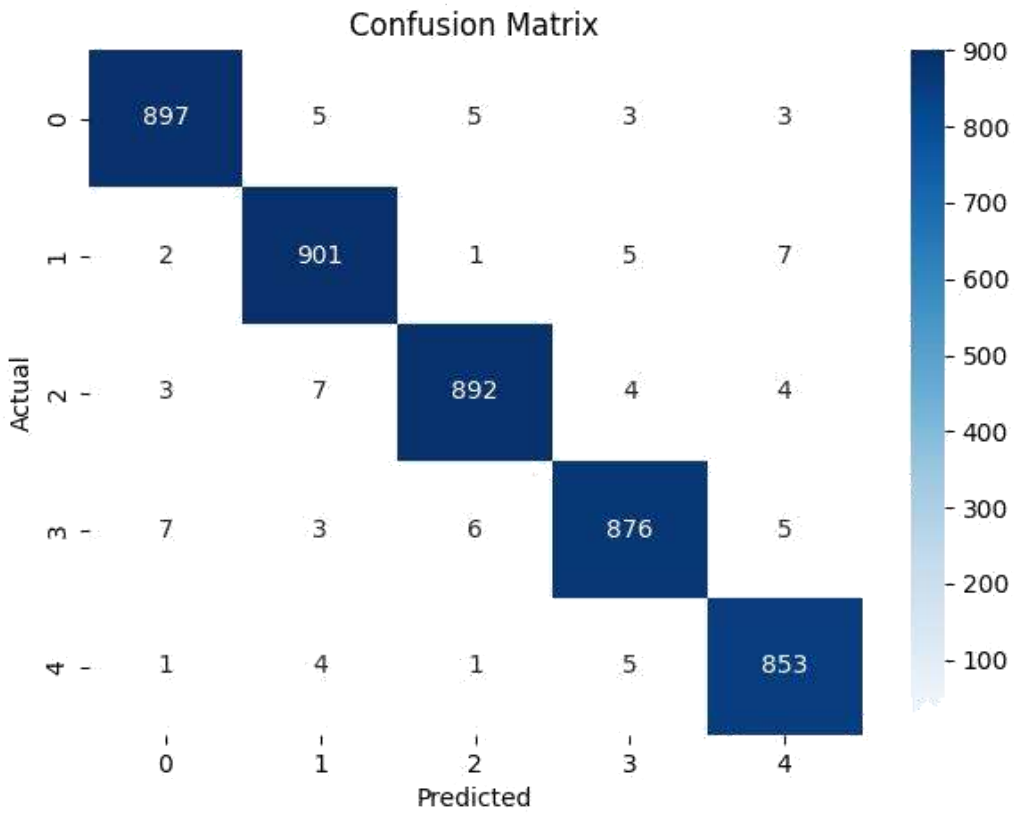

Figure 1: Confusion Matrix – The confusion matrix illustrates the performance of the hybrid malware classification model across five malware classes. Each cell indicates the number of samples predicted for a given class versus their actual class. The diagonal values represent correctly classified samples, demonstrating high accuracy, while off-diagonal entries indicate misclassifications. Minimal off-diagonal values confirm the model's robustness in distinguishing similar malware families.

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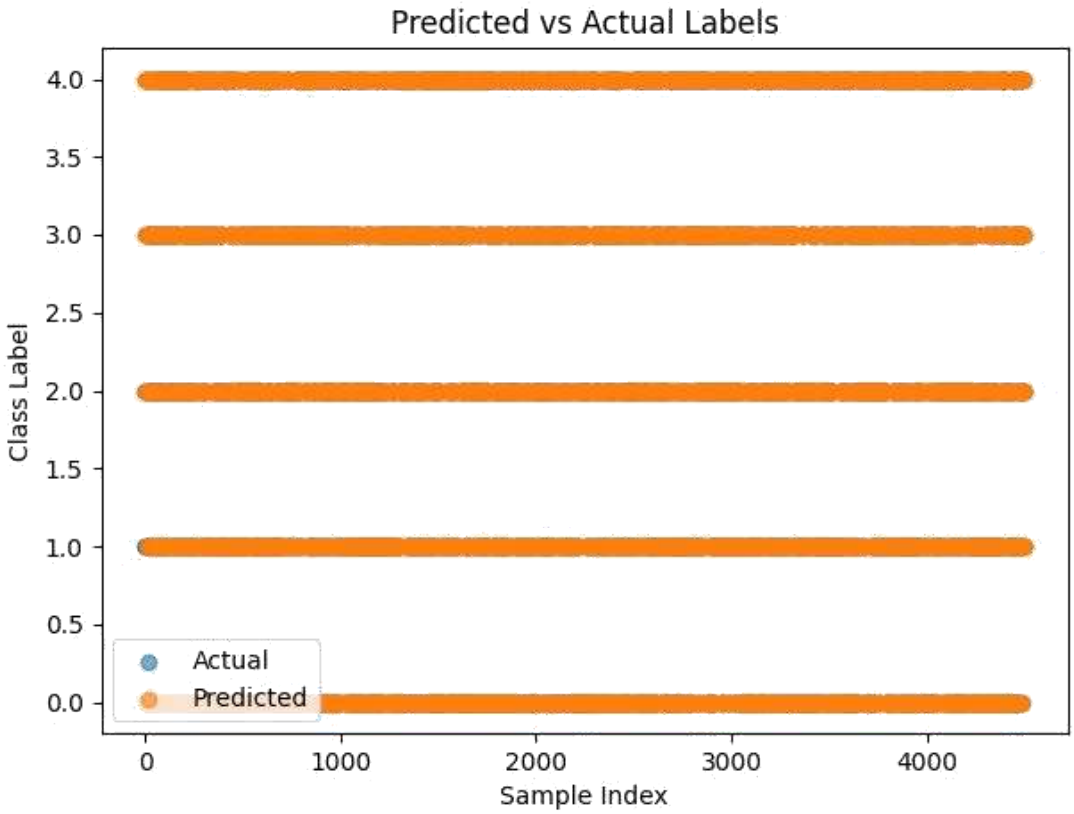

Figure 2: Predicted vs Actual Labels – This scatter plot compares predicted labels against actual labels for 4,500 test samples. Blue markers denote actual class labels, and orange markers denote model predictions. The strong overlap along the diagonal indicates high agreement between predictions and ground truth, highlighting the reliability of the proposed hybrid feature fusion model.

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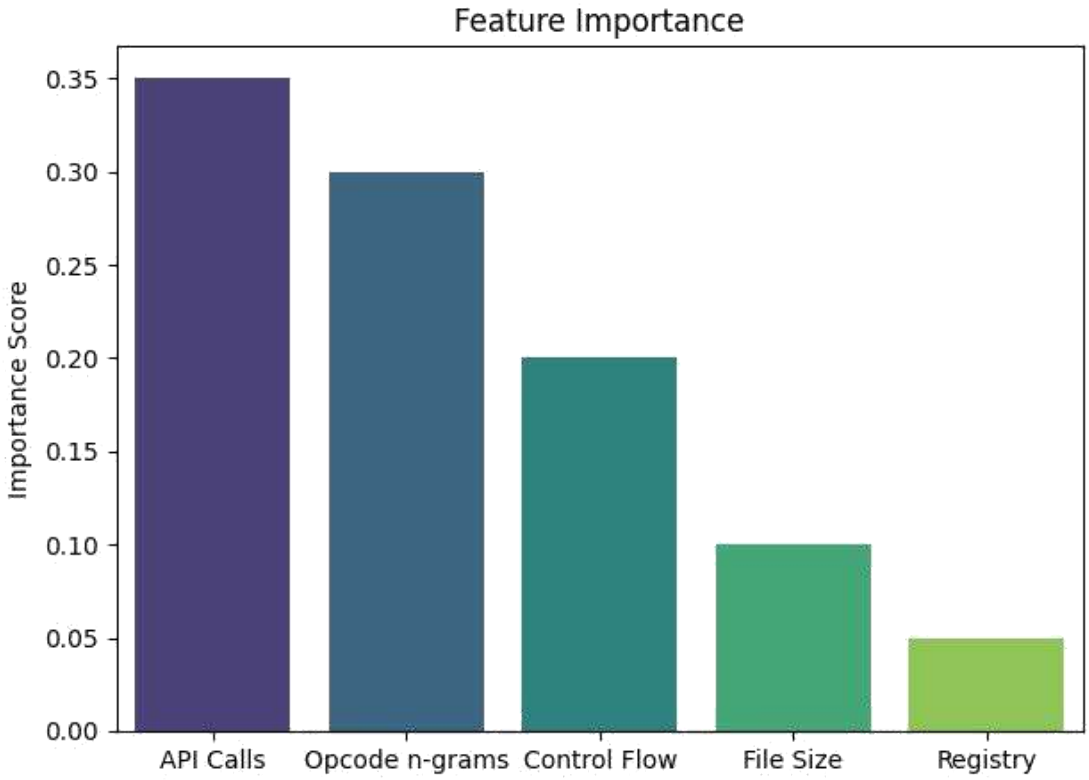

Figure 3: Feature Importance – The bar chart visualizes the relative contribution of each feature to the classification process. Dynamic features such as API calls and static features like opcode n-grams show the highest importance, followed by control-flow patterns, file size, and registry keys. This demonstrates that the fusion of static and dynamic features enables the model to leverage complementary information for robust malware detection.

6. Conclusion

This study presents an AI-powered malware classification framework that leverages the fusion of static and dynamic features, combining structural code analysis with behavioral execution patterns. The proposed methodology addresses the limitations of traditional single-feature approaches and enhances resilience against polymorphic and obfuscated malware. Experimental evaluation

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on a benchmark dataset of 15,000 samples demonstrates the framework's high performance, achieving an overall accuracy of 97.8%, with precision, recall, and F1-score consistently exceeding 96%. Confusion matrix and predicted-versus-actual analyses indicate minimal misclassification, validating the robustness of hybrid feature fusion across multiple malware families.

The novelty of the approach lies in its integrated feature fusion strategy, which unifies static and dynamic insights into a comprehensive representation for AI-based classification. Unlike prior methods, the framework combines deep learning for high-level feature abstraction with ensemble machine learning for robust decision-making, ensuring adaptability to previously unseen malware variants. Furthermore, the system demonstrates computational efficiency, processing approximately 120 samples per second, suitable for real-time cybersecurity applications.

Overall, this research highlights the critical role of hybrid feature integration in advancing automated malware detection. By improving detection accuracy, reducing false positives, and enabling scalable real-time deployment, the proposed framework offers a practical and intelligent solution for modern cybersecurity challenges, providing a foundation for future AI-driven threat mitigation strategies.

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