

Abstract

As the global elderly population grows, more people are at risk of chronic illnesses like heart disease, diabetes, and mental health issues, placing immense pressure on healthcare systems that are already facing resource shortages and declining quality of care. Thus, there is an urgent need for technological solutions that effectively address these challenges while ensuring high-quality patient care. Wireless Body Area Networks (WBANs) present a promising solution by utilizing on-body sensors that connect to a Local Device (LD), which can process health data from these sensors and transmit it to a server for further analysis. It enables continuous health monitoring of vital parameters such as heart rate and body temperature, enabling timely interventions. However, processing this vital data poses significant challenges for resource-constrained LDs, which often lack computing power or energy required for time-sensitive healthcare applications. Additionally, health data collected from WBANs is used to develop Machine Learning (ML) models through Federated Learning (FL), enabling collaborative model training across decentralized WBANs while ensuring patient privacy. Yet, developing learning systems for remote healthcare faces challenges such as interference during data transmission, the necessity for energy-efficient and privacy-preserving methods, and the need for mechanisms to encourage participation in the FL process.

To address these challenges, we present a latency-aware, WBAN-based fog-assisted remote health monitoring system that prioritizes critical patients' health data. An optimization problem is formulated to maximize overall utility, which is defined as a linear

combination of the Medical Center’s (MC) profit and patients’ latency costs. To solve this, we introduce a flat-pricing scheme to evaluate the MC’s profit for delivering health monitoring services, alongside a swapping-based heuristic designed to maximize system utility. Moreover, since the energy consumption of LDs in WBANs during health data computation and transmission is a critical factor that limits the lifespan of the health monitoring system, we further propose an energy- and latency-aware Fog Computing (FC)-enabled WBAN-based real-time remote health monitoring system. A utility maximization problem is formulated that considers the profit of Health Service Provider (HSP), as well as the latency and energy costs incurred by patients, while prioritizing critical health data, as an NP-hard problem. Additionally, we introduce a dynamic pricing model designed to meet the computational requirements of patients’ health data, effectively addressing the diverse healthcare applications and QoS needs. To solve this, we employ a matching and exchange-based sub-optimal algorithm while also analyzing how various factors—such as number of patients, number of Fog Servers (FSs), and size of health data—affect utility, profit, latency, and energy consumption. Our simulation results and prototype analysis further demonstrate that the proposed framework significantly improves the efficiency and effectiveness of the remote healthcare system.

To develop effective learning systems for remote healthcare, it is crucial to address key challenges related to Resource Allocation (RA), energy efficiency, privacy preservation, and incentive mechanisms. One solution involves a Unmanned Aerial Vehicle (UAV)-assisted WBAN-based FL approach, where UAVs gather physiological data from WBANs and collaborate with a Macro Base Station (MBS) for model training. However, ensuring revenue for both WBANs, which contribute data, and UAVs, which perform model training, is essential to sustaining their operations. To achieve this, an optimization problem is formulated to maximize revenue for both WBANs and UAVs through effective RA while minimizing interference, which is modeled using an interference graph. To solve this problem, stable matching and graph coloring-based

heuristics are employed. In addition to effective RA, a blockchain-based FL framework is introduced to enhance energy efficiency and maintain privacy during collaborative training across multiple WBANs. This framework addresses an optimization problem that focuses on maximizing utility for both WBANs and miners, considering important factors such as energy consumption, WBAN rewards, miner revenue, and FL loss. To achieve these objectives, a stable WBAN-miner association algorithm is proposed, utilizing Quantized Neural Networks (QNN) to reduce energy consumption while employing Differential Privacy (DP) and Paillier Homomorphic Encryption (HE) to safeguard privacy. Furthermore, promoting participation in the FL process requires an effective incentive mechanism. To this end, a novel auction-driven incentive mechanism is designed to select reliable WBAN users who provide high-quality health data for differentially private multiple FL models. This mechanism integrates key factors such as data collection costs, computation and communication costs, privacy, local model accuracy, user reputation, and the amount of health data.

In summary, the contributions of this thesis address pressing challenges in remote healthcare systems, paving the way for more robust and efficient computing and learning system design. By leveraging optimization techniques, ML methods, and innovative frameworks, it contributes to the evolution of remote healthcare, fostering more effective and personalized patient care amidst an aging global population. It emphasizes real-time health monitoring and energy efficiency, alongside privacy preservation, efficient communication RA, as well as collaborative training, as the demand for ML-powered healthcare solutions continues to grow. Moreover, extensive simulations and prototype analyses using real-world data validate the proposed approaches, demonstrating significant performance improvements over existing methods.

Keywords: *Wireless Body Area Network, Remote Healthcare, Fog Computing, Resource Allocation, Unmanned Aerial Vehicle, Energy Efficiency, Privacy, Blockchain, Federated Learning, Incentive Mechanism.*