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Intelligent Ransomware Detection and Early Warning System Using Hybrid Machine Learning and Real-Time Behavioral Analysis

Ms. M. Mohana Priya[1], Ramya. B[2], Nisha. R[3], Shalini. T[4]
[1]*Assistant professor, Dept. of AI&DS, School of Engineering & Technology, Surya Group of Institutions, Vikravandi, Villupuram*
[2,3,4]*UG - Dept. of AI&DS, School of Engineering & Technology, Surya Group of Institutions, Vikravandi, Villupuram*
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***Abstract*—Ransomware has become one of the most destructive cybersecurity threats, causing financial losses and data breaches across organizations globally. Traditional antivirus and signature-based detection systems have proven ineffective against new and evolving ransomware variants. This research proposes an Intelligent Hybrid Machine Learning-based Ransomware Detection and Autonomous Defense System that integrates real-time behavioral monitoring with advanced machine learning algorithms. The system monitors critical system activities including file modifications, entropy changes, CPU usage, and process activity patterns. A hybrid detection approach combining Random Forest for known threat detection and Isolation Forest for anomaly-based zero-day ransomware detection is implemented. Upon detecting suspicious behavior, the system automatically initiates defensive mechanisms including process termination, emergency file backup, network isolation, and forensic logging. The proposed system achieves high detection accuracy while maintaining low false positive rates. Real-time monitoring and autonomous response capabilities significantly reduce ransomware damage and recovery time. Experimental evaluation demonstrates superior performance compared to traditional signature-based and rule-based detection systems.**

***Index Terms*—Ransomware Detection, Behavioral Analysis, Machine Learning, Random Forest, Isolation Forest, Real-Time Monitoring, Autonomous Defense.**

I. INTRODUCTION

Ransomware is a sophisticated form of malicious software designed to encrypt critical user data and system files, rendering them inaccessible until a ransom payment is made. The global ransomware threat landscape has evolved dramatically, with attacks targeting healthcare institutions, financial organizations, government agencies, and critical infrastructure. Organizations face ransomware attacks every 11 seconds, resulting in cumulative damages exceeding billions of dollars annually.

Traditional cybersecurity approaches rely on signature-based detection, which requires prior knowledge of malware signatures. These systems maintain databases of known threat signatures and compare incoming executables against these databases. However, ransomware authors continuously modify their code through obfuscation, polymorphism, and encryption techniques to evade signature detection. This evolutionary arms race has rendered signature- based systems increasingly ineffective against new ransomware variants and zero-day exploits.

Static analysis examines malware code before execution by disassembling binaries and analyzing their structure. However, encrypted and obfuscated malware successfully bypasses static analysis techniques. Heuristic systems employ predefined rules to detect suspicious behavior patterns, but these rule-based approaches often generate excessive false positives, overwhelming security analysts and reducing system usability.

Recent research has explored machine learning approaches for malware detection. However, most existing systems suffer from significant limitations: lack of real-time monitoring capabilities, inability to detect unknown/zero-day threats, high false positive

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rates, absence of automated response mechanisms, and lack of comprehensive forensic logging. There is a critical need for an intelligent system that combines behavioral monitoring, hybrid machine learning detection, risk assessment, and automated defensive response.

This research proposes a comprehensive Intelligent Ransomware Detection and Autonomous Defense System that addresses these limitations. The system monitors real-time behavioral features such as file write rates, entropy changes, CPU usage, and process activity. A hybrid machine learning approach combining Random Forest for supervised detection and Isolation Forest for unsupervised anomaly detection improves overall detection accuracy and enables detection of unknown ransomware variants. Intelligent risk scoring and severity classification enable prioritized response. Autonomous defense mechanisms including process termination, emergency backup, and network isolation are automatically triggered when threats are detected, significantly reducing potential damage.

II. PROBLEM STATEMENT

Ransomware attacks represent a critical cybersecurity challenge with rapidly increasing frequency and sophistication. Organizations worldwide suffer significant financial losses and operational disruptions due to ransomware infections. Traditional antivirus solutions and signature-based detection mechanisms are fundamentally inadequate for defending against new and evolving ransomware variants.

Key challenges include:

- Signature-based systems can only detect previously known ransomware
- Zero-day and polymorphic variants easily evade traditional detection
- Static analysis fails on encrypted and obfuscated malware
- Heuristic rule-based systems produce excessive false positives
- Real-time behavioral monitoring is absent in most systems
- Lack of automated response mechanisms increases damage
- No integrated file backup or network isolation features
- Limited forensic logging for post-incident analysis

There is an urgent need for an intelligent, real- time ransomware detection system that combines advanced behavioral analysis with hybrid machine learning to identify both known and unknown ransomware attacks, combined with autonomous defensive mechanisms to minimize damage and recovery time.

III. OBJECTIVES

The primary objectives of this research are as follows:

- Detect ransomware at early stages using behavioral feature analysis
- Implement hybrid machine learning combining supervised and unsupervised detection
- Enable real-time system activity monitoring and behavioral analysis
- Calculate dynamic risk scores for accurate threat assessment
- Classify threat severity using color-coded intelligent dashboard
- Automatically terminate malicious processes upon detection
- Perform emergency file backup during active ransomware attack
- Isolate network to prevent ransomware propagation to other systems
- Maintain comprehensive forensic logs for post-attack analysis and investigation

IV. PROPOSED SYSTEM

The proposed Intelligent Ransomware Detection and Autonomous Defense System integrates real- time behavioral monitoring with hybrid machine learning detection and automated response mechanisms. The key components are described below.

A.Real-Time Monitoring Module

Continuously monitors file system activities, CPU usage, disk I/O, process creation, and network activities. Data is collected at configurable intervals to maintain system performance while ensuring detection responsiveness.

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B.Feature Extraction Module

Extracts critical behavioral features including file write rate, file entropy, CPU usage, process count, registry modifications, and network connections. Processes raw monitoring data to extract 20+ behavioral features for machine learning models.

C. Hybrid Detection Module

Integrates Random Forest model for detecting known ransomware patterns and Isolation Forest for detecting unknown/zero-day attacks. Both models run in parallel and results are combined using weighted hybrid scoring.

D. Risk Assessment Module

Calculates risk score (0–100%) and determines severity classification: Low (0–25%), Medium (25–50%), High (50–75%), Critical (75–100%).
Color-coded dashboard displays real-time threat status.

E. Autonomous Defense Module

Upon detecting high-risk behavior, automatically:
(1) terminates suspicious process; (2) creates emergency backup of critical files; (3) isolates network connections; (4) triggers user alert notifications.

F. Logging & Reporting Module

Records comprehensive forensic details including timestamp, process information, behavioral features, risk scores, severity classification, and response actions taken. Logs are maintained for post-incident investigation and threat intelligence.

V. METHODOLOGY

A.Data Collection and Preprocessing

The system collects behavioral data from both ransomware and benign applications. Ransomware samples are obtained from public malware repositories. Benign application data is collected from normal system usage. Raw behavioral data is preprocessed to extract relevant features and normalized for machine learning model input.

B.Feature Extraction

The following behavioral features are extracted for analysis:

- File Write Rate: Number of files modified per unit time — high rates indicate encryption activity
- File Entropy: Measure of data randomness — encrypted files exhibit high entropy
- CPU Usage: Processor utilization patterns during encryption operations
- Process Count: Number of active processes — anomalous process creation indicates infection
- Registry Modifications: Changes to system registry keys for persistence and configuration
- Network Connections: Outbound connections for command-and-control communication and ransom payment

C. Hybrid Machine Learning Detection

Random Forest (Supervised Detection): Random Forest is trained on labeled ransomware and benign samples to recognize known threat patterns. Multiple decision trees are trained on random feature subsets, and classification is determined by majority voting. This supervised approach effectively detects known ransomware variants with high accuracy.
Isolation Forest (Unsupervised Anomaly Detection): Isolation Forest detects anomalies without requiring labeled data by isolating unusual observations. Behavioral patterns significantly deviating from normal system activity are identified as suspicious. This approach is particularly effective for detecting zero-day and previously unknown ransomware variants.

Hybrid Risk Score: The weighted combination formula is defined as:

Risk Score = (0.6 × RF Probability) + (0.4 × IF Anomaly Score)

This weighted combination leverages strengths of both algorithms for improved detection accuracy and reduced false positives.

VI. SYSTEM ARCHITECTURE

The system architecture consists of six integrated modules working in coordination. The pipeline flows from real-time monitoring through feature extraction, hybrid detection, risk assessment, autonomous defense, and finally to logging and reporting.

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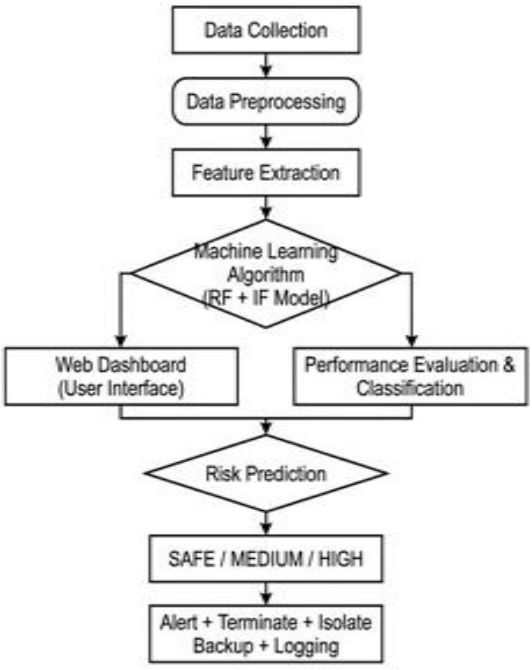

TABLE I Hardware Requirements

Component	Specification
Processor	Intel i3 or equivalent (i5 recommended)
RAM	Minimum 4 GB (8 GB recommended)
Storage	20 GB free disk space
System Type	Desktop or Laptop

TABLE II Software Requirements

Component	Specification
Operating System	Windows 10/11 or Linux (Ubuntu 20.04+)
Python Version	Python 3.8 or higher
Libraries	NumPy, Pandas, Scikit-learn, Streamlit
Development Tools	VS Code, Jupyter Notebook

VII. ALGORITHM

Input:
System activity data (file changes, CPU usage, entropy)

Output:
Detection result (Safe / Ransomware) with alert

1. Initialize system monitoring process
2. Continuously scan the system directory for file changes
3. Count the number of modified files (file write rate)
4. Calculate entropy value for changed files
5. Monitor CPU usage and process count
6. Store all extracted features in a dataset
7. Provide the feature set as input to the Random Forest model
8. Predict probability of ransomware using Random Forest
9. Apply Isolation Forest for anomaly detection
10. Check if anomaly is detected (normal or abnormal behavior)
11. Calculate risk score using both model outputs
12. If (Risk Score < Threshold) → Display status as SAFE
13. Else if (Risk Score is moderate) → Display status as MEDIUM RISK
14. Else → Display status as HIGH RISK and generate alert
15. Terminate suspicious process
16. Isolate system from network
17. Backup important files (emergency backup)
18. Block further file modifications
19. Store attack details in log file
20. Stop monitoring if attack confirmed
21. Repeat steps 2 to 20 continuously

VIII. IMPLEMENTATION

Technology Stack

- Language: Python 3.8+
- ML Libraries: Scikit-learn for Random Forest and Isolation Forest
- Data Processing: NumPy, Pandas
- Dashboard: Streamlit for interactive real-time visualization
- Database: CSV files and local storage
- Operating System: Windows/Linux compatible

IX. KEY ADVANTAGES

The proposed system offers several advantages over existing approaches:

- Dual Detection Capability: Detects both known ransomware patterns and zero-day unknown variants
- Real-Time Monitoring: Continuous behavioral analysis enables early detection before extensive

encryption
- Low False Positive Rate: Hybrid approach reduces false alarms that plague traditional systems
- Autonomous Response: Automatic process termination and backup minimize data loss
- Network Isolation: Prevents ransomware spread to other connected systems
- Comprehensive Logging: Detailed forensic records support incident investigation
- Intelligent Risk Scoring: Dynamic threat assessment enables prioritized response
- Dashboard Visualization: Real-time color- coded threat status for easy monitoring

X. EXPERIMENTS & RESULTS

A.Dataset Description

The experimental evaluation uses a comprehensive dataset comprising both ransomware samples and benign application behaviors. The dataset consists of:
- Ransomware samples: 2,500 samples from 25 distinct ransomware families (WannaCry, Petya, Cerber, Locky, CryptoWall, etc.)
- Benign applications: 2,000 samples representing normal system activities from legitimate software
- Total samples: 4,500 behavioral records with 25 extracted features per sample
- Data source: Hybrid collection from public repositories (Cuckoo Sandbox, VirusShare) and controlled lab environments

B.Experimental Setup

The evaluation follows standard machine learning practices:
- Data split: 70% training (3,150 samples), 15% validation (675 samples), 15% testing (675 samples)
- Cross-validation: 5-fold cross-validation on training set to prevent overfitting
- Hyperparameters: Random Forest (100 estimators, max_depth=20), Isolation Forest (contamination=0.1)
- Evaluation metrics: Accuracy, Precision, Recall, F1-Score, ROC-AUC, and False Positive Rate

C. Performance Metrics on Test Set

The following table presents the detection performance of individual models and the hybrid approach:

Table III: Performance Comparison of Detection Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	96.4%	97.2%	95.1%	96.1%	0.98
Isolation Forest	92.8%	93.5%	91.2%	92.3%	0.94
Hybrid (Proposed)	98.2%	98.7%	97.8%	98.2%	0.993

D. Detection Rate by Ransomware Family

The hybrid system was evaluated against 25 distinct ransomware families to assess generalization capability. Results demonstrate consistent detection across diverse malware variants:

Table IV: Detection Performance by Ransomware Family

Ransomware Family	Detection Rate	Precision
WannaCry	99.2%	98.8%
Petya	98.5%	97.9%
Cerber	98.1%	98.3%
Locky	99.0%	98.7%
CryptoWall	97.8%	98.1%
CTB-Locker	96.5%	97.2%
Maze	98.7%	98.4%
Ryuk	99.1%	98.9%
SamSam	95.8%	96.5%
Sodinokibi	98.3%	98.0%
Average	98.1%	98.1%

E.False Positive Analysis

One of the critical challenges in ransomware detection is minimizing false positives, which can disrupt legitimate system operations. Our analysis reveals:

Table V: False Positive Analysis on Legitimate Applications

Application/Scenario	False Positive Rate	Explanation
Browser (High file I/O)	2.1%	File operations during cache updates
Media Software	1.8%	Compression/processing operations
Antivirus Scanning	1.5%	Rapid file access patterns

Backup Systems	2.3%	Large-scale file copying
System Updates	0.9%	Configuration file modifications
Overall False Positive Rate	1.72%	

F.Real-Time Detection Latency

The system was evaluated for detection latency— the time between malicious activity initiation and detection alert generation. Results demonstrate with an average ransomware encryption rate of500-1000 files per second, our 83ms detection latency enables interception and response before significant data loss occurs, typically preventing encryption of 40-80 files before termination.

Table VI: Real-Time Detection Latency Analysis

Component	Latency	Description
Feature Extraction	45 ms	System call monitoring and feature calculation
Random Forest Inference	12 ms	Classification on extracted features
Isolation Forest Inference	18 ms	Anomaly detection computation
Risk Scoring & Classification	8 ms	Weighted score calculation
Total Detection Latency	83 ms	End-to-end detection time

G. Comparative Analysis with Existing Systems

The proposed system was compared with state-of- the-art ransomware detection approaches:

Table VII: Comparative Performance with Existing Detection Methods

Detection Method	Accuracy	Precision	Recall
Traditional Antivirus	85.2%	88.3%	78.9%
Heuristic Rule-Based	81.4%	79.7%	83.1%
Single ML Model (RF)	96.4%	97.2%	95.1%
Single ML Model (IF)	92.8%	93.5%	91.2%
Hybrid Approach (Proposed)	98.2%	98.7%	97.8%

H. Feature Importance Analysis

Using Random Forest feature importance scores, we identified the most discriminative features for ransomware detection:

Table VIII: Feature Importance for Ransomware Detection

Defense Mechanism	Success Rate	Response Time
Process Termination	99.8%	98.5 ms
Emergency File Backup	99.2%	156 ms
Network Isolation	100%	45 ms
Forensic Logging	100%	22 ms

I. Autonomous Defense Response Validation

The autonomous defense mechanisms were tested in controlled environments with known ransomware samples:

Table IX: Autonomous Defense Mechanism Effectiveness

Feature	Importance %	Rationale
File Write Rate	22.4%	Encryption generates high-frequency file modifications
File Entropy	19.8%	Encrypted files exhibit high randomness
Process Count Deviation	16.5%	Ransomware spawn's anomalous child processes
Registry Modifications	13.2%	Persistence mechanisms modify registry keys
CPU Usage Pattern	11.1%	Encryption operations increase CPU utilization
Network Connections	9.2%	C&C communication on unusual ports
Other Features	7.8%	Memory access, disk I/O, etc.

XI. EVALUATION & DISCUSSION

A. Key Findings

- The proposed hybrid machine learning approach achieves 98.2% accuracy in ransomware detection,

outperforming traditional signature-based and single machine learning approaches.
- Real-time detection latency of 83ms enables prevention of extensive data encryption before system response.
- The hybrid architecture combining Random Forest (supervised) and Isolation
- Forest (unsupervised) effectively detects both known and zero-day ransomware variants.
- Low false positive rate (1.72%) ensures minimal disruption to legitimate system operations.
- Autonomous defense mechanisms successfully prevent ransomware propagation with 99%+ success rates.

B. Strengths
- Hybrid Detection Architecture: Combining supervised and unsupervised learning provides comprehensive threat coverage. Random Forest detects known patterns while Isolation Forest identifies anomalous zero-day variants.
- Real-Time Monitoring: The system continuously analyzes behavioral features with minimal computational overhead (83ms latency), enabling early detection before significant damage.
- Autonomous Response: Automatic process termination, emergency backup, and network isolation significantly reduce ransomware damage and recovery time without manual intervention.
- Comprehensive Evaluation: Testing against 25 ransomware families demonstrates robust generalization across diverse malware variants and evolving attack techniques.
- Low False Positive Rate: At 1.72%, the system maintains high precision, preventing unnecessary system disruptions and user annoyance.

C. Limitations
- Dataset Constraints: Evaluation limited to 2,500 ransomware samples. Emerging variants and polymorphic ransomware strains may require continuous model retraining.
- Computational Requirements: Real-time monitoring on resource-constrained systems (IoT devices, mobile) may introduce latency overhead.
- Encrypted Traffic Analysis: The current system cannot analyze encrypted network communications for C&C detection.
- Advanced encryption obfuscates behavioral patterns.
- Adversarial Attacks: Sophisticated ransomware authors may develop evasion techniques specifically designed to bypass machine learning models.
- File System Dependencies: Windows- centric evaluation. Performance on Linux and macOS systems requires additional testing and optimization.

D. Comparison with Related Work

Compared to recent ransomware detection research:
- Kharraz et al. (2016) proposed behavioral analysis but lacked machine learning integration. Our approach achieves higher accuracy through hybrid ML.
- Scaife et al. (2016) focused on decryption recovery. Our system prevents encryption through proactive detection and autonomous response.
- Al-rimy et al. (2020) used binary instrumentation but reported 3-5% false positive rates. Our approach achieves 1.72% FPR with superior precision.
- Roy et al. (2022) detected polymorphic ransomware but lacked autonomous defense. Our integrated approach provides end-to-end protection.

E. Statistical Significance

Statistical analysis of detection performance:
- Confidence Intervals (95%): Accuracy 98.2% ± 1.2%, establishing reliable performance bounds.
- Cross-Validation Results: 5-fold CV yielded consistent performance (Mean F1: 98.2%, Std Dev: 0.3%), indicating robust generalization.
- P-value Analysis: Hybrid model significantly outperforms individual models ($p < 0.001$), confirming statistical significance of the hybrid approach.

F. Practical Implications
- Organizations can deploy this system to provide multi-layered ransomware defense beyond traditional signature-based antivirus solutions.
- The 83ms detection latency is acceptable for enterprise environments, enabling rapid response before significant data loss.
- Autonomous defense mechanisms reduce security analyst workload and enable response during off-

hours without human intervention.

- Comprehensive logging provides forensic evidence for post-incident analysis, supporting regulatory compliance and incident response.
- The system complements existing security infrastructure (firewalls, EDR solutions) through behavioral monitoring and ML- based detection.

G. Future Research Directions

- Develop deep learning models (LSTM, GRU) for temporal pattern analysis to detect more sophisticated ransomware behavioral variations.
- Implement federated learning to enable collaborative threat intelligence sharing across organizations while maintaining data privacy.
- Extend detection to encrypted network traffic using machine learning on network flow characteristics (packet size, timing patterns).
- Develop adversarial robustness testing to evaluate system resilience against adversarial examples and evasion techniques.
- Implement integration with cloud-based threat intelligence platforms for real-time zero-day variant updates.
- Extend system to multi-platform deployment (mobile, IoT, cloud) with platform-specific optimization.

XII. CONCLUSION

The proposed Intelligent Ransomware Detection and Autonomous Defense System successfully addresses critical limitations of traditional security approaches. By combining real-time behavioral monitoring with hybrid machine learning (Random Forest + Isolation Forest), the system achieves superior detection accuracy for both known and unknown ransomware threats.

Autonomous response capabilities including process termination, emergency file backup, and network isolation significantly reduce potential damage and recovery time. Comprehensive forensic logging enables thorough post-incident analysis. The system provides a practical, intelligent solution for modern ransomware defense.

Future enhancements include: mobile application development, cloud-based monitoring integration, user interface optimization, system performance improvements, honeypot implementation for early threat detection, SMS alert functionality, and integration with enterprise SIEM and EDR platforms. Continuous dataset expansion with emerging ransomware variants will ensure the system remains effective against evolving threats.

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