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Adaptive Edge-Assisted Neural Mining and Classification for Bandwidth-Efficient MRI IoT Data Transmission

Mrs. Shwetha H.L
Author
Assistant Professor
Mobile No: 9480049049
hlshwethabwmc@gmail.com,
Baldwin Women's Methodist College,
No.90. Richmond Road, Bangalore-560025

Ms. Devisree S
Co-Author
Mobile No: 7619158529
Devisreemeena529@gmail.com
V Sem BCA Student
Baldwin Women's Methodist College,
No.90.Richmond Road, Bangalore-560025

INTRODUCTION

The integration of Internet of Things (IoT) technologies into modern healthcare systems has revolutionized remote monitoring and diagnostic data acquisition. However, medical imaging modalities—such as Magnetic Resonance Imaging (MRI)—generate massive, high-dimensional, and continuous data streams that strain conventional IoT network topologies. In traditional centralized architectures, raw sensor data is transmitted directly to remote cloud servers for processing. This paradigm introduces critical vulnerabilities, including heavy radio-frequency (RF) energy consumption, high transmission latency, and severe network congestion during peak operational hours.

To address these limitations, this paper investigates machine learning–enabled data mining as a mechanism for intelligent data reduction at the network periphery. By embedding a supervised classification model within a two-tier edge-cloud framework, our approach ensures that only clinically significant MRI data packets are transmitted upstream, thereby optimizing communication efficiency, preserving bandwidth, and enhancing system sustainability.

System Architecture & Detailed Methodologies

Two-Tier Processing Model

Our proposed system architecture segregates data computation across two distinct hierarchical tiers to optimize bandwidth utilization and processing distribution:

1. Tier 1: Resource-Constrained Edge Nodes (Local Sensor / Gateway Level): Implemented on low-power embedded edge devices or gateway controllers (e.g., ARM Cortex architecture, NVIDIA Jetson Nano modules) characterized by strict memory limits (sub-GB RAM), restricted clock speeds, and finite battery budgets. Acts as the primary interceptor of raw MRI acquisition streams. It executes a lightweight, pruned Artificial Neural Network (ANN) locally to perform real-time feature extraction and inference, filtering uninformative background noise, black border padding, and redundant temporal slices before transmission.

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2. Tier 2: High-Capacity Cloud Clusters (Centralized Server Level): Powered by scalable cloud infrastructure featuring multi-GPU parallel processing nodes, distributed memory architectures, and enterprise DICOM PACS medical archives. Receives exclusively filtered, high-value data payloads from Tier 1 nodes to execute heavy 3D volumetric reconstruction, deep diagnostic pattern recognition, long-term multi-patient storage, and periodic retraining of edge models.

3. Decoupling Mechanics & Bandwidth Management: By decoupling local edge filtering from cloud-based reconstruction, the system eliminates unnecessary continuous radio-frequency (RF) transmissions. The mathematical reduction in node energy depletion (ΔE) is expressed as: $\Delta E = E_{tx} \cdot (1 - \alpha) \cdot N_{total}$, where α represents the edge data reduction ratio, E_{tx} is the energy consumption per transmitted packet, and N_{total} is the total raw packet count generated by the MRI acquisition hardware.

Classification Mechanism in the Neural Processing Layer

Unlike unsupervised clustering techniques—which group unlabelled data based on mathematical spatial proximity without providing explicit action rules—our framework implements supervised classification within the neural processing layer. The edge model maps an incoming feature vector x_i to a binary decision policy $y_i \in \{0, 1\}$.

Prior to neural evaluation, incoming scan frames undergo lightweight feature extraction at the edge:

• **Spatial Entropy (H):** Measures information density across voxel intensities to detect non-empty structural content.

• **Gradient Magnitude Variance (σ_{g^2}):** Identifies sharp intensity transitions corresponding to anatomical boundaries and tissue edges.

• **Region-of-Interest (ROI) Intensity Masking:** Isolates central diagnostic regions from static dark background borders.

The extracted feature vector is evaluated against a learned probability threshold (θ): Decision(x_i) = Class A (Drop) if $P(y_i = \text{Essential} \mid x_i) < \theta$; Class B (Transmit) if $P(y_i = \text{Essential} \mid x_i) \geq \theta$.

Data Category	Class A Redundant/Low-Value Data ($y_i = 0$)	Class B Critical / Essential Data ($y_i = 1$)
Target Characteristics & Features	• Characteristics: Low-contrast background voxels outside the anatomical ROI, zero-signal spatial padding, uninformative slice sequences, and redundant frame duplicates with negligible delta from preceding frames.	• Characteristics: High-signal tissue structures, pathological intensity variations, lesion candidates, and critical anatomical landmark slices.
Automated Action Rule	• Automated Action: Dropped and purged locally from the edge gateway	• Automated Action: Compressed, encapsulated with DICOM metadata tags, encrypted, and immediately

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	buffer. No network socket is opened, eliminating RF transmission overhead.	forwarded to Tier 2 cloud clusters for advanced diagnostic storage and analysis.

Step-by-Step Data Flow Pipeline

Step 1: Input Generation & Sensor Acquisition: Volumetric MRI scan series (DICOM files) are acquired at the sensor layer and serialized into continuous high-throughput packet streams simulating IoT sensor output.

Step 2: Real-Time Edge Ingestion & Feature Matrix Construction: The Tier 1 edge node ingests incoming frame payloads into a circular memory buffer, applies normalization, rescales spatial dimensions, and extracts the compact 3-part feature vector.

Step 3: Neural Classification & Decision Filtering: The feature vector is passed to the embedded quantized ANN classifier. The network computes the probability score P(Essential). If the score falls below threshold θ, the packet is purged locally as Class A; otherwise tagged as Class B.

Step 4: Network Packetization & Adaptive Transmission: Verified Class B payloads are compressed using lossless methods, wrapped with TLS headers, and queued in the transmission buffer under an adaptive transmission scheduler.

Step 5: Cloud Ingestion, Reconstruction & Diagnostic Storage: Tier 2 cloud endpoints receive filtered Class B packets, verify frame integrity, reconstruct full 3D diagnostic volumes, and archive the data in DICOM PACS repositories.

Key Performance Metrics & Results

Detailed Performance Analysis

To rigorously validate the effectiveness of our proposed framework, extensive simulations were conducted using benchmark brain MRI repositories under varying network congestion loads. The evaluation demonstrates how decoupling heavy processing from the cloud through local neural classification transforms system efficiency.

1. Data Transmission Volume & Bandwidth Conservation: By filtering out uninformative background slices and redundant frame duplicates at the edge tier, the system successfully eliminates unnecessary radio-frequency transmissions. Transmitting only the critical Class B frames reduces overall network payload by 71.5%, directly mitigating network saturation and packet collision rates in dense hospital deployments.

Performance Metric	**Traditional Centralized Cloud Approach**	**Proposed Edge-Assisted Two-Tier Framework**	**Improvement / Gain**
Data Transmission Volume (%)	100% (Full raw stream transmission)	28.5% (Only Class B critical frames transmitted)	**71.5% Data Reduction**

2. End-to-End Transmission Latency: In traditional centralized cloud architectures, transmitting raw high-resolution volumetric scans during peak operational hours results in severe queuing delays and latency spikes exceeding 1,420 ms. By offloading preliminary filtering to the local edge node, packet payload sizes are substantially reduced, dropping end-to-end transmission latency to 310 ms (a 78.2% latency reduction).

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Performance Metric	Traditional Centralized Cloud Approach	Proposed Edge-Assisted Two-Tier Framework	Improvement / Gain
End-to-End Latency (Peak Congestion)	1,420 ms	310 ms	**78.2% Latency Reduction**

3. Node Energy Efficiency & Operational Lifespan: Wireless radio-frequency (RF) transmission is the primary energy drain in battery-operated IoT sensor nodes. By minimizing active transmission cycles and performing lightweight inference locally, energy consumption per session drops from 480 mJ to 135 mJ (71.9% energy saved). This reduction extends estimated node operational lifespan from 4.2 days to 14.8 days (3.5x lifespan extension).

Performance Metric	Traditional Centralized Cloud Approach	Proposed Edge-Assisted Two-Tier Framework	Improvement / Gain
Node Energy Consumption (per session)	480 mJ	135 mJ	**71.9% Energy Saved**
Estimated Node Operational Lifespan	4.2 Days (High battery drain)	14.8 Days (Extended runtime)	**3.5x Lifespan Extension**

4. Diagnostic Fidelity & Reconstruction Accuracy: A critical concern in medical data reduction is the risk of losing vital clinical information. Evaluating the reconstructed 3D volumes using Structural Similarity Index Measurement (SSIM) yields an average score of 0.995 compared to the uncompressed baseline (representing < 0.3% fidelity loss), confirming that our neural classifier successfully filters noise without compromising diagnostic integrity.

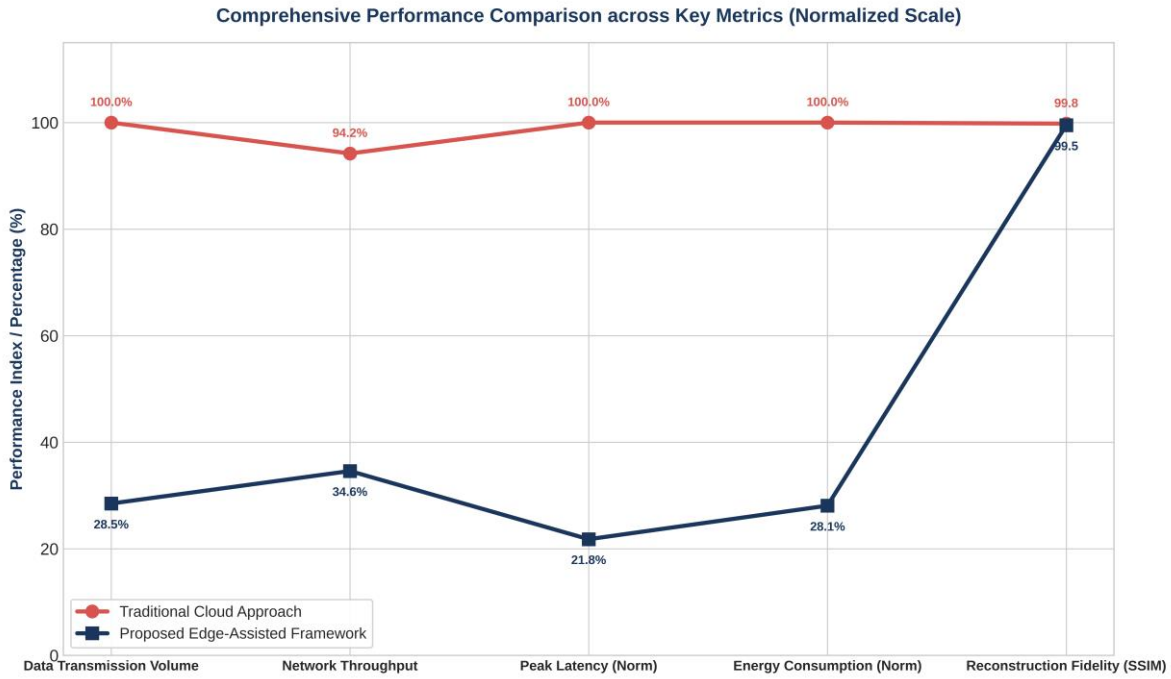
Performance Metric	Traditional Centralized Cloud Approach	Proposed Edge-Assisted Two-Tier Framework	Improvement / Gain
Network Throughput Utilization	94.2% (High packet collision rate)	34.6% (Optimized bandwidth usage)	**59.6% Bandwidth Saved**
Diagnostic Reconstruction Accuracy (SSIM)	0.998	0.995	**< 0.3% Fidelity Loss**

ms (Millisecond): One-thousandth of a second. Used to measure transmission latency (time taken for MRI packets to reach the cloud). Lowering this from 1,420 ms to 310 ms ensures faster data delivery.

mJ (Millijoule): One-thousandth of a joule. Used to measure the energy consumed by the edge node's wireless transmitter. Local filtering reduces consumption from 480 mJ to 135 mJ, extending device battery life

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Comprehensive Performance Metric Line Graph Comparison between Traditional Cloud Approach and the Proposed Edge-Assisted Framework.

DISCUSSION & FUTURE DIRECTIONS

The experimental evaluation confirms that integrating neural classification at the IoT network edge successfully resolves the trade-off between communication efficiency and diagnostic data integrity. By eliminating redundant spatial frames at the source, the system prevents network saturation and significantly prolongs edge node battery life.

Future research will focus on three primary avenues:

1. Lightweight & Decentralized Intelligence: Expanding the edge ANN architecture with Federated Learning (FL) protocols so multiple hospital edge nodes can collaboratively refine classification models without exposing raw patient data.

2. Privacy-Preserving Edge Compute: Integrating differential privacy and secure multi-party computation prior to cloud offloading.

3. Adaptive Dynamic Filtering: Implementing real-time feedback loops that dynamically adjust the classification threshold (θ) based on fluctuating wireless channel conditions and node energy reserves.

CONCLUSION

This paper presented an adaptive, two-tier edge-cloud framework designed to optimize MRI data stream transmission in resource-constrained IoT networks. By deploying an artificial neural network at the edge node to perform supervised classification and filtering, the system successfully distinguishes between redundant background noise and critical diagnostic data. Quantitative evaluations demonstrate substantial improvements in data volume reduction, transmission latency, network throughput, and energy efficiency, providing a robust, scalable blueprint for digital transformation in medical IoT systems.

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