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Fast and peer-to-peer vital signal learning system for cloud-based healthcare

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HIGHLIGHTS

- A peer/organization can learn the biosignal dataset and share the knowledge with its neighbors.
- The proposed model eliminates the imbalanced sharing and learning process of centralized model.
- The proposed model accelerates the performance in terms of computation and communication costs.
- High accuracy is achieved in diagnosing clinical events.

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ABSTRACT

Wearable devices in the Internet of Things (IoT) make home-based personal healthcare systems popular and affordable. With an increasing number of patients, such healthcare systems are challenged to store and process enormous volumes of data. Some medical institutions employ Cloud services to meet requirements of analyzing big data without considering sharing their own knowledge which could increase diagnostic accuracy. In order to obtain such collaborative healthcare community in the Cloud environment, we propose a peer-to-peer (p2p) learning system which is fast, robust and learning-efficient. Our proposed system continuously collects vital biosignals from wearable devices of users (e.g., chronic patients living alone at home) and analyzes the biosignals in real-time with Extreme Learning Machine (ELM). The traditional centralized learning models suffer in having huge communication costs to share massive amounts of personal vital biosignal data among the institutions for the training purpose. Our proposed p2p learning model can overcome this limitation by allowing every institution to maintain its own raw data while also being updated by other institutions' shared knowledge a.k.a semi-model which is lightweight output during the training process, as well as being smaller than raw data. The extensive experimental analysis demonstrates that our proposed p2p learning model is efficient in learning and sharing for patient diagnosis. We also show the potential impact under different network topologies, network sizes and the number of learning peers.

1. Introduction

Investment in the global health information technology market is expected to increase tremendously from US $96.8 billion in 2013 to US $210.3 billion by 2020 [1]. Such a significant increase clearly reflects how the public and government agencies are focusing on improving healthcare systems, which is leading to longer life expectancy and less healthcare expenditure [1,2].

Current Cloud based e-health systems prevalently use different machine-learning techniques to learn and predict health abnormalities in people [3]. These automatic decision support systems can improve the quality of clinical outcomes (e.g., reducing medical errors) as well as improving organizational outcomes (e.g., financial and operational benefits). Moreover, the machine-learning methods can improve health monitoring systems of people in their daily lives by continuously learning from patients' health-related information (e.g., vital biosignals). Generally, there are two key roles in the healthcare diagnostic system: data collection and decision making.

In terms of data collection, recent advances in IoT are driving further in smart healthcare systems, providing data with broader types [4]. With approximately 90 million wearable devices in different fields including healthcare in 2014 [5], a new segment of IoT has emerged as "Wearable IoT" (WIoT). Healthcare systems with WIoTs lead a gradual shift from hospital-centered systems

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to a person-centered environment [6–8]. The systems also allow customized collection of biological data operating with certain end-user applications. For example, portable devices like smartphones and smartwatches can collect different kinds of continuous biological signals such as heart rate, blood pressure, pulse and electrocardiogram (ECG) [9] at long-term rates in a specific time window (e.g., every min) from wearable body sensors [10] (e.g., Shimmer [11]). By receiving those data, intelligent systems in specific medical institutions can respond to hospital patients [12–14] or patients at home [7,15–17].

Toady, many healthcare IoT solutions are provided by different companies (Microsoft,[1] Alter Calsoft Labs[2] and KAA[3]) to help patients and hospitals. These solutions also follow the two key roles described above by adopting various IoT devices to remotely monitor patients. The patients' data are collected from the IoT devices continuously and are transmitted to the Cloud. After analyzing the data in the Cloud, a proper response is sent that is related to the patients' health status in real time.

1.1. Motivation

State-of-the-art healthcare systems can benefit from machine-learning technologies by detecting symptoms of different diseases according to time-period vital signals which are collected from various wearable devices. By receiving those discrete data samples, a healthcare system is trained over time (e.g., an hour or half an hour) to fit new data and thus is able to diagnose new time-period records with higher accuracy. However, even leveraging the processing power of the Cloud, most machine-learning algorithms still consume large amounts of time in training, which introduces new challenges in the efficient and real-time training process.

In addition, medical institutions usually employ private Cloud services to store data and accelerate training processes [18], but sharing the dataset with other institutions has been rarely considered. The healthcare systems in other institutions can improve their diagnostic accuracy by learning the shared data (the more datasets are available, the more accurate diagnosis a healthcare system can provide). Considering the typical architecture of Distributed Data Mining approaches [19], we could easily design a data-sharing model, which is beneficial in terms of sharing and learning the data in a centralized manner. Firstly, every client gathers data and sends them to the central server. Secondly, the central server updates its own classifier from those data. Finally, the latest updated classifier is synchronized to all clients. However, the centralized model certainly faces some noticeable limitations as below.

- Intensive central dependence: All clients depend on the central server and are isolated from other clients. During the maintenance or failure period of the central server, clients are not able to receive any update from the central server.
- Imbalanced sharing and learning processes: The central server requires intensive computation and communication resources if the size of data samples and the number of clients increase significantly.

1.2. Contributions

In order to overcome the issues of the centralized model in terms of sharing the raw data, we introduce a peer-to-peer (p2p) learning model for the Cloud-based healthcare system where one medical institution extracts a semi-model (lightweight output during the training process) from patients' biosignal training data up to a certain stage and then transmits the semi-model to other neighbor peers. A comparison between the traditional centralized model and our proposed decentralized p2p system is shown in Fig. 1. The main advantage of our proposed model lies in eliminating dependence on the central server.

Our proposed healthcare system aims to perform fast and accurate diagnoses with patients' biosignal data. We use extreme learning machine with semi-model (ELM-SM) as the main classifier for prediction. Extreme learning machine (ELM) is a Single Hidden Layer Feedforward Neural Networks (SLFNs) which does not need to tune the hidden layer and shows excellent efficiency in terms of computational time and great success in medical diagnosis [20–22]. In addition, many existing studies provide fantastic running applications for the remote healthcare system [23,24]. Our proposed system focuses on the p2p learning process and can be integrated with existing applications to monitor patients' health conditions.

The main contributions of this paper are summarized as follows.

- We present a p2p learning model which allows medical institutions to share and learn the semi-model rather than the raw data, which reduces the computational overhead of different institutions in learning the raw biosignal. More specifically, the lightweight semi-model is extracted from enormous training samples based on the learning process of ELM, providing faster learning and less sharing time than that using raw data.
- We introduce a new method to filter the semi-models based on their versions so that the healthcare institutions avoid learning the same semi-models. This means we eliminate the redundant sharing of semi-models among the healthcare institutions. This version is generated by MD5 algorithm [25] and represents the unique dataset.
- Our extensive experimental analysis from publicly-available biosignal data presents that the proposed p2p learning model is efficient and effective in terms of learning time and size of data exchanged among peers.

1.3. Outline

The rest of this paper is organized as follows. Section 2 describes the related works. Sections 3 and 4 provide the preliminaries of our proposed work and detail methodology respectively. Section 5 discusses the experimental analysis and finally, Section 6 concludes the paper.

2. Related works

Nowadays various research works have been providing promising solutions on smart healthcare systems; however they suffer from some limitations. The [26] analyzes different challenges in healthcare systems where the big data issue is addressed by adopting Cloud platforms used in many studies. For example, [27] introduces a home-based monitoring system with Hidden Markov Model (HMM). The [28] develops a healthcare framework to diagnose patients' state using video and audio signals, while [29] enhances the monitoring system by introducing the patients' position. The [23] and [24] propose a future application of a ubiquitous healthcare system with different bio-signals. The [23] employs Cloud, biosensor and smartphone to monitor patients with chronic lung disease. The authors develop an application on the iPhone Operating System (iOS) to show the analysis result from the Cloud. Similar to [23], the [24] shows a healthcare system with a smartphone application and health information management server. The

1 https://www.microsoft.com/en-au/internet-of-things/healthcare.
2 https://www.altencalsoftlabs.com/healthcare-iot-platform/.
3 https://www.kaaproject.org/healthcare/.