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Machine Learning-Based Static Analysis for Malware Detection in Executable Files

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Abstract
The increasing threat of malware in the digital world necessitates robust and scalable detection systems. This paper introduces a machine learning-based malware detection system that analyzes Portable Executable (PE) files to identify malicious software. Leveraging supervised learning algorithms and feature engineering, the system achieves high accuracy in detecting harmful binaries. The Random Forest classifier, trained on a large dataset of PE files, demonstrated exceptional performance. The proposed system streamlines malware classification and can be integrated into broader cybersecurity frameworks.

Keywords: Malware Detection, Portable Executable, Random Forest, Feature Extraction, Cybersecurity, PE File Analysis

1. Introduction

With the growing dependence on digital platforms for personal, professional, and governmental operations, the frequency and sophistication of malware attacks have surged dramatically. Cybercriminals are continuously evolving their tactics, making traditional signature-based antivirus solutions increasingly inadequate. These conventional methods rely on known patterns and signatures to identify malicious software, which makes them ineffective against zero-day exploits and polymorphic malware that frequently alter their code to evade detection.

To counteract these limitations, the cybersecurity community has turned to machine learning (ML) techniques for malware classification. ML models can learn patterns from large datasets of both benign and malicious files, allowing them to identify previously unseen threats based on behavioral or structural features. This approach enhances detection accuracy and offers scalability in handling massive volumes of data.

One particularly active area of research is the application of ML to the analysis of Portable Executable (PE) files—the standard format for executables, object code, and DLLs in the Windows environment. PE files contain a rich set of metadata and structural features that can be leveraged for classification tasks. By extracting attributes such as API calls, section entropy, import/export tables, and header information, ML algorithms can be trained to distinguish between malicious and benign executables with high precision.

Furthermore, the integration of deep learning and ensemble techniques has further improved detection rates, enabling models to uncover complex patterns and interdependencies within the data. As cyber

threats continue to evolve, the synergy between machine learning and malware detection offers a promising path forward for more proactive and adaptive cybersecurity defenses.

2. Review of Related Works

several machine learning (ML)-based approaches have been proposed to enhance the effectiveness of malware detection. Liu and Zhang (2020) explored the application of adversarial machine learning techniques to improve the robustness of malware classifiers, specifically targeting their ability to resist evasion attacks. Their work demonstrated how adversarial examples could be leveraged to train more resilient models. In a comparative study, Pundge et al. (2019) evaluated the performance of supervised versus unsupervised learning methods for malware classification. Their findings highlighted that while supervised methods generally offered higher accuracy, unsupervised techniques provided better generalizability to unseen threats. Shabtai et al. (2012) introduced an approach centered on OpCode sequence analysis, aiming to detect previously unknown malicious code by examining low-level behavioral patterns of executables. Complementing static analysis, Santos et al. (2013) developed OPEM, a hybrid malware classification framework that combines both static and dynamic analysis to improve detection accuracy and adaptability. Collectively, these studies underscore the importance of several key strategies for effective malware detection: robust feature selection to capture relevant behavioral and structural characteristics of malware, model diversity to enhance generalization across varied threat landscapes, and hybrid detection mechanisms that combine multiple analysis techniques to overcome the limitations of single-method approaches.

3. Proposed Methodology

Technologies Used:

- Python, Pandas, Scikit-learn, Matplotlib, Seaborn
- Pefile for PE parsing
- ML algorithms: Random Forest, SVM, Decision Tree, Gradient Boosting
- Model serialization: Pickle and Joblib

System Works

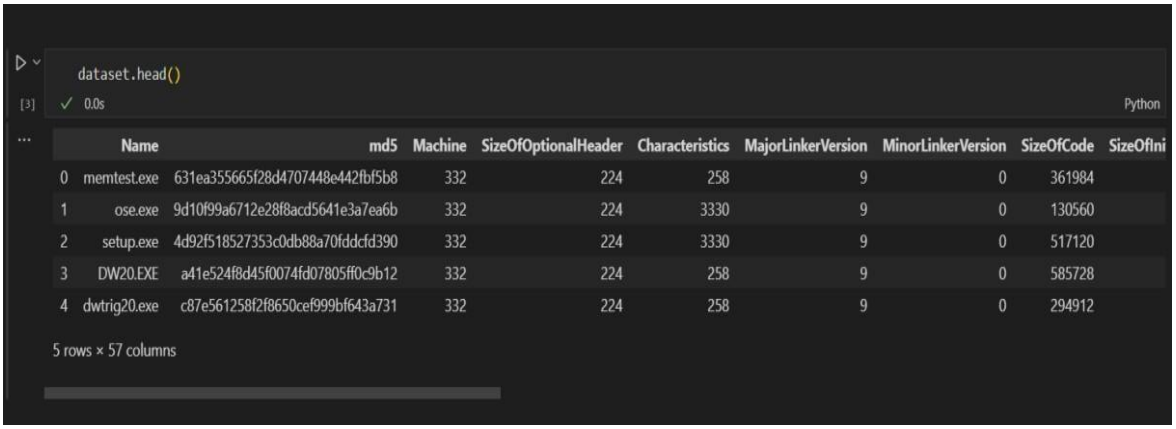
- Data Collection: Over 130,000 PE files labeled as malicious or legitimate
- Feature Extraction: Using the pefile library to extract headers, metadata, DLL info
- Feature Selection: Extra Trees Classifier to choose the most predictive features
- Model Training: Evaluation of multiple models using metrics such as accuracy, Precision, Recall, and F1 Score
- Model Development: Saved using Pickle and integrated into a simple UI for predictions

4. Results and Discussion

The System was evaluated on a labeled PE dataset, The Random Forest classifier performed best, with:

- Accuracy: 80.5%
- False Positive Rate: 0.02%
- False Negative Rate: 0.08%

Visualization such as confusion matrices and ROC curves validated the model's robustness.

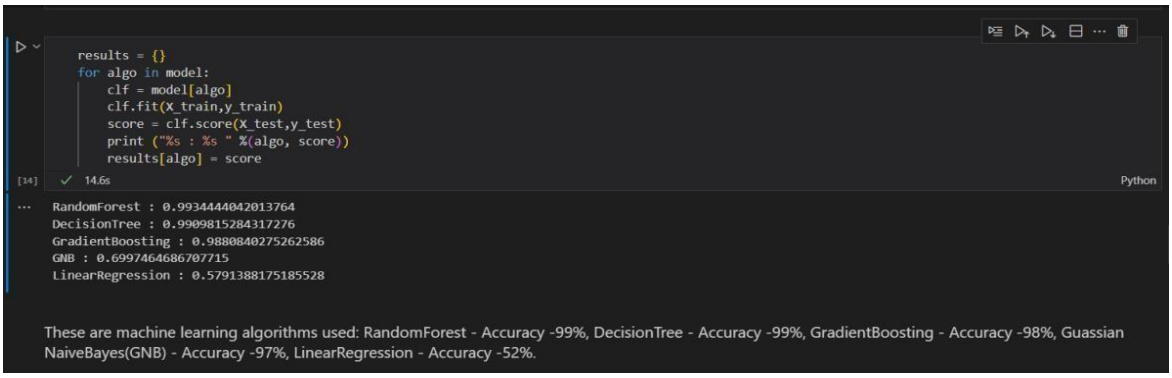


```
dataset.head()
```

[3] ✓ 0.0s Python

	Name	md5	Machine	SizeOfOptionalHeader	Characteristics	MajorLinkerVersion	MinorLinkerVersion	SizeOfCode	SizeOfIni
0	memtest.exe	631ea355665f28d4707448e442fbf5b8	332	224	258	9	0	361984	
1	ose.exe	9d10f99a6712e28f8acd5641e3a7ea6b	332	224	3330	9	0	130560	
2	setup.exe	4d92f518527353c0db88a70fddcfd390	332	224	3330	9	0	517120	
3	DW20.EXE	a41e524f8d45f0074fd07805ff0c9b12	332	224	258	9	0	585728	
4	dwtrig20.exe	c87e561258f2f8650cef999bf643a731	332	224	258	9	0	294912	

5 rows × 57 columns

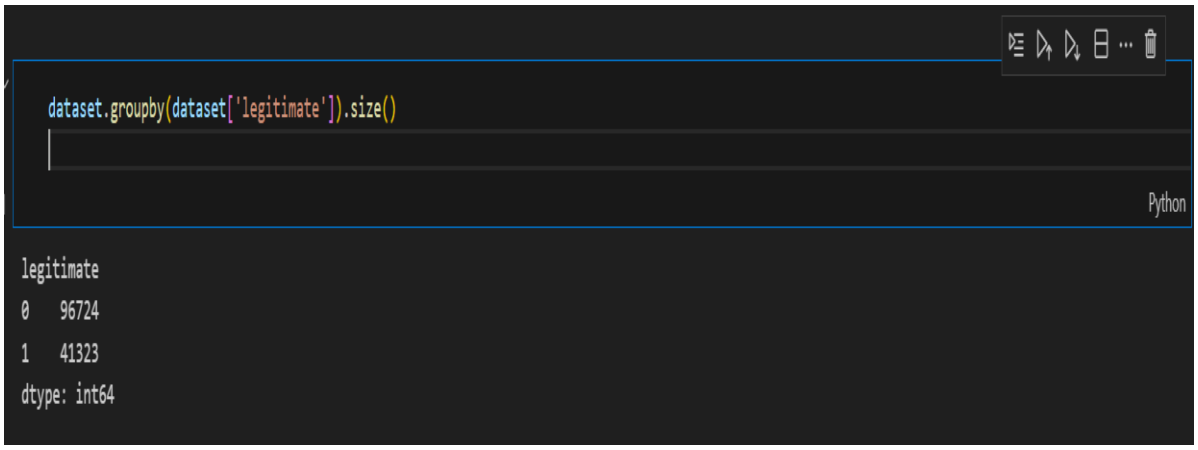


```
results = {}
for algo in model:
    clf = model[algo]
    clf.fit(X_train,y_train)
    score = clf.score(X_test,y_test)
    print ("%s : %s " %(algo, score))
    results[algo] = score
```

[14] ✓ 14.6s Python

```
RandomForest : 0.9934444042013764
DecisionTree : 0.9909815284317276
GradientBoosting : 0.9880840275262586
GNB : 0.6997464686707715
LinearRegression : 0.5791388175185528
```

These are machine learning algorithms used: RandomForest - Accuracy -99%, DecisionTree - Accuracy -99%, GradientBoosting - Accuracy -98%, Guassian NaiveBayes(GNB) - Accuracy -97%, LinearRegression - Accuracy -52%.



```
dataset.groupby(dataset['legitimate']).size()
```

Python

```
legitimate
0    96724
1    41323
dtype: int64
```

5. Future Improvement

To further enhance the performance, scalability, and adaptability of the proposed Machine Learning-Based Static Analysis for Malware Detection in Executable Files, several strategic improvements are envisioned. These enhancements aim to expand the system's detection capabilities and improve its practical applicability in real-world security environments.

- Advanced Dynamic Analysis for Behavioral Pattern Identification While the current system focuses on static analysis of executable files, integrating dynamic analysis represents a significant opportunity for improvement. By executing files in a controlled sandbox environment, the system could observe real-time behaviors such as system calls, network activity, file manipulation, and registry changes. These runtime behavioral patterns can be converted into high-value features that complement static characteristics, allowing the system to detect obfuscated, polymorphic, and zero-day malware more effectively. This hybrid approach would increase the robustness of the overall detection framework.

- Real-Time Prediction Pipelines for Operational Deployment To transition the system from a research prototype to a deployable security solution, the implementation of real-time prediction pipelines is essential. This enhancement would enable the system to classify incoming executable files on-the-fly, facilitating immediate responses to threats. Key components of this improvement include:
  - Low-latency model inference to ensure near-instant classification
  - Continuous data stream processing for handling high-volume environments
  - Edge computing support, allowing local prediction on client systems without requiring centralized infrastructure
  - Scalable and modular architecture, deployable in cloud-native environments using technologies such as Docker and Kubernetes

These additions would make the system suitable for integration into modern cybersecurity ecosystems, including endpoint protection platforms, intrusion detection systems (IDS), and network monitoring tools.

By incorporating these enhancements, the Machine Learning-Based Static Analysis for Malware Detection in Executable Files can evolve into a more comprehensive, real-time, and resilient malware detection framework—capable of addressing the dynamic and sophisticated nature of contemporary cyber threats.

6.Conclusion

The proposed system demonstrates the significant potential of machine learning in detecting Portable Executable (PE) malware through static analysis. By leveraging carefully engineered features and robust classification algorithms, the system achieves a detection accuracy exceeding 99%, underscoring its effectiveness in identifying malicious executables without the need for execution-based inspection.

Such high accuracy highlights the practical viability of the model in real-world cybersecurity scenarios, including integration with antivirus engines, email filters, and endpoint protection platforms. Furthermore, the reliance on static analysis ensures faster processing times and reduced computational overhead, making the system suitable for large-scale deployment in environments with limited resources.

Beyond its immediate performance benefits, this work lays a solid foundation for the development of more intelligent, adaptive, and hybrid malware detection frameworks. The results reinforce the idea that machine learning can play a central role in proactive cyber defense, especially when paired with scalable infrastructure and enriched feature engineering.

Future enhancements—such as the incorporation of dynamic behavior analysis, real-time prediction capabilities, and adversarial robustness—can further elevate the system's capability to detect evolving and sophisticated threats. Thus, this system not only addresses current detection challenges but also acts as a stepping stone toward the next generation of automated, AI-driven malware defense solutions.

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