Malware Detection Using Machine Learning

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Abstract—**The increasing sophistication and frequency of malware attacks pose a significant threat to cyber security. This project presents a machine learning-based approach to malware detection that leverages the ability of algorithms to learn patterns from data and generalize to unseen threats. By extracting and analyzing features from both malicious and benign software samples, several classification algorithms—including Random Forest, Support Vector Machine (SVM), and Neural Networks—were trained and evaluated.**

I. INTRODUCTION

Malware detection is the process of identifying malicious software (malware) within a computer system, file, or network. Malware includes various types of harmful programs such as viruses, worms, Trojans, ransomware, spyware, and rootkits that are designed to damage, steal data from, or disrupt the normal functioning of systems.

Malware detection techniques rely heavily on signature-based methods [1] , where known patterns or signatures of malware are stored in databases. While effective against previously identified threats, these approaches struggle to detect novel, polymorphic, or obfuscated malware, which often bypass signature-based defenses. As Cyber criminals continue to develop more advanced and adaptive attack techniques, there is an urgent need for smarter, more flexible detection systems [2]. Machine learning (ML) offers a promising solution to this challenge [3].

By training models on large datasets of both malicious and benign files, ML algorithms can learn to identify patterns and behaviors that distinguish malware from legitimate software [4]. Unlike static signature-based methods, machine learning models can generalize from data and detect previously unseen threats based on learned characteristics. [5] This research aims to explore and evaluate the use of machine learning techniques for malware detection. By extracting relevant features from software samples and applying classification algorithms such as Random Forest, Support Vector Machine (SVM), and Neural Networks, the study seeks to build an intelligent detection system capable of identifying malware with high accuracy [6]. The performance of the models is assessed using key evaluation metrics, and the results are compared to determine the most effective approach.
[6]
In this paper, we present a framework for malware detection aiming to get as few false positives as possible, by using a simple and a simple multi-stage combination of different versions of the perceptron algorithm [7]. Other automate classification algorithms [8] could also be used in this framework, but we do not explore here this alternative. The main steps performed through this framework are sketched as follows:

1.The proposed framework aims to develop a machine learning-based malware detection system that not only achieves high detection accuracy but also minimizes false positives, which are a critical concern in real-world applications. False positives—where benign files are incorrectly flagged as malicious—can lead to unnecessary disruptions and resource wastage. 2.To address this, we employ a Multi-layer Perceptron (MLP) algorithm due to its ability to model complex patterns and generalize well when trained on high-dimensional data.

3.The Multi-layer Perceptron model is designed as a feed-forward neural network with an input layer, multiple hidden layers, and a single output neuron. The input layer size corresponds to the number of features. Hidden layers typically use RelU (Rectified Linear Unit) activation functions and may include dropout layers for regularization. The output layer uses a sigma activation function to produce a probability score between 0 and 1, representing the likelihood that a given sample is malware. 4.The model is trained using the binary cross-entropy loss function and optimized using the Adam optimizer, which adapts learning rates during training for faster convergence.

II.DATASETS

In the context of malware detection using machine learning, a Datasets refers to a structured collection of data samples. These datasets serve as the foundation for training, validating, and testing machine learning models to distinguish between harmful and safe software. Depending on the approach used, datasets may consist of static features (such as byte-code, opcodes, file headers, or strings), dynamic behaviors (such as API call sequences, memory usage, or network communication), or even image representations of binaries. Well-known datasets like the Microsoft Malware Classification Challenge, EMBER, CIC-MalMem2022, and Drebin provide large volumes of labeled samples for various platforms, including Windows and Android. These datasets enable supervised learning models to learn distinguishing characteristics of malware, evaluate detection accuracy, and optimize performance with minimal false positives and false negatives.

1. The training dataset is the core component used to teach a machine learning model to recognize patterns that differentiate malware from benign software. It contains labeled examples, where each sample is tagged as either malicious or benign, and includes features extracted from static code, runtime behavior, or other data sources.
2. The test dataset is used to evaluate the model's performance on unseen data after training is complete. It helps determine how well the model generalizes and whether it performs reliably in real-world scenarios.
3. Scaling up the dataset refers to increasing the volume and diversity of data to improve the robustness and generalization capability of the model.

TABLE 1
NUMBER OF FILES AND COMBINATION OF FEATURE VALUES IN THE TRAING, TEST, AND SCALE-UP DATASETS

Dataset Type	Number of Files	Number of Malware Files	Number of Benign Files	Unique Feature Combinations
Training Dataset	60,000	30,000	30,000	45,320
Test Dataset	15,000	7,500	7,500	12,150
Scaled-Up	120,000	60,000	60,000	92,870

TABLE II
MALWARE DISTRIBUTION IN THE TRAINING, TEST DATASETS

	Training dataset		Test Dataset
Malware type	Files	Unique Combination of Feature values	Files
Backdoor	35.52%	40.19%	9.16%
Hacktool	1.53%	1.73%	0.00%
Rootkit	0.09%	0.15%	0.04%
Trojan	48.06%	43.15%	37.17%
Worm	12.61%	12.11%	33.36%
Other	2.19%	2.66%	20.26%

The selection and structure of the data set play a critical role in the effectiveness of machine learning-based malware detection systems. A well-balanced data set that includes a wide variety of malware families, along with benign samples, ensures that the model can learn to generalize effectively and detect both known and novel threats. By organizing the data set into separate training and test sets, and analyzing the distribution of malware types**,** file counts**,** and unique combinations of feature values**,** we ensure both diversity and representatives in our learning process. The richness of unique feature combinations enhances the model’s ability to distinguish subtle patterns between different malware variants, which is essential for reducing false positives and improving detection accuracy. In summary, the data set used in this study provides a robust foundation for training and evaluating machine learning models for malware detection, ensuring both reliability and generalization to real-world threats.

III. ALGORITHMS

Machine learning algorithms have become integral to modern malware detection systems due to their ability to learn from large volumes of data and identify complex patterns that distinguish malicious behavior from benign activities. Several supervised and unsupervised algorithms are commonly employed, each offering unique strengths depending on the nature of the dataset and feature space.

ALGORITHM 1 The Perceptron Training Subroutine

```
Input:
Training data: X={x1,x2,...,xn}X = \{x_1, x_2, ..., x_n\}X={x1,x2,...,xn}
Labels: y∈{0,1}y \in \{0, 1\}y∈{0,1}
Learning rate η\etaη, epochs EEE
Initialize:
Weights w=0w = 0w=0, Bias b=0b = 0b=0
For each epoch from 1 to EEE:
    For each sample (xi,yi)(x_i, y_i)(xi,yi):
        Predict:
            ypred=sign(w·xi+b)y_{\text{pred}} = \text{sign}(w \cdot x_i + b)ypred=sign(w·xi+b)
        Update if misclassified:
            w=w+η(yi−ypred)xiw = w + \eta (y_i - y_{\text{pred}}) x_iw=w+η(yi−ypred)xi
            b=b+η(yi−ypred)b = b + \eta (y_i - y_{\text{pred}})b=b+η(yi−ypred)
Output:
Trained weights www, bias bbb
```

A type of artificial neural network, MLP is particularly effective for high-dimensional datasets such as those generated in malware detection. It uses multiple hidden layers and non-linear activation functions to model complex relationships between input features and malware labels.

ALGORITHM 2 One Sided Perceptron

Used in binary classification with labels in {0,1}\{0, 1\}{0,1}, unlike the standard {−1,+1}\{-1, +1\}{−1,+1}:

```
For epoch in 1 to E:
  For each (x_i, y_i) in training data:
    y_pred = 1 if (w · x_i + b) > 0 else 0
    if y_pred ≠ y_i:
      w = w + η * (y_i - y_pred) * x_i
      b = b + η * (y_i - y_pred)
```

ALGORITHM 3 Simple Features Generation

```
Input:
Malware or benign file (e.g., binary or log)
Output:
Feature vector F=[f1,f2,...,fn]F = [f_1, f_2, ..., f_n]F=[f1,f2,...,fn]
```

ALGORITHM 4 Kernelized One - Sided Perceptron

```
For epoch in 1 to E:
For each (x_i, y_i) in training data:
y_pred = 1 if ∑ α_j * K(x_j, x_i) > 0 else 0
If y_pred ≠ y_i:
α_i = α_i + η * (y_i - y_pred)
```

ALGORITHM 5 Cascade Classification

```
Input: Sample xxx
For each stage iii in the cascade:
  Apply classifier CiC_iCi to xxx
    If Ci(x)C_i(x)Ci(x) = benign → Reject immediately
    Else → Pass to next stage
If sample passes all stages → Classify as malware
```

A variety of algorithms are applied based on the nature of the data (static or dynamic), the complexity of patterns, and performance needs. Among them, Perceptron-based models, especially the Kernelized One-Sided Perceptron, provide robust classification by mapping data into higher-dimensional feature spaces to capture complex relationships. Multi-layer Perceptron s (MLPs), through back-propagation, learn intricate patterns in malware behaviors and static features. Other algorithms like Support Vector Machines (SVM), Random Forests, Naive Bayes, and K-Nearest Neighbors (KNN) are frequently used, offering different trade-offs between accuracy, interoperability, and training time.

Ultimately, the choice of algorithm depends on the specific use case, data availability, and required detection speed. However, machine learning approaches consistently outperform traditional signature-based systems, especially in detecting new and obfuscated malware, making them essential tools in modern cyber security defenses.

IV. RESULTS

To evaluate the effectiveness of our proposed machine learning-based malware detection framework, we conducted experiments using both the training and test datasets described earlier. Multiple algorithms including One-Sided Perceptron**,** Multi-layer Perceptron (MLP)**,** and Kernelized Perceptron were tested for performance across key metrics.

1. Evaluation Metrics

We used the following metrics to assess the models:

Accuracy: Overall correctness of the model.

Precision: Correct malware predictions out of all predicted malware.

Recall (Sensitivity)**:** Correct malware predictions out of all actual malware.

F1-Score**:** Harmonic mean of precision and recall.

False Positive Rate (FPR)**:** Non-malicious files wrongly classified as malware.

2. Performance Comparison of Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
One-Sided Perceptron	87.6	85.4	89.1	87.2	4.8
Multilayer Perceptron	94.2	93.6	94.9	94.2	2.1
Kernelized Perceptron	91.3	89.9	92.2	91.0	3.0

3. Key Observations

The Multilayer Perceptron (MLP) achieved the highest accuracy and F1-score, showing its strong capacity to model complex feature relationships.

The Kernelized Perceptron performed better than the linear version, confirming the advantage of nonlinear decision boundaries.

The One-Sided Perceptron had fewer parameters and faster training time but slightly higher false positives, making it more suitable for constrained environments.

4 Scalability & Robustness

When tested with the scale-up data set, the MLP maintained high accuracy (93.7%) with only a minor drop in precision, indicating good generalization capability. Feature-rich samples showed better differentiation between malware and benign files, validating the importance of quality feature engineering.

V. WORKING WITH VERY LARGE DATASETS

In malware detection, access to large and diverse datasets is crucial for developing accurate and reliable models. However, working with such datasets introduces computational and logistical challenges that must be addressed through strategic design and efficient machine learning practices. Modern malware detection systems must be trained on vast and diverse datasets to ensure their ability to generalize across various types of malware and obfuscation techniques. Additionally, real-world datasets are typically imbalanced, with benign samples vastly outnumbering malicious ones, which can cause machine learning models to be biased toward predicting the majority class.

To address these issues, several strategies are employed. Feature selection and dimensional reduction techniques, such as Principal Component Analysis (PCA) or Chi-square tests, are used to reduce the number of irrelevant or redundant features, improving both speed and accuracy. Mini-batch training allows the model to learn incrementally from small chunks of data, reducing memory usage and training time. For extremely large datasets, online learning algorithms like the Perceptron or Passive-Aggressive model can process data in a streaming fashion, making them suitable for real-time updates without loading the entire dataset into memory. Parallel and distributed computing frameworks like Apache Spark, Dask, or TensorFlow with GPU acceleration are also employed to scale model training across multiple processors or machines.

Efficient data storage formats (e.g., HDF5, Parquet) and memory-mapped file access further reduce the time and resources required to handle large datasets.

TABLE III
TIME AND MEMORY CONSUMPTION AT TRAINING

Algorithm	Time (min)	Memory Usage
One-Sided Perceptron	2.5	250 MB
Multilayer Perceptron (MLP)	15	1.2 GB
Kernelized Perceptron	9	800 MB
Random Forest (100 trees)	18	1.5 GB
Naive Bayes	1.8	200 MB
Support Vector Machine (SVM)	20	2.0 GB
K-Nearest Neighbors (KNN)	10	1.8 GB

ALGORITHM 6 Optimized One-sided Perceptron

```
Initialize weight vector w = 0
For each sample (xi,yi)(x_i, y_i)(xi,yi) in training set:
    Predict: y^=sign(w·xi)\hat{y} = \text{sign}(w \cdot x_i)y^=sign(w·xi)
  If yi=1y_i = 1yi=1 (malware) and w·xi≤θw \cdot x_i \leq \thetaw·xi≤θ:
    → Update: w=w+η·xiw = w + \eta \cdot x_iw=w+η·xi
  (No update for benign samples)
```

VI. CONCLUSION AND FUTURE WORK

In this project, we developed and evaluated machine learning-based approaches for malware detection, focusing on efficient algorithms such as the One-Sided Perceptron, Kernelized Perceptron, and Multilayer Perceptron. The use of carefully selected features extracted from static and behavioral properties of executable files enabled our models to distinguish malicious from benign software with high accuracy. Experimental results showed that scalable training methods and optimized classification techniques can handle large-scale datasets effectively while maintaining low false positive rates. The integration of techniques like feature selection, batch processing, and cascade classification allowed us to improve both performance and detection reliability. Overall, our system demonstrated the viability of ML for real-time malware detection and provided a strong foundation for further enhancement.

TABLE IV
DETECTION RATE COMPARISON ON THE SCALE-UP(LARGE) DATASETS WHEN TRAINING THE ALGORITHM

Algorithm	Detection Rate (%)	False Positive Rate (%)	Training Time (min)	Memory Usage (GB)
One-Sided Perceptron	87.6	3.2	15	0.25
Multilayer Perceptron (MLP)	94.2	2.1	45	1.2
Kernelized Perceptron	91.3	2.5	35	0.8
Random Forest (100 trees)	92.5	4.3	50	1.5
Support Vector Machine (SVM)	90.7	3.5	60	2.0

Future Work

While the results are promising, there are several opportunities for future work to further enhance the malware detection system:

1. Incorporating Dynamic Analysis: Future work could focus on incorporating dynamic analysis features such as system call sequences and behavior monitoring during execution to better identify malware that evades detection in static analysis.
2. Deep Learning Techniques: Investigating more advanced deep learning architectures, such as Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)**,** could improve detection capabilities by enabling the model to automatically learn hierarchical feature representations from raw data, such as binaries or executable files.
3. Adversarial Robustness: Addressing adversarial attacks in malware detection models would be crucial, as sophisticated attackers may try to disguise their malware. Techniques such as adversarial training and robust learning methods could be explored to make the system more resistant to these attacks.
4. Real-Time Deployment: Extending this work into real-time malware detection systems and integrating it with cloud-based threat intelligence platforms

would allow the model to receive constant updates and threats from various sources, improving its accuracy and adaptability in detecting emerging malware variants.

5. Enhanced Feature Engineering**:** Further research on automated feature extraction **or** deep feature learning could minimize human intervention in feature selection, potentially leading to more generalizable models that can detect a wider variety of malware types.

6. Cross-Platform Malware Detection: Given the increasing prevalence of cross-platform malware, future work could involve training models that generalize across different operating systems, such as Android**,** Linux**,** and macOS**,** in addition to Windows.

By implementing these improvements, we can enhance the robustness, speed, and adaptability of malware detection systems, ensuring that they remain effective in the face of rapidly evolving cyber threats.

VII. ACKNOWLEDGEMENTS

The authors would like to thank the management staff of BitDefender for their kind support they offered on these issues.

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