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A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system

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HIGHLIGHTS

- A wearable sensor-based system is proposed for activity prediction using Recurrent Neural Network (RNN) on an edge device (i.e., personal computer or laptop).
- The input data of the system are obtained from multiple wearable healthcare sensors such as electrocardiography (ECG), magnetometer, accelerometer and gyroscope sensors.
- Then, an RNN is trained based on the features. The trained RNN is used for predicting the activities.
- The system has been compared against the conventional approaches on a publicly available standard dataset. The experimental results show that the proposed approach outperforms other traditional methods.
- Graphics Processing Unit (GPU) in the edge device is utilized to take the advantage of fast computation of experimental data.

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ABSTRACT

An increase in world population along with elderly people is causing fast rises in healthcare costs. Technologies (e.g., Internet-of-Things, Edge-of-Things, and Cloud-of-Things) in healthcare systems are going through a transformation where health monitoring of people is possible without hospitalization. The advancement of sensing technologies helps to make it possible to develop smart systems to monitor human behaviors continuously. In this work, a wearable sensor-based system is proposed for activity prediction using Recurrent Neural Network (RNN) on an edge device (i.e., personal computer or laptop). The input data of the system are obtained from multiple wearable healthcare sensors such as electrocardiography (ECG), magnetometer, accelerometer and gyroscope sensors. Then, an RNN is trained based on the features. The trained RNN is used for predicting the activities. The system has been compared against the conventional approaches on a publicly available standard dataset. The experimental results show that the proposed approach outperforms other traditional methods. Graphics Processing Unit (GPU) in the edge device is utilized to take the advantage of fast computation of experimental data.

1. Introduction

Lately, technologies (i.e., Internet of Things (IoT) and Could of Things (CoT)) have started contributing in healthcare domains [27]. They are currently in the process of providing many opportunities to develop smart healthcare solutions with intelligent services in distinguished environments such as home, office, and hospitals. In such vast systems, there would be a numerous number of IoT devices and sensors. To handle the huge data from the devices and sensors, the data are transferred to clouds for high-performance computing and vast data storage. Such combination of cloud and IoT (Cloud–IoT) can make the healthcare system eligible for real-time applications. However, it is still a big challenge to handle the massive data obtained from increasingly healthcare devices and sensors. To lessen the pressure on the clouds, Edge-of-Things (EoT) computing is proposed recently to act in-between the sensors and clouds. In such systems, the sensor data computations moved from Cloud to edge devices such as local computers, smartphones, and smart routers. The edge devices basically offer computing and storage capabilities on a small scale in real-time. This work is basically focused on sensor data processing on an edge device such as laptops or personal computer.

Wearable sensors are very popular for many practical applications such as entertainment, security, and medical fields. They can be actively used to accurately recognize people's behavior. Hence, the sensors can be installed and explored to ensure a sound living environment. Thus, wearable sensors can be promising to revolutionize our life very much in the same way as the personal computers. For commercial applications, wearable sensors have been adopted in the form of panic buttons to seek emergency

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and can be considered as a commercial success [21]. For proper utilization of the button, the user should be alert and fit enough to use the button. Besides, the button should be light and comfortable to put on. Recently, wearable sensors have attracted a lot of researchers, especially in the medical sciences to monitor physiological activities. In medical applications, patients' vital signs are monitored such as body temperature and heart rate [21]. Wearable sensors should be light to be worn on the body for standard medical monitoring.

Wearable sensors can be utilized to have necessary treatment at home for patients with diseases such as heart-attacks and Parkinson disease. After an operation, patients usually go through the rehabilitation process where they follow a strict routine. All the physiological signals, as well as behaviors of the patient, are possible to be monitored with the help of wearable sensors. During the rehabilitation stage, the wearable sensors may provide audio feedback or other rehabilitative services. The system can be tuned to the requirement of the individual patient. The patient's health status and behavior can be observed remotely by doctors or caregivers [5,14,8].

Regarding behavior monitoring using wearable sensors, a significant amount of research is undergoing these days for developing the smart system, especially for detecting falls of elderly at home [32,15,18]. Wearable devices are getting attention for commercial purpose. For instance, sensors in devices such as heart rate monitor, smartwatch, and Google's smart glasses are undergoing rapid growth. The wearable technologies seem to impact future medical technologies such as defining the doctor–patient relationship and saving healthcare cost. Observing the rapid growth of wearable technologies, their acceptance will continue in many sectors such as healthcare.

The curiosity about activity research has been growing in context-aware systems for different domain applications [2,23,13]. It handles the integration of sensing and reasoning to be able to better understand people's actions. Research linked to human behavior analysis is becoming relevant in pervasive and mobile computing, surveillance-based security, context-aware computing, health and ambient assistive living. Recognizing body postures and movements is particularly important to aid and improve health systems. Avci et al. reviewed several medical applications of activity pattern recognition for healthcare, wellbeing and sports systems [2]. Regarding medical applications using HAR with wearable sensors, the authors report examples in the literature of healthcare monitoring and diagnosis systems; rehabilitation; systems to get the correlation between movement and emotions; child and elderly care. In addition, they reviewed assisted living and home monitoring systems improving the standard life and ensure medical, safety and well-being of children, seniors, and individuals with cognitive disorders. Preece et al. reported activity classification systems to get links between common diseases and degrees of physical activity [23]. The authors also reviewed systems with daily activity pattern analysis to enhance the procedure and diagnosis of neurological and respiratory disorders. Other reported systems quantify degrees of physical exercise providing feedback and motivating individuals to accomplish physical exercise goals. Guidoux et al. [13] presented an approach predicated on smartphone sensors for estimating energy expenditure recognizing physical activities in free-living conditions. In conclusion, health systems and assistive technologies can take advantage of activity prediction and deliver personalized services.

To date, two main approaches are accustomed to performing the work of activity pattern analysis: video and other sensors. The video-based approach is established mostly on image sequences captured by cameras [25,28,30]. Performance of such systems mainly depends on the image quality. More importantly, video monitoring frequently raises privacy issues of the users. Other sensor-based approaches are often free from such type of issues [6,29,20,10,24,22]. There are some drawbacks to these approaches. For instance, wearing sensors for a long time is cumbersome. Also, there are battery power consumption issues in such sensors. However, the major problem with these wearable sensors is the presence of noise in input data due to sensor errors or noisy environments. Noise in data hampers the human behavior analysis process. For human activity recognition or prediction from sensor data, machine learning techniques should be enough robust to deal with noisy sensor data. Sensor characteristics may change across different subjects or same individual. Hence, to make a successful activity prediction system, it is necessary to utilize stable and robust machine learning techniques to take care of noisy data.

To model time-sequential sequential patterns in input data, Hidden Markov Models (HMMs) have been very commonly used [7]. Recently, deep learning techniques have got much attention by pattern recognition researchers [19,16,9]. Deep Belief Network (DBN) was the first successful deep learning technique used for pattern recognition [19]. Use of RBM makes DBN training quite faster than the typical large artificial neural network. Furthermore, Convolutional Neural Networks (CNN) has become popular due to its improved discriminative power compared to DBN. Basically, CNN is a kind of deep learning consisting of feature extractions as well as some convolutional stacks to create a progressive hierarchy of abstract features. The different necessary parts of a CNN include convolution, pooling, tangent squashing, rectifier, and normalization [9]. CNN-based deep learning is mostly used to efficiently recognize the patterns in a visual scenery, e.g., object detection in large image achieves. CNN is mostly applicable for single image-based pattern recognition rather than temporal information decoding and hence, it has not been much applied to time-sequential input data. However, Recurrent Neural Network (RNN) is a good choice than DBN and CNN since it can offer more discriminative power over others as time sequential information can be encoded or learned through RNNs very well [12,17,31,11,26]. Hence, this work applies RNN to model different activities in wearable sensor data.

Fig. 1 shows a typical schematic architecture for cloud-based healthcare services. In the system, an edge or sink device collects body sensor information to deliver it to the health service broker. The healthcare service broker checks the authentication of the user with the hospital and does the feature extraction from the sensor data. Then, the features are checked with the trained deep learning model and associate the health status with the user. Finally, the healthcare service broker initiates the recommendation to the user and other corresponding authorities such as a family doctor, relatives, and emergencies, if necessary. The whole process relates to many departments. Hence, computationally powerful edge device can process and take some decisions instead of just passing the data to the broker machine [1]. In this way, the whole process could be a little faster than the typical ones, especially for limited healthcare services such as typical daily activity recognition or fall detection. Furthermore, it can reduce the risk related to user data transmission among the multiple clouds during the healthcare process.

This work focuses on processing the healthcare sensor data, features, and activity prediction on fast edge device such as a laptop with GPU in a smart home. Fig. 2 shows a schematic setup of a wearable sensor-based human activity prediction system in a smart room where a user is wearing some healthcare sensors in different body parts such as chest, right wrist, and left ankle. The multimodal sensor data are obtained by an edge device (e.g., laptop with GPU) through the wireless medium. The device then processes the rest of the activity modeling and prediction procedure based on the features and deep learning techniques. Fig. 3 depicts the basic architecture of the proposed system consisting