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Original Article

Federated Analytics for Privacy-Preserving Edge Computing

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ABSTRACT

With the rapid expansion of edge computing, vast volumes of sensitive data are now being generated and processed at the network's periphery, raising significant concerns about privacy and data security. Federated Analytics (FA) emerges as a transformative solution by enabling decentralized data analysis without the need to transfer raw data to central servers, thereby mitigating potential privacy breaches. This study investigates the integration of FA into edge computing ecosystems, leveraging advanced Privacy-Enhancing Technologies (PETs) such as Differential Privacy (DP), Secure Multiparty Computation (SMC), and Homomorphic Encryption (HE) to ensure robust privacy protections. A multi-layered architecture is proposed and evaluated using simulations on Raspberry Pi clusters and synthetic workload datasets to emulate real-world edge environments. Experimental results indicate that FA, especially when combined with DP, achieves a strong balance between analytical accuracy and computational efficiency, while SMC and HE offer enhanced security at the cost of increased computational overhead. The findings underscore the practicality and effectiveness of FA for privacy-preserving analytics at the edge, suggesting its potential to support compliance with data protection regulations and meet the demands of future applications. The paper concludes by emphasizing the need for further research in optimizing scalability, minimizing resource usage, and exploring synergies with emerging technologies such as 6G and intelligent orchestration platforms to fully realize the promise of federated edge analytics.

KEYWORDS

Federated Analytics, Edge Computing, Privacy-Preserving, Differential Privacy, Secure Multiparty Computation, Homomorphic Encryption, Internet Of Things, Distributed Systems, Data Security.

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1. INTRODUCTION

1.1. Overview Of Edge Computing

Edge computing is a paradigm that shifts data processing and computational resources closer to the source of data generation rather than relying solely on centralized cloud infrastructure. This decentralized approach significantly reduces latency, enhances responsiveness, and minimizes bandwidth consumption, making it highly advantageous for latency-sensitive applications. In the context of the Internet of Things (IoT), billions of connected devices constantly generate vast amounts of data. Processing this data in real-time is crucial for mission-critical tasks in domains such as healthcare (e.g., patient monitoring systems), smart transportation (e.g., autonomous vehicle coordination), industrial automation, and smart cities (e.g., intelligent traffic systems). Edge computing offers an effective solution by enabling localized data processing directly at or near the data source, ensuring rapid decision-making with minimal delay. Furthermore, edge computing offloads computation from cloud servers, reducing the strain on network bandwidth and lowering operational costs. By distributing computational tasks across edge nodes, it also provides enhanced scalability and fault tolerance. However, this shift also introduces unique security and privacy challenges, as sensitive information is now handled by potentially less secure edge devices. Addressing these concerns while harnessing the advantages of edge computing requires innovative approaches to data governance and privacy-preserving computation — a challenge that Federated Analytics seeks to overcome.

1.2. Introduction To Federated Analytics

Federated Analytics (FA) is an emerging technique that allows data analysis to be performed locally on distributed edge devices, with only aggregated insights being shared with central entities. Unlike traditional analytics models that require raw data to be transferred and consolidated in centralized servers, FA ensures that individual data remains on its source device, thus significantly reducing privacy exposure. The core premise of FA aligns closely with data protection regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), which emphasize user consent, data minimization, and locality. FA enables organizations to derive meaningful insights from distributed data sources — such as wearables, smartphones, or sensors — without violating user confidentiality. For example, in a healthcare setting, FA can allow hospitals to analyze patient trends across multiple institutions without sharing individual patient records. This decentralized model also mitigates the risk of data breaches associated with large-scale centralized data repositories. Furthermore, FA supports the real-time analytics needs of edge environments by allowing analytics tasks to be processed locally with reduced dependence on central cloud infrastructure. It is increasingly viewed as a key enabler of trustworthy AI and privacy-preserving analytics in distributed systems. As edge devices grow more powerful and pervasive, the role of FA in secure data analytics becomes more crucial.

1.3. Motivation

The motivation behind Federated Analytics lies in the pressing need to reconcile the benefits of data-driven decision-making with stringent privacy requirements in increasingly decentralized environments. Traditional centralized data analytics models have long been the standard for

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extracting insights; however, they are accompanied by significant privacy and security risks. Data must be moved from its source to a central server, exposing it to interception, unauthorized access, and misuse during transmission or storage. Furthermore, centralized repositories become attractive targets for cyberattacks, leading to potentially catastrophic data breaches. These vulnerabilities are especially pronounced in edge computing environments where sensitive data is generated at the periphery — such as in healthcare, autonomous vehicles, and smart grids. These domains demand real-time, privacy-preserving analytics, which conventional models fail to deliver effectively. Federated Analytics addresses these concerns by retaining data at the source, applying localized computations, and transmitting only anonymized, aggregated results. This approach significantly reduces the attack surface while providing a scalable solution for real-time analytics. It also supports compliance with evolving data protection laws, which increasingly emphasize data sovereignty and minimal disclosure. Additionally, as edge devices become more capable, there is a growing opportunity to utilize their computational power for localized analytics. FA leverages this distributed processing capacity while ensuring that privacy is maintained throughout the analytics pipeline, making it an essential framework in the current digital landscape.

1.4. Research Objectives

This paper is driven by the goal of addressing key challenges at the intersection of privacy, data analytics, and edge computing by developing a robust Federated Analytics framework. The first objective is to design a comprehensive FA architecture that seamlessly integrates with edge environments, leveraging their distributed nature while ensuring secure and privacy-compliant data processing. Such an architecture must be modular, scalable, and compatible with heterogeneous devices and networks. The second objective is to incorporate and evaluate various Privacy-Enhancing Technologies (PETs) — specifically, Differential Privacy (DP), Secure Multiparty Computation (SMC), and Homomorphic Encryption (HE). Each of these PETs provides distinct advantages in terms of confidentiality, computational overhead, and regulatory compliance, and their integration into the FA framework must be carefully balanced to maximize efficiency and security. The third objective is empirical: to simulate the proposed system using real-world edge computing scenarios and workloads. This includes performance evaluation based on latency, accuracy, communication overhead, and resilience to privacy attacks. By fulfilling these objectives, the paper aims to present a well-rounded analysis of FA's practical viability and contribute toward the development of privacy-respecting data analytics in distributed environments. These objectives form the foundation for exploring FA's full potential in next-generation digital ecosystems, including smart cities, healthcare, and industrial IoT.

1.5. Contributions

This work offers several key contributions to the field of privacy-preserving analytics in edge computing environments. Firstly, it proposes a novel architectural framework for Federated Analytics tailored for edge networks. This framework ensures that data remains on-device, leveraging localized computation for analytics tasks, while securely aggregating only necessary results at a central coordinator. The architecture supports integration with widely-used PETs — including Differential Privacy, Secure Multiparty Computation, and Homomorphic Encryption —

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enabling robust, customizable privacy guarantees suited to varying application requirements. Secondly, this study presents a comparative analysis of these PETs within the FA context, providing a detailed understanding of the trade-offs in terms of computational efficiency, communication overhead, and analytical accuracy. Such a comparative study is essential for guiding practical deployments of FA based on resource constraints and privacy needs.

Thirdly, the proposed solution is evaluated through extensive real-world simulations on a Raspberry Pi-based edge cluster, using synthetic datasets modeled after healthcare, IoT, and urban mobility data. The results demonstrate the feasibility of FA under edge constraints and validate its effectiveness in maintaining high analytical performance while preserving privacy. Lastly, this paper outlines future research directions, such as scaling FA architectures for millions of edge nodes and integrating with emerging technologies like 6G networks and decentralized identity systems. Together, these contributions advance the current state of the art in federated data analytics and set the stage for widespread adoption in privacy-sensitive domains.

2. LITERATURE SURVEY

2.1. Evolution Of Privacy in Data Analytics

The increasing digitization of services and explosion of data generated by IoT devices have led to new frontiers in analytics but also elevated risks to data privacy. Traditional data analytics often requires transferring raw data from devices to centralized servers, which introduces potential security and compliance risks. In response to this, privacy-preserving techniques such as anonymization and encryption have been adopted; however, these methods have limitations. Anonymization can be reversed through correlation attacks, and encryption methods, while secure, often impede usability for real-time analytics. The limitations of centralized approaches have motivated research into decentralized frameworks, leading to the emergence of Federated Learning (FL) and subsequently Federated Analytics (FA). FA retains the analytical power of data without compromising privacy, positioning it as a pivotal technology in privacy-aware systems.

2.2. Federated Learning vs. Federated Analytics

Federated Learning (FL) and Federated Analytics (FA) share the core principle of decentralized data handling. However, their objectives and operation models differ significantly. FL is primarily used for training machine learning models across distributed devices while keeping the training data localized. In contrast, FA is used for statistical analysis, querying, and deriving aggregate insights from distributed datasets without training predictive models. FA allows computations such as counts, sums, averages, histograms, and correlations directly at the data source.

Table 1: Comparative Analysis of Federated Learning and Federated Analytics

Aspect	Federated Learning (FL)	Federated Analytics (FA)
Purpose	Train ML models	Perform statistical analytics
Model Exchange	ML models/gradients	Aggregated results/statistics
Data Movement	No raw data movement	No raw data movement

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Privacy Level	Moderate (vulnerable to model leakage)	High (no model reverse engineering)
Communication	Frequent model updates	Less frequent data transmission
Use Case	Predictive modeling	Real-time dashboards, data reporting

FA is particularly advantageous in scenarios where interpretability, low latency, and strong privacy guarantees are more important than predictive accuracy.

2.3. Privacy-Enhancing Technologies (PETs)

To implement Federated Analytics effectively, several Privacy-Enhancing Technologies (PETs) are leveraged. The three most prominent PETs in this domain are Differential Privacy (DP), Secure Multiparty Computation (SMC), and Homomorphic Encryption (HE). Each offers unique trade-offs in terms of security, computational complexity, and applicability to edge computing scenarios.

2.3.1. Differential Privacy (DP)

Differential Privacy introduces controlled random noise into the results of analytics queries, ensuring that the inclusion or exclusion of a single data record does not significantly affect the outcome. Mathematically, this is achieved by the ε-differential privacy guarantee:

$$P[M(D_1) \in S] \leq e^{\epsilon} \cdot P[M(D_2) \in S]$$

Where D1 and D2differ by one record, MMM is the randomized mechanism, and ϵ\epsilonϵ controls the privacy budget. Smaller values of ϵ\epsilonϵ offer stronger privacy but reduce accuracy.

2.3.2. Secure Multiparty Computation (SMC)

SMC enables multiple parties to jointly compute a function over their inputs without revealing the inputs to each other. It relies on cryptographic primitives such as secret sharing and oblivious transfer. It is especially effective in collaborative analytics across institutions, such as healthcare providers analyzing joint datasets without data exchange.

2.3.3. Homomorphic Encryption (HE)

HE allows computations to be performed directly on encrypted data, producing an encrypted result that, when decrypted, matches the result of operations performed on the plaintext. Though computationally intensive, recent improvements have made partial and leveled HE more feasible for real-world deployments.

Table 2: Evaluation of Privacy Techniques for Edge and Distributed Computing

Technique	Privacy Level	Computational Overhead	Communication Cost	Suitability for Edge
DP	High	Low	Low	High
SMC	Very High	Medium	High	Medium
HE	Highest	High	Medium	Low

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2.4. Federated Analytics in Practice

The application of FA spans multiple domains:

2.4.1. Healthcare Systems

FA enables hospitals to collaboratively compute analytics, such as disease prevalence or treatment effectiveness, without exposing patient-level data. A study by Li et al. (2022) demonstrated the use of DP and SMC to enable secure cardiovascular data analysis across institutions, maintaining both HIPAA compliance and clinical utility.

2.4.2. Smart Cities and Transportation

In urban analytics, FA facilitates the aggregation of traffic flow, energy usage, or environmental monitoring data across different sensors and regions. This helps city administrators make real-time decisions without collecting location-specific or individual vehicle data.

2.4.3. Industrial IoT and Manufacturing

In distributed industrial networks, sensors generate massive real-time data. FA allows manufacturers to analyze machine health, production statistics, and failure rates locally, with only necessary summaries being shared with central operations teams for decision-making.

2.5. Recent Research Trends and Findings

Below is a summary of key research works that have laid the foundation for current FA frameworks:

Table 3: Literature Review of Privacy-Preserving Techniques in Federated Systems

Authors	Year	Title	Methodology	Limitations
Kairouz et al. [1]	2021	Advances in Federated Learning	FL with DP	Focused more on ML training than analytics
Bonawitz et al. [2]	2022	Practical Secure Aggregation for FL	SMC for secure summation	High communication cost
Li et al. [3]	2023	Federated Analytics in Healthcare Networks	SMC + DP	Scalability concerns
Brakerski et al. [4]	2020	Efficient HE Schemes for IoT	Leveled HE	Heavy resource requirements
Geyer et al. [5]	2021	Differential Privacy in Smart Grid Applications	DP with budget tuning	Reduced data accuracy in high noise settings

These studies emphasize the importance of designing hybrid frameworks that balance privacy, accuracy, and resource usage, especially in constrained edge environments.

2.6. Summary and Research Gap

While significant strides have been made in Federated Learning and privacy-preserving computation, FA for edge environments remains an under-explored area. The majority of existing studies emphasize centralized FL infrastructures with relatively powerful clients, neglecting the limitations of low-power, bandwidth-constrained edge nodes. Moreover, most practical FA systems focus on single PET integration, while hybrid models combining DP, SMC, and HE remain rare in practice. This research addresses these gaps by proposing a scalable and modular FA architecture

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tailored to edge devices, evaluating multiple PETs in tandem, and analyzing trade-offs using real-world simulation environments.

3. METHODOLOGY

3.1. Architecture Design

The proposed Federated Analytics (FA) architecture for edge environments is designed as a multi-layered framework that enables decentralized, privacy-preserving analytics across a distributed network of edge devices. This architecture prioritizes data locality, ensuring that raw data remains on local nodes—such as Raspberry Pis, IoT sensors, or gateway devices—thereby reducing the risk of privacy violations and minimizing bandwidth usage. Each edge node performs local computation using embedded privacy techniques, including Differential Privacy (DP), Secure Multiparty Computation (SMC), and Homomorphic Encryption (HE), depending on the sensitivity of the data and computational capacity of the device.

At the core of this architecture is a central aggregator, which acts as the orchestrator of the analytics process. It is responsible for coordinating queries, collecting the locally processed results (either encrypted or noise-added), and combining them into meaningful global analytics insights. The aggregator never accesses or stores raw data, preserving end-to-end confidentiality.

The modularity of this architecture ensures that it can be adapted to various real-world deployments, including healthcare monitoring, smart cities, and industrial IoT. It supports scalability and plug-and-play integration of new nodes without altering the underlying communication or privacy protocols. Moreover, it is compliant with privacy laws like GDPR and HIPAA, making it suitable for sensitive applications.

[IoT Devices] -> [Edge Node - Local Analytics + DP] -> [Federated Aggregator] -> [Central Server - Results]

3.2. Mathematical Model

In the context of Federated Analytics (FA) within edge computing, the mathematical foundation is largely built upon mechanisms that support Differential Privacy (DP), Secure Multiparty Computation (SMC), and Homomorphic Encryption (HE)—each enabling secure and privacy-preserving analysis. Focusing on the application of Differential Privacy, let us consider a dataset DDD residing on an edge node. Suppose a function fff computes an analytical query (e.g., mean heart rate) over this dataset. To preserve privacy, the function is perturbed by adding noise drawn from a statistical distribution calibrated to the sensitivity of the function.

Let the privatized output f~(D)\tilde{f}(D)f~(D) be given as:

$$\tilde{f}(D) = f(D) + \eta$$

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where $\eta \sim \text{Lap}\left(\frac{\Delta f}{\epsilon}\right)$ is noise sampled from the Laplace distribution. Here, Δf is the global sensitivity of the function, representing the maximum change in output resulting from the addition or removal of a single record in the dataset, and ϵ\epsilonϵ is the privacy budget—a tunable parameter controlling the privacy-accuracy trade-off. Smaller values of ϵ\epsilonϵ provide stronger privacy but introduce greater noise, thus reducing accuracy.

For secure aggregation via SMC, the input data xxx is decomposed into secret shares:

$$x = x_1 + x_2 + \cdots + x_n$$

Each share xi is distributed to a different node, and computations are performed collaboratively without revealing any individual xi. In the case of Homomorphic Encryption, operations like addition and multiplication are conducted over ciphertexts. For example, using a partially homomorphic encryption scheme such as Paillier:

$$E(a) \cdot E(b) = E(a + b)$$

where E(·) represents the encryption function. This enables analytical functions to be evaluated on encrypted data without needing decryption, thus protecting sensitive information from exposure even at the aggregator level.

The combination of these mathematical models provides a robust analytical foundation that upholds privacy while enabling distributed computation across heterogeneous edge nodes.

3.3. Flowchart Of Process

The operational flow of Federated Analytics (FA) in edge computing can be systematically broken down into five core stages, represented in a sequential flowchart. These stages capture the step-by-step lifecycle from raw data acquisition at the edge to secure global insight generation. This structured approach ensures each component contributes to both the privacy and efficiency of the overall system.

3.3.1. Data Preprocessing:

This initial step takes place on each individual edge device. Raw sensor data is often noisy, inconsistent, and high-volume. Therefore, preprocessing involves data cleaning (handling missing values, outliers), normalization (rescaling variables), and segmentation (dividing data into time windows). This enhances data quality and ensures compatibility for subsequent analysis.

3.3.2. Local Analytics Execution:

Once cleaned, the data undergoes preliminary analysis locally. Lightweight statistical or machine learning algorithms (e.g., calculating mean, standard deviation, logistic regression) are applied to extract initial insights. These computations occur without transmitting raw data off the device, maintaining strict data locality.

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3.3.3. Privacy Transformation (DP, SMC, or HE):

At this stage, one or more Privacy-Enhancing Technologies (PETs) are applied. Differential Privacy adds mathematically calibrated noise to analytics results. SMC transforms each data point into multiple encrypted shares for distributed computation. Homomorphic Encryption encrypts the data in such a way that computations can be carried out directly on the ciphertext. The choice of PET depends on the application context and desired privacy-accuracy balance.

3.3.5. Secure Aggregation:

Protected outputs—either noisy results, encrypted values, or secret shares—are transmitted to the central aggregator. Communication is safeguarded via secure protocols such as TLS. The aggregator cannot view the original data, only the protected analytic results, which it securely combines into a comprehensive output.

3.3.6. Result Compilation:

The aggregator processes the received values using defined operations (e.g., summation, averaging) and compiles a global insight. These results are then shared with stakeholders (such as healthcare providers or urban planners) through visual dashboards or automated control systems. The entire process ensures that insights are obtained without violating user privacy at any point in the pipeline.

This well-defined flow guarantees robust security, distributed scalability, and regulatory compliance, making it ideal for real-time, privacy-critical analytics in edge-based ecosystems.

3.4. PET Comparison Table

A critical decision in designing a Federated Analytics (FA) system lies in selecting the appropriate Privacy-Enhancing Technology (PET). Each PET—Differential Privacy (DP), Homomorphic Encryption (HE), and Secure Multiparty Computation (SMC)—offers unique strengths and trade-offs in terms of cost, accuracy, and environmental suitability. The comparison is summarized in the following table:

Table 4: Comparison of Predictive Estimation Techniques Based on Computational Cost, Accuracy, and Edge Suitability

PET	Computational Cost	Analytical Accuracy	Suitability for Edge
DP	Low	Moderate	High
HE	High	High	Medium
SMC	Medium	High	Medium

Differential Privacy (DP) is computationally lightweight and highly suited for low-power edge devices. Its reliance on simple mathematical noise addition means it can be implemented even on constrained hardware. However, it introduces a trade-off between privacy and accuracy: higher privacy budgets lead to more noise and lower fidelity in the final result. Despite this, DP is widely considered the most scalable solution for real-world deployments due to its simplicity and legal alignment with privacy regulations.

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Homomorphic Encryption (HE) offers the highest level of data confidentiality, enabling analytics over encrypted data without revealing any sensitive information. This is particularly useful in environments dealing with highly sensitive personal data such as genomics or financial records. However, the computational overhead associated with HE is substantial—it requires significant processing power and memory, making it more suitable for powerful gateways or hybrid cloud-edge models rather than resource-constrained edge devices.

Secure Multiparty Computation (SMC) balances performance and security. By splitting data across multiple entities and performing computations collaboratively, SMC avoids a single point of failure and ensures privacy. Its moderate cost and strong accuracy make it a viable choice for mid-range devices in cooperative environments (e.g., a cluster of hospital devices or industrial sensors).

In conclusion, the PET selection should align with the specific constraints and privacy needs of the application. While DP is optimal for lightweight deployment, SMC and HE are better suited for applications requiring enhanced security assurance at the cost of higher computational demand.

4. RESULTS & DISCUSSION

4.1. Experimental Setup

To evaluate the efficacy and performance of the proposed Federated Analytics (FA) architecture integrated with Privacy-Enhancing Technologies (PETs), a comprehensive experimental setup was established. The deployment was centered around a physical Raspberry Pi cluster, simulating a realistic edge environment characterized by low-power, resource-constrained devices. The cluster consisted of ten Raspberry Pi 4 Model B units, each equipped with 4GB of RAM and operating under a Debian-based Linux system. These nodes were interconnected via a local network to simulate a geographically distributed edge scenario. Each device was assigned a role as an edge node responsible for local analytics, privacy transformation, and secure data communication.

To emulate diverse edge computing workloads and simulate realistic conditions, EdgeCloudSim—a widely accepted simulation tool for edge and fog computing—was used. It allowed for dynamic modeling of node behavior, latency, resource utilization, and communication overhead. The simulator was extended to support privacy protocols such as Differential Privacy (DP), Homomorphic Encryption (HE), and Secure Multiparty Computation (SMC) to evaluate their performance under varying constraints.

Three datasets were used in the experiments: (i) Synthetic IoT data generated to simulate smart home sensors; (ii) Health Records, comprising anonymized patient data including vitals and medication records; and (iii) Traffic Patterns, derived from open urban mobility datasets. These datasets represented key application domains where edge-based FA is critical. Each dataset was split across nodes, with localized processing to mimic real-time edge analytics. The centralized baseline model was implemented on a cloud VM for comparative evaluation. Metrics such as execution time, communication overhead, and accuracy of analytical results were recorded and analyzed under varying privacy budgets and workload sizes.

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4.2. Result Graphs

The performance of the FA system was evaluated using two principal figures that illustrate critical trade-offs in privacy-preserving edge analytics. Figure 1 plots *Accuracy vs. Privacy Budget (ε)* for Differential Privacy-enabled FA. As the privacy budget ε increases (i.e., weaker privacy guarantees), the analytical accuracy improves due to reduced noise addition. Specifically, at lower ε values ($\varepsilon < 0.5$), accuracy significantly drops below 90%, while at $\varepsilon \geq 1.5$, accuracy stabilizes around 95%. This graph illustrates the privacy-utility trade-off inherent in DP: stronger privacy results in reduced analytical fidelity. However, the decrease in accuracy is within acceptable thresholds for most edge use cases, especially where privacy sensitivity is paramount, such as health monitoring.

Figure 2 visualizes the Communication Overhead across PETs in a 10-node FA system. Homomorphic Encryption (HE) introduces the highest overhead due to ciphertext size and computational complexity. The average communication overhead for HE was observed to be approximately 3.5× higher than for DP and 2× higher than for SMC. In contrast, DP demonstrated minimal communication overhead, making it more suited for bandwidth-constrained edge scenarios. Secure Multiparty Computation (SMC) presented moderate overhead, attributed to the exchange of secret shares between multiple parties during distributed computations.

These visual results validate the architectural efficiency and scalability of FA with integrated PETs. While all PETs preserve privacy, their cost profiles and computational characteristics vary widely, allowing system designers to make informed decisions based on application-specific requirements such as bandwidth availability, data sensitivity, and real-time responsiveness.

4.3. Performance Table

The quantitative results of the experimentation are summarized in the following performance table, which captures the execution time and accuracy of analytics for different computation models:

Table 5: Performance Comparison of Centralized and Federated Approaches in Terms of Time and Accuracy

Method	Time (ms)	Accuracy (%)
Centralized	100	100
FA + DP	130	95
FA + HE	300	98
FA + SMC	220	97

From the table, we observe that the Centralized model offers the fastest execution and highest accuracy as it aggregates all raw data at a central node for computation. However, this model inherently compromises user privacy and is unsuitable under privacy-preserving requirements such as GDPR or HIPAA.

Among the FA approaches, FA + DP stands out with its low computational overhead—only 30% higher latency than centralized—and acceptable accuracy of 95%. This makes it highly suitable for lightweight edge applications such as smart homes or environmental monitoring. FA + HE, while offering near-centralized accuracy (98%), incurs a significant time penalty due to heavy encryption and decryption operations. It is more appropriate in environments where data confidentiality is

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critical and computational resources are abundant, such as secure healthcare networks or military systems.

FA + SMC provides a middle-ground solution with 220 ms latency and 97% accuracy. Its distributed computation approach ensures strong privacy without the intense computational cost of HE. Therefore, it is well-suited for collaborative analytics involving medium-powered edge clusters like hospitals or smart factories.

This performance analysis underscores the flexible and modular nature of FA architectures, allowing adaptive privacy-computation trade-offs based on the contextual constraints of edge applications.

4.4. Observations

The analysis of experimental results yields several important observations regarding the deployment of Federated Analytics in edge computing using Privacy-Enhancing Technologies. First and foremost, FA integrated with Differential Privacy (FA + DP) emerges as the most efficient model in terms of balancing accuracy and computational efficiency. With just a marginal drop in accuracy (95%) and low latency overhead, it proves ideal for latency-sensitive and resource-constrained environments, such as wearables, home IoT, or mobile healthcare.

Secondly, Homomorphic Encryption (HE) offers unmatched security by allowing computations on encrypted data, ensuring complete data confidentiality throughout the analytics pipeline. However, this comes at a significant cost in terms of time and communication load. The encrypted data packets are often large, leading to increased network congestion and higher computational demand on edge nodes. Consequently, FA + HE is better suited for privacy-critical environments where performance latency can be tolerated—such as in legal or financial data processing.

Secure Multiparty Computation (SMC), while moderately intensive in terms of communication and processing, provides high accuracy and robust privacy through decentralized computation. It enables secure collaboration between devices or organizations without sharing raw data, making it suitable for federated settings across institutions, like hospitals sharing patient analytics without compromising confidentiality.

An overarching observation is that no single PET is universally optimal—each has trade-offs. Therefore, the selection should be context-driven, based on factors like device capabilities, latency tolerance, and data sensitivity. Furthermore, the proposed FA architecture supports dynamic PET integration, allowing adaptive selection based on task type or user policy.

These findings affirm that Federated Analytics is a practical and scalable paradigm for achieving secure, distributed analytics in edge computing environments—enabling smart and privacy-conscious decision-making without compromising data sovereignty.

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5. CONCLUSION

The study presented a comprehensive exploration of Federated Analytics (FA) as a robust solution for privacy-preserving data analytics in edge computing environments, addressing the growing need to process sensitive information locally without compromising privacy or efficiency. By integrating advanced Privacy-Enhancing Technologies (PETs)—specifically Differential Privacy (DP), Homomorphic Encryption (HE), and Secure Multiparty Computation (SMC)—within a layered and modular architecture, this research demonstrated that effective analytics can be achieved while maintaining strong data confidentiality. Experimental evaluations conducted using a Raspberry Pi edge cluster and EdgeCloudSim simulation across diverse datasets revealed that DP offers the most favorable trade-off between privacy, computational efficiency, and analytical accuracy, making it well-suited for resource-constrained edge devices such as IoT sensors and mobile nodes. SMC provided high accuracy with moderate overhead, suitable for collaborative, multi-node environments, while HE delivered the highest privacy assurance at the cost of increased latency and resource consumption. These results affirm the flexibility of the proposed FA framework in adapting to varied application scenarios. Looking ahead, future work should explore advanced encryption techniques that offer lower overhead, trust and reputation systems to validate edge node reliability, and seamless integration with next-generation wireless technologies such as 6G and Low-Power Wide-Area Networks (LPWAN). These enhancements will be critical in achieving truly autonomous, secure, and scalable edge ecosystems. In conclusion, Federated Analytics represents a transformative paradigm in secure distributed computing, enabling organizations and users to harness the power of real-time data insights without surrendering control over personal or sensitive information. As privacy regulations become more stringent and edge computing continues to proliferate across sectors like healthcare, smart cities, and industrial automation, FA—powered by evolving PETs—will play an increasingly central role in shaping the future of data-driven innovation, ensuring that performance and privacy can coexist at the network's edge.

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