Chapter 1

Introduction

The world's population is aging due to increasing life expectancy and falling fertility. Virtually every country in the world is experiencing growth in the number and proportion of older persons in their population. This shift in the distribution of a world's population towards older ages is known as *population aging*. Globally, the share of the population aged 65 years or over increased from 6 percent in 1990 to 9 percent in 2019. According to the United Nations, that proportion is projected to rise further to 16 percent by 2050, so that one in six people in the world will be older adults (aged 65 years or over) [1]. In 2019, there were an estimated 703 million older adults in the world. This number is projected to double to 1.5 billion by 2050. The oldest-old population (aged 80 years or over) is projected to triple, from 143 million in 2019 to 426 million in 2050 [1]. According to the World Health Organization, this population aging will continue and even accelerate as shown in Figure 1.1 [3].

The number of people aged between 20 and 64 years per person aged 65 years or more declines as the population ages. This is expressed in the Old-Age Dependency Ratio (OADR) and is defined as the number of old-age dependents (persons aged 65 years or over) per 100 persons of working age (persons aged 20 to 64 years). Globally, there were 16 persons aged 65 years or over per 100 persons aged 20-64 years in 2019.

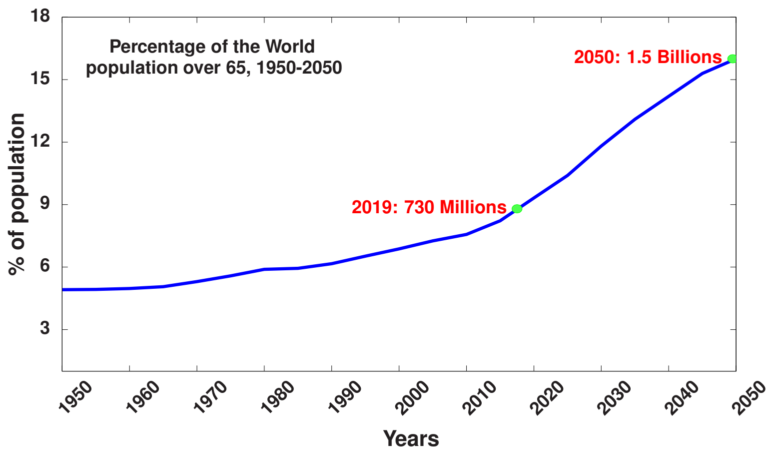

Figure 1.1: Percentage of older adults in the world during 1950 and 2050 [1].

In 2050, the global OADR is projected to increase to 28 older persons for every 100 working age persons. This means that there will be more elderly people but less young people able to take care of them and provide the necessary funds.

Older adults are at significant risk of having multiple chronic diseases and associated functional impairment [4]. Functional impairment refers to limitations in carrying out day-to-day household activities and chores or experiencing interference in engaging in activities outside of the home. As they continue to age, older adults live with a growing number of complex health issues that adversely affect their day-to-day functioning and overall quality of life. For many older adults, these concerns are further compounded by the presence of cognitive impairment such as dementia, which usually happens in the elderly population [4]. The prevalence of dementia rises sharply with age in which there is deterioration in memory, thinking, behavior, and the ability to perform everyday activities. A significant challenge in dementia is achieving an accurate and timely diagnosis. If the patient can have proper medical treatment at an early stage, then the dementia growth can be delayed by months to years. It is considered to be one of the greatest challenges for health and social care in the 21st century. Around 50 million people worldwide have dementia today, a number that is predicted to triple by 2050 [3].

Moreover, the number of older adults who live alone at home is also increasing worldwide due to industrialization, urbanization, over-population, and the problem of accommodation in urban areas. Also, because of the ongoing novel coronavirus disease (COVID-19) pandemic, healthcare experts and doctors advised older adults to live in isolation since they have a high risk of contracting the virus. Individuals need to complete Activities of Daily Living (ADL) to function independently at home. ADL includes necessary self-care activities performed by individuals daily necessary for independent living at home, such as eating, cooking, drinking, dressing, or taking medicine [5–12]. Many older adults with mental illnesses and chronic diseases have difficulties in performing ADL tasks.

Despite different medical and cognitive problems, older adults, as they age, desire to live independently in their own homes for as long as possible rather than move to an aged care facility [13]. Such people could remain in their homes longer than might otherwise be possible if they had some modest form of support and monitoring. The need to provide care for these people and reduce the burden placed on the healthcare system and caregivers underlines the growing significance of assistive technologies. *Assistive technology* can be defined as "software or hardware used to provide independence and enable a person to perform and function that was otherwise difficult due to disability" [14]. Such technologies focus on enhancing existing health care services to help the elderly live a quality of life independently in their places and extend the period of time that an elderly can live self-sufficiently. Thus, these technologies help elderly people *age in place*. Staying in your own home as you grow older instead of moving to an outside facility (like nursing home, care home for the aged, *etc.*) is called *aging in place* [15].

One of the significant challenges of developing assistive technologies for the elderly is developing acceptable technologies. Several studies [16–18] suggest that the elderly are willing to incorporate technology into their everyday lives. Different sensor modalities used to gather human activities information for assistive technologies include environmental sensors, wearable sensors, and video sensors. For this purpose video or wearable sensors data is a widely explored research area [19–28]. However, video sensors are not practical due to privacy issues, and the accuracy of wearable sensors relies upon the body attachment position. For non-privacy invasive assistive services, this work considers environmental sensors, such as PIR motion and magnetic door sensors. These sensors are embedded in the environment or in objects of daily living. Their non-intrusive characteristics make them suitable for the assistive technologies where user acceptance and privacy are needed.

Smart homes have become widely popular, especially in providing healthcare and assistive services. The smart home employs various sensors, actuators, and computational elements, which have its objective to help the inhabitants in many possible situations and assist them with daily activities. A common method for assessing the cognitive and physical wellbeing of elderly is ADL. Therefore, ADL Recognition (ADLR) in smart homes is crucial for developing advanced assistive services. Smart home can provide better services to assist older people if it anticipates what activities inhabitants will perform ahead of time. For example, a smart home can prompt inhabitants to initiate essential activities like taking medicine using activity prediction.

In this study, our aim is to create persuasive systems by employing non-privacy invasive monitoring technologies (*e.g.,* environmental sensors) that support the elderly who choose to live alone in their homes for longer. To do so, this thesis focuses on addressing real-time/online ADL recognition, future ADL prediction, and detection of dementia at an early stage. The motivation behind our work is based on the limitations of the existing literature in these areas, which we will discuss in the next section.

The rest of the chapter is organized as follows: Next section presents the motivation of this thesis. Section 1.2 presents the contribution of the research work and Section 1.3 outlines the organization of the thesis.

1.1 Motivation of the Research Work

The work in this thesis is motivated by the limitations of the existing work, as discussed next. The first limitation is the assumption (or expectation) of balanced class distributions. Whereas many real-life datasets follow a *long-tailed class distribution*, *i.e.*, a few classes account for most of the data, while most classes are under-represented [29]. The long-tailed class distribution can result in a biased learning algorithm optimized to favor the majority classes while failing to identify the discriminant features that are needed to recognize the minority classes. This behavior is termed the *class-imbalance problem*, and it is intrinsically exhibited in nearly all of the collected ADL databases. Such datasets are termed as *long-tailed datasets*. The following points illustrate why long-tailed class distribution occurred in ADL datasets:

- *Repeated ADL:* An inhabitant repeatedly performs some ADL (*e.g.*, toilet hygiene, eating) as compare with other ADL (*e.g.*, bathing, taking medicine). Such repeated ADL creates more sensor events and the main causes of long-tailed class distribution.
- *Interaction with multiple sensors:* An inhabitant interacts with a large number of sensors when they performs some ADL (*e.g.*, cooking) as compare with other ADL (*e.g.*, sleeping). Such more interaction creates a large number of sensor events, even in short time duration.
- *Duration of activity:* The duration of activity is also responsible for long-tailed class distribution. For example, leave/enter home activity generates very few sensor events as compared with eating activity.

To the best of our knowledge, we are among the first to address the class-imbalance problem in real-time/online ADL recognition.

The second limitation of the prior work [19–28] is the use of *video* or *wearable sensors*. The video sensors are the best in terms of accuracy; however, these sensors are not practical in smart home settings due to privacy-invasiveness. The use of wearable sensors is also not suitable in smart home settings because of their natural flaws, such as the discomfort of wearing, short battery life, require regular maintenance, and could be easily lost or forgotten [6,30]. To overcome this limitation in this work, we consider environmental sensors, such as PIR motion and magnetic door sensors, for unobtrusive ADL recognition and early dementia detection. The non-intrusive characteristics of such sensors make them practically useful and especially for older and disabled adults. In addition to above limitations, prior work [6, 19–28, 30–38] either use hand-crafted features or high-level features to recognize the ADL. We effectively combine both sources of information to lift the ADL recognition performance.

1.2 Contributions of the Thesis

In this thesis, we develop smart sensing based approaches for supporting the independent living of the elderly. Essentially, we investigate early dementia detection, future ADL prediction, online ADL recognition addressing class imbalance problem, and recognizing ADL through transfer learning. The research questions addressed in the thesis are summarized below:

- How to detect dementia at an early stage by using unobtrusive sensor data?
- How to predict *labels*, *locations* and *starting times* of future unobserved activities. Specifically we address three important questions: *which activity will happen next?, where will it happen?, and when will it happen?*
- How to recognize the activities of daily living online with the long-tailed datasets?
- How to utilize the existing labeled data collected in a smart home to recognize ADL in a new smart home with no labeled data?

Considered assumptions

In this thesis, the following assumptions are made to fulfill the objectives presented above.

Assumption 1: Only non-privacy invasive sensors are considered.

The inhabitant's privacy is paramount, and their feelings about the intrusiveness of the used sensors have to be considered. Therefore, video sensors are rejected due to their intrusive characteristics. Wearable sensors may be uncomfortable and inconvenient for inhabitants, and also their accuracy relies upon the body attachment position [6, 30]. They have other natural flaws also, such as short battery life, require regular maintenance, and could be easily lost or forgotten. We consider environmental binary sensors, such as PIR motion and magnetic door sensors, for gathering human activity and movement information. These sensors are considered acceptable solutions for sensing smart homes and are widely used in existing works [6, 30, 31, 33–35, 39, 40]. Moreover, they are small in size, low-cost, suitable to supply constant supervision, easy to install, and flexible. However, environmental binary sensors can provide a very low level of semantic information.

Assumption 2: Single resident scenario is considered.

According to assumption 1, only environmental binary sensors are used for both ADL recognition and early dementia detection. In the case where multiple residents live in the same household, it is impossible to distinguish which resident is generating the events observed through environmental sensors. It is, therefore, necessary to make the assumption that a single resident is living in a smart home. One way to relax this assumption is to consider that each resident wears a sensor that allows itself to be identified (*e.g.* RFID tag) and therefore knowing who has generated which sensor event.

This thesis assumes the limit of a single resident. Still, the methods presented in this work may apply to each resident individually if RFID tags are used in the multi-resident scenario that allows each sensor event to be assigned to a unique resident.

Assumption 3: Only sequential or interleaved activities are assumed.

This work considers activities performed in a sequential or interleaved fashion (*i.e.,* more than one activity is performed by a person switching from one to another). We assume here that activities are not simultaneous, *i.e.,* only a single activity is performed at each time instant. This assumption is realistic in our scenario since older adults can't be expected to perform more than one activity at a time point. Well-established real-world datasets [41] also validate this assumption.

1.3 Organization of the Thesis

The rest of the thesis is organized as follows.

Chapter 2: This chapter presents the existing work on supporting the independent living of the elderly. For this, we consider the problems of early dementia detection, future ADL prediction, online ADL recognition addressing the long-tailed class distribution problem, and recognizing ADL through transfer learning. We review the state-of-art solution approaches for these problems. We categorized the existing work based on the underlying sensor modalities utilized to gather data and different feature extraction methods.

Chapter 3: This chapter proposes an early dementia detection system by classifying the elderly travel patterns. If the patient can have proper medical treatment at an early stage, then the dementia growth can be delayed by months to years. Inefficient travel patterns are one of the first indicators of progressive dementia. We use the environmental passive sensor signals for sensing the movements of the elderly. The system segments the movements into travel episodes and classifies them using a recurrent neural network. The advantage of using a recurrent neural network is that it directly deals with the raw movement sensory data and does not require any domain-specific knowledge. Finally, the system handles the unbalanced classes of travel patterns using the focal loss and enhances the discriminative power of the deeply learned features by the center loss function. We conduct several experiments on real-life datasets to verify the accuracy of the system.

Chapter 4: This chapter proposes a multi-task activity prediction system that jointly predicts labels, locations, and starting times of future activities. The observed sequence of previous activities characterizes future activities. The experimental results illustrate that the multi-task system comparatively gives higher accuracy than the single-task system. We use publicly available four real datasets to evaluate the system's performance. In addition, we validate the effectiveness of the system on collected data.

Chapter 5: This chapter proposes an online system that recognizes the ADL while addressing the class imbalance problem. The system first generates hand-crafted and high-level features by using conventional learning and deep learning, which cover the advantage of both technologies to recognize the ADL. Next, the system uses an ensemble technique to concatenate the generated features. Finally, the system minimizes a loss function, which is a linear combination of focal loss for addressing the long-tailed class distribution problem and center loss for enhancing the discriminative power of the deeply learned features. The proposed ADLR system considers data collected from environmental sensors such as infrared motion and magnetic door sensors for unobtrusive ADL recognition. The non-intrusive characteristics of such sensors make them practically helpful, especially for older and disabled adults. We conduct several experiments on real-life long-tailed datasets to verify the accuracy of the system.

Chapter 6: This chapter proposes a transfer network for activities of daily life recognition through unsupervised domain adaptation between heterogeneous smart homes with different spatial layouts and sensor deployment. The proposed network utilizes maximum mean discrepancy to minimize the difference in distributions. We show the effectiveness of our approach by experimenting on real-world smart home datasets.

Chapter 7: This chapter summarizes the main findings of the thesis. We also discuss some future directions for supporting the independent living of the elderly. Some critical and relevant research papers and technical reports are listed in References. In the end, we furnish the List of Publications from the research work presented in this thesis.