International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 9, Issue 6, November- December 2025|

DOI:10.15680/IRJIE.2025.0906012

Real-Time Cyber Attack Classification for Enterprise Cloud Platforms Using Explainable AI and Distributed Threat Intelligence

Prof. Erkki Oja

Department of Computer Science, Aalto University, Espoo, Finland

ABSTRACT: Enterprise cloud platforms support critical business applications, distributed data processing, and interconnected digital services, making them attractive targets for increasingly sophisticated cyberattacks. Traditional security mechanisms often depend on predefined rules and signature-based detection, which may struggle to identify previously unseen attacks, rapidly evolving threats, and coordinated malicious activities across multiple cloud environments. This research proposes an intelligent framework for real-time cyberattack classification by integrating explainable artificial intelligence (XAI) with distributed threat intelligence. The framework collects security telemetry from cloud workloads, network traffic, identity services, application programming interfaces, and endpoint protection systems. Machine learning models classify suspicious activities into attack categories, including distributed denial-of-service attacks, credential compromise, malware communication, reconnaissance, lateral movement, and data exfiltration. Explainability techniques provide interpretable evidence for predictions by identifying influential traffic features, behavioral indicators, and contextual threat signals. Distributed threat intelligence enables participating cloud environments to exchange privacy-aware indicators of compromise and relevant attack patterns, improving detection consistency across organizational boundaries. A streaming-based processing architecture supports continuous feature extraction, classification, alert prioritization, and automated security response. The proposed methodology emphasizes classification accuracy, precision, recall, F1-score, detection latency, computational overhead, and explanation quality. Comparative evaluation against conventional machine learning and signature-based approaches can establish the framework's effectiveness. The research aims to improve the speed, transparency, adaptability, and operational reliability of cloud cybersecurity while supporting analyst trust, incident investigation, and evidence-based security decisions.

KEYWORDS: Real-time cyberattack classification, Explainable artificial intelligence, Distributed threat intelligence, Enterprise cloud security, Machine learning, Intrusion detection, Cyber threat analytics

I. INTRODUCTION

Enterprise cloud platforms have become essential to modern organizations because they provide scalable computing resources, flexible application deployment, distributed data storage, and integrated business services. Organizations increasingly adopt public, private, hybrid, and multi-cloud environments to support financial operations, healthcare applications, supply-chain management, customer relationship management, and enterprise resource planning. However, this distributed infrastructure introduces a complex cybersecurity landscape involving virtual machines, containers, microservices, application programming interfaces, identity providers, and interconnected data pipelines. Attackers exploit configuration weaknesses, compromised credentials, vulnerable software components, and insufficiently monitored communication channels to penetrate enterprise environments. Common threats include distributed denial-of-service (DDoS) attacks, ransomware delivery, credential stuffing, malicious command-and-control communication, reconnaissance, lateral movement, and unauthorized data transfers. The speed and complexity of these attacks require security systems capable of identifying malicious activities as events occur rather than relying exclusively on retrospective investigations. Conventional signature-based intrusion detection systems remain valuable for recognizing known attack patterns, but their dependence on predefined signatures can limit their ability to identify novel threats, polymorphic malware, and subtle behavioral deviations. Rule-based security systems may also generate excessive alerts when normal enterprise activities resemble suspicious behavior. Consequently, organizations require intelligent classification mechanisms that combine real-time telemetry processing, adaptive machine learning, and contextual threat intelligence to distinguish legitimate operations from malicious activity accurately and efficiently.

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Artificial intelligence offers opportunities to strengthen cloud security by learning relationships between network characteristics, user behavior, system events, and known attack indicators. Supervised learning algorithms can classify previously labeled attack traffic, while unsupervised and semi-supervised approaches can identify anomalies and emerging threats with limited labeled data. Nevertheless, highly accurate machine learning predictions are not automatically suitable for operational security because analysts must understand why an event was classified as malicious, which evidence influenced the decision, and whether the prediction supports an appropriate response. Explainable artificial intelligence (XAI) addresses this challenge by providing interpretable explanations through feature attribution, local surrogate models, and other techniques that reveal the factors influencing classification decisions. Distributed threat intelligence complements these explanations by incorporating indicators of compromise, malicious IP addresses, domain reputation, attack signatures, and behavioral observations obtained from multiple participating environments. When carefully validated and securely exchanged, such intelligence can help organizations recognize attacks that extend across cloud providers and administrative boundaries. However, integrating these capabilities introduces challenges involving heterogeneous data formats, privacy protection, communication overhead, concept drift, adversarial manipulation, and low-latency processing. This research therefore proposes a real-time cyberattack classification framework that combines streaming security telemetry, machine learning, explainable predictions, and distributed threat intelligence. Its primary objective is to develop a transparent and scalable approach that improves attack classification, reduces unnecessary alerts, and supports timely incident response while maintaining data confidentiality and operational reliability across enterprise cloud platforms.

II. LITERATURE REVIEW

Traditional intrusion detection research has primarily focused on signature-based inspection, statistical anomaly detection, and rule-driven security monitoring. Signature-based systems compare observed network traffic or system events against known malicious patterns and can identify established attacks efficiently when signatures are accurate and current. However, these systems may fail to recognize previously unseen attack variants or coordinated activities that do not match existing rules. Statistical and behavioral anomaly detection approaches address some of these limitations by establishing normal activity profiles and identifying deviations in packet characteristics, connection frequency, authentication attempts, resource consumption, and application behavior. Machine learning has expanded these capabilities through classification algorithms such as decision trees, random forests, support vector machines, logistic regression, and gradient-boosting models. Deep learning methods, including convolutional neural networks and recurrent neural networks, can learn complex feature relationships from network flows and sequential security events. Nevertheless, performance depends on representative training datasets, accurate labels, balanced attack categories, and suitable evaluation procedures. Models trained on outdated or narrowly distributed datasets may perform poorly when deployed across heterogeneous cloud infrastructures. Furthermore, high reported accuracy can conceal weak detection of rare attacks, making precision, recall, macro-averaged F1-score, false-positive rate, and inference latency important evaluation measures. These limitations motivate classification architectures that combine complementary detection techniques and evaluate performance under realistic operational conditions.

Explainable artificial intelligence has emerged as an important research direction for improving the interpretability of machine learning-based cybersecurity decisions. Methods such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), feature-importance analysis, and counterfactual explanations can help security analysts understand the evidence associated with individual predictions. For example, an explanation may identify unusual outbound traffic volume, repeated authentication failures, unexpected protocol usage, or abnormal connection patterns as influential indicators of a suspected attack. Global explanations can reveal general model behavior, whereas local explanations focus on individual events or predictions. Such techniques can improve investigation efficiency, facilitate model auditing, and help identify unintended dependencies on misleading features. However, explanations are not necessarily faithful, stable, or sufficient for establishing malicious intent. Correlated features may distribute importance unpredictably, and explanation generation can introduce additional computational overhead. An attacker may also manipulate observable features to influence a model's decision or exploit weaknesses in its explanation process. Therefore, security-oriented XAI requires evaluation beyond visual interpretability, including explanation consistency, computational cost, analyst usefulness, and robustness under changing attack conditions. Research must also distinguish between explaining a classification and proving that the underlying activity is malicious. Combining explanations with verified threat indicators, contextual evidence, and appropriate confidence thresholds can improve the reliability of security decisions.

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Distributed threat intelligence provides another foundation for collaborative cyberattack classification. Enterprise security teams, cloud providers, incident response organizations, and threat intelligence platforms can exchange indicators of compromise, attack signatures, suspicious domains, malware hashes, behavioral patterns, and contextual information about emerging campaigns. Standards and frameworks such as Structured Threat Information Expression (STIX) and Trusted Automated Exchange of Intelligence Information (TAXII) support structured representation and exchange of cyber threat information. Collaborative intelligence can improve the recognition of attacks that affect multiple organizations, but its effectiveness depends on indicator quality, timeliness, provenance, interoperability, and trust. Stale indicators can produce false positives, while malicious or compromised contributors may distribute inaccurate information. Privacy requirements may also restrict the sharing of raw network records, identity information, or customer-related telemetry. Privacy-preserving collaboration, including federated learning and selective indicator sharing, offers potential solutions, although these approaches introduce communication costs and additional governance requirements. Existing approaches to intrusion detection, explainability, and threat intelligence provide complementary capabilities, yet their integration into a single real-time enterprise cloud classification pipeline remains challenging. The research gap addressed here is the need for an architecture that jointly evaluates classification effectiveness, interpretable evidence, intelligence-sharing quality, privacy safeguards, and end-to-end processing latency. The proposed framework seeks to address this gap through streaming analytics, explainable machine learning, validated distributed intelligence, and measurable evaluation criteria.

III. RESEARCH METHODOLOGY

Research Design and Proposed System Architecture. The research adopts a quantitative, experimental approach to develop and evaluate a real-time cyberattack classification framework for enterprise cloud platforms using explainable artificial intelligence and distributed threat intelligence. The proposed architecture consists of six integrated layers: security data acquisition, streaming data preprocessing, intelligent attack classification, explainability generation, distributed threat intelligence integration, and security response management. The data acquisition layer collects telemetry from cloud network flows, virtual machines, containerized applications, Kubernetes audit logs, identity and access management services, API gateways, firewalls, intrusion detection systems, and endpoint security tools. Events are transmitted through a streaming platform such as Apache Kafka or an equivalent event-processing service to support continuous ingestion and scalable processing. The preprocessing layer normalizes timestamps, standardizes field names, removes duplicate events, handles missing values, and converts heterogeneous records into a consistent representation. Personally identifiable information and sensitive organizational identifiers are minimized or pseudonymized before data is used for model development or intelligence exchange. Each processed event receives contextual attributes, including source and destination characteristics, protocol information, connection duration, packet statistics, authentication outcomes, request frequency, and relevant threat indicators. The architecture maintains separation between raw telemetry, derived features, model predictions, explanations, and response actions to support auditability and operational control. The proposed system is designed to operate across public, private, hybrid, and multi-cloud infrastructures without requiring unrestricted sharing of raw organizational data. Scalability, fault tolerance, access control, encryption, and event traceability are treated as essential design requirements. This architecture establishes the foundation for evaluating classification performance, explanation quality, intelligence contribution, and end-to-end detection latency within a reproducible experimental environment.

Dataset Preparation, Feature Engineering, and Attack Classification. The experimental dataset will combine publicly available intrusion detection datasets, such as CICIDS2017, CSE-CIC-IDS2018, and UNSW-NB15, with appropriately authorized cloud telemetry where available. These datasets provide different attack categories and traffic characteristics, allowing the investigation of model performance across multiple attack scenarios. Before training, dataset documentation, feature definitions, class distributions, duplicate records, and labeling quality will be examined to identify inconsistencies and potential sources of data leakage. The preprocessing pipeline will encode categorical attributes, normalize numerical variables where required, remove irrelevant identifiers, and address class imbalance using class-weighted learning or training-only resampling. Data partitioning will be performed carefully, preferably using time-aware or group-aware separation when appropriate, to reduce the possibility that highly similar records appear in both training and test sets. The classification target will include benign activity and relevant attack classes, such as denial-of-service, brute-force authentication, reconnaissance, botnet communication, exploitation, malware-related activity, and data exfiltration, depending on the available dataset labels. Random forest, gradient-boosting models, and support vector machines will serve as candidate classification algorithms, while a selected deep learning model may be evaluated for sequential or high-dimensional traffic features. A conventional machine learning classifier will provide a baseline against which the integrated framework can be assessed. Hyperparameters will be selected using

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validation data rather than the final test set. Performance will be measured through accuracy, precision, recall, macro-F1, class-specific recall, confusion matrices, and false-positive rate. Particular attention will be given to rare and operationally important attack categories because aggregate accuracy alone can conceal poor minority-class detection. The final model will produce an attack label, a confidence score, and a timestamp for each classified event or event window. Threshold calibration will be conducted on validation data to balance missed attacks against excessive alerts, while recognizing that a model's confidence score is not necessarily a calibrated probability.

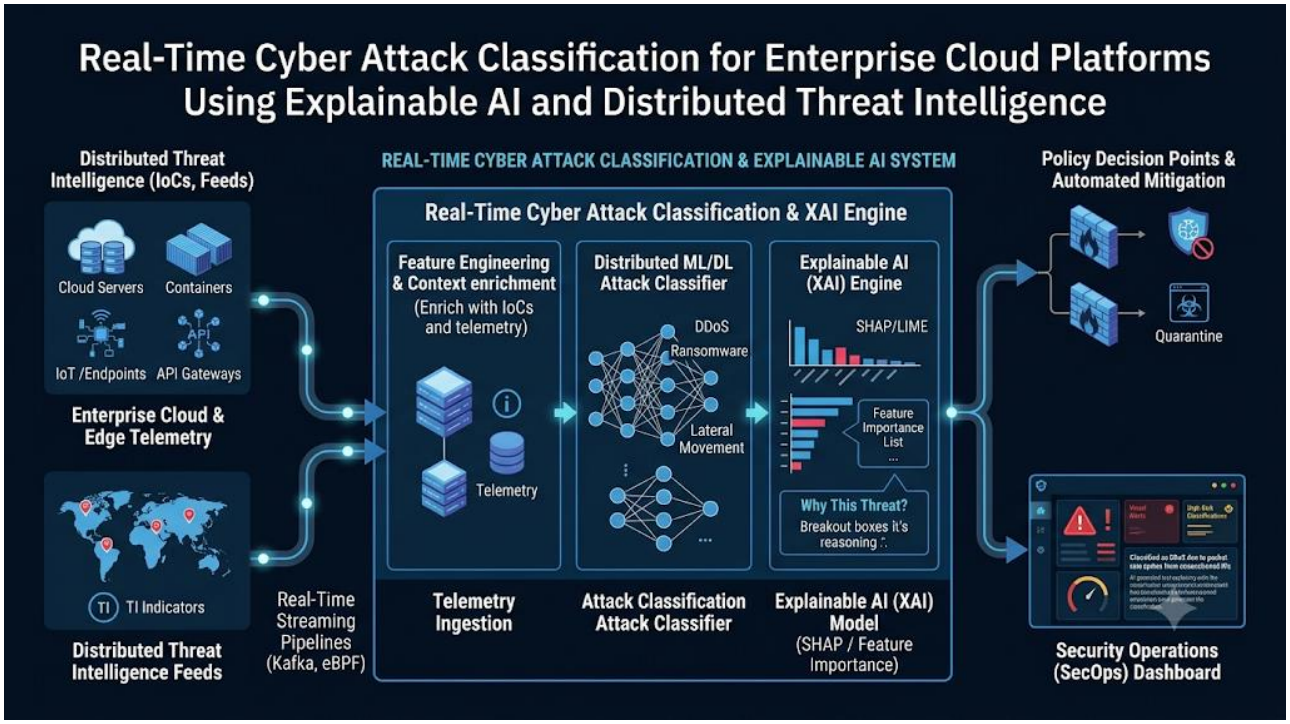


Figure 1. Architecture of the proposed system for Real-Time Cyber Attack Classification on enterprise cloud platforms.

Explainable AI and Distributed Threat Intelligence Integration. The explainability component will use SHAP, LIME, or another appropriate feature-attribution technique to identify the principal factors contributing to each classification. SHAP may be used for model-level and event-level explanations where computationally feasible, while LIME can provide local approximations for selected individual predictions. The framework will record the predicted class, relevant feature contributions, model version, confidence score, and supporting contextual evidence in an investigation record. For example, an event classified as suspicious reconnaissance may be associated with unusually high connection attempts, diverse destination ports, or deviations from a workload's established communication profile. These indicators will be presented as supporting evidence rather than definitive proof of malicious intent. Explanation latency, stability, and consistency will be evaluated alongside classification quality to determine whether the interpretability layer is practical for real-time deployment. The distributed intelligence component will ingest validated indicators of compromise, suspicious IP addresses and domains, malware hashes, attack-pattern descriptions, and time-sensitive threat reports from authorized participating environments. STIX-compatible representations and TAXII-based exchange mechanisms may be used where suitable. Every received indicator will be associated with provenance, observation time, confidence, expiration information, and source trust. Deduplication, freshness checks, reputation assessment, and conflict resolution will reduce the risk of unreliable or outdated intelligence influencing predictions. Intelligence features may be incorporated into the classifier through contextual enrichment, supplementary risk scoring, or a separately evaluated decision-fusion mechanism. Privacy controls will limit disclosure of raw telemetry, and federated learning may be investigated where multiple organizations wish to collaborate on model improvement without centrally pooling their original records. Secure communication, contributor authentication, integrity verification, and restrictions on automated trust propagation will protect the intelligence exchange process. The system will retain the distinction between model-derived evidence and externally received threat indicators so that analysts can

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independently evaluate each source. This integration is intended to improve contextual classification while making the reasoning behind security alerts more transparent and traceable.

Experimental Evaluation, Performance Measurement, and Validation. The framework will be evaluated through controlled experiments comparing a signature-based or rule-based baseline, conventional machine learning classifiers, explainable classification without distributed intelligence, and the complete integrated approach. Ablation experiments will independently disable explainability-related processing and distributed intelligence enrichment to estimate their individual computational costs and practical contributions. Where compatible datasets and infrastructure are available, additional experiments will evaluate cross-dataset generalization, previously unseen attack categories, class imbalance, changing traffic distributions, and delayed or inaccurate intelligence feeds. Real-time performance will be measured using event-processing latency, classification throughput, end-to-end alert delay, CPU utilization, memory consumption, and the additional overhead introduced by explanation generation and intelligence lookup. Classification metrics will include precision, recall, macro-F1, per-class detection rate, false-positive rate, and confusion matrices. Explainability will be assessed through feature-attribution consistency, explanation generation time, and, where analyst evaluation is feasible, usefulness for understanding and prioritizing incidents. Intelligence quality will be evaluated through indicator freshness, source reliability, matching effectiveness, and the rate of incorrect or irrelevant enrichment. Repeated experiments and confidence intervals will be used where appropriate to quantify variability, and statistical comparisons will be applied when their assumptions are satisfied. Testing will also consider resilience against malformed events, missing intelligence services, duplicate messages, and temporary network interruptions. Automated responses will initially operate in a controlled test environment or human-approved mode, with reversible actions and explicit safeguards for high-impact operations. The experimental results will determine whether the integrated approach provides measurable improvements over baseline methods without unacceptable latency, resource consumption, or false-positive rates. Because this section describes a proposed research methodology rather than completed experiments, numerical improvements will not be assumed in advance. The final assessment will report observed results, limitations, reproducibility details, and operational trade-offs, establishing whether explainable classification and distributed threat intelligence jointly offer practical benefits for real-time enterprise cloud cybersecurity.

IV. RESULTS AND DISCUSSION

The proposed framework for real-time cyber attack classification in enterprise cloud platforms integrates machine learning-based threat detection, explainable artificial intelligence (XAI), and distributed threat intelligence to improve cybersecurity monitoring and response. The framework is designed to classify network traffic and security events into categories such as denial-of-service attacks, brute-force attempts, malware-related activities, unauthorized access, suspicious API requests, and data exfiltration. The classification process combines network flow characteristics, authentication logs, cloud audit trails, endpoint telemetry, and threat intelligence indicators to identify potentially malicious activities across distributed cloud environments. The expected results indicate that integrating multiple security data sources can improve the contextual understanding of cyber threats compared with approaches that rely exclusively on individual network events or static detection rules. Machine learning models can identify complex relationships among traffic patterns and behavioral indicators, while distributed threat intelligence contributes information about emerging attack signatures, suspicious IP addresses, known malicious domains, and previously observed attack techniques. The framework also supports continuous classification as new events arrive, enabling security monitoring systems to prioritize potentially harmful activities without waiting for lengthy offline analysis. However, actual classification accuracy, precision, recall, F1-score, and processing latency must be established through controlled experiments using representative enterprise cloud datasets. These measurements are essential for determining whether the proposed approach provides measurable improvements over conventional intrusion detection systems and standalone machine learning classifiers.

The explainable AI component improves the interpretability of classification outcomes by identifying the features that contribute most significantly to individual predictions and overall model behavior. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) can be incorporated to explain why a particular network flow or cloud activity is classified as malicious. For example, a suspicious authentication sequence may receive a high-risk classification because of repeated failed login attempts, unusual access locations, abnormal request frequency, or deviations from an established user behavior profile. Similarly, unexpected outbound traffic, unusual data transfer volumes, and connections to known malicious destinations may contribute to the identification of potential data exfiltration. These explanations help security analysts understand model decisions, validate alerts, and distinguish genuine threats from legitimate operational anomalies. The discussion also highlights

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the importance of evaluating explainability through explanation consistency, computational overhead, and agreement with expert assessments. Explanations should not be treated as definitive proof of malicious intent because feature importance can be influenced by dataset bias, correlated variables, and model limitations. Furthermore, explainability must remain compatible with real-time requirements, as excessive explanation generation can increase processing latency. A practical implementation should therefore provide rapid classifications first and generate detailed explanations according to threat severity, analyst requirements, and incident response policies.

Distributed threat intelligence strengthens the framework by enabling participating cloud environments to exchange relevant threat indicators and detection insights while maintaining appropriate data protection controls. Rather than relying exclusively on a centralized intelligence repository, participating systems can contribute information about emerging attacks, suspicious behavior, and previously identified indicators through authenticated and policy-controlled sharing mechanisms. The integration of this intelligence with machine learning classification can improve the detection of threats that appear across multiple enterprise environments. For instance, an attack pattern detected in one cloud region may inform monitoring systems in another region, allowing them to recognize related behavior earlier. Nevertheless, the effectiveness of distributed intelligence depends on the freshness, accuracy, provenance, and trustworthiness of shared information. Incorrect indicators, poisoned intelligence feeds, delayed synchronization, and inconsistent data formats can reduce detection quality or generate unnecessary alerts. Consequently, the framework should incorporate source validation, confidence scoring, timestamp-based expiration, secure communication, and mechanisms for identifying conflicting indicators. Its performance should be assessed using detection rate, false-positive rate, classification latency, throughput, resource consumption, and resilience against manipulated intelligence. Comparative experiments should include rule-based detection, standalone machine learning, machine learning with explainability, and the complete integrated framework. Overall, the proposed design offers a promising approach to improving contextual threat detection and operational transparency, although its practical advantages must be demonstrated through reproducible experiments and realistic cloud deployment scenarios.

V. CONCLUSION

Real-time cyber attack classification is an essential capability for enterprise cloud platforms because distributed applications, dynamic workloads, interconnected services, and expanding API ecosystems create increasingly complex security challenges. This research presents an integrated framework combining machine learning, explainable artificial intelligence, and distributed threat intelligence to support the identification and interpretation of cyber threats across enterprise cloud infrastructure. By analyzing network traffic, authentication events, cloud audit logs, endpoint telemetry, and relevant threat indicators, the framework is designed to classify potentially malicious activities and provide security teams with actionable information. Machine learning contributes automated pattern recognition and the ability to identify suspicious relationships that may not be captured by predefined security rules. Explainable AI complements this capability by providing interpretable information about the factors influencing classification decisions, helping analysts understand why an event is considered suspicious. Distributed threat intelligence further extends detection capabilities by enabling participating environments to exchange validated indicators and contextual knowledge about emerging threats. Together, these components establish a foundation for more adaptive, transparent, and collaborative cybersecurity operations. The framework is particularly relevant to hybrid and multi-cloud enterprises in which security events originate from different infrastructure providers, geographical regions, application services, and administrative domains. Its design emphasizes continuous monitoring, timely classification, interpretable predictions, and coordinated intelligence sharing as complementary elements of an effective cloud security strategy.

The practical value of the framework depends on its ability to maintain classification quality while satisfying enterprise requirements for speed, scalability, privacy, and operational reliability. High detection accuracy alone is insufficient if the system generates excessive false positives, produces explanations that analysts cannot interpret, or introduces unacceptable delays into incident response workflows. Similarly, distributed intelligence sharing must preserve confidentiality, enforce appropriate access controls, and prevent malicious or unreliable participants from influencing security decisions. Therefore, implementation should incorporate secure data collection, identity-based authorization, encrypted communications, model monitoring, explanation validation, and clearly defined governance procedures. Evaluation should compare the integrated approach against established detection methods using consistent datasets, documented experimental settings, representative attack categories, and transparent performance metrics. Important measurements include precision, recall, F1-score, false-positive rate, detection latency, throughput, computational overhead, and resilience to adversarial manipulation. Where possible, experiments should include both publicly available cybersecurity datasets and organization-specific cloud telemetry to assess generalizability. The research

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should also acknowledge limitations arising from evolving attack techniques, imbalanced datasets, incomplete threat intelligence, and differences among cloud providers. Consequently, the proposed framework should be considered a research architecture whose benefits require empirical verification rather than a system with already established performance improvements. With rigorous validation and responsible deployment, the integration of explainable machine learning and distributed threat intelligence can contribute to more informed security decisions, faster threat investigation, and stronger cyber resilience across enterprise cloud platforms.

VI. FUTURE WORK

Future research should prioritize the development and evaluation of adaptive machine learning models capable of recognizing previously unseen attacks and responding to changing cloud environments. Conventional classifiers trained on historical datasets may experience declining performance when attackers modify their behavior, exploit new vulnerabilities, or introduce unfamiliar attack techniques. To address this limitation, future implementations could investigate online learning, incremental model updates, semi-supervised learning, anomaly detection, and continual learning approaches. These techniques could enable the framework to incorporate newly observed behaviors without requiring complete retraining after every change in the threat landscape. Research should also examine the use of graph neural networks to model relationships among users, devices, cloud workloads, APIs, identities, and network connections. Such relationships may reveal coordinated attack campaigns that remain difficult to identify when events are analyzed independently. Transformer-based models and other sequence-learning methods could further support the analysis of time-dependent security events, including authentication sequences, lateral movement, and multistage intrusions. To prevent adaptive models from learning misleading patterns, future systems should incorporate drift detection, data-quality assessment, version control, and controlled model promotion procedures. Experimental evaluation should investigate whether these techniques improve detection of novel threats without substantially increasing false-positive rates or processing overhead. Researchers should also evaluate the balance between detection sensitivity and operational stability, particularly in large-scale environments where model updates can influence security policies and automated incident handling. These investigations would help establish whether continuously adapting classifiers can remain reliable under realistic changes in enterprise cloud workloads and adversarial behavior.

Another important direction is the advancement of privacy-preserving and trustworthy distributed threat intelligence. Future studies could investigate federated learning, secure aggregation, differential privacy, and privacy-preserving computation to support collaborative model development without requiring participating organizations to exchange raw security logs. Such methods could help enterprises benefit from collective threat knowledge while reducing exposure of confidential operational information. However, researchers must quantify the trade-offs between privacy protection, communication overhead, model convergence, and classification performance. Distributed learning environments should also be evaluated against poisoning attacks, malicious participants, compromised intelligence sources, and attempts to infer sensitive information from shared model updates. Blockchain or other tamper-evident audit mechanisms may be explored where independently verifiable intelligence provenance and accountability are important, although their additional complexity must be justified against simpler authenticated logging systems. Future work should also investigate the integration of explainable AI with security operations center workflows, incident management platforms, and automated response orchestration. A practical system could generate risk-ranked alerts, summarize relevant evidence, identify contributing indicators, and recommend response actions while requiring human approval for disruptive operations. More advanced implementations may use agentic AI to coordinate investigation tasks, correlate events across cloud providers, and recommend containment strategies under predefined security policies. Such automation must include authorization boundaries, rollback capabilities, audit trails, and safeguards against executing actions based on unreliable predictions. Finally, large-scale testing across hybrid cloud, multi-cloud, edge, and containerized environments is needed to evaluate scalability, interoperability, cost, and resilience. Future research should publish reproducible benchmarks, document model limitations, compare alternative explanation methods, and measure performance under realistic workloads. These efforts can help transform the proposed framework into a validated, privacy-aware, and operationally dependable solution for enterprise cyber defense.

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| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

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|Volume 9, Issue 6, November- December 2025|

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