**A Hybrid ML-Based Malware Detection Using Static Analysis and Live Threat Intelligence Feeds**

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**Abstract:** Machine Learning for Malware Detection is addresses the increasing cybersecurity challenges posed by malicious software. Leveraging Kaspersky's APIs and Python, this paper combines real-time threat intelligence with machine learning to develop a robust malware detection framework. The system processes datasets containing malicious and benign software, extracts relevant features, and trains models using popular Python libraries such as Scikit-learn, Tensor Flow, and Pandas. Key methodologies include supervised learning for malware classification, anomaly detection for identifying novel threats, and ensemble modelling to enhance accuracy.

Kaspersky's APIs provide real-time updates on emerging threats, ensuring the system remains adaptive to the evolving malware landscape. This paper demonstrates the potential of integrating cutting-edge machine learning techniques with industry-leading cybersecurity tools to create an effective, adaptable, and scalable malware detection system. It offers a proactive approach to combating cyber threats, ensuring greater safety for individuals and organizations in a rapidly digitizing world.

1. **INTRODUCTION**

In the contemporary digital epoch, the pervasive interconnectivity facilitated by the internet has ushered in an era of unprecedented reliance on online services. This dependency, however, has concomitantly amplified the criticality of cybersecurity, rendering it an indispensable facet of modern technological infrastructure. Among the myriad threats that plague digital ecosystems, malware stands as a particularly insidious adversary.

Malware, an umbrella term encapsulating a diverse array of malicious software engineered to disrupt, damage, or illicitly access computer systems. These intrusions pose substantial risks to individuals, businesses, and governmental entities, potentially leading to data breaches, financial losses, and operational disruptions.

Traditional antivirus solutions, while foundational to cybersecurity defences, often grapple with the dynamic and rapidly evolving nature of cyber threats. The emergence of polymorphic and metamorphic malware, coupled with zero-day exploits, necessitates a paradigm shift towards more adaptive and intelligent security mechanisms. Machine learning (ML), a subset of artificial intelligence, presents a compelling avenue for augmenting malware detection capabilities. By enabling systems to discern patterns and learn from data, ML facilitates the identification of subtle indicators of malicious activity that may elude conventional signature- based methods.

This paper endeavours to harness the potent synergy between Kaspersky's application programming interfaces (APIs), celebrated for their extensive threat intelligence, and the versatility of the Python programming language to architect a sophisticated malware detection system. The primary objective is to leverage ML algorithms to scrutinize expansive datasets encompassing both malware and benign files, extracting salient features that serve as reliable discriminators. By seamlessly integrating Kaspersky's real time threat data, the system is designed to remain abreast of the latest advancements in malware tactics, techniques, and procedures (TTPs).

Python, a language renowned for its rich ecosystem of data science and machine learning libraries, facilitates the implementation of diverse ML models, spanning supervised and unsupervised learning paradigms. Supervised learning techniques, such as decision trees, random forests, and support vector machines, can be employed to classify files based on labeled datasets. Conversely, unsupervised learning methods, such as clustering algorithms, can identify anomalous patterns and potential threats without requiring pre-labeled data.

***Key Components of the Malware Detection System:***

*Data Acquisition and Pre-processing:* Collection of a diverse dataset comprising both benign and malicious files.

*Feature extraction:* Analyzing file characteristics such as file headers, executable code sections, API calls, and byte sequences.

*Data cleaning and normalization:* Handling missing values, outliers, and scaling features for optimal ML model performance.

*Kaspersky API Integration:* Utilization of Kaspersky's APIs to access real-time threat intelligence, including malware signatures, behavioral analysis, and reputation data.

* Implementation of API calls to query and retrieve relevant threat information.
* Updating local databases with information retrieved from Kaspersky APIs.

*Machine Learning Model Development:* Implementation of various ML algorithms, including supervised (e.g., Random Forest, SVM, Gradient Boosting) and unsupervised (e.g., Isolation Forest, One-Class SVM) learning techniques.

* Model training and validation using appropriate evaluation metrics (e.g., accuracy, precision, recall, F1-score).
* Hyperparameter tuning for optimal model performance.

*Real-time Detection and Alerting:*

* Development of a system capable of analyzing files in real-time.
* Implementation of an alerting mechanism to notify users of potential malware threats.
* Logging and reporting of detected malware.

*System Evaluation and Optimization:*

* Comprehensive evaluation of the system's performance using benchmark datasets.
* Continuous monitoring and optimization of the system to maintain its effectiveness against evolving threats.
* Version control and code maintainability.

The paper significance extends beyond the mere development of a malware detection system. It seeks to demonstrate the efficacy of ML in proactively identifying and mitigating malware threats, thereby contributing to the broader field of cybersecurity. By constructing a robust, real-time malware detection system, we aim to not only fortify digital defenses but also catalyze future research and innovation in the realm of cyber defence.

Furthermore, this paper emphasizes the importance of utilizing industry- grade threat intelligence, such as that provided by Kaspersky, to enhance the accuracy and reliability of malware detection systems. By integrating real- time data on emerging threats, the system can adapt to the ever-changing landscape of cyberattacks, ensuring that it remains effective against the latest malware variants.

The expected outcomes include:

* Development of a machine learning-based malware detection system.
* Integration of Kaspersky's APIs.
* Evaluation of various machine-learning algorithms.
* Real-time threat detection capabilities.
* Contribution to the cybersecurity community.

1. **LITERATURE REVIEW**

Anderson et al. (2018) [1] explored machine learning-based malware detection using dynamic and static analysis techniques. Their research highlighted the effectiveness of decision trees and neural networks in classifying malware based on extracted features from executable files.

Saxe and Berlin (2015) [2] introduced a deep learning approach for malware classification, leveraging artificial neural networks (ANNs) to analyze raw byte sequences from executable files. The study demonstrated the superiority of deep learning over traditional signature-based methods.

Kolter and Maloof (2006) [3] developed an early machine learning framework for malware detection, applying Naïve Bayes and Support Vector Machines (SVMs) to distinguish between benign and malicious software. Their work laid the foundation for modern MLbased cybersecurity applications.

Huang and Stokes (2016) [4] researched the use of convolutional neural networks (CNNs) for malware classification. By transforming malware binaries into grayscale images, the study showed how deep learning could recognize patterns indicative of malicious behavior.

Raff et al. (2018) [5] introduced the MalConv neural network, a novel approach to malware detection that processes raw binary files without requiring manual feature extraction. This method significantly reduced the reliance on handcrafted features while maintaining high detection accuracy.

Amos et al. (2016) [6] demonstrated the effectiveness of recurrent neural networks (RNNs) in detecting malware through sequential data analysis. Their work emphasized the role of sequence modeling in identifying sophisticated malware evasion techniques. Kolosnjaji et al. (2017) [7] explored the combination of deep learning with static and dynamic analysis methods for malware detection. Their hybrid approach improved classification accuracy and reduced false positives.

Ucci et al. (2019) [8] provided a comprehensive review of machine learning techniques in malware detection, comparing feature engineering strategies and ML models, including ensemble learning methods like Random Forests and Gradient Boosting.

Sebastio and Villatoro (2020) [9] investigated anomaly detection techniques for identifying zero-day malware threats. Their study displayed the power of unsupervised learning in detecting previously unknown malware variants.

Vinayakumar et al. (2019) [10] presented a large-scale malware detection system using deep learning and big data techniques. By leveraging cloud-based architectures, they improved scalability and efficiency in real-time threat analysis.

1. **PROPOSED SYSTEM**

The proposed system employs machine learning (ML) techniques integrated with Kaspersky's APIs to enhance malware detection. This system shifts from traditional signature-based methods to a data-driven approach, leveraging real-time threat intelligence and advanced algorithms for improved accuracy and adaptability. The key Features of proposed system.

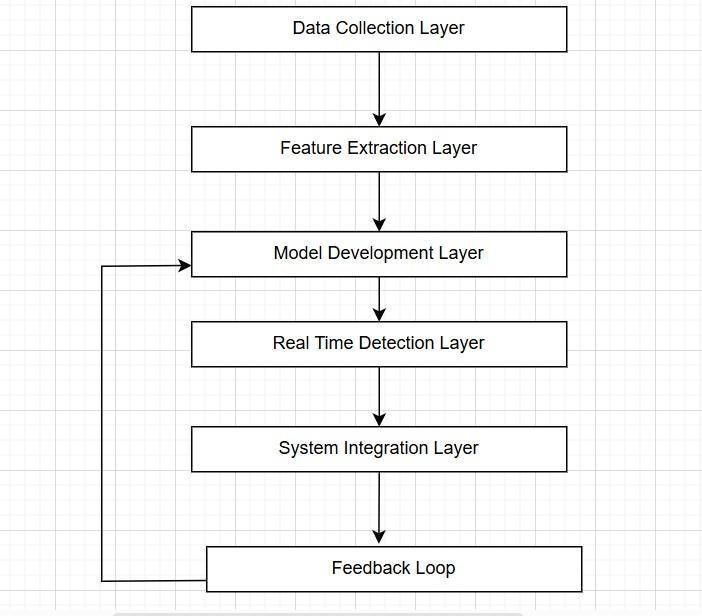
*Machine Learning Models:* Utilizes supervised learning, anomaly detection, and ensemble methods for malware classification. Extracts meaningful features from malware behaviour and patterns for improved detection.

*Integration with Kaspersky's APIs:* Real-time threat intelligence and updates from Kaspersky to stay ahead of emerging threats.

*Data-Driven Detection:* Combines static and dynamic analysis features with ML to identify malware, including zero-day threats.

*Automation and Adaptability:*  Automatically updates the model with new data to adapt to evolving malware patterns.

**System Architecture**



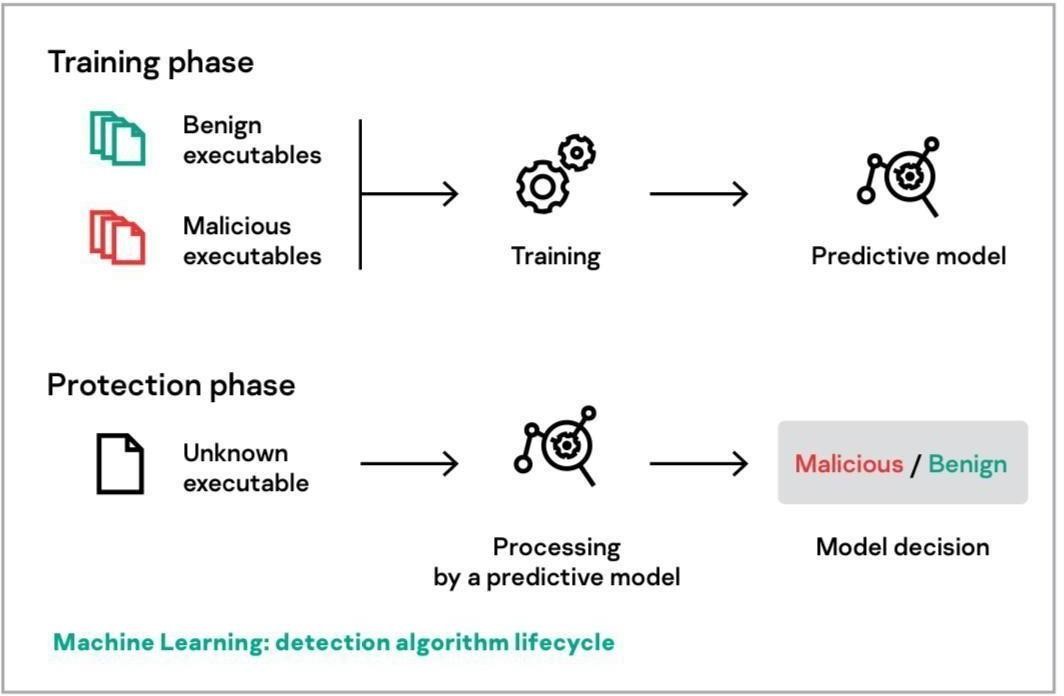
The general architecture of machine learning-based malware detection involves several sequential stages, each contributing to the overall detection process. It begins with data collection, where raw data is gathered from static files, dynamic analysis, or public datasets to ensure a diverse and comprehensive dataset. Next, in the pre-processing phase, the data is cleaned, transformed, and standardized to prepare it for analysis, involving steps like deobfuscation, feature extraction, and normalization. The feature engineering stage identifies and extracts meaningful attributes from the data, which may include static features (e.g., file metadata, opcodes), dynamic features (e.g., API calls, memory usage), or a combination of both for enhanced accuracy.

The prepared data is then fed into the model training phase, where supervised, unsupervised, or deep learning algorithms are used to build a classification or anomaly detection model. The trained model is evaluated in the model testing and evaluation phase using metrics like accuracy, precision, recall, and false positive rate to ensure its reliability and effectiveness.

Once the model meets performance requirements, it is deployed in realworld environments such as endpoint security systems or intrusion detection frameworks, where it scans and classifies files or behaviours as benign or malicious in the deployment and monitoring phase.

A feedback loop continuously updates and improves the model by incorporating new malware samples, retraining the model with updated datasets, and optimizing its architecture to handle evolving threats.

This modular approach, integrating data collection, preprocessing, training, and deployment with iterative feedback, ensures the system remains robust, adaptive, and capable of addressing emerging malware challenges effectively.



The image illustrates the machine learning detection lifecycle in two phases:

***1. Training Phase***: Labelled data of benign and malicious executables is used to train a predictive model, which learns to identify patterns distinguishing malware from safe files.

***2. Protection Phase:*** The trained model processes unknown executables and classifies them as either malicious or benign based on the learned patterns.

This process ensures accurate and automated malware detection, with ongoing refinement through iterative updates.

Below is a structured representation of the malware detection and classification methodology, articulated as algorithmic steps appropriate for inclusion in a research paper. These steps are modular and reflect the logical sequence and integration of various machine learning and cybersecurity techniques referenced in your framework.

***Algorithm: Multi-Stage Malware Detection and Classification Framework***

**Input:**

* Raw malware samples (binary format) and associated metadata
* Labeled datasets for supervised learning and Unlabeled data for anomaly detection and clustering

**Output:**

* Malware classification label
* Anomaly risk score
* Cluster/group assignment
* Model update (in online learning scenario)

***Step 1: Web-Based Malware Sample Acquisition***

* 1. Deploy a web scraping tool (e.g., Scrapy) to harvest binary samples and

contextual metadata from malware repositories and threat intelligence sources.

1.2. Parse and store downloaded samples in a secured and indexed dataset repository.

***Step 2: Feature Extraction Using N-Gram Analysis***

2.1 For each binary sample, convert the raw byte stream or opcode sequence into a

fixed-length sequence of *n*-grams.  
2.2. Compute the frequency distribution of each unique *n*-gram.  
2.3. Construct feature vectors representing statistical patterns of byte/opcode

sequences for each sample.

***Step 3: Supervised Machine Learning for Malware Classification***

3.1. Split the feature dataset into training and testing subsets.  
3.2. Train multiple classifiers:

* **Support Vector Machine (SVM):** Utilize a kernelized SVM (e.g., RBF) for high-dimensional margin-based classification.
* **Random Forest:** Employ an ensemble of decision trees with bagging to reduce variance and mitigate overfitting.
* **Convolutional Neural Network (CNN):** Represent byte sequences as image-like matrices (if applicable) and apply deep convolutional architectures to model complex patterns.
  1. Evaluate classifiers using standard metrics (accuracy, precision, recall, F1-score)

and retain best-performing models for deployment.

***Step 4: Anomaly Detection for Zero-Day Threat Identification***

4.1. Train anomaly detection models on benign-labeled feature data:

* **One-Class SVM:** Constructs a decision boundary enclosing normal data.
* **Isolation Forest:** Identifies anomalies by isolating observations through random partitioning.

4.2. Score each new or unlabeled sample using the trained anomaly detection model; classify outliers as potential zero-day malware.

***Step 5: Clustering for Behavioural Grouping and Novelty Detection***

5.1. Apply clustering algorithms such as K-Means or DBSCAN on feature vectors to group similar samples.

5.2. Analyze cluster density and distance metrics to identify novel variants or outliers that may correspond to emerging malware families.

***Step 6: Online Learning for Continuous Model Adaptation***

6.1. Incorporate algorithms capable of incremental learning (e.g., Online SVM, AdaBoost.M1).

6.2. Upon receiving new labeled instances:

* Update model parameters without retraining from scratch.
* Adjust classification boundaries or weights based on new information.

6.3. Facilitate near real-time learning, especially useful for adapting to rapidly evolving threat landscapes.

***Step 7: System Integration via RESTful APIs***

7.1. Implement RESTful APIs to facilitate external interactions with the system.

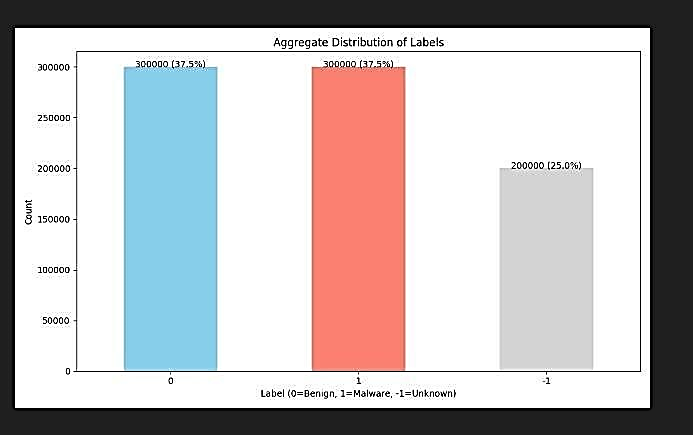
7.2. Provide endpoints for:

* Submitting binary samples (POST /predict)
* Supplying analyst feedback (POST /feedback)
* Retrieving classification and risk assessment reports (GET /report)

7.3. Ensure interoperability with other security platforms (e.g., SIEM, endpoint detection systems) for seamless threat intelligence exchange.

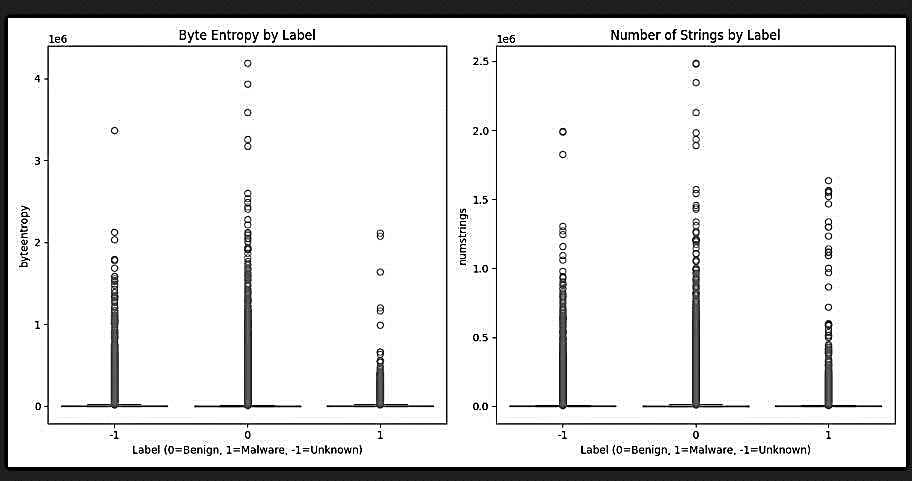
This multi-stage pipeline leverages both traditional machine learning and deep learning paradigms, coupled with anomaly detection and clustering, to provide a robust, adaptive framework for malware classification and threat detection. Integration with real-time systems via APIs ensures operational readiness for deployment in enterprise or research-oriented cybersecurity infrastructures.

If needed, this algorithmic structure can be converted into LaTeX format or integrated into a methodology section for scholarly publication.



Aggregate Distribution of Labels

The dataset consists of three distinct labels: Benign (0), Malware (1), and Unknown (-1), each representing different classifications within the cybersecurity domain. A bar chart illustrates the frequency distribution of these labels, showing that both Benign and Malware categories each comprise 300,000 instances, accounting for 37.5% of the total data. Meanwhile, the Unknown label, representing ambiguous or unclassified cases, consists of 200,000 occurrences, making up 25.0% of the dataset. This distribution provides a crucial overview of the dataset composition, aiding in the understanding of classification trends and informing analytical decisions in cybersecurity research.



The image contains two scatter plots that visually compare different metrics by label. The left plot, titled "Byte Entropy by Label," represents the distribution of byte entropy across three categories: -1 (Unknown), 0 (Benign), and 1 (Malware). The y-axis ranges from 0 to 4e6, with most data points clustered near the lower values, while a few outliers reach higher entropy levels. The right plot, "Number of Strings by Label," follows a similar structure, illustrating the count of strings within the same label categories. The y-axis extends up to 2.5e6, showing a concentration of data points at the lower end, with occasional outliers. These plots offer insights into entropy and string frequency variations among different labels, which can be useful in distinguishing benign, malware, and unknown files in cybersecurity research. Let me know if you need adjustments.

1. **CONCLUSION**

Machine Learning for Malware Detection demonstrates the effectiveness of integrating machine-learning techniques with realtime cybersecurity intelligence to enhance malware detection capabilities. By leveraging Kaspersky’s APIs and popular Python libraries such as Scikit-learn, TensorFlow, and Pandas, the system ensures an adaptive and scalable approach to identifying malicious software.

The implementation of supervised learning for malware classification, anomaly detection for zero-day threats, and ensemble modeling significantly improves detection accuracy while minimizing false positives. Additionally, the system benefits from real-time threat intelligence, enabling continuous updates against evolving cyber threats. This paper highlights the potential of AI-driven cybersecurity solutions in combating modern malware threats.

The combination of machine learning models and industry-standard security tools not only enhances detection efficiency but also provides a proactive approach to cybersecurity. As cyber threats continue to evolve, further research can explore deep learning architectures, federated learning, and cloudbased deployment to enhance detection accuracy and scalability. By bridging the gap between AI and cybersecurity, this paper contributes to creating a safer digital environment, offering valuable insights for both individuals and organizations in mitigating cyber risks.

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