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Home Automation In Elderly Fall Detection Using IOT And Machine Learning

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ABSTRACT
Many of these elderly people live alone and independently, but those suffering from chronic diseases or disabilities are at risk of accidents that will require assistance. Assisted living technologies are evolving with time to give people a better life. Activities of daily living (ADL) systems have been playing an important role in assessing and monitoring the quality of life of elderly people for many years. With the recent advancement and integration of Internet of Things (IoT) devices within ADL systems, the number and quality of services offered has increased significantly. In this project, one such attempt is made to design a multipurpose wearable intelligent device which helps the elder the right time. One of these vital services is medicine remainder, abnormal behaviour detection such as fall detection, temperature changes and heart rate based on the data collected from IoT devices within smart homes. This device alert caregivers to potential health or safety issues from a few or thousands of miles away. All alerts can be sent via text, email. The proposed architecture will collect all the data from different medical IoT sensors and relay them to the cloud, where the system will process and help us monitor the health of older people. The paper has proved the feasibility and practicality by running the experiment; the system can genuinely operate in home health care.
Keywords — Internet of Things, smart home, elderly care, fall detection, ADL systems.

I. INTRODUCTION

Biological properties can be measured and altered using electronics, magnetics, photonics, sensors, circuits, and algorithms. Applications range from basic biological science to clinical medicine, and enable new discoveries, diagnoses, and treatments by creating novel circuits, devices, systems, and analyses. Medical practitioners require the measurement of many biometrics. Effective sensors applied to the patient are required to measure vital signs (heart rate, blood pressure, temperature, respiration rate, pO2) or detailed data such as ECG. Sensors must be comfortably worn, easy to apply, and provide verifiably accurate data throughout the intended use period.

• Vital Signs sensors use mechanical, electrical, thermal, or optical means to monitor dynamic body functions that are traditionally measured manually and intermittently – heart rate, respiration rate, blood pressure, and temperature.

• Blood characteristics such as glucose and oxygen levels can be measured trans dermally, reducing the need for finger sticks and blood draws. Sensors can also perform diagnostics based on perspiration chemistry.

• Some implants have active components that need to communicate with other system components. In this case, a radio “sensor” may need to be worn to receive the data the implant is transmitting.

• Health outcomes depend on activity levels, which can be monitored with accelerometers and GPS sensors. Physical therapy and exercise can be monitored with sensors that measure angles, distances, and forces.

II. RELATED WORKS

A. *Literature survey*:

M. Gochoo, S. B. U. D. Tahir, A. Jalal, and K. Kim proposed a system that monitors personal locomotion behaviours using body-worn sensors in indoor and outdoor environments. The system collects sensor data from a wearable device and uses machine learning to recognize activities like walking, running, and standing. The study tests the system using real-world data and demonstrates its effectiveness in detecting and classifying personal locomotion behaviours in different environments. The system has potential applications in healthcare, sports, and security [1]. A. Jalal, M. A. K. Quaid, S. B. U. D. Tahir, and K. Kim proposed a study by Combining accelerometer and gyroscope data improves activity detection accuracy and provides insights into optimal placement of sensors, potential applications in healthcare and fitness [3]. The study proposes a system for human behavioural pattern recognition using statistical features and a reweighted genetic algorithm applied to data collected from wearable sensors. It is evaluated and compared to other machine learning algorithms, showing its potential applications in healthcare and security domains [5]. Machine learning algorithms can then be used to analyse the data from these sensors to determine if a fall has occurred. These algorithms can be trained on large datasets of fall and non-fall events to improve their accuracy in detecting falls [8][9]. K-ary tree hashing classifier is a machine learning algorithm used to analyse data from wearable devices and model human behaviour. It can be used to develop personalized interventions to promote healthy habits and lifestyles [4]. The cloud can be used to process data from these devices, allowing for more complex analysis and faster processing times. Edge devices, such as local sensors or gateways, can also process the data locally, reducing the need for data transfer to the cloud and improving response times [8].

B. *Existing System:*

Monitoring systems for the elderly offer a variety of features, such as voice-activated services, movement sensors, video monitoring, personal emergency response systems, medical monitoring, and comprehensive artificial intelligence home systems. Smart Clothing collects the elderly's electrocardiogram (ECG) and motion signals, and the home gateway is used for data transmission. StackCare is a smart home monitoring system that allows families and carers to monitor older individuals living in their own home. Life Alert Systems is the most well-known emergency and monitoring system among seniors and their family members, offering a variety of services and solutions. Medical alert systems and devices are simple elderly monitoring systems that don't have video capabilities, but many allow for two-way communication with emergency responders.

The current system is used for normal inpatients only, and under abnormal conditions, patients depend on nurses or doctors. The system checks the health only, and vision based system takes time to predict the fall event.

III. PROPOSED SYSTEM

Remote monitoring of older adults and detecting dangers in the state of human health have become essential elements of modern telemedicine. A method and system for recording acceleration and body position data from elderly or disabled persons is proposed. The fall monitoring system includes signal feature extraction and interpretive methods for characterizing accelerations and body positions during fall events. The system can detect health and life threatening fall events in elderly persons, and can autonomously notify nursing personnel or family members that the person is in need of immediate assistance. The advancement in computational power and big data processing has led to the modern-day data analytics, and this project presents an edge computing framework for real-time fall detection.

Smartphones are widely used devices for fall detection, but they are prone to damage in the case of a fall and are costly to be replaced. We developed affordable sensors device, which pre-processed the data using Apache Flink and sent it to the next level of analytics when the magnitude exceeded a predefined threshold. At this level, the data was analysed using TensorFlow where a pretrained LSTM model was used to classify the data as fall or non-fall.

IV. METHODOLOGY

The proposed device is based on a Atmega8 Microcontroller and a collection of Heart Rate sensor (MAX30201), Blood Oxygen sensor (MAX30201), Body Temperature sensor (TMP117) and fall detection sensor (MPU6050). The device collects updated information about the health situation of the patient and sends it to the family of the patient and the healthcare centre. It can also send a call for emergency in case of a critical health issue. The fall detection algorithm uses the LSTM model that has been trained on the UMAfall dataset to predict if a fall has occurred or not. The values of the accelerometer are read and converted into the features that required to obtain a prediction. The features are then used to test the model and get a prediction.

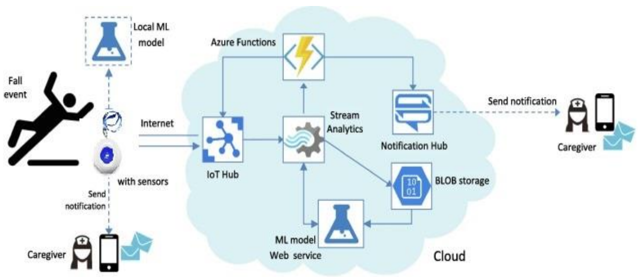

Fig. 1 Model Diagram

1) ***Sensors:*** multiple sensors can be used to retrieve data from the patients.
2) ***Edge device:*** a node at the edge computing platform acts in the pull mode. It retrieves data from the sensors and enables basic data pre-processing and analytics in order to reduce the size of the data to be processed at the next phase and/or uploaded to a remote server or on the cloud.
3) ***Streaming data-processing engine:*** a streaming data-processing engine at the edge computing node retrieves the data and performs real-time analysis such as filtering, noise removal, feature extraction, and summarization as necessary.
4) ***Data store:*** cleaned and pre-processed data coming out of the stream engine are stored temporarily on the edge platform.
5) ***Data analytics engine:*** further analysis of the data is enabled by this analytics engine where pre-trained machine learning models can be deployed on the edge platform to classify the data.

V. SYSTEM ARCHITECHTURE

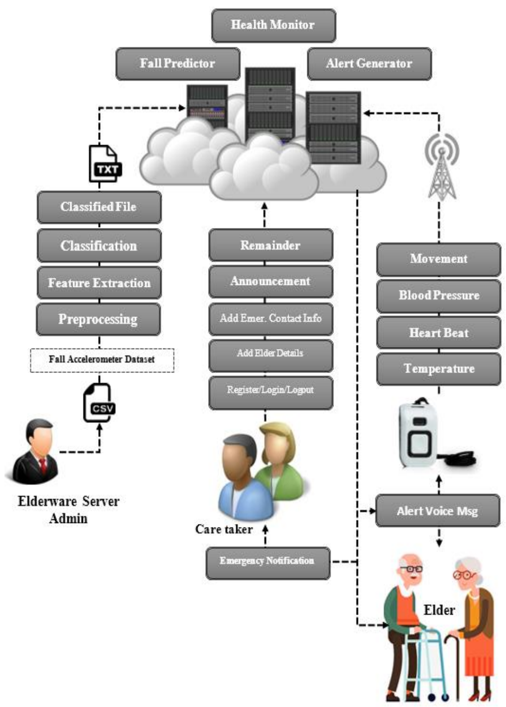

Fig. 2 Architechture Diagram

A. Block Diagram

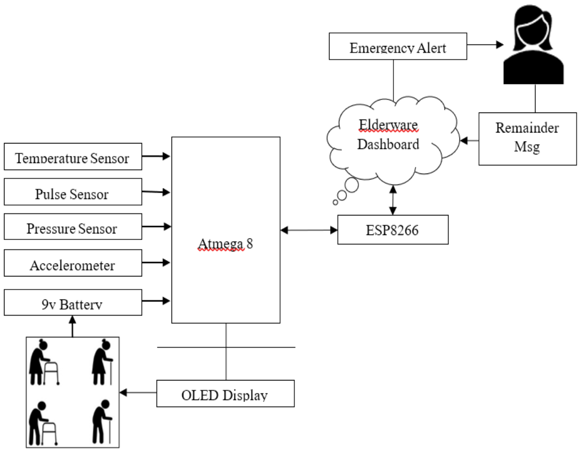

Fig. 3 Block Diagram

B. Block Description

In this section, we present the system model and the security model, as well as design goals. The system consists of five entities: trusted authority, patients, cloud storage, and service providers. Trusted authority initializes the system, provides registration service, generates system public keys, system master keys, and secret keys for other entities. Patients share the health data (e.g., heart rate and blood pressure), which can be collected by e-healthcare devices or manually input by themselves. Patients encrypt their shared data and send the cipher text to a fog node. fog node can be a health gateway or a router in physical proximity of patients. fog node master's healthcare background and powerful computation capabilities. It pre-processes and re-encrypts the shared cipher text and then transmits the new cipher text to a cloud storage. Cloud storage is a remote third-party server that has powerful storage capabilities. It stores and manages the shared cipher text transmitted from the fog node. Service providers can be doctors, researchers, insurance companies, and drug manufacturers. Service providers use their attributes to access the shared cipher text for learning health data and providing healthcare services.

VI. DATASET DESCRIPTION

UMAFall, a new dataset of movement traces acquired through the systematic emulation of a set of predefined ADLs (Activities of Daily Life) and falls. The files contain the mobility traces generated by a group of 19 experimental subjects that emulated a set of predetermined ADL (Activities of Daily Life) and falls. The traces are aimed at evaluating fall detection algorithms. In opposition to other existing databases for FDSs, which only include the signals captured by one or two sensing points, the testbed deployed for the generation of UMAFall dataset incorporated five wearable sensing points, which were located on five different points of the body of the participants that developed the movements. As a consequence, the obtained data offer an interesting tool to investigate the importance of the sensor placement for the effectiveness of the detection decision in FDSs. The dataset, which is publicly available in Internet 29 30 and which is planned to be progressively augmented with new samples in the near future, is intended for the evaluation of fall detection systems. The presence of multiple sensors in the architecture employed to obtain the data can facilitate a systematic offline research of the impact of the sensor position on the efficacy of fall detectors

V. CONCLUSIONS

The independent life of elder persons could be altered significantly afterward a fall. Based on health state of the elders, nearly ten percent of the persons fall would endure severe injuries, or may even pass away straight afterward a fall when no intermediary aid is presented. For preventing the serious effects of this fall, consistent fall detection is required. This project presents an intelligent IoT enabled elderly health and fall detection model using LSTM network for smart eldercare. In this project, a fall detection system that combined a health monitoring and fall detection hardware was developed. Although this project demonstrated that the implementation of deep learning in automatic fall detection systems can enhance fall detection performance, the use of deep learning in embedded systems greatly increases the computing time. The results proved that the proposed systems can significantly enhance the detection rate of locomotion actions.

VII. FUTURE ENHANCEMENT

In the future, we plan to introduce more variety of locomotion from different environments such as smart environments, healthcare facilities, and sports complexes into our system via multiple types of sensors. Detection of different activities apart from fall detection, and recognize and report in the cases of anomalies

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