Collaborative Fog Computing: Fog Head Selection and Data Compression in Internet of EEG-Healthcare Things

A BTP Report

BTP Batch: B25SSR01

Bachelor of Technology

in

Computer Science and Engineering

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December 2025

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the BTP entitled **"Collaborative Fog Computing: Fog Head Selection and Data Compression in Internet of EEG-Healthcare Things"** in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology at the Indian Institute of Information Technology Sri City, is an authentic record of my own work carried out during the period January 2025 to December 2025 under the supervision of **Dr. Sreeja SR**.

The matter presented in this report has not been submitted by me for the award of any other degree of this or any other institute.

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

(Dr.Sreeja SR)

Abstract

The Internet of EEG-Healthcare Things (IoEHT) enables continuous and real-time monitoring of brain activity for time-critical healthcare applications such as epilepsy detection and neurological disorder diagnosis. However, EEG systems generate large volumes of data, resulting in increased latency, bandwidth utilization, and energy consumption when processed using centralized cloud computing.

This project proposes a collaborative fog computing framework that integrates mathematical modeling, efficient EEG data compression, and optimal fog head selection. A delay, energy, and storage model is developed to analyze system performance. For EEG data reduction, a hybrid compression technique combining K-Means clustering, delta encoding, and arithmetic coding is proposed.

Experimental evaluation using the Bonn EEG dataset demonstrates superior compression ratio, reduced compression time, and low decompression overhead. Furthermore, an integrated DEMATEL–MOORA multi-criteria decision-making approach is employed to select the optimal fog head from heterogeneous fog devices based on computational capability, memory, and energy efficiency. Results indicate that the A15 Bionic chip achieves the highest MOORA score and is selected as the optimal fog head.

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Chapter 1

Introduction

The rapid advancement of smart healthcare technologies has led to the integration of medical sensing devices with communication networks, resulting in the Internet of Healthcare Things (IoHT). Among various biomedical signals, Electroencephalography (EEG) is widely used to measure the electrical activity of the human brain and plays a vital role in the diagnosis and monitoring of neurological disorders such as epilepsy, brain injuries, and sleep-related abnormalities. EEG-based healthcare applications are highly time-sensitive and require reliable, low-latency data processing to support real-time medical decision making.

Recent developments in wireless and wearable EEG devices have enabled continuous patient monitoring outside traditional clinical environments. However, EEG systems generate large volumes of data due to high sampling rates and multi-channel recordings. Transmitting raw EEG data directly to centralized cloud servers results in increased latency, high bandwidth consumption, and elevated energy usage. These limitations make pure cloud-based architectures unsuitable for time-critical healthcare applications.

Fog computing has emerged as an effective solution to address the limitations of cloud-centric systems by bringing computation closer to data sources. In a fog computing environment, intermediate fog nodes process data locally before forwarding it to the cloud. This reduces communication delay, lowers bandwidth requirements, and improves overall system responsiveness. For EEG-based healthcare systems, fog computing enables faster analysis and timely response, which are crucial for critical medical scenarios.

Despite its advantages, fog computing introduces new challenges due to the heterogeneous nature of fog devices. Fog nodes differ in processing power, memory capacity, and energy efficiency. Selecting an inappropriate fog device as the fog head can degrade system performance and increase energy consumption. Therefore, an intelligent fog head selection mechanism that considers multiple performance criteria is essential.

In addition to fog head selection, efficient EEG data handling is required to further reduce network load and storage overhead. EEG signals exhibit temporal redundancy, making data compression an effective approach for reducing data size without compromising signal quality. However, compression techniques must be computationally efficient and preserve clinically important information.

This project proposes a collaborative fog computing framework for Internet of EEG-Healthcare Things that integrates mathematical modeling, efficient EEG data compression, and optimal fog head selection. A hybrid compression technique combining K-Means clustering, delta encoding, and arithmetic coding is employed to reduce EEG data size. Furthermore, a Multi-Criteria Decision-Making (MCDM) approach using DEMATEL and MOORA is used to select the most suitable fog head from a set of heterogeneous fog devices. The proposed framework aims to improve system performance, reduce latency and energy consumption, and enhance the efficiency of EEG-based healthcare applications.

Chapter 2

Related Work

With the increasing adoption of Internet of Healthcare Things (IoHT), several studies have focused on improving the efficiency of healthcare monitoring systems using edge and fog computing architectures. EEG-based healthcare applications, due to their time-critical nature and large data volume, have received significant attention in recent research.

Several researchers have investigated fog and edge computing as alternatives to traditional cloud-centric architectures for healthcare systems. Fog computing enables data processing closer to medical sensors, thereby reducing latency and improving real-time responsiveness. Studies have shown that fog-enabled healthcare systems significantly outperform cloud-only systems in terms of delay and bandwidth efficiency, especially for continuous monitoring applications such as EEG, ECG, and EMG analysis.

EEG data compression has been widely explored to reduce storage and communication overhead in IoHT networks. Traditional lossless compression techniques such as Huffman coding and Discrete Cosine Transform (DCT)-based methods have been applied to EEG signals. While these methods provide data reduction, their compression efficiency is limited when applied directly to raw EEG signals. Recent works have introduced clustering-based approaches, where similar EEG samples are grouped to reduce redundancy before encoding. These techniques achieve better compression performance but often increase computational complexity.

To address this, hybrid compression techniques combining clustering, differential encoding, and entropy coding have been proposed. Delta encoding exploits the temporal correlation in EEG signals by storing differences between consecutive samples, while arithmetic coding further reduces statistical redundancy. Although these hybrid approaches achieve higher compression ratios, their integration with fog computing environments remains relatively unexplored.

Fog head selection is another critical challenge in fog computing systems. Fog environments consist of heterogeneous devices with varying computational capabilities, memory sizes, and energy characteristics. Selecting an appropriate fog head directly impacts system performance, energy efficiency, and reliability. Several studies have applied Multi-Criteria Decision-Making (MCDM) techniques such as AHP, TOPSIS, and VIKOR for fog resource selection. However, these methods often assume independent criteria, which may not reflect real-world dependencies among system parameters.

DEMATEL has been used to analyze causal relationships among criteria and identify influential factors in complex systems. When combined with ranking methods such as MOORA, DEMATEL enables more accurate and objective decision making by incorporating both interdependencies and relative importance of criteria. Recent research has demonstrated the effectiveness of integrated DEMATEL–MOORA approaches in cloud and fog resource optimization problems. However, limited work has applied this approach specifically to fog head selection in EEG-based healthcare systems.

Based on the reviewed literature, it is observed that existing studies either focus on EEG data compression or fog resource selection independently. There is a lack of integrated frameworks that jointly address efficient EEG data compression and optimal fog head selection under a unified fog computing architecture. This project addresses this gap by combining a hybrid EEG compression technique with a DEMATEL–MOORA-based fog head selection mechanism to enhance the performance of Internet of EEG-Healthcare Things systems.

Chapter 3

Problem Statement and Contributions

3.1 Problem Statement

The rapid growth of Internet of Healthcare Things (IoHT) has enabled continuous monitoring of patients using wearable and wireless biomedical devices. Among various biomedical signals, Electroencephalography (EEG) plays a crucial role in diagnosing and monitoring neurological disorders. However, EEG-based healthcare applications generate large volumes of data due to high sampling rates and multi-channel recordings, leading to challenges in terms of latency, bandwidth consumption, and energy usage.

Traditional cloud-based processing of EEG data introduces significant communication delays and high energy consumption, which are not suitable for time-sensitive healthcare applications. Fog computing addresses these limitations by enabling computation closer to data sources. However, fog computing environments are inherently heterogeneous, with fog devices varying in processing power, memory capacity, and energy efficiency. Selecting an inappropriate fog head can degrade system performance and increase energy consumption.

In addition, efficient handling of EEG data is essential to reduce network load and storage requirements. Existing EEG compression techniques often involve trade-offs between compression efficiency and computational overhead. Therefore, there is a need for an integrated framework that simultaneously addresses EEG data compression, latency and energy modeling, and intelligent fog head selection for Internet of EEG-Healthcare Things applications.

3.2 Contributions

The key contributions of this project are summarized as follows:

- A collaborative fog computing framework is proposed for Internet of EEG-Healthcare Things that integrates mathematical modeling, EEG data compression, and intelligent fog head selection.
- Mathematical models for system delay, energy consumption, and performance and storage efficiency are formulated to capture the behavior of EEG data processing in fog computing environments. The delay model developed by Abhinash and energy model developed by Druva Sai, while the performance and storage model was developed by Surya. These models were derived through extensive study of existing research literature and adapted to the proposed system architecture.
- A hybrid EEG data compression scheme combining K-Means clustering, delta encoding, and arithmetic coding is designed and implemented. This compression pipeline was jointly developed and evaluated by Druva Sai, Surya, and Abhinash after experimenting with multiple compression approaches and selecting the most effective solution based on performance metrics.
- An intelligent fog head selection mechanism based on Multi-Criteria Decision-Making (MCDM) is proposed using DEMATEL and MOORA techniques. The DEMATEL-based criterion analysis was carried out by Surya, while the MOORA-based ranking and implementation were performed by Druva Sai. Abhinash contributed to understanding and analyzing MCDM concepts and their applicability to fog computing environments.

Chapter 4

Proposed Methodology

4.1 System Architecture

The proposed system architecture is designed for the Internet of EEG-Healthcare Things and follows a three-layer model consisting of EEG sensing devices, fog computing nodes, and cloud servers. This architecture is developed to support time-critical healthcare applications by reducing latency, bandwidth usage, and energy consumption.

At the lowest layer, EEG devices continuously acquire brain signals from patients using non-invasive sensors. These devices generate large volumes of raw EEG data due to high sampling rates and continuous monitoring. Transmitting raw EEG data directly to the cloud is inefficient and leads to increased communication delay and network congestion.

To address this issue, a fog computing layer is introduced between EEG devices and the cloud. Fog nodes are deployed closer to EEG devices and act as intermediate processing units. These fog nodes perform key tasks such as EEG signal processing, data compression, and temporary storage. By processing EEG data locally at the fog layer, the system significantly reduces transmission delay and bandwidth requirements.

Only the compressed EEG data is forwarded to the cloud layer. The cloud server is primarily used for long-term data storage, advanced analytics, and historical data access by healthcare professionals. This division of responsibilities ensures that time-sensitive operations are handled at the fog layer, while computationally intensive and non-real-time tasks are delegated to the cloud. Overall, the proposed architecture improves system responsiveness, scalability, and reliability for EEG-based healthcare applications.

4.2 Mathematical Modeling

4.2.1 Delay Model

The delay model captures the total time required to process an EEG task in the system. It includes four major components: transmission delay, propagation delay, processing delay, and queuing delay. Transmission delay represents the time taken to transmit EEG data over the wireless channel and depends on available bandwidth and signal quality. Propagation delay accounts for the physical distance between EEG devices, fog nodes, and cloud servers. Processing delay depends on the computational capability of the fog device, while queuing delay represents waiting time due to resource contention. This model helps in analyzing latency behavior in time-critical EEG healthcare applications.

The total delay experienced by task i is given by:

$$D_i^{\text{Total}} = D_i^{\text{trans}} + D_i^{\text{prop}} + D_i^{\text{proc}} + D_i^{\text{queue}} \tag{4.1}$$

The transmission delay is expressed as:

$$D_i^{\text{trans}} = \frac{D_s}{B \log_2 (1 + \text{SNR})} \tag{4.2}$$

The propagation delay is defined as:

$$D_i^{\text{prop}} = \frac{\text{dist}_{\text{EEG},k} + \text{dist}_{k,i}}{V} \tag{4.3}$$

The processing delay is given by:

$$D_i^{\text{proc}} = \frac{n}{C_i^{\text{avg}}} \tag{4.4}$$

4.2.2 Energy Model

The energy model estimates the total energy consumption of fog nodes during EEG task execution. It considers three components: processing energy, transmission energy, and idle energy. Processing energy depends on the execution time of EEG tasks, while transmission energy is influenced by the duration of data transfer. Idle energy accounts for the power consumed by the fog device when it is not actively processing tasks. This model is essential for evaluating the energy efficiency of fog devices and selecting an optimal fog head.

The total energy consumption of node i is:

$$E_i^{\text{Total}} = E_i^{\text{proc}} + E_i^{\text{trans}} + E_i^{\text{idle}} \tag{4.5}$$

The processing energy is computed as:

$$E_i^{\text{proc}} = e^{\text{proc}} \times D_i^{\text{proc}} \tag{4.6}$$

The transmission energy is calculated by:

$$E_i^{\text{trans}} = e^{\text{trans}} \times D_i^{\text{trans}} \tag{4.7}$$

4.2.3 Performance and Storage Model

The performance and storage model evaluates how efficiently a fog node utilizes its available memory resources. Storage efficiency is computed using weighted contributions from primary and secondary memory utilization. This ensures that fog head selection does not overload memory resources. Additionally, the Cycles Per Instruction (CPI) metric relates processing speed with instruction execution, providing insight into the computational efficiency of fog devices.

The storage efficiency is defined as:

$$SE = \alpha \left(\frac{PM_i^{\text{occ}}}{PM} \right) + \beta \left(\frac{SM_i^{\text{occ}}}{SM} \right) \tag{4.8}$$

$$\text{CPI} = \frac{C_i^{\text{avg}}}{\text{MIPS} \times 10^6} \tag{3.9}$$

4.3 EEG Data Compression

The proposed compression pipeline consists of:

- K-Means clustering
- Delta encoding
- Arithmetic coding

EEG signals are highly time-dependent and exhibit significant temporal redundancy, making them suitable for data compression. Efficient compression is essential in EEG-based healthcare systems to reduce network load, storage requirements, and energy consumption, while preserving clinically important information.

In this project, a hybrid EEG data compression pipeline is proposed that combines K-Means clustering, delta encoding, and arithmetic coding. This multi-stage approach exploits both signal similarity and temporal correlation to achieve high compression efficiency.

In the first stage, K-Means clustering is applied to the EEG signal samples. Similar EEG values are grouped into clusters, and each sample is replaced by its corresponding cluster centroid. This reduces the number of unique values in the signal and organizes the data in a more compact form.

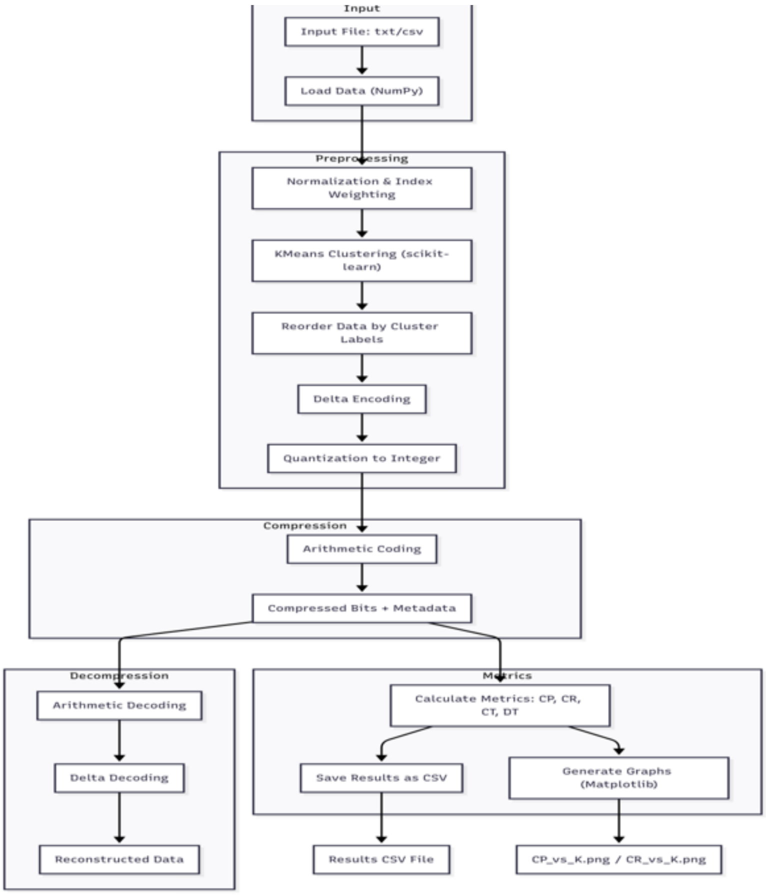

Figure 4.1: EEG Data Compression and Evaluation Workflow

In the second stage, delta encoding is performed on the clustered EEG signal. Instead of storing absolute values, the difference between consecutive samples is stored. Since EEG signals change gradually over time, the resulting delta values are typically small, which further reduces data size.

In the final stage, arithmetic coding is applied to the delta-encoded data. Arithmetic coding compresses the data based on the probability distribution of delta values, assigning shorter codes to more frequently occurring values. This stage removes statistical redundancy and produces a highly compact compressed bitstream.

The proposed compression pipeline achieves high compression ratio, reduced storage requirements, and low computational overhead, making it suitable for real-time EEG processing in fog computing environments.

4.4 Fog Head Selection Using DEMATEL+MOORA

Fog computing environments consist of heterogeneous devices with varying computational capabilities, memory capacities, and energy characteristics. Selecting an appropriate fog head is a critical decision, as the fog head is responsible for coordinating data processing and communication within the fog layer.

In this project, fog head selection is treated as a Multi-Criteria Decision-Making (MCDM) problem. Multiple performance-related and energy-related criteria must be considered simultaneously to ensure efficient system operation. The considered criteria include minimum and maximum clock speed, number of cores, MIPS, primary and secondary memory, total energy consumption, unit energy consumption, and idle energy.

The DEMATEL method is first applied to analyze the interdependencies among these criteria. DEMATEL identifies which criteria have a stronger influence on system performance and assigns appropriate weights based on their cause–effect relationships. This ensures that more influential criteria contribute more significantly to the final decision.

After determining the criterion weights using DEMATEL, the MOORA method is applied to rank the available fog devices. Each fog device is evaluated using weighted benefit and cost criteria. Performance-related parameters such as clock speed, cores, and MIPS are treated as benefit criteria, while energy-related parameters are treated as cost criteria. The fog device with the highest MOORA score is selected as the optimal fog head.

This integrated DEMATEL+MOORA approach provides a systematic, objective, and data-driven method for fog head selection, ensuring balanced performance and energy efficiency in the proposed EEG-based fog computing system.

Chapter 5

Experimental Results

5.1 Dataset Description

The experimental evaluation in this project is carried out using two datasets: the Bonn EEG dataset for evaluating EEG data compression performance and a fog device dataset for evaluating fog head selection using the DEMATEL–MOORA approach.

5.1.1 EEG Dataset

The Bonn EEG dataset is a widely used benchmark dataset for EEG signal processing and healthcare-related research. It contains EEG recordings collected from both healthy individuals and epilepsy patients, making it suitable for evaluating EEG-based healthcare applications.

The dataset is divided into five subsets, namely Z, F, N, O, and S. Each subset consists of 100 single-channel EEG segments, where each segment has a duration of 23.6 seconds. The EEG signals are sampled at a rate of 173.61 Hz, resulting in 4097 samples per segment. All recordings are stored in text file format.

Subsets N and F contain scalp EEG recordings from healthy subjects recorded under different conditions such as eyes open and eyes closed. Subsets S and O contain EEG recordings from epilepsy patients during seizure-free intervals, captured from different brain regions. Subset Z contains EEG recordings captured during epileptic seizure activity.

All EEG signals are band-limited to a frequency range of 0.5–85 Hz. In total, the dataset contains 500 EEG segments across all subsets. The diversity of EEG signal characteristics across these subsets enables a comprehensive evaluation of the proposed compression technique under different physiological conditions.

5.1.2 Fog Device Dataset

For fog head selection, a dataset consisting of eight heterogeneous fog devices is considered. The selected fog devices represent a mix of embedded platforms, single-board computers, and high-performance processors commonly used in edge and fog computing environments.

Each fog device is characterized using multiple performance-related and energy-related parameters. These include minimum and maximum clock frequency, number of cores, Million Instructions Per Second (MIPS), primary memory, secondary memory, total energy consumption, unit energy consumption, and idle energy. These parameters collectively capture the computational capability, memory capacity, and energy efficiency of each fog device.

The fog device dataset forms the basis for the Multi-Criteria Decision-Making analysis. DEMATEL is applied to analyze interdependencies among the criteria and derive their relative importance, while the MOORA method is used to rank the fog devices and select the optimal fog head. The use of a heterogeneous fog device dataset ensures that the proposed selection approach is realistic and applicable to practical fog computing scenarios.

ID	Processor	C_{min}	C_{max}	Cores	MIPS	PM (GB)	SM (GB)	Total Energy (J)	Idle Energy
F1	Nvidia Jetson Nano	1.43	1.43	4	9000	4	64	335700	16785
F2	Raspberry Pi 4 Model B	1.5	1.5	4	12000	4	128	90000	4500
F3	NVIDIA Jetson Xavier NX	1.4	1.9	6	9000	8	128	335700	16785
F4	Intel Celeron N4000	1.1	2.6	2	8800	4	32	162000	8100
F5	Snapdragon 888	1.8	2.84	8	12000	8	32	234000	11700
F6	A15 Bionic chip	1.8	3.23	6	15000	6	128	72000	3600
F7	AMD Ryzen 3 2200U	2.5	3.4	2	20000	4	128	126000	6300
F8	AMD Ryzen 3 5300U	2.6	3.8	4	12080	8	128	162000	8100

Table 5.1: Fog Device Dataset and Performance Parameters

5.2 Compression Performance

This section evaluates the compression performance of the proposed EEG data compression architecture using the Bonn EEG dataset. The performance is analyzed in terms of compression ratio, compression power, compression time, and decompression time. The proposed model is compared with existing compression techniques across all five EEG subsets (Z, F, N, O, and S).

As shown in Fig. 5.1, the proposed compression model consistently achieves the highest compression ratio across all datasets. An average compression ratio exceeding 96% is observed for all EEG subsets, indicating significant data size reduction. In comparison, existing methods exhibit noticeably lower compression ratios, highlighting the effectiveness of the proposed hybrid compression pipeline.

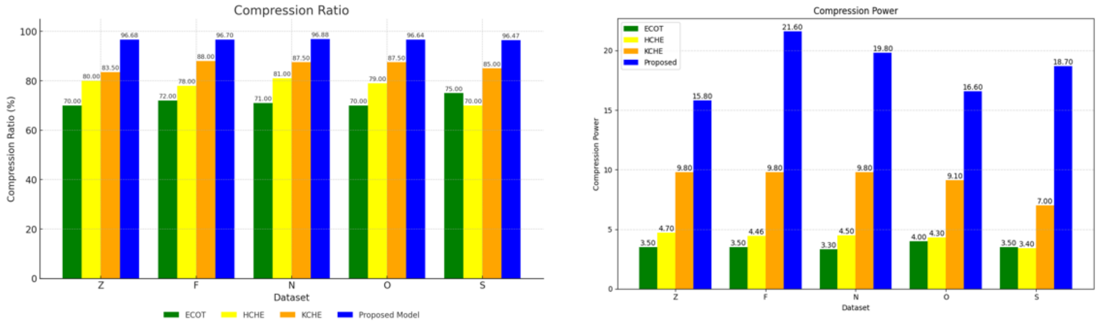

Figure 5.1: Comparative analysis of compression ratio and compression power across different models

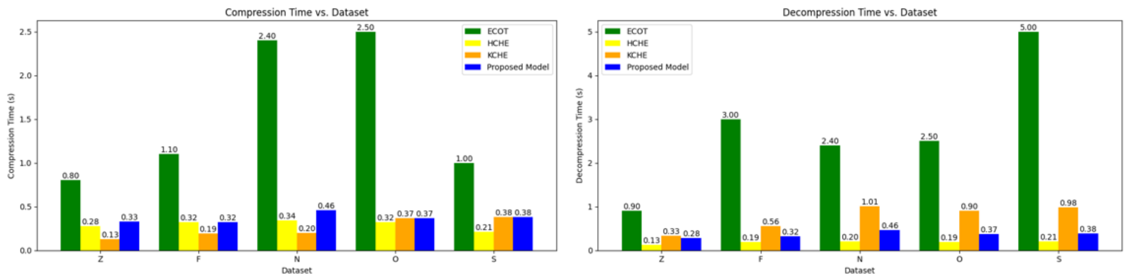

Figure 5.2: Comparison of compression time and decompression time across datasets

Compression power, which reflects the efficiency of data reduction per unit processing effort, is also significantly higher for the proposed model. The improved compression power demonstrates that the proposed approach not only reduces data size but does so efficiently, making it suitable for resource-constrained fog computing environments.

Fig. 5.2 illustrates the compression and decompression times for different EEG datasets. The proposed model achieves lower compression and decompression times compared to traditional methods, despite its higher compression ratio. This is primarily due to the structured compression pipeline that combines K-Means clustering for data grouping, delta encoding for temporal redundancy removal, and arithmetic coding for statistical compression.

Across all datasets, the proposed method maintains stable performance with only minor variations, indicating robustness to different EEG signal characteristics such as seizure and non-seizure activity. The reduced compression and decompression times confirm the suitability of the proposed approach for real-time and time-critical EEG-based healthcare applications.

Overall, the results demonstrate that the proposed compression architecture achieves a favorable balance between high compression efficiency and low computational overhead, making it well suited for deployment in fog-based Internet of EEG-Healthcare Things systems.

5.3 Fog Head Selection Results

This section presents the results of fog head selection using the integrated DEMATEL–MOORA multi-criteria decision-making approach. The objective is to identify the most suitable fog device to act as the fog head by considering multiple performance and energy-related criteria.

A total of eight heterogeneous fog devices are evaluated, including embedded platforms, single-board computers, and high-performance processors. The selection criteria include minimum and maximum clock frequency, number of cores, MIPS, primary and secondary memory, total energy consumption, unit energy consumption, and idle energy. DEMATEL is first applied to analyze the interdependencies among these criteria and to derive their relative weights. The obtained weights reflect the influence of each criterion on overall system performance.

Using the DEMATEL-derived weights, the MOORA method is employed to rank the fog devices. Performance-related parameters such as clock speed, cores, MIPS, and memory are treated as benefit criteria, while energy-related parameters are treated as cost criteria. The MOORA score for each fog device is computed as the difference between the weighted sum of benefit criteria and the weighted sum of cost criteria.

The final MOORA ranking results indicate that the *A15 Bionic chip* achieves the highest MOORA score of 0.205362 and is ranked first with a relative performance of 100%. This result demonstrates that the A15 Bionic chip offers the best balance between computational capability and energy efficiency among all evaluated fog devices. The AMD Ryzen 3 2200U and AMD Ryzen 3 5300U achieve the second and third ranks, respectively, due to their strong processing performance but comparatively higher energy consumption.

Devices such as the Raspberry Pi 4 Model B and Snapdragon 888 achieve moderate rankings, indicating balanced but limited performance under the considered criteria. Fog devices such as the Nvidia Jetson Nano and Nvidia Jetson Xavier NX are ranked lower due to higher energy consumption and lower overall weighted performance scores.

In addition, criterion influence analysis reveals that the number of cores and total energy consumption have the highest impact on the final ranking, as their removal results in the largest changes in rank. This highlights the importance of computational parallelism and energy efficiency in fog head selection for EEG-based healthcare applications.

Overall, the DEMATEL–MOORA-based selection process provides a systematic and data-driven approach for identifying the optimal fog head. Based on the results, the A15 Bionic chip is selected as the optimal fog head for the proposed fog-based Internet of EEG-Healthcare Things architecture.

ID	Processor	MOORA Score	MOORA Rank	Relative Performance (%)
F6	A15 Bionic chip	0.205362	1	100.000000
F7	AMD Ryzen 3 2200U	0.191810	2	93.401015
F8	AMD Ryzen 3 5300U	0.160886	3	78.342675
F2	Raspberry Pi 4 Model B	0.106145	4	51.686959
F5	Snapdragon 888	0.089365	5	43.515636
F4	Intel Celeron N4000	0.059555	6	28.999743
F3	NVIDIA Jetson Xavier NX	-0.038774	7	-18.880868
F1	Nvidia Jetson Nano	-0.067281	8	-32.762132

Table 5.2: MOORA-based ranking and relative performance of fog devices

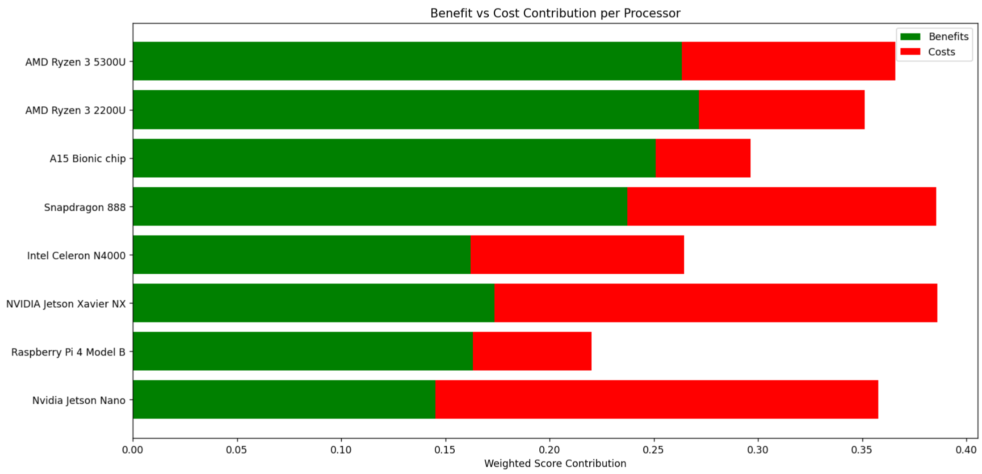

Figure 5.3: Benefit and cost contribution of selection criteria for fog devices

Chapter 6

Conclusion and Future Work

This project presented a collaborative fog computing framework for Internet of EEG-Healthcare Things applications, focusing on efficient EEG data compression and optimal fog head selection. The proposed architecture enables computation to be performed closer to EEG sensing devices, thereby reducing communication latency and network load while improving system responsiveness.

A hybrid EEG data compression scheme combining K-Means clustering, delta encoding, and arithmetic coding was developed and evaluated using the Bonn EEG dataset. Experimental results demonstrated that the proposed compression approach achieves a high compression ratio while maintaining low compression and decompression times across all EEG subsets. The improved compression performance significantly reduces data transmission and storage requirements, making the approach suitable for resource-constrained fog computing environments.

To address the challenge of selecting an appropriate fog head in a heterogeneous fog environment, an integrated DEMATEL–MOORA-based multi-criteria decision-making approach was employed. Multiple performance and energy-related criteria were considered to ensure a balanced evaluation. The results identified the A15 Bionic chip as the optimal fog head, offering the best trade-off between computational capability and energy efficiency.

Overall, the combined use of efficient EEG compression and intelligent fog head selection enhances the feasibility of deploying real-time EEG-based healthcare applications in fog computing environments. The proposed framework provides a systematic and scalable solution for reducing latency, bandwidth usage, and energy consumption in Internet of EEG-Healthcare Things systems.

Future Work

Although the proposed framework demonstrates promising results, several extensions can be explored in future research. Real-time deployment of the system using actual EEG acquisition hardware and fog devices would allow evaluation under practical operating conditions. Adaptive and learning-based compression techniques, such as deep learning or reinforcement learning, can be investigated to further improve compression efficiency for dynamic EEG signals.

In addition, future work may incorporate security and privacy-aware fog head selection mechanisms to address sensitive medical data concerns. The proposed framework can also be extended to multi-fog and multi-patient scenarios, as well as integrated with other biomedical signals such as ECG and EMG to build a more comprehensive healthcare monitoring system.

List of Symbols and Notations

Symbol	Description
D_s	Size of EEG data (in bits or bytes)
B	Bandwidth of the communication network (Hz)
SNR	Signal-to-Noise Ratio of the communication channel
$\text{dist}_{EEG,k}$	Distance between EEG device and fog head
$\text{dist}_{k,i}$	Distance between fog head and i^{th} fog device
V	Propagation speed of the signal in the transmission medium
n	Number of CPU cycles required to process one bit of data
C_i^{avg}	Average clock frequency of the i^{th} fog device
T^n	n^{th} task waiting in the processing queue
e^{proc}	Energy consumption per unit time for processing
e^{trans}	Energy consumption per unit time for data transmission
PM_i^{occ}	Primary memory occupied by the i^{th} fog device
SM_i^{occ}	Secondary memory occupied by the i^{th} fog device
PM	Total available primary memory
SM	Total available secondary memory
α, β	Weighting factors for primary and secondary memory usage
MIPS	Million Instructions Per Second
CPI	Cycles Per Instruction

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