Abstract

Internet of Things (IoT) applications in healthcare span across a multitude of devices such as wearable sensors on the body, smartphones in the pocket, bedside monitors in clinics, and ambient systems in homes or vehicles. These devices are mostly distributed and located close to patients to enable timely health monitoring and decision support. Evolving IoT architectures transcend from centralized cloud computing to Edge Intelligence (EI), where data processing and analytics are performed at the network edge. This shift is motivated by the need for real-time insights and strict privacy requirements in medical applications. Edge-based healthcare IoT systems provide context-aware intelligence by processing sensitive medical data locally on devices and also preserve patient data privacy and security.

The deployment of EI in healthcare IoT faces critical challenges due to the inherent heterogeneity of medical devices. These devices differ in sensor modalities, processor capabilities, and model structures. The data they generate are not independent and identically distributed (non-IID). In addition, patient data are fragmented between these heterogeneous devices, leading to only partial and localized views of the health state. This fragmentation makes global reasoning and coherent inference difficult. As a result, we require collaborative mechanisms for training, inference, and causality that are heterogeneity-aware. For instance, some of the devices in the network are resource-constrained, due to which they lag behind in learning. Furthermore, network connectivity at the edge can be intermittent. This introduces issues of coordination of model updates and decision-making across devices in real time. Consequently, orchestrating collaborative intelligence and generating its explanation across distributed edge networks remain equally challenging.

This work develops a collaborative EI framework for healthcare IoT. It provides methods to learn safely from heterogeneous health devices, coordinate peers under resource constraints, and derive actionable temporal relations without violating data locality. First, we propose an inclusion-aware Federated Learning (FL) approach that mitigates straggler bias without abandoning slow or low-resource clients. We focus on the resource constraints of stragglers and introduce split learning as a mechanism for their inclusion. Second, we develop an abstention learning mechanism for federated models to calibrate uncertainty using risk–coverage reasoning. Third, we propose decentralized peer coordination that fuses local inferences and uncertainties. In this framework, collaboration is triggered only when the expected utility exceeds the communication cost. Fourth, we present a decentralized and lag-aware method for temporal–causal tracing that reconstructs interpretable chains across devices. Fifth, we introduce lightweight and temporally grounded explanations on mobile devices that generate patient-centric narratives from distributed healthcare sources. Sixth, we propose a blockchain system for decentralized learning and coordination in time-critical settings. It safeguards model privacy, supports update governance, and provides latency auditing. In the final two chapters, we apply EI techniques to real-life applications. We develop a smartphone-based stress recommender system that performs local scoring and selective companion matching. We also develop an edge acoustic pipeline for pulmonary state tracking that combines data-independent learning with temporal state progression modeling.

This research analyzes the efficiency and robustness of these approaches under client and resource heterogeneity. It demonstrates calibrated behavior at controlled coverage, reduced communication and latency for near-patient inference, and recovery of temporally consistent, clinically plausible relations from fragmented logs within realistic edge compute and memory. Therefore, this thesis introduces EI in healthcare IoT systems that learn from diversity, acknowledge uncertainty, coordinate when appropriate, and explain their temporal logic of action.

Keywords: Edge intelligence (EI), Internet of Things (IoT), Federated Learning (FL), Heterogeneity, Uncertainty calibration, Risk–coverage, Abstention learning, Decentralized coordination, Causal tracing, Temporal explanations, Privacy-preserving analytics.