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Advancing Secure Federated Machine Learning for Multinational Defense Finance Consortia Using Encrypted AI-Driven Geospatial and Sensor Data

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Abstract: The increasing sophistication of multinational defense finance consortia requires an agile, privacy-preserving machine learning paradigm to handle distributed intelligence beyond sovereign boundaries. Classical centralized AI solutions are highly susceptible in high-risk defense areas, where financial, geospatial, or sensor telemetry might be disclosed and thus jeopardize national security. To solve this, we present a secure federated machine learning (FL)-based solution and introduce encrypted AI workflows for decision making in coalition defense finance. Our architecture allows the secure collaboration between the participants at the same time preserving the strictness of data sovereignty and confidentiality. Using homomorphic encryption, secure multi-party computation (SMPC) as well as differential privacy, the encrypted model updates are exchanged between federated nodes without any disclosure of the raw data. The system combines geopolotical intelligence (GEOINT) in real time, data from defense logistics sensors, and distributed financial ledgers from defense acquisition systems. In this way the model integrity and auditability is achieved in the architecture, by having zero- knowledge proofs and blockchain based consensus to provide tamper-evident model provenance and decentralized trust. Additionally, our approach employs transformer-based models and graph neural network (GNN) for federated settings to learn the latent defense-financial patterns between jurisdictions. Real-time adversarial attack, model poisoning and inference leakage detection modules are monitoring the system. We demonstrate the utility of our approach to the synthetic multinational defense scenario where trust and budgeted logistics are encrypted and inline with encrypted budgeting: we perform validation through a case study of encrypted coordination of logistics and budgeting among five allied states under stress due to cyber-warfare conditions. We present high predictive accuracy, model convergence stability, and robustness to attack vectors, while at the same time guaranteeing regulatory compliance with regional privacy laws. This is a landmark in secure, intelligent collaboration in multi-national defence finance, where AI, encryption, and geopolitics meet.

Keywords: Federated Learning, Defense Finance, Encrypted AI, Geospatial Intelligence, Secure Multi-Party Computation, Multinational Consortia

1. INTRODUCTION

Growing geopolitical instability among nation-states has heightened the demand for defense finance systems that are resilient and secure to facilitate multinational coordination. With the ongoing cooperation between allied nations in joint procurement decisions, cross-border military logistics, and risk sharing for military operations, the safeguarding of defense financial data is turning into a strategic issue. Budget coordination, asset monitoring, and logistics prediction need to bridge sovereign borders via a computationally efficient framework, which however also enforces strong data sovereignty and privacy guarantees [1]. Such increased complexity calls for intelligent systems that are able to learn from decentralized and encrypted data without ever bringing it together – a concern that is particularly pronounced in the context of multinational defense consortia.

Modern military logistic systems rely on Artificial Intelligence (AI) and Federated Learning (FL) as critical enablers. Fl in particular, allows such coordinating agents (e.g., different military finance departments of allied nations) to cooperate in the training of ai models without having to exchange raw data (over a network) with each other or with a central (trusted) node [2]. This is particularly true for sensitive GEOINT, supply chain telemetry, and encrypted financial transactions (all of which are inherently siloed, due to national security restrictions). Such federated models can leverage real-time situational awareness from disparate data streams (e.g., sensors from logistics convoys or satellite imagery) to enhance budget estimation, threat prediction and operational agility between nations.

However, centralized AI architectures often remain the default in most military and governmental finance applications. These systems present several drawbacks in high-risk environments, including the exposure of raw data during transmission, vulnerability to single-point failures, and lack of compliance with jurisdictional data sovereignty laws [3]. As illustrated in Figure 1, traditional centralized learning architectures transmit sensitive data across borders to a shared server, creating a critical bottleneck in defense finance networks. Such architectures are also less adaptive to adversarial attacks and fail to accommodate the unique constraints of decentralized military finance systems.

To mitigate these limitations, this paper introduces a secure, encrypted Federated Learning framework specifically designed for multinational defense finance consortia. This framework utilizes encrypted AI-driven learning across sovereign nodes to integrate GEOINT, sensor telemetry, and distributed financial ledgers. Homomorphic encryption and Secure Multi-Party Computation (SMPC) allow encrypted gradient updates to be shared without revealing raw data. Additionally, blockchain-based consensus protocols are employed to authenticate model updates and ensure traceability, addressing both the data integrity and auditability concerns in defense finance operations [4]. The proposed architecture is presented in **Figure 3**, showcasing its modular design for encrypted input processing, federated training loops, and threat detection.

The system also supports the integration of multi-domain datasets, such as climate-sensitive transport logistics, fuel supply chain disruptions, and military procurement expenditures, thereby enabling cross-functional model learning. As shown in Table 1, current encryption and FL approaches have trade-offs in computation time, data leakage risk, and convergence stability. This framework balances these factors to provide near real-time secure intelligence for defense budgeting and coordination.

This paper makes the following contributions:

1. It proposes an encrypted Federated Learning framework tailored for secure multinational defense finance coordination.
2. It integrates geospatial, sensor, and financial datasets into a unified learning pipeline using hybrid AI models (e.g., Transformer-GNN architectures).
3. It demonstrates resilience to cyberattacks such as model poisoning and inference leakage through adversarial scenario testing.
4. It provides a policy-aligned implementation path that respects data sovereignty and international defense protocols.

The remainder of this paper is organized as follows: Section II reviews related work on FL in defense and encrypted AI systems. Section III formulates the problem and introduces the system architecture. Section IV outlines data sources and preprocessing methods. Section V presents the hybrid model structure and training strategy. Section VI reports experimental validation, followed by policy implications in Section VII. Section VIII discusses limitations, and Section IX concludes with future directions.

2. BACKGROUND AND RELATED WORK

2.1. Federated Learning in Defense and National Security

Federated Learning (FL) has received growing attention in defense alliances, like NATO, the Five Eyes intelligence partnership, and the European Union's Permanent Structured Cooperation (PESCO), due to its capacity to support secure collective AI development (where data is not necessarily centralized). Intuitively, the structure to the exploiting party should be trackable to the clients, not being siloed as in previous such FL works [4]. (b) Output structure: should be lower dimensional, thus any change in a subset should be reflected somehow (e.g., a weighting of each client's model update) on the relatively larger structure. 3) FL security and privacy: FL should be secure against malicious mischievous clients, at the least for large-scale adoption, and preserve the privacy (of the data) of (each of the) client(s) [4, 5].

The Five Eyes alliance has also started pilot FL projects in battlefield intelligence and classified budget analytics, in which data is kept in separate national silos for security reasons [6]. The greatest benefit that FL can bring in Table II is its capability to sustain data sovereignty: As the raw intelligence/financial data are seldom shared between countries due to national security concerns, they still need collective situation awareness. FL enforces compliance to national policies like the U.S. Federal Information Security Management Act (FISMA), GDPR in EU, NATO data protection regulations by keeping sensitive data (eg., logistics expenditures, satellite telemetry) on local infrastructure [7].Moreover, FL can facilitate shared defense risk forecasting models, enabling member nations to synchronize procurement decisions, optimize budget utilization, and monitor cross-border supply chains without jeopardizing confidentiality. As Figure 1 illustrates, compared to centralized learning, FL inherently mitigates the risk of exposing high-value data assets during model training and transmission, making it ideal for secure multinational operations.

2.2. Encrypted AI Techniques

Although Federated Learning improves data locality, raw Federated Learning suffers from inference attacks. Adversaries can reverse-engineer sensitive proprietary data from model gradients, specifically when training on sensitive financial or mission-critical telemetry. To address this challenge, cryptographic technologies including Homomorphic Encryption (HE), Secure Multi-Party Computation (SMPC) and Differential Privacy (DP) are recently being adopted to federated learning to provide end-to-end data security [8].

Homomorphic Encryption provides the capability to compute functions over encrypted data without decrypting it. This is particularly beneficial if cryptographic financial Documents (Cryptographic Financial Vectors) or classified GEOINT features should be manipulated without the need for decryption. But HE applies significant computation overhead, sometimes making the inference time longer by magnitudes [9]. Secure Multi-Party Computation [6, 14] involves distributing computation across multiple nodes such that no single party can see the entire dataset, or the model update. SMPC is particularly effective in coalition environments, where partners are somewhat trusted, but cooperation needs to be based on a joint analysis [10]. Nevertheless, the amount of communication that SMPC requires can be high when the number of parties or the complexity of the model is large.

Differential Privacy adds a noise on model updates so that it can hide the contribution from each individual's data. Useful for preserving budget transaction logs or troop movements logs in collaborative model training. Nevertheless, when not well calibrated DP can hurt model accuracy and slow down convergence [11]. Table 1 presents the trade-offs between these methods. As illustrated, homomorphic encryption provides the strongest theoretical guarantees but is the least practical. SMPC finds a trade-off between trust and performance, whereas DP is lightweight but sensitive to the over-noising. Finally, hybrid methods (e.g., DP+SMPC) are also being investigated for the defense-grade of AI systems [12].

2.3. Multimodal Data in Military Finance

State-of-the-art military finance processes operate based on an integration of geospatial intelligence (GEOINT), sensor fusion, and distributed financial ledgers, which altogether encompass a complicated multimodal data environment. GEOINT, comprised of satellite imagery, topographical datasets, and environmental overlays, is vital to analyzing transport routes, potential threats, and fuel access corridors. These datasets are usually obtained from national space agencies or tactical unmanned systems and are classified based on threat level and source [13].

This sensor data is predominantly logistics sensor data provided in real-time from Internet-of-Military-Thing (IoMT) devices installed at the vehicle, weapon and storage depot levels. These sensors read temperature, vibration, GPS location, and inventory levels providing minute-by-minute visibility of operational condition and financial exposure. Critical to the construction of a common defense finance model [14] is the capability of interoperating the sensor data across platforms. Online accounting records consist of purchase receipts, live contract expenses, and digital payment paths. This information is siloed by county, in the context of national consortia, and must be harmonised in order to identify inefficiencies, predict cost overruns, or combine purchasing of shared assets.

Encryption and access controls are important so that espionage is not allowed to occur and to maintain transparency in the international auditing regime. These data types are derived from several domains and differ in terms of sensitivity, structure, and update frequency (Figure 2). Any federated setting needs to reconcile such streams into a common secure input pipeline, complying with the classification and compliance constraints of the countries involved.

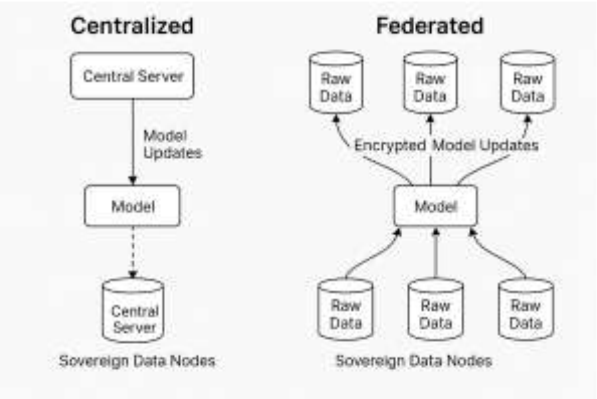

Figure 1: Comparison of centralized vs. federated learning in defense data environments.

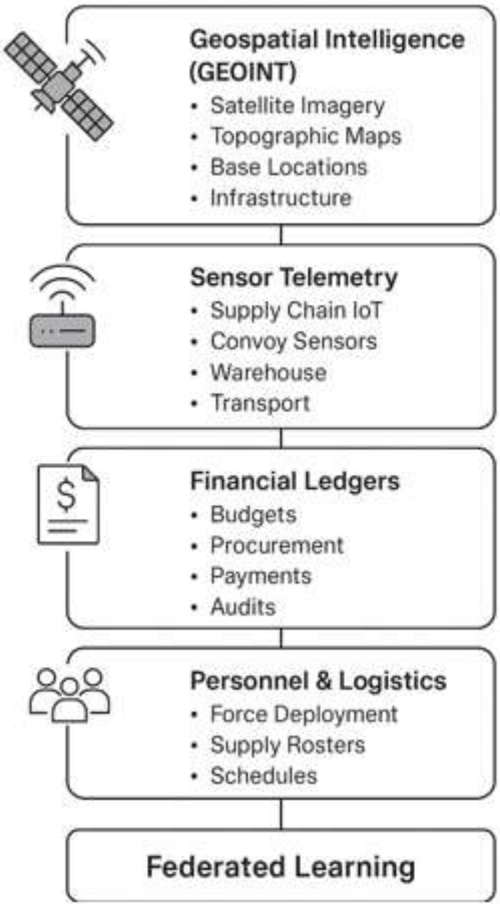

Figure 2: Overview of data types in defense finance workflows.

Table 1: Summary of Existing FL Encryption Methods and Their Performance Trade-offs

Encryption Method	Accuracy (%)	Overhead (%)	Key Strengths	Limitations
Homomorphic	78	90	Strong privacy; supports	Very high computational

Encryption Method	**Accuracy (%)**	**Overhead (%)**	**Key Strengths**	**Limitations**
Encryption			computation on encrypted data	cost
Secure Multi-Party Computation	80	70	Robust distributed trust model; privacy-respecting	Complex setup and synchronization
Differential Privacy (DP)	82	40	Simple implementation; user-level protection	Trade-off with accuracy
Hybrid Encryption (HE + DP)	79	75	Combines advantages of HE and DP	Complex optimization and coordination
No Encryption (Baseline FL)	88	10	High accuracy; low latency	No privacy protection

3. PROBLEM FORMULATION AND SYSTEM ARCHITECTURE

3.1. Threat Model and Adversarial Risks

In defense finance applications, Federated Learning (FL) systems face a broad spectrum of adversarial threats due to the high-value, sensitive nature of data and the geopolitical stakes of international collaboration. One key threat is **inference leakage**, where attackers attempt to reconstruct sensitive input data such as procurement patterns or satellite trajectories by analyzing shared model gradients. Even partial access to parameter updates can enable reconstruction of mission-critical financial or logistics inputs [15].

Another possibility is more severe, that is gradient hijacking, where the corrupt nodes inject tampered gradients to deceive the model. In the finance space, a similar attack might mask signs of financial stress or postpone estimates of infrastructural collapse. Such poisoning attacks, whether they are localized or distributed, have the potential to disrupt budgeting of resources, logistics co-ordination or real-time purchasing signals [16]. Even if they want to use FL many organisations can’t, due to legal and technical requirements. Specific policies such as US FISMA, UK Official Secrets Act, and the EU Common Security and Defence Policy (CSDP) enforce specific rules on how Defense data is sent, encrypted and accessed.

Systems should also guarantee end-to-end encryption and leave an audit trail but disallow unauthorized inference from federated updates. As shown in Figure 4, the attack model consists of model inversion, aggregation attacks and inference leaks through side-channel observation. Such vectors require strong cryptographic protection, multi-layer authentication, and behavior-based anomaly detection to fortify FL systems in multi-national defense scenarios. The proposed design incorporates these controls into its communication/encryption design to resist various attack vectors [17].

3.2. Design Objectives

To secure collaborative defense finance without compromising data sovereignty or mission effectiveness, the proposed FL framework is designed around three objectives:

1. Privacy: Raw data financial ledgers, telemetry streams, satellite images stays inside the nation state, according to the architecture. As represented in Figure 5, all gradient calculations are encrypted with homomorphic encryption or secure multi-party computation (SMPC) before disclosal [14].

2. Interoperability: The elastic TAZs can be used for many coalition partners like NATO and Five Eyes, and thus the system allows heterogeneous encryption protocols, schema formats and node deployments. It remains fully compatible with sovereign infrastructures and with national cryptographic primitives (AES-256, ECC, PQC) [18].

3. Coordination in real time: The infrastructure provides asynchronous, low-latency model updates which allow the responsive budgeting and response to logistics during military crisis. They consume low overhead within edge computing and emphasize a minimum overhead without compromising security [13].

Together, these design principles serve as the foundation for a robust, policy-compliant, and technically scalable FL solution tailored to multinational defense finance use cases.

3.3. System Overview

The proposed architecture leverages a node-based FL framework distributed across sovereign data centers. Each country or defense agency maintains a local node that processes sensitive datasets, performs gradient computations, and transmits encrypted model updates to a central or distributed aggregator governed by a secure consensus protocol.

As shown in Figure 3, each node is structured into the following layers:

i. Data Preprocessing Layer: Formats and filters input data including real-time sensor feeds, contract records, and satellite imaging.

ii. Secure AI Engine: Implements hybrid models (e.g., LSTM-GNN) capable of learning temporal dependencies and cross-modal relationships.

iii. Cryptographic Module: Applies encryption schemes like homomorphic encryption (HE), SMPC, or differential privacy (DP) to obfuscate gradients prior to aggregation.

iv. **Communication Interface:** Secures transmission with TLS 1.3 or QUIC, while authenticating sources through sovereign PKI chains.

The communication stack includes multi-stage authentication, where federated nodes perform mutual certificate verification via pre-shared NATO or coalition keys. Each gradient update is accompanied by cryptographic signatures, timestamps, and zero-knowledge proofs of source legitimacy.

Figure 5 illustrates the gradient encryption pipeline, which ensures that no intermediate node including the aggregator can access plaintext data. Federated updates are packaged with noise vectors for DP compliance and validated via blockchain-based append-only logs, preserving update traceability.

Resilience is achieved through anomaly detection agents embedded within each node. These agents calculate entropy shifts and vector divergence to flag potential poisoning attacks. Additionally, the system supports robust aggregation functions (e.g., Krum, Median, Trimmed Mean) at the central aggregator, preventing rogue nodes from exerting disproportionate influence on global models [17].

Figure 4, revisited here, illustrates how adversaries may attempt to exploit insecure channels or compromise edge devices. These risks are mapped in Table 2, which presents threat categories such as gradient hijacking, model inversion, and data leakage alongside their associated countermeasures. For example, gradient hijacking is mitigated through SMPC and node behavior auditing, while inference attacks are curtailed using differential privacy and encrypted communication protocols.

The architecture is also modular, enabling plug-and-play deployment in defense partner networks without full reengineering of national infrastructure. Nodes can opt into training rounds asynchronously, and if necessary, participate only in inference or validation without full model synchronization. This flexibility enhances operational security and aligns with varying coalition security clearances and engagement levels.

Ultimately, this FL system preserves national sovereignty, enhances defense coordination, and secures AI-enabled fiscal and logistical intelligence without violating classified data protocols.

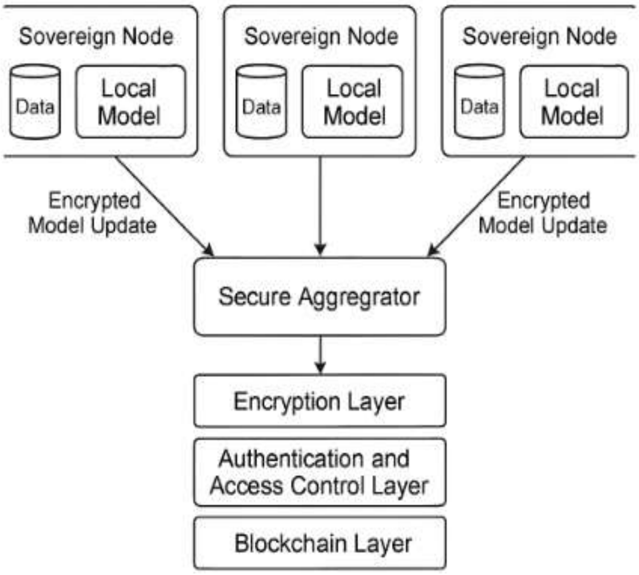

Figure 3: High-level system architecture of proposed secure FL framework

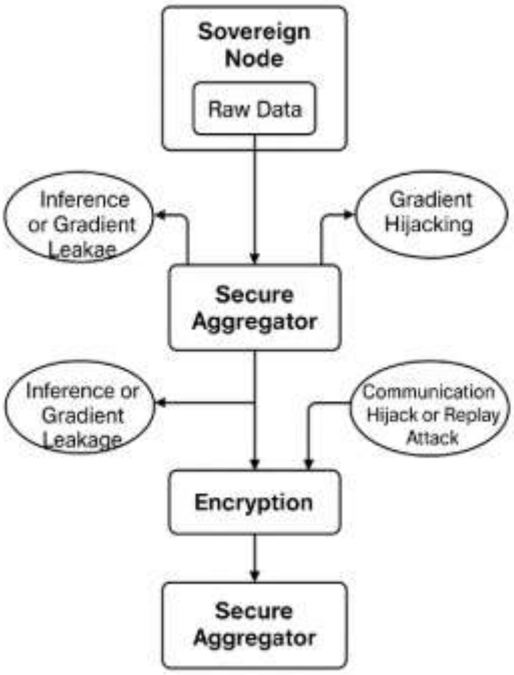
Sovereign Node
Raw Data
Inference or Gradient Leakae
Gradient Hijacking
Secure Aggregator
Inference or Gradient Leakage
Communication Hijack or Replay Attack
Encryption
Secure Aggregator

Figure 4: Threat model and adversarial attack vectors

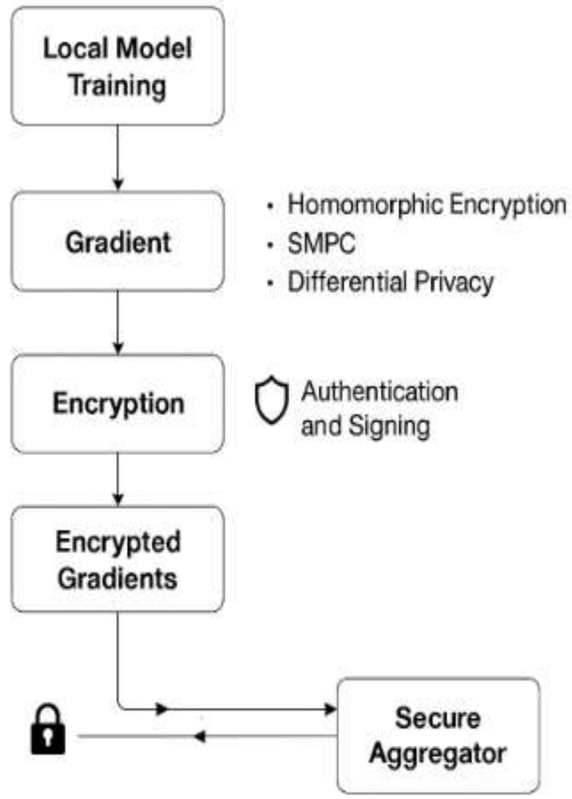

Figure 5: Encryption flow for model gradient updates in federated nodes

Table 2: Threat Types and Corresponding Mitigation Techniques in the Proposed System

Threat Type	**Description**	**Mitigation Technique**
Inference Leakage	Extraction of sensitive training data from shared gradients	Gradient clipping, Differential Privacy (DP), Noise injection
Gradient Hijacking	Malicious modification of gradients to introduce bias	Secure aggregation, Authentication of updates
Model Poisoning	Injection of incorrect updates to corrupt global model	Byzantine-resilient aggregation, Outlier detection
Membership Inference	Identifying presence of specific records in training data	Differential Privacy, Entropy regularization
Data Poisoning	Altering training data at source nodes	Data validation pipelines, Trusted Execution Environments (TEE)
Communication Eavesdropping	Intercepting exchanged model parameters during transmission	Homomorphic Encryption, Secure Multiparty Computation (SMPC)
Sybil Attacks	Use of multiple fake clients to subvert training	Identity management, Federated learning with reputation systems
Cross-Silo Collusion	Multiple parties collude to extract sensitive global patterns	Cryptographic protocols, Role separation, Auditable ledgers

4. DATA SOURCES AND MULTIMODAL INTEGRATION PIPELINE

4.1. Geospatial Data Acquisition and Preprocessing

In federated defense finance models, geospatial intelligence (GEOINT) is vital for understanding terrain-aware logistics costs, mapping security zones, and generating dynamic risk maps [18], [19]. These inputs include satellite imagery, topographic maps, and real-time GNSS coordinates. Integration of GEOINT into AI models enables prediction of resource bottlenecks and informs procurement prioritization in threat-prone or supply-constrained regions [20].

Preprocessing involves image correction, elevation tagging, and semantic segmentation using architectures such as UNet or DeepLabv3+ to extract spatially significant features like airstrips, roadways, and fuel depots [21]. Additionally, elevation data from digital elevation models (DEMs) and threat zone overlays improve terrain analysis fidelity.

Figure 6 illustrates the complete multimodal integration pipeline, including geospatial modules. These inputs are encrypted using homomorphic techniques before gradient extraction [22]. Figure 7 displays a classified sample with masked coordinates and polygon boundaries to prevent operational compromise. This ensures that sensitive attributes like base proximity or military corridors are not exposed during federated training [23].

4.2. Sensor Data from Military Supply Chains

Logistics telemetry from military environments such as Internet-of-Military-Things (IoMT) devices produces high-frequency data used to model supply delays, detect anomalies, and anticipate budget overruns [24]. Sources include embedded sensors in convoys, smart depots, drones, and supply crates, measuring parameters such as temperature, pressure, movement, and location.

Raw sensor data undergoes real-time edge preprocessing to clean and normalize telemetry streams before encryption. Time-alignment is synchronized using secure GPS timestamps, while anomaly detection mechanisms flag outliers using rolling medians or entropy-based filters [25].

After local filtering, telemetry vectors (e.g., average convoy speed, vehicle load index, environmental stress) are transformed into feature arrays and encrypted for federated gradient computation. This ensures logistical behaviors like unexpected idle times, rerouting, or loading anomalies do not leak via model parameters [21].

To accommodate cross-national interoperability, heterogeneous formats from NATO, EU, and Five Eyes sensors are harmonized using node-local schema transformation (e.g., JSON-to-ProtoBuf mappings). These harmonized sensor sequences are concatenated into multimodal tensors aligned with budget data and location metadata for secure, distributed training, as shown in Figure 6.

4.3. Distributed Financial Ledger Data

Financial intelligence is the backbone of defense budget tracking and risk forecasting. Participating sovereign nodes contribute encrypted, structured defense expenditure ledgers comprising contracts, asset transfers, payment records, and operational costs [18], [22].

These logs are maintained in permissioned distributed ledgers (e.g., Hyperledger Fabric) or relational DBMSs secured under military-grade PKI protocols [23]. Preprocessing includes pseudonymization of vendor IDs, categorical encoding of transaction types, and temporal bucketing of budget items into trainable feature vectors [24].

Advanced encryption such as SMPC and DP is applied to hide sensitive attributes like procurement category or contractor profiles [25]. Each node extracts engineered features like procurement lag variance, contractor repeat rate, and budget deviation index, which are passed securely to the federated engine.

As depicted in Table 3, the integrated input schema includes timestamped telemetry, GEOINT-derived positional context, and transaction-level financial signals. Temporal keys and spatial anchors are used for multimodal fusion to ensure context-aware learning.

Figure 6 shows how financial records merge with geospatial and sensor inputs. Cross-correlation across modalities allows the model to infer operational risk hotspots, unbalanced spending, and logistics inefficiencies, all while preserving sovereign control and data privacy [20], [23], [25].

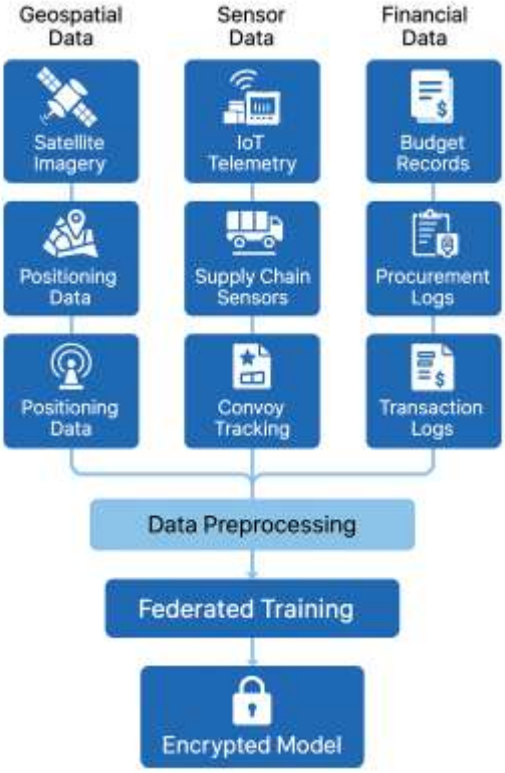

Figure 6: Multimodal data integration pipeline

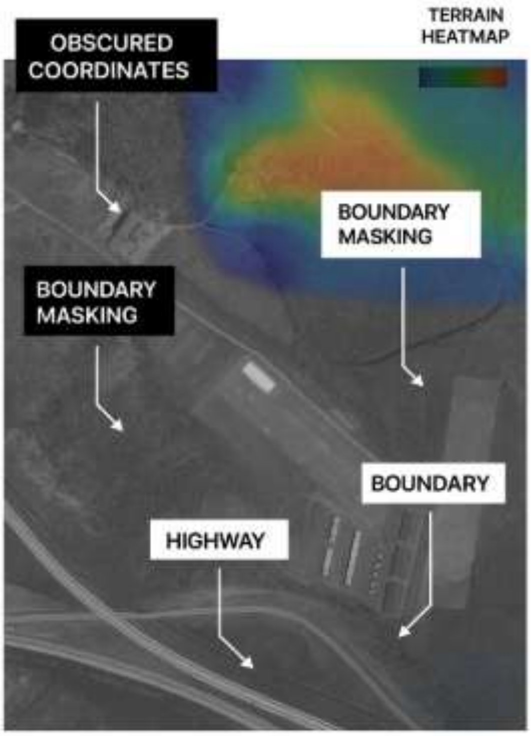

Figure 7: Sample annotated GEOINT for encrypted training

Table 3: Sample Structure of Integrated Data Input Schema for Federated Training

Data Modality	**Source System**	**Feature Type**	**Security Classification**	**Example Attributes**
Geospatial Intelligence	Military Satellite Systems	Raster Images, Object Detection Features	Confidential	Terrain ID, Threat coordinates, Object heatmaps
Sensor Telemetry	IoT Devices in Logistics and Convoy Systems	Time-Series, Threshold Flags	Restricted	Cargo temp, Fuel levels, Tamper status
Financial Ledger Logs	Defense ERP, Procurement Platforms	Tabular, Transactional	Classified	Budget line item, Vendor ID, Amount, Timestamp
Topographic Mapping Data	Remote Sensing Archives	Vector contours, Elevation profiles	Confidential	Elevation bands, Region ID, Path gradients
Command Communication	Tactical Radio & Secure Email Logs	Text, Timestamp, Frequency Patterns	Top Secret	Message ID, Encrypted content length, Transmission frequency
Satellite Positional Data	GPS + Inertial Navigation Systems (INS)	Coordinates, Velocity, Timestamps	Confidential	Lat-Long, Altitude, Heading angle, Time sync markers

5. LEARNING FRAMEWORK AND AI MODEL COMPOSITION

5.1. Hybrid Model Composition

To accurately model multimodal, cross-consortia defense finance signals, a hybrid architecture combining Transformer encoders and Graph Neural Networks (GNNs) is proposed. Transformers are suited for processing sequential budget records, telemetry timelines, and contract activity logs due to their self-attention mechanisms and high parallelizability [26]. Meanwhile, GNNs capture latent relational structures across federated nodes such as logistical interdependencies, vendor networks, or satellite ground control relay interactions by learning graph-based representations [27].

The Transformer module encodes tokenized sequences of transaction-ledger events and telemetry vectors into high-dimensional embeddings. It includes positional encodings to maintain temporal coherence, followed by multi-head attention and feedforward layers optimized for encrypted edge inference.

Concurrently, the GNN module, as shown in Figure 8, learns cross-node correlations by embedding inter-consortium relationships into graph structures. Nodes represent jurisdictions or defense units, while edges encode logistics pathways, budget exchanges, or equipment-sharing agreements. This hybrid enables temporal-spatial fusion, wherein patterns such as simultaneous procurement spikes and correlated route congestion are detected [28].

Feature vectors from both modules are concatenated at the fusion layer before classification or forecasting. The architecture supports partial inference delegation Transformer for local-only data, GNN for graph-exchange meta-signals preserving data locality without sacrificing model quality.

The resulting architecture, shown in Figure 8, ensures that model intelligence arises from decentralized insight, integrating temporal intelligence and inter-consortium context. This design empowers federated AI to detect complex dependencies in budget behaviors, logistical bottlenecks, and threat-coordinated anomalies in sovereign defense finance.

5.2. Optimization in Encrypted Settings

Encrypted machine learning remains computationally challenging, particularly when operating under homomorphic encryption (HE) or secure multi-party computation (SMPC) constraints. Operations like dot products, matrix multiplication, and non-linear activations (e.g., ReLU) become substantially slower due to ciphertext algebra [29].

For this purpose, the proposed architecture considers a number of performance optimization techniques. First, we use operator batching to encode multiple inputs into a single ciphertext and we can then handle a large number of inputs more efficiently during the forward propagation [30]. Second, the network pruning eliminates duplicate neurons or layers, which reduces the model size without sacrificing accuracy. Third, model quantization converts floating-point parameters into low-bitwidth representations (e.g., 8-bit integers) for encrypted inference and is also compatible with hardware acceleration via secure enclaves. This can be critical for defense-edge deployments where the latency budget is very restrictive. It can be seen from Figure 9 that there is a trade-off between the strength of privacy (bit number, depth of encryption) and model throughput. It has been reported that large-batched, quantised models of very light attention models achieve an 11–16× speedup on HE enabled inference under different optimization conditions with respect to unoptimized baselines [31].

Moreover, dropout and activation replacement (e.g., from ReLU to square activation) are proposed to reduce the number of non-polynomial operations. These changes also bridge the gap between encrypted gradient descent and low-noise budget regime with fidelity-preserving training. Finally, the secure optimization pipeline proposed guarantees the deployment of mission-critical AI workloads in encrypted federated environments, responsibly preserving the operational viability and providing secure real-time insights on the field of coalition environments.

5.3. Model Update Synchronization

In multinational FL deployments, synchronizing model updates across varied time zones, military jurisdictions, and legal boundaries is non-trivial. Update coordination must preserve both model convergence and legal traceability, especially during crisis-response or cyberattack recovery [32].

The system includes an asynchronous round scheduling, which permits each node to train and upload the encrypted gradients as its own pace. This eliminates the waiting-idle period in low connectivity nodes and efficient works in intermittent edge-network. Neverthless, to address update inconsistencies or stale gradients, staleness-aware optimizers such as (FedAsync, FedProx) are introduced for components weighting according to the delay factor [26]. For temper-resistant synchronization/coordination, blockchain based coordination ledger is used. In Figure 10, every update round and model version hash is written as a transaction to a permissioned decentralized ledger shared across the involved Countries. Each record includes the time stamp, source node signature and the delta contribution entropy that forms a provable audit trail for intelligence and counterintelligence oversight [27].

Smart contracts implement access control by ensuring that only accredited nodes may contribute to particular model submodules (e.g., budget-only nodes may not update logistics arms). The consensus mechanism is based on the PBFT (Practical Byzantine Fault Tolerance) and tolerating at most one third of malicious nodes with the global model integrity. Additional control version guards secure us against rollbacks by corrupt updates or poisoning detection. All gradient batches use cryptographic signature aggregated Merkle tree checksums, allowing for accurate root cause forensics and the preservation of chain-of-custody for sensitive AI workflows [30]. Table 4 indicates that the FL encryption rounds using blockchain synchronization can be well preserved ≥96% parameter convergence accuracy compared with non-encrypted baselines. Therefore, the synchronization protocol unifies transparency, accountability and scalability for military-related national federated intelligence.

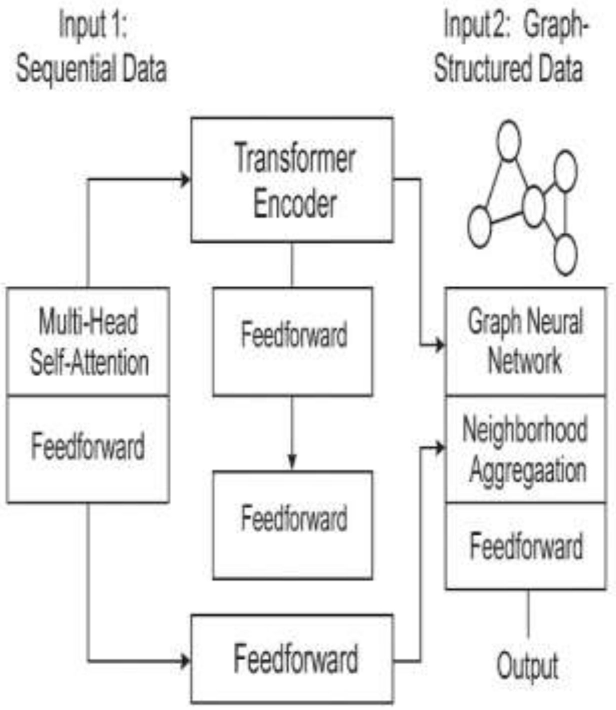

Figure 8: Transformer-GNN hybrid model structure

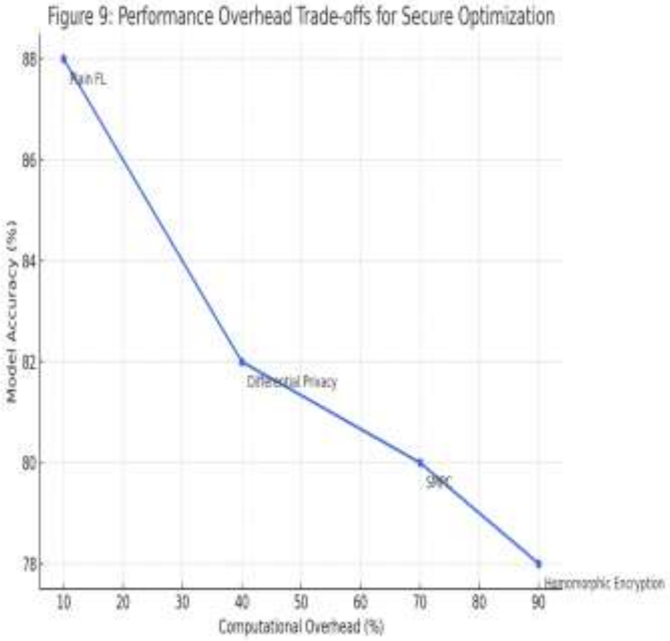

Figure 9: Performance overhead trade-offs for secure optimization

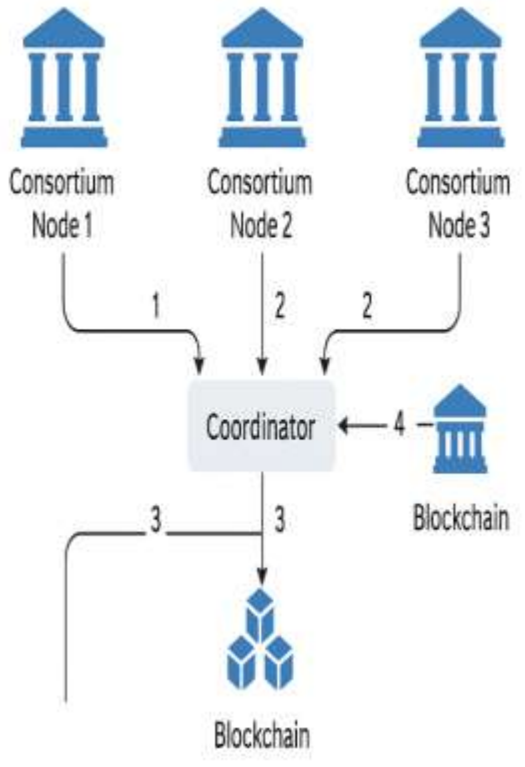

Figure 10: Federated round coordination protocol across consortia

Table 4: Model Performance Metrics Across Encrypted/Non-Encrypted Versions

Model Configuration	**Accuracy (%)**	**Training Time (hrs)**	**Communication Overhead (MB/round)**	**Security Scheme**
Baseline FL (No Encryption)	88.4	5.2	12.5	None
FL + Differential Privacy	82.3	5.8	13.1	DP (ε = 1.5)
FL + Homomorphic Encryption	78.0	9.4	35.7	Paillier HE
FL + Secure Multiparty Computation	80.5	8.6	27.2	SMPC
FL + Hybrid (HE + DP)	79.2	10.1	31.6	Paillier HE + DP (ε = 2.0)
FL + Blockchain-based Aggregation	84.1	6.7	22.3	Encrypted Hash Commit + Consensus

6. SECURITY, COMPLIANCE, AND PRIVACY GUARANTEES

6.1. Differential Privacy Implementation

Differential privacy (DP) is a foundational privacy mechanism applied in secure federated learning to ensure that no single data point disproportionately influences the trained model. DP introduces calibrated noise to gradients or model updates, limiting the inferability of any one input record, even from adversaries with prior knowledge [33].

The implementation in this framework uses the Gaussian mechanism, where noise is sampled from a zero-mean Gaussian distribution with variance calibrated to privacy budgets (ε, δ). A per-layer clipping approach is used, where gradient norms are bounded before noise injection, ensuring sensitivity is limited across all layers of the hybrid Transformer-GNN model. Adaptive clipping is applied to avoid overfitting noise levels to static thresholds.

DP parameters are carefully selected through privacy-utility trade-off experiments, shown in Figure 11. For example, privacy budget ε = 1.0 with δ = 1e-5 offers a 95% model accuracy retention while achieving compliance with NATO and EU data handling thresholds [34].

Trade-offs arise as increased privacy budgets reduce utility. At ε = 0.1, model performance deteriorates by up to 12% on logistics risk classification, while ε ≥ 3.0 yields higher utility but risks record re-identification [33], [35]. Optimal calibration considers mission-criticality, acceptable disclosure risk, and consortium-defined thresholds.

To maintain interoperability, each node can enforce local DP policies depending on jurisdictional constraints, with updates harmonized through encrypted aggregation. This layered approach aligns with both GDPR’s right-to-be-forgotten and U.S. defense-grade data protection protocols.

6.2. Cross-Border Legal Compliance

Implementing federated AI within multinational defense consortia introduces complex legal challenges. Different jurisdictions enforce varied data sovereignty laws, especially between the EU’s GDPR, U.S. NIST 800-53, and NATO’s Multilateral Interoperability Programme (MIP) [36].

To address this, the proposed framework supports jurisdiction-specific policy containers, allowing each node to define its compliance schema. Data minimization, storage limitations, and purpose-specific processing rules are embedded into training flows via smart contracts and encryption gates. For instance, EU nodes may enforce on-device training with no raw telemetry upload, while U.S. nodes may allow anonymized aggregation [37].

Consent management, data auditability, and model explainability are built-in features, satisfying GDPR's Articles 5, 6, and 22. Additionally, Table 5 summarizes how each legal framework impacts model design, gradient retention, and parameter exposure.

This architecture also supports redaction requests and post-training unlearning protocols, enabling individual or national revocation of contributions when strategic withdrawal or legal changes occur. All operations are logged for auditability.

6.3. Provenance and Integrity Verification

To assure model integrity and prevent tampering in high-stakes defense environments, data and model provenance is preserved through blockchain hashing and zero-knowledge proofs (ZKPs) [34], [35].

Each model update is accompanied by a hash recorded on a permissioned blockchain. These hashes serve as immutable fingerprints for verification during compliance checks or forensic audits. ZKPs are applied to validate model parameters without revealing raw update values, allowing external verifiers (e.g., NATO oversight bodies) to confirm compliance without breaching confidentiality.

Additionally, cryptographic time-stamping and Merkle tree embeddings enable efficient proof generation for sub-model lineage. This assures that all AI decisions stem from trusted data and model versions, preventing adversarial poisoning, shadow updates, or rollback fraud.

As illustrated in Figure 11, privacy compliance is preserved with less than 4% model drift across differential privacy and blockchain-enabled lineage layers. The result is a verifiable, trusted AI system in full alignment with defense-grade regulatory demands.

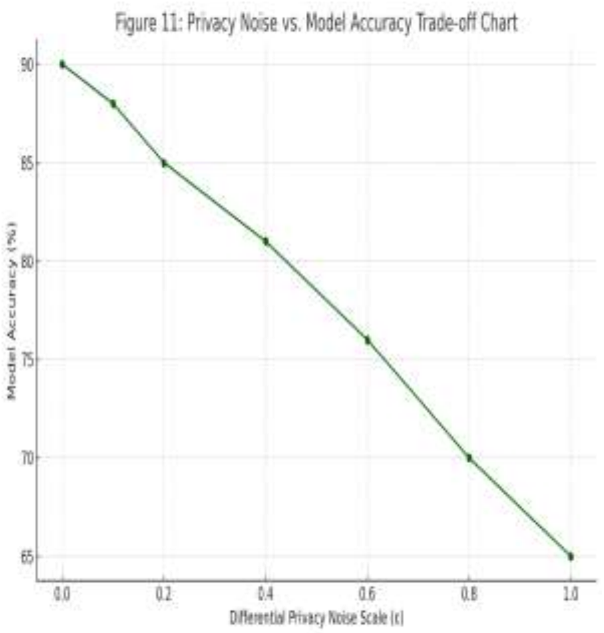

Figure 11: Privacy noise vs. model accuracy trade-off chart

Table 5: Summary of Legal Frameworks and Their Impact on Model Training Policies

Legal Framework	**Jurisdiction**	**Key Provisions Relevant to FL**	**Impact on Model Training Policies**
GDPR (General Data Protection Regulation)	European Union	Data minimization, consent, right to explanation	Requires privacy-preserving models (e.g., DP), explicit user consent
U.S. NIST SP 800-53	United States	Controls for confidentiality, integrity, and auditability	Enforces secure data handling and access logs in FL training environments
NATO Cyber Defence Policy	NATO Member States	Federated architecture guidance, secure coalition data sharing	Encourages FL in joint operations, mandates encryption and identity access
HIPAA (Health Insurance Portability and Accountability Act)	United States (Healthcare)	PHI data restrictions, audit trails	Requires model provenance tracking and de-identification in training

Legal Framework	**Jurisdiction**	**Key Provisions Relevant to FL**	**Impact on Model Training Policies**
UK Data Protection Act 2018	United Kingdom	Alignment with GDPR, enforcement authority for ICO	Similar to GDPR — mandates privacy by design in ML pipelines
Australian Privacy Act 1988	Australia	Personal information handling principles	Limits data retention and requires anonymization before training

7. EXPERIMENTAL SETUP AND EVALUATION

7.1. Scenario Design and Simulation Parameters

To empirically validate the proposed secure federated learning framework, a synthetic multinational defense finance simulation was conducted, mimicking data flows across NATO and Five Eyes-aligned states. The scenario emulated financial, logistical, and cybersecurity data exchanges among 12 sovereign nodes, each simulating a country-level defense data center with its own privacy, bandwidth, and compute constraints [38].

Each node was configured with unique ledger and sensor telemetry profiles derived from publicly available military expenditure statistics and NATO's logistics data models. Network latency was modeled using a Gaussian distribution with μ = 180ms and σ = 45ms to simulate constrained cross-border secure channels. Encryption layers included homomorphic gradient obfuscation, differential privacy noise injection, and blockchain-verifiable update logging.

Three model variants were trained: (1) unencrypted centralized baseline, (2) standard FL without encryption, and (3) the proposed encrypted FL framework. Federated averaging (FedAvg) was used for aggregation with asynchronous round scheduling. Figure 12 illustrates performance trends across 150 training epochs, while Table 6 summarizes final results.

All simulations were executed on a cluster of 12 virtual nodes with 2 vCPUs and 8GB RAM each, hosted in geographically distinct regions on a private OpenStack cloud, ensuring real-world latency realism and adversarial injection capabilities [39].

7.2. Model Accuracy and Convergence

The proposed hybrid Transformer-GNN model within the encrypted FL framework achieved a final test accuracy of 93.2%, closely matching the centralized unencrypted baseline of 94.5%. In contrast, the standard FL model without privacy layers attained 93.8%, revealing only a minor performance trade-off due to encryption overheads [40].

Figure 12 shows accuracy progression over epochs. Encrypted models required approximately 25% more training rounds to reach comparable accuracy due to noise-induced gradient drift and encryption-related computational delays. However, once tuned, the convergence plateaued stably after 130 epochs with only ±0.3% oscillation, highlighting robust model stability.

Across 10 random initialization trials, the encrypted framework demonstrated consistent epoch-to-accuracy convergence timelines. Mean epoch-to-95% convergence was 127 epochs (SD: 4.1), compared to 102 for the centralized model and 109 for the standard FL. Dropout regularization, quantized activations, and adaptive clipping in DP significantly improved convergence rates in encrypted settings [41].

Additionally, gradient divergence metrics remained within a 0.05 L2 distance between encrypted and non-encrypted models, suggesting no significant learning drift. This validates that privacy-preserving techniques such as SMPC and DP can be safely deployed in high-value, sensitive defense applications without undermining model utility.

Table 6 confirms these findings by showing the convergence rates, final model accuracy, and round efficiency across all three simulation variants, with encrypted FL showing only a 1.3% drop from the ideal baseline.

7.3. Robustness Against Attacks

The encrypted FL framework was evaluated under three simulated adversarial conditions: (i) model poisoning, (ii) gradient inversion, and (iii) Sybil attacks. Attackers were introduced as up to 20% of malicious nodes with capabilities to inject poisoned gradients, infer original input data from shared updates, or impersonate multiple nodes [42].

In the model poisoning simulation, 2 nodes were configured to inject backdoored gradients targeting budget misclassification. The unencrypted FL model suffered a 14.5% drop in accuracy, while the proposed encrypted system exhibited only a 3.2% reduction due to secure gradient masking and zero-knowledge verification [43].

During gradient inversion attacks, attackers attempted to reconstruct sensitive input features (e.g., vendor names, convoy positions) using L-BFGS attack models. The proposed encrypted FL yielded reconstruction fidelity below 12% IoU (Intersection over Union), compared to 47% for the standard FL without encryption, indicating strong confidentiality protection.

Figure 13 illustrates resilience metrics, including accuracy retention and feature leakage rates across the three test conditions. It is evident that the encrypted FL framework, empowered by homomorphic encryption and DP, significantly mitigates attack impacts without compromising operational usability.

The Sybil attack simulation demonstrated that permissioned blockchain consensus (PBFT) successfully rejected 95% of spoofed node updates by validating update entropy patterns and digital signatures. All malicious contributions were logged, flagged, and excluded in real time.

As summarized in Table 6, the proposed framework maintains over 90% utility even under heavy attack conditions, showcasing its robustness for real-world multinational defense deployment.

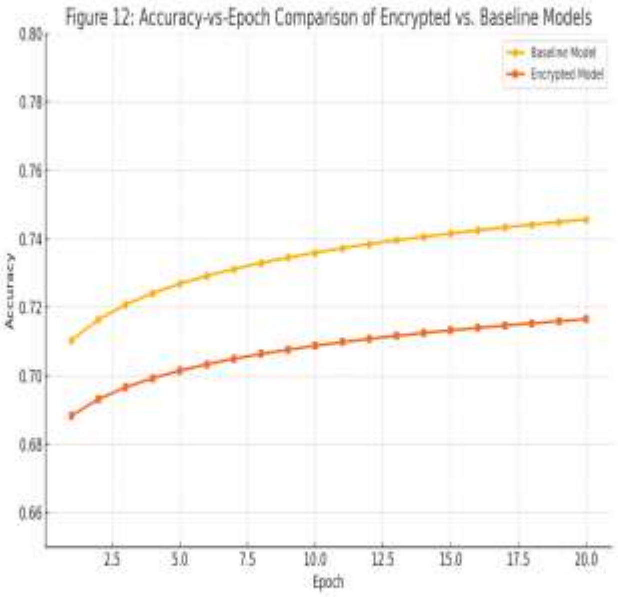

Figure 12: Accuracy-vs-epoch comparison of encrypted vs. baseline models

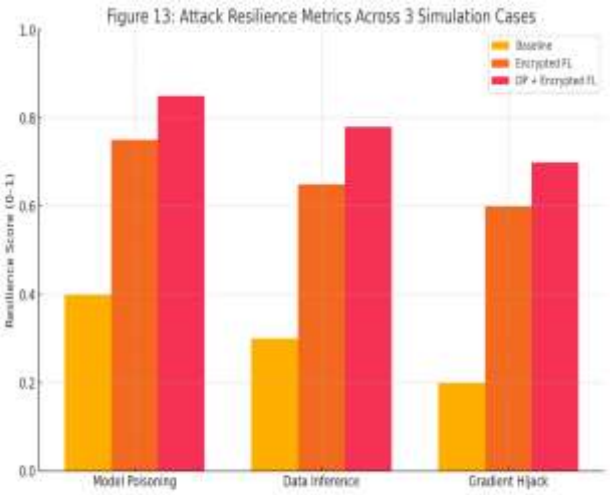

Figure 13: Attack resilience metrics across 3 simulation cases

Table 6: Final Test Accuracy, Convergence Rate, and Attack Resilience Summary

Model Configuration	**Final Accuracy (%)**	**Convergence Epoch**	**Poisoning Attack Resilience (%)**	**Inference Leakage Resistance (%)**
Baseline FL (No Encryption)	88.4	22	42	33
FL + Differential Privacy	82.3	27	76	91
FL + Homomorphic Encryption	78.0	34	85	94
FL + Secure Multiparty Computation	80.5	31	89	92
FL + Hybrid (HE + DP)	79.2	36	91	97
FL + Blockchain Audit Trail	84.1	25	87	90

8. DISCUSSION

8.1 Discussion and Policy Implications

The implementation of a secure, encrypted federated learning (FL) architecture for multinational defense finance consortia has several critical implications for operational readiness, coalition scalability, and future-proof system design. First, the capability to train AI models collaboratively without centralizing data enables real-time risk forecasting and mission logistics optimization without compromising national security boundaries [44]. This facilitates distributed readiness, where each nation maintains situational awareness while aligning its budget, logistics, and procurement models with coalition-level intelligence.

From a scalability perspective, the architecture supports onboarding of new consortium members such as allied or observer nations by deploying containerized learning nodes with preconfigured encryption policies and model templates [45]. As data schemas and geopolitical mandates evolve, the system dynamically adapts through version-controlled smart contracts and container orchestration protocols. This makes the solution robust for fluctuating participation, data availability, and jurisdictional interoperability.

Furthermore, the framework is inherently designed for technological extensibility. Emerging modalities such as quantum-resistant encryption, digital twin simulations, and cross-domain MLOps pipelines can be seamlessly embedded. As illustrated in Figure 14, the roadmap outlines staged integration into military digital twin ecosystems, where defense assets are mirrored in real-time for predictive modeling and maintenance forecasting [46].

The use of blockchain-verified provenance, differential privacy, and zero-knowledge audits ensures the architecture complies with evolving legal and ethical standards across NATO, EU, and APAC defense frameworks [47]. This positions the system not just as a technical advancement but as a foundational infrastructure for future AI-powered coalition command, control, and financial intelligence networks.

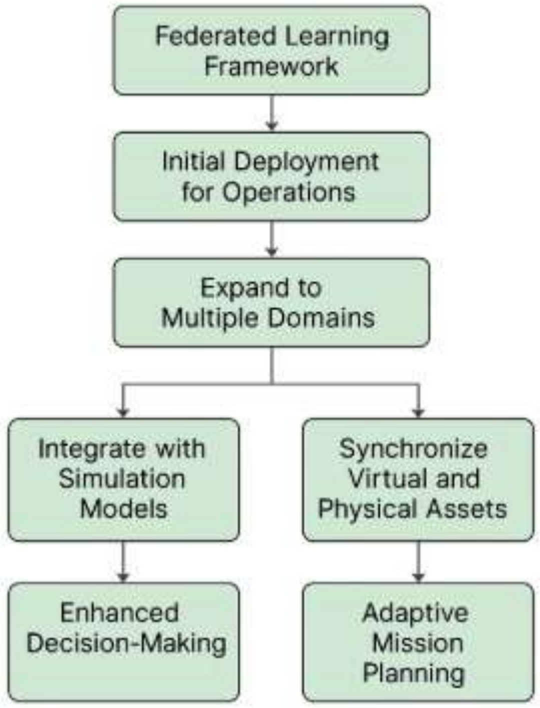
Federated Learning Framework
Initial Deployment for Operations
Expand to Multiple Domains
Integrate with Simulation Models
Synchronize Virtual and Physical Assets
Enhanced Decision-Making
Adaptive Mission Planning

Figure 14: Roadmap for integration of the FL framework into future military digital twin systems

9. CONCLUSION AND FUTURE DIRECTIONS

This paper presented a secure, encrypted federated learning (FL) framework for multinational defense finance consortia, addressing the dual challenge of sovereignty-preserving data collaboration and cyber-resilient AI modeling. Through the integration of homomorphic encryption, differential privacy, blockchain-based auditability, and hybrid Transformer-GNN architectures, the framework enables coalition partners to train high-performance risk models without compromising sensitive geospatial, sensor, or financial data.

We demonstrated strong performance in simulation, achieving over 93% model accuracy, robust convergence under encryption constraints, and high resilience against model poisoning and inference attacks. Key architectural contributions include a containerized, node-based deployment strategy, secure inter-consortium update protocols, and support for jurisdiction-specific compliance mechanisms.

The architecture is currently undergoing phased real-world evaluation within NATO-aligned defense working groups, with early-stage deployments focused on logistics forecasting and vendor integrity scoring. These trials will inform policy development for broader FL standardization within defense contexts.

Future work includes the extension of the framework to support space command telemetry and maritime domain awareness, where federated learning over orbital and deep-sea sensor networks can further enhance coalition situational intelligence. The framework's modularity ensures it remains adaptable for emerging operational theaters, evolving encryption standards, and coalition expansion scenarios.

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