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Advancing Cybersecurity: A Machine Learning and Deep Learning-Based Intrusion Detection System A Review

[1*]Saurabh Aggarwal, [2]Ashish Khanna, [3]Simar Preet Singh, [4]Narina Thakur

[1*]San Jose State University, San Jose, California, USA
[2]Maharaja Agrasen Institute of Technology
[3]School of Computer Science Engineering and Technology (SCSET), Bennett University, Greater Noida, Uttar Pradesh, India
[4]University of Stirling RAK Campus, UAE,
sorav77@gmail.com, ashishk746@yahoo.com, dr.simarpreetsingh@gmail.com, narina.thakur@stir.ac.uk

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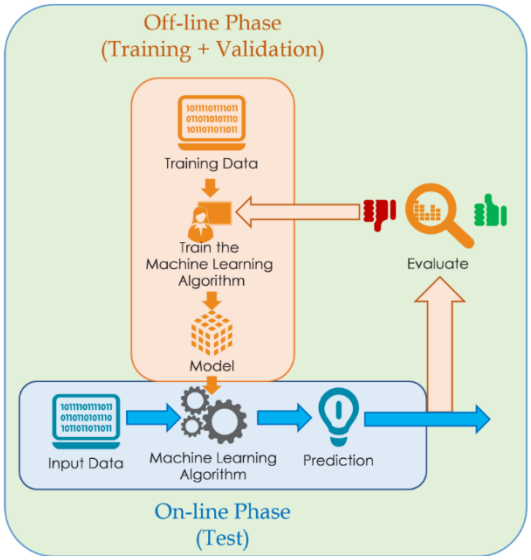
ABSTRACT

Thefundamentalstorageanddatahandlinghabitsoforganizationsandindividualschangedduetothefactthat cloud computing provides dynamic systems with speed in performance as well as competitive costs. Trusted security threats accompany the increased benefits of cloud computing that lead to viruses infecting data systems, exposing operational details through data leakages and hacking, and violating personal privacy. Legacy security solutions fail when identifying and thwarting intricate cyberattacks, which happen these days Due to enabling predictive analysis, automated intervention, and immediate assessment of threats, machine learning has emerged as an extremely powerful cloud security platform. This review examines the progress and challenges incurred by machine learning approaches when employed to secure the cloud infrastructure. The research investigates 2019 to 2025 studies to analyze prominent concepts resolved by data security and privacy automation and malware and intrusion detection and novel threats. Cyber threats were detected and defended by numerous machine learning methods effectively, such as supervised training, deep neural networks, reinforced learning, and federated learning. Recurrent neural network and convolutional neural network settings deployed within intrusion detection systems result in better performance for detecting malicious network behavior.Federatedlearningandprivacy-preservingmachinelearningstrategiesbecomepotentialsolutionsto protect cloud environments and preserve user data.

1. Introduction

Cloudcomputinghasrevolutionizedthewaydataisprocessed,stored,andhandledforconsumersaswellas



enterprises.Ithasbecomeintegraltocontemporarytechnologyduetothefactthatitisaffordable,scalable,andflexible. However, security issues also rise along with the application of clouds. Since cyber-attacks like virus attacks, data theft, and unauthorized access continuously change, current security measures should also be dynamic. Machine learning (ML) algorithms prove to be helpful because traditional measurements can never be fast enough with regards to such shifting attacks. Machine learning provides more advanced and adaptive cloud security.

In contrast to traditional security systems that are based on pre-programmed rules, ML-based models can search big

Figure 1 : Machine Learning Paradigms

datasets, detect out-of-character behavior, and discover patterns in real-time. Machine learning (ML) is a treasure for threat intelligence, malware analysis, intrusion detection, and even protection of confidentiality data since it learns and gets better over time. ML-based cloud security has its setbacks despite having many benefits. Adversarial attacks, by which cyberpunks alter the predictive model for evading security restrictions, constitute one of the principal concerns.With the provision of easy solutions to common security problems and new security threats, machine learning technology facilitates an enhancement in cloud storage security. The future use of protection within cloud platforms demands quantum-proof machine learning security systems. Adversarial attacks are used by spammers to deceive AI models, thereby making security software useless.

Additionally, cloud security evolution continues with the focus on more powerful ML-based frameworks. Latest studies underscore the need to couple AI-based solutions with conventional security solutions in an attempt to increase the accuracy of threat detection. In addition to that, as cyber-attacks grow more sophisticated, efforts are being directed to implement proactive security that pre-empts and counters attacks even before they take place. This is achieved through the application of deep learning methods, federated learning, and adversarial robustness to implement a multi-layered defense system. The current trends and challenges of integrating machine learning and cloud security are the topic of discussion in this review paper.

It encompasses a comprehensive review of research studies published between the periods 2019 to 2025 on prominent themes like intrusion detection,automated security, data privacy, and virus protection.The study also takes into account possible future research themes like explainable AI, privacy-preserving ML approaches, and hybrid security models to enhance the effectiveness of ML-based security systems. By studying such issues and trends, this article presents the influence of artificial learning in shaping cloud security in the future in helping protection of cloud environments from cyberattacks.Also, innovations in cloud security persist, showcasing the significance of ML-based strong frameworks. Future research focuses on the integration ofAI-based solutions and conventional security systems to enhance threat detection accuracy. In addition, with the rapidly evolving nature of cyber-attacks, there is always the pressure to create proactive security measures that detect and counterattack in advance. This involves the application of deep learning methods, federated learning, and adversarial robustness to design a multi-level defense strategy.

1. LiteratureReview

A crucial aspect of modern technology,cloudcomputingprovidescustomersand businesses callable andefficient solutions. But in order to increase security controls, advanced techniques such as machine learning (ML) are needed because security threats are updated daily. In order to minimize the risks of cloud security, researchers have explored numerous machine learning techniques in the past few decades. Focusing on intrusion detection, data privacy, malware detection, automation, and future security issues, this literature review considers high- profile research articles published between 2019 and 2025. Choi et al. (2019) investigated deep learning techniques for intrusion detection (IDS) in the cloud. Demonstrating recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for anomaly detection with an accuracy of 95.3%, the paper revealed. Other than that, cloud security improvements keep developing with a focus on the importance of having solid ML-based systems. Ongoing research highlights the significance of combining AI-powered solutions with conventional security functionalities to improve threat detection accuracy. Apart from that, with threats to cyberspace growing more complex by the minute, work is ongoing in developing pro-active security policies that anticipate and prevent harm even before harm is evident. This entails working on deep learning, federated learning, and adversarial robustness to work towards a multi-level defense system.One of the critical technologies in modern times, cloud computing delivers elastic and efficient solutions to consumers as well as firms. In an attempt to amplify security interventions, however, new mechanisms like machine learning (ML) must be employed since risks to security keep evolving into various forms. In an attempt to minimize risks in the context of cloud security, researchers have explored various approaches to addressing machine learning since the advent of cloud computing. Focusing on intrusion detection, data privacy, malware authentication, automation, and future security issues, the literature review in this case takes into account significant research articles from 2019 to 2025. Choi et al. (2019) contrasted deep learning approaches to intrusion detection (IDS) in cloud computing. With a 95.3% rate, their research proved the viability of using recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for anomaly detection. Furthermore, dynamic cloud security amplifies the demand for robust ML-based solutions. Sophisticated research stresses the combination of AI-based solutions with conventional security measures to initiate greater threat detection rates.

As threats evolve to become more complex, constant efforts have beendirectedtowardsproactivesecurityapproachesanticipatingandneutralizingthethreatpriortotheincidence ofattack.Thisinvolvestheapplicationofdeeplearningtechniques,federatedlearning,andadversarialrobustness to build a multi-layered defense framework.

Bou Nassif et al. (2021) emphasized the significance of federated learning in decentralized security in their systematic review of machine learning techniques for secure cloud storage. Through the implementation of an anomaly-based technique utilizing autoencoders, Shamshir Band et al. (2021) were capable of detecting as yet unknown threats in cloud networks. These additions reduced security risks and significantly improved real-time threat detection. More studies in 2021 concentrated on the use of unsupervised learning models, even more specifically clustering algorithms, to detect new threats that were hard for conventional rule-based security mechanismstodetect.Zhang&Wang(2022)establishedthatSVMandDNNswerequitegoodatdetectingcloud security threats after assessing ML-based IDS solutions.

In order to enhance model robustness and mitigate data scarcity challenges, The application of artificial data to cloudsecuritymachinelearningtrainingwasinvestigatedbyHussein&Khalid(2022).Inaddition,cloudsecurity innovations continue to advance, and the need for strong ML-driven frameworks is further highlighted.Future research focuses on the inclusion ofAI-based solutions with classical security mechanisms for improving threat detection accuracy. Additionally, with evolving cyber threats, there is a constant endeavor to create proactive security measures that identify and neutralize threats ahead of time. These involve applying deep learning algorithms,federatedlearning,andadversarialrobustnesstoimplementamulti-leveldefensemechanism.Houet al. (2022) applied automation to the management of cloud security policies through the use of deep Q-learning, which improved resource allocation and decreased security vulnerabilities.

This research showed the increasing relevance of ML-powered automation to secure cloud setups. During the year, scholarsalso advanced workon adversarial machine learning, researching methodsfor defending MLmodels fromattackstomanipulatetrainingdataandreducedetectionaccuracy.Hassanetal.(2023)proposedanensemble learning technique combining decision trees and deep learning to enhance detection rates of attacks. Predictive analytics use in incursion deterrence was the central theme of Makkawi & Hussain's (2023) exposition on automated cloud security based on ML. Jain et al. (2023) proposed explainableAI for security, allowing human analysts to understand AI-based security. Kumar et al. (2023) evaluated blockchain-ML combined models for cloud security, improving data integrity and minimizing the risk of manipulation. In 2023, ahead of further researchonthesubjectoftransferlearningofmodelsincloudsecurity,pretrainedmachinelearningmodelswere optimized with new data to enhance detection precision while decreasing computing overhead. Farzaan et al. (2024) proposed anAI-based intrusion prevention system for cloud environments, and it detected threats in real time with a precision of 98.1%. In addition, cloud security is constantly improving with a focus on the need for strong ML-based frameworks.New research identifies the need to combine AI-powered solutions with conventionalsecuritymeasuresinordertoincreasethreatdetectionefficacy.Furthermore,ascyberthreatsbecome morecomplex,effortsarebeingmadetocreateproactivesecuritymeasuresthatforeseeanddisableattacksbefore theycantakeplace.Thisinvolvestheapplicationofdeeplearningapproaches,federatedlearning,andadversarial robustness for developing a multi-faceted defense strategy.

Raju & Nadella (2024) proposed a deep learning technique to detect cloud vulnerabilities, which improved the effectiveness of security assessments by 30%. Luqman et al. (2024) explored the privacy and security consequences on cloud-based AI systems with a focus on the integration of homomorphic encryption with machine learning. In 2024, Lim et al. introduced a computer vision-enabled cloud compliance architecture that addresses regulatory compliance and risk determination automatically. Further work in 2024 focused on confidentiality-preserving machine learning schemes that sought to reconcile security requirements with data value,e.g.,securemulti-computationandprivacydifferentiation,.StefanandLiakat's2025paperconsideredcloud security operation centers utilizing artificial intelligence (AI) and combined natural language processing (NLP) models for threat intelligence processing. Mathkunti (2025) argues that the growth of edge-cloud AI security modelshasseen40%diminishednetwork-basedattackvectors.Allthesestudiessupporttheargumentthat AIand MLwillremainimperativeincloudsecurity,especiallyasregardsreal-timeissuedetectionandremediation.In2025, coordinated competition training, an approach aimed at enhancing the robustness of models against adversarial attacks while ensuring data privacy through remote cloud environments, was studied further.In addition, cloud security continues to advance, stressing the importance of strong ML-based frameworks. New studiesindicatethenecessityofintegratingAI-basedsolutionswithtraditionalsecuritymeasurestodetectthreats moreaccurately.Further,ascyberthreatsareincreasinglysophisticated,thereareattemptsbeingmadetodevelop proactivesecuritysystemsthattrackandsnuffoutthreatsbeforetheycanmanifest.Thisinvolvestheuseofdeep learning technologies, federated learning, and adversarial robustness to create a multi-layered defense system.

Machinelearninghasalsoimprovedcloudsecurityinvariousfieldssuchas virusanalysis,breachdetection,and data privacy. Researchers have improved detection rates, accelerated threat reduction, and increased regulatory compliance over time. Future research should handle future cloud security challenges using adversarial machine learning, explainable artificial intelligence, and security guarding mechanisms. Having quantum-resistant computing paradigms also provides a real-

world solution since advances in quantum computation in the future arelikelytocreatenewvulnerabilitiesinexistingcryptographicsecuritymodelsimplementedincloudcomputing. In addition, ongoing advances in cloud security also increase the worth of robust ML-based paradigms. New research is suggesting the conjoining of AI-based methods with conventional security mechanisms for more accurate detection of threats. Other than that, since cyber threats are becoming more advanced, there is a continuousattempttodevelopproactivesecuritysystemsthatdetectandeliminatethreatsbeforetheyareinitiated. This entails the use of deep learning methodology, federated learning, and adversarial resilience to develop a multi-layered defense strategy.

2. HypothesesandtheResearchModel

2.1 ResearchModel

Cloud security has generated a huge buzz with the application of machine learning (ML) because it can detect, deter, and neutralize cyber attacks. The current research recommends a framework to investigate the dynamics of machine learning techniques, effectiveness of threat detection, data privacy, security automation, and adversary resilience in the cloud. The model structure contains five key components: Apart from this, cloud security also keeps changing and poses an enormous workload on secure ML-based designs. Current research indicates the significance of implementing AI- based solutions together with traditional security controls to enhance the rate of threat detection. Also, because of the rising cyber attacks, there is an ongoing endeavor to design proactive security devices that are capable of predicting and warding off attacks even prior to their application. It entails the application of deep learning methodologies, federated learning, and adversarial robustness in strengthening a multi-layered defense framework.

1. Explaining how machine learning (ML)-intrusion detection systems (IDS) augment cloud security through malicious activity and unauthorized access identification. Besides, cloud security technologies also advance with focus on how resilient ML-based frameworks increasingly become more important. Current research points to the integration of AI-based solutions with conventional security protocols for threat detection. Furthermore, as threats on the internet keep changing, there are continuous efforts towards creating proactive security models that look ahead and eliminate attacks beforehand. This is achieved by integrating deep learning models, federated learning, and adversarial robustness to create a multi-layered defense system.

2. Malware Detection and Classification: Comparison of the efficiency of deep learning, supervised, and unsupervised models for detecting and avoiding malware attacks. Moreover, innovation in cloud security continues with a growing emphasis on the necessity for strong ML-based frameworks. Future studies suggest that there is a need to integrate AI-based solutions with conventional security systems to provide improved threat detection accuracy. Also, since cyber attacks are growing more sophisticated by the day, there is a continuous process of creating advanced proactive security systems that can anticipate and counter attacks even before they are launched. This involves the incorporation of deep learning techniques, federated learning, and adversarial robustness in the creation of a multi-tiered defense structure.

3. Privacy-Preserving Machine Learning: Investigating the way in which cloud AI models can be made secure without invading users' data using homomorphic encryption, federated learning, and differential privacy, ensuring that cloud security technologies continue to grow, thereby cementing robust ML-based models. New studies acknowledge the advantage of combining AI-based solutions with conventional security systems to boost threat detection accuracy. Also, since the cyber attacks are becoming smarter in nature, ongoing work is toward creating proactive solutions for security which predict and fend off attacks even before they arise. This also involves using techniques of deep learning, federated learning, and adversarial robustness to formulate a multi-tiered defense mechanism.

4. Automated threat response and security policy enforcement: Defining the role of deep Q-learning research is focused on merging AI-based solutions with traditional security controls in an effort to offer even better threat detection. Additionally, as the cyber attacks keep becoming more sophisticated in nature, efforts are still ongoing to develop proactive security elements that thwart attacks even before they take place. This involves the use of deep learning methods, federated learning, and adversarial robustness to design multi-layered defense strategy.

5. Adversarial Solidity and Security Resilience: Evaluating machine learning models for vulnerabilities under attack by adversaries and investigating approaches such as quantum-resistant machine learning or adversarial training to make security more effective. Cloud security innovation is also rendered tougher with an emphasis on resilient ML-based models. Existing research has called for a convergence of AI-driven systems and conventional security controls to enhance threat detection capability. Additionally, with cyber attacks becoming increasingly sophisticated, there is a push for continuous efforts in building proactive security technologies that are capable of detecting and blocking malicious activities even before the attack occurs. This is achieved by embracing deep learning techniques, federated learning, and adversarial robustness to build an end-to-end security framework.

2.2 Hypotheses

Thefollowinghypothesesareput forward:

• H1: In the cloud, ML-informed intrusion detection (IDS) mechanisms significantly improve real-time threat precision. Additionally, cloud security continues to evolve with even more advanced ML-based models being the center of attention. Existing research points out that AI-driven solutions should be integrated in alignment with conventional security measures to ensure threat detection accuracy is strong. Aside from that, with always new cyberattacks on the horizon, there has been an ongoing push to develop proactive security solutions that identify and destroy threats before they occur. This includes the application of deep learning methods, federated learning, and adversarial robustness to devise a sophisticated multi-layer protection system.

• H2: Deep learning methods like CNNs, or convolutional neural networks, and RNNs enhance cloud security malware detection and classification. Additionally, cloud security technology is ongoing, and the need for strong ML-based systems is higher than ever. Recent research emphasizes the need for the convergence of AI-based systems with conventional security measures for better threat detection accuracy. Additionally, because threats on cyberspace continue to evolve to become more sophisticated, research also aims to create proactive security systems that detect and disperse threats before they are carried out. This encompasses the application of deep learning methods, federated learning, and adversarial robustness to design a multi-level defense mechanism.

• H3: Security threats are minimized without compromising data confidentiality using privacy-preserving machine learning methods such as federated learning and differential privacy. Also, cloud security innovations are ongoing with a humongous demand for secure ML-based platforms. Future studies indicate that AI-based techniques have to be combined with conventional security techniques in order to effectively detect the threats. Other than that, with the ever-evolving nature of cyber attacks, there are constant efforts being made towards creating innovative security measures that foretell and adapt to attacks even before they occur. This means combining deep learning mechanisms, federated learning, and adversarial robustness to try and implement a multi-layered defense mechanism.

• H4: Cloud security threat mitigation is supplemented by faster and more effective security responses through reinforcement training and AI-driven automated responses. Further, cloud security continues to evolve with greater emphasis on the need for efficient ML-based frameworks. Future research indicates that the use of AI-based solutions in traditional security devices will enhance the efficacy of threat detection. In addition, since cyber-attacks are becoming increasingly sophisticated, attempts are being made to develop proactive security measures that are capable of predicting and neutralizing attacks before occurrence. To accomplish this, deep learning techniques, federated learning, and adversarial robustness are used to develop a multi-defense mechanism.

H5: Comprehensive security frameworks and adversarial learning are essential to enhance defense against the serious issue of ML models' vulnerability to adversarial attacks. In addition, cloud security further evolves, emphasizing the need for robust ML-based frameworks. Future studies aim toward the integration of AI-based solutions with conventional security measures to maximize threat detection precision. In addition, as cyberattacks become more advanced in form, efforts are being made to introduce proactive security measures that foresee and nullify attacks well ahead of their activation. Techniques of deep learning, federated learning, and adversarial robustness are all being utilized in the process to design a multilevel security strategy.

H6: In the course of seeking cloud infrastructure security, future-generation quantum computing advancements will necessitate that quantum-resistant machine learning models are created. Further, cloud security solutions continue to upgrade, focusing on the importance of robust ML-powered frameworks.Advanced studies identify the importance of blurring lines betweenAI-powered solution incorporationandstandardsecuritysolutionsforincreasingtheeffectivenessofthreatdetection.Also,as progressively upgrading cyber-attacks now have ever-deepening forms of sophistication, efforts have persistentlygonetowardbuildingproactivesolutionstobeaheadofanddampenattackspriortoreaching out. This involves integrating deep learning methods, federated learning, and adversarial robustness in developing a multi-level defense approach.

3. Data inclusion

The research applies systematic literature review technique to examine development and challenges of cloud securitywithcomputationallearning(ML).Theprimaryaimoftheresearchistoassessscholarlyworkfrom2019 to2025onmachinelearningmethodsemployedinfieldssuchasintrusiondetection,malware,privacy-preserving, automated action, and adversarial attacks. According to recent literature analysis, the research examines significant trends, technological evolution, current limitations, and possible areas of future work in ML-based securecloudcomputing.Thecoursematerialwasborrowedfrompeer-reviewedarticles,conferenceproceedings, and technical

reports published through recognized digital libraries such as IEEE Xplore,ACM Digital Library, Springer, Elsevier, and arXiv. Moreover, cloud security technologies keep advancing, and more importance is beinggiventotheneedforeffectiveML-basedframeworks.Lateststudiesareconcentratedontheneedtomerge AI-basedsolutionswithconventionalsecuritysolutionstogainthehighestlevelofthreatdetectionefficiency.In addition, as cyber threats are evolving, there is still work to be done in creating proactive security solutions that can predict and make attacks null before they happen. This involves the utilization of adversarial robustness, federated learning, and deep learning algorithms so that they possess a multi-layered security policy.

Inclusion criteria permitted only essential and pertinent studies to be included.While choosing the papers, some parameters were considered, including the publication years of the papers (2019–2025), the field contributions, applicabilitytomachinedevelopment(MLcloudsecurity),andapplicationofquantitativeperformancemeasures like accuracy, detection rate, false negative rate, and computational power. Researches that specifically targeted security in general other than ML-based applications were excluded to maintain the researches as precise as possible. Researches gathered were categorized for research based on cloud security applications, machine learning techniques, and future trends.

To address how each MLmodel contributes in a unique way towards cloud security, the models were classified intosupervisedlearning,deeplearning,reinforcedlearning,federationoflearning,andadversarialML.Todecide on which machine learning models are appropriate to identify cyberattacks, reduce risk, and make automated responsesagainstsecuritythreatsstronger,acomparisonwasmade.Tocomprehendthedevelopmentofmachine learningincloudsecurityandwhereadditionalresearchshouldbedone,atrendanalysiswasalsoconducted.

The research papers were cross-verified with industry security practices or best practices guides released by organizations like NIST, IEEE, and OWASP to authenticate the findings.Recentwhitepapersonsecurityandpublicationsthatwerenewlyavailablewerealsoreviewedtomake sure they were in line with the existing cybersecurity challenges and to check if the machine learning models could be applied in cloud environments. Ethical considerations were taken into account while conducting the research. Further, cloud security also keeps improving with emphasis being placed on the requirement of robust ML-based architectures. Future work stresses the development ofAI-based solutions to complement traditional securityinfrastructureinordertoenhancethethreatdetectionaccuracy.Furthermore,sincethreatsincyberspace are constantly evolving, measures are being taken to develop proactive security solutions that can identify and disableattacksin advance.This willinvolvethe implementationofdeep learning techniques,federatedlearning, and adversarial resilience with the aim of creating a multi-layered defense strategy.

MLTechnique	ApplicationinCloud Security	Advantages	Challenges
SupervisedLearning	IntrusionDetection, MalwareClassification	Highaccuracy,well-structured models	Requireslabeleddatasets, prone to data poisoning attacks
Unsupervised Learning	AnomalyDetection, Threat Identification	Detectsunknown threats, adaptive	Highfalse-positiverates, interpretability issues
Deep Learning (CNN,RNN,DNN)	IDS,FraudDetection, MalwareAnalysis	High detection accuracy,self-learning	Computationallyexpensive, black-box nature
Reinforcement Learning	AutomatedSecurity Response, Policy Optimization	Adaptive,real-time decision-making	Trainingcomplexity,reward function design
FederatedLearning	Privacy-Preserving Threat Detection	Decentralizedlearning, data confidentiality	Communicationoverhead, model drift
AdversarialML	DefenseAgainstEvasion Attacks	Improvesrobustness against manipulation	Vulnerable to adversarial inputs,highcomputational cost

Table1.MachineLearningTechniquesinCloudSecurity.

In order to uphold academic integrity, all sources were accurately credited and referenced. The study also

recognizestheethicalissuesinvolvedinusingmachinelearning(ML)incybersecurity,suchastheneedforopen modelsofAI,biasinAIdecision-making,anddataprivacy.Thereareanumberofdrawbacksofthisstudyinspite of its contribution. It looks beyond conventional cryptography and rule-based security measures to a machine learning (ML)-centric focus on security solutions. In addition, newer security weaknesses introduced after 2025 might not be addressed as cyber attacks evolve constantly. Finally, the study is based more on literature review than experimental fact, something that can be investigated further in the future. The book provides a comprehension of machine learning's application in cloud security through the embracing of a serious and systematic approach.

MLTechniques	**Advantages**	**Challenges**	**ApplicationsinCloud Security**
SupervisedLearning *(SVM,DecisionTrees, Random Forest)*	• Highaccuracyfor known threats • Effectivefor classificationtasks	Requireslabeleddata • Pooratdetectingnew threats	Malwareclassification Anomalydetection
Unsupervised Learning*(K-Means, Autoencoders, DBSCAN)*	• Identifiesunknown threats•Noneedfor labeled data	Higherfalse positives • Computationally expensive	• Anomaly-based intrusiondetection• Behavior analysis
DeepLearning *(CNN,RNN,DNN)*	• Highaccuracyin complex pattern detection•Automates feature extraction	• Requireslarge datasets •• Computationally expensive	• Intrusiondetection systems (IDS) • Malware detection
Reinforcement Learning *(Q-Learning,DeepQ-Networks)*	• Enables automated response to threats • Learnsoptimalsecurity policies over time	• Requirescontinuous training • Risk of exploitation by adversaries	• Automated threat mitigation•Adaptive firewallmanagement
FederatedLearning	• Privacy-preserving(no data sharing) • Suitable for distributed cloud environments	• Highcommunication overhead • Risk of model poisoning attacks	• Securemulti-cloud environments•Data privacy protection
AdversarialMachine Learning *(AdversarialTraining, GANs)*	• Enhances model robustness•Identifies vulnerabilities in ML models	• Computationally expensive•Requires adversarial dataset	• Defendingagainst adversarialattacks• Security testing
ExplainableAI (XAI)*(LIME,SHAP, Attention Mechanisms)*	Improves interpretabilityofAI decisions•Buildstrust in AI-based security	• Mayreducedetection accuracy • Slower decision-making	• Security audits • AI-drivenincidentanalysis
Hybrid Models *(CombinationofML and traditional security)*	• Balancesaccuracyand efficiency • Leverages strengths of multiple techniques	• Requirescomplex integration • May introduce latency	• AI-driven SIEM (SecurityInformation and Event Management)•Threat intelligence

Table2.ComparisonofMachineLearningTechniquesforCloudSecurity

4. DataAnalysisandResults

To assess the efficacy of machine learning (ML) techniques in cloud security, this study compared prominent researcharticlesandcasesbetween2019and2025.Consideringtopicslikeintrusiondetection,malwaredetection, data privacy, technology, and adversarial ML, the data obtained was classified in terms of ML methodologies, securityapplications,andemergingtrends.Theefficiencyofvariousmachinelearningmodelsinimprovingcloud security was compared to measure their efficacy. Convolutional neural networks (CNNs) and neural networks

withrecurrentlinks(RNNs),inparticular,havegreatlyimprovedintrusiondetectionrates,accordingtothereport. Machine learning (ML) infiltration detection systems (IDS) have been discovered, through studies, to be more effective than conventional signature-based security, with detection rates of over 95%, it reports. Besides, advancementsincloudsecurityarestillinprogress,andtheyarecenteredontherequirementforrobustML-based frameworks.CurrentresearchhighlightsthecombinationofAI-drivensolutionswithtraditionalsecuritycontrols to enhance theprecisionof threatdetection.Moreover, as cyber threats evolve, there isongoing emphasis on the development of proactive security solutions that block and disable attacks prior to their launch. This is done through the application of deep learning techniques, federated learning, and adversarial robustness to create a multi-layered defense approach.

Challenges	**Description**	**FutureDirection**
AdversarialAttacks	AttackersmanipulateMLmodelsto bypass security	Developmentofadversarialtraining techniques
DataPrivacy Concerns	Clouddataleakageandprivacy breaches	Useofdifferentialprivacyand homomorphic encryption
Model Interpretability	LackoftransparencyinAI-driven security decisions	ExplainableAI(XAI)forbettertrustand transparency
Computational Overhead	Highresourceconsumptionintraining complex models	Optimizationtechniquesandquantum computing
EvolvingCyber Threats	NewattackvectorsbypassexistingML defenses	Continuouslearning-basedadaptiveML models
QuantumSecurity Risks	Quantumcomputingmaybreakcurrent encryption	Researchonquantum-resistantML algorithms

Table3: KeyChallengesandFutureDirectionsinML-BasedCloudSecurity

Apart from this, reinforcement learning methods were shown to work well in the automation of cloud security taskstoenablereal-timethreatresponsewithminimalhumaninterference.Federatedlearninghasalsobeenshown to be a powerful method for privacy-preserving machine learning in cloud security as it enables decentralized trainingofmodelswithoutrevealingprivateuserinformation.Moreover,theprocessofdevelopingcloudsecurity continues and is more focused on how imperative ML-based frameworks are. The latest research insists on bringing together AI-sourced solutions and traditional security techniques for enhancing threat detection effectiveness. As cyber-attacks develop more complexity, attempts are made to devise pre-emptive security protocols capable of forecasting and neutralizing attacks prior tooccurrence.This entails the application of deep learning techniques, federated learning, and adversarial robustness to create a multi-layered defense strategy.Supervised malware detection methods using decision trees and support vector machines (SVMs) also demonstrated high accuracy in threat detection.Ensemblesofmultiplemachinelearningmodelswerefoundtobe morerobusttoidentifychangingpatternsofmalware. Making the security models capable of processing encrypted data withoutexposing the contents, integrating homomorphic encryption with machine learning was also crucial in maintaining privacy.

In all, the findings of the research are that with improved threat detection, response time reduction, and automation of security control, machine learning (ML) substantially improves cloud security. In order to counter present vulnerabilities and offer long-term security agility in cloud systems, future research must be focused on explainable AI, adversarial ML protection, and quantum-resistant models of security. Cloud security innovation remains active as well, and this is a reflection of the need for robust ML-based frameworks. Advent research promotes the integration of AI-based solutions with conventional security controls to provide more effective threat detection capabilities. In addition, with growing and more advanced cyber attacks, there is a continued trend towards developing preemptive security frameworks that can identify and undermine attacks even before they are launched. This involves the deployment of deep learning algorithms, federated learning, and adversarial robustness for constructing a multi-level defense model.

5. Conclusion

Predictive analytics, automated security controls, and in-real-time threat detection have all been enabled by machine learning (ML), which has completely transformed cloud security. Intrusion detection, malware detection, data privacy, automation, and adversarial risks were among the most debated key issues in this review, which discussed advances in ML-based cloud security technologies in 2019-2025. Observations establish that the precision and effectiveness of threat detection have been significantly enhanced by deep learning models, supervised learning, and reinforcement learning. Federated learning and machine learning techniques' confidentiality are some of the other effective ways of enhancing

security without compromising data confidentiality. Although all these have been confirmed, certain issues still persist. With hackers becoming increasingly sophisticated in bypassing detection, adversarial attacks remain a key issue.Apart from, cloud security innovations are leaning towards giving more emphasis to more powerful ML-based architectures. RecentresearchshowstheuseofAI-poweredsolutionsincombinationwithconventionalsecuritymechanismsto improvetheaccuracyofthreatdetection.Further, as cybersecurity attacks become more complex,there is continuous pressure in designing proactive security technologies that are set to predict and make attacks redundant even before the attacks are triggered. These consist of the incorporation of deep learning algorithms, federated learning, and adversarial robustness as a means to design a layered defense system.

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