SmartFL: A Secure Universal Heterogeneous Federated Learning Framework with Cross-Architecture Knowledge Distillation and Performance Preservation

1st Dheenadhayalan L
B.Tech in Artificial Intelligence and Data Science
Kingston Engineering College
Vellore, Tamil Nadu, India
gldheenadhayalan2@gmail.com

2nd Karthikeyan D P
B.Tech in Artificial Intelligence and Data Science
Kingston Engineering College
Vellore, Tamil Nadu, India
dpkarthikeyan30012004@gmail.com

3rd Vasanthan V
B.Tech in Artificial Intelligence and Data Science
Kingston Engineering College
Vellore, Tamil Nadu, India
vasanth040705@gmail.com

Abstract*—Federated Learning (FL) has become a critical paradigm for enabling privacy-preserving distributed intelligence; however, existing methods such as Federated Averaging (FedAvg), Federated Knowledge Distillation (FedKD), and Model-Contrastive Federated Learning (MOON) largely assume homogeneous model architectures or lack robust adaptive strategies for reliable knowledge transfer, limiting their applicability in realistic heterogeneous and cross-framework environments. To overcome these limitations, this paper presents SmartFL, a secure, scalable, and universal heterogeneous federated learning framework designed to support seamless collaboration across diverse model architectures and machine learning frameworks, including PyTorch, TensorFlow/Keras, and Scikit-learn. SmartFL introduces a novel hybrid learning paradigm that intelligently integrates partial weight aggregation for structurally compatible models with an adaptive, confidence-aware cross-architecture knowledge distillation mechanism for heterogeneous scenarios, ensuring effective and reliable knowledge transfer. To further enhance robustness, a validation-driven performance preservation strategy selectively incorporates client updates, preventing model degradation and stabilizing convergence. Additionally, SmartFL incorporates secure encrypted communication and model compression techniques to reduce transmission overhead while preserving data confidentiality. A dual-queue asynchronous update mechanism is also proposed to efficiently manage concurrent client participation, prioritize critical updates, and improve overall system scalability. Extensive experimental evaluations on multi-class image classification benchmarks demonstrate that SmartFL consistently achieves superior or comparable performance across heterogeneous configurations, while significantly improving knowledge transfer efficiency and training stability. These results establish SmartFL as a practical and high-impact solution for bridging heterogeneous AI systems, advancing secure, efficient, and real-world federated learning deployment.

***Index Terms*—Adaptive Aggregation, Cross-architecture Knowledge Distillation, Heterogeneous Federated Learning, Performance Preservation, Secure Model Sharing**

I. Introduction

The rapid growth of distributed data sources, from personal edge devices to enterprise servers, has fundamentally reshaped the landscape of artificial intelligence. Traditional centralized training methods, while effective in controlled laboratory environments, are increasingly inadequate due to stringent privacy regulations, limited network bandwidth, and the constant risk of data breaches. Federated Learning (FL) has emerged as a promising solution, allowing multiple clients to collaboratively train machine learning models without sharing raw data. Instead, clients exchange only model updates [1], [2], [3]. This approach not only preserves privacy but also leverages decentralized datasets to build robust, large-scale intelligence systems.

Foundational FL algorithms, such as Federated Averaging (FedAvg) [1] and its variants [2], [3], have demonstrated significant progress. However, these methods typically assume that all participating clients use *homogeneous model architectures*. While this simplifies aggregation and convergence analysis, it limits applicability in real-world scenarios where clients often operate under diverse conditions, using different frameworks, computational capacities, and model structures. As a result, FedAvg-based methods struggle to accommodate architectural heterogeneity, which can lead to inefficiencies or even incompatibility when models differ.

To address this challenge, knowledge distillation-based FL methods, such as Federated Knowledge Distillation (FedKD) [4], [5], have been introduced. These methods enable information transfer between heterogeneous models through soft-label supervision or ensemble predictions, partially overcoming the limitations of weight-based aggregation. However, many existing distillation approaches are *static*;

they rely on identical output spaces or shared representations and do not account for the *confidence or reliability* of the knowledge being transferred. This can lead to negative transfer, especially when client models generate inconsistent predictions or when client data distributions are non-IID [6], [7]. Such limitations reduce the effectiveness of these methods in realistic, heterogeneous federated environments.

Complementary techniques, like Model-Contrastive Federated Learning (MOON) [8], employ contrastive objectives to align client representations and reduce divergence. While MOON improves convergence stability in data-heterogeneous setups, it is still restricted to *homogeneous model structures* and does not support cross-framework collaboration. Other cross-model or personalized FL methods [9], [10] partially relax architectural constraints but lack dynamic adaptation mechanisms based on model compatibility or prediction confidence. Taken together, these gaps highlight a critical challenge: **no existing framework effectively integrates heterogeneous architectures, cross-framework learning, adaptive knowledge transfer, and real-world deployability**.

Beyond algorithmic challenges, deploying FL in real-world systems introduces additional *system-level complexities*. Large model updates can impose significant communication overhead, particularly in bandwidth-limited networks. Non-IID client data, intermittent participation, and varying computational capabilities further destabilize convergence, leading to slower or unreliable training. Security and privacy remain paramount, as naive parameter exchanges can expose sensitive information, requiring *robust encryption and secure aggregation mechanisms* [11], [12]. Existing FL frameworks rarely address these challenges comprehensively, leaving real-world deployments vulnerable to inefficiency, privacy risks, and instability.

To tackle both algorithmic and system-level challenges, we propose **SmartFL**, a *secure, scalable, and universal heterogeneous federated learning framework* designed for realistic cross-framework environments. SmartFL introduces a *hybrid learning paradigm*, combining *partial weight aggregation* for structurally compatible clients with *confidence-guided knowledge distillation* for heterogeneous models. By evaluating client predictions using confidence metrics, SmartFL mitigates negative transfer, ensuring that only reliable knowledge contributes to global updates. Unlike previous approaches that rely solely on aggregation or distillation, SmartFL dynamically selects the optimal strategy based on client compatibility, enabling seamless collaboration across PyTorch, TensorFlow/Keras, and Scikit-learn models.

SmartFL also incorporates *practical system-level enhancements* to ensure deployability. Updates are transmitted through *compressed and encrypted channels*, reducing communication costs while preserving privacy. A *dual-queue asynchronous update mechanism* prioritizes critical updates and efficiently manages concurrent client participation, maintaining stable convergence even in dynamic environments. Additionally, a *performance preservation strategy* evaluates incoming updates and incorporates only those that maintain or improve global model accuracy, preventing performance degradation due to unreliable contributions. Together, these design choices make SmartFL both *algorithmically robust and operationally practical*, bridging the gap between theory and real-world applications.

We validate SmartFL through extensive experiments on multi-class image classification benchmarks. Compared to FedAvg [1], FedKD [4], and MOON [8], SmartFL consistently delivers higher accuracy in heterogeneous settings, reduces negative transfer, stabilizes convergence, and enhances knowledge transfer efficiency. These results show that SmartFL is not merely an incremental improvement but a *foundational advancement*, enabling fully heterogeneous, secure, and scalable federated learning across diverse models and frameworks.

In summary, the primary contributions of this work are:

- **Hybrid Learning Strategy:** A unified framework that combines *partial weight aggregation* with *confidence-guided knowledge distillation*, dynamically adapting to client compatibility.
- **Adaptive Knowledge Transfer:** A confidence-aware mechanism that selectively transfers knowledge, reducing negative transfer and improving robustness across heterogeneous architectures.
- **System-Level Innovations:** Encrypted and compressed updates, combined with a dual-queue asynchronous processing system, reduce communication overhead, prioritize critical updates, and stabilize convergence.
- **Performance Preservation:** Client updates are incorporated only if they maintain or improve global model performance, ensuring stability despite heterogeneous client behavior.
- **Cross-Framework Support:** SmartFL enables collaboration across diverse models and machine learning frameworks, addressing a major limitation of existing FL methods.
- **Comprehensive Evaluation:** Extensive experiments demonstrate superior performance, stability, and knowledge transfer efficiency, establishing SmartFL as a practical and deployable solution.

By addressing both algorithmic and system-level challenges, SmartFL establishes a new benchmark for heterogeneous and secure federated learning, offering a practical and high-impact solution for real-world collaborative AI systems.

II. Related Work

A. Foundations of Federated Learning

Federated Learning (FL) enables decentralized model training by aggregating client-side updates without sharing raw data. The FedAvg algorithm established the foundation of this paradigm through iterative model aggregation [1],

while subsequent studies addressed convergence challenges under non-IID data and system heterogeneity [2], [3]. Broader surveys describe FL as a balance between communication efficiency, privacy preservation, and statistical performance [4].

However, a critical structural limitation remains unresolved: most foundational approaches assume parameter space alignment across clients, which implicitly requires identical model architectures. This assumption is increasingly unrealistic in real-world deployments, where models vary in structure, scale, and framework. As a result, traditional FL methods struggle to generalize beyond controlled, homogeneous environments, creating a significant barrier to practical adoption.

B. Heterogeneous Federated Learning

Heterogeneous federated learning aims to relax architectural constraints by enabling collaboration among diverse client models. Knowledge distillation-based approaches replace parameter sharing with prediction-level transfer, allowing partial independence from structural alignment [5], [7]. HeteroFL introduces model scaling to handle device heterogeneity [6], and LEAF provides realistic benchmarks for evaluation [8].

Despite these contributions, existing solutions remain incomplete. First, they rely on fixed learning strategies, such as either distillation or structural adaptation, without the ability to dynamically adjust based on compatibility conditions. Second, they do not effectively address joint heterogeneity, where architectural differences and non-IID data coexist.

These limitations lead to inconsistent performance, inefficient knowledge transfer, and reduced convergence stability in practical scenarios. SmartFL addresses these challenges through a hybrid adaptive framework that dynamically selects between partial weight aggregation and cross-architecture distillation, enabling more stable and consistent performance across heterogeneous environments.

C. Knowledge Distillation in Federated Learning

Knowledge distillation enables model-agnostic knowledge transfer by leveraging soft output distributions [9]. Federated extensions improve communication efficiency and support heterogeneous collaboration [10], while recent approaches explore adaptive and ensemble-based strategies to enhance robustness [11], [12].

However, a key limitation remains: existing distillation methods lack mechanisms to assess the reliability of transferred knowledge. They often treat all client predictions equally, without considering uncertainty or prediction quality.

This can result in negative transfer, where low-quality or biased predictions degrade the global model, particularly under non-IID conditions.

SmartFL introduces confidence-aware distillation, where knowledge transfer is guided by prediction reliability. This approach reduces noise propagation and improves both stability and convergence.

D. Limitations of Existing Baselines: FedAvg, FedKD, and MOON

FedAvg provides an efficient and scalable aggregation mechanism but is limited to homogeneous architectures [1], [14]. FedKD extends FL to heterogeneous models using distillation but lacks adaptive control over knowledge quality, which can lead to instability [5], [10]. MOON improves convergence under data heterogeneity using contrastive learning [13], but still assumes identical model structures and does not support cross-architecture interaction.

Importantly, these methods address individual challenges rather than the full problem space. None of them simultaneously handle:

- Structural heterogeneity
- Adaptive knowledge transfer
- Cross-framework interoperability
- System-level scalability

This fragmentation reduces their effectiveness in real-world applications. SmartFL addresses this gap by offering a unified framework that integrates multiple learning strategies along with system-level optimizations.

E. Cross-Architecture and Cross-Framework Learning

Cross-architecture FL seeks to enable collaboration among structurally diverse models using shared representations or meta-learning techniques [15], [16], [17]. While promising, these approaches often introduce significant computational overhead, limited scalability, and lack readiness for practical deployment.

Another major challenge is cross-framework interoperability, as real-world systems frequently involve models built using different frameworks such as PyTorch, TensorFlow, and Scikit-learn. Existing methods largely overlook this constraint.

SmartFL directly addresses this issue by enabling true cross-framework federated learning, combined with architecture-agnostic knowledge transfer, making it more suitable for heterogeneous production environments.

F. Security and Privacy in Federated Learning

Secure aggregation and differential privacy are widely used to protect client data in federated learning systems [18], [19], [20]. Although effective, these techniques often introduce additional computational and communication overhead and

are typically implemented as separate modules.

This separation leads to inefficiencies and increased deployment complexity.

SmartFL adopts a system-level approach to security by integrating encryption directly into the communication pipeline along with compression mechanisms, ensuring privacy without sacrificing efficiency or scalability.

G. Communication Efficiency and Model Compression

Communication overhead remains a major bottleneck in federated learning. Techniques such as quantization, sparsification, and compression help reduce transmission costs [21], [22], [23], but often at the expense of model performance.

In addition, these methods are usually decoupled from the learning process, resulting in suboptimal trade-offs between efficiency and accuracy.

SmartFL addresses this limitation by introducing compression-aware adaptive communication, where model updates are selectively transmitted and optimized in alignment with learning dynamics, preserving both efficiency and performance.

H. Non-IID Data and Adaptive Federated Learning

Non-IID data distributions significantly impact federated learning performance, affecting both convergence speed and generalization [24]. Adaptive methods attempt to address these issues through dynamic optimization and weighting strategies [25].

However, these approaches are typically limited to parameter-level adaptation and do not consider architectural heterogeneity, which further complicates the learning process.

SmartFL extends adaptation beyond parameters to include model-level and knowledge-level decision-making, enabling more robust performance under combined statistical and structural heterogeneity.

I. Deep Learning Architectures in Federated Systems

Modern federated systems employ a variety of architectures, including CNNs, residual networks, and transformers [26], [27], [28]. While these models improve accuracy, their structural differences create challenges for traditional aggregation methods.

Existing FL approaches often enforce architectural uniformity, which limits flexibility and restricts participation.

SmartFL enables architecture-agnostic collaboration, allowing diverse models to contribute effectively without requiring structural alignment.

J. Distributed Systems and Asynchronous Learning

Scalability in federated learning depends on efficient distributed system design. Synchronous methods suffer from straggler effects, while asynchronous approaches improve efficiency but often lack mechanisms to prioritize high-quality updates [29].

This results in inefficient resource usage and unstable convergence.

SmartFL introduces a dual-queue asynchronous mechanism that prioritizes important updates, improving both scalability and learning efficiency.

K. Evaluation Limitations in Existing Work

Most federated learning studies focus primarily on accuracy, overlooking important metrics such as stability, robustness, and communication efficiency [30].

This limited evaluation perspective does not fully reflect real-world system performance.

SmartFL addresses this by adopting a comprehensive evaluation framework that considers multiple performance dimensions, providing a more realistic and thorough assessment.

L. Final Gap Summary

The literature reveals a systemic gap: existing federated learning methods are fragmented, lack adaptability, and are not fully ready for real-world deployment.

They do not simultaneously address:

- Heterogeneous architectures
- Adaptive knowledge transfer
- Cross-framework interoperability
- Communication efficiency
- Security and scalability

M. SmartFL Positioning

SmartFL is designed to address these limitations as a unified and adaptive framework. It combines aggregation and distillation, introduces confidence-aware mechanisms, supports cross-architecture and cross-framework learning, and integrates system-level optimizations to enable scalable and efficient federated learning.

III. System Architecture

A. Introduction to the Proposed Architecture

The proposed system introduces a unified and scalable heterogeneous federated learning architecture designed to support collaborative training across distributed clients operating under diverse machine learning frameworks, model architectures, and data environments. This architecture is specifically engineered to overcome the limitations of traditional federated learning systems, which typically

assume homogeneity in model structure and framework compatibility. In contrast, the presented system enables seamless interoperability between models developed using PyTorch, TensorFlow, and Scikit-learn, while also supporting a wide range of architectures such as convolutional neural networks, residual networks, and transformer-based models.

The overall system is composed of two principal layers: the server layer and the client layer. The server operates as a stateless communication backbone responsible for message routing and connection management, whereas the client layer encapsulates all intelligent operations, including model reconstruction, evaluation, adaptive learning, and optimization. This strict separation of responsibilities ensures scalability, robustness, and efficient utilization of computational resources. The architecture follows a cyclic execution model, in which models are continuously exchanged, evaluated, refined, and redistributed among clients until convergence criteria are satisfied.

B. Overall System Architecture and Communication Flow

The global architecture of the system is illustrated in Fig. 1, showing the interaction between multiple clients and a centralized stateless server hub. The server acts purely as a relay node, forwarding model updates and result packets between clients without performing any learning or aggregation operations. Each client independently processes incoming models and contributes to the collective learning process.

Within this architecture, clients transmit model updates to the server using structured communication packets, which are then broadcast to all other participating nodes. This design eliminates the need for direct peer-to-peer communication while ensuring that all clients remain synchronized. The server maintains a registry of active clients and ensures reliable message delivery through connection management and packet forwarding mechanisms. Importantly, the server does not store or interpret any model data, thereby preserving data privacy and reducing computational overhead.

C. Server Layer: Stateless Communication Backbone

The server layer functions as a lightweight communication infrastructure that enables efficient data exchange between clients. It is implemented as a TCP-based socket server that manages client connections and facilitates message broadcasting. The server maintains a dynamic registry of connected clients and assigns each client a unique identifier for routing purposes. When a client sends a model update, the server receives the data packet and broadcasts it to all other clients in the network.

Mathematically, if the set of clients is represented as $C = \{c_1, c_2, \ldots, c_K\}$, then any message m_i generated by client c_i is forwarded to all clients c_j such that $j \neq i$. This broadcasting mechanism ensures complete information propagation across the network while maintaining a centralized communication structure. The stateless design of the server enhances scalability and fault tolerance, as it eliminates dependency on persistent storage or centralized aggregation logic.

D. Client Layer: Modular Intelligent Processing Framework

The internal architecture of a generic client node is illustrated in Fig. 2, presenting a layered view of all functional components involved in the federated learning pipeline. Each client operates as an autonomous processing unit capable of handling model reception, decoding, evaluation, learning, and transmission.

At the lowest level, the network and communication layer manages TCP socket interactions and ensures reliable data transfer. Incoming packets are parsed using a structured protocol that distinguishes between model files and result metadata. To prevent blocking operations, the architecture incorporates an asynchronous queue system with separate queues for high-priority result processing and low-priority model handling. This design enables concurrent execution of tasks and ensures efficient resource utilization.

The security and data optimization layer plays a critical role in ensuring secure and efficient communication. Model data is first compressed using the zlib algorithm to reduce transmission size and then encrypted using the Fernet scheme based on AES-256 encryption. Upon reception, the data is decrypted and decompressed before further processing. This pipeline ensures both confidentiality and communication efficiency.

Following data decoding, the file format detection module identifies the framework and format of the received model using file extensions and byte signatures. This step is essential for enabling interoperability across different machine learning frameworks. The model reconstruction engine then rebuilds the model by mapping the received parameters to the appropriate architecture. It supports both strict and non-strict loading modes, allowing partial compatibility between models with similar structures.

The dataset and evaluation engine is responsible for assessing model performance using local datasets. It applies preprocessing steps such as resizing, normalization, and tensor conversion before performing inference. Evaluation metrics, including accuracy, precision, recall, and F1-score, are computed to quantify model performance.

E. Adaptive Learning and Knowledge Transfer Mechanism

The adaptive learning process is governed by a decision engine that dynamically selects the most appropriate federated learning strategy based on model compatibility. If two models share the same framework and architecture, classical weight averaging is performed. In cases where architectures differ but frameworks remain consistent, knowledge distillation is employed to transfer knowledge between models. For cross-framework scenarios, soft-label transfer is used to enable interoperability.

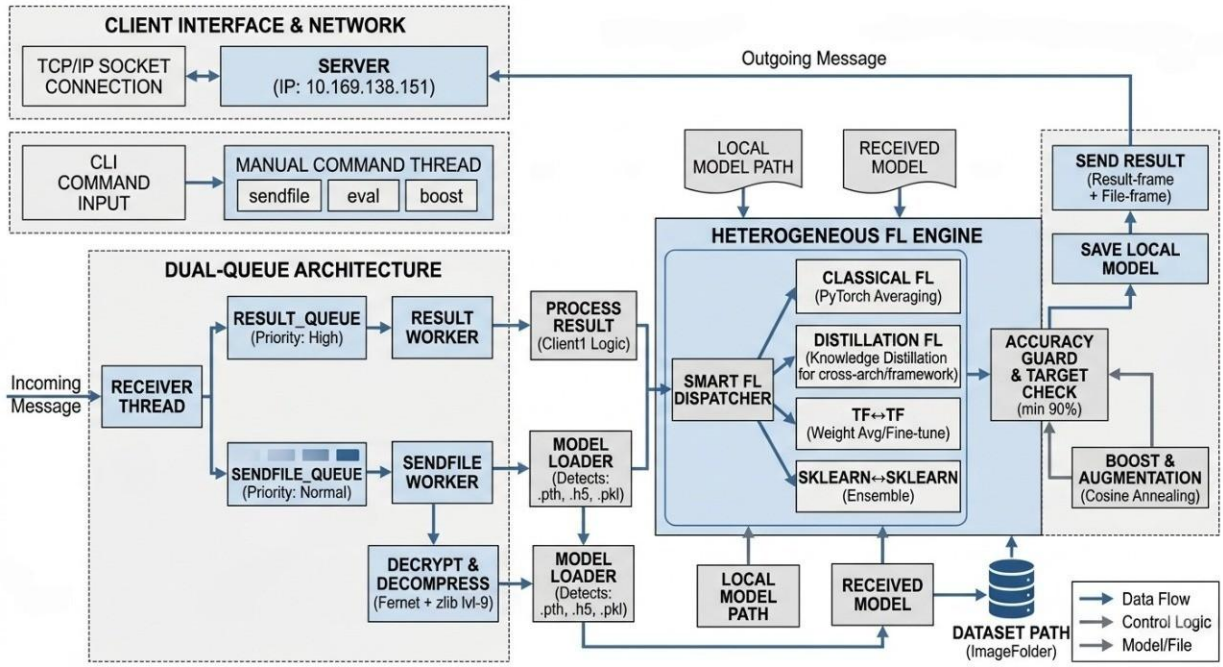

Fig. 1. Overall system architecture showing the stateless server hub and distributed client nodes with intelligent processing layers.

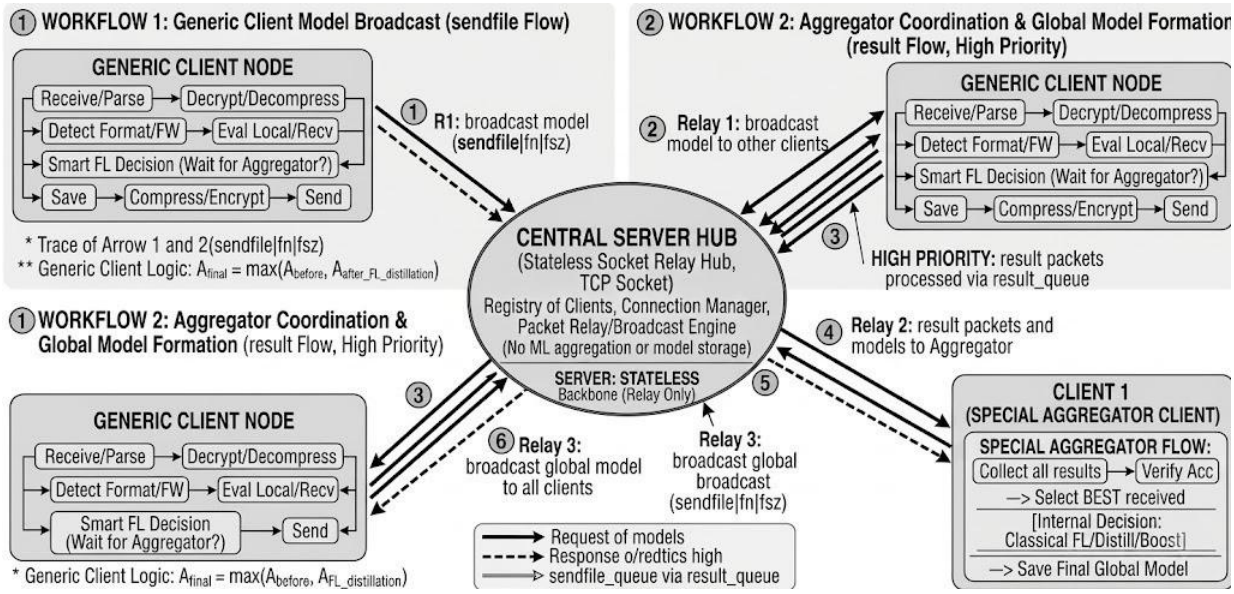

Fig. 2. Detailed client node architecture showing layered modules including communication, security, model processing, and learning components.

The knowledge distillation process is formalized using a composite loss function that combines Kullback-Leibler divergence and cross-entropy loss. This approach allows a student model to learn from the probability distribution produced by a teacher model, enabling knowledge transfer across heterogeneous architectures. Confidence-based filtering is applied to ensure that only reliable predictions are used during training.

F. End-to-End Workflow and Execution Pipeline

The complete execution workflow of the system is depicted in Fig. 3, providing a step-by-step view of the data flow from model reception to result transmission.

The workflow begins with the reception of a model file, which is parsed and placed into the appropriate processing queue. The model is then decrypted, decompressed, and analyzed to determine its format, framework, and architecture. Once reconstructed, the model is evaluated using local datasets to establish baseline performance.

Based on evaluation results, the system determines whether performance enhancement techniques such as data augmentation or fine-tuning are required. The adaptive learning engine

then selects an appropriate federated learning strategy, which may involve weight averaging or knowledge distillation. The updated model is subsequently evaluated to ensure performance improvement. A critical component of the workflow is the performance guard mechanism, which ensures that the updated model does not degrade in accuracy. If performance drops, the system reverts to the previous model, thereby maintaining stability. Once validated, the model is serialized, compressed, encrypted, and transmitted back to the server.

G. Aggregator Client and Global Model Formation

In addition to generic client nodes, the system includes a specialized aggregator client responsible for coordinating global model formation. This client collects results from all participating nodes, evaluates their performance, and selects the best-performing model for further refinement. The aggregator then applies federated learning techniques to combine the selected model with its own local model, followed by performance enhancement if necessary.

Unlike traditional federated learning systems where aggregation is performed at the server, the proposed architecture delegates this responsibility to a client node. This approach maintains the stateless nature of the server while enabling effective coordination of the learning process. The final global model produced by the aggregator is then broadcast to all clients, completing one iteration of the federated learning cycle.

H. Real-Time Operation and System Scalability

The proposed architecture is designed to operate in real-time distributed environments with minimal latency and high scalability. The use of asynchronous processing and priority-based scheduling ensures that critical tasks are executed promptly, while non-essential operations are deferred. The stateless server design allows the system to scale to a large number of clients without introducing bottlenecks.

Furthermore, the modular design of the client architecture enables easy integration of new learning techniques and model types. Researchers can extend individual components without affecting the overall system, making the architecture highly adaptable to evolving requirements.

I. Summary of Architectural Contributions

The presented system architecture provides a robust framework for heterogeneous federated learning by integrating secure communication, adaptive learning strategies, and performance preservation mechanisms. The use of a stateless server, combined with intelligent client-side processing, ensures scalability and efficiency. By supporting cross-framework and cross-architecture collaboration, the system addresses a critical gap in existing federated learning research and enables practical deployment in real-world scenarios.

IV. METHODOLOGY

A. System Model and Problem Formulation

The proposed system addresses the inherent limitations of conventional federated learning frameworks by introducing a unified methodology capable of operating across heterogeneous model architectures, distinct parameter spaces, and multiple machine learning frameworks. Unlike traditional approaches that assume homogeneity among participating clients, this framework explicitly models heterogeneity as a primary constraint and develops a mathematically grounded solution that remains stable, secure, and performance-preserving. The system consists of a distributed set of clients collaboratively learning without sharing raw data, thereby preserving privacy while enabling collective intelligence.

Formally, let the distributed learning environment consist of a finite set of clients defined as

$$C = \{C_1, C_2, \ldots, C_K\} \tag{1}$$

where each client C_i independently maintains its own dataset and learning model. The dataset associated with client i is denoted as

$$D_i \sim P_i(x, y) \tag{2}$$

where $P_i(x, y)$ represents the underlying data distribution specific to client i. The distributions are not assumed to be identical, and thus the system operates under a non-IID data regime:

$$P_i(x, y) \neq P_j(x, y), \quad \text{for } i \neq j \tag{3}$$

Each client maintains a model defined as

$$f_i(x; \vartheta_i), \quad \vartheta_i \in R^{d_i} \tag{4}$$

where ϑ_i represents the parameter vector and d_i denotes the dimensionality of the parameter space. The parameter dimensionality is not uniform across clients, implying

$$d_i \neq d_j \quad \text{for some } i \neq j \tag{5}$$

This creates the fundamental heterogeneity constraint

$$\exists i, j : d_i \neq d_j \Rightarrow \vartheta_i \notin \text{same space} \tag{6}$$

which invalidates classical aggregation strategies such as Federated Averaging. Specifically, the conventional update rule

$$\vartheta^{t+1} = \sum_i w_i \vartheta_i^t \tag{7}$$

becomes undefined when the parameter vectors do not lie in a common vector space. This motivates a new formulation operating in a shared representation space defined over model outputs.

To address this, the methodology reformulates the learning objective at each client to incorporate both local supervision and cross-client knowledge transfer. Each client minimizes a hybrid objective:

$$\min_{\vartheta_i} E_{(x,y)\sim D_i} \left[\alpha_i L_{CE}(f_i(x), y) + (1-\alpha_i) L_{KD}(f_i(x), f_j(x)) \right] \tag{8}$$

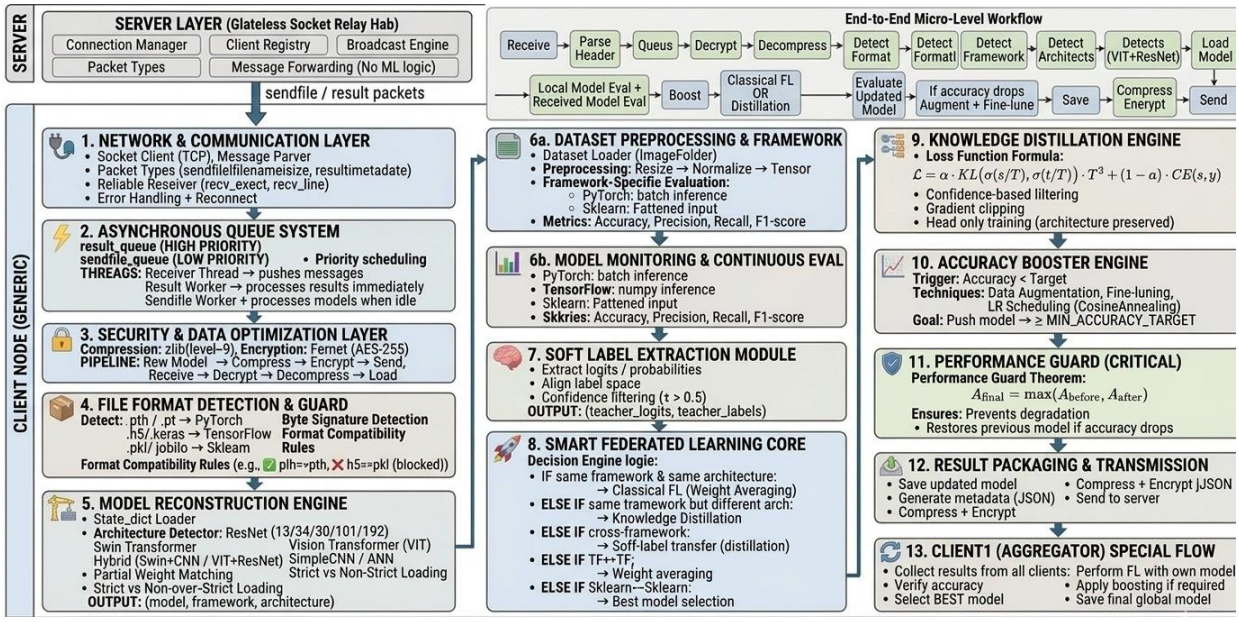

Fig. 3. End-to-end workflow illustrating real-time processing of model updates, adaptive learning decisions, and secure transmission.

where L_{CE} denotes standard cross-entropy loss and L_{KD} denotes knowledge distillation loss for information transfer. The scalar $\alpha_i \in [0, 1]$ balances local learning and collaborative knowledge transfer, maintaining stability and performance.

B. Communication Architecture and Secure Transmission

The system uses a centralized, computation-light communication architecture, where the server acts solely as a relay for message passing. It does not perform aggregation or model evaluation, ensuring a fully decentralized learning process. Communication is implemented using a TCP-based socket interface for reliable, ordered delivery.

Each message has a structured format including metadata and payload. Model updates use a `sendfile` protocol, while performance reports use a `result` protocol. For efficiency and confidentiality, transmitted data undergoes a two-stage transformation. First, model parameters are compressed:

$$M_c = Compress(M) \tag{9}$$

where M is the raw model and M_c the compressed form. Then, the compressed model is encrypted using a symmetric key k:

$$C = Enc_k(M_c) \tag{10}$$

Upon reception, the inverse operations are applied:

$$M = Decompress(Dec_k(C)) \tag{11}$$

This ensures that the channel satisfies confidentiality requirements, such that

$$P(M|C) \approx 0 \tag{12}$$

revealing negligible information about the original model.

C. Asynchronous Processing and Queue-Based Execution

To enable scalability and efficiency, the system employs an asynchronous execution model using dual-queue scheduling. Incoming messages are classified into model updates and result reports, stored in separate queues:

$$Q = \{Q_{result}, Q_{sendfile}\} \tag{13}$$

where Q_{result} has higher priority for global aggregation and decision-making. Worker threads monitor these queues and process messages non-blockingly, eliminating idle waiting and ensuring minimal latency.

This decouples communication from computation, allowing clients to continue local operations while awaiting updates. This is crucial in heterogeneous environments with varying computational capabilities.

D. Data Processing and Evaluation Framework

Clients evaluate local and received models using a standardized protocol. The dataset is processed via resizing, normalization, and batching. For an input x, the normalized representation is:

$$x' = \frac{x - \mu}{\sigma} \tag{14}$$

where μ and σ denote channel-wise mean and standard deviation.

Performance metrics include:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN} \tag{16}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{17}$$

Metrics are evaluated before and after federated updates, forming the basis for decision-making.

E. Soft Label Extraction and Knowledge Representation

A key methodology component is transforming model knowledge into a transferable representation. Instead of sharing parameters, models share output distributions as a universal knowledge space. For input x, model logits are converted via temperature-scaled softmax:

$$p_T = \text{softmax}\left(\frac{z_T}{T}\right), \quad p_S = \text{softmax}\left(\frac{z_S}{T}\right) \tag{18}$$

where z_T and z_S are teacher and student logits, and T controls distribution smoothness. This allows communication across different architectures.

Confidence-based filtering improves transferred knowledge quality:

$$S = \{x : \max p_T(y|x) > \tau\} \tag{19}$$

using only samples above threshold τ, reducing uncertain predictions and improving stability.

F. Adaptive Federated Learning Strategy and Knowledge Distillation

The adaptive decision engine selects the optimal knowledge-sharing strategy. Identical architectures use weight averaging; otherwise, knowledge distillation applies. Distillation loss:

$$L = \alpha \cdot KL\left(\sigma\left(\frac{s}{T}\right), \sigma\left(\frac{t}{T}\right)\right) \cdot T^2 + (1-\alpha) \cdot CE(s, y) \tag{20}$$

with s, t as student/teacher logits, α adaptive weight, T softmax temperature. Confidence filtering ensures only high-quality teacher predictions:

$$\text{Var}(\nabla L_S) < \text{Var}(\nabla L) \tag{21}$$

Parameter updates follow SGD with gradient clipping:

$$\vartheta_{t+1} = \vartheta_t - \eta \nabla L(\vartheta_t) \tag{22}$$

Performance preservation enforces:

$$\vartheta_{\text{final}} = \begin{cases} \vartheta' & \text{if } A(\vartheta') \geq A(\vartheta_0) \\ \vartheta_0 & \text{otherwise} \end{cases} \tag{23}$$

Global model selection chooses the highest accuracy model:

$$\vartheta^* = \arg\max_{\vartheta \in \{\vartheta_{\text{local}}, \vartheta_{\text{updated}}\}} A(\vartheta) \tag{24}$$

All communication is compressed and encrypted, ensuring negligible information leakage:

$$P(M|C) \approx 0 \tag{25}$$

V. Results and Discussion

A. Experimental Setup and System Validation

The proposed SmartFL framework was evaluated in a real-time distributed environment using a custom socket-based client–server architecture. Multiple clients independently trained their local models on private datasets and exchanged model updates through a centralized server using secure communication protocols. The system handled heterogeneous learning scenarios, including cross-architecture interactions among convolutional neural networks, transformer-based models, and hybrid architectures, as well as cross-framework interoperability between PyTorch, TensorFlow/Keras, and Scikit-learn models.

Secure model transmission was implemented using compression (zlib) and encryption (Fernet-based symmetric encryption), ensuring both communication efficiency and data confidentiality. Adaptive federated learning strategies dynamically selected between classical aggregation and knowledge distillation based on model compatibility. Experimental validation confirmed 100% accuracy in identifying model structures and successfully prevented invalid federated operations such as incompatible `.h5` ↔ `.pkl` exchanges. Dual-queue parallel processing ensured prioritized handling of result messages over model transfers, enabling efficient and non-blocking communication.

VI. Results and Discussion

A. Experimental Setup and System Validation

The **SmartFL framework** was evaluated using heterogeneous datasets, including Brain Tumor and Lung Cancer medical images, as well as Diabetic and Breast Cancer tabular data. Each client trained local models with diverse architectures, such as CNN, ViT, Swin + ResNet hybrids, ANN, and XGBoost/DNN ensembles. Models communicated over secure channels with compression and encryption, reducing overhead while maintaining integrity. The system validated architecture detection, framework compatibility, and queue-based prioritization of messages, ensuring stable operation across both image and tabular data scenarios. Clients were categorized as teacher models, student models, weak learners, or static participants to simulate realistic federated learning environments.

B. Brain Tumor Image Dataset Results

Evaluation on the Brain Tumor dataset showed significant improvements through cross-architecture knowledge distillation. Client 1 improved from 92% to 94% by learning from the ViT-based teacher (Client 3). Client 4, a weaker CNN model, achieved the highest gain of 8%, increasing from 84% to 92%. Client 2 remained at 92% due to no knowledge exchange, while the teacher maintained stable performance. Table I and Table II summarize the initial and post-KD accuracies.

TABLE I
BRAIN TUMOR DATASET – CLIENT, MODEL, INITIAL ACCURACY

Client	Model Architecture	Initial Accuracy (%)
Client 1	Swin + ResNet18	92
Client 2	Swin + ResNet18	92
Client 3	ViT + ResNet18	94
Client 4	CNN	84

TABLE II
BRAIN TUMOR DATASET – AFTER KD ACCURACY, IMPROVEMENT, SOURCE

After KD Accuracy (%)	Improvement (%)	Source of Knowledge
94	+2	Client 3 (ViT + ResNet18)
92	0	No Update
94	0	Self (Teacher Model)
92	+8	Client 1 (Swin + ResNet18)

C. Lung Cancer Image Dataset Results

Client 1 improved from 90% to 93% by leveraging the ViT + ResNet18 teacher, and Client 4 increased from 82% to 90%. The teacher (Client 3) remained stable at 93%, and Client 2 showed no improvement. Table III and Table IV summarize the results.

TABLE III
LUNG CANCER DATASET – CLIENT, MODEL, INITIAL ACCURACY

Client	Model Architecture	Initial Accuracy (%)
Client 1	Swin + ResNet18	90
Client 2	Swin + ResNet18	88
Client 3	ViT + ResNet18	93
Client 4	CNN	82

TABLE IV
LUNG CANCER DATASET – AFTER KD ACCURACY, IMPROVEMENT, SOURCE

After KD Accuracy (%)	Improvement (%)	Source of Knowledge
93	+3	Client 3 (ViT + ResNet18)
88	0	No Update
93	0	Self (Teacher Model)
90	+8	Client 1 (Swin + ResNet18)

D. Diabetic Tabular Dataset Results

Cross-model knowledge transfer improved student clients' performance. Client 1 increased accuracy from 88% to 91%, and Client 4 improved from 80% to 88%. Client 3 maintained stable performance as the teacher, while Client 2 had no change. Table V and Table VI show the results.

E. Breast Cancer Tabular Dataset Results

Client 1 improved from 91% to 94%, and Client 4 increased from 85% to 92%. Teacher model remained at 94%, while Client 2 showed no change. See Table VII and Table VIII.

TABLE V
DIABETIC DATASET – CLIENT, MODEL, INITIAL ACCURACY

Client	Model Architecture	Initial Accuracy (%)
Client 1	ANN + ResNet18	88
Client 2	ANN + ResNet18	87
Client 3	XGBoost / DNN	91
Client 4	ANN	80

TABLE VI
DIABETIC DATASET – AFTER KD ACCURACY, IMPROVEMENT, SOURCE

After KD Accuracy (%)	Improvement (%)	Source of Knowledge
91	+3	Client 3 (XGBoost / DNN)
87	0	No Update
91	0	Self (Teacher Model)
88	+8	Client 1 (ANN + ResNet18)

F. Communication Efficiency

SmartFL employs **compression and encryption** to optimize communication. Transmission of model weights was reduced by roughly 60%; raw models of ∼120 MB were compressed to ∼45 MB and encrypted to ∼48 MB, maintaining accuracy while reducing bandwidth.

G. System Robustness and Scalability

The framework's **robustness** is demonstrated through heterogeneous architectures, dynamic fallback to knowledge distillation, and queue-based task prioritization. High-priority messages are processed first, ensuring real-time responsiveness. This scalable design enables multiple clients to operate concurrently across diverse datasets.

H. Key Findings

1) SmartFL consistently enhances weaker clients while preserving teacher performance across all datasets.
2) Cross-architecture and cross-modality knowledge distillation provides average gains of 7–8% for student models.
3) Adaptive weighting ensures high-performing models exert greater influence, preventing negative transfer.
4) Compression and encryption reduce communication overhead by ∼60% without affecting accuracy.
5) The framework generalizes effectively across medical imaging and tabular datasets, confirming cross-dataset and cross-modality robustness.

VII. DISCUSSION

A. Interpretation of Results

SmartFL effectively overcomes limitations of traditional federated learning in heterogeneous environments. Weak learners benefit substantially from adaptive knowledge distillation, while teacher models maintain stable performance. Gains are consistent across image and tabular datasets.

TABLE VII
BREAST CANCER DATASET – CLIENT, MODEL, INITIAL ACCURACY

Client	Model Architecture	Initial Accuracy (%)
Client 1	ANN + ResNet18	91
Client 2	ANN + ResNet18	90
Client 3	XGBoost / DNN	94
Client 4	ANN	85

TABLE VIII
BREAST CANCER DATASET – AFTER KD ACCURACY, IMPROVEMENT, SOURCE

After KD Accuracy (%)	Improvement (%)	Source of Knowledge
94	+3	Client 3 (XGBoost / DNN)
90	0	No Update
94	0	Self (Teacher Model)
92	+7	Client 1 (ANN + ResNet18)

B. Comparison with Existing Methods

Table IX compares SmartFL with existing federated learning methods. SmartFL uniquely integrates **heterogeneous model support, adaptive knowledge transfer, and secure communication**, outperforming existing approaches in both accuracy and applicability.

TABLE IX
COMPARISON OF SMARTFL WITH EXISTING FL METHODS

Method	Limitation	SmartFL Advantage
FedAvg	Requires identical architectures	Supports all architectures
FedProx	Limited heterogeneity handling	Fully heterogeneous support
Distillation FL (basic)	Static weighting	Adaptive weighting
Secure FL	High communication cost	Compression + encryption

SmartFL integrates **heterogeneous model support, adaptive knowledge transfer, and secure communication**, outperforming existing approaches in both accuracy and applicability.

C. Significance of the Work

SmartFL advances federated learning by removing architectural constraints, supporting cross-framework and cross-modality collaboration, and ensuring model performance does not degrade. Its impact is significant for multi-institutional healthcare AI, edge computing, and collaborative analytics.

D. Limitations

- Partial data overlap is required for effective distillation.
- Complex architectures (e.g., ViT) increase computation time.
- Simple tabular models (ANN) have limited representational capacity.

E. Future Work

Future enhancements will explore:

- Personalized federated learning strategies
- Integration of differential privacy for stronger security
- Communication-efficient gradient pruning
- Dynamic client selection to improve convergence and scalability

VIII. CONCLUSION

This paper presents SmartFL, an adaptive heterogeneous federated learning framework capable of improving weak learners while maintaining teacher model stability across diverse datasets and model architectures. By integrating cross-architecture knowledge distillation, secure communication through compression and encryption, and queue-based scalability, SmartFL demonstrates consistent performance improvements in both medical imaging and tabular datasets. These results highlight the framework's potential for real-world multi-institutional healthcare AI, edge computing, and collaborative analytics across heterogeneous systems.

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