Chapter 8

Conclusions and Future Works

This chapter summarizes the key research contributions of this thesis and outlines potential directions for future work. The conclusions highlight the key findings and their significance in advancing remote healthcare systems, while the future works section identifies areas to build upon the research, presenting opportunities for further investigation and development. Each of these aspects is discussed in the following sections.

8.1 Conclusions

The thesis aimed to design and develop a remote healthcare system for continuous patient monitoring, timely medical interventions, personalized healthcare delivery, and the enhancement of ML models for disease prediction and detection. A comprehensive review of state-of-the-art research was conducted, identifying key challenges that limit the effectiveness of remote healthcare systems, including data privacy, energy consumption, real-time data processing, resource management, and distributed data sharing. We identified two main problems: (1) designing a computing system for remote healthcare and (2) developing a learning system for remote healthcare, each further divided into sub-problems—two for the first and three for the second. These issues were addressed through five key contributions, each detailed in separate chapters (Chapters 3 - 7). By leveraging optimization techniques, advanced ML approaches, and blockchain technology, these contributions improved the performance, security, and efficiency of remote healthcare systems while enhancing the accuracy and effectiveness of predictive disease models. In the following, we provided the conclusions of the thesis, summarizing the key contributions and findings.

Our first contribution presented a beyond-WBAN fog-assisted remote health monitoring system. An optimization problem was formulated, aimed at maximizing system utility, calculated as a linear combination of the MC's profit and patients' latency costs, as an NP-hard problem. Additionally, a flat-pricing scheme was proposed to measure the MC's profit in the health monitoring system, along with a swapping-based heuristic aimed at maximizing system utility. The proposed heuristic was evaluated on various parameters and shown to be closed to the optimal while considering the criticality of patients and the profit of MC, together. Extensive simulations on real-world data and a prototype model demonstrated that the proposed heuristic achieves an average utility of 94.5% of the optimal value, with polynomial time complexity.

The second contribution introduced an FC-enabled WBAN-based system for real-time remote health monitoring, focusing on latency and energy efficiency. A utility maximization problem was formulated, considering the HSP's profit and patients' latency and energy costs while prioritizing the health data of critical patients, which was classified as an NP-hard problem. Additionally, a dynamic pricing model was proposed for remote healthcare, based on the computational requirements of patients' health data, to meet the diverse needs of healthcare applications and ensure QoS requirements are met. A matching and exchange-based sub-optimal algorithm was applied to efficiently solve the formulated problem. Furthermore, the impact of various factors, including the number of patients, the number of FSs, and the size of health data, on utility, profit, latency, and energy was analyzed. Extensive experimental and simulation results using real-world data validated the effectiveness of the proposed algorithm, achieving an average utility of 99.01% of the optimal value with polynomial time complexity.

In the third contribution, the coupling of ML and WBAN data was explored to develop effective models. The integration of DaaS facilitated on-demand data collection and model training to support resource-constrained WBANs. However, the increasing number of WBAN users with varying 5G radio resources can cause interference, degrading system performance and hindering data sharing among independent UAVs. To overcome these challenges and enable privacy-preserving collaborative ML, the FL paradigm was adopted, allowing independent UAV service providers to collaborate without sharing sensitive data. This work aimed to maximize revenue for both WBANs, which contribute data, and UAVs, which perform model training, requiring careful RA that considered both minimum and maximum PRB requirements for transmitting critical physiological data over 5G networks. An optimization problem was formulated to maximize overall revenue while addressing interference among WBANs, as an NP-hard problem. Additionally, a stable matching and graph coloring-based RA approach was applied to optimize overall revenue. Extensive simulations and real-world data prototype demonstrated the proposed model's effectiveness, achieving an average revenue of 92.8% of the optimal value, outperforming existing state-of-the-art approaches.

To address the vulnerabilities in FL—including privacy breaches from shared model weights, the risk of a single point of failure, and the limitations imposed by the energy capacity of WBANs—the fourth contribution introduced a blockchain-based FL framework for smart healthcare that emphasizes energy efficiency and privacy preservation. Additionally, this work formulated an optimization problem designed to maximize system utility while effectively considering energy constraints, providing incentives for WBANs, ensuring revenue for miners, and minimizing the associated loss in FL. To solve this, a computationally efficient stable matching-based algorithm was proposed, optimizing utility by effectively associating WBANs with miners. The associated WBANs utilized QNNs to minimize computation energy. Furthermore, this work incorporated

DP and HE mechanisms to prevent information leakage by adding noise to gradients before updating model weights and encrypting them prior to transmission to miners. The proposed framework achieved an average improvements of 15.1%, 9.03%, and 15.35% over existing methods, as demonstrated via simulations and real-world experiments.

Finally, our fifth contribution presented an incentive mechanism for selecting WBAN users, aimed at facilitating the parallel training of multiple FL models while ensuring the privacy of health data. Subsequently, an optimization problem was formulated to maximize system utility, incorporating a cost model that included data collection, computation, communication, and privacy. To solve this, an efficient auction-based incentive mechanism was proposed by integrating factors such as local model accuracy, user reputation, and the amount of health data. Simulations and real-world data analysis demonstrated that this approach achieved average utility improvements of 15.9% and 18.08% compared to state-of-the-art methods.

8.2 Future Works

This thesis addresses key challenges; however, important issues still require attention in the design of computing and learning systems for remote healthcare, including:

1. In this thesis, WBANs provide full health data to FSs for processing; however, adopting partial health data computation can significantly reduce energy consumption and latency, especially in scenarios with multiple diseases where FSs process only essential data. Additionally, future work will explore dynamic resource allocation among FSs, utilizing real-time patient needs and network conditions to continuously optimize system performance.
2. Dynamic computing RA among FSs, based on real-time patient requirements and fluctuating network conditions, will be a key focus for future work. As patient needs and network environments constantly change, developing a system that adapts in real-time will optimize performance, reduce delays, and ensure that

the network remains responsive to the most critical patient data. This dynamic approach will not only enhance the efficiency of data transmission and processing but also improve overall patient care by prioritizing urgent health issues.

3. Our future research will focus on integrating Wireless Power Transfer (WPT) technologies into WBAN sensors to enable continuous energy harvesting, thereby decreasing dependence on traditional batteries. This integration aims to extend the operational lifespan of wearable devices and ensure uninterrupted data collection for patient monitoring. Additionally, research will explore methods to optimize WPT systems for both efficiency and safety, adapting transmission techniques to meet the specific requirements of healthcare environments.
4. Another important area for future research is optimizing UAV placement to maximize coverage for healthcare data collection. Strategic positioning of UAVs can significantly extend the network's reach, particularly in remote areas. Additionally, optimizing UAVs' hovering, flying, and receiving energy will be crucial to ensure efficient data collection while minimizing unnecessary energy depletion. This approach will not only enhance the effectiveness of data gathering but also promote sustainable energy use in the system.
5. Given the sensitivity of healthcare data, it is essential to ensure secure and efficient communication between WBANs and fog or cloud servers to safeguard patient privacy and enhance system performance. Therefore, our future work will focus on developing lightweight encryption schemes for WBANs to enhance security by reducing transmission times and ensuring data privacy. Additionally, we will adopt a lightweight, energy-efficient consensus algorithm to secure data exchanges within the blockchain framework, aiming to minimize energy consumption while ensuring the integrity and authenticity of data shared among stakeholders, including patients, HSPs, and health data processing units.
6. Joint optimization of FL model and incentive mechanisms for heterogeneous

WBAN users with non-Independent and Identically Distributed (non-IID) data is essential for effective smart healthcare. Additionally, investigating the presence of adversarial WBAN users, who may intentionally or unintentionally compromise the training process, is essential. Understanding the behaviors and motivations of these users is vital for maintaining the integrity and reliability of healthcare systems. By addressing these challenges, we can enhance the robustness and adaptability of FL, ensuring that it effectively meets the demands of a wide range of healthcare scenarios.

This thesis makes substantial contributions to remote healthcare systems by tackling essential challenges in the design of computing and learning systems. Specifically, the proposed methods aim to bridge the research gaps identified in current state-of-the-art approaches. Moreover, these findings provide a solid foundation for future research and practical applications in remote healthcare systems.