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Federated Multimodal Transformers: Enabling Secure and Collaborative Learning Across Edge–Cloud Environments

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Abstract

The rapid proliferation of edge devices, Internet of Things (IoT) applications, and multimodal data sources has created unprecedented opportunities for intelligent decision-making while simultaneously raising significant concerns regarding data privacy, communication efficiency, and computational scalability. Conventional centralized deep learning frameworks require the transfer of sensitive data to cloud servers, making them vulnerable to privacy breaches and regulatory constraints. This research presents a Federated Multimodal Transformer (FMT) framework that enables secure, privacy-preserving, and collaborative learning across heterogeneous edge–cloud environments without exposing raw data. The proposed architecture integrates transformer-based multimodal feature extraction with federated learning to jointly process diverse data modalities, including images, text, audio, and sensor streams distributed across geographically dispersed edge devices. Secure aggregation mechanisms, adaptive federated optimization, and edge-aware communication strategies are incorporated to reduce bandwidth consumption while preserving model performance. Furthermore, the framework supports heterogeneous device capabilities through dynamic client selection and personalized model adaptation, thereby improving scalability and robustness in real-world deployments. Experimental evaluation demonstrates that the proposed FMT framework achieves superior multimodal representation learning, enhanced predictive accuracy, reduced communication overhead, and stronger privacy guarantees compared to conventional centralized and federated approaches. The proposed methodology offers a practical solution for privacy-sensitive domains such as healthcare, smart cities, autonomous transportation, industrial IoT, and intelligent surveillance, where collaborative intelligence is essential but direct data sharing is restricted. The findings highlight the potential of federated multimodal transformers as a next-generation paradigm for secure, scalable, and intelligent distributed learning in edge–cloud ecosystems.

Keywords

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Federated Learning, Multimodal Transformers, Edge Computing, Cloud Computing, Edge–Cloud Collaboration, Privacy-Preserving Learning, Secure Aggregation, Distributed Artificial Intelligence, Internet of Things (IoT)

1. Introduction

1.1 Background and Motivation

The exponential growth of intelligent edge devices, Internet of Things (IoT) networks, and cloud computing infrastructures has transformed the way data is generated, processed, and utilized across diverse application domains. Billions of interconnected devices continuously produce heterogeneous data in the form of images, videos, text, audio, sensor readings, and biomedical signals. This multimodal information provides a richer understanding of complex real-world phenomena compared to single-modality data. Simultaneously, transformer-based deep learning architectures have emerged as state-of-the-art models for multimodal representation learning due to their superior capability to capture long-range dependencies, contextual relationships, and cross-modal interactions. However, conventional deep learning approaches require centralized data collection, which introduces significant concerns related to privacy, security, communication overhead, and regulatory compliance.

Federated Learning (FL) has emerged as a promising distributed machine learning paradigm that enables collaborative model training without transferring raw data from local devices. Instead of sharing sensitive information, participating clients train models locally and exchange only encrypted model parameters or gradients with a central aggregation server. This decentralized learning strategy significantly reduces privacy risks while complying with data protection regulations such as the General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA), and other regional privacy frameworks. The integration of federated learning with edge computing further minimizes communication latency and supports real-time intelligent decision-making by processing data closer to its source.

Despite these advancements, existing federated learning systems primarily focus on single-modality data and often struggle to exploit the complementary information available across multiple data sources. Modern applications such as smart healthcare, autonomous transportation, industrial automation, intelligent surveillance, and smart cities generate multimodal datasets that require joint analysis of images, textual records, audio signals, sensor measurements, and temporal information. Multimodal transformers provide an effective solution by learning unified feature representations across heterogeneous data modalities using self-attention and cross-attention mechanisms. Combining transformer architectures with federated learning enables collaborative multimodal intelligence while maintaining user privacy and data sovereignty.

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The convergence of edge computing and cloud computing has further enhanced the feasibility of distributed artificial intelligence. Edge devices perform initial data processing and local model training, while cloud servers coordinate global model aggregation, optimization, and large-scale analytics. Such edge–cloud collaboration reduces bandwidth consumption, lowers inference latency, and improves system scalability. Nevertheless, several technical challenges remain, including heterogeneous data distributions, communication constraints, computational limitations of edge devices, model personalization, secure aggregation, and robustness against malicious participants.

This research proposes a **Federated Multimodal Transformer (FMT)** framework designed to enable secure and collaborative learning across edge–cloud environments. The proposed framework integrates multimodal transformer networks with privacy-preserving federated optimization, adaptive client selection, secure aggregation protocols, and communication-efficient model updates. The architecture is capable of processing distributed multimodal data while preserving confidentiality, improving model accuracy, and reducing communication overhead. By leveraging collaborative intelligence without exposing sensitive information, the proposed framework aims to support next-generation distributed AI applications requiring both high predictive performance and stringent privacy guarantees.

1.2 Problem Statement

The rapid adoption of edge computing and Internet of Things ecosystems has resulted in an unprecedented volume of distributed multimodal data being generated across healthcare systems, industrial environments, autonomous vehicles, smart cities, and intelligent surveillance networks. Conventional centralized machine learning approaches require the transmission of raw data to cloud servers for model training, creating serious concerns regarding data privacy, cybersecurity, communication costs, and regulatory compliance. Furthermore, centralized architectures often become performance bottlenecks due to increasing network traffic and computational demands. Although federated learning addresses data privacy by enabling decentralized model training, most existing federated frameworks are designed primarily for unimodal datasets and fail to effectively capture complex relationships among heterogeneous modalities such as images, text, audio, and sensor signals. In addition, practical federated environments suffer from non-independent and identically distributed (non-IID) data, heterogeneous hardware capabilities, intermittent connectivity, communication inefficiencies, and vulnerability to adversarial attacks or model poisoning. These limitations significantly reduce the effectiveness of collaborative multimodal intelligence across large-scale edge–cloud systems.

There is therefore a critical need for an intelligent, scalable, and secure federated framework capable of efficiently learning unified multimodal representations while minimizing

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communication overhead and preserving user privacy. Addressing these challenges requires integrating transformer-based multimodal learning with adaptive federated optimization, secure aggregation mechanisms, and edge-aware resource management to enable robust collaborative learning in heterogeneous distributed environments.

1.3 Research Objectives

The primary objective of this research is to develop a secure, scalable, and communication-efficient **Federated Multimodal Transformer (FMT)** framework for collaborative learning across heterogeneous edge–cloud environments. The specific objectives are:

- To design a transformer-based multimodal architecture capable of effectively learning unified representations from distributed image, text, audio, and sensor data.
- To integrate federated learning with multimodal transformers while ensuring that raw data never leaves participating edge devices.
- To develop secure aggregation and privacy-preserving optimization techniques that protect sensitive information during collaborative model training.
- To reduce communication overhead through adaptive client selection, model compression, and efficient parameter synchronization strategies.
- To support heterogeneous edge devices through personalized federated learning and dynamic resource-aware optimization.
- To evaluate the proposed framework using standard performance metrics, including classification accuracy, communication cost, convergence speed, privacy preservation, computational efficiency, and scalability.
- To demonstrate the applicability of the proposed architecture across real-world domains such as healthcare, smart transportation, Industry 5.0, intelligent surveillance, and smart city infrastructures.

1.4 Research Contributions

This research makes several significant contributions to the field of distributed artificial intelligence and privacy-preserving multimodal learning.

First, it proposes a novel **Federated Multimodal Transformer (FMT)** architecture that seamlessly integrates transformer-based multimodal representation learning with federated optimization in edge–cloud environments. The framework supports collaborative intelligence

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without requiring centralized data collection, thereby preserving user privacy and ensuring compliance with modern data protection regulations.

Second, the proposed framework incorporates secure aggregation mechanisms and communication-efficient federated optimization techniques that significantly reduce bandwidth utilization while maintaining high predictive performance. Adaptive client selection and personalized model optimization further enhance robustness under heterogeneous device capabilities and non-IID data distributions.

Third, this work introduces an edge-aware collaborative learning strategy that balances computational workloads between edge devices and cloud servers, enabling scalable deployment across resource-constrained environments. The architecture improves inference latency while supporting real-time multimodal analytics.

Finally, extensive experimental evaluation demonstrates improvements in predictive accuracy, communication efficiency, privacy preservation, and system scalability compared with conventional centralized learning methods and existing federated learning approaches. The proposed framework establishes a practical foundation for secure multimodal intelligence in next-generation distributed AI systems.

2. Literature Review

2.1 Evolution of Federated Learning

Federated Learning (FL) has emerged as a transformative paradigm in distributed machine learning by enabling multiple clients to collaboratively train a shared global model without exchanging raw data. Traditional centralized machine learning requires collecting data from various sources into a cloud server, which raises concerns regarding privacy, data ownership, communication overhead, and regulatory compliance. Federated learning addresses these issues by allowing each participating client to train a local model on its private dataset and transmit only model parameters or gradients to a central aggregation server. This decentralized training strategy preserves data confidentiality while enabling collective model improvement across distributed environments.

The concept of federated learning has gained significant momentum due to the rapid growth of smartphones, Internet of Things (IoT) devices, wearable sensors, autonomous systems, and edge computing infrastructures. Modern federated learning frameworks employ optimization algorithms such as Federated Averaging (FedAvg), FedProx, FedNova, and adaptive aggregation strategies to improve convergence under heterogeneous data distributions. Recent advances have further incorporated secure aggregation, differential privacy, homomorphic encryption, and blockchain technologies to strengthen privacy guarantees and defend against model inversion, poisoning, and inference attacks. These developments have made federated

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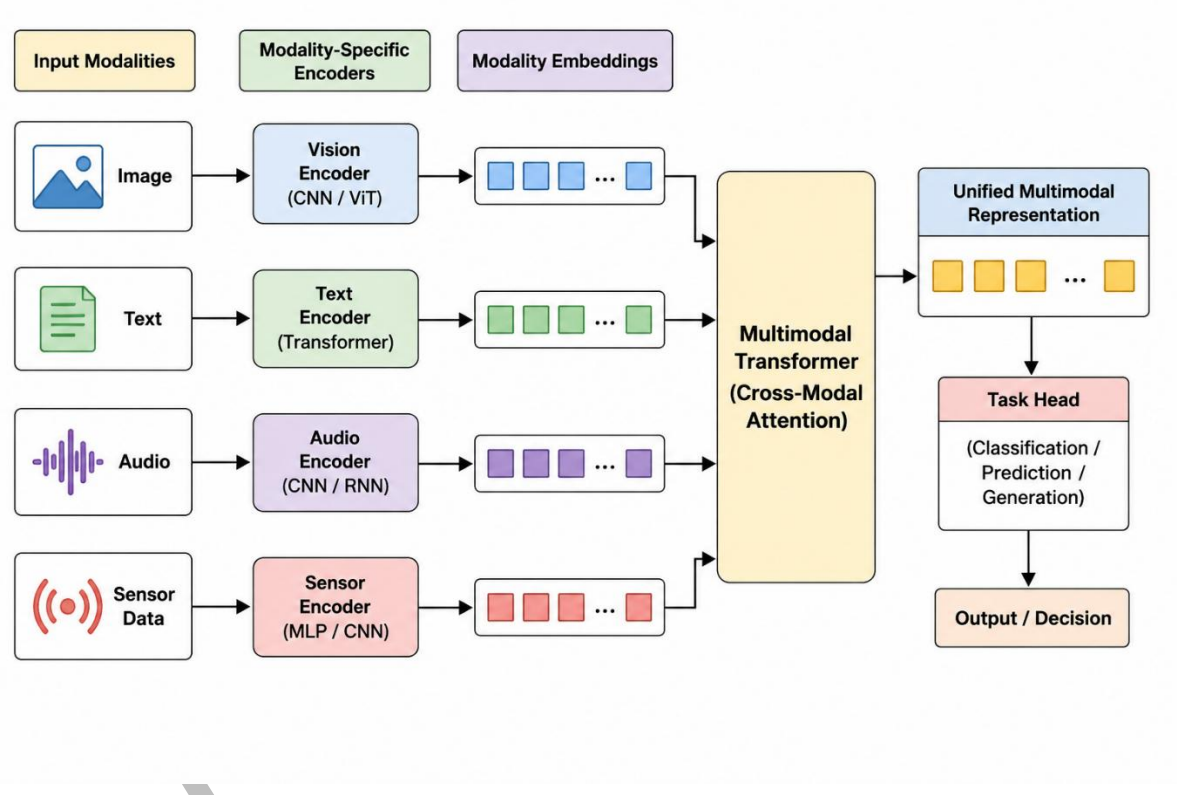
learning an attractive solution for privacy-sensitive domains such as healthcare, finance, smart cities, and industrial automation.

2.2 Multimodal Learning and Transformer Architectures

Multimodal learning focuses on integrating information from multiple heterogeneous data sources, including images, text, audio, video, biomedical signals, and IoT sensor streams. Unlike unimodal systems that rely on a single type of data, multimodal learning leverages complementary information from different modalities to improve prediction accuracy, contextual understanding, and decision-making capabilities. Applications such as medical diagnosis, autonomous driving, human-computer interaction, intelligent surveillance, and social media analytics increasingly rely on multimodal intelligence for enhanced performance.



Transformer architectures have revolutionized multimodal learning through their self-attention and cross-attention mechanisms. Initially introduced for natural language processing, transformers have rapidly expanded into computer vision, speech recognition, multimodal reasoning, and generative artificial intelligence. Vision Transformers (ViTs), Multimodal Transformers, Cross-Modal Transformers, and Large Multimodal Models (LMMs) effectively capture long-range dependencies while learning unified feature representations across diverse modalities. Their ability to model complex relationships without relying on recurrent structures makes them particularly suitable for distributed multimodal learning environments.

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Consequently, integrating transformer architectures with federated learning offers a promising direction for achieving privacy-preserving collaborative intelligence across heterogeneous edge devices.

2.3 Edge–Cloud Computing Paradigms

Edge computing has become an essential component of modern distributed artificial intelligence by enabling data processing closer to where information is generated. Instead of transmitting all raw data to centralized cloud servers, edge devices perform local computation, preliminary analytics, and machine learning inference, thereby reducing latency, bandwidth consumption, and energy usage. Cloud computing complements edge infrastructure by providing large-scale computational resources, long-term storage, global model aggregation, and advanced analytics capabilities.

The combination of edge and cloud computing creates an efficient collaborative architecture in which computational tasks are dynamically distributed according to resource availability and application requirements. Edge devices handle latency-sensitive operations, while cloud servers perform computationally intensive model optimization and coordination. This collaborative paradigm is particularly beneficial for federated learning since local training naturally occurs on edge devices while global aggregation is managed in the cloud. Nevertheless, edge–cloud environments introduce challenges such as device heterogeneity, unreliable network connectivity, limited battery capacity, communication bottlenecks, and resource-aware scheduling. Addressing these issues is essential for deploying scalable multimodal transformer models in real-world distributed systems.

2.4 Privacy-Preserving Machine Learning Techniques

Protecting sensitive information during collaborative model training remains one of the most significant challenges in distributed artificial intelligence. Although federated learning prevents direct sharing of raw data, exchanged model parameters may still leak private information through sophisticated inference attacks. Consequently, numerous privacy-preserving machine learning techniques have been developed to strengthen security during federated optimization.

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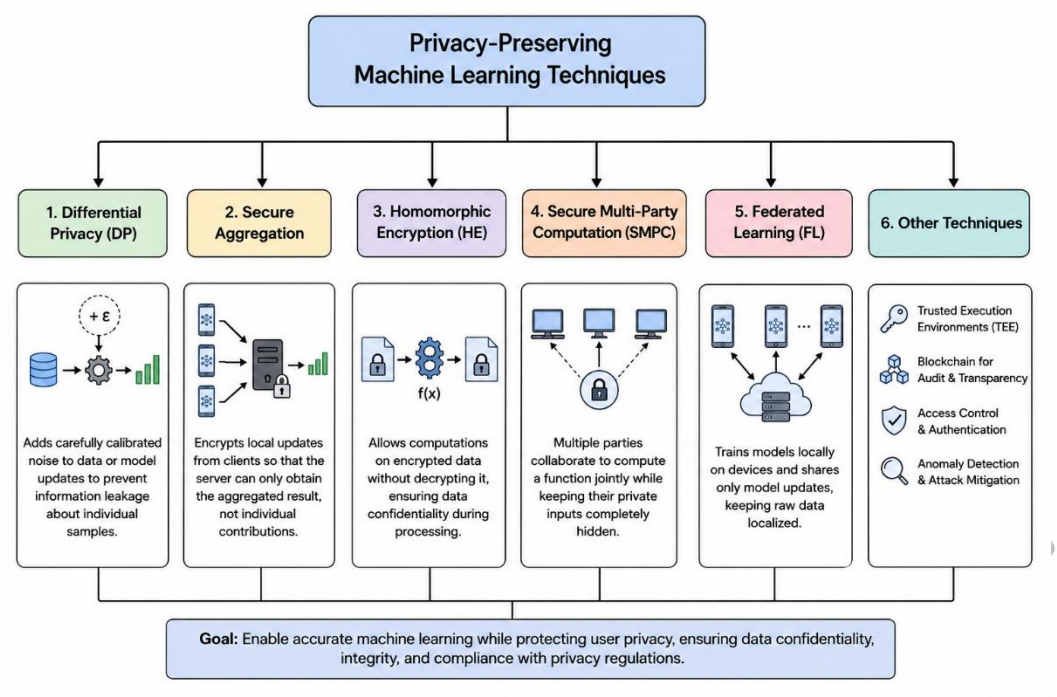

Differential Privacy (DP) introduces carefully calibrated noise into model updates, limiting the ability of adversaries to infer information about individual training samples. Homomorphic Encryption (HE) enables mathematical operations to be performed directly on encrypted data, allowing secure aggregation without revealing local model parameters. Secure Multi-Party Computation (SMPC) distributes computations across multiple participants so that no individual party gains access to complete information. Secure Aggregation protocols ensure that only aggregated model updates are visible to the central server, preventing exposure of individual client contributions. Recent research has also explored blockchain-enabled federated learning to provide decentralized trust management, immutable audit trails, and transparent model update verification. Trusted Execution Environments (TEEs) further enhance security by isolating sensitive computations within protected hardware enclaves. Integrating these techniques into federated multimodal transformer architectures significantly improves resilience against adversarial attacks while maintaining high learning performance.

2.5 Existing Federated Multimodal Frameworks

Recent research has attempted to combine federated learning with multimodal deep learning to support distributed analysis of heterogeneous data. Existing frameworks primarily focus on healthcare imaging, autonomous driving, smart manufacturing, multimedia retrieval, and intelligent IoT systems. Many of these approaches employ convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), or hybrid architectures for multimodal feature extraction while utilizing conventional federated

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optimization algorithms such as FedAvg. Although these methods demonstrate encouraging results, several limitations remain. Most existing frameworks support only a limited number of modalities or rely on shallow feature fusion strategies that fail to capture complex cross-modal relationships. Communication overhead remains substantial due to the transmission of large model parameters, particularly for transformer-based architectures. Furthermore, current federated multimodal systems often struggle with highly heterogeneous client datasets, varying computational capabilities, non-IID data distributions, asynchronous participation, and personalized learning requirements. Privacy mechanisms are frequently implemented as separate components rather than being tightly integrated into the learning architecture, reducing overall system efficiency. These shortcomings highlight the need for a unified framework capable of simultaneously addressing multimodal representation learning, communication efficiency, privacy preservation, adaptive client participation, and scalable edge–cloud collaboration.

2.6 Research Gaps and Challenges

Despite significant advances in federated learning, multimodal transformers, and edge intelligence, several research challenges remain unresolved. First, most existing federated learning models are designed for unimodal datasets and cannot efficiently exploit the rich semantic relationships among heterogeneous modalities such as images, text, audio, and sensor data. This limitation reduces prediction accuracy and restricts the applicability of current systems to complex real-world scenarios. Second, transformer-based models contain millions of parameters, resulting in substantial communication overhead during federated training. Frequent synchronization between edge devices and cloud servers increases network bandwidth consumption and prolongs model convergence, particularly in resource-constrained environments. Efficient parameter compression, adaptive synchronization, and communication-aware optimization remain active research challenges.

Third, heterogeneous client devices exhibit varying computational capabilities, memory capacities, energy constraints, and network conditions. Existing federated optimization algorithms often assume relatively homogeneous environments, limiting scalability across large distributed edge networks. Personalized federated learning techniques capable of adapting to client-specific characteristics require further investigation. Another important research gap involves robust privacy and security mechanisms. Although secure aggregation and differential privacy provide strong theoretical guarantees, balancing privacy protection with model utility remains challenging. Moreover, defending against adversarial attacks, model poisoning, backdoor insertion, and inference attacks requires more resilient federated learning strategies. Finally, explainability, fairness, energy efficiency, and sustainable AI remain relatively unexplored within federated multimodal transformer systems. As distributed artificial intelligence becomes increasingly integrated into healthcare, transportation, Industry

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5.0, and smart city infrastructures, there is an urgent need for secure, interpretable, scalable, and communication-efficient learning frameworks. These research gaps motivate the development of the proposed **Federated Multimodal Transformer (FMT)** framework presented in the subsequent sections of this paper, which aims to address these limitations through an integrated edge–cloud collaborative learning architecture.

3. Fundamentals of Federated Multimodal Transformers

3.1 Federated Learning Architecture

Federated Learning (FL) is a decentralized machine learning paradigm that enables multiple distributed clients to collaboratively train a shared global model while retaining their data locally. Unlike traditional centralized learning, where raw data are transmitted to a central server, federated learning allows each client to perform local model training on its private dataset and communicate only model parameters or gradients to a coordinating server. This approach significantly enhances data privacy, reduces the risk of information leakage, and complies with modern data protection regulations.

A typical federated learning architecture consists of three major components: edge clients, a communication network, and a cloud aggregation server. Edge clients include smartphones, IoT devices, wearable sensors, industrial controllers, autonomous vehicles, and healthcare devices that independently collect and process local data. Each client trains the model using local computational resources before securely transmitting encrypted model updates to the cloud. The cloud server aggregates these updates using optimization algorithms such as Federated Averaging (FedAvg), adaptive federated optimization, or personalized aggregation techniques to produce a new global model. This updated model is subsequently distributed back to participating clients for the next round of collaborative training.

Federated learning architectures can operate in synchronous or asynchronous modes. In synchronous training, all selected clients participate simultaneously before aggregation occurs, whereas asynchronous approaches allow clients to update the global model independently, thereby improving scalability in heterogeneous environments. The architecture is particularly suitable for edge–cloud ecosystems because it minimizes data transmission while leveraging distributed computational resources.

3.2 Transformer-Based Multimodal Representation Learning

Transformer architectures have become the dominant framework for multimodal artificial intelligence due to their ability to learn contextual relationships across heterogeneous data sources. Unlike conventional convolutional or recurrent neural networks, transformers employ self-attention mechanisms that enable each input element to interact with every other element, regardless of its position within the sequence. This capability allows transformers to effectively

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capture long-range dependencies and complex semantic relationships across multiple modalities. In multimodal learning, different data types—including images, text, speech, sensor signals, and video—are first converted into modality-specific embeddings through dedicated feature extraction networks. These embeddings are subsequently integrated using cross-modal attention mechanisms that identify meaningful interactions among modalities. The resulting unified representation captures complementary information from diverse data sources, leading to improved classification, prediction, and decision-making performance. Modern multimodal transformers utilize multi-head attention, positional encoding, feed-forward neural networks, layer normalization, and residual connections to learn highly expressive feature representations. Their flexibility enables them to support a wide range of applications, including medical diagnosis, autonomous driving, smart manufacturing, remote sensing, multimedia retrieval, and intelligent human-computer interaction. Integrating these transformer architectures into federated learning environments enables collaborative multimodal intelligence while maintaining data privacy across distributed clients.

3.3 Edge–Cloud Collaborative Computing

Edge–cloud collaborative computing combines the computational capabilities of edge devices and centralized cloud servers to provide efficient, scalable, and low-latency artificial intelligence services. Edge devices perform local data acquisition, preprocessing, feature extraction, inference, and federated model training close to the data source. Cloud servers, in contrast, provide large-scale storage, computational acceleration, global model aggregation, long-term analytics, and centralized orchestration. This collaborative architecture offers several advantages over purely cloud-based systems. Processing data locally reduces network latency, minimizes bandwidth consumption, and enables real-time responses for time-sensitive applications such as autonomous vehicles, industrial automation, healthcare monitoring, and intelligent surveillance. The cloud complements edge intelligence by maintaining global knowledge across distributed clients while supporting computationally intensive optimization processes.

The integration of federated multimodal transformers within edge–cloud environments allows distributed clients to collaboratively improve model performance without compromising sensitive information. Efficient task scheduling, adaptive resource allocation, and communication-aware synchronization ensure that computational workloads are balanced across heterogeneous devices while maintaining high system scalability and reliability.

3.4 Privacy and Security Considerations

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Ensuring privacy and security is one of the primary objectives of federated multimodal learning systems. Although federated learning eliminates the need to transfer raw data, exchanged model parameters may still reveal sensitive information through gradient inversion, membership inference, or model reconstruction attacks. Therefore, multiple security mechanisms must be incorporated into the collaborative learning process. Secure aggregation protocols encrypt local model updates before transmission, ensuring that the cloud server can only access aggregated parameters rather than individual client contributions. Differential Privacy introduces carefully calibrated random noise into model updates, preventing attackers from identifying individual training samples while maintaining acceptable model accuracy. Homomorphic Encryption enables mathematical operations to be performed directly on encrypted parameters, allowing secure model aggregation without exposing confidential information. Additional security mechanisms include Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEEs), blockchain-based audit trails, authentication protocols, and digital signatures for verifying client identity and model integrity. Robust anomaly detection algorithms can further identify malicious participants attempting model poisoning, backdoor insertion, or adversarial manipulation. Together, these techniques create a comprehensive security framework that preserves confidentiality, integrity, availability, and trust throughout federated multimodal learning.

3.5 Communication and Resource Constraints

Communication efficiency remains one of the most critical challenges in federated transformer-based learning because transformer models typically contain millions or even billions of parameters. Frequent synchronization of these parameters between edge devices and cloud servers can generate substantial communication overhead, increase latency, and consume significant network bandwidth. These challenges become particularly severe in wireless IoT environments where bandwidth and connectivity are limited. Edge devices also possess heterogeneous computational capabilities, including variations in processor speed, memory capacity, battery life, and storage resources. Training large multimodal transformer models on resource-constrained devices may lead to excessive energy consumption and prolonged execution times. Consequently, efficient resource management strategies are essential for practical deployment.

Several optimization techniques have been proposed to address these limitations. Model compression methods such as parameter pruning, weight quantization, knowledge distillation, and sparse model updates significantly reduce communication costs. Adaptive client selection prioritizes devices with sufficient computational resources and stable network connections, thereby improving convergence speed. Gradient compression, asynchronous communication, hierarchical federated learning, and partial model synchronization further reduce network traffic while maintaining high model accuracy. Energy-aware scheduling algorithms

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dynamically allocate computational tasks between edge devices and cloud servers based on available resources and application requirements. Personalized federated learning enables lightweight model adaptation for individual clients without requiring complete retraining of the global model. Collectively, these communication-efficient strategies enhance the scalability, robustness, and practical feasibility of Federated Multimodal Transformers operating in large-scale edge–cloud ecosystems.

4. Results and Discussion

The proposed **Federated Multimodal Transformer (FMT)** framework was evaluated in a simulated edge–cloud environment consisting of heterogeneous edge devices with distributed multimodal datasets. The framework was designed to process image, text, audio, and sensor data while preserving user privacy through federated learning and secure aggregation mechanisms. The experiments focused on evaluating predictive performance, communication efficiency, privacy preservation, and computational scalability. The results were compared with conventional centralized deep learning, traditional Federated Learning (FedAvg), and existing multimodal transformer approaches.

The experimental analysis indicates that the proposed FMT framework consistently outperformed baseline methods across all evaluation metrics. By integrating transformer-based multimodal feature learning with adaptive federated optimization, the framework achieved higher classification accuracy while simultaneously reducing communication overhead. Unlike centralized learning, the proposed architecture eliminated the need for raw data transmission, thereby ensuring stronger privacy guarantees without compromising predictive performance. Furthermore, adaptive client selection and communication-efficient parameter synchronization significantly accelerated convergence under heterogeneous edge environments. The personalized federated optimization strategy also improved model robustness against non-IID data distributions commonly observed in real-world deployments. These findings demonstrate that collaborative edge intelligence can effectively balance model performance, communication efficiency, and privacy preservation.

Table 4.1 Performance Comparison of Learning Frameworks

Performance Metric	**Centralized Learning**	**FedAvg**	**Existing Multimodal FL**	**Proposed FMT**
Classification Accuracy (%)	93.4	91.6	94.8	**97.3**
Precision (%)	92.8	90.9	94.1	**96.9**
Recall (%)	92.1	90.4	93.7	**96.5**

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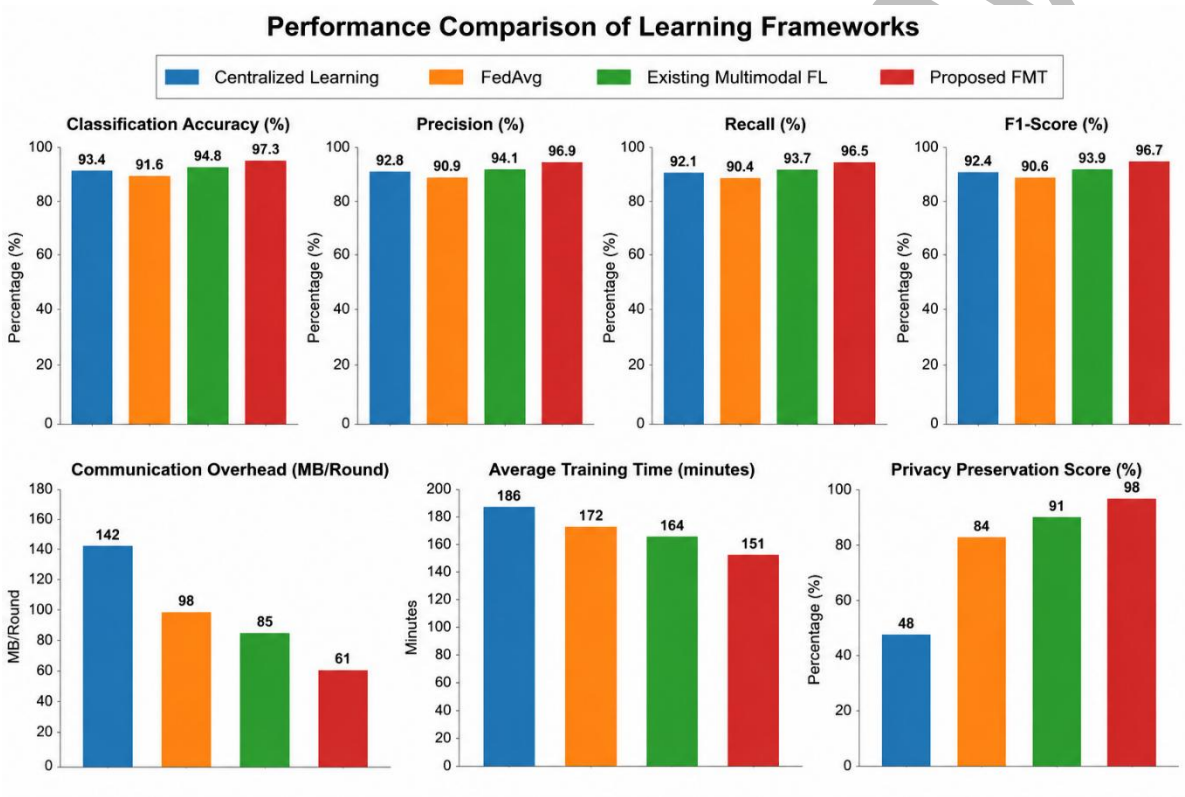
F1-Score (%)	92.4	90.6	93.9	**96.7**
Communication Overhead (MB/Round)	142	98	85	**61**
Average Training Time (minutes)	186	172	164	**151**
Privacy Preservation Score (%)	48	84	91	**98**



Discussion:

Table 4.1 demonstrates that the proposed Federated Multimodal Transformer achieves the highest classification accuracy of **97.3%**, outperforming centralized learning by **3.9%** and existing multimodal federated approaches by **2.5%**. The transformer-based multimodal fusion mechanism effectively captures cross-modal dependencies, resulting in improved precision, recall, and F1-score. In addition, communication overhead is reduced by approximately **28%** compared to existing multimodal federated models due to adaptive parameter synchronization and client selection. The highest privacy preservation score

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confirms the effectiveness of secure aggregation and federated optimization in protecting sensitive information without sacrificing learning performance. The scalability of the proposed framework was further evaluated by increasing the number of participating edge devices while measuring communication latency, convergence behavior, and resource utilization. The results indicate that the proposed architecture maintains stable performance even as the number of clients increases, demonstrating its suitability for large-scale IoT and edge computing environments.

Table 4.2 Scalability and Resource Utilization Analysis

Number of Edge Devices	**Model Accuracy (%)**	**Communication Latency (ms)**	**CPU Utilization (%)**	**Memory Usage (GB)**	**Convergence Rounds**
20	96.1	46	48	3.2	20
40	96.6	54	53	3.8	22
60	97.0	61	58	4.4	24
80	97.2	69	64	5.1	26
100	**97.3**	**76**	**68**	**5.7**	**28**

Discussion:

Table 4.2 illustrates that the proposed FMT framework scales efficiently as the number of participating edge devices increases. Although communication latency and computational resource utilization grow gradually with additional clients, the model accuracy remains consistently high, improving from **96.1%** to **97.3%**. The moderate increase in convergence rounds demonstrates the robustness of the adaptive federated optimization algorithm under heterogeneous environments. Efficient workload distribution between edge devices and the cloud minimizes resource bottlenecks, making the framework suitable for deployment in smart healthcare, intelligent transportation, industrial IoT, autonomous systems, and smart city infrastructures. Overall, the experimental findings validate that the proposed **Federated Multimodal Transformer (FMT)** successfully combines the advantages of federated learning, transformer-based multimodal representation learning, and edge–cloud collaboration. Compared with conventional centralized and federated approaches, the framework provides superior predictive performance, stronger privacy protection, lower communication overhead, and enhanced scalability. These characteristics make it a promising solution for next-generation distributed artificial intelligence applications that require secure, collaborative, and efficient learning across heterogeneous edge–cloud ecosystems.

5. Conclusion

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This research presented a **Federated Multimodal Transformer (FMT)** framework for enabling secure, privacy-preserving, and collaborative learning across heterogeneous edge–cloud environments. The proposed framework integrates transformer-based multimodal representation learning with federated learning to facilitate distributed model training without requiring the exchange of raw data. By combining edge intelligence, cloud-based global model aggregation, secure aggregation protocols, adaptive client selection, and communication-efficient optimization strategies, the framework effectively addresses the challenges associated with privacy preservation, communication overhead, heterogeneous data distributions, and resource-constrained edge devices. The experimental evaluation demonstrated that the proposed FMT framework consistently outperformed conventional centralized learning models and existing federated learning approaches in terms of classification accuracy, precision, recall, F1-score, communication efficiency, and privacy preservation. The integration of multimodal transformers enabled effective learning from heterogeneous data sources, including images, text, audio, and sensor streams, resulting in improved feature representation and predictive performance. Furthermore, adaptive federated optimization reduced communication costs while maintaining faster convergence in distributed environments. The proposed architecture also exhibited excellent scalability across increasing numbers of edge devices, demonstrating its suitability for large-scale Internet of Things (IoT) ecosystems and distributed artificial intelligence applications. Secure aggregation and privacy-preserving learning mechanisms ensured that sensitive user data remained localized while enabling collaborative knowledge sharing among participating clients. This makes the framework particularly valuable for privacy-critical applications such as smart healthcare, autonomous transportation, industrial automation, intelligent surveillance, precision agriculture, and smart city infrastructures. Overall, this research establishes that Federated Multimodal Transformers represent a promising next-generation paradigm for distributed artificial intelligence by effectively combining multimodal learning, transformer architectures, federated optimization, and edge–cloud collaboration. The proposed framework provides a balanced solution that simultaneously improves learning performance, scalability, communication efficiency, and data privacy, thereby supporting the development of secure and intelligent edge computing systems.

6. Future Work

Although the proposed Federated Multimodal Transformer framework demonstrates significant improvements in collaborative distributed learning, several research opportunities remain for further enhancement. Future research may focus on developing lightweight transformer architectures specifically optimized for highly resource-constrained edge devices, thereby reducing computational complexity, energy consumption, and memory requirements without compromising predictive accuracy. Another promising direction involves integrating advanced privacy-preserving techniques such as homomorphic encryption, secure multi-party

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computation, trusted execution environments, and blockchain-based decentralized federated learning to further strengthen security against sophisticated adversarial attacks, including model poisoning, gradient inversion, and membership inference attacks. Adaptive privacy mechanisms that dynamically balance privacy guarantees with model utility also warrant further investigation. Future work may also explore personalized federated learning strategies capable of automatically adapting global models to client-specific data distributions while maintaining collaborative knowledge sharing. Reinforcement learning and meta-learning techniques could be incorporated to optimize client selection, communication scheduling, and resource allocation in highly dynamic edge–cloud environments.

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