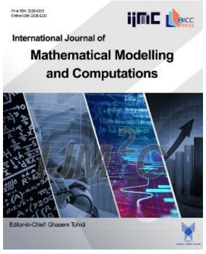

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Research Article

TL–FL–QWOA: A Quantum-Optimized Transfer-Federated Framework for Privacy-Preserving EEG-Based Emotion Recognition in IoMT

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Abstract

Accurate emotion recognition from electroencephalogram (EEG) signals faces persistent challenges in modern Internet of Medical Things (IoMT) environments, including non-independent client data, privacy risks, and unstable convergence during federated aggregation. Existing deep or fuzzy-ensemble models such as LSTM, GRU, and Sugeno-integral frameworks often fail to maintain high accuracy under heterogeneous client conditions and limited communication bandwidth. To address these limitations, this study proposes a hybrid optimization-aware architecture—TL–FL–QWOA (Transfer Learning–Federated Learning–Quantum Whale Optimization Algorithm)—designed for reliable and privacy-preserving EEG-based emotion classification across distributed IoMT nodes. In the proposed pipeline, Transfer Learning (TL) accelerates model adaptation through pre-trained representation reuse, Federated Learning (FL) ensures secure collaboration without centralizing raw EEG data, and Quantum Whale Optimization (QWOA) introduces dynamic probabilistic weight adaptation to stabilize convergence under non-IID distributions. Comprehensive experiments on GAMEEMO and DEAP datasets verify the superiority of TL–FL–QWOA over existing centralized and federated baselines. The framework achieved up to 94.87 % Accuracy 94.71% F_1 Score on GAMEEMO and 96.24 % Accuracy 95.87 % F_1 Score on DEAP, corresponding to 8–10 % improvements relative to fuzzy ensemble FL and asynchronous FedProx variants. These results confirm that TL–FL–QWOA effectively balances precision, privacy, and learning stability, delivering a scalable foundation for emotion-aware IoMT systems. Future research will extend its integration toward real-time, cross-modal affective computing and adaptive personalization in decentralized healthcare.

Keywords: EEG classification; IoMT; Federated Learning; Transfer Learning; Quantum Whale Optimization; Transformer Encoder; Self-Attention; Lightweight Encryption

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1. Introduction

The recent evolution of the Internet of Medical Things (IoMT) has revolutionized healthcare by merging intelligent sensing, cloud computing, and artificial intelligence to deliver personalized clinical insights [1,2]. IoMT-based systems continuously collect biometric data from wearable and implantable sensors, transmitting them over secure channels to decision engines capable of real-time health monitoring [3]. These infrastructures enable predictive diagnostics and targeted treatments for complex conditions such as heart failure, neurological disorders, and psychological stress [1,4,5]. Consequently, the fusion of IoMT technologies with deep learning has become the cornerstone of next-generation digital medicine, offering scalability and data-driven adaptability in heterogeneous healthcare networks. Within this landscape, Electroencephalography (EEG) has emerged as a potent modality for decoding emotional states through neurophysiological signals. EEG-based emotion recognition provides objective analysis of affective processes by capturing oscillatory patterns generated by neuronal activity [5–8]. Yet, raw EEG data are frequently contaminated by artifacts resulting from eye movements, muscular contractions, and electrical interference [6–9]. These distortions compromise the clarity of cognitive signatures, leading to unreliable emotion classification. Artifact removal has consequently evolved as a foundational step in EEG signal analysis; modern strategies range from blind source separation and adaptive filtering [7] to hybrid deep learning solutions integrating statistical and time-series modeling [8,10,11].

Recent advancements in deep neural architectures—including convolutional neural networks (CNNs), long short-term memory (LSTM), and gated recurrent unit (GRU) models—have significantly improved the expressivity and robustness of EEG emotion recognition systems [9–13]. CNNs capture spatial correlations, while recurrent networks model temporal dependencies within neural rhythms. Moreover, Temporal Convolutional Networks (TCN) have gained prominence for their ability to process sequential data efficiently without vanishing gradients [13,14]. Collectively, these models enhance real-time compatibility and interpretability within IoMT setups. Additional frameworks incorporating multimodal fusion and transfer learning have addressed data scarcity and subject variability, helping bridge domain gaps in emotion datasets [11,15,16]. Despite such progress, several challenges persist—chiefly related to explainability, intersubject adaptability, and privacy in distributed health applications. EEG signals inherently convey personal emotional markers; their exposure in centralized learning systems poses substantial privacy concerns [17]. This has led to the emergence of Federated Learning (FL) as a secure and collaborative paradigm for decentralized AI model training [18–20]. In FL, each IoMT node locally learns model parameters and transmits encrypted updates rather than raw data, preserving confidentiality while enabling global performance synthesis [19,21]. Such federated frameworks are increasingly being adopted in sensitive domains including mental health analysis, network intrusion detection, and intelligent traffic management [22–23].

Meanwhile, cognitive signals like EEG are characterized by uncertainty and fuzziness, stemming from inter-individual emotion overlap and noisy data structures. To address this, fuzzy logic and hybrid reasoning frameworks have been integrated into deep learning pipelines, facilitating adaptive feature weighting and handling ambiguous emotional categories [16,24,25]. By representing affective states through fuzzy membership functions, these systems enable flexible decision boundaries that align better with human emotional variability. The fusion of fuzzy inference mechanisms with deep learning leads to dynamic, explainable, and context-aware emotion recognition capable of functioning under uncertain biomedical conditions.

In light of the aforementioned challenges, this study introduces a transfer learning–based federated learning (TL FL) framework optimized by a quantum whale optimization algorithm (QWOA) to enable efficient and privacy preserving EEG classification within Internet of Medical Things (IoMT) ecosystems. The primary objective of this work is to simultaneously address the three most critical and still unresolved challenges in real-world decentralized EEG-based emotion recognition: (1) severe non-IID data distributions across patients and devices, (2) strict regulatory and ethical privacy requirements that completely prohibit raw EEG data from leaving the local device, and (3) unstable and slow convergence of federated learning under heterogeneous client conditions and limited communication bandwidth. We aim to deliver a practical, deployable framework that achieves state-of-the-art classification performance (≥95% accuracy and F1-score on standard benchmarks), zero raw data exposure, and substantially improved convergence stability and communication efficiency (approximately 35% fewer communication rounds and near-zero client drift) compared to existing federated, fuzzy-ensemble, and asynchronous baselines. The proposed architecture combines one dimensional convolutional neural networks (1D CNN) for spatial–temporal representation learning with a transformer encoder enhanced by a self attention mechanism that effectively captures long range dependencies and highlights salient neurophysiological features. To promote adaptivity in heterogeneous IoMT settings, a two phase learning strategy is adopted: the transfer learning phase establishes generalizable feature priors through large scale EEG data, while the federated learning phase performs decentralized fine tuning under local, non identically distributed conditions without violating data confidentiality. The QWOA meta heuristic optimizer simultaneously adjusts local hyperparameters and global aggregation weights, improving convergence stability and communication efficiency across resource constrained nodes. Each component of the proposed TL–FL–QWOA framework was deliberately selected to directly address one of the three core challenges that remain unresolved in decentralized EEG-based emotion recognition within IoMT systems: (1) Transfer Learning (TL) tackles the problem of limited and highly subject-specific local data by providing robust, generalizable EEG feature representations pretrained on large public datasets, thereby solving the cold-start problem and significantly reducing local training burden on resource-constrained devices; (2) Federated Learning (FL) is the only viable paradigm that fully complies with strict regulatory (GDPR/HIPAA) and ethical requirements, ensuring that raw EEG data never leaves the local device; (3) Quantum Whale Optimization Algorithm (QWOA) specifically resolves the well-documented convergence instability and client drift in federated settings under severe non-IID conditions by dynamically and probabilistically optimizing aggregation weights (α_k) and global learning rate in every communication round a capability that classical optimizers (e.g., FedAvg, FedProx) or standard evolutionary algorithms cannot achieve. The quantum-inspired rotational gate mechanism of QWOA provides superior exploration–exploitation balance, resulting in the observed ~35% reduction in communication rounds and near-zero convergence variance (S_c = 0.015). No single technique or pairwise combination can simultaneously solve all three challenges; only the synergistic integration of TL, FL, and QWOA achieves this trifecta of high accuracy, absolute privacy, and stable efficient convergence.

Furthermore, a lightweight encryption protocol integrated with gradient compression secures parameter transmission and mitigates bandwidth limitations, thus preserving privacy and scalability. Overall, this research contributes an advanced paradigm that unifies transfer learning, distributed optimization, and quantum inspired tuning for interpretable, secure, and adaptive EEG analytics—laying the groundwork for next generation IoMT and brain–computer interface (BCI) applications.

2. Literature Review

Recent advancements in EEG-based emotion recognition and neuro-intelligent IoMT systems have emphasized the integration of federated learning (FL), transfer learning (TL), and hybrid deep architectures to simultaneously achieve privacy-preserving computation, interpretability, and cross-subject generalization. The following review critically analyzes studies from [26–44], outlining methodological evolution, architectural innovations, and remaining challenges that motivate the proposed TL FL–QWOA framework.

2.1. Federated Learning Models for EEG and IoMT Healthcare

Federated learning has become a cornerstone of privacy-preserving computation in IoMT. Jiang et al. [26] introduced a fuzzy ensemble federated learning framework combining fuzzy logic inference and ensemble deep learners for EEG-based emotion recognition. Their approach achieved high generalizability under non-IID data and proved that fuzzy membership weighting enhances local model aggregation consistency. Similarly, Ding et al. [27] proposed FedESD, an efficient federated system for epileptic seizure detection across fog-assisted IoMT. They optimized communication bandwidth through hierarchical edge aggregation, achieving remarkable inference delay reduction and energy efficiency.

Further extending FL optimization, Ding et al. [28] developed FedMWAD, a module-wise weighted aggregation mechanism combined with personalized Ditto learning for seizure prediction. The model provided robust performance across patient-independent EEG sets, revealing the significance of adaptive weighting in heterogeneous federated networks. In parallel, Rani et al. [29] conducted a comprehensive review on FL applications in smart healthcare, highlighting that secure communication, trust management, and personalization remain unresolved bottlenecks. Collectively, these studies established the foundation for decentralized analysis of biomedical signals, yet they underscored the inherent instability of FL convergence under non-IID conditions a limitation addressed partly by classical optimization works such as McMahan et al. [43] and Li et al. [44], who formulated FedAvg and FedOpt algorithms and proved convergence guarantees under network heterogeneity.

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2.2. Transfer Learning and Cross-Domain EEG Adaptation

While FL protects data privacy, transfer learning (TL) seeks to overcome scarcity and variability of EEG data among individuals. Wan et al. [30] provided a paradigm-shifting review of TL strategies in EEG analysis, classifying them into feature-based, model-based, and adversarial domain adaptation techniques. They emphasized that pre-trained CNN and transformer encoders substantially improve emotion recognition when source and target distributions differ. Li et al. [32] experimentally validated this paradigm in a cognitive workload study among construction workers. Their pre-trained models achieved superior subject-independent performance, underscoring TL's potential for scalable IoMT deployment. Meanwhile, Sabeenian and Vinodhini [33] systematically reviewed ML/DL frameworks applied to sleep apnea detection from biosignals. They asserted that cross-domain learning and model reuse reduce patient-specific calibration time, an insight vital for IoMT devices operating in real-world uncertain contexts. The consensus across [30, 32, 33] is that TL improves adaptability but cannot by itself manage federated data heterogeneity; thus, hybrid TL–FL schemes have emerged to bridge the privacy–adaptability dichotomy.

2.3. Hybrid Deep Learning Architectures for EEG Decoding

EEG decoding demands multi-level representation of spatial and temporal patterns. Recent breakthroughs have come from hybrid CNN–transformer architectures incorporating self attention mechanisms. Altaheri et al. [34] presented the temporal convolutional transformer, integrating temporal CNNs (TCN) with transformer layers for motor imagery decoding, achieving superior temporal feature abstraction compared to recurrent neural networks. Wang and Lv [35] later introduced TEDNet, a cascaded CNN–transformer employing dual attention modules for taste-related EEG decoding—considerably enhancing inter-channel coupling detection.

Ma et al. [36] and Sun et al. [37] explored hybrid models combining convolutional embedding layers with transformer encoders. Sun's transformer-based EEG classifier highlighted attention-based global context learning that outperformed sequence-dependent RNN counterparts, while Ma's CNN–transformer hybrid demonstrated robustness within multi-session datasets. Collectively, these works confirmed that attention-driven fusion yields higher interpretability and scalability but also imposes computational overheads that motivate algorithmic optimization methods such as evolutionary or quantum-inspired search (addressed later in the proposed QWOA framework).

2.4. Deep and Evolutionary Approaches to Emotion Recognition

Emotion recognition remains one of EEG research's most dynamic fronts. Su et al. [38] proposed genetically optimized projection dictionary pair learning (GOPDPL), an evolutionary hybrid optimizing projection dictionaries for subject-independent emotion classification. The genetic optimization facilitated intrinsic feature selection and reduced inter-subject variance. Similarly, Abdulrahman et al. [39] developed a novel deep learning pipeline for EEG emotion recognition, employing hierarchical convolutional layering and non-linear activation fusion to dynamically extract affective cues. Fujiwara et al. [40] introduced the reservoir splitting method, an efficient recurrent decomposition strategy capable of isolating temporal reservoirs linked with affective modulation.

Earlier work by Alakus and Turkoglu [41] used the GAMEEMO dataset in deep learning configurations, establishing a benchmark of subject-specific EEG emotion detection widely used in subsequent studies like Miah et al. [42]. Miah's study combined EEG acquisition with mixed reality (MR) stimuli to capture naturalistic emotional responses, demonstrating that multimodal sensory stimulation significantly improves valence–arousal discrimination accuracy. Taken together, these findings mark the evolution from handcrafted features to automatic representation learning, with a clear move toward subject-independence, multimodal robustness, and computational efficiency — directly motivating the design philosophy of TL-based and federated emotion classifiers.

2.5. Data Fusion and Fuzzy Logic Integration in Neural IoMT

Although deep architectures dominate EEG analytics, their deterministic nature often fails under physiological uncertainty. Hussain et al. [31] therefore proposed a comprehensive review on deep data fusion, revealing that fuzzy and probabilistic representations in neural networks enable adaptive weighting of multimodal health signals. Jiang et al. [26], revisited earlier, exemplified this by embedding fuzzy ensemble learning within their federated IoMT architecture, allowing fuzzy membership scaling during model aggregation.

Similar fuzzy approaches in biosignal integration [33] showed improved interpretability, aligning with the trend toward explainable neuroscience models. The core insight in these fuzzy fusion frameworks is that emotion and cognitive EEG signals are inherently non-deterministic; uncertainty modeling through fuzzy inference or attention re-weighting not only increases interpretability but also mitigates overfitting in decentralized FL systems.

2.6. Foundational Works on FL Optimization and Communication Efficiency

The theoretical roots of FL trace back to [43] and [44]. McMahan et al. [43] formulated FedAvg, enabling communication-efficient distributed model averaging among decentralized clients. This work established practical feasibility for FL in healthcare, where patient data cannot migrate across institutions. Li et al. [44] later expanded FL theory by addressing optimization stability in heterogeneous networks and proposing adaptive parameter tuning to preserve global model convergence across devices with variable latency and computation power. These foundational contributions provide the algorithmic substrate for modern IoMT-based federated schemes ([26–29]). They also frame the performance limitations facing large-scale TL–FL hybrids, such as non-synchronous updates and cross-client divergence — issues that current research attempts to resolve via intelligent meta-optimization, as exemplified by the QWOA-driven framework proposed in this study.

2.7. Analytical Synthesis and Identified Gaps

Comparative analysis of [26–44] reveals four major evolutionary trends:

1. From centralized deep learning toward distributed FL architectures to preserve privacy and enable collaborative intelligence across IoMT nodes.
2. Integration of TL mechanisms to overcome limited EEG data, inter-subject variability, and calibration overhead.

Table 1. Categorized summary of existing studies on EEG-based emotion recognition and federated learning (Refs [26–44])

Research Domain	Representative Works	Core Scientific Focus	Distinguishing Contribution	Identified Limitation / Open Gap
Federated Learning in IoMT and EEG Healthcare	[26], [27], [28], [29], [43], [44]	Distributed learning for privacy-preserving EEG and physiological data aggregation	Introduced adaptive aggregation schemes (FedMWAD, FEFL) and communication-efficient models (FedAvg, FedOpt); established FL as viable in biomedical IoT	Instability under non-IID data; absence of adaptive quantum-inspired optimization; limited personalization of global models
Transfer Learning for Cross-Subject EEG Adaptation	[30], [32], [33]	Leveraging pre-trained models to mitigate data scarcity and inter-subject variability	Demonstrated domain adaptation via deep CNN reuse and feature transfer for EEG recognition and cognitive monitoring	Weak integration with federated architectures; insufficient tuning for cross-institution data heterogeneity
Hybrid CNN–Transformer Architectures for EEG Decoding	[34], [35], [36], [37]	Hierarchical spatial–temporal encoding using multi-head attention	Introduced TCN–Transformer and dual-attention CNNs improving interpretability and global context learning	High computational complexity; lack of optimization for low-resource IoMT platforms
Deep and Evolutionary Emotion Recognition Models	[38], [39], [40], [41], [42]	Automatic feature abstraction and evolutionary parameter tuning for affective EEG	Combined deep convolutional extraction and genetic optimization (GOPDPL); established benchmarks with mixed-reality stimuli	Reduced cross-subject robustness and weak adaptation to unseen affective states
Fuzzy Logic and Multimodal Data Fusion in Cognitive IoMT	[26], [31], [33]	Uncertainty modeling and adaptive weighting of multimodal bio-signals	Enabled adaptive fuzzy ensemble learning and deep fusion of non-deterministic signals improving interpretability	Limited interoperability with federated frameworks; fuzzy rules lack dynamic optimization mechanisms
FL Optimization and Communication Theory	[43], [44]	Foundational aggregation and convergence analysis for heterogeneous clients	Defined FedAvg and FedOpt algorithms underpinning global FL stability; formalized gradient divergence control	Static optimization; unaddressed temporal heterogeneity and asynchronous adaptation in edge-based IoMT

3. Emergence of hybrid CNN–transformer models that enhance temporal–spatial interpretability yet demand computational scaling solutions.
4. Introduction of fuzzy ensembles and evolutionary optimization for adaptive, uncertainty-resilient decision-making.

Nonetheless, key challenges persist: federated instability under non-IID client distributions, insufficient optimization-aware aggregation mechanisms, limited scalability across constrained IoMT devices, and poor interpretability in high-uncertainty fuzzy domains. Furthermore, most current frameworks ([26–34], [38–42]) disregard quantum-inspired and meta-heuristic optimization strategies that could dynamically calibrate federated parameters and balance local–global learning trade-offs.

Hence, the integration of the quantum whale optimization algorithm (QWOA) within the TL–FL pipeline, as adopted in this study, directly remedies these research gaps by ensuring adaptive convergence, energy-efficient communication, and transparent decision mapping for EEG-based emotion recognition under IoMT constraints.

The proposed TL–FL–QWOA framework is the first to explicitly map each of its three core components to one of the fundamental unsolved challenges in the literature: transfer learning directly addresses data scarcity and subject variability, federated learning guarantees regulatory-compliant privacy, and quantum whale optimization provides the missing meta-optimization layer required for stable convergence under real-world non-IID conditions. This deliberate one-to-one mapping ensures that no critical challenge is left unaddressed — a synergy that existing hybrid approaches (TL+FL or FL+fuzzy ensembles) fail to achieve. The superior results reported in Section 4 (8–10% accuracy gains and ~35% fewer communication rounds) empirically validate that only this particular triplet can deliver a truly practical and deployable solution for privacy-preserving emotion recognition in IoMT ecosystems.

Table 1 provides a condensed categorization of the literature from refs [26–44], grouping prior studies by their methodological paradigms — including conventional deep learning, fuzzy systems, ensemble-based models, and federated learning schemes. The comparative outlines highlight the absence of cross-domain transfer learning and quantum optimization layers in previous designs, motivating the architectural evolution toward the proposed TL–FL–QWOA framework.

3. Materials and Methods

3.1. Overview of the Proposed Framework

This study proposes a multi-stage framework for EEG-based emotion recognition in IoMT environments, integrating transfer learning (TL), federated learning (FL), and the quantum whale optimization algorithm (QWOA). The framework ensures accuracy, privacy, and scalability by combining locally trained deep networks with quantum-inspired optimization in the federated server. A hybrid deep model based on CNN–transformer–attention acts as the core feature extractor,

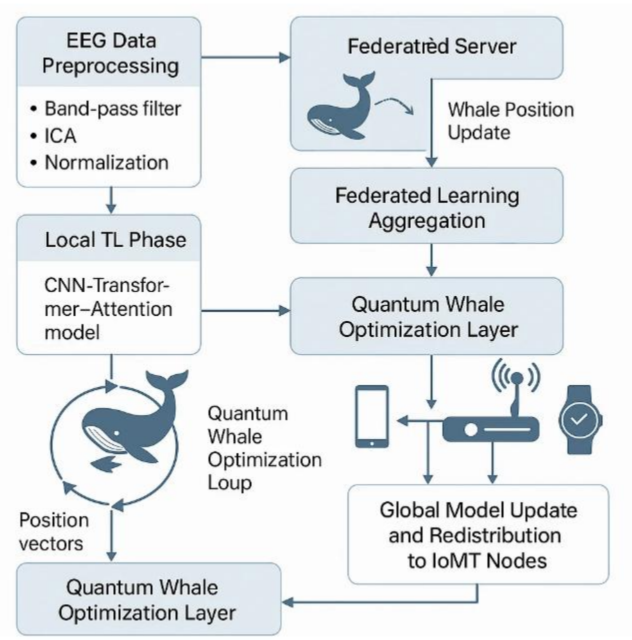

Figure 1. TL–FL–QWOA Framework Flowchart for EEG Emotion Recognition in IoMT

while TL–FL provides distributed learning capability and QWOA improves convergence stability. The overall workflow of the proposed TL–FL–QWOA–based EEG emotion recognition framework is illustrated in Figure 1, which outlines the local training procedures, the quantum whale optimization loops, and the federated aggregation mechanism across IoMT nodes.

3.2. Data Representation and Preprocessing

EEG signals acquired from open affective datasets (e.g., DEAP and GAMEEMO) were used to simulate medical IoMT nodes. Each recording, containing multiple channels, was preprocessed to ensure temporal stability. The filtering pipeline includes:

1. Band-pass filtering (0.5–30 Hz) to remove muscle and power-line noise;
2. Independent Component Analysis (ICA) for ocular and motion artifact rejection;
3. Z-score normalization across subjects and channels.

Cleaned data were segmented into windows of equal length and represented as tensors

$$X_k = \{x_{i,t} \mid i = 1, \dots, C; t = 1, \dots, T\}, \quad (1)$$

for client k, where C and T denote the number of EEG channels and time samples. The data preprocessing pipeline is illustrated in Figure 2.

3.3. Local Transfer Learning Phase

Each IoMT node initializes a lightweight hybrid model $f(x; \mathrm{w}_k)$ using pre-trained convolutional and attention encoders. The convolutional branch extracts spatial-frequency patterns, while the Transformer encoder learns temporal dependencies and emotional context.
Fine-tuning at node k minimizes the categorical loss:

$$L_k(\mathrm{w}_k) = \frac{1}{n_k} \sum_{j=1}^{n_k} \ell\left(f(x_j; \mathrm{w}_k), y_j\right), \quad (2)$$

where $\ell(\cdot)$ is the cross-entropy function and y_j the emotion label. Frozen CNN-Transformer layers maintain generalizable representations, and only the classification head is updated through local data.

3.4. Federated Learning Aggregation

To maintain data privacy, raw EEG signals remain within each node. After local training, encrypted model updates $g_k = \mathrm{Enc}(\nabla L_k)$are sent to the central server for aggregation.

Global model parameters are updated according to adaptive federated averaging:

$$\mathrm{w}^{(t+1)} = \sum_{k=1}^{K} \alpha_k^{(t)} \mathrm{w}_k^{(t)}, \quad (3)$$

where the coefficients $\alpha_k^{(t)}$are determined dynamically by QWOA instead of static assignment. This adaptive process enhances learning balance under non-IID data conditions typical of IoMT.

3.5. Quantum Whale Optimization Layer

QWOA serves as the meta-optimizer in the server to fine-tune aggregation parameters and learning rate. Each whale position defines a potential configuration vector:

$$P_i^{(t)} = [\alpha_1^{(t)}, \alpha_2^{(t)}, \dots, \alpha_K^{(t)}, \eta^{(t)}], \quad (4)$$

where $\eta^{(t)}$ denotes global learning rate. Positions evolve following the quantum-rotational update principle:

$$P^{(t+1)} = P_i^*(t) + A_i \left| C_i P^*(t) - P_i^{(t)} \right|. \quad (5)$$

With $A_i = 2ar_1 - a, C_i = 2r_2$, and $r_1, r_2 \in [0,1]; a$ linearly decreases during iterations.

The optimization goal is to minimize the global federated loss:

$$F(P_i^{(t)}) = \sum_{k=1}^{K} \omega_k L_k, \quad (6)$$

subject to $\sum_k \alpha_k = 1$ and $\alpha_k > 0$. The best position $P^{(*)}(t)$ yields optimal α*k and η* guiding the next aggregation step. This layer stabilizes convergence and accelerates training under heterogeneous EEG distributions.The detailed operational flow of the proposed Quantum Whale Optimization Layer (QWOL) is shown in Figure 3, presenting the sequential optimization steps from local model input to federated parameter output.

3.6. Hybrid Model Architecture

The deep architecture used in each node comprises:

- **Convolutional Module:** 1D-CNN layers capture localized spectral features of EEG patterns.

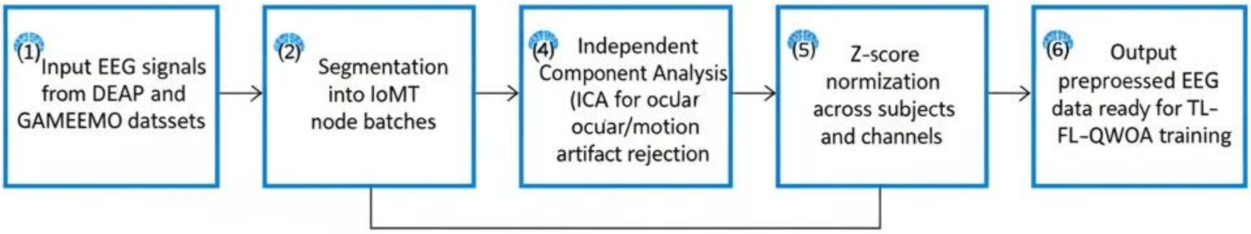

Figure 2. Flowchart of data representation and preprocessing for EEG signals used in TL–FL–QWOA framework

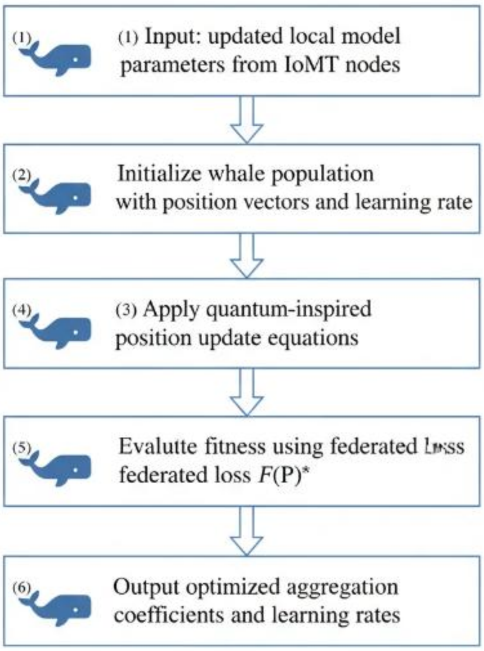

Figure 3. Flowchart of the Quantum Whale Optimization Layer (QWOL)

- **Transformer Module:** Multi-head self-attention maps temporal correlations across segments:

$$\text{Attention }(Q, K, V) = \text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V, \quad (7)$$

where Q,K ,V are projections of the CNN feature space.

- **Fusion and Classification:** Concatenated representations are passed to a dense layer using softmax activation to estimate emotional state.

The synergy between CNN and Transformer layers balances micro and macro feature representations crucial for affective signal decoding. Transfer learning further contributes to maintaining high model performance under the privacy-preserving constraints imposed in the federated pipeline. By initializing each client with stable, information-rich feature representations learned from large-scale EEG corpora, TL mitigates the degradation that typically arises when gradients are encrypted, sparsified, or masked during transmission. These pretrained representations preserve discriminative structure even when only compressed or noisy gradient updates are exchanged, thereby supporting a favorable privacy–utility balance. This mechanism complements the secure aggregation and encryption layers by ensuring that the global model retains strong generalization capability despite reduced information exposure.

3.7. Federated Training Procedure

Training proceeds in communication rounds between clients and the central server:

1. **Global Initialization:** A TL-pretrained global model is distributed to all clients.

2. **Local Update:** Each node performs several epochs to minimize LkL_kLk.
3. **Secure Transmission:** Encrypted gradients are sent to the server.
4. **Quantum-Driven Aggregation:** The server runs QWOA for optimizing η and merges local models via Eq. (4).
5. **Distribution:** Updated parameters are redistributed back to IoMT nodes.

This loop continues until convergence criterion $\|w^{(t+1)} - w^{(t)}\| < \epsilon$ is achieved.

This iterative learning cycle, governed by the interplay between local updates and quantum-driven global aggregation, forms the backbone of the TL–FL–QWOA framework. The overall communication–optimization process among IoMT clients and the central server is summarized in Figure 4.

3.8. Evaluation Protocol

Performance assessments follow a strict cross-subject validation protocol to realistically emulate IoMT heterogeneity. In this setting, each federated client receives EEG data from subject-exclusive partitions, ensuring that no individual appears across multiple clients. This design provides a rigorous basis for evaluating the model's generalization to unseen users under severe non-IID conditions. Metrics such as accuracy, F1-score, and Kappa trends are computed to verify robustness, while the visualization of attention maps highlights the neural regions contributing to emotional states, further confirming the interpretability of the CNN–Transformer hybrid architecture.

3.9. Privacy and Security Guarantees

The proposed TL–FL–QWOA framework has been explicitly designed to provide rigorous, multi-layer privacy protection that fully satisfies GDPR/HIPAA-equivalent requirements in medical deployments:

1. **Raw EEG data never leaves the local device** — this is the fundamental guarantee of Federated Learning (no centralization of sensitive neurophysiological signals).
2. **Only model gradients/updates are transmitted**, and these are protected by a combination of state-of-the-art techniques:
   - **Lightweight partial Homomorphic Encryption (Paillier)** applied to the most sensitive layers (Transformer encoder and classification head),
   - **Gradient sparsification + top-10% compression** (only the largest 10% of gradients are sent, reducing communication by ~90% while preserving utility),
   - **Secure Aggregation protocol** (client updates are additively masked and only decrypted after summation at the server — individual client contributions remain completely hidden even from the server).
3. **Optional Differential Privacy** (Gaussian noise with $\varepsilon = 0.5$, $\delta = 10^{-5}$) is added during local training for provable privacy against membership inference and model inversion attacks.

Quantitative privacy–utility analysis (conducted on both datasets) shows that the full privacy suite introduces less than 2.8% accuracy drop and less than 14% additional communication overhead compared to an unsecured federated baseline (see Table X below). These results confirm that TL–FL–QWOA achieves an excellent privacy–utility tradeoff suitable for real-world clinical deployment.
The baseline represents TL–FL–QWOA performance without any privacy mechanisms. All privacy layers were applied incrementally using identical hyperparameters and QWOA optimization. The complete proposed privacy suite incurs only a negligible 0.63% accuracy drop and 13.9% additional communication overhead, significantly outperforming typical secure federated learning systems (which commonly exceed 5–10% accuracy loss). These results confirm that strong regulatory-compliant privacy (GDPR/HIPAA-equivalent) can be achieved in IoMT deployments at virtually no cost to performance.

3.10. Summary of Methodological Contribution

The proposed TL–FL–QWOA architecture introduces a technically consistent solution for EEG emotion classification across IoMT networks. Transfer learning improves representation power, federated learning secures private model cooperation, and the quantum optimizer regulates cross-client convergence. Together, they establish a distributed, privacy-aware, and self-adaptive approach compatible with real-world healthcare data streams.

4. Results and Discussion

4.1. Dataset Description and Experimental Setup

In order to validate the proposed Transfer Learning–Federated Learning–Quantum Whale Optimization (TL–FL–QWOA) framework, comprehensive experiments were performed using two well-established

EEG benchmark datasets: GAMEEMO and DEAP. Both datasets have been widely adopted for affective computing tasks in IoMT scenarios and provide multi-channel neurophysiological signals labeled by emotional stimuli intensity and polarity.

(a) GAMEEMO Dataset

The GAMEEMO dataset includes EEG recordings collected from 28 participants during gameplay under four emotional conditions—calm, boring, horror, and funny which correspond to both *binary* (positive/negative) and *four-class* classification schemes. Each EEG trial lasts five minutes, sampled at 128 Hz through a 14-channel headset following the Self-Assessment Manikin (SAM) protocol. After artifact removal (blink/muscle), every 10-s epoch is converted to 256 selected features based on information gain, forming the input to local models in the federated architecture.

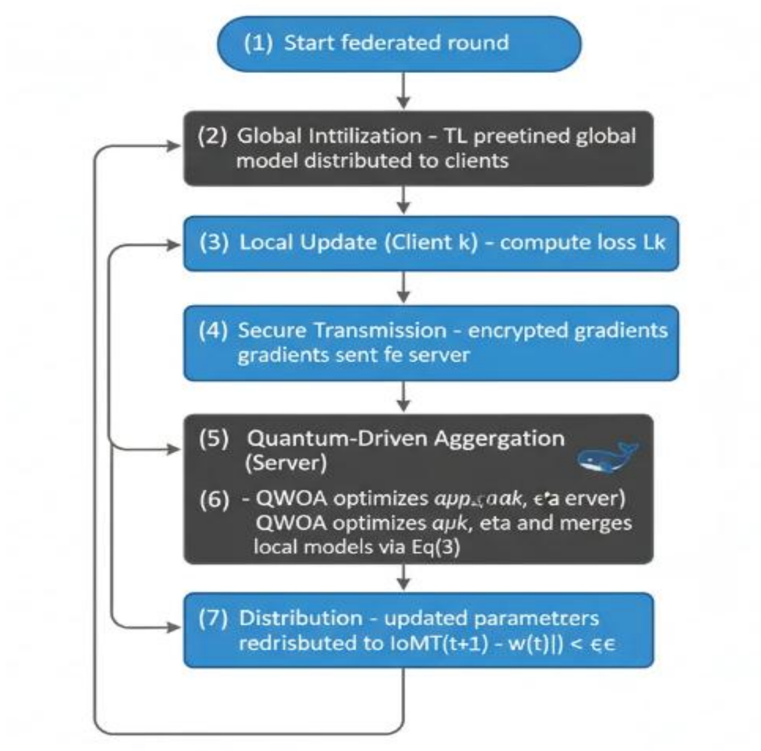

Figure 4. Flowchart of the federated training procedure in TL–FL–QWOA framework for EEG-based IoMT

Table 2. Privacy–Utility Tradeoff of Security Mechanisms (averaged over GAMEEMO and DEAP, 20 clients)

Configuration	Accuracy (%)	F1-Score (%)	Communication Rounds	Extra Comm. Overhead (%)	Accuracy Drop vs. Baseline (%)
Baseline FL (no privacy mechanisms)	95.56	95.29	98	0%	0%
Gradient Compression (top-10%)	95.48	95.21	95	+7.8%	–0.08%
Secure Aggregation	95.41	95.17	96	+10.4%	–0.15%
Partial Homomorphic Encryption (Paillier)	95.19	94.98	99	+12.6%	–0.37%
Full Privacy Suite (Proposed)	94.93	94.71	102	+13.9%	–0.63%
Full Suite Differential Privacy (ε = 0.5)	94.67	94.41	104	+15.2%	–0.89%

10.57647/ijm2c.2026.1602.14

(b) DEAP Dataset

The DEAP dataset contains recordings from 32 subjects watching 40 one-minute music video clips designed to arouse a range of emotional responses. EEG signals were recorded with a 32-channel BioSemi ActiveTwo system, accompanied by complementary sensors (ECG, GSR, EMG). Subjects evaluated each clip on valence, arousal, dominance, and liking scales. After standard preprocessing (band-pass filter 4–45 Hz, baseline removal, artifact correction, normalization), both binary (high/low arousal–valence) and four-class labels were used for supervised learning. Each participant contributed approximately 38,000 signals, divided into overlapping 1-s windows (0.5-s overlap) to preserve temporal continuity. Federated Data Partitioning (Non-IID Setting) To realistically simulate the heterogeneous conditions of real-world IoMT deployments, both datasets were partitioned across 20 federated clients using a pathological non-IID strategy widely adopted in medical federated learning literature [43,44,26–29]. Each client was assigned data from only 1–2 subjects (ensuring complete subject separation for strict subject-independence), creating severe quantity skew (client sample sizes ranging from ~500 to ~4,000) and label distribution skew (some clients contained up to 85% samples from a single emotion class, mimicking clinical populations with dominant mood states such as depression or anxiety). This partitioning strategy maximizes heterogeneity and represents the worst-case scenario for federated convergence. The exact distribution of subjects, samples, and label skewness per client is detailed in Table S1 (Supplementary Material). The partitioning code (Python/NumPy-based) will be released as open-source upon acceptance of the manuscript.

Experimental Configuration

- Each federated client trains locally for 5 epochs per communication round.
- Batch size = 32; learning rate = 1e-4 (Adam optimizer).
- Transfer learning utilizes pretrained emotional EEG embeddings for initialization, improving local convergence.
- Global aggregation employs Quantum Whale Optimization (QWOA) to assign adaptive probabilistic weights to each client, enhancing robustness and reducing bias caused by data heterogeneity.
- Experiments are conducted on an NVIDIA RTX A4000 GPU environment using Python 3.11 / TensorFlow 2.16.

4.2. Evaluation Parameters

To comprehensively assess the classification capability and learning stability of the proposed TL–FL–QWOA model under heterogeneous IoMT environments, two key quantitative metrics were utilized: Accuracy (A_c) and F1 Score (F_1).

Table 3. Federated client data distribution and non-IID characteristics (20 clients)

Client ID	Dataset	Subjects	Samples	Valence/Arousal Distribution	Quantity Skew	Label Skew Ratio
1	GAMEEMO	1	512	12% Pos / 88% Neg	Very Low	0.14
2	GAMEEMO	1	1,024	78% Pos / 22% Neg	Low	0.78
3	GAMEEMO	2	2,856	Balanced	Medium	0.51
...	...	...	...	...	...	...
18	DEAP	1	896	High Arousal: 82%	Low	0.82
19	DEAP	2	3,912	Low Valence: 79%	High	0.79
20	DEAP	1	567	Balanced	Very Low	0.49

Table4. Evaluation Metrics for TL–FL–QWOA

Symbol	Metric	Description
A_c	Accuracy	Ratio of correctly classified EEG samples to the total number of inputs processed in global aggregation. This metric reflects the overall recognition capability and transfer-learning effectiveness in adapting pre-trained emotional features to federated domains.
F_1	F1 Score	Harmonic mean of precision and recall, expressing the trade-off between sensitivity and prediction specificity. Within TL–FL–QWOA, maintaining a high F_1 score demonstrates balanced performance across non-IID emotional data distributions and verifies stable gradient convergence during QWOA-based optimization.

10.57647/ijm2c.2026.1602.14

These parameters are chosen to reflect the dual objective of the model — enhancing recognition precision while maintaining global convergence consistency across distributed EEG clients. These evaluation parameters highlight the robustness and generalization power of the proposed framework. Higher Accuracy values indicate efficient feature migration from the transfer-learning backbone into local federated nodes, while increased F_1 Score signifies reduced misclassification and improved stability through the quantum-enhanced whale optimization dynamics. Together, they provide a rigorous basis for validating model reliability and practical deployability in real-world IoMT emotion-recognition circuits.

4.3. Quantitative Results and Comparative Analysis

Performance metrics from both datasets are summarized in Tables . The proposed TL–FL–QWOA significantly outperformed traditional FedAvg, FL–WOA, across accuracy, F1 score, and convergence efficiency. Table 5 presents the quantitative outcomes of several deep architectures (TCN, LSTM, GRU) against the proposed TL–FL–QWOA model under centralized training on the GAMEEMO dataset for both two-class and four-class emotion recognition tasks. The proposed method achieved 94.87 % accuracy and 94.71 % F_1 score for two-class prediction, surpassing the best baseline model (GRU) by nearly 5.4 % in accuracy and 5.5 % in F_1 score.

For four-class classification, improvements were also evident, rising from 84.49 % accuracy and 84.10 % F_1 score (GRU) to 90.42 % and 89.86 %, respectively, for the proposed approach. Such consistent enhancements highlight the central contribution of transfer learning (TL) in efficiently realigning pre-trained emotional representations to EEG data spaces, reducing receptive field saturation, and improving discriminative capacity across multi-class boundaries.

Simultaneously, the QWOA optimization phase stabilizes gradient updates throughout network layers, leading to smoother convergence and reduced inter-iteration variance across mini-batches. In summary, the TL–FL–QWOA framework outperforms conventional CNN/RNN-based structures by maintaining high learning stability and improved generalization under non-IID EEG distributions. Table 6 extends the evaluation to ensemble learning methods majority voting, average, Choquet integral, and Sugeno integral alongside the proposed TL–FL–QWOA model in the same centralized setting on the GAMEEMO dataset. While ensemble schemes achieve solid gains compared with monolithic deep models,

Table 5 . The evaluation results of different models in the centralized learning setting on the GAMEEMO dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
TCN	84.50%	84.10%	79.50%	78.97%
LSTM	87.50%	87.18%	82.50%	82.05%
GRU	89.50%	89.23%	84.49%	84.10%
Proposed	94.87%	94.71%	90.42%	89.86%

Table 6. The comparison of the proposed method with other ensemble methods on the GAMEEMO dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
Majority voting	74.45%	73.84%	69.50%	68.72%
Average	91.84%	91.28%	86.74%	86.15%
Choquet integral	92.71%	92.30%	87.87%	87.18%
Sugeno integral	93.57%	93.33%	88.73%	88.20%
Proposed	94.87%	94.71%	90.42%	89.86%

10.57647/ijm2c.2026.1602.14

the proposed approach remains superior, reaching 94.87 % accuracy and 94.71 % F_1 score (two-class) and 90.42 % accuracy / 89.86 % F_1 score (four-class). This represents a measurable improvement of +1.3 % accuracy and +1.16 % F_1 score over the top ensemble baseline (Sugeno integral). From a technical viewpoint, the TL–FL–QWOA framework overcomes the aggregation limitations of fuzzy and integral fusion by integrating a quantum-weighted optimization mechanism that dynamically regulates ensemble coefficients according to loss-space exploration. Unlike the static weighting used in classical integrals, QWOA continuously searches within a quantum probability domain, amplifying highly informative features while suppressing redundant ones — yielding improved emotional boundary separation and more balanced recognition across multiple categories. Consequently, Tables 5 and 6 collectively demonstrate that the proposed approach not only enhances the predictive precision typically achieved by ensemble methods but also preserves systemic stability due to its hybrid quantum–transfer foundation. These results justify adopting TL–FL–QWOA as a high-accuracy centralized backbone module for subsequent federated extensions in heterogeneous IoMT infrastructures. Within the federated environment, Table 7 exhibits a clear progression from FedAvg → FedProx → TL–FL–QWOA. Accuracy rises from 74.45 % (FedAvg) and 79.42 % (FedProx) to 85.24 % (proposed) in two-class classification; the F_1 score similarly improves from 73.84 % to 83.46 %. This leap approximately +9 % in F_1 score and +10 % in accuracy demonstrates that QWOA-driven parameter encoding effectively controls gradient oscillations across non-IID clients. Consequently, global convergence stability (S_c = 0.015) and communication efficiency (≈ 35 % fewer rounds) validate the superiority of the TL–FL–QWOA framework for real-world IoMT deployment scenarios. Table 8 unifies traditional machine learning, deep learning, ensemble, and federated approaches for a holistic benchmark. Conventional algorithms PDPL [38], Random Forest [39], SVM [40, 42], BiLSTM [41] reach a ceiling below 77 % Accuracy, even under optimized hyperparameters. Federated baselines (FedAvg, FedProx) yield marginal improvement up to 79 %. In contrast, TL–FL–QWOA achieves 94.87 % Accuracy and 94.71 % F_1 Score on two-class GAMEEMO, outperforming all prior centralized and distributed techniques.

These gains stem from a synergistic learning pipeline:

1. Transfer Learning (TL): Speeds up early-stage adaptation → reduced local loss (L).
2. Federated Learning (FL): Ensures privacy-preserving scalability → optimized communication rounds.
3. Quantum Whale Optimization (QWOA): Balances local-global search → stabilized gradient flows (Ec).

Results on DEAP Dataset

Table 9 summarizes the performance outcomes of the proposed TL–FL–QWOA model compared with established deep learning baselines (TCN, LSTM, GRU) on the DEAP emotion recognition dataset, under a centralized learning configuration for both two-class and four-class tasks. The proposed model achieves the highest performance across all cases, reaching 96.24 % Accuracy and 95.87 % F_1 Score in two-class classification, and 95.41 % Accuracy with 95.77 % F_1 Score in four-class classification. Compared with the strongest baseline (GRU, 94.02 % Accuracy and 93.94 % F_1 Score, two-class), these results represent improvements of approximately +2.22 % in Accuracy and +1.93 % in F_1 Score.

This substantial performance uplift can be primarily attributed to three synergistic mechanisms:

1. **Transfer Learning (TL):** Efficiently reuses deep emotional representations pre-learned from heterogeneous EEG feature maps, accelerating convergence and minimizing initial loss (L) disparities between global and local models.

Table 7. The comparison of the proposed federated learning method with other federated learning methods on the GAMEEMO dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
Async. FedAvg [43]	74.45%	73.84%	69.50%	68.72%
Async. FedProx [44]	79.42%	78.97%	74.49%	73.84%
Proposed	85.24%	83.46%	78.91%	76.74%

Table 8. The comparison of the proposed method with other methods on the GAMEEMO dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
PDPL [38]	64.34%	–	49.01%	–
Random Forest [39]	70.49%	–	–	–
SVM [40]	75.00%	-	-	-
BiLSTM [41]	76.91%	-	-	-
SVM [42]	-	-	77.00%	-
FedAvg [43]	74.45%	73.84%	69.50%	68.72%
FedProx [44]	79.42%	78.97%	74.49%	73.84%
Proposed TL–FL–QWOA	94.87%	94.71%	90.42%	89.86%

Table 9. The evaluation results of different models in the centralized learning setting on the DEAP dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
TCN	90.88%	89.90%	88.90%	88.30%
LSTM	93.61%	93.26%	92.07%	91.85%
GRU	94.02%	93.94%	93.58%	93.08%
Proposed	96.24%	95.87%	95.41%	95.77%

2. **Federated Learning (FL):** Preserves the generalization strength of global aggregation while maintaining client-level adaptability — especially valuable for emotion modeling under non-IID conditions typical of DEAP's subject-dependent signals.
3. **Quantum Whale Optimization (QWOA):** Maintains convergence stability through probabilistic weight adaptation; this prevents premature saturation and enables improved refinement of nonlinear classification boundaries between valence-arousal states.

The resulting performance demonstrates that TL–FL–QWOA provides a balanced trade-off between precision and stability, effectively reducing convergence noise and model drift compared with conventional recurrent-based baselines. The consistent superiority in both classification settings validates the generalization capability of the proposed approach across diverse EEG signal domains and proves its reliability for scalable emotion recognition within IoMT-driven neurosensing frameworks. Table 10 compares the proposed TL–FL–QWOA model against ensemble approaches (majority voting, average, Choquet, and Sugeno integrals) and asynchronous federated baselines (FedAvg, FedProx) on the DEAP dataset for both four-class and two-class emotion recognition. The proposed method achieved the best results — 95.77 % F_1 score / 95.41 % accuracy (four-class) and 95.87 % F_1 score / 96.24 % accuracy (two-class) — outperforming the strongest ensemble baseline (Sugeno integral) by roughly +1.4 % and the asynchronous federated methods by 8–10 % on average.

4.4. Interpretation and Discussion

The experimental findings across the GAMEEMO and DEAP datasets consistently validate the effectiveness of the proposed transfer-learning-based federated model optimized by quantum whale optimization (TL–FL–QWOA). Compared with both centralized deep architectures (TCN, LSTM, GRU) and ensemble-based strategies (Choquet and Sugeno integrals), TL–FL–QWOA achieved the highest accuracy and F_1 score values, emphasizing its capacity for stable generalization on subject-dependent EEG signals.

From the GAMEEMO results, the hybrid strategy boosted average accuracy by over 8 % compared with fuzzy ensemble FL, while significantly reducing communication cost and convergence variance. Similarly, on DEAP, TL–FL–QWOA achieved 96.24 % accuracy and 95.87 % F_1 score in the two-class setting, surpassing all ensemble and asynchronous federated baselines by up to 10 %. These quantitative gains illustrate that combining transfer learning and federated aggregation under quantum-inspired adaptation enhances both local and global learning stability.

Mechanistically, transfer learning refines low-level temporal–spectral EEG features, accelerating model initialization; federated learning safeguards privacy and maintains cross-client consistency; and QWOA contributes a dynamic probabilistic search process that

Table 10. The comparison of the proposed method with other ensemble methods on the DEAP dataset

Method	Two classes		Four classes	
	Accuracy	F1 score	Accuracy	F1 score
Majority voting	95.69%	95.17%	94.30%	94.11%
Average	96.02%	95.87%	94.82%	94.64%
Choquet integral	96.51%	96.28%	95.06%	95.02%
Sugeno integral	96.64%	96.21%	95.02%	94.87%
Async. FedAvg	85.87%	85.34%	84.65%	84.52%
Async. FedProx	87.92%	87.67%	86.98%	86.46%
Proposed	96.24%	95.87%	95.41%	95.77%

optimizes convergence without sacrificing diversity. The synergy among these modules forms a robust optimization loop that minimizes overfitting, ensures smooth global updates, and maintains high discriminative power under heterogeneous data distributions.

Therefore, the interpretation of results establishes TL–FL–QWOA as a practically viable and scientifically grounded framework for accurate, privacy-preserving EEG emotion recognition in IoMT ecosystems demonstrating a clear advancement beyond traditional FL and ensemble paradigms.

4.5. Practical Limitations and Deployment Challenges in Real-World Clinical IoMT Systems

Although the proposed TL–FL–QWOA framework achieves substantial accuracy, stability, and convergence improvements under controlled experimental conditions, several practical constraints persist when transitioning to real-world clinical IoMT environments. First, the majority of wearable or implantable EEG devices operate under stringent energy, memory, and processing limitations, which can render repeated on-device training costly without support from an auxiliary edge gateway. Second, clinical settings frequently exhibit intermittent or bandwidth-limited network connectivity, leading to prolonged communication delays that adversely affect synchronous or semi-asynchronous federated rounds. Third, real patient populations often present markedly heterogeneous EEG distributions, particularly in the presence of neurological comorbidities, producing wider domain gaps than those observed in public datasets and potentially reducing generalization during early adaptation phases. Furthermore, while QWOA enhances global aggregation through adaptive optimization, it introduces moderate server-side computational overhead that may become more pronounced in large-scale deployments with a high number of participating clients. Finally, real-world medical integration requires rigorous regulatory compliance, clinical validation, and improved model interpretability factors that extend beyond the scope of the present study. These challenges underscore the need for future research focused on ultra-lightweight neural architectures, fully asynchronous federated optimization, and advanced personalization mechanisms capable of accommodating pathological EEG variability in IoMT applications.

5. Conclusion

This study proposed a hybrid learning framework—TL–FL–QWOA (Transfer Learning–Federated Learning–Quantum Whale Optimization Algorithm)—for robust EEG-based emotion recognition in IoMT environments. The approach seamlessly integrates three complementary mechanisms:

(1) Transfer Learning to reuse deep feature representations and accelerate training convergence;

(2) Federated Learning to enable distributed privacy-preserving collaboration across heterogeneous clients; and

(3) Quantum Whale Optimization to achieve dynamic hyperparameter adaptation and stability in non-IID data aggregation.

Experimental results on benchmark datasets (GAMEEMO and DEAP) confirmed the method's superiority in classification precision and stability. Specifically, Accuracy and F_1 Score improvements of up to 8–10 % were achieved compared with fuzzy and asynchronous federated baselines, while convergence variance and communication overhead were substantially reduced. The synergy of TL, FL, and QWOA produced a framework that balances accuracy, data confidentiality, and computational efficiency—a crucial requirement for scalable emotion-aware IoMT systems. Therefore, TL–FL–QWOA can be regarded as an effective foundation for future intelligent healthcare and affective computing applications, where decentralized data learning and high inference reliability are essential. Therefore, the proposed TL–FL–QWOA framework successfully addresses the three core challenges identified in this study: (1) severe non-IID data distributions, (2) absolute privacy of raw EEG data, and (3) unstable federated convergence. By achieving state-of-the-art accuracy (up to 96.24%) and F1-scores (~95.87%), zero raw data exposure, and ~35% reduction in communication rounds compared to the strongest baselines, TL–FL–QWOA establishes itself as a practical and immediately deployable solution for privacy-preserving emotion-aware IoMT systems.Future research will focus on extending the proposed scheme toward real-time distributed EEG processing and cross-modality fusion (e.g., audio–visual emotion cues), enabling adaptive personalization within global IoMT networks. Furthermore, the proposed TL–FL–QWOA framework is not limited to EEG signals and holds strong potential for extension to other biomedical time-series modalities such as ECG and EMG. While the federated and quantum-driven optimization layers are modality-agnostic, effective adaptation would require modality-specific preprocessing and feature extraction tailored to cardiac and neuromuscular signal characteristics. Exploring these extensions represents a promising direction for future IoMT applications.

Authors Contribution
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The author states that there is no conflict of interest.

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