Edge-AI in LoRa-based Health Monitoring: Fall Detection System with Fog Computing and LSTM Recurrent Neural Networks

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***Abstract*—Remote healthcare monitoring has exponentially grown over the past decade together with the increasing penetration of Internet of Things (IoT) platforms. IoT-based health systems help to improve the quality of healthcare services through real-time data acquisition and processing. However, traditional IoT architectures have some limitations. For instance, they cannot properly function in areas with poor or unstable Internet. Low power wide area network (LPWAN) technologies, including long-range communication protocols such as LoRa, are a potential candidate to overcome the lacking network infrastructure. Nevertheless, LPWANs have limited transmission bandwidth not suitable for high data rate applications such as fall detection systems or electrocardiography monitoring. Therefore, data processing and compression are required at the edge of the network. We propose a system architecture with integrated artificial intelligence that combines Edge and Fog computing, LPWAN technology, IoT and deep learning algorithms to perform health monitoring tasks. In particular, we demonstrate the feasibility and effectiveness of this architecture via a use case of fall detection using recurrent neural networks. We have implemented a fall detection system from the sensor node and Edge gateway to cloud services and end-user applications. The system uses inertial data as input and achieves an average precision of over 90% and an average recall over 95% in fall detection.**

***Index Terms*—IoT; Edge Computing; Healthcare Monitoring; LoRa; LPWAN; RNN; LSTM; Fall Detection;**

I. INTRODUCTION

Health monitoring plays an important role in disease diagnosis and treatments. For instance, electrocardiogram (ECG) monitoring or fall detection systems can help to detect abnormalities and send messages to caregivers about the abnormalities in real-time. Recently, fall detection systems using wearable devices are widely used because of several advantages such as light-weight, low-cost, energy efficiency and non-intrusiveness [1]–[4]. These wearable devices often collect 3-dimensional (3-D) acceleration or 3-D angular velocity or both of them from a human body. The devices then transmit the collected data to a gateway which forwards the data to cloud. However, there are still drawbacks in these systems. For instance, they cannot function properly in many scenarios like areas with unstable or lack of a Internet connection.

LoRa is one of the most prominent Low Power Wide Area Network (LPWAN) technologies [5]. The LoRa modulation scheme characterizes for enabling long-range and low power transmissions [6]. LoRa is widely used in many IoT applications from farming, agriculture monitoring, flood detection to metering in smart cities [7]–[9]. The potential of LoRa can be leveraged mostly in areas with poor connectivity or lack of infrastructure, but also in dense urban environments to reduce the number of access points and power consumption. Taking the above considerations into account, Lora seems to be a good candidate to overcome the limitations of the existing cloud-based healthcare monitoring systems that rely on traditional WAN technologies such as Bluetooth or Wi-Fi.

However, Lora cannot support high data rate (i.e., 250 kbps in theory). In practice, the data rate is much lower such as a few bytes per message and a few messages per day, due to strict regulations of Lora duty cycle (i.e., approximate 1% duty cycle). It is challenging to satisfy both requirements of high data-rate applications (i.e., fall detection based on wearable devices) and Lora duty cycle regulations.

In this paper, we propose an advanced architecture combining Edge computing, Fog computing, LoRa, and IoT-based technologies. The proposed architecture can inherit the benefits of these technologies to enhance quality of service. The proposed architecture can help to overcome the limitations the existing health monitoring IoT-based systems (e.g., fall detection or ECG monitoring IoT-based systems) and satisfy both requirements of high data rate-applications and Lora duty cycle regulation. We demonstrate the proposed architecture via a use case of fall detection. In addition, we propose and implement Edge-AI algorithms based on neural networks at Edge gateways for improving quality of service. In particular, a system with the proposed architecture and Edge-AI can detect human fall cases more accurately and dynamically in different scenarios.

The remainder of the paper is organized as follows: In Section II, we present related work in wearable sensors-based fall detection and implementations of systems relying on artificial intelligence. Section III introduces the proposed system architecture; while Section IV describes the implemented prototype and analyses experimental results. Section V concludes the work.

II. Related work and motivation

Many efforts have been devoted to develop fall detection IoT-based systems [10], [11]. Pivato *et al.* [12] introduce a fall detection system which uses a wearable device to collect and send 3-D acceleration data to a gateway for fall detection. In [13], authors utilize a smartwatch to collect and send acceleration to a smartphone which acts as a gateway for processing data. When a fall case is detected, the smartphone sends a notification message via 3G/4G to caregivers. Ngu *et al.* present a smartwatch-based IoT fall detection system. The system is able to run Support Vector Machine and Naive Bayes machine learning algorithms to create the fall model and detect a fall case with a high level of accuracy. Noury *et al.* present an extensive survey of literature on fall detection [1]. The authors summarize that many proposed methods had an accuracy of nearly 100%, which is essential in applications where a person's life might be at risk. However, in practical scenarios, this figure decreases dramatically. Therefore, they defended the necessity of a common framework for accurately evaluating fall detection systems and protocols.

More recently, researchers have been applying deep learning techniques for fall detection using both active and passive sensors. In [14], the authors use image processing to detect falls based on video feeds. They use convolutional neural networks (CNN) and a fully connected neural network for extracting features and classifying situations, respectively. Their method has an accuracy ranging from 90% to 96%. We propose the use of a wearable device, instead, as the number of scenarios where it can be used is broader, requires less amount of data to be analyzed and similar performance can be achieved. Other authors have explored the use of cameras or radio waves [15], [16].

Fakhrulddin *et al.* develop a fall detection method for body sensor networks using CNNs [17]. The authors use data from two accelerometers as input to the network and obtain an accuracy varying from 75% to 92% depending on the dataset used. In our work, we defend that recurrent neural networks (RNN) are a better alternative to CNN because of the importance of time as a factor in the decision process. RNNs have been effectively used by Musci *et al.* for designing an accurate fall detection method tested over the SisFall dataset [18]. The authors developed a method for analyzing data online in real-time that was executed with the aid of GPUs. In our work, we focus on similar methods for resource constraint single-board computers that operate as edge gateways.

In summary, higher accuracy and adaptability to a wider range of situations can be achieved with deep learning when compared to threshold-based fall detection or SVM classification. In particular, recurrent neural networks show promising results in fall detection applications. However, previous works focus on the analysis part or assume that cloud computational capabilities are available. This requires full sequences of raw data to be transmitted to the cloud and increases the alert latency. Instead, we propose the use of lightweight analysis algorithms that can run on edge gateways. At the same time, this enables the system to be deployed in rural areas or scenarios with poor connectivity as the amount of data that is transmitted over the Internet to cloud servers can be decreased several orders of magnitude.

III. System architecture

We propose a five-layer system architecture consisting of wearable devices (sensor layer), smart edge gateways (edge layer), LoRa access points (fog layer) and cloud services (cloud layer) and end-user terminals (application layer). The proposed architecture can be used for different health monitoring applications such as cardiovascular or diabetes monitoring.

Sensor nodes in the proposed architecture can collect different types of data including e-health (e.g., electroencephalography (EEG) electrocardiography (ECG), electromyography (EMG), and blood pressure) and contextual data such as temperature, humidity, and air quality. The combination of both e-health and contextual data helps to improve the accuracy of disease diagnosis and analysis. The collected data is sent via Bluetooth Low Energy (BLE) to an Edge gateway for data processing.

At Edge-gateways, artificial intelligence algorithms are applied to enhance quality of service. For instance, the AI-service can detect a human fall with a high level of accuracy. Then, the results are sent to a Lora-based access point for storing in a distributed manner and processing with some advanced algorithms. Finally, the processed data or results are sent to cloud servers for final data processing and global storage. This mechanism helps to reduce latency of sending a large amount of data via LoRa network. In addition, this can ensure that the bandwidth can be efficiently utilized and LoRa duty cycle regulations are satisfied. Furthermore, Edge-gateways can provide many advanced services such as distributed storage, security, and localization. These services altogether with services implemented at Fog-assisted LoRa-based access points help to improve the quality of healthcare services. For instance, a Fog-cloud-based push notification service sends real-time messages to caregivers in case of a fall or an abnormality. Due to the scope of the paper, Fog services are not discussed. More detailed information of the Fog services is discussed in our previous papers [19]–[22].

The proposed architecture can help to reduce the computational load on the sensor nodes by switching heavy computational tasks from sensor nodes to Edge-gateways. In case of fall detection systems, data is processed with advanced algorithms such as AI-based activity categorization algorithms. Only results such as generic activity status are sent to the Fog-assisted access points which then transmit to cloud servers. End-users can use terminal applications to access results stored in cloud servers.

IV. Experimental Analysis

In order to test the feasibility of the proposed architecture, we have implemented the complete system for the use case of fall detection. Wearable devices equipped with inertial measurement unit (i.e., MPU9250 3-axis accelerometer, 3-axis

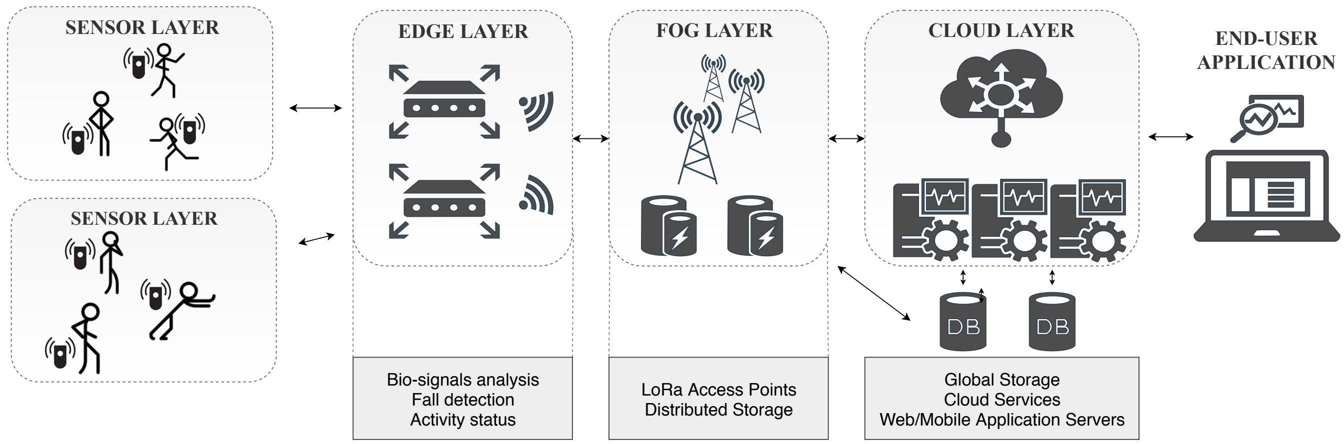

Fig. 1. Proposed System Architecture

gyroscope, and 3-axis magnetometer) to collect and transmit the data to an Edge-gateway via Bluetooth Low Energy (BLE). The sensor node is equipped an AVR 8-bit MCU and supplied with 3.3 V. The gateways have been implemented using a Raspberry Pi 3 Model B running Ubuntu Mate Desktop with a Dragino LoRa shield with communication via SPI. The LoRa access point is also implemented with a Raspberry Pi single board computer and a LoRa shield, directly connected to the Internet. For this experiment, we have used raw LoRa with customized data format and encryption, instead of using LoRaWAN as the link a network layer over LoRa. This allows us to customize further the transmission frequencies and packet structures. Data from the inertial measurement unit is analyzed at the edge gateway and then only information about the status of the patient and instant notifications in case of a fall are transmitted over LoRa. A PostgreSQL database is used as a cloud storage solution and the web monitoring application for end-users is implemented using Django and Apache on CentOS.

The deep learning algorithms have been trained and evaluated with a public dataset. However, we have implemented the wearable sensor node in a way such that the data format is equivalent to that of the used dataset. Data is normalized and preprocessed before the analysis step so that data from different sensors can be used with the same algorithm, enabling flexibility in the design of the sensor node.

A. *Edge-AI: LSTM RNN for Fall Detection*

We have implemented a recurrent neural network (RNN) with long short-term memory layers (LSTM) cell layers. A recurrent neural network is, essentially, a special case of densely connected neural networks where time is introduced in the form of connections across consecutive time steps. They are particularly useful in applications involving time series data such as handwriting or speech recognition. Though RNNs inherently store previous states, in practice they present vanishing and exploding gradient problems in their raw form. To reduce the impact of these problems, LSTM cells help to decrease the vanishing gradient problem allowing longer-term memory within the neural network [23].

We have used Keras and Tensorflow as its backend to implement an LSTM RNN using Keras and Tensorflow as its back-end [24]. We have run several tests and compared the accuracy of the model with different network structures.

For training and assessing the accuracy of the models, we have used the MobiAct Dataset [25]. The dataset contains acceleration, angular velocity and orientation data. In particular, we use a subset containing two daily activities (standing, lying) and four types of falls: forward-lying (fall forward from standing, using hands for dampening), front-knees-lying (fall forward from standing, first impact on knees), sideways-lying (fall sideways from standing, bending legs), and back-sitting-chair (fall backward while trying to sit on a chair).

We have implemented different RNN models with a variable number of hidden layers and their sizes. The best results have been obtained with three hidden layers, two of them LSTM and one fully connected layer. The input data size is 10 points, and the output of the network is a single value (probability of fall occurring in the input data). Therefore, the proposed model has a total of 5 layers with 2 dropout operations after the LSTM layers.

B. *Results*

We have tested the efficiency of five different RNNs and compared their accuracy in terms of precision (*TP/(TP+FP)*) and recall (*TP/(TP+FN)*), where *TP,FP* are true/false positives, and *TN,FN* are true/false negatives.

Figure 2 shows the distribution of the results in the form of boxplots, with 20 data points for each model. We started the test with a simple RNN model (M1) with 2 hidden LTSM layers with 23 neurons each, which allows us to obtain an average precision of $91.90\% \pm 4.46\%$, and an average recall of $62.36\% \pm 2.83\%$. Even though the precision is good, the standard deviation in both cases is high and the recall is too low. More robust results have been obtained with 30 neurons/layer (M2); 10 neurons/layer and an additional fully

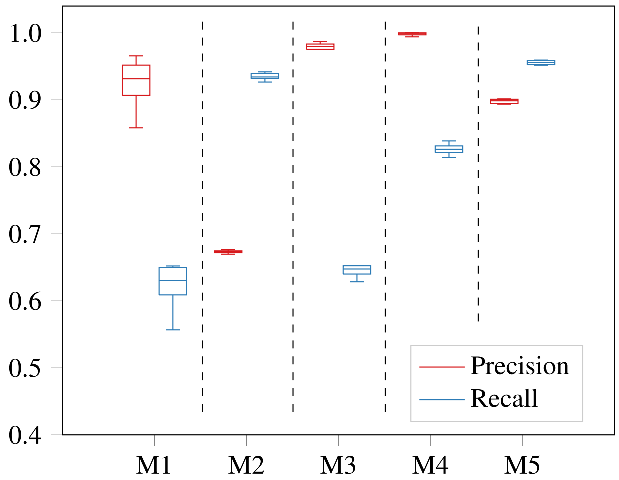

Fig. 2. Precision and recall for the five different implemented models.

connected layer of 10 neurons (M3). An improved recall was obtained when adding a dropout stage of 50% after the two LSTM layers of M3 (M4). Finally, the best recall was achieved when using two dropout stages after each of the LSTM laters (M5), of 30% and 20% respectively. At the same time, the standard deviation of the results was significantly reduced.

In summary, the best performance was obtained with a neural network with 3 hidden layers and two dropout stages. The final precision achieved was of $90.10\% \pm 3\%$, and a recall of $95.30\% \pm 0.8\%$. This shows an improvement in comparison to our previous work [2], [4], where threshold-based fall detection was implemented. After the data analysis, only 10 bytes of data have to be transmitted from the Edge gateway to the Fog-assisted access point and to the cloud if a fall is detected, including the unique device ID and the user status. This reduces the bandwidth usage and allows hundreds or thousands of devices to use the same LoRa access point due to the infrequent transmissions. The LoRa transmission has been tested in an urban environment in Turku, Finland. A range of over 4km has been achieved with the LoRa access point over a hill. This long-range has been achieved partly due to the low buildings in the area. The transmission range can be significantly extended for a system deployed in rural areas.

V. Conclusion

We have proposed a system architecture for health monitoring with Edge and Fog computing. We have put an emphasis on the use of LPWAN technology to enable deployment of such systems in rural areas. Taking into account the network capacity in these scenarios, robust data analysis and compression algorithms are deployed in the edge layer to lower the size of transmitted data, improving the system latency.

We have shown how high accuracy in a fall detection system can be achieved by means of an LTSM RNN implemented to run on the edge gateways. This enables real-time alerts and notifications, and waives the need for raw data to be transmitted to cloud servers for online analysis. Furthermore, when combined with BLE at the sensor node and LoRa transmission from edge to fog layers, we are able to simplify the sensor node design and potentially increase its battery life, while allowing operation in areas with poor connectivity.

Future work will include further improvement of our prediction model and more extensive performance analysis. Moreover, we will evaluate our method with real-time data from the implemented sensor node, and the system architecture will be tested as a whole. Finally, we will expand our model to classify different daily activities apart from fall detection.

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