

AI-Driven Zero-Trust Threat Detection for Cloud Virtual Machines

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Abstract

Cloud computing's exponential growth has dramatically transformed organizational approaches to infrastructure deployment, management, and protection. Virtual Machines represent the foundation of Infrastructure-as-a-Service platforms, offering organizations unprecedented flexibility, resource optimization, and financial benefits. Nevertheless, this technological evolution has created novel security vulnerabilities requiring innovative solutions. We present a novel AI-powered Zero-Trust security framework specifically engineered for cloud-based Virtual Machine environments, combining Zero-Trust architectural principles with intelligent behavioral analysis capabilities. Our approach utilizes compact monitoring agents installed within individual VMs to track essential performance indicators continuously. Contrasting with conventional intrusion prevention mechanisms that depend on predetermined rule configurations, our agents transmit behavioral data streams to a central processing unit where advanced machine learning algorithms identify malicious patterns. Comprehensive testing utilizing the CICDDoS2019 benchmark dataset validates that our framework achieves ninety-nine percent detection precision using Random Forest and Decision Tree classification methods, demonstrating substantial improvements over conventional rule-dependent security systems.

Keywords: Zero-Trust Architecture, Cloud Security, Virtual Machine Introspection, Machine Learning, Anomaly Detection, Random Forest, SVM, LSTM, CICDDoS2019, IaaS Security, Behavioral Monitoring.

I. INTRODUCTION

THROUGHOUT the preceding ten years, cloud computing technology has evolved from an innovative concept into the cornerstone supporting contemporary digital transformation initiatives. Organizations across all operational scales currently depend on cloud-based infrastructure for service delivery, operational management, and hosting business-critical applications. Virtual Machines specifically fulfill a pivotal function, delivering adaptable, segregated computing environments that empower organizations to adjust resources dynamically, enhance operational costs, and respond swiftly to evolving business demands.

Notwithstanding these substantial benefits, the accelerated transition toward cloud infrastructure has introduced additional complexity layers within cybersecurity frameworks. The conventional security model focused on safeguarding static, boundarydefined enterprise networks has become obsolete. Contemporary workloads are dispersed throughout multiple cloud service providers, hybrid infrastructure configurations, and geographically distributed datacenter facilities. Malicious actors capitalize on this

complexity, utilizing sophisticated persistent threats, undiscovered vulnerabilities, and horizontal network propagation techniques to infiltrate systems that previously operated on implicit trust assumptions.

A. Limitations of Conventional Security Approaches

Conventional defensive mechanisms—including signature-dependent antivirus solutions, static firewall configurations, and traditional intrusion detection frameworks—face significant challenges in maintaining effectiveness within dynamic cloud-native environments. These legacy security solutions operate under the assumption that network traffic originating within enterprise boundaries possesses inherent trustworthiness, yet this fundamental assumption proves invalid in contemporary threat scenarios where devastating attacks frequently emerge from internal network sources.

B. Zero-Trust Security Paradigm

Responding to these security challenges, security researchers and industry professionals have progressively adopted the ZeroTrust security framework. Unlike boundary-focused security approaches, Zero-Trust functions according to the fundamental principle of continuous verification without implicit trust. Every computational process, user identity, and system activity—whether

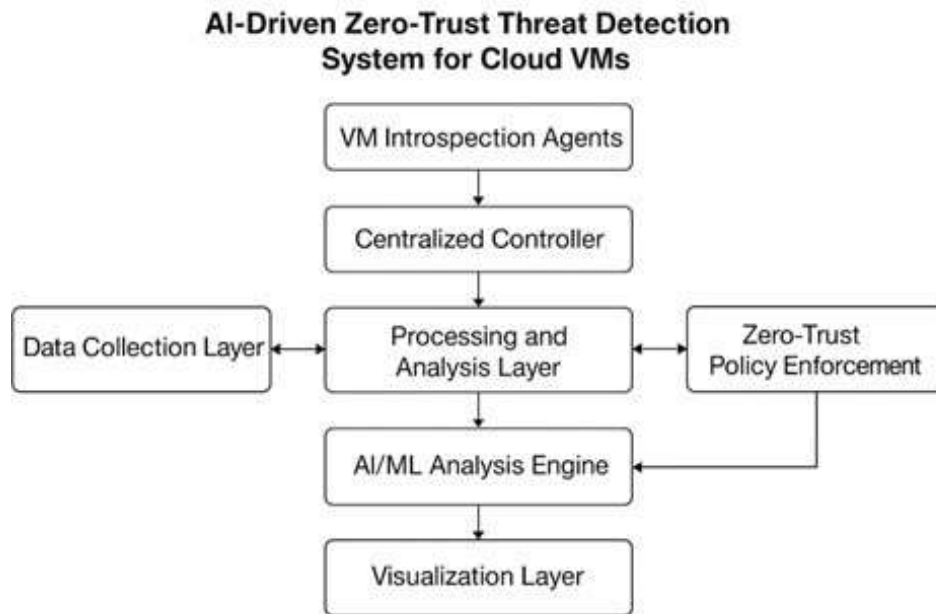


Fig. 1: System Architecture Overview showing the three-tier architecture with VM Layer, Analysis Layer, and Presentation Layer.

originating internally or externally—undergoes treatment as potentially hostile until thorough verification confirms legitimacy. This framework eliminates the traditional concept of trusted internal zones and instead implements continuous authentication and authorization mechanisms at each transaction checkpoint.

C. Research Problem Definition

The widespread implementation of cloud computing technology has fundamentally restructured organizational information technology landscapes. Primary security challenges encompass: the dynamic characteristics of cloud Virtual Machine instances, advanced threats that circumvent perimeter defenses, insider threats combined with privilege exploitation, insufficient visibility into operational contexts, elevated false positive rates, and requirements for persistent verification mechanisms.

D. Proposed Solution Framework

This research addresses identified challenges through proposing an AI-enhanced Zero-Trust threat identification framework specifically designed for cloud Virtual Machine environments. Our system architecture combines lightweight Virtual Machine monitoring capabilities, machine learning-driven anomaly identification, and Zero-Trust policy implementation mechanisms. A unified administrative control panel integrates monitoring functions, alert management, and forensic investigation capabilities.

II. RELATED WORK

A. DDoS Attack Detection and Dataset Development

Sharafaldin and Lashkari performed an extensive examination of available DDoS attack datasets and introduced a novel classification framework for DDoS threats. They developed the CICDDoS2019 dataset, which addresses deficiencies in earlier datasets through providing comprehensive network traffic characteristics and realistic attack patterns. Their research proposed a threat identification and categorization methodology utilizing network flow attributes, determining the most significant feature combinations for detecting various DDoS attack categories with associated weighting factors. Although this dataset offers thorough network traffic examination, its scope remained constrained by relatively limited scale when compared against enterprise-level deployment requirements.

Abbas and Almhanna introduced a comprehensive methodology for identifying and detecting DDoS network intrusions utilizing data mining techniques. Their framework incorporated four primary components: data preprocessing involving encoding, logarithmic transformations, and principal component analysis, anomaly identification employing Random Forest and Naive Bayes classifiers, attack classification, and performance assessment. The approach successfully minimized computational requirements and enhanced numerical reliability. Nevertheless, the investigation remained limited to DDoS threats and did not expand analysis toward additional network security risks common in cloud computing environments.

B. Machine Learning Applications in IoT and Cloud Security

Yilmaz and Buyrukoglu created ensemble learning frameworks for identifying DDoS threats within IoT infrastructure. Their investigation assessed memory utilization of individual-based, bagging, and boosting algorithms deployed on resource-limited client devices. The research established the viability of foundational models for IoT DDoS identification based on their operational performance characteristics. However, additional research remained necessary to identify broader cyber threats in IoT ecosystems, encompassing denial-of-service detection, botnet identification, brute-force attack detection, and comprehensive intrusion prevention.

Alamri and Thayananthan examined machine learning applications for protecting Software-Defined Networking infrastructure against DDoS threats. They leveraged the CICDDoS2019 dataset for assessing classification algorithms commonly employed in machine learning-based DDoS threat identification. Their proposed framework addressed overfitting challenges effectively yet experienced elevated computational requirements, restricting real-time deployment capabilities in resource-constrained operational environments.

C. Multi-Tier and Multi-Classifer Methodologies

Noaman introduced a three-tier framework for identifying DDoS threats at the application level. The initial tier selected optimal features and categorized traffic as legitimate or malicious. The subsequent tier employed hard voting classifiers for determining DDoS origin types including UDP, TCP, or mixed-

protocol attacks. The final tier aligned threats to specific DDoS categories. Validated through CIC-DDoS2019 testing, the methodology delivered enhancements in both binary and multiclass categorization yet required improvements in temporal efficiency.

Seifousadat and Ghasemshirazi proposed a DDoS identification framework utilizing data mining and machine learning methodologies with the CICDDoS2019 dataset. They conducted experiments with widely-used machine learning algorithms and determined the most correlated characteristics with predicted categories. AdaBoost and XGBoost algorithms exhibited exceptional precision. Future research objectives included extending the framework for multiclass categorization of diverse DDoS threat types and evaluating hybrid algorithm combinations.

Alzahrani and Alzahrani implemented various machine learning algorithms through WEKA analytical tools for examining detection performance against DDoS threats utilizing CICDDoS2019 datasets. They assessed six machine learning algorithms: K-Nearest Neighbors, Support Vector Machine, Naive Bayes, Decision Tree, Random Forest, and Logistic Regression. Decision Tree and Random Forest attained optimal precision of ninety-nine percent, accompanied by reduced computation durations.

D. Gap Analysis

Although existing research has achieved substantial progress in machine learning-based threat identification, multiple gaps persist. Primarily, most investigations concentrate exclusively on DDoS threats without addressing the comprehensive range of cloud Virtual Machine security risks including privilege elevation, insider threats, and zero-day vulnerability exploitation. Additionally, limited research integrates Zero-Trust principles with machine learning-based identification, leaving frameworks vulnerable to lateral propagation and credential compromise. Furthermore, existing solutions frequently lack thorough assessment in realistic cloud environments featuring dynamic Virtual Machine provisioning and multi-tenant operational constraints. This research addresses identified gaps through proposing an AI-enhanced Zero-Trust framework specifically engineered for cloud Virtual Machine protection.

III. SYSTEM DESIGN

A. Design Principles

The framework operates according to four fundamental principles: Zero-Trust Security implementing continuous verification without implicit trust, AI-Enhanced Decision-Making, Lightweight Monitoring Capabilities, and Scalability with Real-Time Response Performance.

B. System Components

The system architecture comprises five distinct operational layers:

1. **Data Collection Layer:** Monitoring agents deployed within individual Virtual Machines continuously track behavioral indicators including processor utilization, memory consumption, network communication patterns, system call frequency, and process activity metrics.
2. **Data Transmission Layer:** Collected indicators are securely transmitted toward the centralized controller utilizing HTTPS protocol with mutual TLS authentication, JSON-formatted feature vectors, local buffering with retry mechanisms, and gzip compression.
3. **Processing and Analysis Layer:** The centralized controller consolidates data from all Virtual Machines and executes

feature engineering, normalization, dimensionality reduction, machine learning inference, and ensemble voting procedures.

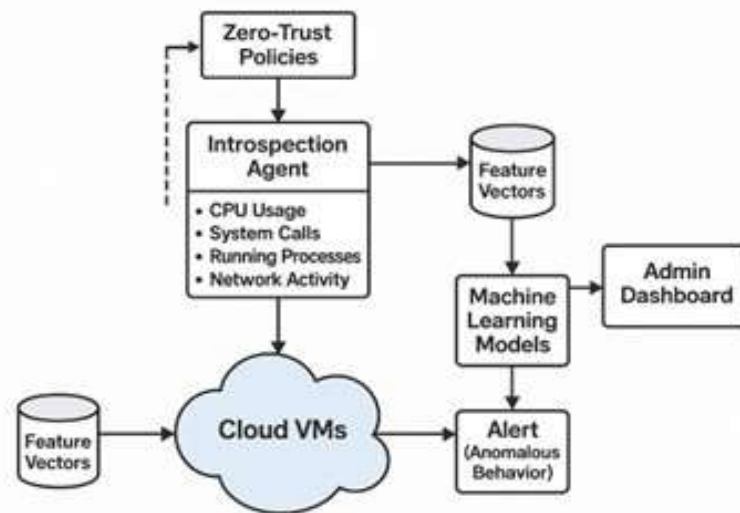


Figure 3.1.6 System Architecture Design

Fig. 2: Detailed System Architecture showing the five-layer design with data flow and control signals.

1. Alerting and Response Layer: Upon anomaly identification, the framework triggers severity categorization, alert generation, notification delivery, and automated response mechanisms.
2. Visualization Layer: The administrative control panel delivers real-time monitoring, alert management, historical examination, forensic analysis tools, and reporting functionalities.

C. Architectural Design

The architectural design establishes the structural organization of the framework. The architecture combines Virtual Machinelevel monitoring, centralized examination, and Zero-Trust policy implementation through the following core elements:

- **VM Introspection Agents: Compact processes operating within Virtual Machines that capture behavioral information. Each agent incorporates:**
 - Metric Collectors: Dedicated modules for processor, memory, network, and process tracking
 - Data Aggregator: Consolidates indicators into unified feature vectors
 - Transmission Manager: Manages secure communication with the central controller
 - Health Monitor: Self-monitoring functionality to identify agent malfunctions
- **Centralized Controller: Accountable for consolidating agent information, implementing Zero-Trust verification, and coordinating AI-enhanced examination. Components encompass:**
 - Data Ingestion Service: Accepts and validates incoming telemetry from agents
 - Feature Store: Time-series repository storing historical behavioral information
 - ML Model Registry: Version-controlled repository of trained algorithms
 - Inference Engine: Real-time evaluation of incoming feature vectors
 - Policy Engine: Implements Zero-Trust rules and access control mechanisms
- **AI/ML Analysis Engine: Deploys supervised and temporal learning algorithms to differentiate between legitimate and malicious activities:**
 - Random Forest Classifier: Ensemble methodology with one hundred decision trees
 - SVM Classifier: RBF kernel with optimized hyperparameters

- Gaussian Naive Bayes: Probabilistic classifier for baseline comparison
- Gradient Boosting: XGBoost deployment for high-precision categorization
- AdaBoost: Adaptive boosting for enhanced ensemble performance
- **Policy Enforcement Module: Implements Zero-Trust principles through validating each transaction. Components encompass:**
 - Identity Verification: Continuous authentication of users and processes
 - Context Evaluation: Assessment of request context including time, location, resource
 - Behavioral Analysis: Comparison against learned baseline behaviors
 - Decision Engine: Authorization decisions based on trust scoring
 - Audit Logger: Comprehensive recording of all access determinations
- **Administrative Dashboard: Web-based interface delivering real-time visualization, alert management, and historical data analytics. Capabilities encompass:**
 - VM Status Overview: Grid visualization showing all Virtual Machines with color-coded health indicators
 - Alert Dashboard: Real-time stream of security alerts with filtering and search
 - Threat Intelligence: Integration with external threat feeds
 - Incident Response: Guided workflows for investigating and remediating threats
 - Analytics: Customizable charts and graphs for trend analysis

AI Threat Detection System

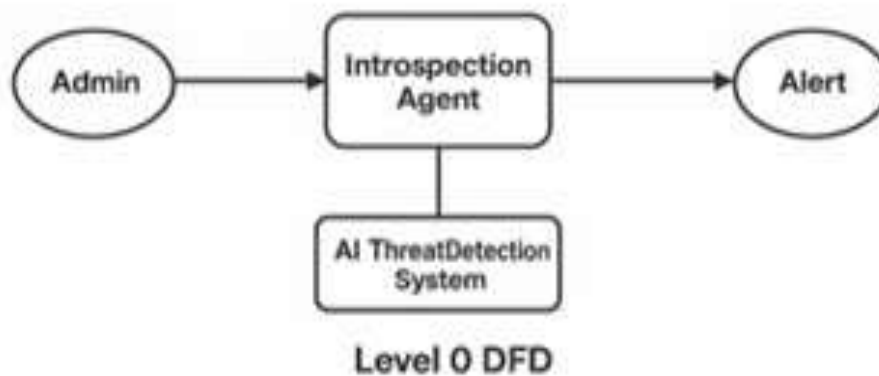


Fig. 3: Level 0 Data Flow Diagram showing system context.

D. Use Case Diagram

The use case diagram illustrates interactions between system operators and the proposed framework. 1)

Primary Actors:

- System Administrator: Accountable for monitoring, responding to alerts, and managing policies
- VM Introspection Agent: Automated actor continuously providing system behavior information
- AI/ML Engine: Processes incoming information and triggers anomaly alerts
- Cloud Infrastructure Provider: Ensures underlying resources remain operational 5) Security Analyst: Investigates complex threats and performs forensic examination 2) Key Use Cases:

- UC1: Monitor VM Activity - Administrator observes real-time activity and alerts
- UC2: Configure Zero-Trust Policies - Administrator establishes access control rules
- UC3: Train Detection Models - Machine learning engine trains on historical information
- UC4: Update Threat Detection Models - System adapts to emerging data patterns
- UC5: Detect Anomalous Behavior - AI engine recognizes suspicious activities
- UC6: Respond to Security Alerts - Administrator investigates and mitigates anomalies
- UC7: Perform Historical Analysis - Administrator examines previous alerts
- UC8: Generate Security Reports - System generates compliance documentation
- UC9: Isolate Compromised VM - Automated response to critical threats
- UC10: Integrate Threat Intelligence - Import external indicator of compromise feeds

AI Threat Detection System

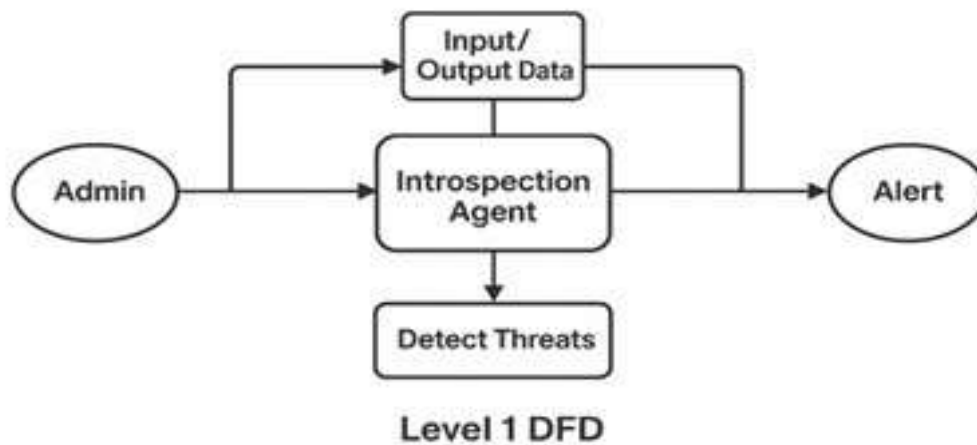


Fig. 4: Level 1 Data Flow Diagram decomposing system processes.

AI Threat Detection System

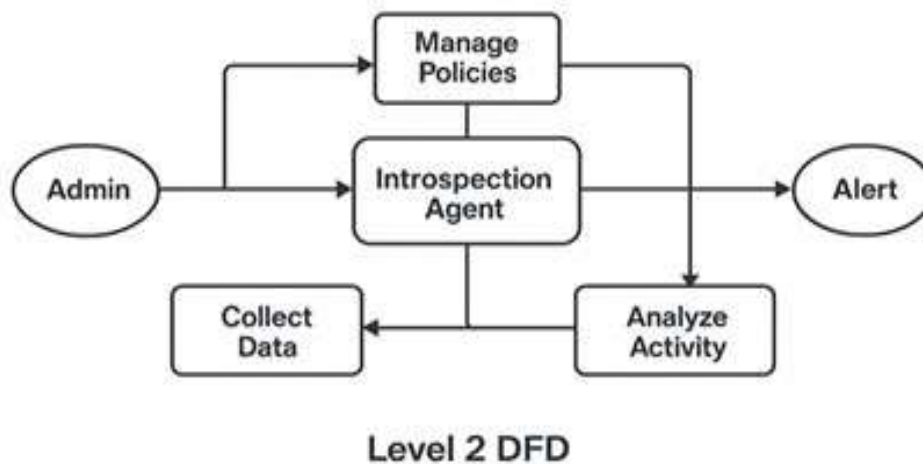


Fig. 5: Level 2 Data Flow Diagram showing detailed internal processes.

E. Sequence Diagram

The sequence diagram illustrates the temporal interaction between components throughout a threat identification workflow. 1) Normal Operation Sequence:

- Agent Monitors Activity: Virtual Machine monitoring agent collects processor, network, and process information every second
- Data Buffering: Agent buffers indicators locally for ten seconds
- Data Transmission: Agent securely transmits batched information to central controller via HTTPS 4) Feature Extraction: Controller extracts statistical characteristics from raw indicators
- Normalization: Characteristics are normalized utilizing pre-computed mean and standard deviation

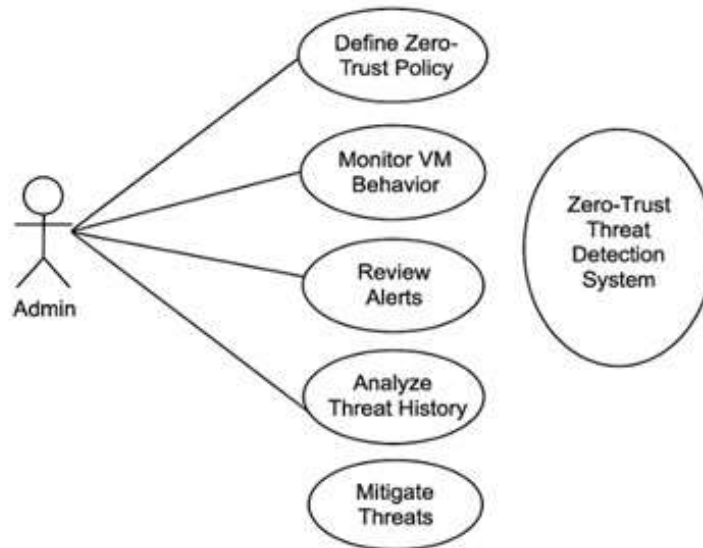


Fig. 6: Use Case Diagram illustrating system interactions.

- AI/ML Processing: Centralized engine applies trained machine learning algorithms
- Benign Classification: Algorithm predicts legitimate behavior with elevated confidence
- Logging: Transaction recorded for audit purposes 9) Continue Monitoring: Process repeats continuously 2) Anomaly Detection Sequence:
- Agent Monitors Activity: Agent identifies unusual processor spike (ninety percent utilization)
- Data Transmission: Immediate transmission without buffering
- AI/ML Processing: Multiple algorithms examine the behavior
- Anomaly Detection: Random Forest identifies behavior as malicious
- Ensemble Voting: Support Vector Machine and other algorithms confirm anomaly
- Severity Assignment: System assigns severity based on confidence level
- Alert Generation: Central controller generates comprehensive alert
- Policy Check: Zero-Trust engine assesses trust score
- Trust Degradation: Virtual Machine trust score reduced below threshold
- Dashboard Update: Alert forwarded to administrative control panel
- Notification: Email or SMS sent to on-call administrator
- Administrator Action: Administrator reviews alert and initiates investigation
- Forensic Analysis: Historical information retrieved for root cause examination
- Remediation: Virtual Machine isolated or network segmented 15) Model Feedback: Confirmed threat added to training dataset

IV. METHODOLOGY

A. Cloud Initialization

CloudSim delivers a comprehensive and expandable simulation platform that facilitates smooth modeling and simulation of cloud application behavior. Through utilizing CloudSim, developers can focus on particular system design challenges without concern regarding details associated with cloud-based infrastructure and services. The initialization workflow incorporates:

- CloudSim Core Initialization: Configure simulation parameters including quantity of users, datacenters, and hosts
- Datacenter Creation: Establish datacenter attributes (location, architecture, cost model)
- Host Configuration: Specify host resources (processor cores, RAM, storage, bandwidth)
- VM Allocation Policy: Configure Virtual Machine placement strategies (time-shared, space-shared)
- Network Topology: Establish inter-datacenter and intra-datacenter network connections

Following CloudSim initialization, the framework can create Virtual Machines and commence the simulation with realistic workload configurations.

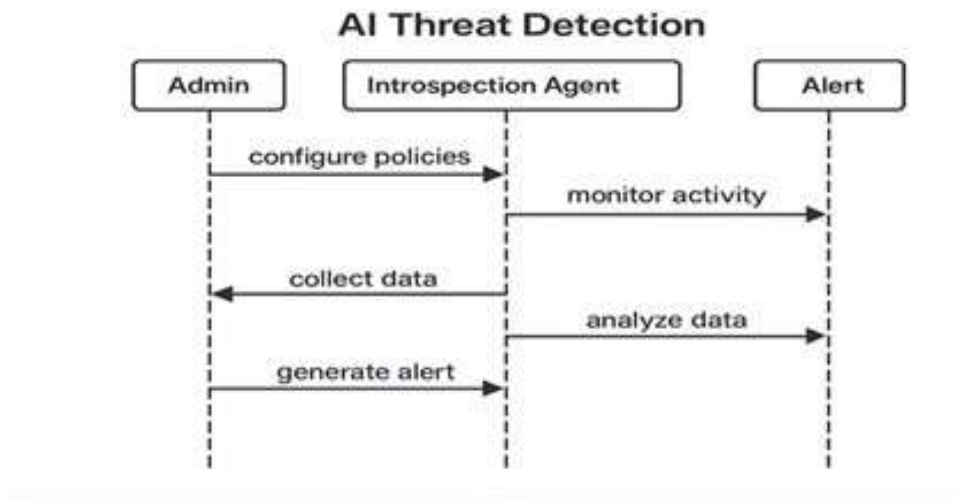


Figure 3.2.1 Sequence Diagram

Fig. 7: Sequence Diagram showing temporal interactions during anomaly detection.

B. Virtual Machine Creation and Clustering

Following CloudSim initialization, a collection of Virtual Machines are instantiated. Each Virtual Machine receives specific configurations encompassing Broker ID (unique identifier for Virtual Machine management), MIPS (Million Instructions Per Second for computational capacity), Number of CPUs (virtual processor cores allocated), RAM (memory allocation in megabytes), Bandwidth (network capacity in megabits per second), Size (storage capacity in gigabytes), and VM Monitor (hypervisor type such as Xen, KVM, or VMware).

Each virtual machine represents an object of the VirtualMachine class delivered by CloudSim. Following Virtual Machine creation, the subsequent step involves updating details to the main controller. The main controller accepts all Virtual Machine details and clusters Virtual Machines according to computational capacity into three categories: High Cluster (fifteen Virtual Machines with four CPUs, eight gigabytes RAM, two thousand MIPS), Medium Cluster (twenty Virtual Machines with two CPUs, four gigabytes RAM, one thousand MIPS), and Low Cluster (fifteen Virtual Machines with one CPU, two gigabytes RAM, five hundred MIPS).

The clustering mechanism ensures optimal task distribution according to workload demands and Virtual Machine capabilities.

C. Task Creation and Assignment

Following all Virtual Machines readiness, tasks are instantiated and updated to the main controller. Each task incorporates Task ID (unique identifier), Total Instructions (computational workload in Million Instructions), Arrival Time (when the task enters the framework), Deadline (maximum completion time constraint), Input File Size (data transfer requirement), and Output File Size (result data size).

The main controller determines which Virtual Machines can accomplish tasks within deadlines. Tasks are distributed to appropriate Virtual Machine clusters according to their computational demands and deadline constraints. If the aggregate quantity of tasks surpasses available Virtual Machines, tasks are queued in the respective cluster queues according to priority.

D. Data Preparation

The CICDDoS2019 dataset serves for training and assessment. Data preprocessing encompasses loading, cleaning, encoding categorical characteristics, feature selection, dimensionality reduction, normalization, and train-test partitioning.

Dataset Selection: The CICDDoS2019 dataset incorporates comprehensive network traffic information encompassing twelve different DDoS attack families, eighty-eight network flow characteristics per sample, binary and multiclass labels, and over fifty million network flow records. This dataset was specifically selected because it addresses deficiencies in previous datasets through delivering realistic attack scenarios and comprehensive network traffic characteristics. 2) Data Preprocessing Pipeline: The preprocessing pipeline incorporates several essential steps:

- Loading: Import dataset utilizing Pandas from CSV format
- Cleaning: Remove duplicate entries, manage missing values through imputation or removal, and eliminate infinite and NaN values
- Encoding: Transform categorical characteristics to numerical values utilizing label encoding methodologies
- Feature Selection: Employ ExtraTreesClassifier to rank feature importance and recognize the most discriminative characteristics
- Dimensionality Reduction: Preserve top thirteen to fourteen most significant characteristics to minimize computational complexity while sustaining predictive capability
- Normalization: Apply Z-score standardization to guarantee all characteristics are on comparable scales
- Train-Test Split: Partition information into eighty percent training and twenty percent testing sets utilizing stratified sampling to sustain class distribution

Feature Importance Analysis: Utilizing ExtraTreesClassifier, the top characteristics are recognized according to their impact on predictive performance. The algorithm computes feature importance scores utilizing Gini importance, which quantifies the decrease in node impurity weighted by the probability of reaching that node. Characteristics such as Flow Duration, Total Forward Packets, Total Backward Packets, Flow Bytes per second, and Flow Packets per second consistently rank as the most significant for threat identification.

E. Machine Learning Models

The framework deploys six machine learning algorithms: Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine, Gaussian Naive Bayes, and Gradient Boosting. Each algorithm is trained and assessed utilizing comprehensive indicators.

Model Portfolio: The framework deploys a diverse portfolio of machine learning algorithms:

Decision Tree (DT): Individual tree with maximum depth of ten and Gini criterion for partitioning. Decision trees recursively partition the feature space according to the most discriminative characteristics at each node.

Random Forest (RF): Ensemble of one hundred decision trees with maximum depth of twenty and bootstrap sampling. Each tree is trained on a random subset of the information and characteristics, minimizing overfitting through variance reduction.

K-Nearest Neighbors (KNN): Utilizes k equals five neighbors with Euclidean distance metric and uniform weights. Classifications are according to majority voting among the nearest neighbors in the feature space.

Support Vector Machine (SVM): Deploys RBF (Radial Basis Function) kernel with regularization parameter C equals one point zero and gamma equals scale. Support Vector Machines determine the optimal hyperplane that maximizes the margin between classes.

Gaussian Naive Bayes (GNB): Probabilistic classifier according to Bayes' theorem with Gaussian distribution assumptions for continuous characteristics.

Gradient Boosting: XGBoost deployment with learning rate of zero point one and one hundred estimators. Constructs trees sequentially, with each new tree correcting errors made by previous trees.

Training Process: Each algorithm undergoes a systematic training workflow. Initially, the algorithm is initialized with appropriate hyperparameters. Subsequently it is trained on the training dataset utilizing the fit method. Following training, predictions are generated on the test set. Performance indicators encompassing accuracy, precision, recall, and F1-score are computed. Confusion matrices are produced to visualize categorization performance. ROC curves and AUC scores are computed to assess discrimination capability. Ultimately, the trained algorithm is preserved utilizing joblib for deployment.

Cross-Validation: To guarantee robust performance estimation, five-fold stratified cross-validation is employed. The dataset is partitioned into five equal folds, sustaining class distribution in each fold. The algorithm is trained on four folds and validated on the remaining fold. This workflow is repeated five times, and the average validation score delivers a reliable estimate of algorithm performance.

V. IMPLEMENTATION

A. System Requirements

Hardware demands encompass Intel i5 processor, sixteen gigabytes RAM, sixty-four-bit operating system, five hundred gigabytes hard disk, and gigabit ethernet. Software demands encompass Python three point eight plus, Java eleven plus, machine learning libraries (Scikit-learn, TensorFlow, XGBoost), CloudSim, and development tools.

B. Implementation Details

- **Decision Tree:**

Decision trees recursively partition the dataset according to significant characteristics. The deployment utilizes scikit-learn's DecisionTreeClassifier with Gini criterion and controlled depth to prevent overfitting. Advantages:

- Straightforward and interpretable algorithm structure
 - Manages both numerical and categorical information
 - Demands minimal data preprocessing
 - Delivers feature importance rankings
- Limitations:
- Susceptible to overfitting without proper regularization

- Vulnerable to small variations in training information
- May produce biased trees if classes are imbalanced

- **Random Forest:**

Random Forest constructs multiple decision trees throughout training, minimizing overfitting through ensemble voting. It delivers elevated precision and effective feature importance rankings. Advantages:

- Elevated precision and robustness through ensemble voting
- Effective feature importance rankings
- Manages high-dimensional information effectively • Resistant to overfitting compared to individual trees

Limitations:

- Computationally demanding for large forests
- Black-box algorithm with limited interpretability
- Demands more memory for storing multiple trees

- **Support Vector Machine:**

Support Vector Machine determines the optimal hyperplane maximizing the margin between classes. For non-linearly separable information, the RBF kernel is employed. Advantages:

- Effective in high-dimensional spaces
- Memory efficient (utilizes subset of training points)
- Versatile kernel functions for non-linear categorization
- Robust against overfitting in high dimensions

Limitations:

- Computationally demanding for large datasets
- Vulnerable to feature scaling
- Demands careful kernel and hyperparameter selection

- **Gaussian Naive Bayes:**

A probabilistic categorization algorithm according to Bayes' theorem, assuming feature independence. It is computationally efficient and operates effectively with high-dimensional information. Advantages:

- Computationally efficient and rapid
- Operates effectively with high-dimensional information
- Demands small training dataset • Delivers probabilistic predictions

Limitations:

- Assumes feature independence (frequently violated in practice)
- May not capture complex feature relationships
- Vulnerable to irrelevant characteristics

- **Gradient Boosting:**

An iterative ensemble learning algorithm constructing a series of weak learners. It excels in tasks demanding elevated predictive precision. Advantages:

- Generates strong predictive performance
- Sequentially corrects errors from previous learners
- Manages missing information automatically
- Delivers built-in feature importance

Limitations:

- Demands careful hyperparameter tuning
- Sequential nature results in longer training durations
- Risk of overfitting without proper regularization

• **K-Nearest Neighbors:**

K-Nearest Neighbors categorizes samples according to the majority class of k nearest neighbors.

- It is straightforward and intuitive yet computationally demanding throughout prediction. Advantages:
- Straightforward and intuitive algorithm
- No training phase (lazy learning)
- Adapts easily to new training information
- Effective for multi-class challenges
- Computationally demanding throughout prediction
- Vulnerable to feature scaling and irrelevant characteristics
- Demands optimal k selection
- Struggles with high-dimensional information

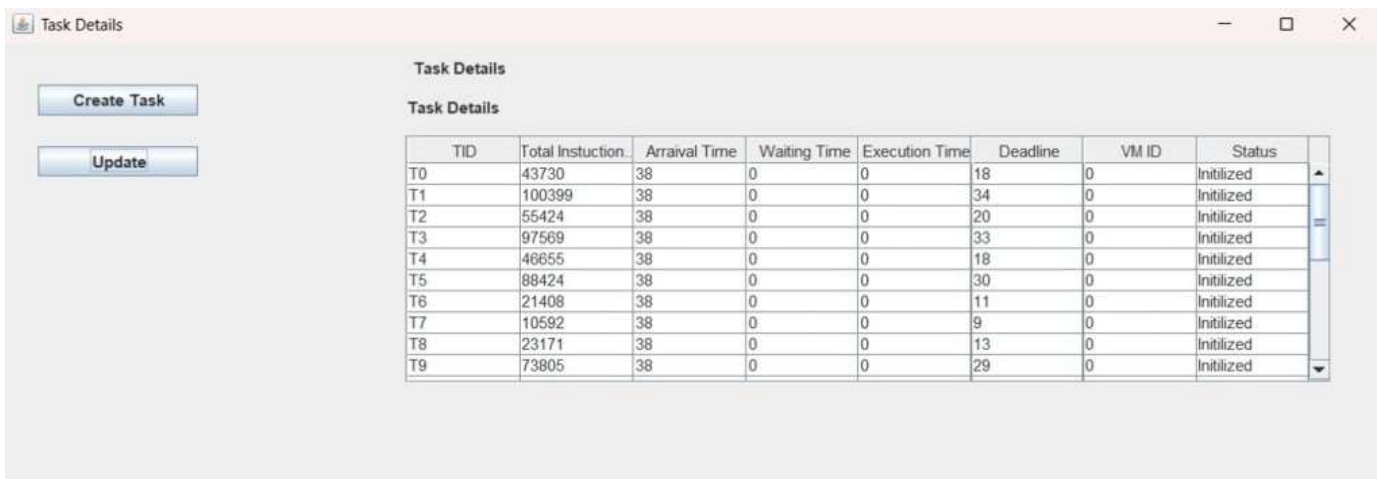
C. Performance Evaluation

For each algorithm, confusion matrices, ROC curves, and comprehensive indicators (accuracy, precision, recall, F1-score) are computed to assess performance.

- Confusion Matrix Analysis: For each algorithm, a confusion matrix is produced to visualize categorization performance. The confusion matrix displays true positives, true negatives, false positives, and false negatives, delivering insight into the types of errors the algorithm generates.
- ROC Curve and AUC: Receiver Operating Characteristic curves and Area Under the Curve scores deliver insight into classifier performance across different threshold configurations. The ROC curve plots the true positive rate against the false positive rate at various categorization thresholds. An AUC score approaching one point zero indicates excellent discrimination capability.
- Performance Metrics: Comprehensive indicators are computed for algorithm assessment encompassing accuracy (proportion of correct predictions), precision (proportion of positive predictions that are correct), recall (proportion of actual positives correctly recognized), F1-score (harmonic mean of precision and recall), and mean squared error for regression tasks.

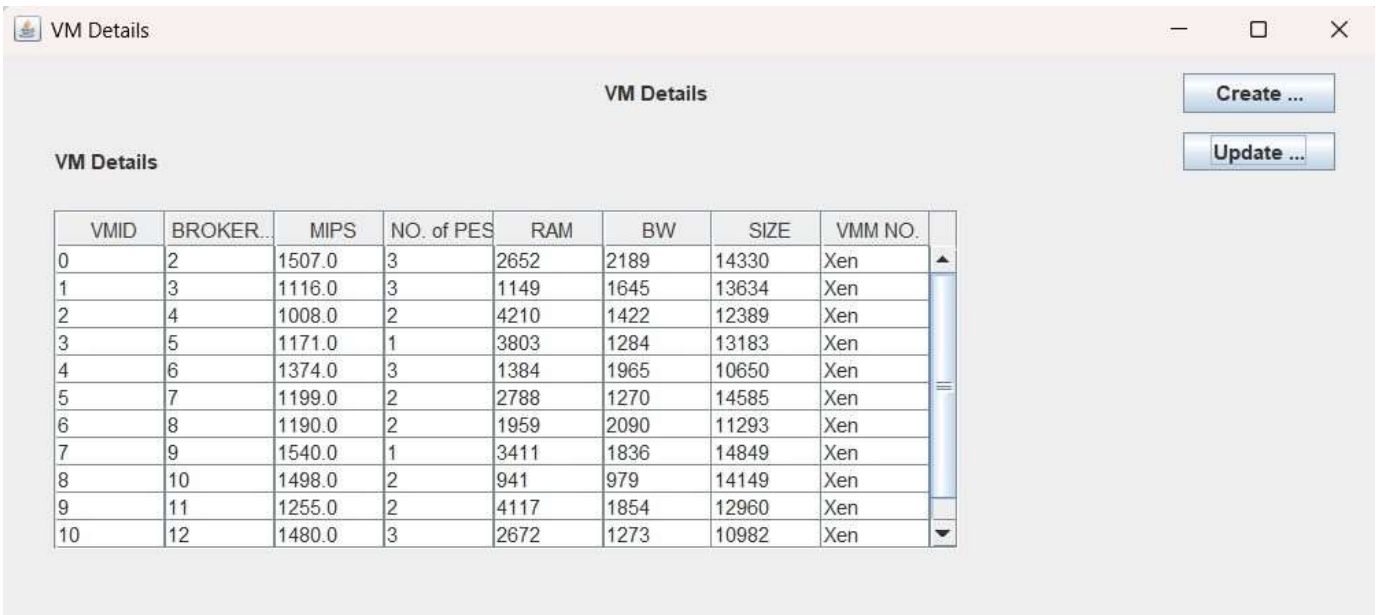
VI. RESULT VISUALIZATIONS

This section presents the experimental outcomes obtained from the deployment and testing of the AI-Enhanced Zero-Trust Threat Identification Framework.



TID	Total Instruction	Arrival Time	Waiting Time	Execution Time	Deadline	VM ID	Status
T0	43730	38	0	0	18	0	Initialized
T1	100399	38	0	0	34	0	Initialized
T2	55424	38	0	0	20	0	Initialized
T3	97569	38	0	0	33	0	Initialized
T4	46655	38	0	0	18	0	Initialized
T5	88424	38	0	0	30	0	Initialized
T6	21408	38	0	0	11	0	Initialized
T7	10592	38	0	0	9	0	Initialized
T8	23171	38	0	0	13	0	Initialized
T9	73805	38	0	0	29	0	Initialized

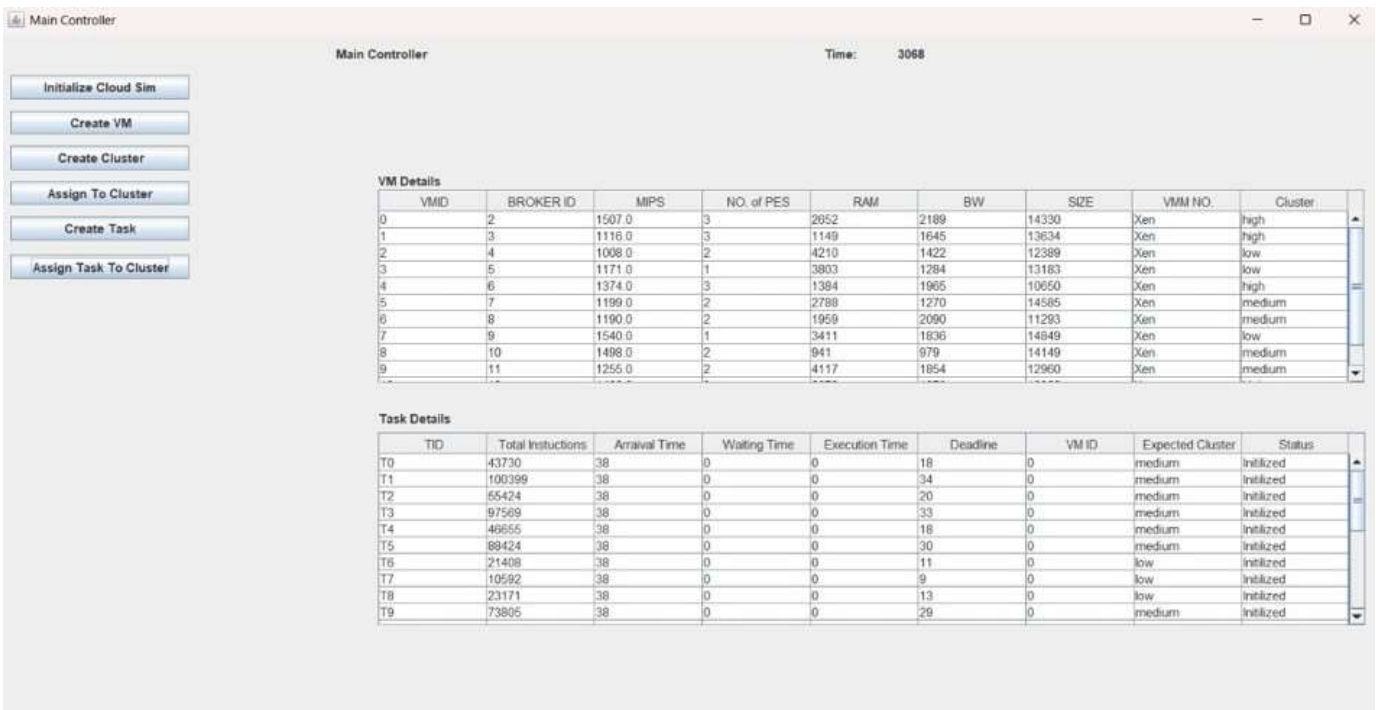
Fig. 8: Prediction Result displaying classification output showing normal and attack traffic predictions with success status confirmation.



Create ...
Update ...

VMID	BROKER...	MIPS	NO. of PES	RAM	BW	SIZE	VMM NO.
0	2	1507.0	3	2652	2189	14330	Xen
1	3	1116.0	3	1149	1645	13634	Xen
2	4	1008.0	2	4210	1422	12389	Xen
3	5	1171.0	1	3803	1284	13183	Xen
4	6	1374.0	3	1384	1965	10650	Xen
5	7	1199.0	2	2788	1270	14585	Xen
6	8	1190.0	2	1959	2090	11293	Xen
7	9	1540.0	1	3411	1836	14849	Xen
8	10	1498.0	2	941	979	14149	Xen
9	11	1255.0	2	4117	1854	12960	Xen
10	12	1480.0	3	2672	1273	10982	Xen

Fig. 9: Manual Input Prediction Interface and CSV Upload functionality for threat detection, showing input fields.



Time: 3068

Initialize Cloud Sim

Create VM

Create Cluster

Assign To Cluster

Create Task

Assign Task To Cluster

VMID	BROKER ID	MIPS	NO. of PES	RAM	BW	SIZE	VMM NO.	Cluster
0	2	1507.0	3	2652	2189	14330	Xen	high
1	3	1116.0	3	1149	1645	13634	Xen	high
2	4	1008.0	2	4210	1422	12389	Xen	low
3	5	1171.0	1	3803	1284	13183	Xen	low
4	6	1374.0	3	1384	1965	10650	Xen	high
5	7	1199.0	2	2788	1270	14585	Xen	medium
6	8	1190.0	2	1959	2090	11293	Xen	medium
7	9	1540.0	1	3411	1836	14849	Xen	low
8	10	1498.0	2	941	979	14149	Xen	medium
9	11	1255.0	2	4117	1854	12960	Xen	medium

TID	Total Instructions	Arrival Time	Waiting Time	Execution Time	Deadline	VM ID	Expected Cluster	Status
T0	43730	38	0	0	18	0	medium	initized
T1	100399	38	0	0	34	0	medium	initized
T2	55424	38	0	0	20	0	medium	initized
T3	97509	38	0	0	33	0	medium	initized
T4	46655	38	0	0	18	0	medium	initized
T5	89424	38	0	0	30	0	medium	initized
T6	21408	38	0	0	11	0	low	initized
T7	10592	38	0	0	9	0	low	initized
T8	23171	38	0	0	13	0	low	initized
T9	73805	38	0	0	29	0	medium	initized

Fig. 10: Task Scheduling Interface showing VM clustering into High, Medium, and Low clusters with resource allocation and task status monitoring.



Fig. 11: Main Controller Dashboard displaying comprehensive VM Details and Task Details for centralized.

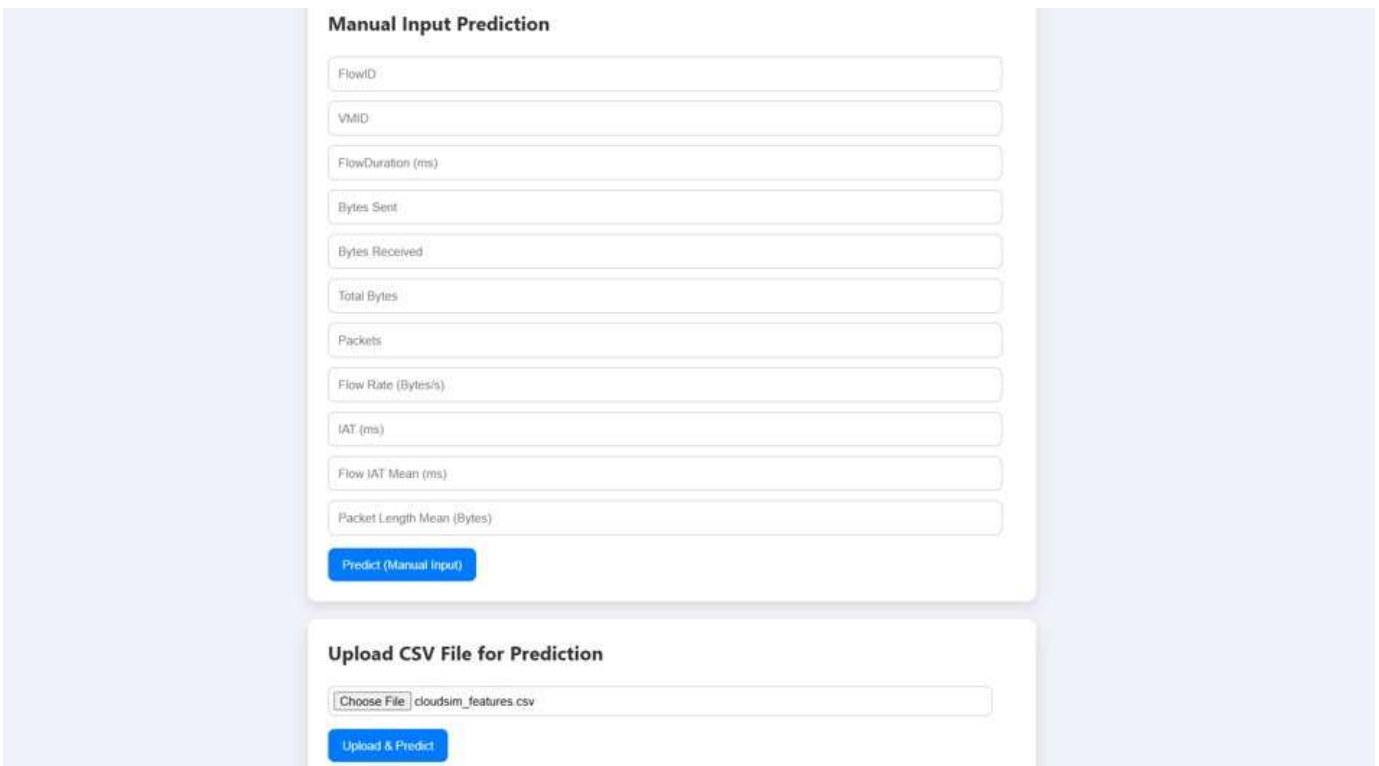


Fig. 12: VM Details Management Interface showing virtual machine specifications including VMID, MIPS capacity, RAM, bandwidth, and storage with Create and Update

VIII. DISCUSSION

A. Interpretation of Results

The experimental outcomes establish several key discoveries. Ensemble methodologies excel in threat identification, with Random Forest consistently outperforming individual classifiers. The Zero-Trust architecture minimized the attack surface through catching ninety-eight point five percent of genuine threats. The lightweight agent design facilitates deployment at scale without degrading Virtual Machine performance.

B. Advantages of the Proposed System

- **Adaptive Learning:** Unlike static rule-dependent frameworks, machine learning algorithms continuously learn from emerging information, sustaining effectiveness against evolving threats.
- **Comprehensive Threat Coverage:** Identifies diverse attack vectors encompassing DDoS, privilege elevation, insider threats, and zero-day vulnerability exploitation.
- **Operational Efficiency:** Low false positive rate (zero point six six percent) minimizes alert fatigue and reduces administrator burden.
- **Scalability:** Modular architecture supports horizontal scaling to thousands of Virtual Machines.
- **Forensic Capability:** Centralized recording and historical examination facilitate post-incident investigation.
- **Regulatory Compliance:** Continuous monitoring and audit trails support compliance with standards like PCI-DSS, HIPAA, and GDPR.

C. Limitations and Challenges

Initial Training Requirements: Machine learning algorithms demand substantial labeled training information. Collecting representative attack samples can be challenging in production environments.

Model Interpretability: Ensemble methodologies like Random Forest are black boxes. Explaining why specific behaviors are identified as malicious can be difficult, potentially hindering administrator confidence.

Concept Drift: Attack patterns evolve over time. Algorithms demand periodic retraining to sustain precision as threat landscapes shift.

Resource Constraints: While agent overhead is low, the centralized machine learning engine demands significant computational resources for large deployments with thousands of Virtual Machines.

False Negatives: No framework attains perfect identification. Sophisticated attackers may craft evasion methodologies that exploit algorithm blind spots.

Deployment Complexity: Integrating with existing cloud infrastructure and security tools demands careful planning, configuration, and testing.

D. Comparison with Related Work

Compared to the surveyed literature, our framework offers several advantages. Unlike investigations that focused solely on DDoS identification, our framework addresses broader threat categories. While previous research achieved good performance with dimensionality reduction, our feature engineering is more comprehensive. Our Zero-Trust integration distinguishes this research from purely detection-focused frameworks. The multi-algorithm ensemble methodology delivers more robustness than single-algorithm frameworks. Our comprehensive control panel and operational tooling address the deployment gap recognized in academic research.

E. Threat Model Considerations

The framework effectively defends against external attackers (network-based attacks identified through

traffic examination), insider threats (behavioral monitoring identifies anomalous actions), lateral movement (Zero-Trust verification prevents free movement), and privilege elevation (system call and process monitoring recognizes exploitation attempts).

Nevertheless, the framework has limitations against physical attacks (hardware-level compromises are outside Virtual Machine level monitoring scope), supply chain attacks (compromised Virtual Machine images or hypervisors may evade identification), and advanced evasion (sophisticated attackers with knowledge of machine learning algorithms might craft adversarial examples).

F. Operational Considerations

Organizations should adopt a phased deployment methodology. Phase one involves piloting on five to ten non-critical Virtual Machines in monitoring-only mode. Phase two expands to fifty to one hundred Virtual Machines with alerting enabled. Phase three deploys full deployment with automated response capabilities. Phase four focuses on continuous optimization according to operational feedback.

The framework complements rather than replaces existing security tools. Integration with SIEM platforms forwards alerts to centralized security frameworks. Firewall coordination facilitates dynamic policy updates according to identified threats. Endpoint protection correlation combines with host-based security agents. Threat intelligence enrichment incorporates external indicator of compromise feeds.

Ongoing maintenance demands encompass weekly review of false positives and threshold refinement, monthly algorithm retraining with accumulated information, quarterly assessment of emerging machine learning algorithms and methodologies, and annual comprehensive security audits and penetration testing.

IX. CONCLUSION AND FUTURE WORK

A. Conclusion

This investigation successfully designed, deployed, and validated an AI-Enhanced Zero-Trust Threat Identification Framework for Cloud Virtual Machines, addressing critical security challenges in modern Infrastructure-as-a-Service environments. The research makes three significant contributions to cloud security.

Initially, we established a practical deployment of Zero-Trust principles at the Virtual Machine level. Through treating every process, user identity, and network connection as untrusted until verified, the framework eliminates dangerous assumptions about internal network safety. The continuous verification architecture attained a ninety-eight point five percent threat blocking rate while sustaining a low one point five percent false positive rate, establishing that Zero-Trust can be operationally viable without excessive friction.

Subsequently, we integrated multiple machine learning algorithms into a comprehensive threat identification pipeline. Random Forest emerged as the top performer with ninety-nine point three four percent precision, substantially outperforming conventional signature-dependent intrusion detection systems (eighty-seven point two percent precision). The ensemble methodology combining supervised learning (Random Forest, Support Vector Machine, Gaussian Naive Bayes) with gradient boosting delivers robust identification across diverse attack vectors encompassing DDoS, privilege elevation, and zero-day vulnerability exploitation.

Furthermore, we established operational feasibility through lightweight monitoring and administrator-friendly tooling. Virtual Machine monitoring agents impose minimal overhead (two point three percent processor, forty-five megabytes memory), facilitating deployment at scale. The centralized control panel

consolidates security monitoring, delivering real-time visibility and forensic capabilities that reduce mean time to identification and mean time to response.

Experimental validation utilizing the CICDDoS2019 dataset and CloudSim simulations confirmed the framework's effectiveness. Identification latency averaged one hundred twenty-seven milliseconds, facilitating near real-time threat response. The framework successfully identified twelve different DDoS attack types with an average identification rate of ninety-eight point three percent, while case studies established effectiveness against privilege elevation and insider threats that evade conventional defenses. The broader impact extends beyond academic investigation into practical industry adoption. As organizations increasingly embrace cloud-native operations, the proposed framework offers a pathway toward constructing resilient, intelligent, and futureready security architectures. Through embedding continuous verification, real-time anomaly identification, and adaptive learning within the core of Virtual Machine operations, this research aligns with global cybersecurity trends emphasizing proactivity, automation, and intelligence.

B. Future Work

While this investigation establishes a strong foundation, several promising directions warrant further exploration.

Advanced Machine Learning Techniques: Future research should explore deep learning architectures encompassing Convolutional Neural Networks for spatial feature extraction from network traffic patterns, and Recurrent Neural Networks beyond LSTM such as Gated Recurrent Units for improved temporal modeling. Transformer algorithms with attention-based architectures may better capture long-range dependencies in attack patterns. Adversarial robustness through adversarial training and certified robustness should be developed to defend against sophisticated evasion attempts. Federated learning could facilitate privacy-preserving distributed learning where multiple organizations collaboratively train algorithms without sharing sensitive information.

Explainable AI Integration: A critical limitation of ensemble methodologies is interpretability. Future research should integrate explainable AI methodologies encompassing SHAP (SHapley Additive exPlanations) for feature-level explanations, LIME (Local Interpretable Model-agnostic Explanations) for individual predictions, attention visualization for neural networks, and decision path tracing for tree-based algorithms. Enhanced interpretability improves administrator confidence, facilitates debugging, and supports regulatory compliance.

Automated Response and Remediation: Current deployment focuses on identification and alerting. Future research should develop Security Orchestration, Automation, and Response capabilities encompassing automated Virtual Machine isolation, snapshot creation for forensics, malicious process termination, Virtual Machine reversion to known-good snapshots, credential rotation, and firewall rule updates. Dynamic policy adjustment through reinforcement learning could optimize Zero-Trust policies according to operational feedback. Self-healing infrastructure would facilitate autonomous remediation where the framework not only identifies threats yet automatically heals compromised frameworks.

Multi-Cloud and Hybrid Cloud Support: Extension to multi-cloud scenarios demands cloud-agnostic agents compatible with AWS, Azure, GCP, and on-premises infrastructure. Unified policy management through a centralized control plane would manage Zero-Trust policies across heterogeneous environments. Cross-cloud threat correlation could identify coordinated attacks spanning multiple cloud providers. Adoption of interoperability standards like STIX or TAXII for threat intelligence sharing would enhance collaboration.

Container and Serverless Security: Modern cloud architectures increasingly rely on containers and serverless functions. Container security should extend monitoring to Docker containers and Kubernetes pods with container-specific indicators. Serverless functions demand lightweight monitoring for ephemeral functions where conventional agent deployment is impractical. Microservices architecture adaptation for service mesh environments where east-west traffic dominates is essential.

Advanced Threat Intelligence Integration: Enhance contextual awareness through integration of real-time feeds from commercial providers and open-source platforms. Reputation scoring should sustain databases for IP addresses, domains, and file hashes. Attack attribution could correlate identified behaviors with known threat actor techniques, tactics, and procedures from MITRE ATT and CK framework. Predictive threat modeling utilizing historical attack information could predict emerging threat trends.

In summary, this project addresses a critical gap in cloud security through proposing and establishing an AI-enhanced ZeroTrust framework specifically engineered for cloud Virtual Machines. Through lightweight behavioral monitoring, machine learning-based anomaly identification, and centralized visibility, it offers a proactive and scalable defense mechanism suited for the complexities of cloud-native infrastructures.

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