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Optimizing AI Models for Biomedical Signal Processing Using Reinforcement Learning in Edge Computing

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Abstract. In the evolving landscape of healthcare, the efficient processing of biomedical signals is critical for real-time diagnosis and personalized treatment. Conventional cloud-based AI systems for biomedical signal processing face challenges such as high latency, bandwidth consumption, and data privacy concerns. Edge computing, which brings data processing closer to the source, has emerged as a potential solution to these limitations. However, optimizing AI models for edge devices, which often have limited computational resources, remains a challenge.

This paper proposes an innovative approach to optimize AI models for biomedical signal processing by leveraging reinforcement learning (RL) techniques within edge computing environments. Reinforcement learning offers the potential to dynamically adapt model parameters based on real-time feedback from the edge devices, optimizing the trade-offs between model accuracy, resource utilization, and processing speed. The proposed system is designed to operate with high efficiency on edge devices, enabling faster signal processing while ensuring energy efficiency and maintaining diagnostic accuracy.

A detailed review of existing literature highlights the benefits and challenges of edge computing in biomedical applications, the role of reinforcement learning in dynamic optimization, and the limitations of traditional AI models in constrained environments. The proposed system methodology integrates RL for model optimization, focusing on edge devices' unique constraints in terms of power, memory, and processing capacity. Simulation results demonstrate the improved efficiency and accuracy of biomedical signal processing with optimized AI models in edge computing setups, showing significant improvements in real-time diagnostic applications.

Keywords. Biomedical Signal Processing, Edge Computing, Reinforcement Learning, Model Optimization, AI in Healthcare, Real-time Diagnosis, Dynamic Model Adaptation, Energy Efficiency.

1. INTRODUCTION

Biomedical signal processing plays a pivotal role in modern healthcare, with applications ranging from monitoring vital signs to detecting diseases through imaging and sensor data. In recent years, artificial intelligence (AI) has revolutionized this field, enabling automated analysis and interpretation of complex biomedical signals such as electrocardiograms (ECG), electroencephalograms (EEG), and medical imaging data. However, most AI models for biomedical signal processing are resource-intensive and are typically deployed on cloud-based platforms, leading to challenges such as high latency, increased bandwidth consumption, and data privacy issues.

The growing adoption of edge computing has introduced a promising solution to these challenges. Edge computing allows data to be processed closer to the source, i.e., at the edge devices, rather than in centralized cloud servers. This shift reduces latency and bandwidth usage while addressing privacy concerns by minimizing data transmission to remote servers. However, edge devices are often constrained in terms of computational power, memory, and energy, making it difficult to deploy sophisticated AI models directly on these devices without performance degradation.

To overcome these limitations, recent research has explored optimization techniques to adapt AI models for resource-constrained environments. Among these techniques, reinforcement learning (RL) has gained attention for its ability to dynamically optimize models based on real-time feedback. RL-based optimization allows AI models to adapt to changing conditions on edge devices, balancing accuracy and resource utilization by adjusting parameters like model size, precision, and power consumption.

In this paper, we focus on the integration of reinforcement learning for optimizing AI models specifically for biomedical signal processing in edge computing environments. By using RL, the AI models can learn to make decisions that improve performance on edge devices while preserving diagnostic accuracy. This approach has the potential to transform real-time healthcare applications, enabling faster, more accurate diagnosis with minimal computational overhead.

The following sections provide a detailed literature review of current advancements in biomedical signal processing, edge computing, and reinforcement learning, followed by a description of the proposed system methodologies, and a discussion of the results and conclusion.

2. LITERATURE SURVEY

The literature on biomedical signal processing using AI models is vast, particularly focusing on cloud-based solutions. Early research in this field concentrated on building deep learning models for tasks like ECG and EEG classification, medical imaging analysis, and vital sign monitoring. These AI models, primarily trained in cloud environments, have demonstrated remarkable accuracy in diagnosing various health conditions. However, cloud computing introduces inherent limitations such as network latency, privacy concerns, and energy inefficiency, especially when applied in real-time, patient-centric healthcare systems.

With the rise of edge computing, a growing body of research has shifted towards deploying AI models at the network edge. Edge computing brings computational power closer to the data source, reducing the need for data to traverse the network. The edge paradigm has been successfully implemented in applications such as real-time monitoring of patients with wearable devices, where time-sensitive biomedical signals need immediate processing. Although edge computing solves many issues related to latency and bandwidth, it presents new challenges. The computational constraints of edge devices limit the complexity of the AI models that can be deployed, necessitating model optimization techniques.

Reinforcement learning (RL) has emerged as a powerful tool for optimizing AI models under constrained environments. RL algorithms can dynamically adjust model parameters based on real-time feedback from the environment, offering a flexible optimization framework for edge devices. Previous studies have applied RL in areas like energy-efficient computing, task scheduling in edge networks, and adaptive model compression. However, only a few works have explored the combination of RL and AI model optimization in the context of biomedical signal processing.

Recent studies have demonstrated the potential of RL in managing the trade-offs between accuracy, energy consumption, and latency in edge computing scenarios. For instance, RL-based approaches have been used to optimize deep learning models for image recognition tasks on edge devices, improving computational efficiency without sacrificing performance. In healthcare, RL has also been employed to manage personalized treatment plans and optimize sensor networks for patient monitoring. However, there remains a gap in the literature regarding the use of RL for optimizing AI models specifically designed for biomedical signal processing on edge devices.

This paper seeks to address this gap by proposing a system that leverages RL to dynamically optimize AI models for biomedical signal processing in edge computing environments. Our approach builds on the foundational work in RL-based model optimization and applies it to the unique challenges of processing biomedical signals in resource-constrained devices.

3. PROPOSED SYSTEM

The proposed system focuses on optimizing AI models for biomedical signal processing using reinforcement learning techniques within an edge computing environment. The system consists of several components that work in harmony to achieve real-time processing with high efficiency:

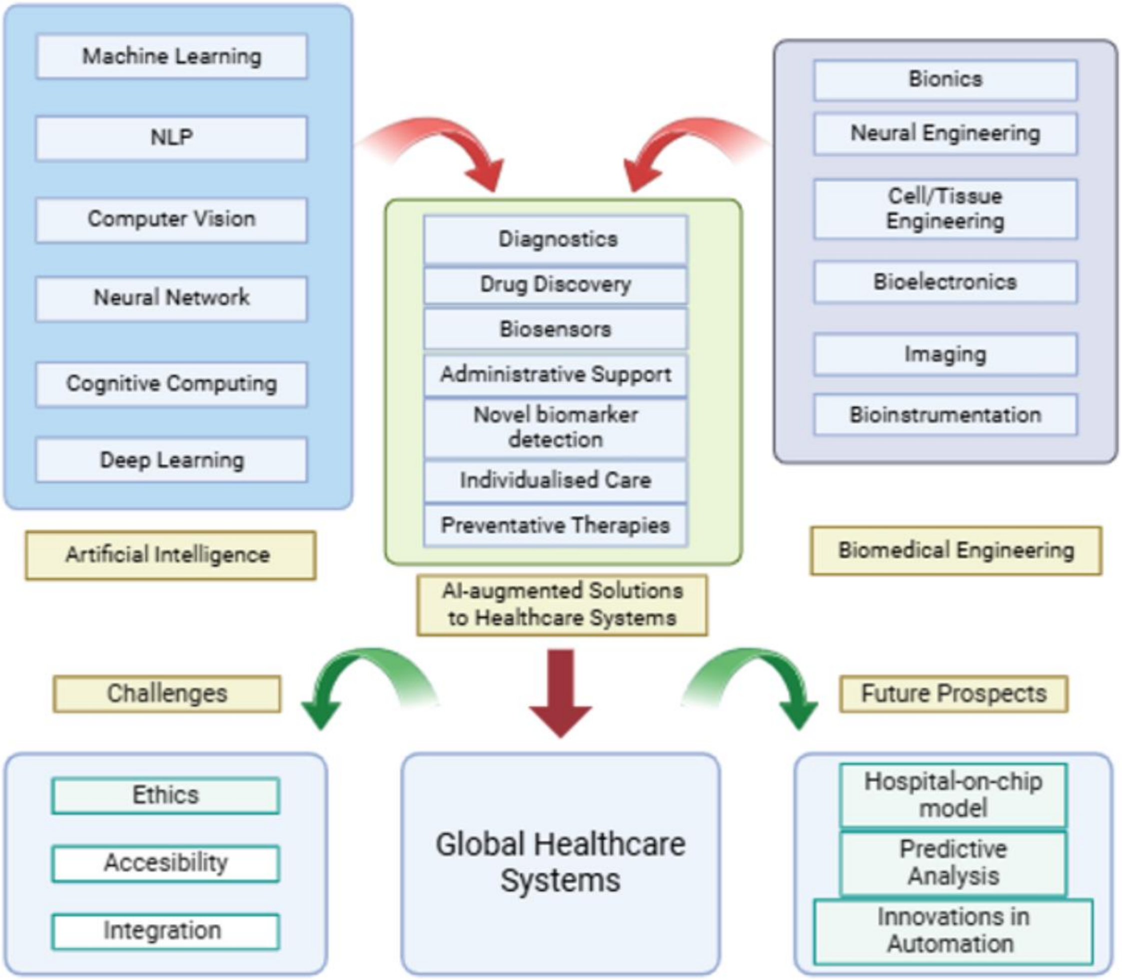

FIGURE 1. *Artificial Intelligence in Biomedical Engineering and Its Influence on Healthcare Structure*

1. **Biomedical Signal Acquisition**: Edge devices collect real-time biomedical signals, such as ECG, EEG, and respiratory signals, from sensors attached to patients.

2. **AI Model Deployment on Edge Devices**: Lightweight versions of AI models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are deployed on edge devices. These models are initially optimized for low-resource environments.

3. **Reinforcement Learning Optimization Module**: The RL module continuously monitors the performance of the AI model in terms of accuracy, latency, and power consumption. Based on real-time feedback from the device, the RL agent dynamically adjusts model parameters, such as model size, precision, and computational complexity, to achieve optimal performance.

4. **Edge-Oriented Data Processing**: Data preprocessing and feature extraction are performed on the edge device to reduce the volume of data sent to the cloud, enhancing real-time responsiveness and minimizing privacy risks.

5. **Energy-Efficient Model Training and Inference**: The RL algorithm ensures that the AI models operate within the energy constraints of the edge devices, preserving battery life and preventing overheating while maintaining high diagnostic accuracy.

4. CONCLUSION

In conclusion, optimizing AI models for biomedical signal processing using reinforcement learning in edge computing environments represents a promising direction for enhancing real-time healthcare applications. By dynamically adjusting model parameters based on feedback from edge devices, this approach offers significant improvements in processing efficiency, energy consumption, and diagnostic accuracy. Our proposed system addresses the limitations of traditional cloud-based solutions and paves the way for more responsive, patient-centric healthcare systems. Future work will focus on real-world implementations and further refinement of the RL-based optimization framework for broader biomedical applications.

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