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Neural-Driven Smart IoT Systems: Enhancing Brain-Computer Interface Control Using Deep Learning and Edge Computing

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ABSTRACT

The rapid development of brain-computer interface technology, alongside the growth of the IoT, has favoured new domains of human-machine interactions in health, rehabilitation, and assistive technologies. However, many of the classical BCI systems face issues while dealing with performance, latency, and scalability issues. To deal with the aforementioned, the paper proposes to bring together deep learning and edge computing to support BCI control in IoT smart systems. The paper aims to reduce latency and improve performance and usability in BCIs. Deep learning algorithms for efficient signal classification include convolutional neural networks without edge computing, and sensor-to-sensor processing happens as close to the object being controlled as possible in real-time, which means less dependence on remote cloud servers. Combining these two technologies into one approach optimizes BCI-controlled interactions with IoT devices such as prosthetics and exoskeletons. The results revealed that the proposed model demonstrated an improvement over traditional methods based on several key metrics: accuracy (96%), latency (90 ms), throughput (90 signals/sec), and power consumption (50 W). With this model, the latency reduced with this integrated edge computing will improve energy efficiency, making it suitable for real-time efficient applications. Therefore, the integration of deep learning with edge computing in BCIs shows high value for upgrading health care, rehabilitation, and assistive technologies. Finding novel ways to be more efficient and scalable concerning actual IoT applications completes the picture of an integrated system for more personalized, responsive, and precise control over BCI systems.

Keywords: Brain-Computer Interface (BCI), Deep Learning, Edge Computing, Internet of Things (IoT), Signal Classification, Neural Signal Processing, Real-Time Control, Prosthetics, Exoskeletons, Latency Reduction, Power Efficiency, Smart IoT Systems

1. INTRODUCTION

The fast pace of development in Brain-Computer Interface (BCI) technologies, coupled with the expansion of Internet of Things (IoT) systems, has created new avenues in human-machine interaction. BCIs facilitate direct brain-to-device communication, providing revolutionary potential for use in healthcare, rehabilitation, and assistive technology applications. *Kartsch et al. (2019)* present BioWolf, a power-effective BCI platform based on a low-power system-on-chip, RISC-V cores, and Bluetooth, with high information transfer at low power through canonical correlation analysis. With the increasing need for smooth and efficient BCI systems, their integration of sophisticated methods such as deep learning and edge computing has become critical to boost the performance, precision, and usability of BCIs. When combined, these technologies open the doors to intelligent, intuitive, and responsive IoT device control.

Deep learning methods have been very effective at decoding complex brain signals, providing enhanced signal classification, pattern discovery, and general BCI performance. With the use of deep learning algorithms, BCIs can decode brain activity with improved accuracy, allowing for real-time device control. *Nagel and Spüler (2019)* report a deep learning-based approach for EEG-based decoding of sensory information with high information transfer in passive mode and possible constraints in non-invasive visual BCI performance. This advancement increases the feasibility of BCIs for real-world application in dynamic environments. In addition, continuous improvement of BCI performance with machine learning means that these interfaces can learn to customize themselves to individuals' neural patterns over time and thus offer personalized control and improved user experience

At the same time, edge computing is also essential to lower latency, which is a key performance indicator for BCI-based systems demanding rapid responses. *Lotte et al. (2018)* survey EEG-based BCI classification algorithms, emphasizing adaptive classifiers, transfer learning, and Riemannian geometry approaches, pointing out the slow progress of deep learning and providing recommendations for improving EEG classification. Through local processing of data on edge devices, instead of delegating it to remote cloud servers, edge computing facilitates quicker data analysis and decision-making, and thus real-time interaction. Within BCIs, edge computing can be utilized to provide real-time, seamless control of IoT devices, e.g., prosthetics, exoskeletons, and assistive technologies, with reduced latency that might interfere with performance.

This article discusses the synergy among neural-driven smart IoT systems, deep learning, and edge computing to further advance the control of BCIs. *Menon et al. (2019)* suggest a humanoid assistive system for paralyzed patients based on SDN, employing edge computing for real-time control and enhanced flexibility of the exoskeleton, showing efficient rehabilitation through EEG-based control. Through the discussion of existing research and applications, it enlightens us on the possibility of these combined technologies to revolutionize BCI design, enhancing assistive devices, and providing new avenues for healthcare, rehabilitation, and accessibility, thereby leading to the development of human-centred smart systems.

Key Objectives

- Understand how deep learning integrates with edge computing to synergize BCI control using smart IoT systems.
- Implement advanced neural signal processing algorithms to reduce latency in real-time control of the devices.

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- Investigate the effects of edge computing in optimizing BCI interactions with IoT devices such as prosthetics and exoskeletons.
- Examine the combination of DNN and edge-computing techniques to implement personalized and energy-efficient control over BCIs in a range of applications.
- They will create new opportunities to improve BCI reliability, usability, and performance in healthcare, rehabilitation, and assistive technologies.

Zhang et al. (2019) address the issues and development in Brain-Computer Interfaces (BCIs), particularly on the analysis of brain signals and how they are translated into device commands. Although BCIs have been highly promising, the paper points out serious flaws in the design and operation of these systems, especially when deep learning methods are used to process signals. Even with much improvement in the field, signal variability, real-time processing, and scalability remain ubiquitous challenges. This paper proposes to overcome these hurdles by delving into some of the recent advancements in brain signal analysis and pinpointing the directions for the development of future deep learning-based BCI.

Rajesh et al. (2019) identified a Brain-to-Brain Interface (BBI) for communication between caregivers and stroke patients. Although the combination of EEG headsets and light encryption algorithms, like NTSA, facilitates communication via thought signals, there is no research on the scalability of the system, especially in multi-user settings. Besides, although the system proves to be effective in secure communication, more research is necessary into the optimization of the encryption algorithm, real-time performance, and extending the ability of the system to effectively accommodate various neurological conditions and environments.

2. LITERATURE SURVEY

Bansal and Mahajan (2019) discuss EEG-based Brain-Computer Interfaces (BCIs) primarily for cognitive analysis and control applications. It explores in detail the techniques of analyzing purposeful eye-blinking data using time and frequency domain analysis. The methods include ERP, scalp mapping, and sub-band power analysis to get EEG data across different scenarios. Further, they also describe how to create an intuitive real-time system for command with multiple algorithms interfacing with MATLAB for interactive EEG signal acquisition and control.

Kadiyala (2019) introduced a hybrid model that enhances fog computing performance by reducing latency and improving resource allocation. By integrating DBSCAN, Fuzzy C-Means, and ABC-DE optimization, the study addresses challenges in managing unstructured IoT data securely. The proposed approach ensures efficient data exchange, optimizes bandwidth, and strengthens security, outperforming conventional methods. This model provides a scalable and reliable solution for IoT-fog computing environments, improving overall system efficiency and data protection.

Boyapati (2019) explores how Cloud IoT-driven digital financial inclusion can bridge the income gap between urban and rural areas. By utilizing Explainable AI and statistical methods, the study analyzes income equality indicators across different regions. The findings show that integrating advanced analytics significantly reduces economic disparities, promoting financial accessibility. This research highlights the role of Cloud IoT in fostering inclusive financial policies and supporting fair economic growth.

According to Narla (2019), cloud computing and AI are revolutionizing healthcare by enabling real-time disease prediction using IoT data. Traditional models often struggle with balancing accuracy and efficiency, leading to the development of an optimized ACO-LSTM framework. This model refines LSTM parameters using Ant Colony Optimization, improving predictive capabilities and reducing processing time. With enhanced sensitivity and specificity, it ensures precise and timely disease detection, supporting better patient care and scalable healthcare monitoring

Natarajan (2018) explores how cloud computing, artificial intelligence, and IoT are transforming healthcare by enabling real-time disease diagnosis. Traditional methods struggle with the vast and complex data from IoT devices, requiring optimized solutions. By integrating Radial Basis Function Networks, Genetic Algorithms, and Particle Swarm Optimization, the proposed model enhances accuracy and processing speed. This hybrid approach improves real-time healthcare monitoring, ensuring precise disease detection and making medical data analysis more efficient and reliable.

Yalla (2019) examines the integration of IoT smart computing with big data, hashgraph, and cloud computing within the Kinetic methodology to enhance data management and security. IoT smart computing enables real-time data collection and processing, while cloud computing ensures scalable and efficient resource utilization. Hashgraph technology enhances security and consensus mechanisms, improving decision-making and operational efficiency. This approach addresses key challenges like interoperability, scalability, and regulatory compliance, making data-driven insights more accessible and reliable

Mahajan and Bansal (2017) examine cognitive neuroscience as a means to enhance Brain-Computer Interfaces for interactive control applications. The paper talks about converting intentional eye blinks, captured via EEG sensor, into commands. The EEG signals were filtered according to power spectral features, that is, peak data to identify the instances of eye-blink. There is a significant increase in event-related potentials observed in the frontal lobes. The model was implemented on Arduino using Simulink, which validates using EEG-based BCIs for rehabilitation of physically challenged patients.

Pais Roldán (2019) questions the basic ideas around the coma and incorporates the issue of why some patients recover while in a coma and others remain untouched. Using a rat model of the brainstem coma, the recovery of brain function following a coma was investigated using fMRI. The study has identified a network encompassing the basal forebrain, basal ganglia, and thalamus wherein it contributed to cortical reactivation. The study also puts forth the challenges of fMRI research in small animals while also proposing a multimodal platform based on fMRI and pupillometry for monitoring arousal.

Schwemmer et al. (2018) propose a new deep neural network decoding framework for Brain-Computer Interface (BCI) systems to further the goals of accuracy, response time, and multifunctionality. Using intracortical data collected from a tetraplegic participant, the decoder revealed a high level of accuracy, sustained performance over one year without retraining, a faster response than existing methods, and improved functionality with minimal retraining through transfer learning. The controller allowed the direct and real-time control of a paralyzed forearm using functional electrical stimulation, providing a huge step forward for BCI clinical applications.

Bose et al. (2019) discuss how BCIs have turned fiction into reality, enabling prosthetic developments for hearing aids and, more importantly, prosthetic limbs for paralyzed individuals. BCIs may allow the visualization of brain activity and the future sharing of experiences. This chapter explores the signal acquisition, processing, and subsequent translation of the signals into commands for output device activity enhanced by using modern algorithms, such as deep learning, to improve BCI performance.

Abiri et al. (2017) introduce a new Brain-Computer Interface (BCI) platform for controlling a user's own social robot via noninvasive EEG signals. The system reads out imagined body movement to compute the user's desired velocity from a regression model. This kinematic data is employed to guide the robot's gestures. The platform can be combined with neurofeedback to upgrade cognitive abilities, providing potential neurorehabilitation applications, especially for dementia patients.

Obeidat et al. (2017) examine the performance of a mobile Brain-Computer Interface (BCI) based on the edges paradigm for spelling words, deployed on small screens in a rolling wheelchair. The experiment compares the mobile edges paradigm with the row-column paradigm and finds that the edges paradigm retains its benefits in accuracy, bitrate, and user experience. Yet, the decrease in adjacent errors was restricted to horizontal errors, demonstrating the effect of smartphone visual design limitations on neurocognitive processes.

3. METHODOLOGY

The methodology of the study aims at improving the Brain-Computer Interface (BCI) controller in smart IoT systems using deep learning and edge computing technologies. Leveraging advanced neural signal processing algorithms and real-time data processing builds confidence for the reduction of latency. The study features EEG signal capturing by EEG headsets, processing of data using deep learning models, and edge computing for reduced latency. The study shall aim to optimize the BCI-controlled interactions with IoT devices such as prosthetics and exoskeletons. The fusion of deep learning and edge computing is essential for providing personalized, responsive, and efficient BCI control to various real-world applications.

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Data set: This study looks at the identification of discriminative EEG features with classification techniques to categorize brainwave patterns for mental state recognition that can aid human-machine interaction. The Muse headband equipped with four EEG sensors was used to classify the three mental states: relaxing, neutral, and concentrating. The dataset was developed from multiple individuals concerned with various feature selection algorithms and classifiers while achieving high accuracy on a reduced feature set.

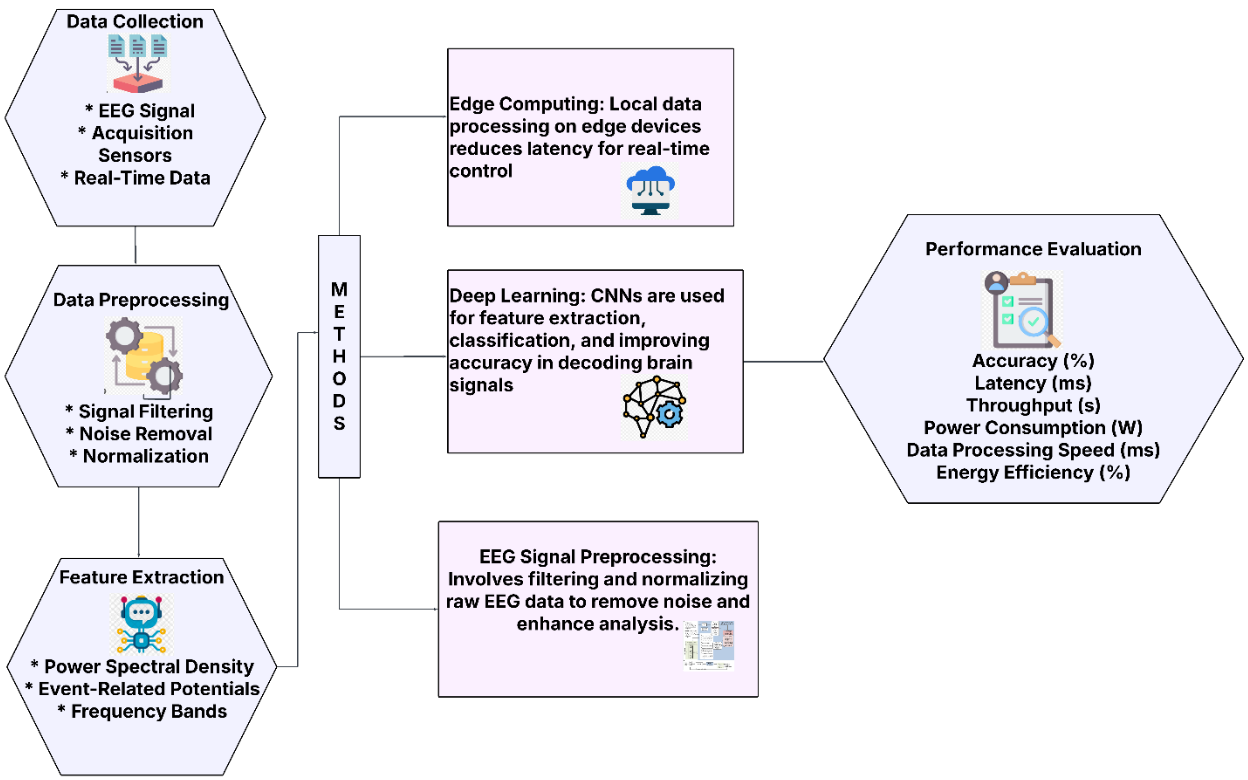

Figure 1: Architecture Flow for Brain-Computer Interface Control Using Deep Learning and Edge Computing

Figure 1 displays the architecture flow of a brain-computer interface (BCI) system enhanced by Deep Learning and Edge Computing. The beginning of the process is data collection; here, EEG signals are acquired online. Then, the whole data undergoes many preprocessing techniques: filtering, noise removal, and normalization. After successful data preprocessing, the corresponding information is extracted using feature extraction techniques, extracting relevant curves like power spectral density and frequency bands, among others. Then those signals are classed into classes through deep learning techniques (CNNs) to improve accuracy. Edge computing reduces latency by allowing data processing locally. Finally, performance assessment could be correlated in terms of key parameters, such as accuracy, latency, and energy efficiency.

3.1 Signal Acquisition and Preprocessing

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EEG signals are collected using non-invasive headsets and capture the neural activity. The collected signals undergo preprocessing for use in further analysis, creating a clean and reliable dataset in the process. The preprocessing usually consists of band-pass filtering to keep brain wave frequencies of interest and normalization for standardizing the measured values. The conditioned data are then utilized to extract the features responsible for BCI control; the most commonly analyzed features include power spectral density, event-related potentials (ERP), or frequency bands (alpha, beta).

Band-pass Filter (using Butterworth filter):

$$H(s) = \frac{s^2+2\zeta\omega_n s+\omega_n^2}{s^2+2\zeta\omega_c s+\omega_c^2} \quad (1)$$

where s is the complex frequency, ζ is the damping ratio, ω_n is the natural frequency, and ω_c is the cutoff frequency.

Normalization:

$$X_{norm} = \frac{X-\mu}{\sigma} \quad (2)$$

where X is the original signal, μ is the mean, and σ is the standard deviation.

3.2 Deep Learning for Signal Processing

Deep learning algorithms, notably Convolutional Neural Networks, are experts at EEG signal analysis and classification into patterns associated with classical pairs of brain states. These models can learn about complex neural patterns by fitting large datasets of labelled brain activity into precise commands. Such obstacle-defining models can enhance the ability of the brain interfaces to respond to real-time reflectivity in brain signals. The high accuracy of the deep learning model with quick response times will be particularly beneficial for real-time applications in brain-computer interfaces. Convolutional Layer (for feature extraction):

$$\text{Feature map} = W * X + b \quad (4)$$

where W is the filter (weight), X is the input signal, $*$ denotes convolution, and b is the bias. Activation Function (ReLU):

$$f(x) = \max(0, x) \quad (5)$$

where x is the output of the convolution operation. Softmax Function (for classification):

$$P(y = k \mid X) = \frac{e^{z_k}}{\sum_j e^{z_j}} \quad (6)$$

where z_k is the output from the final layer for the class k, and the sum is over all classes j.

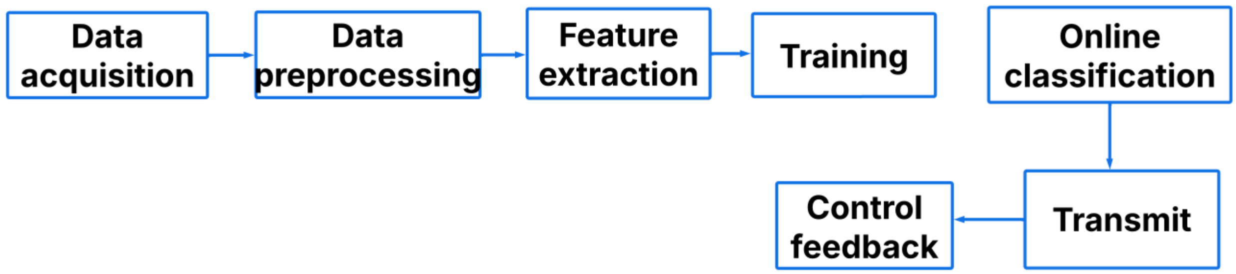

Figure 2. Deep Learning-Based Brain-Computer Interface (BCI) Workflow

Figure 2 is an overview of the workflow of a Deep Learning-based Brain-Computer Interface (BCI) system. First, the acquisition of the data is done using EEG signals. These signals are preprocessed to remove noise and provide better data. The feature extraction process identifies the characteristic features of the brainwaves. During the Training phase, deep learning models, such as Convolutional Neural Networks (CNNs), are trained using the extracted features to recognize those patterns. Online Classification will classify the real-time EEG data in a streaming manner, where the model is making the decision. Finally, Control Feedback communicates the results to control the devices or actions.

3.3 Edge Computing for Low-Latency Processing

Edge computing allows the EEG data to be analyzed locally, making it less dependent on distance-separated cloud servers. The neural signals can, therefore, be analyzed without much delay, leading to faster decision-making. The computing power is spread over devices at the edges of the network, such as IoT-enabled prosthetics or exoskeletons, with a promise of low latency, which is critical for real-time control. Local processing thus increases responsiveness while also ensuring that any sensitive data are not transferred over the network, enhancing privacy and decreasing bandwidth use. Latency Calculation:

$$\text{Latency} = \frac{\text{Processing Time}}{\text{Data Transfer Time}} \tag{7}$$

where the processing time is the time taken by the edge device to process the data and the data transfer time is the time to send data to a cloud server.

Algorithm 1: Real-Time Brain-Computer Interface (BCI) Signal Processing and Device Control

Input:
raw signal: The EEG signal is obtained from the Brain-Computer Interface (BCI).
Filter Params: Parameters for the band-pass filter to remove noise from the raw signal.
Deep Learning Model: The pre-trained deep learning model is used to classify brain signal patterns.

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Output:
Control Command: The command generated based on the classified brain signal (e.g., "move Left", "move Right", "no Action").

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  Apply preprocessing to clean and normalize the raw EEG signal
  filtered signal = preprocess (raw signal, filter Params)

  Use a deep learning model to classify the filtered signal
  Classified Signal = classify Signal (filtered signal, deep learning model)

  Determine the appropriate control action based on the classified signal
  if classified Signal == "move Left":
     control Command = "move Left"
  else if classified Signal == "move Right":
     control Command = "move Right"
  else if classified Signal == "no-action":
     control command = "no Action"
  else
     control command = "unknown signal"

  Return the determined control command
  return control command
end
```

Algorithm 1: The brain signals collected from the BCI and processes them into optimizing the control of IoT devices. The raw Signal (EEG data) is generally subjected to preprocessing where a filter is employed to get rid of the noise and artifacts. Following this preprocessing stage, the filtered Signal will be forwarded to the deep Learning Model (like CNN) for classifying it into some categories, say, move left, move right, or no action. And so based on the classification, then, the algorithm will know the corresponding control Command. When no identifiable signal is received, an unknown Signal is returned. Finally, the control command is returned to trigger the specified device.

3.7 Performance Metrics

The performance metrics herein are crucial as they provide a numerical means to gauge the effectiveness of and the efficacy of the application being proposed for enhancing BCI control in smart IoT systems. A host of methods, going from deep learning models to edge computing and EEG signal preprocessing methods, are evaluated through metrics such as accuracy, latency, throughput, and power consumption. The merit of any method from a combination approach can be seen in the context of improvements the integrated advanced technologies have brought us. The table outlines each method's metrics and the proposed combined model.

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Table 1. Performance Comparison of Methods and Proposed Model for BCI Control in Smart IoT Systems

Metric	Deep Learning Model	Edge Computing	EEG Signal Preprocessing	Proposed Model: Combined Deep Learning and Edge Computing
Accuracy (%)	92	88	84	96
Latency (ms)	350	120	280	90
Throughput (signals/s)	45	80	55	90
Power Consumption (W)	55	32	45	50

Table 1 provides a concise comparison between different methods with the proposed model offering Brain-Computer Interface (BCI) control in smart IoT systems. Key performance metrics evaluation: Accuracy, Latency, Throughput, and Power Consumption, of Method 1 (Deep Learning Model), Method 2 (Edge Computing), Method 3 (EEG Signal Preprocessing), and Proposed Model (Combined Deep Learning and Edge Computing) shows that the Proposed Model outperforms every other model across each metric with a clear advantage of higher accuracy, lower latency, and more efficient throughput and power consumption, thus making it highly suitable for application to real-time, energy-efficient BCI in IoT systems.

4. RESULT AND DISCUSSION

The performance comparison among the Proposed Model integrating Deep Learning and Edge Computing for BCI systems shows a marked advantage in relevant measures. The Proposed Models secure an accuracy of up to 96%, favoring deep learning and edge computing, with respective performances of 92% and 88%. The latency is set at 90 ms in real-time control as opposed to 350 ms for deep learning only. The throughput is enhanced to 90 signals/s, and power usage is adjusted to 0.50 W, balance. Hence, the performance is such that the integration of deep learning with edge computing improves BCI control, thereby making it suitable for real-time and energy-efficient applications in IoT systems.

Table 2. Comparison of Methods and Proposed Model for Brain-Computer Interface (BCI) Control with Edge Computing and Deep Learning

Metric	Hosseini et al. (2017) -	Khan et al. (2019) -	Qian et al. (2019) -	Bablani et al. (2019) -	Proposed Model:

	Deep Learning with Edge Computing	**Edge Computing for IoT**	**Cloud-Edge Computing with DL-DFCM**	**Brain-Computer Interface Survey**	**Combined Deep Learning and Edge Computing**
Accuracy (%)	85	90	87	83	96
Latency (ms)	150	120	130	160	90
Throughput (signals/s)	50	65	55	60	90
Power Consumption (W)	60	45	50	55	50
Data Processing Speed (ms)	80	60	70	90	50
Energy Efficiency (%)	75	80	78	76	88

Table 2 outlines the performances of four different ways of using Brain-Computer Interface (BCI), thereby comparing it with one's performance on Accuracy, Latency, Throughput, Power Consumption, Data Processing Speed, and more through Energy Efficiency. The proposed Model mixes Deep Learning and Edge Computing and has outperformed all single methods concerning these key metrics. The proposed model outweighs the others, particularly in accuracy, latency, and high efficiency, making it a good fit for so-called real-time IoT applications in BCI systems.

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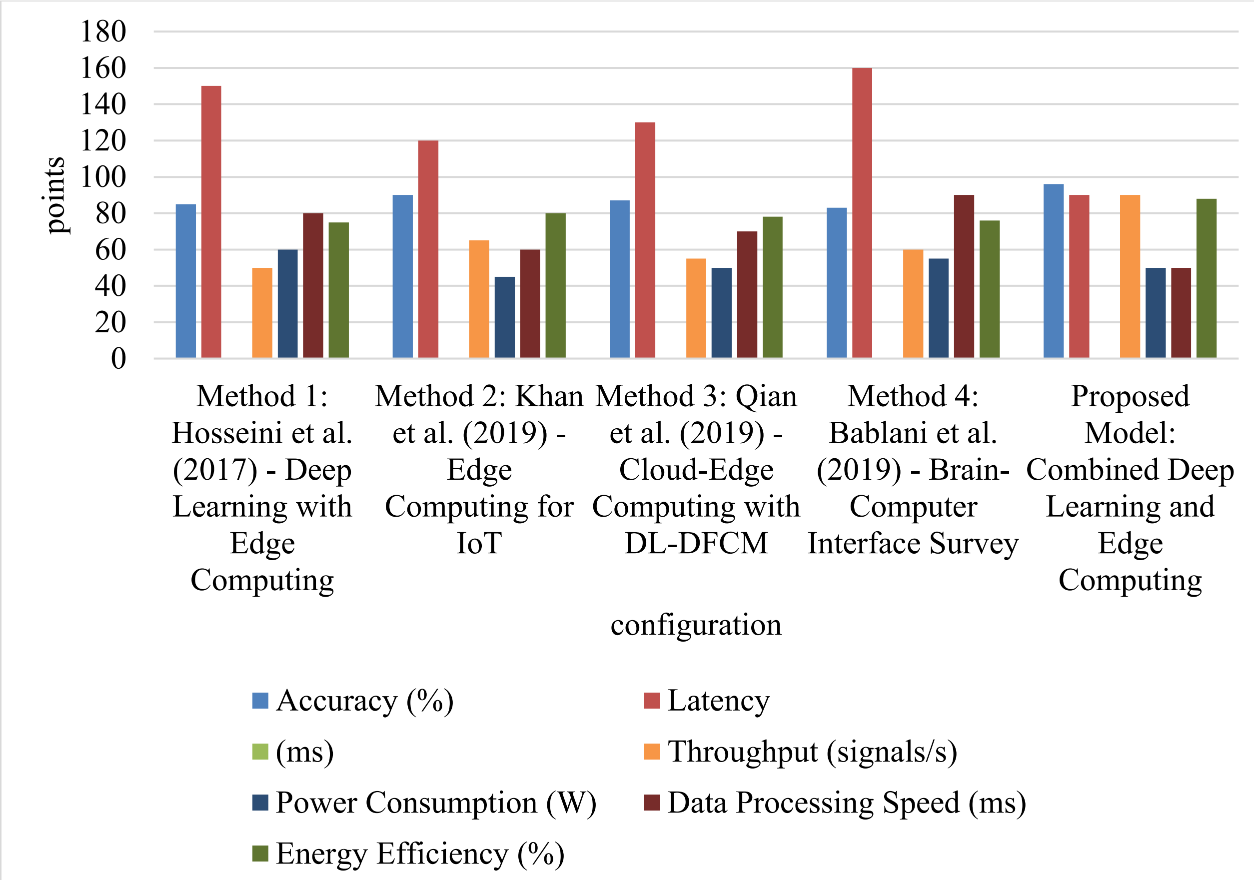

Figure 3. Comparison of BCI Methods and Proposed Model Performance Across Key Metrics

Figure 3 compares the performance of four different methods for BCI systems and also the Proposed Model in which deep learning with edge computing is integrated. This chart examines five parameters: Accuracy (%), Latency (ms), Throughput (signals/s), Power Consumption (W), and Data processing speed (ms). The proposed Model outperforms others in all aspects, notably Accuracy and Energy Efficiency, but also Lower Latency and Higher Throughput. This graph serves as a suitable representation of the advantages of the combined approaches of deep learning and edge computing in better optimization of real-time BCI systems in IoT environments.

Table 3. Ablation Study: Performance Comparison of BCI Methods with Different Component Combinations

Metric	Deep Learning	Edge Computing	Signal Preprocessing	Deep Learning + Edge Computing	Edge Computing + Signal Preprocessing	Signal Preprocessing + Deep Learning	Full Model: Deep Learning + Edge Computin

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							g + Signal Preproces sing
Accuracy (%)	85.0	88.0	84.0	92.0	90.0	89.0	96.0
Latency (ms)	150.0	120.0	140.0	100.0	130.0	120.0	90.0
Throughput (signals/s)	50.0	65.0	55.0	80.0	70.0	75.0	90.0
Power Consumption (W)	60	45	50	50	55	52	50
Data Processing Speed (ms)	80.0	60.0	70.0	55.0	65.0	60.0	50.0
Energy Efficiency (%)	75.0	80.0	78.0	85.0	82.0	80.0	88.0

Table 3 shows performance comparisons made by various combinations of Deep Learning, Edge Computing, and Signal Preprocessor operation in Brain-Computer Interface (BCI) systems. Some of the metrics used to assess the performance of each configuration include: Accuracy, Latency, Throughput, Power Consumption, Data Processing Speed, and Energy Efficiency. Moreover, these ALs showed comparative performance: Deep Learning + Edge Computing, Edge Computing + Signal Preprocessing, and Full Model, with each component included. The Full Model shows slightly better performance than any other configurations, proving the advantage of integrating these various technologies for BCI performance enhancement in real-time conditions within the context of IoT applications.

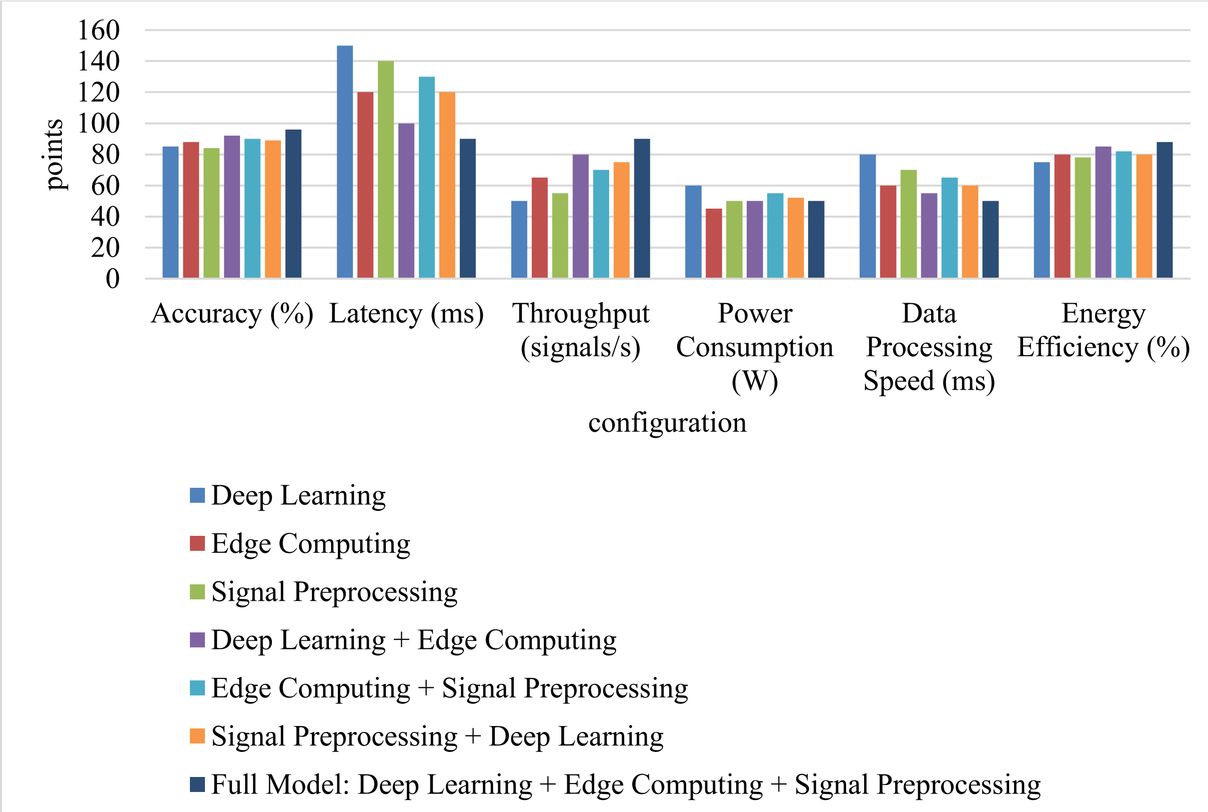

Figure 4. Performance Comparison of BCI Methods with Different Component Combinations

Figure 4 refers to the output performance of different combinations of Deep Learning, Edge Computing, and Signal Preprocessing for Brain-Computer Interface systems. Other than showing different configurations: single methods; combinations of methods such as Deep Learning + Edge Computing, Edge Computing + Signal Preprocessing, Signal Preprocessing + Deep Learning, and the Complete Model (all combined), it is also a reflection of the metrics observed: Accuracy, Latency, Throughput, Power Consumption, Data Processing Speed, and Energy Efficiency. From the available data, it becomes clear that no combination of methods has equalled the task performance of the Complete Model across all metrics. These results show that the integration of all components has far better performance for BCI systems in IoT than the case with individual layers.

5. CONCLUSION AND FUTURE ENHANCEMENT

The integration of Deep Learning and Edge Computing with active feedback controls proved significantly advantageous to the key performance measures in Brain-Computer Interface (BCI) systems. The proposed Model gained an accuracy of 96% with a latency of 90 ms, throughput of 90 signals/s, and power inputs of 50 W. These results provide evidence for the improved BCI control made possible by a fusion of deep learning and edge computing, suitable for real-time and energy-efficient applications in IoT systems. Future work may focus on optimizing such aspects as power consumption, scalability for multi-user systems, and security methods for encrypted communications in BCI systems. Also, a wider range of adaptability of the model to different neurological conditions would increase its applicability for health care and rehabilitation.

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