An innovative AAL system based on neural networks and IoT-aware technologies to improve the quality of life in elderly people

Benito Taccardi and Piercosimo Rametta

Department of Innovation Engineering,
University of Salento,
Lecce, Italy
Email: benito.taccardi@studenti.unisalento.it
Email: piercosimo.rametta@unisalento.it

Pierluigi Carcagnì, Marco Leo
and Cosimo Distante

National Research Council of Italy (CNR),
Lecce, Italy
Email: cosimo.distante@cnr.it
Email: m.leo@isasi.cnr.it
Email: p.carcagni@isasi.cnr.it

Luigi Patrono*

Department of Innovation Engineering,
University of Salento,
Lecce, Italy
Email: luigi.patrono@unisalento.it
*Corresponding author

Abstract: Nowadays more and more elderly people need support in daily activities. This is due to the increase of cognitive diseases and other conditions which lead the elderly to not being self-sufficient. Considering this, providing an Ambient Assisted Living system could improve significantly people life quality and could support caregivers' tasks. The combination of Ambient Assisted Living systems and Information and Communication technologies achieve this purpose perfectly. They exploit internet of things and artificial intelligence paradigms to make daily challenges easier for people with neurodegenerative diseases. This work melds technologies mentioned above providing a smart system for elderly to manage goods and fill in shopping lists. It was possible using software, hardware, and cloud systems combined with a neural network aimed to recognise products. The proposed system has been validated both from a functional point of view through a proof-of-concept and quantitatively by a performance analysis of its components.

Keywords: Ambient Assisted Living; AAL; internet of things; IoT; neural network.

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Biographical notes: Benito Taccardi is a graduate student in Computer Engineering at the University of Salento. His thesis concerned 'Design and implementation of a system based on image recognition and bluetooth low energy beacon-based localisation for dynamic composition and use of the shopping list'. His studies are mainly about development of IoT solutions, development of mobile and web applications and their security.

Piercosimo Rametta received his Master's (Hons.) in Computer Engineering from the University of Salento, Lecce, Italy, in 2013. Since 2013, he has been collaborating with IDA Lab, Department of Innovation Engineering, University of Salento. His research interests include definition and implementation of new mash-up tools for managing smart environments based on IoT devices.

Pierluigi Carcagnì received his Master's in Computer Engineering in 2002 at the University of Salento, Italy. Since 2003 he is a technologist at the National Research Council of Italy. In 2016, he received his PhD at the University of Salento where main research interests were in the field of Computer Vision and Pattern Recognition applied to audience measurements. His research interests include computer vision, machine learning, deep neural networks and development and planning of embedded systems.

Marco Leo received his Master's in Computer Engineering from the University of Lecce in 2001. Since then he is a researcher at the National Research Council of Italy. His main research interests are in the fields of image and signal processing, computer vision, machine learning, and pattern recognition. He participated in a number of national and international research projects facing automatic video surveillance of indoor and outdoor environments, assistive devices for healthcare and rehabilitation, human attention monitoring, real-time event detection in sport contexts, and non-destructive inspection.

Cosimo Distante received his Master's in Computer Science at the University Bari, and PhD in Material Engineering at University of Salento, Italy. His main expertise are in the field of computer vision and pattern recognition. He joined the Faculty of the University of Massachusetts in 1998. He also joined in 2001 in the Italian National Research Council of Italy CNR. Since 2003, he is a Contract Professor for Computer Vision in Computer Engineering at the University of the Salento IT. He is the General Chair of ACIVS, AVSS, ICIAP2021 and program committee of CVPR, ECCV, ICCV. He is also a unit manager of CNR-ISASI.

Luigi Patrono received his MS in Computer Engineering from the University of Lecce, Lecce, Italy, in 1999 and PhD in Innovative Materials and Technologies for Satellite Networks from the ISUFI-University of Lecce, Lecce, Italy, in 2003. He is an Assistant Professor of Computer Networks and Internet of Things at the University of Salento, Lecce, Italy. His research interests include RFID, the internet of things, cloud, wireless sensor networks, and embedded systems. He authored more than 120 scientific papers published in international journals and conferences.

1 Introduction

The number of elderly people is significantly increasing in the last years. This phenomenon is due to several aspects, like the general improvement of people's lifestyle, the adoption of digital assistance systems and the increasing progress in science, research, medicine and technology fields. Some studies, in fact, state that in 2040 more than 50% of people will be over 60 years old; in addition, it is estimated that in the USA, before the end of 2020, one in every six citizens will be more than 65 years old as suggested by Corchado et al. (2008). Indeed, before 2050, there will be more than 2.1 billion people that will be considered elderly, which is twice as much elderly people than the number measured in 2015 (Chen et al., 2018). A huge subset of these people need assistance and continuous supervisions, due to physical and/or neurodegenerative diseases that may affect them; therefore, the assistance of elderly people is going to be a large scale issue. For this reason, several technological solutions have been developed and applied in recent years, aiming to provide a better lifestyle for elderly people, based on customised services for them. Technologies used in order to support people range from body muscle performance detection systems (Addante et al., 2019), to fall systems (Zhang, 2019), up to generic systems for human actions classification (Torres et al., 2017). Other solutions provide services aimed to support daily routine activities, such as digital reminders (Ranjana and Alexander, 2018), emergency replying and emergency notifying mechanisms (Lin et al., 2013) and mobile health systems (mHealth systems), i.e., systems that are based on smartphones, smartwatches, and internet of things (IoT) nodes for indoor tracking of patients (Kay et al., 2011). These solutions are based on different common ideas which mainly characterise the actual implementation of the information and communication Technologies in healthcare, such as the concepts of IoT, neural networks and low power communication among different kind of devices. In the proposed work, IoT technologies have been combined with neural network systems in order to develop a support service for daily activities. In particular, this work, aims to develop an unobtrusive system for shopping list management.

The main goal is to introduce hardware and software solutions to allow people to automatically manage a shopping list by interacting with a smart-board. The smart-box is equipped with a camera that acquires images of the product to be added/withdrawn by the shopping list (stored in the cloud), and a processing unit that automatically recognises the products from the images. Additional facilities are implemented to manage the shopping list trough a smartphone and to make it easier to buy products in the shopping list (nearby shops, best routes, etc.) as well.

This is made possible by four key points:

1 strength of neural networks

2 mobile technologies

3 IoT devices

4 cloud computing.

The IoT device, which is a smart board, has been improved through the implementation of a neural network on board, able to guarantee an high level of confidence in prediction of product classes. This aspect enables the whole system to be more accurate than others and also to reduce drastically the error rating. Consequently, the usage of the neural network concerning Ambient Assisted Living (AAL) field has brought huge advantages in terms of reliability and performance.

Furthermore, mobile technologies and cloud-based software architecture have been used to make the user experience much more appealing. This paper presents a work which is just a feature of a bigger AAL system in which it might be implemented. This work is focused on development of a smart shopping list system. It could help people in daily routine operations and its features can be boosted with a complete AAL system which could improve drastically the lifestyle of people who have neurodegenerative diseases. In the paper a qualitative and quantitative validation has been reported.

The paper is structured as follows. In Section 2, some related works in the field of neural networks and AAL systems are presented. In Section 3, the overall architecture of the proposed solution is introduced, showing the main components of the service. Section 4 presents a deeper description about the used neural network and its performance analysis, whereas, in Section 5, a detailed description of each building block is provided. Section 6 presents a comparison of the proposed solution with other similar systems, highlighting the innovative aspects. Finally, Section 7 summarises the achievements and the future extensions of the proposed AAL system.

2 Related work

The subject of this paper is mainly related to the subject of AAL that is is a very promising approach to address the needs of elderly people. It consists of developing technologies to construct safe environments around assisted peoples and help them maintain independent living (Garcés et al., 2020)

AAL systems leverage the IoT paradigm that is able to guarantee daily used tools and devices connected to the internet, providing useful information to third parties and helping to create smart environments (Farahani et al., 2020). AAL-systems can also benefit from data analysis by well-established machine learning techniques (Farinella et al., 2019). Machine learning is the study of algorithms and statistical models allowing to automatically extract, from raw data, high-level information about, for example, behaviours or health status and to eventually send alarms in case of dangerous situations. Modern machine learning techniques make use of deep learning (DL) that relies on neural models having many internal layers instead of a few of them (as traditional shallow nets do). It involves a huge number of internal parameters whose automatic setup from data observation is the way to represent knowledge about the considered domain. In light of the above, the next subsections report related work concerning both IoT-aware AAL systems and DL techniques.

2.1 IoT-aware AAL systems

There are many solutions which are apparently similar to the system proposed in this paper. Some of the most important mobile applications which could be downloaded from the most important app-stores are 'AnyList'[1], 'Mealime'[2], 'Cozi Family Organizer'[3], and others. These solutions propose different ways to compile a grocery list but none of them is able to carry on this task for people who have a neurodegerative disease or, generally speaking, who have difficulties to perform daily actions. The proposed system, instead, uses several technological solutions which aim to make the shopping list filling operations easier and it is shaped properly for a specific target of users. It does not offer an innovative way of compiling a grocery list rather than an innovative supporting system which will be placed in a wider AAL system. In addition to this, other services provide similar functions. For instance, 'Amazon Fresh'[4] sends food products directly to the user's house in less than two hours, using just Amazon's application. Despite the analysed system does not provide a fulfilling service, it provides help people in need in compiling a shopping list as easy as possible. On the contrary, Amazon performs this operation just like a simple online purchase.

On a wider scope, several approaches, devices and technologies can be involved in the realisation of AAL systems. An AAL system can be as simple as a digital dose reminder system, like the one proposed in Mohammed et al. (2013), which consists of an electronic device useful to remind the user which drugs to take, with the related temporisation and dosage. This device is specifically designed to be low cost, placed in a domestic environment and easy to be configured by any kind of user, like relatives and/or caregivers.

However, more complex AAL systems that have gained an increasing importance in recent years relay on several communication technologies, ranging from wireless sensor networks (WSNs) to IoT and social IoT. As showed in Mainetti et al. (2015), IoT, or to be more precise, web of things (WoT), is a technological field which foresees a close interaction among several devices. These devices provide collection of data and communication amongst them and/or with the remote server. The solution proposed in Yacchirema et al. (2017) uses IoT technologies in order to create a less intrusive AAL system that can monitor daily life of elderly people. Various smart nodes communicate with a common gateway through several different communication methods, like WiFi, ZigBee, Bluetooth, IEEE 802.15.4, 6LowPan. The system is able to monitor ambient and personal parameters, like CO_2 levels into a specific room, temperature, user's hearth rate and his/her GPS position. By monitoring these parameters, events about user's health state can be detected. The system can notify them to the user and to the related formal/informal caregivers. The solution proposed in Mainetti et al. (2016b) shows how an IoT system can monitor and reveals neurodegenerative diseases in humans. Using an unobtrusive set of sensors, this system can collect behavioural data in order to detect changes in them. Attitudinal changes could be a symptom of the beginning of a neurodegenerative disease so they will be collected and caregivers/relatives might be warned promptly. The performance of the proposed system and of the related risk detection algorithm have been evaluated in Almeida et al. (2019). An innovative way to use IoT technologies is presented in Catarinucci et al. (2015), where a system is proposed to monitor the user's state of health and also to collect environmental conditions. Collected data will be sent to a remote server using a REST module[5] in order to make them more accessible. In Silva et al. (2015), a monitoring system based on a WSN composed of humidity and temperature sensors is used to gather data about these parameters into the patient's environment. Collected data are transmitted through the internet to a cloud server, where they are combined in order to compute the dew point of the environment. This calculation is useful to notify to relatives, caregivers or professional figures, about critical situations against patients with respiratory problems. Another critical event of interest in this context is user's fall. The solution proposed in Mainetti et al. (2016a) presents an AAL architecture based on IoT sensors able to guarantee the collection of heterogeneous sensor data as well as the detection of critical events such as the elderly fall. A remote reasoning system processes these data with the aim of generating appropriate events and alerts.

With a wider scope, the system proposed in Corchado et al. (2008) aims to create a framework based on information and communication technologies tools and services that can be deployed in the cities in order to enhance early detection of risk related to frailty and mild cognitive impairments (MCIs), and to provide personalised interventions that can help the elderly population to improve their daily life and also promote positive behaviour changes. A recent emerging approach aims to build a framework suitable for integrating social networking concepts into the IoT realm, which leads to the so-called social IoT (SIoT) paradigm. The work described in Miori and Russo (2017) provides an elderly monitoring service enabling heterogeneous devices belonging to different domotic systems and protocols to directly share data, so that they can be supervised by medical and caregiver staffs.

Focusing on the application of neural networks in conjunction with IoT devices for AAL solutions, there are still few works in this field. In Liu et al. (2018), a mechanism for estimation of elderly postures through a triaxial acceleration sensor placed on the waist and a pressure sensor placed under the insoles is presented. Collected data are elaborated by a back propagation (BP) neural network, which is able to distinguish the posture of the elderly, such as standing, sitting, walking, and falling down. The work presented in Oniga and Süt (2014) deals with the development of a complex assistive system with adaptive capability and learning behaviour, based on a smart and assistive environment, a human activity and health monitoring system, an assistive and telepresence robot, and a cloud service. The main goal is to foster independent daily life assistance of elderly or people with disabilities by using IoT technologies.

2.2 State-of-art about DL technologies

Following the advent of DL technologies, that has achieved successes in many visual perception tasks (Leo et al., 2019), the analysis of food in images has become a field of research of great interest. Most of works in literature deal with the recognition of food dishes (i.e., food ready to be eaten) mainly for food diary applications (Martinel et al., 2018). Very few efforts have been made for the recognition of goods as available on the shelves (e.g., in a market, grocery or warehouse) that is rightly the issue that has to be faced in order to smartly manage a shopping list. Besides, these works rely on training data containing isolated items (or at least a single class of items) on a homogeneous background (namely *in vitro* training data) (Follmann et al., 2018). This way the classifier cannot reach a high level of generalisation in recognition issues since it cannot generalise knowledge and then to gather satisfying recognition performances. For this reason, systems trained on data acquired as they appear on the shelves of a warehouse (namely *in situ* training) are more desirable (Merler et al., 2007). A seminal work towards this challenging research direction is in Jund et al. (2016) where the Freiburg Groceries Dataset was introduced. It consists of 5,000 images covering 25 different classes of groceries, with at least 97 images per class. The authors also used it to fine-tune the weights of the three fully-connected layers of a net having Caffenetwork architecture (Jia et al., 2014). Unfortunately, the system in Jund et al. (2016) only dealt with American grocery items and then it cannot be straightforwardly used to recognise items on the shelves in other countries. This is due to different packaging processes and marketing of different types of vegetable, fruits and ingredients. This paper overcomes this drawback by introducing a system able to also recognise grocery items available in the Italian market. This is achieved by extending the dataset in Jund et al. (2016) and by introducing a deep neural network able to improve classification performance and then making the classification step most suitable to be exploited in the proposed system architecture.

3 Overall system architecture

The proposed system aims to improve users' daily routine providing an intelligent device which helps them to manage grocery shopping list. The system recognise smartly the presence of a product facing the system itself. Thanks to neural network module, the system is able to recognise foods put in front of it with a good level of accuracy. Recognised object will be saved on a cloud system that is available on the mobile application. Mobile application plays a support role in this context. According to this, the smartphone application is used as a virtual shopping list that could be consulted always and everywhere. Items placed in mobile application could be deleted in every moment. The interaction between the system and the cloud infrastructure is is performed in a real-time fashion. The electronic device provided by the system, should be placed in a routine context which is easily accessible. Figure 1 shows a real context of system operation.

From an architectural point of view, the proposed smart AAL system, able to support elderly people to manage a grocery shopping list, is a complex system composed of different parts: a mobile application, a smart board able to detect objects through a neural network approach, and a back-end server implemented in the cloud. This architecture is depicted in Figure 2, and can be further detailed as follows:

- *Smart board:* It is the central point of the whole architecture. It is based on a microcomputer equipped with a camera and placed in a specific location of user's house, so the user can easily interact with it. Basically, the smart board is in charge of

  1. taking the picture of the product to be inserted in the shopping list
  2. pre-processing the image in order to improve its quality and to reduce unnecessary data
  3. passing the image to the neural network in order to identify the product
  4. sending the information about the identified product to the cloud Server through internet, in order to update and manage the shopping list.

The smart board is composed of two different modules: hardware and software modules. The hardware modules is composed of a set of sensors and other circuit elements. This module has as main goal to allow a physical interaction with user, such as providing buttons, camera and distance sensor. These modules are really important for starting the main features supplied by smart board. Modules described before are essential for the other system modules, especially for the neural network one. Smart board also provides an API[6] module which is in charge of establishing communications with remote server. Furthermore it has a business logic module[7] which has the aim to process information coming from users' interactions.

It is supposed that the smart-board will placed in a fixed location within users' houses. For this reason, it was decided that the board will be powered by a power socket. The smart-board is provided by a power supply which delivers 12.5 [W] (5 [V] and 2.5 [A]), however it need to be plugged into classic domestic power sockets. The distance sensor requires 10 [mW] that can be fully provided by the smart-board itself.

- *Neural network:* It is developed on a software component implemented on the smart board, which receives as input the pre-processed picture taken by the camera and provides as output the estimated product category, with a related confidence percentage.
- *Mobile application:* This is a multi-platform smartphone application meant to manage the shopping list through the user's smartphone. It interacts with the cloud server to get and update the items of the shopping list and it notifies the user when he/she is in the nearby of shops and supermarkets. This mechanism is built upon BLE[8]-beacon and GPS-based geolocation and it is also able to provide the best path to the nearest shop according the current user position. As the smart board, also the mobile application has an API module which provides connections between itself and remote cloud server.

  Mobile application's business logic consist of a set of methods which process users' inputs and manage outputs which will be shown on the smartphone screen.
- *Cloud server:* It is in charge of storing and managing all the information collected and used by the smart boards and the mobile applications, like user profiles, shopping lists, registry of shops and beacons, etc. It manages the related database and provides the needed APIs for interaction. It is placed remotely and devices can communicate with it through specific an internet address. It has three main modules. The first module consists of a set of public/private methods that manage API's interfaces. This module is queried by mobile app and smart board. The database stores data obtained by the cloud server (this is made possible thanks to a mapping operation which generates a set of object relational mapping – ORM files). The last module is the server's business logic that consists of a set of methods aimed to manage data streams and also it provides some processing in order to format properly output and input data.

The proposed system implements just one specific feature of a more complex AAL system which might be able to perform operations like first aid assistance, collection of data about users' habits, drug-reminder and other AAL features which improve drastically subjects' lifestyle affected by neurodegenerative diseases.

Figure 1 Diagram showing the main phases of the proposed system's workflow (see online version for colours)

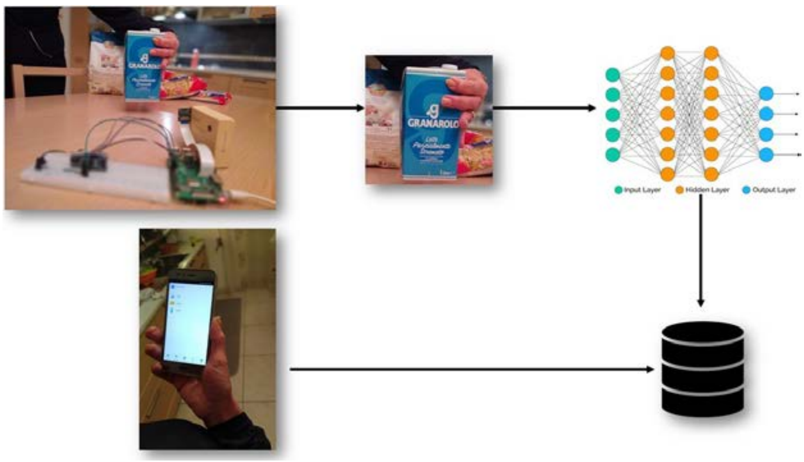
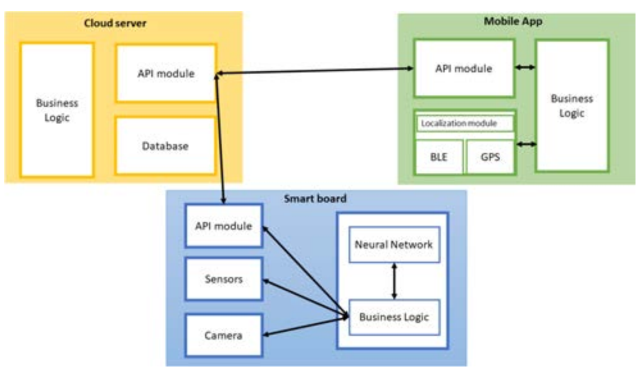


Figure 2 Overall system architecture of the proposed solution (see online version for colours)



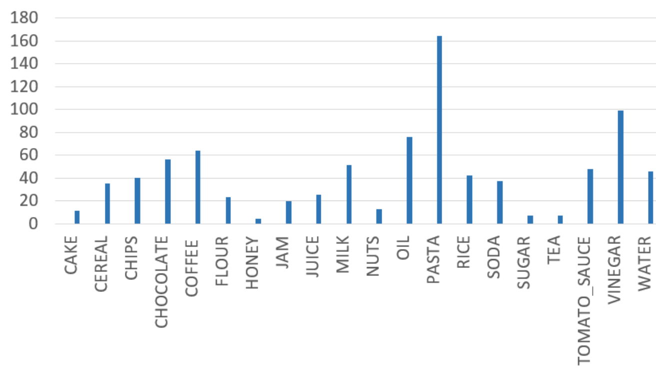
4 Neural network and DL

As depicted in Section 3, the proposed smart AAL system has a software component aimed at recognising Italian grocery items from images. The recognition is carried out by a deep neural network trained on a large number of labelled data. In this section, the aforementioned key aspects of object recognition are described. On the one side, a new dataset has been built by extending the Freiburg Groceries Dataset (Jund et al., 2016) and, on the other side, a more efficient network architecture has been introduced.

4.1 The dataset

Starting from the Freiburg Groceries Dataset, a set of 868 additional images was annotated and added to it. The main bulk of the Freiburg Groceries Dataset consisted of 4,947 images of 25 grocery classes, with 97 to 370 images per class. In Figure 3 the breakdown of the new images in the grocery classes is shown. The criterion by which the examples were added was that of guaranteeing a greater increase in the classes of the starting dataset in which there was a greater discrepancy in appearance compared to Italian products. This led, among all, to add many examples to the class representing pasta items since in Italy, due to local traditions, pasta has many types of packaging, related to the production processes (handmade-like, wire-drawn and so on) but also to sizes.

Figure 3 The breakdown of the 868 additional images in the grocery classes (see online version for colours)



In Figure 4 some significant new examples of the dataset are reported. The first row shows some examples of Italian pasta whereas in the second row some examples of the classes rice, oil, milk and coffee are reported.

4.2 Neural network architecture

The considered recognition task is not trivial since it has to be robust with respect to many acquisition issues: scale (the distance between the item and the camera can vary), rotation, partial occlusions (items are in hand), illumination (items are acquired at home), intra-class variance (items in the same class can look differently) and inter-classes similarity (items in different class can look similar, e.g., rice and pasta packs) and so on. For this reason, complex neural architectures have to be used to fine represent the appearance and to this end, convolutional neural networks have been chosen in this paper. The downside is that it is well-known that large deep networks need a huge amount of training data to learn complex invariances and this is particularly true when a new CNN has to be trained from scratch. Besides, state-of-the-art detectors, such as faster R-CNN (Ren et al., 2015), require training both a classifier (CNN) to classify regions and a regressor (RPN) to generate region proposal and this makes them further eager of annotated data, i.e., of labelled classes for CNN and labelled bounding boxes for RPN. Unfortunately, the available dataset is far from to be suitable to exploit the aforementioned state-of-the-art detectors and to train very deep architectures. To get around the aforementioned problems, in this paper the fine-tuning approach has been put in place, i.e., a pre-trained CNN has been considered as a starting point to achieve, trough the learning of only parameters in the last layers, a finer ability to face the specific recognition problem. In addition, not very deep networks have been considered in order to avoid ineluctable over-fitting issues. In the light of the above, two network architectures have been evaluated: CaffeNet (Jia et al., 2014) and VGGNet (Simonyan and Zisserman, 2014). CaffeNet architecture contains eight learned layers, five convolutional and three fully-connected. VGGNet is very appealing because of its very uniform architecture. In particular, two different implementations of the VGGNet have been exploited: the first one consists of 16 weight layers (13 convulational layers and three fully-connected layers) whereas the second one consists of 19 weight layers (16 convulational layers and three fully-connected layers). The weight configuration of the VGGNet is publicly available and has been used in many other applications and challenges as a baseline feature extractor. However, VGGNet consists of 138 million parameters (VGGNet 16) and 143 million parameters (VGGNet 19), which can be a bit more challenging to handle than CaffeNet.

Figure 4 Some significant new examples in the dataset (see online version for colours)

The network architectures are reported in Table 1.

Table 1 Implemented CNNs architectures

CaffeNet
8 weight layers
Input 227 × 227 RGB
conv 11-96
maxpool
LRN conv 5-256
maxpool
LRN conv 3-384 conv 3-384 conv 3-256
maxpool
FC-4096 FC-4096 FC-25 soft-max
VGGNet-16
16 weight layers
Input 224 × 224 RGB
conv 3-64 conv 3-64
maxpool
conv 3-128 conv 3-128
maxpool
conv 3-256 conv 3-256 conv 3-256

Notes: From above to below are reported CaffeNet, VGGNet-16 and VGGNet-19 CNNs respectively where the number of learnable layers, corresponding to convolutional and fully-connected (FC) layers, are reported in the second row in each CNN description. Each convolutional layer is denoted with the *conv <receptive field size>* – *<number of channels>* notation. Local response normalisation (LRN) has been employed only in the CaffeNet architecture while the last FC layers have same implementation for all three CNNs where the last one has a number of outputs equal to the number of classes in the considered training dataset. An output softmax function is used for all architectures.

Table 1 Implemented CNNs architectures (continued)

VGGNet-16
16 weight layers
maxpool
conv 3-512 conv 3-512 conv 3-512
maxpool
conv 3-512 conv 3-512 conv 3-512
maxpool
FC-4096 FC-4096 FC-25 soft-max
VGGNet-19
19 weight layers
Input 224 × 224 RGB
conv 3-64 conv 3-64
maxpool
conv 3-128 conv 3-128
maxpool
conv 3-256 conv 3-256 conv 3-256 conv 3-256
maxpool
conv 3-512 conv 3-512 conv 3-512 conv 3-512

Notes: From above to below are reported CaffeNet, VGGNet-16 and VGGNet-19 CNNs respectively where the number of learnable layers, corresponding to convolutional and fully-connected (FC) layers, are reported in the second row in each CNN description. Each convolutional layer is denoted with the *conv <receptive field size>* – *<number of channels>* notation. Local response normalisation (LRN) has been employed only in the CaffeNet architecture while the last FC layers have same implementation for all three CNNs where the last one has a number of outputs equal to the number of classes in the considered training dataset. An output softmax function is used for all architectures.

Table 1 Implemented CNNs architectures (continued)

VGGNet-19
19 weight layers
maxpool
conv 3-512 conv 3-512 conv 3-512 conv 3-512
maxpool
FC-4096 FC-4096 FC-25 soft-max

Notes: From above to below are reported CaffeNet, VGGNet-16 and VGGNet-19 CNNs respectively where the number of learnable layers, corresponding to convolutional and fully-connected (FC) layers, are reported in the second row in each CNN description. Each convolutional layer is denoted with the *conv* <*receptive field size*> – <*number of channels*> notation. Local response normalisation (LRN) has been employed only in the CaffeNet architecture while the last FC layers have same implementation for all three CNNs where the last one has a number of outputs equal to the number of classes in the considered training dataset. An output softmax function is used for all architectures.

The images containing grocery products are the input of the CNNs. The overall network is a combination of function composition and matrix multiplication. In the training phase a label (the class ID) is associated to each input image. The images are forwarded trough the CNN and, for each input–output pair (x_i, y_i), the loss of the model on that pair is the cost of the difference between the predicted output $g(x_i)$ and the target output y_i. To compute this loss a cross-entropy cost function (1)

$$C = -1/n \sum_x y \ln(g(x), \theta) \tag{1}$$

is then computed, where θ is the set of parameters of the CNN. Parameters are then updated according to the gradient descent algorithm, i.e., an iterative optimisation algorithm for finding a local minimum of the cost function. Images are initially resized (227 × 227 for CaffeNet and 224 × 224 for VGGNet). Images feeds convolutional layers (namely conv in Table 1. A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. Subsequently, data go to the fully connected layers (namely FC in Table 1) in which all neurons connect to all neurons in the next layer. Finally the output of the last fully-connected layer is fed to a 25-way softmax level which produces a probability distribution over the 25 class labels. The softmax classifier, as shown in equation (2) formula, is a generalisation of the binary form of logistic regression. A mapping function f is defined such that it takes an input set of data x and maps them to the output class labels, i.e.,

$$softmax(x)_i = \exp(x_i) / \sum_j \exp(x_j) \tag{2}$$

Local response normalisation (LRN) and maxpooling implement normalisation and downsampling of previous layer outputs respectively.

A multinomial logistic regression scheme is used to discover the best parameter configuration. This leads to getting the network configuration that maximises the average across training cases of the log-probability of the correct label under the prediction distribution. This is equivalent to maximising the average across training cases of the log-probability of the correct label under the prediction distribution.

5 Elderly supporting system

This section provides a detailed description of the remaining components of the system architecture, i.e., the smart board, the mobile application and the cloud server, which compose the proposed AAL elderly supporting system. The components are represented in Figure 1 and can be described as follows:

1 *Smart board:* The implementation of the protoypal smart board is based on a RaspBerry Pi 3 B+, equipped with a Raspicam v3 and a 7-inch HDMI monitor in order to display a visual feedback to the user. Moreover, an external circuitry with a distance sensor and a button, linked to board on GPIO's[9] pins, has been implemented, in order to refine image capturing operation. The smart board is composed of several sub-sections, the programming language used for implementation is Python:

- *API module* provides connections between cloud server and smart board. It is in charge of opening HTTP connections and sends/receives data using RESTful APIs.
- *Sensors section* is the section which provides circuitry and sensors which are needed for the whole system. The main goal of this section is to provide physical interactions with user and also to collect products' images properly. As shown in Figure 5, the prototype is equipped with a breadboard on which are connected several components such as: a button, which allows users to start some kind of operations and a distance sensor (model HC-SR04) used to recognise near products. They are connected physically on smart board using RaspBerry's pins.
- *Camera section* is also composed of a physical component, but it is connected directly on the board with a Sunny flex cable, so it is totally separated by the rest of the circuit. Basically camera provides capturing images of products.
- *Business logic* has the role to process all data retrieved from other blocks. It is in charge of showing right outputs, process users' inputs and also processing images coming from the camera in order to send them to neural network. Business logic manages also, neural networks responses and communicate with API module in order to update remote database.

- *Neural network module*, which runs locally (this choice is due to a trade-off between performance and simplicity of the system), is treated deeply in Subsection 4.2. It has in charge the prediction of the right product's category.

A real implementation of the system is showed in Figure 6.

Figure 5 Design schema of the smart board sensor module (see online version for colours)

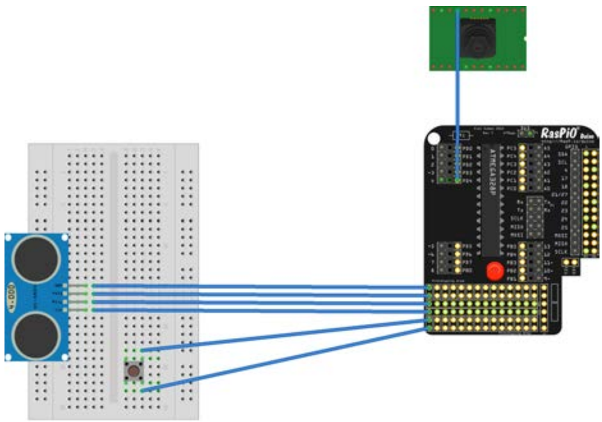
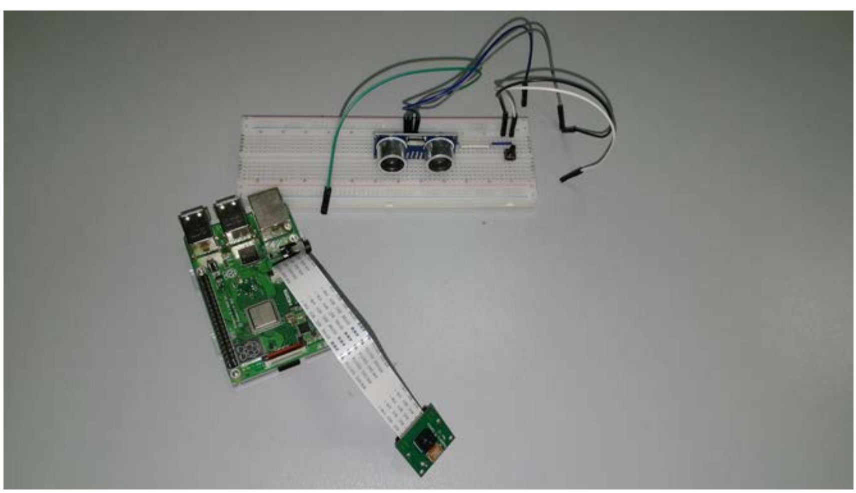


Figure 6 A real implementation of the system described in Figure 5 (see online version for colours)



2 *Cloud server:* It has been developed using Symfony framework[10] and it uses RESTful API[11] method to communicate with external systems, such as: client applications and smart boards. Cloud server is deployed remotely on Heroku cloud service provider.[12] According to the schema shown in Figure 2, the cloud server is composed of three modules.

- *API module:* It provides a public interface which could be queried by external and authorised devices. It consists of a list of endpoints linked with a public internet address. The link is composed of two parts. The first one is a fixed part which matches with the physical address of the remote server. The second part is a dynamic part which is shaped on a specific API. Figure 6 shows how RESTful API's works.
- *Business logic:* This module provides an additional process of the data. Mainly it is in charge of fix data before they are used into queries. Additionally, business logic module retrieves data from the database and sends them to devices through API module.
- *Database:* It is a relational database and it is deployed remotely in a different location of cloud server. They communicate thanks to a one-to-one mapping provided by ORM files generated into the cloud server. The structure of the database is shown in Tables 2, 3, 4 and 5. It contains the essential information for the system.

Figure 7 How RESTful API's module works (see online version for colours)

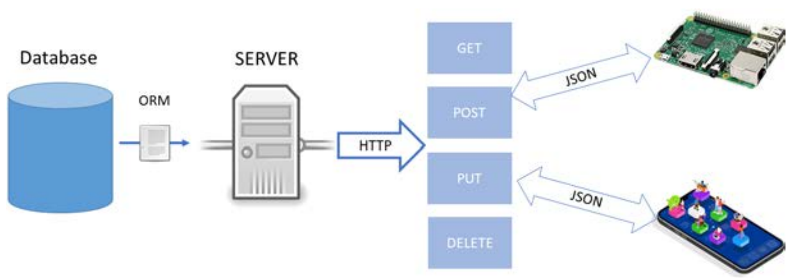


Table 2 Table that represents the entity 'user' into relational model

Entity user	
Attribute name	*Attribute description*
email	Represents user's email
username	Represents user's name or his/her nickname
password	Is user's secret password
is_connected	Is a Boolean field that indicates if a user is connected or not with a smart board

Table 3 Table that represents the entity 'product' into relational model

Entity product	
Attribute name	*Attribute description*
product_name	Represents the name of a product
path	Is the path of the product's icon into server file system
purchased	Represents a Boolean field that indicates if the specific product has been bought (value = true) or not (value = false)

Table 4 Table that represents the entity 'market' into relational model

Entity market	
Attribute name	*Attribute description*
UUID	Is the market beacon UUID
name	Is the name of market
lat	Represents market geographic latitude
lon	Represents market geographic longitude

Table 5 Table that represents the entity 'category' into relational model

Entity category	
Attribute name	*Attribute description*
category_name	Is the name of the category

3 *Mobile application:* The application has been developed using Ionic framework in order to obtain a multi platform application (Yang et al., 2017). It has been tested over iOS and Android devices and it represents the client side. Users could use the application to consult and modify the remote shopping list. It is composed of several modules.

- *Business logic:* It is in charge of processing all kind of information coming from the user inputs. This module binds user inputs with application behaviours.
- *API module:* It consists of a REST provider service which provides main methods to communicates with public interface provided by cloud server. This module can also retrieve and manipulate requested data coming from cloud server. cloud server responses have a JavaScript Object Notation (JSON) format, therefore REST processes JSON responses in order to obtain objects.
- *Localisation module:* Its role consists of providing methods to localise users. Localisation methods might be composed of two different types according to the different situations in which users want to use them.

  a Localisation using BLE-beacon. This type of localisation exploits BLE-beacons to retrieve users' positions. It also uses native Bluetooth to connect the application with outer beacons.

  b Localisation using GPS. This type of localisation allows users to draw paths across supermarkets which fulfill products which are in users' shopping list.

  Bluetooth low energy-based localisation is implemented using EddyStone beacon plugin, a Ionic's plugin designed properly for beacons detection. The precision of BLE-based localisation depends mostly from two factors: smartphones and beacons themselves. Beacons might differ in types and models and their power might vary drastically. On the other hand, smartphones' bluetooth features might vary as well. They depend mainly from the version of bluetooth which is installed on devices. For these reasons, is impossible to forecast the precision of BLE-based localisation.

On the contrary, GPS-based localisation exploits the GPS antenna provided by smartphones, which means that the precision is comparable with others localisation systems.

Notably, it is important to notice that a combination of smartphone and smart-board has been choosen for this system. Apparently, this solution could be seen as a unnecessary complexity. The reasons of this choice lies in the fact that smart-board guarantees a wider range of additional sensors which cannot be plugged in a smartphone. In addition to this, smart-board will be placed in a wider AAL system in which this service will play just a specific task. For this reason, additional sensors might be plugged in on smart-board such as glucometer, humidity sensors, sphygmomanometer and others. Secondly, a smart-board-based approach for image acquisition results to be more user-friendly then a smartphone-based one. It is assumed that the majority of users which represent the right target of this service, might be untrained in smartphone usage so, the process of image gathering could be compromised therefore a well-designed smart-board might help their experience.

6 Experimental results

The system validation was carried out through two different phases. In the first phase, the performances of the proposed neural networks (in terms of item classification accuracy) were tested on a set of images never provided, during the training. In the second experimental phase, functional validation of the overall system was carried out by exploiting the introduced proof-of-concept. Both phases are detailed in the following subsections.

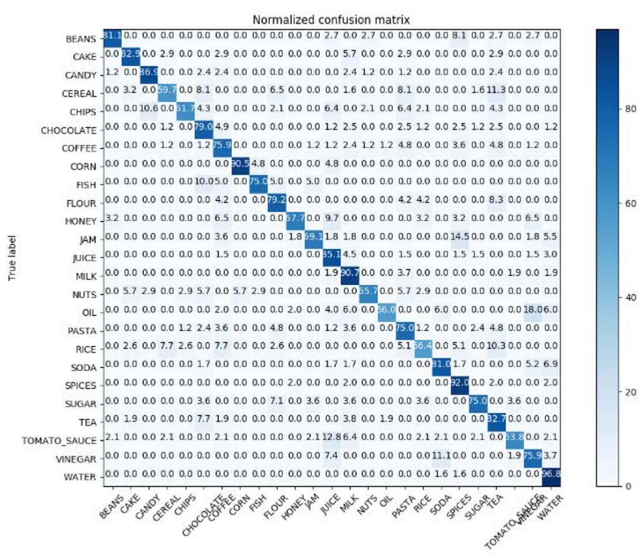
6.1 Evaluation of the neural network component

The neural networks described in Subsection 4.2 were trained as follow. The images in the dataset introduced in Subsection 4.1 were added to the images of the dataset in Jund et al. (2016). 80% of the images in Jund et al. (2016) and 90% of the new images containing Italian goods were used for training the network (training subset). The training subset was enlarged in order to balance data across all classes and this was done by duplicating images from classes with fewer images. At the end of this process, it consisted of 8,038 images. The remaining 1,231 images (testing subset) were used in the final validation. The training subset was subsequently partitioned into five (almost) equally-sized splits, with the images of each class uniformly distributed over the splits. The weights of the CaffeNet architecture were initialised with those of the pre-trained net in Jia et al. (2014), and the fine-tuning process was carried out on layer FC8. The learning rate was set at first to 0.01 with a decreasing factor of 0.1 every 4,000 iterations. Momentum, weight decay and maximum numbers of iterations were set to 0.9, 0.0005 and 10,000 respectively. Similarly, weights in the VGG architectures were initialised to those of the nets pre-trained on the ImageNet dataset (Krizhevsky et al., 2012). For VGG-16 the fine-tuning process was carried out on layers FC7 and FC8, the learning rate was set at first to 0.001 with a decreasing factor of 0.1 every 15,000 iterations; momentum, weight decay and maximum numbers of iterations were set to 0.9, 0.0005 and 45,000 respectively. For VGG-19 the fine-tuning process was carried out on the layer FC8; the learning rate was set at first to 0.001 with a decreasing factor of 0.1 every 8,000 iterations. Momentum, weight decay and maximum numbers of iterations were set to 0.9, 0.0005 and 30,000 respectively. The last model for each network architecture was finally used for evaluation, i.e., the three trained models were then used to automatically assign the labels to the images in the testing subset.

Table 6 Performance on the extended dataset achieved by the three here introduced neural models and compared with those of the leading model in the state-of-the-art

	Precision	*Recall*	*F1 score*
CaffeNet	0.739244	0.634582	0.650897
VGG-NET-16	0.723868	0.6442152	0.694998
VGG-NET-19	*0.793890*	*0.761924*	*0.766871*
Original model by Jund et al. (2016)	0.6863582	0.568125	0.578382

Figure 8 Confusion matrix obtained using the proposed extended dataset and network architecture VGG-19 (see online version for colours)



The results in terms of precision, recall and F1 score are reported in Table 6. The same table reports also the outcomes obtained on the extended dataset by using the leading model in the state of the art proposed by Jund et al. (2016). It is worth noting that all the introduced models overcame the recognition capabilities of the leading state of the art approach and in particular the VGG CNN architecture with 19 weight layers got very encouraging outcomes.

Detailed results for the best performing model (i.e., VGGNet 19) are reported in Figure 8 as a confusion matrix.

Figure 8 shows that classification rate differs among classes and thus it is still necessary to investigate to gather highly performing classification levels for all classes. However, it is worth notice that for the classes relating to the most used consumer goods (such as pasta, oil, milk, fish, and water) the recognition rate was very high. Some improvements are required for cereal, chocolate, soda and chips. This depends on the enormous variance in the appearance that these elements experience that needs to be addressed by a massive and targeted data collection campaign.

It is straightforward to observe that the capability of the net to classify grocery items in the extended dataset has been improved by introducing in the learning set some annotated examples of Italian goods. This allows the system to more accurately cope with the needs of the user as will be demonstrated in the following subsection.

6.2 Proof-of-concept of the overall system

A functional validation of the overall system was carried out by exploiting the proof-of-concept shown in Figure 9. In this use case we can see all interactions among all components of the system. Use case starts by describing how user interacts with the smart board and hits all steps in order to define completely the system's operation. Regarding the smart board synchronisation, once the device is switched on, the user must press the synchronisation button. In the meanwhile, the user must retrieve the personal QR-code from his/her mobile app (after the registration and login phase). Then, the user puts the QR-code in front of the smart board camera and the synchronisation starts. If the process is successful, a message is shown on the display. When the smart board is synchronised, it is ready to identify the products to be included in the shopping list. This task can be carried out simply by putting the product in front of the smart board's camera. As said in Section 3, if the neural network has successfully recognised the product, it is automatically added to the shopping list and the user can open the app to see the new item in the list. When user intends to purchase products on the shopping list, he/she can open map's page and let app to advice nearest market, as shown in Figure 10. Finally, when the user, in a later moment, is nearby markets which are affiliated to the platform, he/she will receive a push notification from the mobile application, notifying that in the near market one or more needed products can be purchased. Once user has bought it, he/she can move it on the 'products purchased list', in order to speed up the addition of the same item on the next shopping session.

Moreover, has been implemented a sound feedback when users touch on a item list in order to improve the usability of the service by elderly people. The main stakeholder is an elderly person who will use this service in order to manage dynamically his/her shopping list of food items. The shopping list may also be presented to caregivers and/or relatives which help the elderly person. Main steps in using this service are:

1 Placing the product in front of the smart board's camera, in order to allow it to recognise the object usign QR-code recognition. A short snippet of Python code which plays the synchronisation module on smart board is reported at Listing 1.

2 Once the product is recognised, it is added to the shopping list shown through the mobile app, where it can be consulted and edited by the user.

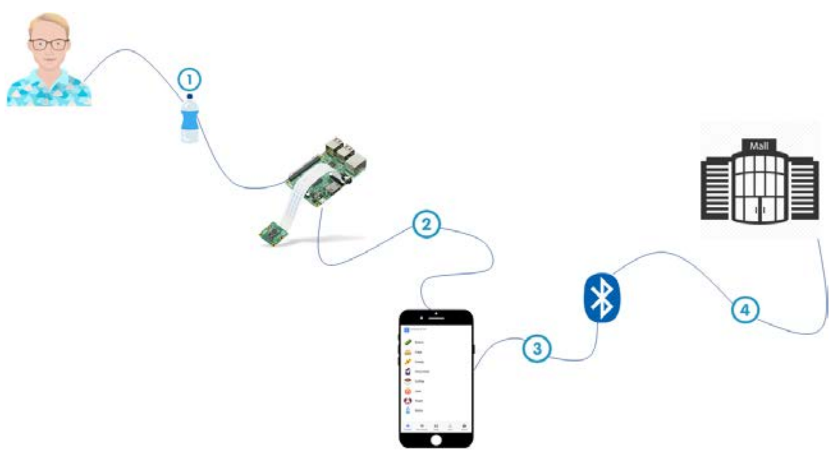
3 By the smartphone's bluetooth (and/or, eventually, the GPS) interface turned on in order to allow outdoor localisation, when the user is nearby a supermarket, the mobile app notifies the user, through a push notification, the possibility to purchase one or more products.

4 Then, the user can remove the item from the current list or store it for the next shopping session.

Listing 1 Synchronisation code

```
while id_user == None:
    camera.capture(qr_image, 'jpeg', use_video_port = True)
    im = Image.open(qr_image)
    id_user = scan.decode(im)
root.update_idletasks()
root.update()
rqst = "https://.../synchronise" + str(id_user);
requests.get(rqst)
```

Figure 9 Proof-of-concept which explains main steps that users should follow in a typical scenario (see online version for colours)

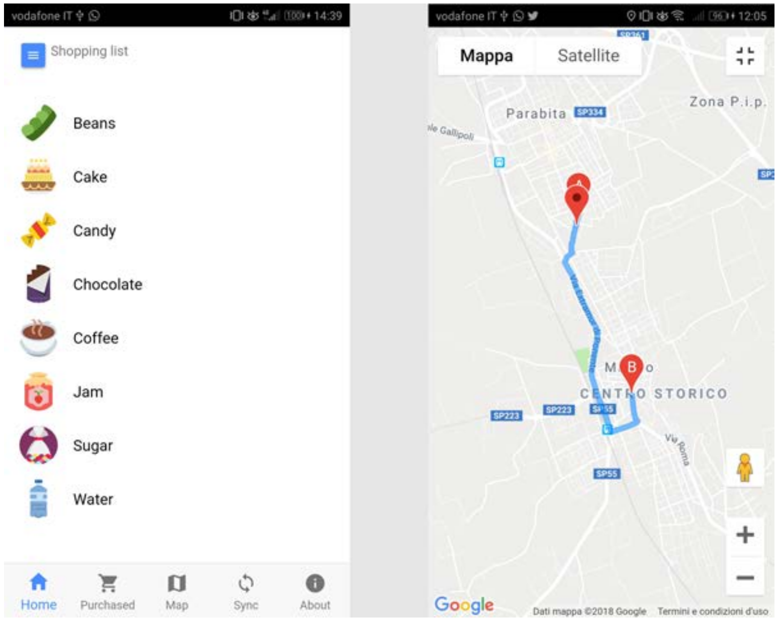


It was chosen a QR-code-based synchronisation for several reasons. Mainly, the synchronisation need to be done just the first time. This means that if the elderly user is not able to use this technology, the operation might be done by a caregiver or by a relative as well. It is important to point out that QR-code will be required during the setup phase only.

Shopping list can be consulted using mobile-app because this solution is the most user-friendly amongst others. Mobile application offers a set of visual interactions and feedbacks that increse the intuitiveness of the whole system. In addition, non-expert users can use the application easily thanks to its user-friendly user interface.

Furthermore, geolocation and navigation features offer a support system for buying listed products. This additional service allows users to save time and fuel. On the other hand, BLE-localisation is a reminder feature based on users' positions. It notifies users when they are enough close to a supermarket which sells items of the shopping list.

Figure 10 App's screens which show the shopping list and map page obtained by a geolocation process (see online version for colours)



6.3 *Practicability of the system*

As an additional experimental phase, the assistive contribution provided by the system is proved by a practical experiment. It is based on a real use case in which the system supported three elderly people's daily routine. The experiment has been spread over three days. Results of system usage are compared with results of the same situations but without the AAL service support. The experiment involved three elderly people who, on three different days, had to recognise and then to remember 15 products per day. Going into details, there was a pantry in which 15 grocery products were stored on each day. Products changed day by day. The subjects were first asked to recognise the grocery products (one at a time). Subsequently, products were hidden and the subject was asked to remember the proposed products on the same day and, from day 2, even on the previous days.

The experiment leverage five metrics to validate system improvement:

- Recognised products. It represents the number of products that the subject correctly recognised on each day.
- Reminded products day 1. It represents the number of products presented on the first day that each subject is able to remember at the end of the has remembered.
- Reminded products day 2. Represents the number of products presented on the second day that each subject has remembered.
- Reminded products day 3. Represents the number of products presented on the third day that each subject has remembered.

- Recognition time. Represents how long the subject has taken to recognise a product.

Table 7 Results of the experiment without AAL system support

	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time (sec)*
Subject 1 (healthy, 78 years old)						
Day 1	15	15	10	/	/	~0
Day 2	15	15	5	9	/	~0
Day 3	15	15	3	4	10	~0
Subject 2 (neurodegenerative disease, 76 years old)						
	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time*
Day 1	15	15	5	/	/	~2
Day 2	15	14	0	6	/	~2
Day 3	15	14	0	1	5	~2
Subject 3 (blindness, 79 years old)						
	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time*
Day 1	15	5	10	/	/	30–120
Day 2	15	6	6	10	/	30–120
Day 3	15	4	5	6	9	30–120

For the test, three different users have been chosen. The first user, a 78 years old woman, is a healthy person. The second tester is a 76 years old woman affected by a neurodegenerative disease. Her disease is at an advanced stages. The last user is a 79 years old man affected by complete blindness due to diabetes. The experiment was carried out in two different stage. In the first stage, the users did not have the support of the proposed system. In the second stage, they could exploit the system to perform the required tasks. Results without system support are reported in Table 7.

The table reports that, on the first day, the subject 1 instantaneously recognised all products and she remembered 10 out 15 of them when products were hidden. The following days the subject 1 continued to correctly recognise the products but she struggled to remember products of previous days.

Subject 2 almost perfectly succeeded in the recognition task, with an accuracy of 95%. On the other hand, she failed in products reminding. She remembered a few products of the same day but she completely failed to remember products of previous days. Recognition time was about of 2 seconds per product.

Subject 3 struggled in recognising products due to his blindness. The reminding activity is quite normal instead and he remembered a reasonable number of products. Blindness has affected also recognition time that is significantly higher than previous subjects.

Table 8 Results of the experiment when the subjects leveraged AAL system

Subject 1 (healthy, 78 years old)						
	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time (sec)*
Day 1	15	13	13	/	/	∼1
Day 2	15	11	13	11	/	∼1
Day 3	15	15	13	11	15	∼1
Subject 2 (neurodegenerative disease, 76 years old)						
	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time*
Day 1	15	13	13	n.d.	n.d.	∼1
Day 2	15	11	13	11	n.d.	∼1
Day 3	15	13	13	11	13	∼1
Subject 3 (blindness, 79 years old)						
	Submitted products	*Recognised products*	*Reminded products day 1*	*Reminded products day 2*	*Reminded products day 3*	*Recognition time*
Day 1	15	12	12	n.d.	n.d.	∼1
Day 2	15	11	12	11	n.d.	∼1
Day 3	15	14	12	11	14	∼1

Outcomes leveraging the AAL system usage are reported in Table 8.

By exploiting the system, the subject 1 became able to remind all recognised products, subject 2 showed a significant improvement in remembering products of previous days and also a slight enhancement in recognition time. Besides, subject 3 showed a huge improvement in recognising products and also in recognition time. The system allowed also the subject to remember products of days before.

Table 9 Improvement carried out by the AAL system

	Improvement in recognising products	*Improvement in reminding products day 1*	*Improvement in reminding products day 2*	*Improvement in reminding products day 3*	*Improvement in recognition time*
Subject 1	–14%	+46%	+30%	+33%	No improvement
Subject 2	–12%	+75%	+50%	+53%	Slight improvement
Subject 3	+48%	+33%	+20%	+33%	Huge improvement

Finally, Table 9 reports enhancements, in percentage, carried out through the use of the AAL system. The first column reports improvements in recognising products. In particular, here it is possible to realise that the blind subject had a significant improvement in his results. The columns related to reminding products clearly show that improvement percentages are all above 20%. This depicts a strong influence on the system in this kind of activity. The last column reports recognition time improvements. The first subject had no improvement in this field but the second and even more the third subject had a significant reduction in recognition time.

These results have clearly highlighted that this system has made daily activities of some elderly subjects easier than before.

The outcomes of this experiment definitively demonstrate that the proposed system is a smart solution to manage a shopping list and that it can help people, especially if affected by neurological or sensory diseases, to keep autonomous and to facilitate day-life activities.

7 Conclusions

This work proposed a smart support system, within an overall AAL system, able to support and help elderly people in daily activities such as do the shopping at the supermarket. It combines IoT technologies, such as sensors, cloud and mobile app, with neural network systems embedded on the smart board. The proposed system architecture is composed mainly of:

1 an always-on smart board which provides products recognition

2 cloud server that manages all data sent by smart board and mobile app

3 mobile application that manages push notifications and indoor and outdoor localisation systems-based respectively on BLE-beacons and GPS.

The core of the work is focused on the neural network, which is in charge to predict properly the right products class with a high level of confidence. The neural network allows to speed up the entire system and also to step up predictions accuracy. The proposed system has been validated through a proof-of-concept. In-depth performance analysis has been carried out on the neural network outcomes in order to evaluate the system effectiveness in terms of average precision, recall and F1-score. Besides, a real case experimental phase has been carried out demonstrating that people, especially if affected by neurological or physical diseases, can benefit in using the proposed system both in terms of recognition accuracy and ability to remind a list of products.

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Notes

1 https://www.anylist.com/.

2 https://www.mealime.com/.

3 https://www.cozi.com/.

4 https://www.amazon.com/AmazonFresh-Grocery/b?ie=UTF8&node=11825099011.

5 REST is the achronym of rapresentational state transfer and it represents a trasmission method over HTTP protocol which is used on distributed systems. A REST call does not require a session-based connection.

6 Is the acronym of application programming interface. They are a libraries collection of a certain programming language, which provide a specific function.

7 The business logic module plays a key role into a software architecture. It is placed between modules for user interface and modules for data accessing.

8 Is the acronym of bluetooth low energy, is a wireless technology for personal area networks which is designed properly for fitness, beacons, healthcare and so on.

9 Is the acronym of general purpose input/output and represents an interface of some electronic device such as microprocessors, microcontrollers and so on.

10 https://symfony.com.

11 Is the acronym of rapresentational state transfer and they are a specif type of API provided by a back-end system. RESTs are based on a HTTP architecture and they allow to communicate with a server exploiting several functions of it such as DELETE, PUSH, PUT, GET, ALTER and so on.

12 https://www.heroku.com.