A Privacy-Aware Framework for Human Fall Detection using Smartphone Inertial Sensors

Human falls defined as when someone unintentionally goes down to a lower place. This is very common thing among the people that are getting old and becomes very more frequent as they get older. According to the World Health Organization report that in each year there are around 28% to 35% of old age people are 65 years and up have a fall, and this number goes up to 32% to 42% for those over age of 70 years (Kalache et al., 2008). Some people who mostly fall are those having certain health issues which includes epilepsy or dementia, that are very often seen in old age peoples. Older peoples that are living alone in apartments have a higher chance of falling (Elliott et al., 2010). These falls can lead to severe physical injuries including bone fractures that can disable a person (Sadigh et al., 2004). Therefore, they can make older people less independent and they cannot live alone which can be very tough on their minds. If we don't take steps to prevent these falls soon, it's expected that the number of fall-related injuries will double by the year 2030 (Igua et al., 2013).

Early detection and treatment of falls is essential to minimize the injuries and reducing the consequences. These people that are fall on the ground which are being stuck on the floor for a long time after falling can lead to severe disease like pneumonia, pressure sores, and even death. The ratio of these accidents in the future can be reduced by using different types of sensors, instruments and gadgets that can identify these accidents and stop to fall old people. It can decrease number of falls that cause major injuries, reduce the number of people that are being handicap for more periods of time and the need for care in nursing homes. This project will aid in the development of such efficient strategies that is useful for the prevention or reduction of falls and the problems being caused by this whether they can be financial, emotional, or physical by community leaders, public health specialists, and medical professionals (Habib et al., 2014).

As sensor and sensor network technology continue to evolve, a wide range of advanced applications are emerging in numerous fields. These applications span from pervasive computing, security, and surveillance to vehicle networks and healthcare. Sensor technology also holds significant potential for various uses in home settings, including activity reminders, fall detection, rehabilitation guidance, and wellness assessment within assisted living systems (Ghayvat et al., 2015)- (Chernbumrog et al., 2103). Among these applications, activity recognition plays an increasingly vital role in bridging the gap between raw sensor data and meaningful high-level applications, particularly in healthcare-related domains (Peetoom et al., 2015) (Ordóñez et al., 2014).

For instance, in the context of wellness evaluation, everyday activities are closely linked to an individual's health status (Suryadevara et al., 2014). We can reduce the overall health issues by using different types of sensors like their location, start time, frequency and duration. We can easily detect changes that come in health states while we are monitoring activities for a long period of time, such as if we monitor an Alzheimer's disease patient for a specific period of time by sitting or lying down, can identify shorter sleep stages and fragment mark sleep disorder. However, by using various sensors is a non-trivial task for recognizing activities due to the due to different human behaviors. In such scenario, different people may perform the same activity in different ways, and even the same person may execute an activity differently at distinct times. Moreover, there are various situations where multiple activities occur concurrently and in an alternating manner which makes challenging to develop a robust activity recognition system (Krishnan and Cook, 2014). Consequently, the activity recognition represents very high growing yet dynamic research area that has gained a lot the attention of researchers across various disciplines, including data mining, pervasive computing, and medical and healthcare domains (Suryadevara et al., 2014), (Krishnan and Cook, 2014).

Aims & Objectives

The main focus of the project is to develop automated systems that can accurately identify and classify elder human activity based on sensor data for enhancing the understanding of elderly human behavior and providing valuable contributions for various applications in healthcare.

Objectives

1. Research analysis on human activities, multiple sensors being used for activity recognition.
2. Identification and discussion about the appropriate strategy for an automatic fall detection system.
3. Analysis of smartphone sensors and smartwatches being utilized for human activity detection.
4. Collection and processing of suitable datasets.
5. Selection and training of machine learning/deep learning models for classification of elders' fall detection and other activities.
6. Application of different cross-validation on the dataset.
7. Training Performance analysis of models based on train/validation loss.

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