JUST TELL ME: A Robot-assisted E-health Solution for People with Lower-extremity Disability

Alexander Coutras
Chatham High School
Chatham, USA
acoutras@icloud.com

Omar Obidat
Department of Computer Science
Montclair State University
Montclair, USA
obidato1@montclair.edu

Michelle Zhu
Department of Computer Science
Montclair State University
Montclair, USA
zhumi@montclair.edu

Weitian Wang*
Department of Computer Science
Montclair State University
Montclair, USA
wangw@montclair.edu

***Abstract*—Robotics technology has been increasingly applied to healthcare contexts to enhance efficiency and safety in healthcare processes in recent years. People with mobility impairments and disabilities often require caretakers in their lives. Fortunately, robots can provide attention and assistance consistently for them instead of human caretakers. Motivated by this, we develop a robot-assisted e-health solution to empower the patients' daily lives and improve their wellbeing in this study. A transfer learning-based approach is proposed to train the robot to understand and identify patients' needs through a small dataset. Using the proposed approach, the robot is able to understand the patient's needs through speech recognition and recognize objects that the patient has requested. The proposed solution is experimentally implemented in real-world human-robot interactive healthcare contexts. Results and analysis indicate the success and accuracy of our approaches.**

Keywords—Robotics, human-robot interaction, E-health, mobility impairments, computer vision, healthcare informatics systems

I. INTRODUCTION

In a conventional healthcare environment, physicians and nurses often have a lot to do. They do not have time to carefully attend to trivial tasks while important tasks are waiting. Doctors have been able to operate for years in this way. However, the introduction of robotics into healthcare contexts has increased efficiency and safety in healthcare processes [1]. With robots trained to perform routine tasks in a healthcare setting, more medical professionals are free to focus their valuable time and energy towards accomplishing important tasks and engaging with their patients. Robots can take care of patients who require basic assistance [2]. Additionally, this human-robot interaction greatly reduces the risk of spreading infectious diseases, an extremely important factor in the context of the Covid-19 pandemic [3]. Robots are also able to make processes such as surgery safer, as they decrease the risk of malpractice due to human errors [4, 5]. Robots are always good companions in healthcare environments and ensure that certain tasks will get done without errors that may happen in human operations. Unlike humans, robots are capable of working at full capacity consistently for long amounts of time, which benefits patients who simply need manual tasks done that are hard to accomplish by themselves. Humans and robots working together will make a healthcare setting operate safely and efficiently in ways that humans alone cannot [6].

People with mobility impairments and disabilities often require full-time caretakers in their lives. These people will need help completing routine tasks in their daily lives, something a human caretaker can accomplish, but the caretakers' time and consistent attention to their patients in order to properly assist them is not the best use of caretakers' energies. Fortunately, robots can provide this extreme attention and assistance consistently [7]. In this study, we will focus on people with lower-extremity disabilities. This means that the target of our study is to help people who have low mobility and are not ambulatory across natural terrain without the assistance of some forms. Essentially, it is difficult for the patient to move around. Thus, daily tasks that require movement become inconvenient and time-consuming without assistance. To this end, we develop a natural and easy-to-use solution that utilizes speech recognition along with transfer learning in order to understand the needs of a patient and properly assist the patient. Using the proposed approach, the robot is able to understand the patient's needs and recognize objects that the patient has requested. Based on the understanding and recognition results, the robot will then pick up and deliver the requested objects to the patient. This is convenient for patients with a lower-extremity disability as their mobility is impaired, which will make the patients' daily lives more efficient and highly improve their wellbeing.

In our robot-assisted e-health solution, we train a robot learning model to recognize 7 different classes using transfer learning algorithms. The robot can identify which of 6 different foods is present as well as if no food is present. In addition, we utilize speech recognition with google for the robot in order to understand the speech requests of the patient. Once the robot has learned to recognize the patient's speech and identify objects, these abilities are leveraged by the patients to serve them such as asking for food from the robot. The real-world human-robot interaction experiments are designed to be as natural as human-human interaction in daily lives. Results and analysis indicate the success and accuracy of our approaches.

II. RELATED WORK

In recent years, several related studies regarding robotics and machine learning in healthcare contexts have been conducted. Part of this is due to the increased need for such studies because of the pandemic. Below we discuss the different ways robotics and machine learning have been applied in healthcare settings.

In healthcare, robotics has many useful applications to make processes safer and more efficient. Bartosiak *et al.* studied the perception of staff in an Italian hospital reacting to the introduction of semi-autonomous robots during a Covid-19 outbreak in order to reduce risks for staff at this hospital [8]. Rantanen *et al.* focused on the usefulness of care robots in-home care services for the elderly [9]. The authors of [10] discussed

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the importance of human-robot interactions in a healthcare environment within a pandemic setting in order to keep staff safe. Holland *et al.* studied the use of service robots in a healthcare environment in order to combat difficulties faced in a pandemic setting such as that of the Covid-19 crisis [11]. Oña *et al.* reviewed the uses of robots in aiding the rehabilitation of a patient with an upper extremity injury [12]. Vallès-Peris *et al.* analyzed the imagined human-robot interactions within a children's hospital of children in order to improve the design of such assistive robots in a real healthcare setting [13]. Vulpe *et al.* proposed the use of a specific type of socially assistive robots in a personalized healthcare setting [14].

However, most of the studies mentioned above mainly focused on the usefulness of robotics applications in healthcare without stressing the importance of natural human-robot interaction. Every human-robot interaction should strive to be as similar as possible to a true human-human interaction. As well as making it easier to interact in general, this allows for the patient in the interaction to feel more comfortable and trusty [15-17], which is significant in a high-quality interaction.

Machine learning is one of the most important advances in recent years and its applications in the healthcare field are exceptionally useful. Gala *et al.* trained a deep learning model to recognize specific pills in a drug trial in order to confirm patients were taking the correct pills and to help substantiate the results of the trial [18]. Arvind *et al.* developed a machine learning algorithm to help predict whether Covid-19 patients would require intubation in the future [19]. Early identification of at-risk patients is key in providing the proper care. Brinati *et al.* analyzed blood test results using machine learning to detect Covid-19 in patients [20]. Similarly, Brunese *et al.* utilized a machine learning model to detect Covid-19 in patients from x-ray images of their chests [21]. Franceschiello *et al.* analyzed eye trajectories using machine learning algorithms and deep convolutional networks to classify patients with spatial neglect (a neurological disorder) [22]. Camara *et al.* trained a convolutional neural network to detect infrarenal abdominal aortic aneurysms from CT and CTA scans [23]. Liu *et al.* constructed a machine learning model to classify acute myeloid leukemia from bone marrow smear images [24].

However, most of the studies described above created and trained conventional ad-hoc machine learning models and algorithms from scratch. This process takes a considerable amount of data to achieve an effective model. Additionally, if the data is too specific to the task at hand, the risk of over-fitting increases. Instead, a transfer learning approach helps to combat over-fitting as well as cuts down on the amount of data required to create an accurate model or algorithm, which makes the process more efficient.

In this study, we will create a human-robot interaction solution that is natural in its design in healthcare contexts. All the patient has to do is to tell the robot which food they want and the robot will hand it to them. We employ speech recognition so that the human can easily communicate with the robot through speech as he would with another human. The robot also asks the human what they want to further create a natural interaction. Upon collecting the food the human requested, the robot hands the human the food and the human can take it as they would in regular human-human interaction. This process promotes a comfortable and trustworthy interaction for the patient. The more comfortable the patient is with the setup, the more efficient the interaction will run. To efficiently create a machine learning model for the robot's food recognition, we utilized transfer learning algorithms. Rather than training a convolutional neural network from scratch, we transferred the aspects of a base network trained to detect images from the ImageNet dataset and then trained this model further to apply to our specific food recognition tasks. This process allowed us to create an accurate model for our task without the need for a large dataset.

III. Approaches

A. Transfer Learning

With a typical machine learning approach, classes have to be trained from scratch. This process requires large amounts of data and time to produce an effective learning model. Transfer learning is a more efficient approach intended to train models faster on less data while still achieving a high level of performance [25]. Training does not need to be restarted for new tasks with the transfer learning technique. Instead, general areas of a pre-trained model can be kept, and the model is only retrained to identify specific objects relevant to the task. In order to produce an accurate model without the need to train on large datasets, the core functionality of one already trained model can be transferred into a new model, and then the new model is refined and trained to identify specific objects [26]. The aspects of the model that recognize objects and generic features are set without training but with transferring. Due to the use of the transfer learning technique, in this study, a small dataset was used to train the model for recognizing the patient's foods, while most of the model was already pre-trained from the ImageNet dataset. This allows an accurate model able to accomplish the task at hand to be created fairly quickly.

B. ResNet50

ResNet50 [27] is the base model used during the process of teaching the robot to identify different foods with transfer learning. The typical convolutional neural network contains sequential connections between convolutional layers. The main problem with this design is that with too many layers the value of the gradient decreases significantly during backpropagation resulting in inaccuracy. In order to improve accuracy after adding more layers, a ResNet has shortcut connections between layers so that the information is passed directly between shallow and deep layers. This allows for a deeper model that maintains high accuracy. ResNet50 is a ResNet model with 50 layers. It was trained on the ImageNet dataset with over 14 million different images and 1000 different classes.

C. Human Speech Instruction Collection and Processing

The structure of the approach is based on an ongoing speech interaction between the patient and the robot. As shown in Fig. 1, the robot begins by asking the patient what they would like. The robot then listens for the patient's speech instructions. Once instructions are detected, they are recognized through google speech recognition and text is created [28, 29]. This text is then used by the robot to take care of the patient's needs. Once that is done, the robot asks if the patient needs anything else and the loop continues. The microphone used is inside the web camera.

The microphone detects sound using the speech recognition package developed via Python.

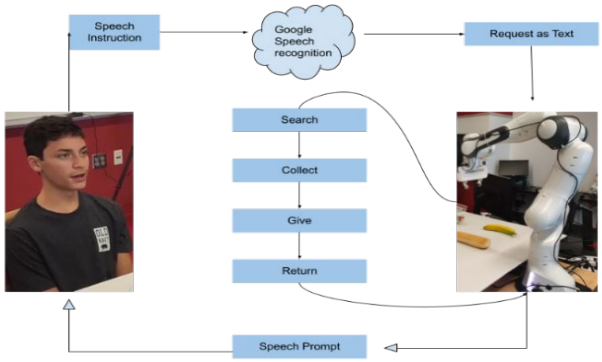

Fig. 1. Human-Robot Speech Interaction Block Diagram.

D. Data Collection for Food Recognition

In our study, the data that is used for object recognition is pictures of foods. These images come from the workspace that is used during the experiment. As shown in Fig. 2, images of different types of foods are first captured from the workspace by a web camera. This camera is attached to the robot end-effector. This camera then takes pictures of each food and saves them to a dataset directory. This directory is later used by the transfer learning model to classify 7 different types of images: 6 different types of foods (bread, banana, cracker, yogurt, bottled water, and orange) as well as when there is no food present. Once this model is trained and saved it can be implemented to recognize the different types of foods in real-time from the same camera attached to the robot end-effector. This allows the robot to identify foods in front of it in the workspace during assistance for the patient. OpenCV [30, 31] was utilized to take multiple pictures of each food and download them into the dataset folder with 7 classes. The images were then scaled into the correct dimensions and regions of interest were extracted before being used for training the network to detect each type of food. 100 images of each kind of food are used in the transfer learning model.

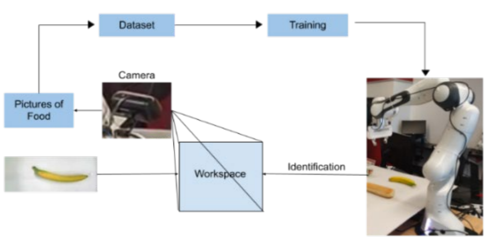

Fig. 2. Data collection with camera for object recognition training.

E. Food Understanding of the Robot

The objective of robot learning is to be able to correctly understand and identify different kinds of foods and select the correct food the patient requested in order to satisfy the needs of the patient. The robot makes use of the transfer learning approach to most efficiently and accurately understand and identify the different classes of foods based on the ResNet50 network in conjunction with the collected local food image dataset. During the real-time human-robot interaction, the robot is able to correctly identify the needs of the human and deliver the requested food in real-time.

In the robot learning process, given the source domain D_S of the ResNet50 network, the learning task T_S of the ResNet50 network, a target food recognition domain D_F , and a food learning task T_F, the transfer learning can output the learning of the target object predictive function $f_f^{\,*}(\,I^{\,'}\,)$ in D_F using the knowledge in D_S and T_S, where D_S does not equal D_F or T_S does not equal T_F, and I represents the acquired food information. In the human-robot interactive healthcare context, for each set of online food information $I^{\,'}$, the understood food class F^* can be obtained from the target predicted results

$$F^* = \underset{f=1,2,\ldots,C}{\arg\max}\, f_f^*(X') \tag{1}$$

where C is the number of classes. C is 7 in this study.

IV. Experimental Results and Analysis

A. Experimental Setup

In this study, as shown in Fig. 3, we build a simulated robot-assisted healthcare context. The experimental platform involves a collaborative robot, a web camera, a workstation, 6 kinds of foods (bread, banana, cracker, yogurt, bottled water, and orange), and a shared workspace. The robot adopted is Franka Emika Panda, which is a 7-DoF collaborative robot [32]. The robot can work with humans safely like human-to-human cooperation in collaborative tasks. A ThinkStation P520 with Intel® Xeon® W-2223 Processor and NVIDIA® RTX™ A4000 16GB GDDR6 serves as the workstation for food image collection and processing, transfer learning development and training, real-time food understanding, and robot motion planning. The Robot Operating System (ROS) is utilized in the robot system control [33, 34]. To plan the robot in human-robot collaborative tasks, the control commands are sent to the libfranka interface, which is a ROS package for Panda to communicate with the FCI controller. The FCI will provide the current robot states and enable the robot to be directly controlled by the commands derived based on the real-time robot's understanding of foods.

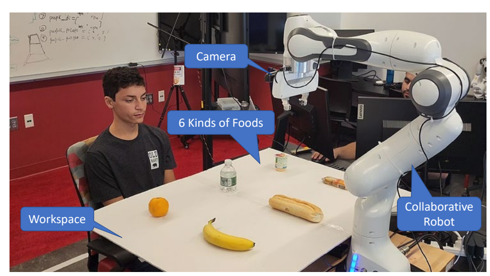

Fig. 3. The experimental platform.

B. Training and Cross-Validation Accuracy and Loss of Food Understanding of the Robot

Before training the robot, the food image dataset is divided into two categories: food training data and food cross-validation data. As presented in Fig. 4, the training accuracy of food understanding of the robot is up to 100% starting from epoch 0. The cross-validation accuracy reaches 100% as well. These results suggest that the accuracy of food training and cross-validation is quite favorable, which means the robot has acquired a well-trained cognition. As the robot employs a small local dataset including 6 classes of foods, it is important to test the robustness of the robot's learned model so that it can respond to the patient in a correct way that understands the foods detected. An overfit or underfit model will result in inaccurate food identification for the patient when interacting with the robot. In order to assess the robot's learned model, the cross-entropy loss function is utilized while tuning model weights in the robot learning procedure. The probability of each food class prediction is compared to the desired food class. After that, a loss value is calculated to penalize the probability according to how far it is from the expected food class. A smaller loss value means a better robot's learned model. As presented in Fig. 5, both the training and cross-validation losses reach about 0. These results suggest that the robot's learned model is highly robust.

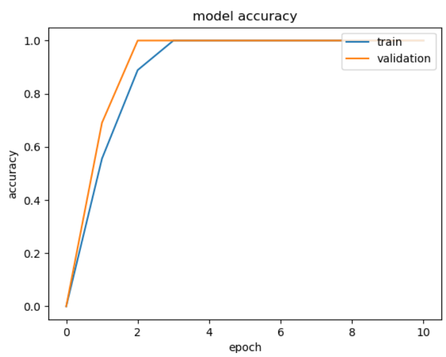

Fig. 4. Training and cross-validation accuracy of food understanding of the robot.

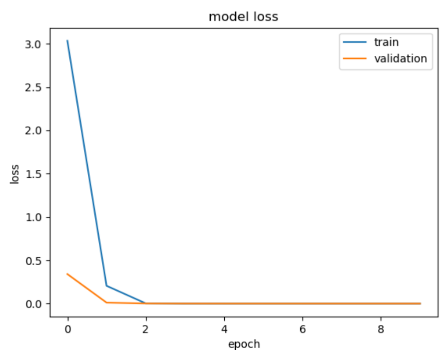

Fig. 5. Training and cross-validation loss of food understanding of the robot.

C. Robot-assisted Object-delivery in Real-world Contexts

During the real-world human-robot interaction experiment, we decided to test three cases. As shown in Fig. 6, in the first case the human subject is requesting a banana out of a list of 6 kinds of foods. The robot at this point has already been trained to identify this list of foods and a camera is attached to the robot allowing our model to use the video stream from the camera as input. The experiment starts with the human subject requesting a banana through speech as presented in Fig. 6 (a). Using voice recognition, the model receives instructions on which food was chosen and then sends instructions to the robot to start scanning the table. The robot starts scanning the workspace as shown in Fig. 6 (b and c) using the camera mounted on it until it finds a banana or the requested item. Once found the model sends instructions to the robot to pick up the banana with the appropriate force as shown in Fig. 6 (d). For each item a different force has been set beforehand. After picking up the food the robot hands it to the human subject (Fig. 6 (e)) and retreats to its original position (Fig. 6 (f)).

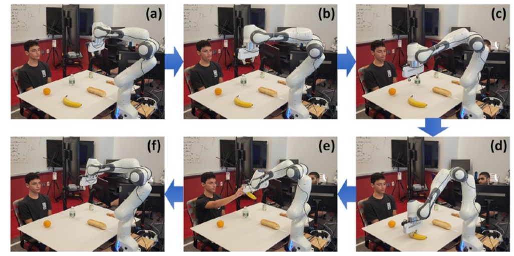

Fig. 6. The human subject requests a banana. (a) Tell the robot. (b). The robot scans all foods. (c) The robot finds a banana. (d) The robot picks up the banana. (e) The robot delivers the banana to the human subject. (f) The robot moves back.

The second case of the experiment is the human subject asks for a different food right after the robot hands him the banana in the first case. The second case is represented in Fig. 7. The next food the human subject asked for is a cracker as shown in Fig. 7 (a). The robot starts scanning the table as shown in Fig. 7 (b and c) until it finds a cracker. Once found the model sends instructions to the robot to pick up the cracker with the appropriate force as shown in Fig. 7 (d). After picking up the food the robot delivers it to the human subject (Fig. 7 (e)) and moves back to its original position (Fig. 7 (f)).

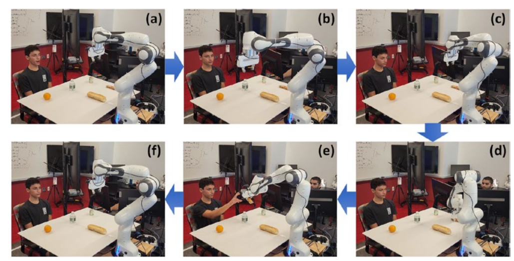

Fig. 7. The human subject requests a cracker. (a) Tell the robot. (b). The robot scans all foods. (c) The robot finds a cracker. (d) The robot picks up the cracker. (e) The robot delivers the cracker to the human subject. (f) The robot moves back.

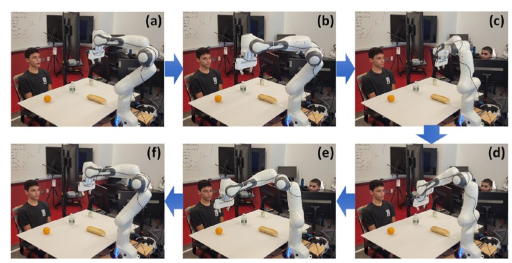

Fig. 8. The human subject requests a banana again. (a) Tell the robot. (b) - (e). The robot scans all foods. (f) The robot does not find a banana and moves back.

The last case during this experiment is the human subject requests again a banana after the previous two cases to demonstrate how the robot would respond if the food is not available. The final case is represented in Fig. 8. The human subject asked for a banana as shown in Fig. 8 (a). The robot begins scanning the workspace as shown in Fig. 8 (b to e) until it has scanned the whole table. The robot then retreats to its original position since it does not find the desired food of the human subject. The robot tells the human subject that the item is not available while it stands by as shown in Fig. 8 (f) awaiting further instructions. These three cases of the human-robot interaction experiment in healthcare contexts validate that the robot can be taught to be a caring companion for humans to assist them in different tasks if they have a lower-extremity disability and their mobility is impaired. Worth noting that the experiment is done to prove the concept and solution proposed in this study but can be easily replicated to include more items and different scenarios in healthcare contexts.

V. Conclusions

In this work, we have developed a robot-assisted e-health solution to empower the patients' daily lives and improve their wellbeing. We have proposed a transfer learning-based approach to train the robot to understand and identify patients' needs through a small dataset. The robot can identify 6 different kinds of foods presented to it. Additionally, we have employed speech recognition for the robot to understand the requests of the patient. Once the robot has learned to recognize the patient's speech and identify objects, these abilities are leveraged by the patients to serve them such as asking for food from the robot. The proposed solution has been experimentally implemented in real-world human-robot interactive healthcare contexts. Results and analysis have suggested the success and accuracy of our approaches. Because of its easy-to-extend nature, the proposed solution can be properly replicated and applied to more different complex healthcare scenarios.

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