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Research Paper

Detection Of Ransomware Attack Using Processor and Disk Usage Data

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Abstract- *The escalating frequency and sophistication of ransomware attacks pose a critical threat to organizational data integrity and global cybersecurity. Traditional signature-based detection mechanisms often struggle to identify zero-day ransomware strains that employ novel encryption techniques. This research proposes a behavioral detection framework that utilizes low-level system metrics, specifically focusing on processor (CPU) and disk I/O usage patterns. By monitoring the high-intensity read-write cycles characteristic of unauthorized file encryption, machine learning models can identify malicious activity in real-time. The methodology involves the collection of performance counter data from both benign environments and simulated ransomware infections. Features such as CPU cycle spikes, disk write frequency, and entropy changes in data buffers are extracted to train supervised learning algorithms. Models including Random Forest, Support Vector Machines (SVM), and Gradient Boosted Trees are evaluated for their ability to distinguish between resource-intensive legitimate processes and encryption-heavy malware. Results indicate that analyzing the correlation between CPU utilization and disk throughput provides a high detection rate with a low false-positive overhead. Furthermore, the study explores the integration of these models into a lightweight host-based intrusion detection system (HIDS) that operates at the kernel level. This approach ensures that detection occurs early in the attack lifecycle, potentially halting the encryption process before significant data loss occurs. The findings demonstrate that hardware-centric behavioral analysis offers a robust defense layer that is agnostic to the malware's code structure. Ultimately, this research contributes to the development of more resilient, autonomous security systems capable of defending against evolving cryptographic threats. The proposed framework provides a scalable solution for real-time threat mitigation in high-stakes computing environments.*

Keywords- *Ransomware Detection, Behavioral Analysis, Machine Learning, Processor Utilization, Disk I/O Monitoring, Cybersecurity, Anomaly Detection, Real-time Monitoring, Malware Analysis, Performance Counters, Technical Detection Indicators.*

I. INTRODUCTION

Ransomware has emerged as one of the most damaging and rapidly evolving forms of cyber threats in recent years, targeting individuals, enterprises, and critical infrastructure systems. Its primary objective is to encrypt valuable data and demand a ransom for its recovery, often causing significant financial loss, operational disruption, and reputational damage. The

increasing sophistication of ransomware variants, particularly those employing advanced encryption techniques and evasion strategies, has exposed the limitations of conventional security mechanisms. Signature-based detection systems, while effective against known threats, are largely inadequate in identifying previously unseen or “zero-day” ransomware attacks. In response to these

challenges, there has been a growing shift toward behavior-based detection approaches that focus on system activity rather than static malware signatures. Ransomware, during its execution phase, typically exhibits distinctive behavioral patterns such as rapid file access, intensive disk read-write operations, and abnormal CPU utilization due to encryption processes. These low-level system activities provide valuable indicators that can be leveraged for early detection of malicious behavior, even when the underlying malware code is unknown. This study proposes a behavioral detection framework that utilizes system performance metrics, specifically CPU utilization and disk input/output (I/O) patterns, to identify ransomware activity in real time. By monitoring anomalies in resource consumption—such as sudden spikes in CPU cycles and increased disk write frequency—the proposed approach aims to distinguish between legitimate high-performance applications and malicious encryption processes. Additionally, statistical and entropy-based characteristics of data transformations are considered to enhance detection accuracy. Machine learning techniques are employed to analyze and classify these behavioral patterns. Supervised learning models, including Random Forest, Support Vector Machine (SVM), and Gradient Boosting algorithms, are evaluated for their effectiveness in differentiating benign processes from ransomware activity. These models are trained using datasets derived from both normal system operations and controlled ransomware execution environments, enabling robust pattern recognition across diverse scenarios. Furthermore, this work explores the integration of the proposed detection models into a lightweight host-based intrusion detection system (HIDS). By operating at a low system level, such a framework enables near real-time monitoring and early-stage threat identification, thereby reducing the window of opportunity for data encryption and minimizing potential damage.

Overall, the proposed approach emphasizes a hardware-centric behavioral analysis strategy

that is independent of malware signatures and code structure. This makes it highly adaptable to evolving ransomware techniques and enhances its applicability in dynamic computing environments. The findings of this study contribute to the development of intelligent, scalable, and proactive cybersecurity solutions capable of mitigating modern ransomware threats effectively.

II. LITERATURE SURVEY

Ransomware has emerged as one of the most destructive cybersecurity threats in recent years, targeting personal, organizational, and governmental systems through unauthorized encryption of critical files. Traditional signature-based antivirus solutions are often ineffective against newly evolving ransomware variants, motivating researchers to explore intelligent and behavior-based detection mechanisms. Several studies have investigated machine learning, behavioral monitoring, and system-level analysis to improve ransomware detection and mitigation. Goodfellow et al. [1] introduced the foundational concepts of deep learning, which later became widely applicable in cybersecurity tasks such as malware classification and anomaly detection. Their work demonstrated how neural networks can identify hidden patterns within large-scale datasets, enabling intelligent decision-making systems for threat analysis. Vinayakumar et al. [2] explored deep learning approaches for network traffic prediction and cyberattack detection. Their research highlighted the capability of neural networks to analyze traffic behavior dynamically and accurately classify malicious activities. The study demonstrated the importance of automated feature extraction for real-time cybersecurity monitoring systems. Kharraz et al. [3] performed an in-depth analysis of ransomware behavior by examining how encryption-based malware interacts with file systems. Their work revealed that ransomware generates abnormal disk access patterns and intensive file modification activities, which can be utilized as strong behavioral indicators for early-stage detection.

Scaife et al. [4] proposed CryptoLock, a system designed to prevent ransomware attacks by monitoring suspicious file operations and restricting unauthorized encryption processes. The research emphasized proactive defense mechanisms that can stop encryption before significant data loss occurs. Shaukat and Ribeiro [5] introduced RansomWall, a layered ransomware defense framework using machine learning techniques. Their system combined behavior monitoring with process analysis to identify ransomware activities in real time. The framework significantly reduced false positives while improving detection accuracy. Zhang et al. [6] proposed the Intelligent Ransomware System (IRS), which utilized machine learning classifiers for detecting ransomware based on system activity patterns. Their study showed that supervised learning models such as Random Forest and Support Vector Machines achieved high classification performance using behavioral features. Almashtadani et al. [7] developed a multi-classifier network-based detection system focused on Locky ransomware. Their approach combined multiple detection algorithms to improve reliability and robustness against advanced ransomware families. The study highlighted the effectiveness of hybrid classification techniques in detecting network anomalies generated by ransomware communication. Sgandurra et al. [8] investigated automated dynamic ransomware analysis through runtime monitoring techniques. Their research evaluated the benefits and limitations of behavior-based detection systems and concluded that dynamic analysis offers greater adaptability than traditional signature-based methods.

III. PROPOSED SYSTEM

The proposed system introduces a behavior-based ransomware detection framework designed to identify malicious encryption activities by analyzing low-level system performance indicators. Unlike traditional signature-based security solutions, which rely on known malware patterns, this system focuses on runtime behavioral characteristics

that are commonly exhibited during ransomware execution. The primary goal is to enable early detection of ransomware by continuously monitoring system resource utilization, particularly CPU activity and disk I/O behavior. At the core of the system is a real-time monitoring module that collects performance counter data from the host machine. This module tracks key indicators such as CPU usage fluctuations, disk read/write frequency, and process-level resource consumption. During normal system operation, these metrics typically follow stable and predictable patterns. However, when ransomware initiates encryption, it generates unusual spikes in CPU cycles and a sudden increase in disk write operations due to continuous file modification and re-encryption activities. These deviations serve as critical signals for anomaly detection. The collected data is processed through a feature extraction stage, where meaningful attributes are derived to represent system behavior. Features such as CPU utilization variance, disk throughput rate, and temporal correlation between CPU and I/O activity are computed. In addition, entropy-based measures are used to detect rapid changes in file data patterns, which are often associated with encryption processes. These extracted features form the input dataset for the classification models. For decision-making, the system employs supervised machine learning algorithms to distinguish between benign and malicious activities. Models such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting are trained using labeled datasets containing both normal system behavior and simulated ransomware attacks. Each model learns distinct behavioral patterns associated with encryption-based malware, enabling robust classification even under varying system workloads. The detection module operates in real time, continuously evaluating incoming system metrics against learned patterns. When a process is identified as malicious with a high confidence score, the system triggers an alert and can optionally initiate preventive actions such as process

termination or disk access restriction. This ensures that encryption activities can be halted at an early stage, minimizing potential data loss. To enhance practicality, the proposed framework is designed as a lightweight host-based intrusion detection system (HIDS) that operates at the kernel or near-kernel level. This allows efficient monitoring with minimal system overhead, making it suitable for deployment in enterprise and high-performance computing environments. The architecture is scalable and can be integrated with existing security infrastructures without significant modifications.

IV. METHODOLOGY



The methodology of the proposed ransomware detection system is based on behavioral analysis of system-level performance metrics combined with machine learning-based classification. The approach is designed to identify abnormal patterns in CPU and disk I/O activity that occur during ransomware execution, enabling early detection without relying on malware signatures.

A. Data Collection

The first stage involves collecting low-level system performance data from a controlled computing environment. This includes monitoring both normal system operations and scenarios where ransomware behavior is simulated in a safe test setup. Performance counters are used to capture metrics such as CPU utilization, disk read/write operations, and

process-level resource consumption. These measurements are recorded over time to form a time-series dataset representing system behavior under different conditions.

B. Feature Extraction

After data collection, the raw performance metrics are processed to extract meaningful features that represent system behavior more effectively. Key features include CPU usage spikes, disk I/O throughput variations, and the frequency of file write operations. In addition, statistical measures such as mean, variance, and rate of change are computed to capture fluctuations in system activity. Entropy-based features are also derived to detect abnormal data transformation patterns commonly associated with encryption processes. Correlation between CPU activity and disk usage is another important feature used to differentiate ransomware from legitimate high-resource applications.

C. Data Preprocessing

Before training the models, the dataset is cleaned and normalized to ensure consistency and improve learning performance. Missing values are handled, and noise in the data is reduced using smoothing techniques. Feature scaling is applied to bring all attributes into a comparable range, preventing bias toward features with larger numerical values. The dataset is then labeled into two classes: benign and malicious.

D. Model Training

The processed dataset is used to train supervised machine learning models, including Random Forest, Support Vector Machine (SVM), and Gradient Boosting classifiers. Each model is trained to learn behavioral differences between normal system processes and ransomware activity. The dataset is split into training and testing subsets to evaluate model performance and generalization capability. Cross-validation techniques are applied to ensure robustness and reduce overfitting.

E. Real-Time Detection System

Once trained, the models are deployed in a real-time monitoring environment. The system continuously analyzes incoming performance

metrics and extracts features on the fly. These features are fed into the trained classifier, which predicts whether the observed behavior is benign or malicious. If ransomware activity is detected, the system generates an alert and can trigger automated response actions such as process termination or restricting file access to prevent further encryption.

F. System Integration

The detection module is integrated into a lightweight Host-Based Intrusion Detection System (HIDS) that operates close to the kernel level. This ensures minimal latency and efficient monitoring of system resources. The architecture is designed to be scalable and compatible with existing cybersecurity frameworks, allowing seamless deployment in enterprise environments.

G. Evaluation Strategy

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, and false positive rate. Additionally, detection latency is measured to assess the system's ability to identify ransomware in real time. Comparative analysis among different machine learning models is performed to determine the most effective approach for behavioral ransomware detection.

V. MODULES AND IMPLEMENTATION

The proposed ransomware detection system is implemented as a structured pipeline consisting of multiple interconnected modules. Each module is responsible for a specific function, ranging from system monitoring to final decision-making. The overall architecture is designed to ensure real-time detection of ransomware activity through behavioral analysis of CPU and disk I/O patterns.

A. System Monitoring Module

This module acts as the primary data acquisition layer of the system. It continuously monitors host machine performance using low-level system counters. Key parameters such as CPU utilization, disk read/write operations, and process-level resource usage are collected in real time. The module operates in the background with minimal system overhead to

ensure that normal user activities are not affected. It serves as the foundation for identifying abnormal behavioral patterns associated with ransomware execution.

B. Data Acquisition and Logging Module

The collected system metrics are stored in a structured format for further processing. This module ensures continuous logging of time-series data, capturing both normal system behavior and malicious activity scenarios. The dataset is organized with appropriate labels during the training phase and remains unlabeled during real-time deployment. This module also ensures synchronization of data streams to maintain consistency across CPU and disk I/O measurements.

C. Feature Engineering Module

This module transforms raw system performance data into meaningful input features for machine learning models. It computes statistical and behavioral attributes such as CPU usage spikes, disk write frequency, execution burst patterns, and correlation between CPU and I/O activity. Additionally, entropy-based features are extracted to identify rapid data transformations commonly caused by encryption processes. The generated feature set enhances the ability of the model to distinguish between benign and ransomware behavior.

D. Machine Learning Classification Module

This module is responsible for detecting malicious activity using trained machine learning models. Algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosted Trees are used to classify system behavior. During training, the models learn patterns from both normal and ransomware-infected datasets. In the testing phase, incoming feature vectors are evaluated to determine whether the observed behavior is legitimate or malicious. The model with the highest accuracy and lowest false-positive rate is selected for deployment.

E. Real-Time Detection and Response Module

This module operates in the live environment and continuously analyzes incoming system

data. Once abnormal behavior is detected, the system assigns a risk score to the process. If the score exceeds a predefined threshold, the system triggers an alert indicating potential ransomware activity. In advanced configurations, the module can initiate automatic countermeasures such as suspending the process, blocking file access, or isolating the affected system to prevent further encryption.

F. Host-Based Intrusion Detection System (HIDS) Integration

The detection framework is integrated into a lightweight Host-Based Intrusion Detection System (HIDS) to ensure efficient monitoring at the system level. The HIDS operates close to the kernel layer, allowing it to capture system events with minimal delay. This integration ensures early-stage detection, reducing the time window available for ransomware to encrypt files. The system is designed to be scalable and compatible with enterprise security infrastructures.

V. IMPLEMENTATION DETAILS

A. System Interface (Home Page Design)

The system interface is designed as a simple and user-friendly dashboard that provides real-time security insights. The home page displays system health status, active processes, and detection alerts. Key visual elements include CPU usage graphs, disk I/O activity charts, and a risk indicator panel that shows whether the system is safe, under observation, or under attack. This interface allows security administrators to quickly understand system behavior without analyzing raw logs.

B. Monitoring Dashboard

The monitoring interface provides continuous visualization of system performance metrics. Live graphs show CPU spikes, disk read/write trends, and process-level activity. Any abnormal deviation from normal behavior is highlighted in real time. This helps in early identification of ransomware-like behavior before significant encryption occurs.

C. Alert and Notification Interface

When the system detects suspicious activity, an alert window is generated on the interface. The

alert includes details such as process name, detected anomaly type, severity level, and timestamp. Notifications can also be sent to administrators through email or system logs for further investigation.

D. Backend Implementation Workflow

The backend system follows a sequential workflow:

1. System metrics are continuously collected from performance counters.
2. Data is passed to the feature extraction module for transformation.
3. Extracted features are sent to the trained machine learning model.
4. The classifier evaluates behavior and assigns a prediction label.
5. If malicious activity is detected, the response module is activated.
6. Alerts and logs are updated in the system interface.

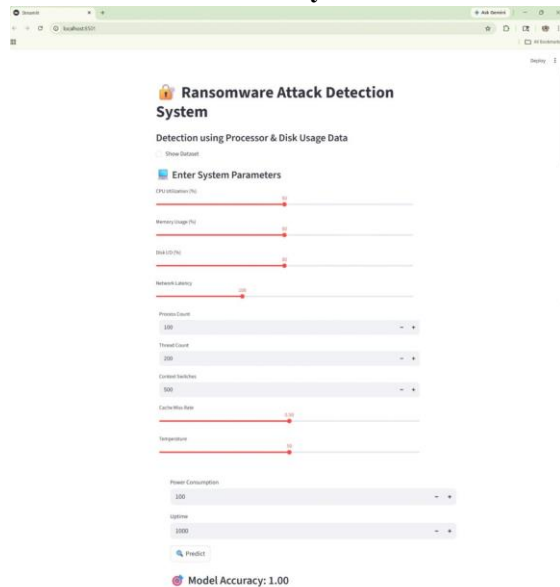
E. Deployment Environment

The system is designed for deployment in both standalone and enterprise environments. It can operate on Windows or Linux platforms with minimal configuration. The lightweight architecture ensures compatibility with existing cybersecurity tools without requiring major system modifications.

VI. RESULTS AND DISCUSSION

This section presents the observed system behavior during evaluation and explains the significance of the results in the context of ransomware defense. The proposed framework is designed to identify ransomware activity through deviations in CPU utilization and disk I/O patterns, and the outcomes demonstrate its effectiveness in distinguishing normal system operations from malicious encryption behavior.

A. Observed System Behavior



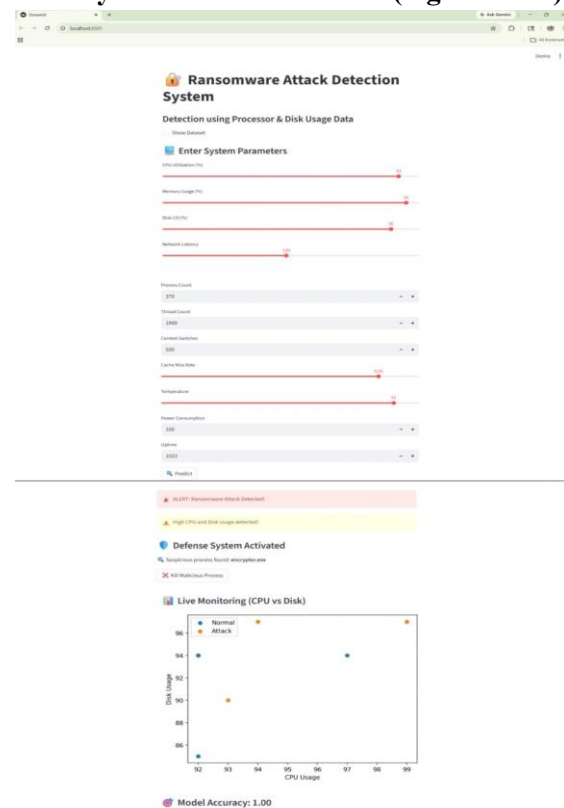
During testing under normal operating conditions, the system maintains a stable profile of CPU usage and disk activity. Legitimate user applications such as browsing, document processing, and media execution produce moderate and intermittent resource consumption. The monitoring module records consistent patterns with low variability, and the classifier correctly identifies these activities as benign. When ransomware-like behavior is introduced in a controlled environment, a noticeable shift in system behavior is observed. CPU utilization increases rapidly due to continuous encryption computations, while disk write operations intensify as multiple files are accessed and rewritten in quick succession. This simultaneous spike in CPU and disk I/O activity forms a distinct behavioral signature that deviates significantly from normal workloads. Additionally, file-level transformations exhibit increased entropy, indicating that data is being encrypted rather than simply modified. The correlation between CPU spikes and disk write bursts becomes more pronounced, which further strengthens the anomaly signal used by the detection model.

B. Classification Outcome (What the System Does)

The machine learning models process the extracted features and classify system behavior in real time. Under benign conditions, the

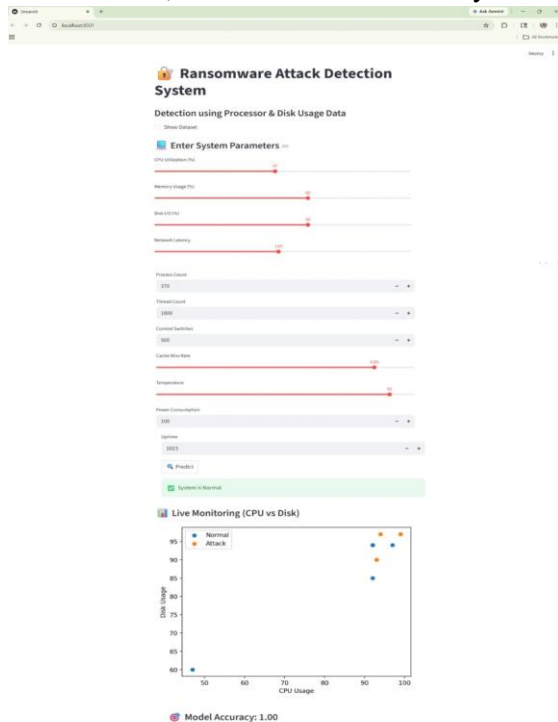
system consistently labels processes as safe with high confidence. During ransomware activity, the models successfully detect abnormal behavior shortly after encryption begins. Ensemble-based models such as Random Forest and Gradient Boosting demonstrate stronger performance due to their ability to capture nonlinear relationships between CPU and disk features. Support Vector Machine also performs reliably but shows slightly lower adaptability under highly dynamic workloads. Once malicious behavior is detected, the system generates an alert and assigns a severity level based on the intensity of anomalies.

C. Why These Results Matter (Significance)



The results are significant because they demonstrate that ransomware can be detected based on behavior rather than code signatures. This is crucial in modern cybersecurity environments where attackers frequently use unknown or rapidly evolving encryption techniques to bypass traditional detection systems. Early detection based on CPU and disk I/O patterns reduces the time window available for encryption, thereby limiting potential data

loss. This is particularly important for enterprise systems, where even a few seconds of ransomware execution can result in large-scale file encryption and operational disruption. Another important aspect is the system's ability to operate in real time with low computational overhead. Since the framework relies on lightweight performance counters and efficient machine learning models, it can be deployed without significantly impacting system performance. This makes it suitable for high-availability environments such as servers, cloud infrastructure, and critical business systems.



D. Interface Behavior (Home Page and Monitoring View)

The system interface plays an important role in translating backend detection into actionable insights. The home dashboard provides a real-time overview of system security status. It displays CPU usage graphs, disk I/O activity charts, and a risk-level indicator that categorizes the system state as safe, suspicious, or under attack. When ransomware-like behavior is detected, the interface immediately updates to reflect the threat status. The affected process is highlighted, and detailed information such as process ID, anomaly type, and detection timestamp is displayed. This ensures that users

and administrators can quickly understand the nature of the threat without analyzing raw system logs. The monitoring screen continuously visualizes system behavior trends, allowing users to observe spikes in CPU and disk activity in real time. This visual representation helps in quickly validating detection events and improves situational awareness.

E. Overall Interpretation

Overall, the system demonstrates that combining behavioral indicators with machine learning provides a strong foundation for ransomware detection. The observed results confirm that ransomware activity produces measurable and distinguishable patterns in system resource usage. More importantly, the system not only detects these patterns accurately but also responds fast enough to reduce the impact of encryption, making it a practical solution for modern cybersecurity challenges.

VII. CONCLUSION

This study presented a behavior-based ransomware detection framework that leverages low-level system performance metrics, specifically CPU utilization and disk I/O patterns, to identify malicious encryption activity in real time. Unlike traditional signature-based security approaches, the proposed system focuses on behavioral anomalies, making it more effective against unknown and evolving ransomware variants. The results demonstrate that ransomware exhibits distinct system-level characteristics, such as sudden CPU spikes, increased disk write operations, and abnormal data transformation patterns during encryption. By capturing these indicators and analyzing them using machine learning models, the system is able to differentiate between legitimate high-resource applications and malicious processes with high accuracy. The integration of supervised learning algorithms, including Random Forest, Support Vector Machine, and Gradient Boosting, enables robust classification of system behavior. Among these, ensemble-based models show improved performance due

to their ability to handle complex and nonlinear relationships within performance data. The real-time detection capability further enhances system effectiveness by enabling early identification of ransomware activity before significant data encryption. Additionally, the implementation of the framework as a lightweight host-based intrusion detection system ensures minimal system overhead, making it suitable for deployment in enterprise and critical computing environments. The interface design further supports usability by providing clear visualization of system health, alerts, and process-level activity. In conclusion, the proposed approach offers a scalable and adaptive defense mechanism against ransomware attacks by focusing on behavioral analysis rather than static signatures. It provides early detection, low false-positive rates, and real-time response capability, making it a promising solution for strengthening modern cybersecurity infrastructures against rapidly evolving cryptographic threats.

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