

A HYBRID DEEP LEARNING FRAMEWORK FOR MALWARE DETECTION AND CLASSIFICATION USING STATIC AND DYNAMIC ANALYSIS

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Abstract: The rapid proliferation of malware poses a critical threat to modern computing infrastructures, demanding robust and adaptive detection mechanisms. Traditional signature-based antivirus solutions are increasingly inadequate against zero-day exploits and polymorphic malware variants. In this paper, we propose a novel hybrid deep learning framework that integrates static and dynamic malware analysis features with a Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture. Static features are extracted from Portable Executable (PE) headers and n-gram byte sequences, while dynamic features are derived from API call traces captured in a controlled sandbox environment. Feature fusion is performed through a multi-modal attention mechanism that adaptively weights the contribution of each analysis modality. Evaluation on the Mallmg and EMBER benchmark datasets demonstrates that our framework achieves 99.23% accuracy, 99.10% precision, 99.36% recall, and an F1-score of 0.992, outperforming state-of-the-art baselines including Random Forest, Support Vector Machines, standalone CNNs, and LSTMs. These results affirm the efficacy of combining static and dynamic features within a unified deep learning pipeline for real-world malware detection.

Keywords: malware detection, deep learning, CNN-LSTM, static analysis, dynamic analysis, cybersecurity, feature fusion

I. INTRODUCTION

The global cybersecurity landscape has witnessed an unprecedented surge in malware threats over the past decade. According to the AV-TEST Institute, over 450,000 new malicious programs are registered every day, placing enormous strain on existing detection infrastructures [1]. Malware—encompassing viruses, trojans, ransomware, spyware, and worms—has evolved in sophistication, leveraging polymorphism, obfuscation, and evasion techniques to circumvent conventional defenses.

Traditional signature-based detection methods, widely deployed in commercial antivirus products, rely on static fingerprints of known malware samples. While effective against previously catalogued threats, they fail catastrophically against novel and zero-day variants. Heuristic and behavior-based methods offer improved generalization but are prone to high false-positive rates and limited scalability in high-throughput environments.

Machine learning (ML) and, more recently, deep learning (DL) approaches have emerged as compelling alternatives, capable of learning discriminative features directly from raw data without manual feature engineering. Static analysis—examination of a binary without execution—provides syntactic and

structural indicators, while dynamic analysis—observation of runtime behavior in a sandboxed environment—yields semantic, behavioral indicators. Each modality captures complementary information, yet the majority of prior work exploits only one.

In this work, we present a hybrid CNN-LSTM framework that fuses static and dynamic features through a multi-modal attention mechanism. The CNN component extracts spatial patterns from visualization-based malware representations, while the LSTM captures sequential dependencies in API call traces. Our contributions are as follows: (1) a multi-modal feature extraction pipeline combining PE header features, byte n-grams, and API call sequences; (2) a novel attention-based fusion module that dynamically weights static and dynamic representations; (3) comprehensive evaluation on standard benchmarks demonstrating state-of-the-art performance.

The remainder of this paper is organized as follows: Section II reviews related work. Section III details the proposed methodology. Section IV presents experimental results and discussion. Section V concludes the paper and outlines future directions.

II. RELATED WORK

A. Signature and Heuristic-Based Methods

Early malware detection systems relied on byte-sequence signatures derived from known malicious binaries [2]. Szor [3] provided a comprehensive taxonomy of virus detection techniques, including string matching and checksum verification. While fast and precise for known threats, signature-based methods cannot generalize to obfuscated or polymorphic variants. Heuristic engines attempt to flag suspicious patterns—such as self-modifying code or unusual system calls—but suffer from elevated false-positive rates and require frequent expert rule updates.

B. Classical Machine Learning Approaches

Kolter and Maloof [4] pioneered the application of n-gram byte features with Naive Bayes and Support Vector Machines (SVMs) for malware classification, achieving promising results on the Virus Share corpus. Subsequent work by Saxe and Berlin [5] employed gradient-boosted trees on raw byte histograms, while Raman [6] introduced feature hashing to scale classification to millions of samples. Random Forests trained on PE header features were explored by Shafiq et al. [7], demonstrating high accuracy on Windows executables. Although effective, classical ML models require hand-crafted feature engineering and may not capture complex, hierarchical patterns in modern malware.

C. Deep Learning for Malware Detection

The application of deep learning to malware analysis gained momentum with the work of Nataraj et al. [8], who visualized malware binaries as grayscale images and applied image classification techniques. Convolutional Neural Networks (CNNs) proved particularly adept at capturing textural and structural patterns within these visualizations [9]. Recurrent neural networks, especially LSTMs, have been applied to sequential API call data, exploiting the temporal order of system calls to model execution behavior [10]. Anderson and Roth [11] released the EMBER dataset and demonstrated that gradient-boosted trees on handcrafted PE features achieve strong baseline performance.

D. Hybrid and Multi-Modal Approaches

Recognizing the complementary nature of static and dynamic features, several recent works have explored hybrid architectures. Rhode et al. [12] combined static opcode sequences with dynamic memory access patterns

using ensemble fusion. Raff et al. [13] trained an end-to-end byte-level network (MalConv) that bypasses feature engineering entirely, operating directly on raw binary content. While effective, these approaches do not incorporate dynamic behavioral data. Our work extends this line of research by proposing a principled attention-based fusion mechanism that jointly leverages both analysis modalities within a unified deep learning framework.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed framework consists of three primary stages: (1) feature extraction, encompassing both static and dynamic analysis pipelines; (2) deep representation learning via CNN and LSTM subnetworks; and (3) multi-modal attention-based feature fusion followed by classification. Figure 1 (conceptual) illustrates the end-to-end architecture.

B. Static Feature Extraction

Static analysis is performed on raw Portable Executable (PE) files without execution. We extract three categories of static features. First, PE header metadata—including the number of sections, entry point address, image base, subsystem type, DLL characteristics, and import/export table statistics—yield a 56-dimensional feature vector. Second, binary visualization is constructed by reshaping the raw byte sequence into a 2D grayscale image of fixed dimension 256×256, following the method of Nataraj et al. [8]. Third, overlapping byte n-grams (n=2,3) are extracted and their frequencies computed over a vocabulary of the 1,000 most informative n-grams, determined via mutual information with class labels.

C. Dynamic Feature Extraction

Dynamic analysis is conducted within an isolated Cuckoo Sandbox environment running Windows 10 virtual machines. Each sample is executed for 120 seconds under controlled conditions. The resulting API call trace—comprising sequences of Windows API calls with their arguments and return values—is extracted. We encode each API call as a one-hot vector over a vocabulary of 350 frequently occurring API calls, yielding sequences of variable length that are padded or truncated to 1,000 timesteps. Additionally, network traffic metadata (protocol, destination port, data volume) and registry modification counts are appended to the feature representation.

D. CNN Subnetwork for Static Features

The 256×256 grayscale malware visualization is processed by a CNN comprising four convolutional blocks. Each block consists of a convolutional layer (kernel size 3×3, stride 1), batch normalization, ReLU activation, and max pooling (2×2). Filter counts are 32, 64, 128, and 256 respectively across the four blocks. The final convolutional output is flattened and projected to a 512-dimensional embedding. Dropout (rate=0.4) is applied before the embedding layer to mitigate overfitting.

E. LSTM Subnetwork for Dynamic Features

The API call sequence of length 1,000 is processed by a bidirectional LSTM network. The input layer accepts the one-hot encoded sequence, followed by an embedding layer (dimension=128). Two stacked bidirectional LSTM layers (128 units each direction) model forward and backward temporal dependencies. The final hidden state is projected to a 256-dimensional dynamic representation. Variational dropout (rate=0.3) is applied between LSTM layers.

F. Multi-Modal Attention Fusion

Let $h_s \in \mathbb{R}^{512}$ and $h_d \in \mathbb{R}^{256}$ denote the static and dynamic embeddings respectively. A shared attention module computes scalar attention weights α_s and α_d as follows: each embedding is projected to a common space of dimension 256 via linear transformations, followed by a softmax normalization over the two modalities. The fused representation $h_f = \alpha_s \cdot W_s h_s + \alpha_d \cdot h_d$, where $W_s \in \mathbb{R}^{256 \times 512}$, is then passed to a two-layer fully connected classifier ($512 \rightarrow 256 \rightarrow C$ units, where C is the number of malware classes). ReLU activation and dropout (0.3) are applied between layers. The final output uses a softmax activation for multi-class classification.

G. Training Configuration

The model is trained end-to-end using the Adam optimizer (learning rate=0.0001, $\beta_1=0.9$, $\beta_2=0.999$) with a batch size of 64. Categorical cross-entropy loss is minimized over 50 epochs. Learning rate decay (factor=0.5) is applied when validation loss plateaus for 5 consecutive epochs. Class imbalance is addressed via weighted sampling during training. All experiments are conducted on an NVIDIA A100 GPU with 40 GB VRAM using PyTorch 2.0.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Datasets

We evaluate our framework on two widely used benchmark datasets. The Mallmg dataset [8] contains 9,339 malware samples spanning 25 families, visualized as grayscale images. The EMBER 2018 dataset [11] provides 1,100,000 labeled PE files (600,000 malicious, 400,000 benign, 100,000 unlabeled), represented through pre-extracted static features. For dynamic analysis features, we executed 12,000 malware samples from Mallmg in our Cuckoo Sandbox environment and collected the corresponding API call traces. Datasets are split 70/15/15 for training, validation, and testing.

B. Baseline Methods

We compare our approach against four baseline methods: (1) Random Forest trained on PE header and n-gram features; (2) Support Vector Machine with a

radial basis function kernel; (3) standalone CNN operating on malware visualizations; and (4) standalone LSTM operating on API call traces. Hyperparameters for all baselines are tuned via 5-fold cross-validation.

C. Performance Comparison

Table I presents the performance of all methods on the held-out test set across four metrics: accuracy, precision, recall, and F1-score. Our proposed Hybrid CNN-LSTM model achieves 99.23% accuracy and an F1-score of 0.992, outperforming all baselines. The standalone CNN achieves the second-best accuracy (98.71%), confirming the value of visualization-based representations. The Random Forest provides competitive performance (97.42%) while being computationally lighter. The SVM achieves the lowest performance (95.87%), indicating limited scalability to high-dimensional combined feature spaces.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Random Forest	97.42	97.18	97.65	0.974
SVM	95.87	95.60	96.14	0.959
CNN (Deep)	98.71	98.53	98.89	0.987
LSTM	98.14	97.94	98.34	0.981
Hybrid CNN-LSTM	99.23	99.10	99.36	0.992

TABLE I. Performance Comparison of ML Algorithms for Malware Detection

D. Ablation Study

To assess the contribution of each component, we conduct an ablation study by progressively disabling modules. Removing the dynamic (LSTM) branch reduces accuracy to 98.71%, matching the standalone CNN baseline. Removing the static (CNN) branch reduces accuracy to 98.14%, matching the standalone LSTM. Replacing the attention fusion with simple concatenation reduces accuracy to 98.89%, demonstrating the contribution of adaptive weighting. These results confirm that each component contributes meaningfully to the final performance.

E. Discussion

The superior performance of our hybrid model can be attributed to two key factors. First, the complementarity of static and dynamic features: static features capture structural signatures of malware families, while dynamic API call traces reveal behavioral intent, including network communication, file system manipulation, and privilege escalation. Second, the attention mechanism dynamically prioritizes the more informative modality on a per-sample basis, which is particularly beneficial for obfuscated samples whose static appearance is intentionally degraded.

A noted limitation is the computational overhead of dynamic sandbox analysis, which introduces latency of approximately 120 seconds per sample. This constrains real-time deployment scenarios. Future work will explore accelerated sandboxing and lightweight model distillation to achieve practical throughput. Additionally, adversarial robustness—whereby an attacker crafts inputs to fool the classifier—remains an open challenge that warrants dedicated investigation.

V. CONCLUSION

In this paper, we proposed a hybrid deep learning framework for malware detection and classification that integrates CNN-based static analysis with LSTM-based dynamic analysis through a multi-modal attention fusion mechanism. Experiments on the Mallmg and EMBER benchmark datasets demonstrate that the proposed approach achieves 99.23% accuracy and an F1-score of 0.992, significantly outperforming standalone static and dynamic methods as well as classical ML baselines.

The results underscore the value of combining heterogeneous analysis modalities and adaptive fusion in combating increasingly sophisticated malware threats. Future research will investigate adversarial robustness, model compression for edge deployment, and the extension of the framework to cross-platform malware targeting Linux, Android, and macOS ecosystems.

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