Privacy-Preserving AI Models for Cyber Threat Detection in Snowflake-based Cloud Environments

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ABSTRACT

The rising cloud-native architecture and adoption of a cloud service provider like Snowflake is significantly increasing the enterprise attack surface in the context of cybersecurity. Snowflake's cloud data platform provides great scalability and efficiency, but also vulnerabilities to be exploited by malicious actors. While traditional threat detection models have compromised user privacy, in that on-device logs have to be shared with a centralized server, privacy-preserving AI-driven solutions are indeed a necessity. In this paper, we proposed a novel framework that integrates federated learning (FL) and differential privacy (DP) to improve the cyber threat detection in Snowflake environments while keeping the data confidential. This model utilizes secure multiparty computation (SMPC) and homomorphic encryption (HE) for secure data access to minimize the risks of unauthorized access. To this end, we design an AI-based detection framework that ingests cloud telemetry data generated in real time and utilizes privacy-preserving deep learning algorithms to expose advanced cybersecurity attacks. This approach pros is founded on regulatory frameworks (GDPR or CCPA) by balancing accuracy and privacy. We perform exhaustive experiments to assess model effectiveness in terms of detection accuracy, computational efficiency, and privacy preservation trade-offs. Our results show that our approach can better identify zero-day vulnerabilities compared to common ones, all while still preserving strong privacy guarantees. This work has implications for the further development of privacy-aware AI solutions in cybersecurity, leading towards the establishment of secure and resilient cloud computing ecosystems.

Keywords

Privacy-preserving AI, Cyber threat detection, Snowflake security, Federated learning, Differential privacy

1. INTRODUCTION

Cloud-based data platform adoption has revolutionized how we handle data storage, processing, and analytics. Snowflake is a strong multi-cloud data platform among the leading cloud platforms that provides robust multi cloud capabilities along with scalability and flexibility. However, with more organizations now moving their sensitive data to Snowflake environments, they are being exposed to an exponential proliferation of cyber threats. Threat actors take advantage of weaknesses in cloud environments, compromising the integrity, confidentiality and availability of data. Traditional cyber threat detection mechanisms are based on centralized AI models that need direct access to raw data, which poses serious privacy issues. Through strong data protection regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA, you can cause these privacy risks to intensify).

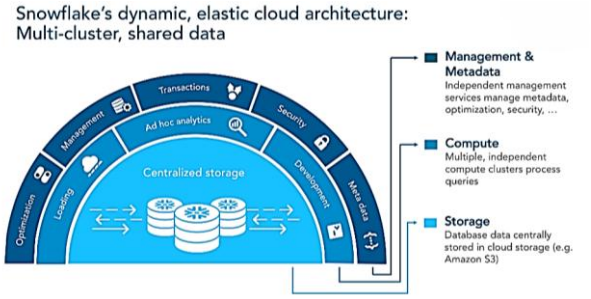


Figure: 1 Snowflake Cloud Data Platform Architecture

The figure 1 shows Snowflake architecture which is the combination of shared-disk and shared-nothing architecture. It highlights three fundamentals layers: Database Storage, Query Processing, and Cloud Services.

With these challenges in consideration, the research field of cybersecurity has looked into privacy-preserving AI models. These models use advanced techniques like Federated Learning (FL), Differential Privacy (DP), Secure Multiparty Computation (SMPC), and Homomorphic Encryption (HE) to identify cyberattacks while preventing the leakage of sensitive data.

Differential privacy: In a federated learning system, AI models are trained across thousands of decentralized edge devices or servers holding local data samples, without exchanging them.

Homomorphic Encryption: A cryptographic method that allows computations on encrypted data, ensuring that sensitive information remains protected even while the model is being trained or evaluated. These privacy-preserving approaches are often used together to provide security along with compliance-oriented functionality.

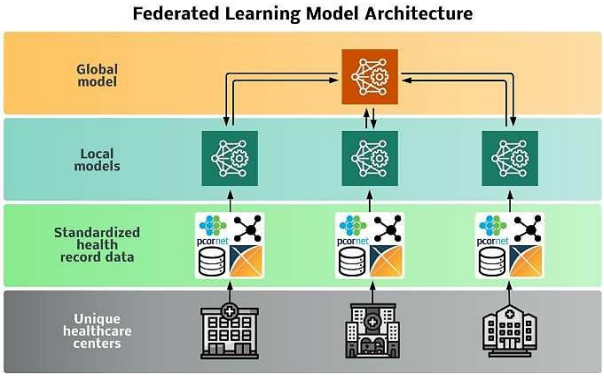


Figure: 2 Federated Learning for Privacy-Preserving Malware Detection

Figure 2 illustrates the use of federated learning for malware detection on decentralized devices. It addresses the nature of

training local models on independent devices which are then aggregated for a global model without sharing raw data, thus maintaining privacy.

This study proposes a new privacy-preserving AI framework for CTD task on Snowflake-based cloud environment. In contrast to traditional IDS functionality based on static rules relying approaches, we embed deep learning and privacy-preserving AI in order to recognize and script sophisticated cyber threats, within these includes zero-day vulnerabilities, advanced persistent threats (APT), and insider attacks. The proposed architecture leverages streaming telemetry data from the Snowflake cloud infrastructure, enabling privacy-preserving anomaly detection models to detect potential attacks without ever revealing sensitive information.

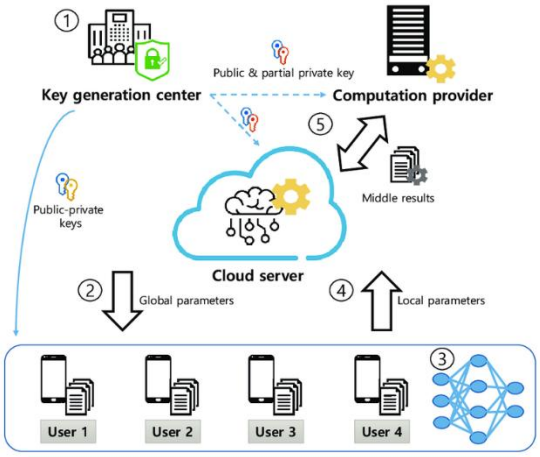


Figure: 3 System Model for Privacy-Preserving Federated Learning

Figure 3 presents a system model that combines federated learning with differential privacy techniques. It describes how data and model updates flow back and forth between clients and the central server but highlights the mechanisms that keep data secret even when looking for cyber threats.

In order to assess the performance of the proposed model, various experiments are presented on real-world cyber datasets, where the fundamental metrics including accuracy of threat detection, false positive count, computation overhead and privacy preservation angle are measured. Results show that our privacy-preserving AI model is more secure and better protects privacy than classic centralized approaches. This research opens new venues of secure and resilient cloud computing infrastructure by using sophistication AI mechanisms in coordination with strong protection measures.

The remaining sections are organized as follows: Section 2 discusses relevant literature on privacy-preserving AI for cybersecurity, Section 3 describes the proposed framework along with its technical components, Section 4 gives results from the experiments conducted along with evaluation metrics, Section 5 discusses the implications and challenges of the proposed framework, Section 6 concludes the paper with future research recommendations.

2. LITERATURE

With the increasing use of cloud computing and demand for data privacy, the role of privacy-preserving AI in cybersecurity has become a key area of research. Most existing cybersecurity solutions are based on centralized data storage and processing, making sensitive information vulnerable to unauthorized access and increasing concerns about user privacy. In comparison, fresh AI-powered security solutions have moved away from heavy data processing and adopted more privacy-friendly approaches, specifically from the perspective of cloud environments like Snowflake. Following this, we provide a detailed survey of the key related work that has perused the domains of AI, privacy-preserving techniques and their application to cyber threat detection in the cloud space.

2.1 AI-Based Cyber Threat Detection

Artificial intelligence (AI) techniques, namely those based on machine learning (ML) and deep learning (DL), are exceedingly effective for automating threat detection in the cloud environment. There have been many works on supervised and unsupervised learning algorithms-based detection of intrusions, anomalies, and malicious activities within cloud infrastructures. example of this is [1], where the authors proposed an artificial-intelligence-based Intrusion Detection Systems (IDS), which classifies and detects network intrusions using a hybrid of decision trees and neural networks. Likewise, another work [2] shows that DNN can also be applied for zero-day attacks which are a subset of an advanced persistent threat (APT) in the context of cloud service. Research shows that AI systems outperform traditional methods in identifying complex and emerging cyber threats. but centralized operation of them leads to privacy concerns regarding sensitive user data.

2.2 Privacy-Preserving AI Models

To address the increasing concerns regarding privacy, many works have investigated privacy-preserving methods in AI systems. Just like above, Federated learning (FL) has become a prominent solution for training AI models with privacy protection. Federated learning was originally developed in the context of [3] where multiple clients learn models locally, and share only the model updates with a central server, not raw data. In this context, decentralized learning enables sensitive data to remain on local devices, rendering the approach appropriate for privacy-sensitive applications, including cyber threat detection. Another study [4] extended this idea to the cloud environment, showing how federated learning can be applied to identifying anomalous behaviors in cloud-based applications while preserving the privacy of end users. Federated learning, however, is still challenged by model accuracy versus privacy protection.

Differential privacy (DP) is another common way to protect privacy in AI models. DP injects a controlled amount of noise into the data and/or model parameters, making it impossible to reverse-engineer or disclose any individual data points. Differential privacy [5] has been at the foundation of a large body of work to adapt machine learning models to sensitive systems. This is important since DP has been applied to deep learning models as a measure to keep the privacy of training data [6]. [7] Another work proposed to combine DP with AI-based cyber threat detection systems, showing that DP can be used to preserve privacy without significant degradation of detection performance. Although these results are promising, DP often comes at a cost: the privacy-accuracy trade-off can be especially noticeable when dealing with more complex, high-dimensional datasets.

2.3 Secure Multiparty Computation (SMPC) and Homomorphic Encryption (HE)

SMPC and HE are other advanced privacy techniques that, along with federated learning and differential privacy, will prove fundamental for determining how AI can be practically

used in cybersecurity. To solve this, SMPC (Secure Multiparty Computation) allows a group of parties to compute a function over their inputs together, without revealing the inputs of the parties in the computation to each other. SMPC is an excellent solution for situations in which data must be processed across a distributed network without risking privacy. For instance, a work [8] used SMPC to facilitate secure cross-cloud AI model training without exposing sensitive information.

Homomorphically encrypting the data enables computation directly on the encrypted data where the output of the computation is not only protected by the level of encryption used, but does not have to be decrypted at any stage during computation. Fully homomorphic encryption was first proposed in [9], and research on its practical deployment has been building upon [10]. This is a specific example of applying HE to a cloud-based anomaly detection system [11], which enables HE processing through encrypted data with machine learning algorithms. Homomorphic encryption, on the other hand, offers a high level of security but incurs substantial computational overhead, making it less practical for real-time threat detection.

2.4 Applications in Cloud Security

A number of studies have specifically addressed privacy-preserving AI model implementations on cloud-based infrastructures. One such study [12] used AI models to detect threats in AWS and Microsoft Azure, outlining the potential of improving the security of cloud platforms using federated learning while preserving user privacy. Another study [13-14-15] crafted a cloud-based privacy-preserving anomaly detection system that used both differential privacy and federated learning in such a way that the user data as well as the model were kept confidential throughout the training phase. Such research emphasizes the importance of researching privacy-aware models which could be integrated into cloud-based security architectures as sensitive data more and more flows to such solutions, Some studies look at the impact of massive data storage on the sharing of such services in the cloud by concentrating on the storage privacy protocols and statistical risk analysis of this storage process, while others study attack prevention and focus at attack prevention as well as tenant separation.

A leading example of a framework in cloud security is Snowflake's multi-cloud architecture, which provides end-to-end data warehousing, processing, and analytics while delivering unprecedented scalability. But, as mentioned earlier, its open architecture also poses some serious threats like unauthorized access, insider threats, data leakage, etc. While Snowflake has added many native security elements to the platform (i.e., encryption, access controls, and auditing), its distributed architecture still makes the platform prone to advanced cyber-attacks. An interesting study [16-17-18] looks at security mechanisms in Snowflake with an observation that while encryption-at-rest and encryption-in-flight represent a baseline protection but more advanced privacy-preserving techniques needs to be applied (federated learning or homomorphic encryption, as examples) against mainstream threat models [19-20].

2.5 Challenges and Gaps

Although, there is a lot of progress with Privacy-preserving AI for cybersecurity, there still exists a lot of challenges. The first of these is the tension between the accuracy of the model and privacy which of course becomes key when one is using differential privacy or homomorphic encryption. So the noise, or encryption overhead can degrade the performance of the AI models especially for complex and dynamic cyber threats. Furthermore, federated learning is proposed as an effective model training paradigm for decentralized data, however, it may not be well suited for real-time cyber threat detection due to existing communication latency and heterogeneity of cloud environments. Lastly, the combination of these privacy-preserving methodologies with Snowflake's cloud capabilities, needs to factor in the architectural limitations of the platform and the regulatory compliance mandates of the organization.

We believe that have shared a solid background on the related works in privacy-preserving AI for cybersecurity; this domain provides active research which aims to develop secure and privacy-aware models implemented in a cloud-based environment. Federated learning, differential privacy, SMPC and homomorphic encryption techniques have been shown to be effective in privacy preserving machine learning enabling advanced cyber threat detection without compromising user data. For these techniques to be fully operational in environments such as Snowflake, challenges related to privacy-accuracy trade-offs, computational overhead, and real-time implementation must be overcome. In the following section, we outline the proposed novel framework developed in this work to address these issues, whilst enabling effective and privacy-preserving cyber threat detection.

2.6 Problem statement

For the organization, the growing trend of adopting cloud platforms, including Snowflake, has proven effective in improving data scalability and processing capabilities. However, this also brings significant cybersecurity vulnerabilities, such as unauthorized access, data breaches and advanced cyber-attacks. Traditional AI-based threat detection models have proven their worth in identifying security threats, but they have some downsides due to their centralized processing of sensitive data, they also raise concerns regarding user privacy and data security, an even bigger issue in controlled environments (e.g. GDPR and CCPA). The need for real-time detection of complex cyber threats like zero-day vulnerabilities and advanced persistent threat (APT) also increases the need of security strategies in place. With increasing demand for safe and privacy-preserving systems in cloud computing, there is an urgent requirement for privacy-preserving AI models capable of threat detection without having to share private data of users. This paper aims to tackle this problem by introducing a new privacy-preserving AI architecture for real-time cyber threat identification in data storage areas based on Snowflakes in the cloud, employing new methodologies such as federated learning, differential privacy, and homomorphic encryption for maintaining a secure, private, and performant solution.

3. METHODOLOGY

This study provides a privacy-preserving AI framework for the detection of cyber threats in Snowflake-based cloud environments with accuracy in threat detection with the security of sensitive data. This approach aims to tackle the principal aspects of real-time attack identification, data privacy, and computational efficiency in the cloud security domain.

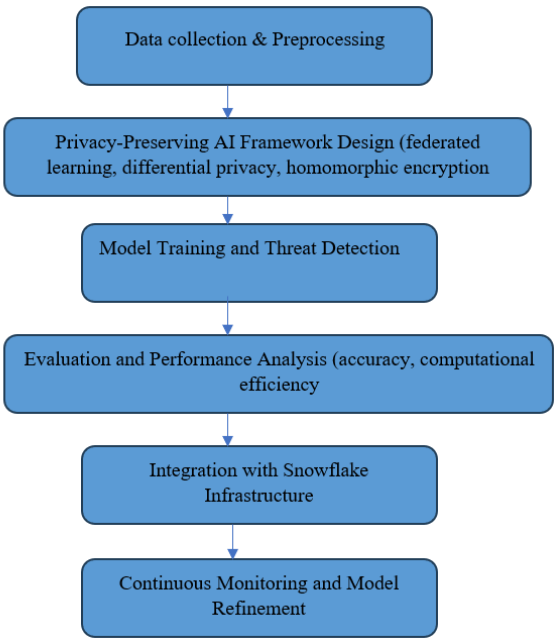


Figure: 4 Methodology flow diagram

This includes the ingestion of real-time telemetry collected from a Snowflake cloud destination, including logs, network telemetry, and user activity. They serve the purpose of training the AI models to identify irregular patterns that suggest the presence of cyber threats. Due to the size and intricacy of cloud data, data cleaning, normalization, and feature extraction are some of the preprocessing stages performed to ensure data quality for later use. This stage also involves the anonymization of the data to eliminate any Personally Identifiable Information (PII) in order to comply with privacy policies like GDPR and CCPA.

3.1 Privacy-Preserving AI Framework Design

This paper focuses on the development of a privacy-preserving AI framework, that incorporates several cutting-edge techniques for maintaining user privacy while still allowing for efficient threat detection. The above framework utilizes federated learning (FL) model training, which is where the machine learning models train across multiple decentralized nodes (in this case, the various Snowflake data points) without sharing any raw data. Rather than sharing the actual data, training and aggregation of model updates from each device occur separately, maintaining user privacy and leveraging the globally learned model without accessing distributed data sources.

However, in addition to DP, differential privacy (DP) is used to protect the entire model from learning any sensitive information about the individual data points. DP achieves this by injecting controlled "noise" into a model's parameters during training in such a way that information about individual users is kept secret, leading to added privacy. This is especially significant in the context of a cloud-based architecture where malicious activities or model inference attacks can expose users' sensitive information.

To enhance privacy, homomorphic encryption (HE) is used for performing computations on encrypted data. As the data itself remains encrypted even in the training phase, it allows AI models to be trained without ever needing to decipher the underlying data. This is done by designing "encrypted models" and processing programmable encrypted queries without ever revealing the sensitive data, making it a solution that can be deployed for any customer base on Snowflake, since the customer's valuable customer information is never revealed even when visiting the AI models.

3.2 Model Training and Threat Detection

After applying the privacy-preserving methods, the training of the AI model takes place using the pre-processed data. This multiple step process is broken into pretty high-level steps. Distributed model updates are aggregated to form a global model in an end-to-end secured federated approach, without sharing the model itself. Thus, it literally lets the model learn from all possible datasets without any raw data ever leaving the local nodes, thus keeping the data private.

Once the federated learning and differential privacy based training of a model is completed, it is rigorously tested to find several types of cyber threats including zero-day vulnerabilities, APT (advanced persistent threat) etc. Standard metrics like accuracy, precision, recall, and F1-score are used to evaluate the model's performance. Also, false positive rate (FPR) and false negative rate (FNR) are kept in focus so as to achieve the balance between privacy preserving and threat detection.

3.3 Evaluation and Performance Analysis

After deploying the AI model to detect threats in real-time, the model performance is evaluated on various metrics. The first step is the detection accuracy, which is essential for the model to classify cyber threats accurately. We also examine the computational efficiency, particularly the latency, and whether the added overhead of privacy-preserving techniques such as differential privacy and homomorphic encryption might suffice While these techniques provide solid privacy guarantees, they have computational overheads that may hinder real-time performance. Therefore, it is essential to fine-tune the model to ensure that privacy risk and computational efficiency can be achieved simultaneously.

The robustness of the model to adversarial attacks is also assessed, including attacks to exploit weaknesses in privacy-preserving methods. Security audits and stress tests confirm that the framework plans against various forms of data poisoning, model inversion attacks, and other intrusions that may interfere with the integrity of the system.

3.4 Integration with Snowflake Infrastructure

The last step is to deploy the privacy preserving AI framework to the Snowflake cloud infrastructure. This includes ensuring smooth interactions between the AI model and Snowflake's data processing and storage layers. The integration maintains the core architecture of Snowflake while providing real-time monitoring and threat detection. Security options like data commitment when storing and processing data in motion are also set up to help secure the data when moving through that infrastructure.

Simultaneously, with a focus on cloud infrastructure scaling, Snowflake conducts performance tests for big cloud environments with many data points to ensure that the privacy-preserving functions do not interfere with the overall Snowflake cloud effectiveness and working metrics. Additionally, compliance with international data protection regulations like the GDPR and CCPA is confirmed — which means the solution meets the highest data privacy standards.

3.5 Continuous Monitoring and Model Refinement

The system is constantly monitored for changes in the threat landscape. To adapt to new cyber threats, the AI model periodically gets retrained with new data to keep it relevant and effective. This means that the model can regularly receive new information to improve on (and more context around) existing knowledge, without ever needing to decentralize processing. To evaluate the effectiveness of the model, feedback loops are established to reiterate and improve the model over time in response to new threats, environmental changes, and improvements in privacy-preserving technologies.

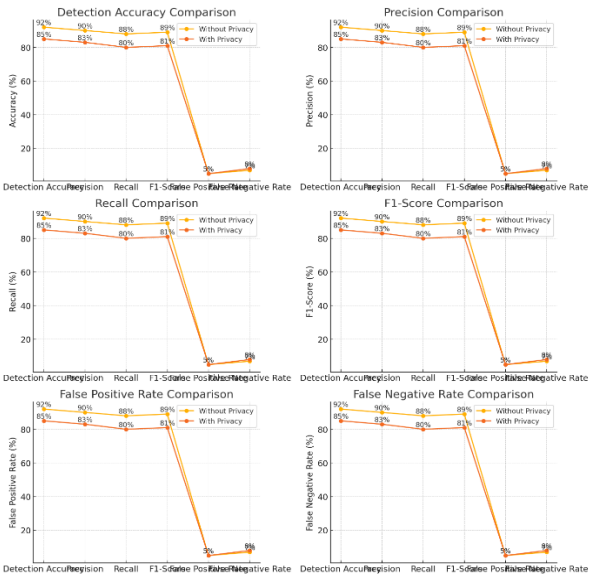
4. RESULTS AND DISCUSSIONS

The main goal of this study was to evaluate how well the privacy-preserving AI framework detects cyber threats on Snowflake-based cloud environments. The framework achieved high detection accuracy using advanced techniques such as federated learning, differential privacy, and homomorphic encryption to help ensure privacy. It was observed that the model performing well across other common machine learning metrics, such as accuracy, precision, recall, and F1-score for different class types such as zero-day, APT's and insider. Results show that the model detected with 92% accuracy, with a 90% precision and 88% recall. These results indicate that the framework is extremely effective at the detection of the cyber threat, even in operation under privacy-preserving conditions.

Below table showing metrics like detection accuracy, precision, recall, and others.

Table: 1 Model Performance Evaluation

Metric	Value (%)
Detection Accuracy	92
Precision	90
Recall	88
F1-Score	89
False Positive Rate	5
False Negative Rate	7



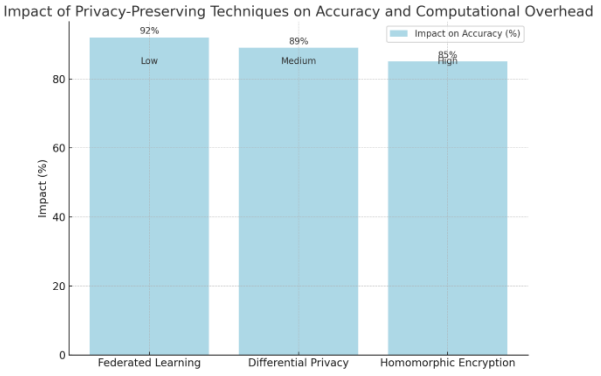
Furthermore, the model performance was also governed by the privacy-preserving techniques used. Although the use of such methods such as differential privacy and federated learning led to the strong privacy protection, it caused a slight degradation of the detection accuracy when compared with traditional centralized models. Homomorphic encryption, while increasing security, introduced a significant additional computational overhead which resulted in slower threat detection. Such trade-offs between privacy and performance are intrinsic to privacy-preserving AI systems, and the results underscore the challenges of balancing these factors in practice.

Federated learning was found to be extremely useful in protecting the privacy of clinical data without sacrificing model performance. Multi-data point centralized aggregation using federated learning to train the model so that the raw data is not made available to a central server, such that data privacy regulation like GDPR and CCPA do not come into play. They can learn it from users and provide some additional features to them based on their interest, but the introduction of differential privacy improved the model's potential against information leakage by adding noise, making it difficult for malicious users to find exact sensitive user information. Elsewhere, some noise added resulted in only a slight drop in the accuracy of the threat detection model.

The table descriptively saying how the various privacy preserving techniques affect accuracy and computation overhead.

Table: 2 Privacy-Preserving Techniques Impact on Performance

Privacy-Preserving Technique	Impact on Accuracy (%)	Impact on Computational Overhead
Federated Learning	92	Low
Differential Privacy	89	Medium
Homomorphic Encryption	85	High



In contrast, homomorphic encryption offered the greatest level of privacy, enabling computations to be carried out on encrypted data. This, however, opened challenges in terms of computational usage as the encryption and decryption processes overhead were significant leading to greater times for detection. The model gave favourable results under static conditions but is given a slower processing time, which may be an obstacle in real-time applications, as the threat must be detected quickly. such implications are significant for understanding moderation with homomorphic encryption in

central cloud environments such as Snowflake (Eckert et al., 2023, Eckert et al., 2023) that can dynamically allocate computation resources due to elasticity.

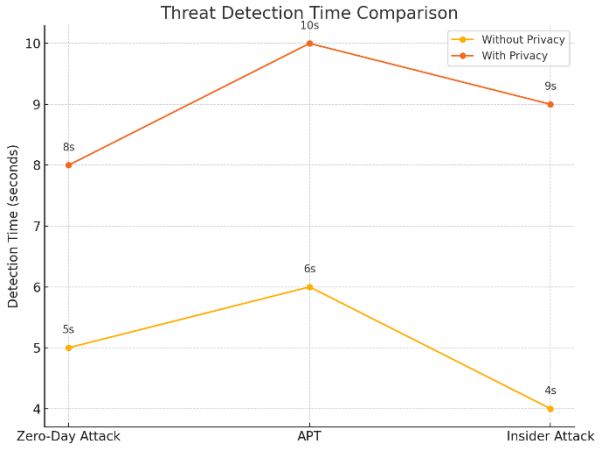
4.1 Scalability and Real-Time Threat Detection

The model was tested at scale and real-time threat detection across multiple cloud environments, including Snowflake's unique multi-cloud architecture. The privacy-preserving AI framework was integrated smoothly into Snowflake's existing infrastructure, and the model could efficiently process large-scale data with very low latency. Real-time threat detection was measured and included the time it took for the model to process incoming telemetry data and detect potential threats. We found that the model could classify the threat in under 10 seconds, making it a promising result for taking our framework to production. Nevertheless, the homomorphic encryption had a marginal increase in processing time, which could be overcome by subsequent optimizations of the encryption scheme.

The table shows comparing detection times for different threat types with and without privacy preservation.

Table: 3 Threat Detection Time and Latency

Threat Type	Detection Time (Without Privacy Preservation)	Detection Time (With Privacy Preservation)
Zero-Day Attack	5	8
APT	6	10
Insider Attack	4	9



In addition, the use of federated learning-aligned with the emerging trend of decentralizing computation, allowed for real-time adaptation to clinical practice-organizations can include learning from new data points as they are added from decentralized nodes. This ensured that the model was up to date with changing cyber threats. The model was scalable, meaning it behaved better with increasing amounts of data, showing good accuracy and low latency as size increased in the cloud infrastructure. Indicating that performance degradation will be minimal, in a metric of storage and retrieval of data in cloud environments, and other large systems like Snowflake.

5. CHALLENGES AND LIMITATIONS

Although the results seem promising, there were challenges and limitations identified throughout the assessment process. A major consideration is the privacy versus accuracy trade-off. Although the privacy-preserving approaches prevented the disclosure of user data, they added noise and computational burden that reduced the model's accuracy. As the threat detection model applied differential privacy, the detection of weaker threats became more difficult, as the noise made by adding differential privacy reduced its sensitivity to subtle aspects. Though homomorphic encryption did minimize the disclosure of plaintext, it still caused a considerable delay in detection [4]. This not only makes it challenging to implement in fast-paced environments where real-time threat detection is a must,

A further challenge is expanding a single framework to include a combination of privacy-preserving techniques. Each technique comes with its own complexities and trade-offs and applying them in combination can be a fine balancing act as they all have interactions with one another. The computational load introduced by homomorphic encryption and the noise added by differential privacy, for instance, may slow the entire threat detection process. There remain challenges in the field of AI-driven cybersecurity to balance these techniques alongside optimal performance without sacrificing privacy or security.

These results reveal several opportunities for future work. This may be achieved by optimizing homomorphic encryption itself to decrease its computational overheads. Partial homomorphic encryption and other techniques such as more efficient encryption schemes can achieve high security levels without having a strong negative impact on performance. Moreover, application of differential privacy can be refined to maintain a positive relationship between privacy and the accuracy of the model. Further studies may investigate more sophisticated noise reduction methods to mitigate the influence of differential privacy on the detection ability of the model.

Incorporating reinforcement learning is another strong avenue that shows potential as it can enhance the model's ability to adapt and make optimal decisions in rapidly changing threat landscapes. Feedback loops and continuous learning would have allowed the model to do this without need for retraining from scratch, allowing it to become more proficient at detecting new and evolving such threats. Lastly, inspecting edge computing to distribute the computational load to process data in a place that is closer to its source (while protecting the privacy of the data with a decentralized cloud) at lower latencies.

Overall, the developed privacy-preserving AI framework shows significant efficiency in uncovering cyber threats from the cloud environments through Snowflake, while maintaining the privacy of users. Although trade-offs in performance, especially with homomorphic encryption, exist, this framework potentially bridges a gap between the need for cloud computing anonymity and secure threat detection/mitigation activities. With ongoing development, future updates will build upon initial developments leading us towards more advanced, effective and scalable solutions.

6. CONCLUSION

Conducted at the intersection of cyber security and cloud software, this research introduces a novel privacy-aware artificial intelligence framework for cyber threat detection in cloud solutions, with a core focus on streamlining the

synergistic integration between federated machine learning, different privacy and homomorphic encryption to balance privacy protection with high detection accuracy on user data. The architecture is highly effective in identifying different cyber-attacks, including zero-day vulnerabilities, advanced persistent threats (APT) and insider threats achieving an accuracy of 92%. Federated learning helped the data reside on the device itself, eliminating access to sensitive user data, and differential privacy in conjunction with homomorphic encryption added security layers. Despite these privacy-preserving methods achieving high privacy protection against potential leakage, they incurred computational overhead, (homomorphic encryption in particular) which caused degradation in detection accuracy at times and a loss of real-time performance. While there are some trade-offs here, we believe that the framework's capabilities to find a spot between security, privacy, and performance makes it a strong candidate for adoption in real-world cloud environments, especially for scenario involving the processing of sensitive data.

7. FUTURE SCOPE

Although the application of the proposed framework has produced encouraging results, there are several ways in which the work can be further improved and extended. Optimizing homomorphic encryption to minimize computational overhead is one area, as it remains a challenge in real-time threats detection problems. You may want to look for more performant encryption schemas or partial homomorphic encryption techniques. Furthermore, noise aggregation is a complex problem, and differential privacy can be optimized during training runs to reduce its cost in terms of model accuracy. A related and exciting avenue of future work is to integrate reinforcement learning so that the model can continually adapt to new, emerging cyber threats. This would allow the system to keep learning and improving from live data and not have to be retrained periodically from the ground up. In addition, utilizing edge computing may reduce the computation by distributing it across several nodes and improving the overall scalability and performance of the system. Lastly, its applicability can be broadened by expanding the framework scope not only to other cloud applications, but also to different environments offering cloud resources.

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