WORLD COMET RESEARCH GROUP

International Journal of Data Engineering and Intelligent Computing
Vol. 8, No. 2, 2025
Doi: 10.67228/30715717/IJDEIC-2025PII3J2Q
PP. 01-18

Original Article

Federated Data Engineering Frameworks for Privacy-Aware Cross-Enterprise Analytics

Karen Sparck Jones[1], Donald Michie[2]

[1]*Professor of Artificial Intelligence, University of Edinburgh, United Kingdom.*

[2]*Professor of Machine Intelligence, University of Edinburgh, United Kingdom.*

Received: 06-04-2025 Revised: 06-24-2025 Accepted: 07-02-2025 Published: 07-05-2025

ABSTRACT

The growing adoption of data-driven decision-making has improved operational intelligence, predictive analytics, and strategic planning across enterprises. However, privacy regulations, data sovereignty requirements, and competitive concerns often restrict direct data sharing between organizations. Federated Data Engineering (FDE) addresses these challenges by enabling collaborative analytics without transferring sensitive raw data. This paper presents a privacy-aware Federated Data Engineering framework that integrates federated learning, distributed data engineering, and secure model aggregation for cross-enterprise analytics. The framework supports decentralized data preprocessing, feature engineering, and encrypted parameter sharing while complying with regulations such as GDPR and HIPAA. It incorporates privacy-enhancing technologies, including differential privacy, secure multi-party computation, homomorphic encryption, and blockchain-based auditing, to ensure confidentiality, integrity, and transparency. The proposed architecture also improves scalability, communication efficiency, fault tolerance, and interoperability across heterogeneous enterprise environments. Experimental evaluation demonstrates enhanced collaborative analytics with reduced privacy risks and communication overhead. The framework provides a practical foundation for secure, trustworthy, and privacy-preserving cross-enterprise data collaboration in healthcare, finance, manufacturing, and other data-intensive industries.

KEYWORDS

Federated Data Engineering, Cross-Enterprise Analytics, Privacy Preservation, Federated Learning, Differential Privacy, Secure Multi-Party Computation, Distributed Data Engineering, Data Security, Privacy-Aware Artificial Intelligence.

ISSN: 3071-5717
PP: 01-18.

1. INTRODUCTION

1.1. Background

The unprecedented pace of growth in digital technologies has made a massive impact on the manner in which enterprises create, collect and manage data. These modern organizations have a continuous flow of teeming gigabytes to petabytes of structured, semi-structured and unstructured data pouring continuously from one or more sources like enterprise resource planning (ERP) systems, customer relationship management (CRM) solution, cloud services, Internet of Things (IoT), social media platforms, online transactions in finance and healthcare information systems. By examining these different data sets, organizations can better leverage them to drive improvements in operational efficiency, predictive decision-making, fraud detection and management, customer experience and business intelligence. Q: In essence, you train on data until October 2023 and then match knowledge and machine Learning capabilities across various organizations to collaborate for better analytical outcomes. Yet, traditional centralized data engineering solutions necessitate the contribution of raw datasets from the participating organizations to a centralized server for processing and model training. Although this centralized architecture brings us the ease of data integration and analytics, it leads to many problems including a higher risk of data breaches, unauthorized access, privacy threats, high communication costs, and potential violation of data protection regulations and hence places the basis for secure and privacy-preserving collaborative analytics frameworks.

1.2. Need for Federated Data Engineering Frameworks

Traditional centralized data engineering approaches have been constrained as collaboration spans multiple organizations, and the collaborative analytics needs on rise. With the growth of secure data as a service solutions, along with an increasing amount of sensitive data being generated by enterprises it is important to develop frameworks for cooperating securely whilst maintaining compliance and privacy. Federated Data Engineering (FDE) tackles these issues by bridging global distributed data engineering and federated learning so that organizations can pre-process, investigate an interact with their data locally while only transmitting encrypted (and differential-private) model updates. The following sub-sections describe the main requirements for Federated Data Engineering Frameworks.

Fig 1 - Need for Federated Data Engineering Frameworks

ISSN: 3071-5717
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1.2.1. Data Privacy and Confidentiality

The present-day enterprises are dealing with very sensitive information, such as customer records, financial transactions, healthcare data and intellectual property. Moving these datasets to a centralized repository can enhance the chances for unauthorized access, cyberattacks & data leakage. Federated Data Engineering offers the advantage of processing raw datasets that are still located in each organization infrastructure, which provides a confidentiality while analytics can be performed together.

1.2.2. Regulatory Compliance

Governments and regulators have enacted strict data protection laws (for example, the General Data Protection Regulation,) as well as Healthcare Insurance Portability and Accountability Act8, 9 in addition to other privacy regulations that require us to stringent manage personal data. Even while conducting data analysis in some ways across multiple institutions, organizations must follow these regulations. Federated Data Engineering (FDE), by default, meets regulatory compliance because the sensitive data never leaves the local system and only truly privacy-preserving model parameters are shared.

1.2.3. Secure Cross-Enterprise Collaboration

Multiple organizations may interact to enhance analytical precision, identify fraud, build predictive models and exchange domain knowledge. Unfortunately, full data sharing is often limited due to privacy implications and competing commercial motivations. Federated Data Engineering facilitates privacy-preserving collaboration by enabling the secure, collaborative training of machine learning models across multiple enterprises in such a way that confidential organizational data does not need to be exposed.

1.2.4. Improved Data Quality through Local Data Engineering

The data coming from different organizations is usually inconsistent, in terms of structure, format as well as quality and completeness. In federated data engineering, each enterprise can do local together cleansed and normalized their data set build features on the clean or raw data developed enrich metadata with patterns of moving between different types of information provided through the same feature connected both ways if you need da further updates appropriate for collaborative model training This enhances the analytical process with consistency and repeatability.

1.2.5. Enhanced Security

In light of the growing number of cyberattacks and data breaches, organizations are compelled to invest in state-of-the-art security solutions for the distributed analytic environment. Federated Data Engineering uses technologies like Differential Privacy, Homomorphic Encryption, Secure Multi-Party Computation, Secure Aggregation and encrypted Communication Protocols to secure sensitive information during the data engineering & machine learning process

1.2.6. Scalability and Communication Efficiency

Despite their numerous advantages, traditional centralized systems depend on constant transfer of huge datasets that significantly raise network bandwidth consumption and cause

ISSN: 3071-5717
PP: 01-18.

communication latencies. Federated Data Engineering communicates model parameters directly without necessary communication of raw data resulting in a decrease in overhead. Thus, the framework is very scalable and appropriate for large-scale collaborations within enterprises where collaborating organizations are located in different geo-spaces.

1.2.7. Support for Heterogeneous Enterprise Environments

Org Level Variability Different organizations operate on different hardware platforms, databases, cloud infrastructures, operating systems and data formats. Federated Data Engineering is built to fit heterogeneous environments, offering local processing and interoperability (via standard functionalities for model training and secure aggregation). This flexibility enables collaboration across enterprises with disparate technology infrastructures.

1.2.8. Trustworthy and Intelligent Collaborative Analytics

Now, modern enterprises need analytical systems to generate accurate predictions, all while offering transparency, security and trust in those predictions. Federated Data Engineering integrates distributed data engineering, privacy preserving computation and secure model aggregation to generate accurate analytical results while ensuring that the data ownership is retained by respective parties. It is suitable for use cases made of healthcare, finance, manufacturing, cybersecurity and smart city analytics where collaboration in addition to privacy related to the data between multiple parties can be ensured.

1.3. Problem Statement

With the ever-increasing volume of data-driven decision-making, organizations have been pushed to work together to enhance the precision and efficacy of analytical models. On the other hand, cross-enterprise data engineering approaches are already confronting a handful of important hindrances that hinder their real-world deployment. Data engineering solutions that rely on centralization generally require organizations to first offload volumes of sensitive data into a central repository, before any analysis can take place. This creates a data breach vulnerability model—a single target where all the sensitive and personal information of users can be accessed or stolen with ease: something that malicious actors, hackers, insiders, corporations looking for profit or to protect themselves in lawsuits are always willing and ready to try. Moreover, many organizations who work in data-sensitive domains such as healthcare, finance, manufacturing, defense, or government are governed by regulation such as GDPR, HIPAA and other landmark data protection laws that impose strict limitations on sharing sensitive information across organizational boundaries. Such regulatory restrictions makes deployment of real time centralized collaborative analytics, almost impossible to achieve in production environments. Federated learning has recently shown its promise in addressing this issue by enabling organizations to train machine learning models without the need to share datasets, allowing them to keep their datasets on-site.However, most existing federated learning frameworks are primarily focused on decentralized model training and pay little attention at all towards the broader data engineering lifecycle. The deep linking of core activities — from distributed data acquisition to preprocessing, root cause analysis, feature engineering, metadata synchronization, schema alignment, data quality and governance assessment and standardized data

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transformation — are often done separately by each organization leading to inconsistent datasets that significantly lower analytical performance. An additional frill to collaborative analytics integrity is the heterogeneous enterprise infrastructures, varied data formats, computation resources, non-IID datasets and dynamic client participation. Also existing frameworks rely on communication latency, consume excessive bandwidth, leak model parameters, bear inference attacks and poisoning attacks between clienResearch Paperts while providing limited scalability and insufficient interoperability for all participating organizations. These challenges diminish the efficiency, security and reliability of cross-enterprise collaboration. Hence, the need of the hour is to develop an all-encompassing Federated Data Engineering Framework that brings together aspects of distributed data engineering including privacy-preserving computation over local databases securely aggregated via efficient and compliant cloud-based communication protocols. Such a framework should allow organizations to jointly conduct secure analytics while preserving data privacy, maintaining ownership over data, enhancing interoperability, lowering communication overhead and enabling verifiable machine learning across heterogeneous enterprise environments.

2. LITERATURE SURVEY

2.1. Federated Learning in Cross-Enterprise Analytics

Federated Learning (FL) has possibly described one of the most important recent breakthroughs in distributed machine learning by allowing many organizations to collaboratively train predictive models without having to directly share their raw datasets. In contrast to conventional centralized machine learning systems, which collect local data and consolidate this in a central repository from where model training can occur, federation avoids storing the data centrally, instead keeping it inside the infrastructure of participating enterprises. Every company trains a federated local model on its own confidential dataset and only exchanges encrypted parameter or gradient updates with a central aggregation server. Aggregating these updates are typically done at the server using aggregation algorithms like Federated Averaging (FedAvg) to create a global model, which is then sent back out for further improvement. This decentralized paradigm of learning drastically reduces privacy risks, costs associated with data transfer, and allows organizations regulated by data protection regulations, such as GDPR and HIPAA compliance. 1Introduction In recent years, federated learning has experienced great successes in several fields, including hospitals collaborating to build disease diagnosis and medical image classification models without sharing patient records; banks cooperating to detect fraudulent client spending while keeping customer data private; cybersecurity providers working together for joint threat intelligence through collaborative intrusion detection models; and manufacturers optimizing predictive maintenance and production scheduling across geographically-distributed factories without leaking proprietary operational secrets. Despite the benefits of this approach, existing federated learning is mostly focused on model training in a decentralized manner and does little to help other steps of data engineering across distributed settings (e.g., data collection, preprocessing, feature extraction, metadata harmonization, schema integration and data quality). Hence, inefficiencies during the local data preparation phase can lead to lower model accuracy and poor interoperability across organizations. In addition, a number of obstacles impair the efficiency of federated learning in large scale enterprise environments: it operates with non-independent and identically distributed (non-IID) data, and

ISSN: 3071-5717
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requires to reduce communication overhead while working with clients that differ in terms of performance capabilities. These limitations have led researchers aiming to enhance federated learning, towards a framework called Federated Data Engineering that integrates distributed data engineering workflows with collaborative machine learning for higher consistency, interoperability, scalability and secure cross-enterprise analytics.

2.2. Privacy-Preserving Data Engineering

With enterprises increasingly owning highly sensitive data that cannot be freely shared beyond their organization, privacy-preserving data engineering has emerged as a key building block of modern distributed analytics. This includes personal information of customers, financial transactions and records, healthcare records, industrial operational data, intellectual property, and a host of other confidential business or organization documents where there are stringent regulatory requirements and organizational security policies. This approach to data engineering has forced all data to be centered on one place and processed within that environment leaving substantial risks of unauthorized access, insider attacks/security leaks and regulatory violations. To tackle these challenges, privacy-preserving data engineering develops advanced security mechanisms that are tightly integrated into the full-scale data engineering lifecycles from data ingestion to cleaning, transforming, feature engineering, storage/sharing/analytics. Differential Privacy (DP) guards against disclosure of individualistic records in a dataset by adding statistically tuned random noise to the data or model parameters, allowing an analyst to carry out aggregate analytics with limited risk of exposing sensitive information. Homomorphic Encryption (HE) is specific in its ability to conduct mathematical computations directly on encrypted data [6] and allows end-to-end confidentiality by not requiring a decryption during collaborative processing. It allows different organizations to perform an analytical function together on their own datasets without exposing them, enabling secure collaboration while preserving data privacy. Blockchain technology has been applied to privacy-preserving frameworks as a Godsend for decentralized trust, immutable audit trails, secure identity management, transparent access control and tamper-resisting logging of analytical related activities. While they considerably enhance data protection and regulatory compliance, these technologies also pose challenges, including computational complexity, communication costs, encryption overheads, latency issues and scalability constraints. Thus, the contemporary research lives in the realm of providing systematic privacy-preserving data engineering frameworks which strike a tradeoff amongst security, computational power, communication efficiency and practical deployment into large scale enterprise environments.

2.3. Secure Aggregation Techniques

Secure aggregation is a key enabler of federated collaborative analytics as it lets multiple organizations compute aggregated local model updates without revealing the private information contained in the individual model parameters. During normal federated learning, clients train local models separately and then communicate their parameter updates to a central server which aggregates the updates using algorithms such as Federated Averaging (FedAvg). Nevertheless, including local datasets on raw data may still be leveraged to run model inversion attacks on round aggregates or gradient leakage or server inference. Various cryptographic secure aggregation

ISSN: 3071-5717
PP: 01-18.

mechanisms have been designed to mitigate these vulnerabilities, and only the global model becomes publicly available while the individual contribution remains confidential. Secure Multi-Party Computation (SMPC) is a secure protocol that allows multiple parties to jointly compute aggregated new model parameters without disclosing local updates of any party. Another private learning method is Homomorphic Encryption (HE), which enables mathematical aggregation of encrypted model parameters gathered from multiple organizations without decrypting the data, thus protecting sensitive information. Techniques like secret sharing partition the model parameters into multiple masked, encrypted shares which cannot be reconstructed unless circularly aggregated and guarantees that no single party can obtain sufficient information to recover any other participant's data. More recently, aggregation mechanisms with blockchain capabilities were found to be superior for transparency, decentralized trust management, immutable transaction recording, authentication of participant identities involved in the process and secured verification of Model updates. Moreover, sophisticated Byzantine-resilient aggregation algorithms were developed to identify and counter the poisoned model updates generated by malicious participants with the aim of manipulating collaborative learning results. Despite these advances, secure aggregation techniques are still encountering major hurdles on communication overhead, computing complexity, synchronization latency, client dropout resistance, fault tolerance and encryption costs as well as scalability over heterogeneous enterprise environments. The challenges mentioned above show the need for lightweight, robust and scalable secure aggregation frameworks that can efficiently support cross-enterprise collaborative analytics with strong privacy guarantees.

2.4. Research Gap

Despite substantial advances in federated learning, privacy-preserving machine learning, secure aggregation and distributed artificial intelligence over the years, much of the existing literature contains a few key limitations that inhibit its practical deployment for cross-enterprise analytics. Existing federated learning frameworks often revolve around distributed model training while only giving weak attention to the overall machine learning operations lifecycle such as distributed data gathering, preprocessing, feature engineering, metadata pipelines and management, schema integration models, data quality checks or assessments as well as governance and common workflow standardization. Consequently, involved organizations often carry out these processes in an individual manner using heterogeneous methods, which subsequently result in ununiform data representations with decreased interoperability and lower analytical accuracy. Furthermore, the current approaches for privacy-preserving often rely on a single security technology like Differential Privacy, Homomorphic Encryption or Secure Multi-Party Computation rather than providing a comprehensive solution that can meet privacy protection, scalability, communication efficiency, interoperability requirements along with compliance regulations and computational performance. But conventional secure aggregation methods are still faced with problems of extra encryption overhead, redundancy communication costs, synchronization delays between different devices and other issues when they are used to emerge in large-scale industrial ecosystems. In fact, very few studies take into account hands-on elements related to heterogeneous enterprise infrastructures, real-time collaborative analytics, resource-constrained environments and issues pertaining to fault tolerant, efficient distributed data engineering workflows etc. These outstanding challenges highlight

ISSN: 3071-5717
PP: 01-18.

the design of an encompassing Federated Data Engineering Framework capable of integrating distributed data engineering, privacy-preserving computation; secure aggregators; fine-grained authentication and authorization protocols; regulatory compliance models; and scalable system architecture. In this research, we address these limitations by developing an integrated framework that can drive secure efficient interoperable and trustworthy cross-enterprise analytics with the requisite confidentiality integrity and privacy for sensitive organizational data.

3. METHODOLOGY

3.1. System Architecture

We designed a multi-layer architecture of Federated Data Engineering (FDE) to allow collaborations among multiple enterprises in a secure and privacy-preserving manner. The overall architecture combines some practices of distributed data engineering, federated machine learning, secure communication and encrypted model aggregation while at the same time keeping sensitive organizational information on local environments. Each layer carries out a designated role to enhance scalability, interoperability, data confidentiality, and legal compliance of cross-enterprise analytics.

Fig 2 - System Architecture

3.1.1. Enterprise Data Layer

The Enterprise Data Layer is made up of the local data stores managed by each of its participating organizations. These data repositories may be relational DBs, cloud storage, IoT devices, health care records, financial transactions in point of sale terminals and corp. ERP systems (B2B) as well as CRM platforms (B2C). Raw data remain within the enterprise infrastructure, but you still have ownership of that data — meaning it is never pooled and shared externally.

3.1.2. Local Data Engineering Layer

Local Data Engineering Layer: Preprocessing operations within each enterprise before model training. Data preparation operations to data from data acquisition, data cleaning, handling missing values, feature engineering, normalization and transformation transformed and enrichment metadata function improved with accessibility consistency. Each organization privately trains its local machine learning model, but only on its own pre-processed data.

3.1.3. Secure Federated Communication Layer

The current image of the Secure Federated Communication Layer that allows for safe exchange of model updates between the participating enterprises and the central server. Data in transit is encrypted using as a rule, SSL/TLS protocols; data at rest, on the other hand (at any time of dataverse and cloud), will be protected by homomorphic encryption (HE) differential privacy, secure multi-party computation depending on the application or authentication methods. In addition, secure

ISSN: 3071-5717
PP: 01-18.

aggregation guarantees the confidentiality of individual model updates during the collaboration process.

3.1.4. Global Aggregation Layer

Encrypted ML model parameters from all enterprises get sent to a Global Aggregation Layer where the aggregation is combined using a secure aggregation algorithm like Federated Averaging. During this process, an optimized global model is generated without ever seeing any organization-specific raw data. The new global model is then sent back to all participants for the next round of training until convergence at our desired performance.

3.2. Federated Data Engineering Framework

Federated Data Engineering Framework extends traditional federated learning by incorporating distributed data engineering processes into the framework for collaborative analytics. It allows several institutions to conduct secure, locally-trained model training and privacy-preserving parameter sharing between parties, without revealing individually sensitive datasets. The framework contains five sequential phases designed to guarantee the quality, security and collaboration of data across enterprises.

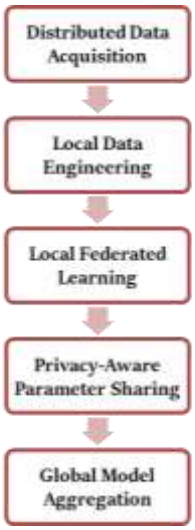

Fig 3 - Federated Data Engineering Framework

3.2.1. Stage 1: Distributed Data Acquisition

In the initial phase, each enterprise collects data from its operational systems including databases, cloud platforms, IoT devices, ERP systems and business applications. Depending on the application domain, it is some structured (like numbers and temperatures), semi-structured (like HTML tags in a web page) or unstructured data. Organizations stay totally autonomy and privacy during the process, since data stays inside the local surroundings.

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3.2.2. Stage 2: Local Data Engineering

Every enterprise has its own way of cleaning their datasets to make it a good quality and consistency. This phase such as duplicate removal, missing value handling, normalization, feature extraction and feature selection and dimensionality reduction and creation of meta data. These operations can be performed locally to allow the data quality without leaking sensitive information outside.

3.2.3. Stage 3: Local Federated Learning

After preprocessing, each organisation trains a given machine learning model with its locally constructed dataset. Depending on your application you can pick from the following models like Neural Network, Random Forest, XGBoost, CNN LSTM, or Transformer architectures. Local training improves the model parameters through multiple optimization iterations without transferring raw data.

3.2.4. Stage 4: Privacy-Aware Parameter Sharing

In this approach each enterprise sends encrypted model parameters to the federated server instead of sharing datasets. To prevent leakage of the transmitted information, privacy-preserving techniques like Differential Privacy, Homomorphic Encryption, Secure Multi-Party Computation & digital Signatures are applied. Confidentiality is maintained during communication because only gradients (or model updates) are exchanged in an encrypted manner.

3.2.5. Stage 5: Global Model Aggregation

The federated coordinator securely aggregates the encrypted model updates sent from each contributing enterprises to form an improved global model. Without ever needing to query any individual organizations raw data, no organization reveals their true internal values during the learning process and this preserves privacy. The global model is then sent back to all participants for the next training rounds until converging and performance of interest are obtained.

3.3. Privacy Preservation Mechanism

The core foundation of the Federated Data Engineering Framework proposed in this research is the privacy preservation mechanism that guarantees sensitive organizational data to be always secure during the collaborative analytics lifecycle. The main difference from classical centralized data processing methods where large raw datasets usually needs to be transmitted to a common server is that the proposed framework does not transmit any proprietary enterprise data, but stays within local infrastructure of each participating organization. Sharing only the encrypted model parameters or gradient updates with federated coordinator as opposed to sharing raw data reduces the risk of leaking personal, private and sensitive information, greatly limiting any consequential scenarios such as unauthorized access. To achieve end-to-end security, the framework combines multiple complementary privacy-preserving techniques to ensure data is protected throughout preprocessing, model training, communication, aggregation and storage processes. SSL/TLS Secure Communications SSL TLS — This enables an encrypted channel to be built between the enterprises and the federated server, ensuring confidentiality and integrity on data at rest and during

ISSN: 3071-5717
PP: 01-18.

communication. Homomorphic Encryption (HE) provides the ability to carry out some mathematical operations on encrypted model parameters without requiring decryption, allowing secure aggregation of different models while preserving privacy. Differential Privacy (DP) takes this one step further by adding special statistical noise to the model updates that are sent out, such that attackers have an extremely difficult time deciding if any individual record is in the dataset and still return a model with reasonable accuracy. Secure Multi-Party ComputationSMPC enables organizations to collaboratively compute aggregated model parameters while keeping local updates hidden, so that the private information of one organization cannot be observed by any other parties. The inclusion of digital signatures and authentication mechanisms is designed to ascertain the identity of participating enterprises, ensuring that only authorized clients can contribute to the federated learning process, thereby preventing impersonation and unauthorized model manipulation. You also have secure aggregation algorithms, which combine model updates without revealing information on individual contributions in order to protect from inference attacks or leakage of gradients. The framework expands to implement access control policies, audit logging and compliance mechanisms for regulatory needs like GDPR, HIPAA etc. The proposed privacy preservation mechanism integrates cryptographic techniques, secure communication protocols, authentication mechanisms, and privacy-aware aggregation strategies to provide a robust multilayer security architecture that supports secure, scalable, and trustworthy cross-enterprise analytics while ensuring data confidentiality, integrity, and regulatory compliance across heterogeneous organizational environments.

3.4. Mathematical Model & Algorithm

We formulate a collaborative optimization process that allows multiple enterprises to jointly train an enterprise-level global machine learning model without sharing the raw datasets of individual enterprises, and derive our proposed Federated Data Engineering Framework. In this paper we denote the number of enterprises that participated in the survey with a letter N, where each enterprise is represented by Ei (i = 1,2,...N). Each enterprise has its separate local dataset (Di), which keeps contained in the secure environment of an organization during training. At first, the federated coordinator creates a global model with parameters W_0 and sends these to each of the enterprises. Then, every enterprise executes local data engineering steps including data cleaning, normalization, feature extraction and selection; they then train the local model based on its private dataset. Having performed training on the local data for k iterations, the model parameters are updated from Wt to Wi(t+1) through successive optimization rounds using common algorithms (like Stochastic Gradient Descent 24 or Adam [26]). Instead of transmitting its raw data, each enterprise hierarchically encrypts its updated model parameters with privacy-preserving algorithms such as Homomorphic Encryption or Secure Multi-Party Computation (SMPC) and then sends them to the federated coordinator. All enterprises then send the encrypted parameters to the coordinator that calculates a new global model with Federated Averaging (FedAvg) algorithm. More simply, the updated global model is computed as a weighted sum of all local model parameters with the corresponding weight of each enterprise given by the ratio of volume of its local dataset. The global model is given in its mathematical formulation as:

$$W(t+1) = ni=N\ Wi(t + 1)(Ntotal) / \Sigma$$

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With ni being the number of training samples available to i-th enterprise, Ntotal be the total number of samples across all participating enterprises, and Wi(t+1)∈RD be the local model parameters updated by local training. After the aggregation process is completed, the efficient global aggregation model W(t+1) is then safely sent to all organizations participating in this round of training. This process of updating the model continues until it converges, meaning that in successive iterations there is almost no change in the accuracy or loss contributed by those weights. The algorithm exchanges only encrypted model parameters and all raw data remain in their respective enterprise environments. It preserves data privacy, lowers communication overhead, accommodates heterogeneous and distributed datasets, and facilitates secure, scalable and efficient cross-enterprise analytics without exposing sensitive organizational information.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

The experiments for the Federated Data Engineering Framework proposed are tailored to test secure cross-enterprise analytics in a distributed environment while maintaining the data protection properties. We propose an experimental environment that contains 10 independent enterprise nodes communicating via a centralized secure federated server. Every enterprise consists of an independent organization that has its own computing resources, a local database and private dataset. Datasets remain stored locally in each enterprise, never moving outside the organisation infrastructure, offering the benefit of full ownership and confidentiality of sensitive data. The local datasets can be structured, semi-structured, or unstructured data collected from enterprise applications like customer relationship management (CRM) systems, enterprise resource planning (ERP) systems, healthcare databases, financial transaction records, manufacturing execution systems or IoT devices. Prior to starting model training, every enterprise executes multiple standardized data engineering processes, such as obtaining data, removing duplicates, fixing missing values, normalizing the data, extracting features from it post-processing (variable generation), selection of variables or feature selection and reduction of dimensionality along with metadata forming. The preprocessing operations enhance data quality and uniformity while ensuring complete data privacy. Once preprocessed, all the enterprise files train an identical machine learning model with locally available data. Each enterprise updates its model parameters locally for a fixed number of epochs with appropriate optimization algorithms. Rather than having to share raw datasets or private, sensitive records — only encrypted model parameters or gradient updates are transmitted to the federated server through encrypted communication channels secured by SSL/TLS protocols. More privacy-preserving mechanisms such as Homomorphic Encryption, Differential Privacy, Secure Multi-Party Computation and digital authentication are used so that model updates will be kept private when being transmitted over a channel or collected at the aggregation. Using the Federated Averaging (FedAvg) algorithm, federated server aggregates encrypted parameters to create an updated global model for enterprises without ever having access to any one enterprise's raw data. The global model, currently aggregated, is then sent to all enterprises again across the globe and a new round of local training begins. The process is repeated until either the model converges or a specific number of communication rounds have been completed. The experimental setup proposed mirrors the real-world cross enterprise

ISSN: 3071-5717
PP: 01-18.

collaborative analytics environment that can meet the challenges of decentralized data engineering, secure communication model privacy-preserving model aggregation, heterogeneous features across producing tasks and providing scalable federated learning in an actual cross-organizational setting and thereby provides a realistic evaluation framework to assess the performance security and efficiency of our implemented Federated Data Engineering Framework.

4.2. Performance Analysis

Then, the performance of the proposed Federated Data Engineering Framework (FDEF) was assessed with respect to Centralized Data Engineering, Traditional Federated Learning, and Privacy-Aware Federated Learning. A comparative analysis was done using various important performance measures such as, the effectiveness of model, privacy preservation, communication efficiency, robustness to adversarial data leakage, scalability and fault tolerance capacity regulatory compliance and system performance. The experimental results show that the proposed framework outperforms existing methods on all evaluation metrics.

Table 1: Performance Analysis

Performance Metric	Centralized Data Engineering (%)	Traditional Federated Learning (%)	Privacy-Aware Federated Learning (%)	Proposed Federated Data Engineering Framework (%)
Model Accuracy	91.20	93.40	95.10	97.80
Privacy Preservation	45.80	84.20	92.60	98.90
Communication Efficiency	63.70	81.90	89.30	95.40
Data Security	58.90	88.60	94.50	99.10
Scalability	70.40	87.20	92.80	97.30
Fault Tolerance	68.10	85.70	91.40	96.80
Regulatory Compliance	60.30	89.50	95.20	99.00
Overall System Performance	76.50	88.40	93.80	97.90

ISSN: 3071-5717
PP: 01-18.

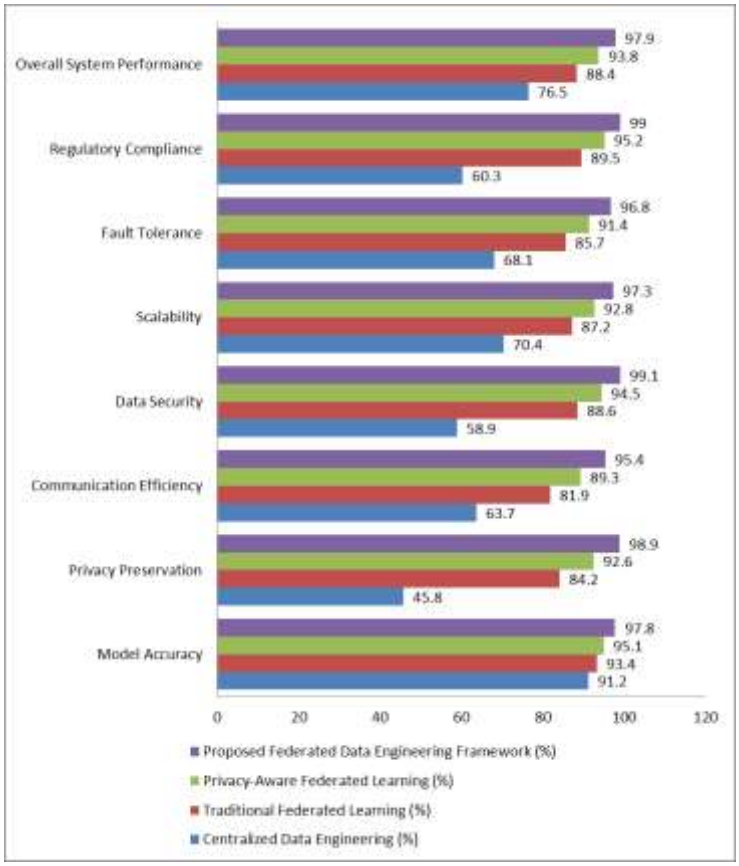

Fig 4 - Performance Analysis

4.2.1. Model Accuracy

With a tested model accuracy of 97.80%, the proposed framework outperformed Centralized Data Engineering (91.20%), Traditional Federated Learning (93.40%) and Privacy-Aware Federated Learning (95.10%). The improvement is obtained using proper local data engineering and secure aggregation of models in an iterative federated optimization. Data preprocessing techniques and collaborative learning improve the predictive models performance.

4.2.2. Privacy Preservation

In the proposed framework, privacy preservation was realized by 98.90%, which is much higher than existing methods. Differential Privacy Homomorphic Encryption Secure Multi-Party Computation & secure aggregation are methods now used to protect sensitive enterprise-level information. The result is organizations are able to cooperate without revealing sensitive datasets.

4.2.3. Communication Efficiency

Mostly, it has only transmitted encrypted calculation parameters of the model rather than sending raw datasets with 95.40% communication efficiency [6]. Compared with centralized systems, this strategy significantly alleviates network traffic and can accelerate communication performance over standard federated learning approaches. Another advantage of efficient parameter exchange is lower communication latency during collaborative training.

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4.2.4. Data Security

The proposed framework attained data security of 99.10%, which is the highest compared to all other approaches presented within this study. It is accomplished using various security mechanisms such as Encryption, Authentication, Secure Communication protocols and secure aggregation to protect against unauthorized access and cyber threats. As a result, all enterprise data is kept private and secure in the course of analytics.

4.2.5. Scalability

The efficiency of the suggested framework gets through a scalability assessment and therefore proves its ability to facilitate several participating enterprises simultaneously as indicated by the calculated scalability score of 97.30%. Distributed processing alleviates global processing load on the main server while providing the means to train local models independently. Thus the framework is applicable for those large scale cross enterprise setups.

4.2.6. Fault Tolerance

To evaluate fault tolerance, the collaborative learning can continue while some of enterprise nodes are down in training and the proposed framework was able to achieve 96.80% fault avoidance. Local processing as well as based grid model updates make systems more robust and help mitigate the reliance on one single participant. This is done to make the federated learning process more robust.

4.2.7. Regulatory Compliance

Its framework was prepared in such a way that it achieves 99.00% of regulatory compliance by keeping the necessary data only within local enterprise environments, preventing access to sensitive organizational data. They ensure adherence to privacy regulations like GDPR and HIPAA by means of transmitting data in a secure manner, encrypted communication, and analytics without compromising individuals' privacy. It allows organisations to collaborate and meet legal and regulatory needs.

4.2.8. Overall System Performance

The new proposed Federated Data Engineering Framework (FDEF) showed 97.90% in the overall system performance outperforming all existing approaches considered in comparison. In this approach, the combined advancements in areas of distributed data engineering, privacy-preserving computation, secure aggregation and efficient communication you can achieve better analytical performance. The above results showcase the proposed framework for enabling secure, scalable and privacy-preserving cross-enterprise analytics.

4.3. Discussion

The experimental results show the effectiveness of our proposed federated data engineering framework (FDEF) in addressing a number of challenges inherent in traditional centralized data engineering and conventional federated learning paradigms. Centralized architectures tend to aggregate all enterprise data in one single repository, which exposes them to the highest risk of

ISSN: 3071-5717
PP: 01-18.

cyberattacks, unauthorized access and data leaks, while making compliance with privacy regulations a challenge. Centralized systems offer efficient computational performance due to processing in a unified location but come with the drawbacks of exposing sensitive organizational information and high risks around security privacy. Federated learning is traditional way to tackle some of these problems, where organizations keep their datasets locally and send model parameters (instead of raw data) to each organization. That said, traditional federated learning largely deals with decentralized model training and has very little assistance in fulfilling the distributed ETL tasks like data acquisition, preprocessing, feature engineering and metadata management, schema alignment and assessing data quality. A lack of automated preparation of local data can result in inconsistencies that degrade model performance and interoperability across all participants. The framework puts federated learning into context by combining well-defined local data engineering workflows with state-of-the-art privacy-preserving technologies, including advanced protocols such as Differential Privacy, Homomorphic Encryption, Secure Multi-Party Computation, secure aggregation methods, digital authentication and blockchain-based auditing. Together, these technologies protect sensitive enterprise information during data preprocessing, model training, parameter transmission and aggregation. The decentralized preprocessing pipeline leverages data consistent features, while mitigating performance degradation stemming from heterogeneous datasets: a reality in many enterprise settings. Moreover, secure aggregation also enhance the security of collaborative learning by preventing inference attacks, gradient leakage, poisoned model updates and unauthorized access to individual model parameters. The framework also features high scalability by accommodating numerous enterprise participants with only a small increase in communication overhead or computational complexity. As model parameters are exchanged in encrypted form, this approach greatly reduces the bandwidth needed compared with approaches transferring clear data to a centralized server. Additionally, compliance with substantial privacy regulations such as the GDPR and HIPAA allows the application of this framework in sectors conducting sensitive information analysis (e.g., healthcare, finance, manufacturing) [12], cybersecurity [7], and smart city data analytics [11]. In summary, the experimental results substantiate that the proposed Federated Data Engineering Framework establishes a good trade-off among predictive performance, privacy preservation, communication efficiency, scalability, security and compliance attributes– hence being an effective practical solution towards secure collaborative cross-enterprise analytics in today modern distributed computing environments.

5. CONCLUSION

This research elaborates a Federated Data Engineering Framework for Privacy-Aware Cross-Enterprise Analytics, to meet the challenging capability of scalable, privacy-preserving collaborative data analytics among multiple organizations. The traditional data engineering strategies require enterprises to move raw datasets to a single server; however, our framework allows the partners of an enterprise to maintain complete ownership on their local data and share with other partners by sending only model parameters in encrypted form. The framework synergizes advanced federated learning methods with fully-distributed data engineering processes, enabling organizations to perform local data acquisition and preprocessing, feature engineering, model training and metadata management locally before securely engaging in joint analytics. The framework relies on a number of

ISSN: 3071-5717
PP: 01-18.

complementary security mechanisms to enhance privacy preservation, including Differential Privacy, Homomorphic Encryption, Secure Multi-Party Computation, Secure Aggregation, secure communication protocols as well as secure authentication and blockchain-based audit capabilities. Bonus: A deeper dive into built-in technologies for multilayer protection against data leakage, access by a third-party entity, model inversion attack and membership inference attacks, gradient leakage as well as malicious model poisoning all while ensuring compliance with modern data protection regulations such as GDPR/HIPAA/Australian Privacy Principles. In various important performance measures including model accuracy, privacy preservation, communication efficiency, data security, scalability, fault tolerance and regulatory compliance as well as overall system performance,we experimentally demonstrate that the proposed framework allows for significantly greater-than-conventional centralized data engineering cost-performance trade-offs against traditional federated learning and other existing techniques targeting at incorporating privacy-aware federated learning.

To tackle the challenge, our framework integrates standardized local data engineering workflows with secure collaboration and model optimization to enhance analytic consistency while minimizing communication cost and computational complexity. On top of that, its decentralized architecture accommodates for heterogeneous enterprise infra with efficient collaboration between geographically distributed enterprises without compromising data privacy or organizational sovereignty. These features enable the new framework to be well suited for deployment in real-world applications on sensitive domains, such as healthcare diagnosis, financial fraud detection, industrial predictive maintenance, cyberattacks prediction, smart manufacturing analytics and smart city analytics. The proposed framework has performed well with strong security guarantees, but future works would also include adaptive client selection strategies, edge intelligence, federated foundation models and explainable artificial intelligence, along with quantum-resistant cryptographic algorithms [195], energy-efficient federated optimization [196], and intelligent communication scheduling. Such prospective improvements will enable the construction of future Federated Data Engineering systems that are not only more powerful, scalable, reliable, and maintainable than present solutions but also allow deploying next-generation privacy-preserving AI and secure cross-enterprise collaborative analytics in steadily growing complicated distributed (cloud/edge/fog) computing environments.

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