Chapter 7

Integrating Computer Vision, Robotics, and Artificial Intelligence for Healthcare:

An Application Case for Diabetic Foot Management

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ABSTRACT

Technological evolution has allowed that tasks, usually performed by humans, can now be performed accurately by automated systems, often with superior performance. The healthcare area has been paradigmatic in the automation of processes, as the need to optimize costs, ensuring the provision of quality care, is crucial for the success of organizations. Diabetes, whose prevalence has increased significantly in the last decade, could be a case of application of several technologies that facilitate diagnosis, tracking and monitoring. Such tasks demand a great effort from health systems, requiring the allocation of material, human and financial resources, under penalty of worsening symptoms and emergence of serious complications. In this chapter the authors will present and explore how different technologies can be integrated to provide better healthcare, ensuring quality and safety standards, with reference to the case of diabetes.

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INTRODUCTION

Diabetes is a metabolic disease characterized by uncontrolled blood glucose regulation mechanisms. This chronic disease occurs when the pancreas does not produce enough insulin or when the body cannot use it effectively. The disease prevalence is on the rise worldwide, affecting 8.8% of the world's adult population in 2017, with the anticipation of a further increase to 9.9% by 2045 (World Health Organization, 2021). Beyond the personal and social consequences of untreated diseases, from a clinical perspective, the diagnostic, monitoring and treatment of this condition represents a major effort for healthcare systems. Material and human resources must be allocated to ensure an adequate tracking of each case guarantying that symptoms are controlled. A bad prognosis can easily lead to severe health conditions.

Chronic hyper-glycemia associated with uncontrolled diabetes damages various organs and systems, causing chronic diabetic complications, leading to disabilities, poor quality of life, and ultimately death. Diabetic peripheral neuropathy (DFN) is a major complication of diabetes mellitus, being the leading cause of foot ulceration and lower extremity amputations (Walicka et al., 2021). All patients with diabetes must have their feet evaluated, at least, once per year for the presence of the predisposing factors for ulceration and amputation (neuropathy, vascular disease, and deformities) (Boulton et al., 2008).

The Semmes-Weinstein monofilament examination is the recommended procedure for screening plantar sensitivity, as an early biomarker for DFN (*Monofilament Testing for Loss of Protective Sensation of Diabetic/Neuropathic Feet for Adults & Children*, 2012). The examination, performed by a clinician, consists of touching the plantar surface with a 10gf calibrated monofilament, on specific test locations, and wait for the patient's sensitivity feedback. This process is widely used but can be improved in several aspects: a) The monofilament quality can vary with usage, environmental temperature and humidity; b) The task can be tedious when large populations must be screened; c) Only a "feel"/"don't feel" feedback is registered while more variables can be observed and considered (image, force, time-tracking, among others) (Martins & Coelho, 2021).

The present chapter aims to describe how modern technologies, such as computer vision, artificial intelligence, cloud storage and computing, and robotics can be integrated and used to tackle healthcare related challenges, contributing to better and more cost-effective services. To describe the involvement of each technology we base our description on an application case for diabetic foot management.

The proposed chapter will be organized as follows. After presenting the underlying motivations and, in general terms, the consequences and prognoses in an unaccompanied evolution of diabetes, we will present a pipeline proposal for the automated management of the diabetic foot, a potential major complication of this condition. The following section will focus on the topic of computer vision. Here, the general architecture of these systems is exposed, followed by a brief explanatory passage of the various stages involved in them. A set of sensors used for image acquisition and processing are presented, followed by an explanation of useful techniques and tools. The following section will be related to robotics, more particularly in their collaborative versions, where their main characteristics are highlighted. In addition, attention will be given to a set of systems and real applications where the use of robotics shows potential in terms of support for medicine, with the intention of framing its use in the development of the proposed system. In the next section, the role of the cloud as a support technology for the system's operation will be discussed and the main advantages and disadvantages of its use will be presented. Finally, the main conclusions are presented and some guidelines for the future are established.

DIABETES

Diabetes is a metabolic disorder characterized by uncontrolled mechanisms of blood glucose regulation. This disorder is directly associated with dysfunctions or organ failures, as a consequence of the human body's inability to produce insulin and manage it properly (*Diagnosis and Classification of Diabetes Mellitus*, 2005). In the next subsections an overview of the disease will be presented as well as techniques and technologies used by physicians to assess and prevent complications resulting from the diabetic foot will be exposed.

Overview

Diabetic patients can be divided in categories named type 1 diabetes and type 2 diabetes. In type 1 diabetes the diagnosis indicates the existence of an absolute deficiency of insulin secretion while in type 2 diabetes, the cause results from a combination of resistance to insulin action and an inadequate insulin secretion response.

Diabetes comprises a heterogeneous set of disorders characterized by elevated blood glucose levels, however, it is possible to differentiate three main groups. The first group distinguishes insulin-dependent diabetes, where the individual lacks residual insulin secretion and therefore requires insulin for survival. In the second group is non-insulin dependent diabetes, where the individual has the ability to control his glucose levels, for example, through weight reduction and exercise, or by having some residual insulin secretion. Finally, the third group encompasses diabetes underlying other diseases, where these are responsible for causing a decrease in fasting glucose and/or a decrease in glucose tolerance in the individual, without meeting any of the criteria defined for the diagnosis of diabetes.

Complications such as neuropathy, retinopathy and nephropathy appear as long-term consequences. Neuropathy is associated with symptoms such as loss of sensation and vascularization, particularly in the extremities, and may result in the need for amputation. Retinopathy is responsible for the potential loss of vision and nephropathy is related to renal failure.

Diabetic Neuropathy

It is known that peripheral neuropathy is the most common in diabetic patients, affecting all body tissues and being responsible for the significant mortality associated with the disorder under study (Aring et al., 2005). The neurological damage in diabetic neuropathy widely involves the entire peripheral nervous system, presenting in two main forms: symmetric sensory-motor polyneuropathy and autonomic neuropathy (cardiovascular, respiratory, digestive, and genitourinary). A diabetic patient may present only one type of neuropathy or develop different combinations. For this reason, the clinical picture of neuropathy may vary from asymptomatic forms to the presence of multiple unspecific somatic or autonomic manifestations. In addition, and although it occurs less frequently, neuropathic injury may be more localized, presenting as focal and multifocal neuropathy (cranial, thoracolumbar radiculoneuropathy, focal memory or amyotrophy). The main manifestations of somatic impairment are numbness and burning sensation in the lower limbs, tingling, stinging in the legs and feet, sensation of discomfort and pain, and diminution or loss of tactile or thermal sensibility, often in the lower limbs. The evaluation and screening of diabetic patients is fundamental since the absence of the typical signs and symptoms of diabetic neuropathy does not exclude its presence.

Clinical Examination of the Diabetic Foot

The identification of diabetic patients at risk of neuropathic foot ulcers and amputation is highly desirable. To this purpose, four types of tests are essentially performed by physicians: pressure detection, vibration detection, thermal sensitivity and tactile sensitivity tests (Smieja et al., 1999).

For pressure detection tests, international procedures recommend the Semmes-Weinstein monofilament (MSW) method, used to assess the touch sensitivity at predefined plantar points. It is considered a non-invasive, low-cost, quick, and easy-to-apply test, often used in routine clinical testing and self-assessment (Dros et al., 2009). The loss of the ability to detect the plantar sensitivity in one or more locations is associated with the loss of nerve function of large fibers, which can lead to foot ulcers and lower limb amputation in diabetic patients.

Another possibility is the use of a tuning fork of 128 Hz to perform the vibratory perception tests. In this evaluation, the examiner holds a tuning fork on the fingertip for 5 seconds, if the patient feels vibration initially, as well as along the 5 seconds, the diagnosis of normal vibration sensation is considered. If the patient detects a vibration sensation at the beginning, but not after 5 seconds, it is considered an abnormal vibration sensation. Finally, if the patient does not reveal any vibratory sensation at any time, the vibration sensation is considered absent (Boulton et al., 2008).

Regarding thermal sensitivity tests, it is stated that diabetic foot complications are often related to the temperature distribution in the plantar region. It is reported that patients, where temperature differences of more than 2.2 °C between one region of the foot and the same region of the contralateral foot, may be in risk of complications in the diabetic foot (Fraiwan et al., 2017).

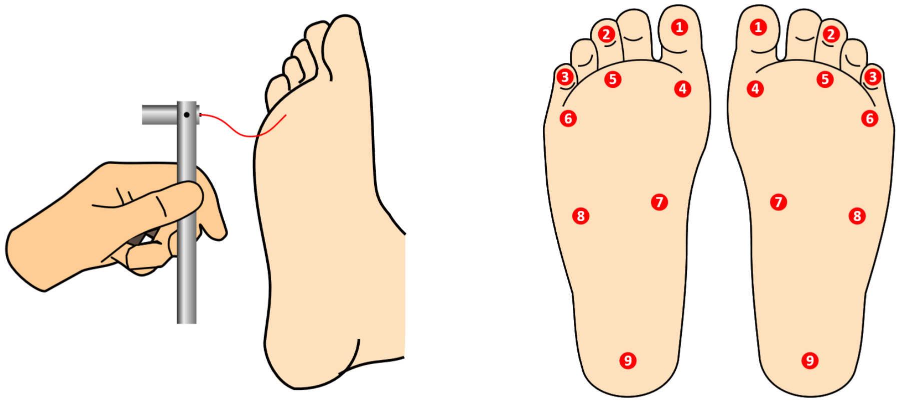
Finally, the tactile sensitivity tests are associated with the Semmes-Weinstein Monofilament Test method and vibratory detection, being part of some skin sensitivity assessment protocols. The two-point discrimination method is often used to evaluate the skin sensitivity of the plantar surface using a discriminator tool. This device is positioned perpendicularly to the plantar surface, with two parallel sharp tips touching the foot surface at the same time. Next, the patient is asked about the detection of the touch sensation of the respective device, indicating if one or two points are touching the skin. The distance between the two tips can be varied and each distance between the touch points is tested three times randomly, considering as the smallest distance perceived between the two points the one with at least two correct answers (Franco & Bohrer, 2012).

The Semmes-Weinstein Method

The Semmes-Weinstein Monofilament Test (SWMT) is used with the purpose of assessing the ability to detect the sensation of pressure in one or more anatomical locations on the plantar surface of the foot in diabetic patients, thus seeking to predict the development of foot ulcers (Lavery et al., 2012).

It is composed of a calibrated monofiber nylon yarn, often identified by a number from 1.65 to 6.65. The higher the value, the stiffer and more difficult to bend it becomes, being the most common and recommended to diagnose peripheral neuropathy the 5.07/10 g monofilament, where a force of 10 g is required to make it possible to bend or twist it. Figure 1a shows a monofilament during the evaluation of plantar surface pressure detection in the points in Figure 1b.

Figure 1. Brief graphical description of the SWMT. On the left (a) the application of the monofilament on the plantar area until it starts to buckle, and on the right (b) the plantar testing sites according with international guidelines, on left and right feet



As far as environmental conditions are concerned, when performing the evaluation using the *SWMT* method, it is required that a quiet and relaxed environment be guaranteed. calm and relaxed environment. In addition, the patient should be positioned in such a way that he is unable to see where and when the monofilament is being pressed. Once these conditions have been met, it is recommended that the first application of pressure be made on the inside of the wrist so that the patient knows what to expect. A sufficient force should be applied to cause the monofilament to bend or kink about 1 cm.

The seven steps involved in the procedure for the assessment of skin sensitivity, using the *SWMT* method are listed:

- Step 1: Wash hands and put on clean gloves. Clean gloves should be worn whenever there is an open area, secretion, or eruption on the foot or ankle. Make sure the examination occurs in a location with good illumination conditions.
- Step 2: Ask the patient to remove shoes and/or socks from both feet, exposing the plantar area.
- Step 3: Explain the procedure to the patient and show the monofilament. (Ensuring the patient understands the procedure and that no harm or risks are present)
- Step 4: Touch the monofilament to the patient's arm or hand so that he or she understands what to expect when you start the monofilament test.

- Step 5: Have the patient close his eyes. When the patient feels the monofilament touching his foot, he should answer "yes".
- Step 6: Hold the monofilament perpendicular to the foot and with a gentle, steady motion, touch the skin until the monofilament bends approximately 1 cm. Hold it against the skin for approximately 2 seconds.
- Step 7: Randomly test 10 sites on each foot as in Figure 2b. Random selection of the test sites will prevent the patient from anticipating the next test area. If there is a bruise, callus, or scar on the foot, apply the monofilament to an adjacent area and never directly. If the patient has amputated toes, test the maximum remaining sites possible.

If all points are tested and the patient feels the monofilament in each of the areas, then there is no record of loss of sensation. On the other hand, if the monofilament is not felt in one area of the foot, this indicates loss of protective sensation in that area, and medical referral is required. With the result of the MSW test it is possible to determine the risk of the patient, thus allowing the need to require a more comprehensive examination to be determined.

Automated Diabetic Foot Screening Technologies

The early detection of diabetic foot complications can protect patients from any dangerous diagnosis that may develop later, preventing complications of lower limb amputation. However, this procedure can be tedious and time-consuming when applied to frequent large-scale screening. For the automation of this task some projects have been developed covering several aspects of the process. Among the four tests exposed (pressure, vibration, thermal and tactile), the most feasible in the task of automating the process are the pressure detection and thermal sensitivity tests, being the second test the one with greater focus on research and development in recent years.

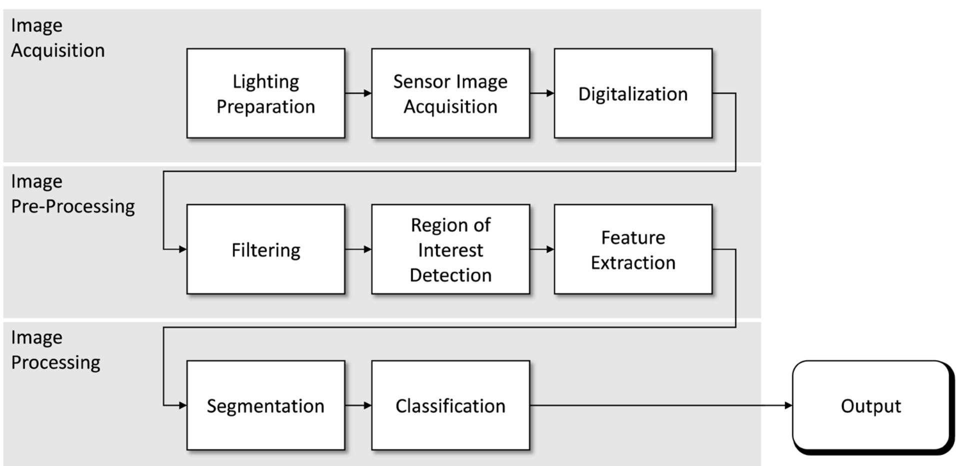
When it comes to pressure detection tests using MSW, the development and research of robotic systems that can support the task of skin sensitivity assessment is still a barely covered topic. In these systems, it is common to develop applications that allow remote transmission of data collected during testing and enable diagnosis of illness in the context of telemedicine (Wilasrusmee et al., 2010).

To perform the thermal sensitivity test it is common to use the thermography technique, considered a promising modality in intelligent telemedicine monitoring systems. Two technologies are distinguished: liquid crystal thermography and infrared thermography. The first one corresponds to a color representation proportional to the temperature of the surface of the feet in contact with the liquid crystal. in contact with the liquid crystal. The second corresponds to the acquisition of thermal images based on the heat emitted by the body (C. Liu et al., 2015). Infrared thermography is classified as non-invasive, being considered the best technology to explore in the context of telemedicine, regarding the thermal analysis of the diabetic foot. As hardware, several technologies are explored, from thermal imaging devices connected to smartphones to portable infrared thermometers. With these approaches, there is a concern to understand the reliability of this type of automated analysis systems, testing them in controlled and uncontrolled environments (Maldonado et al., 2020).

ARTIFICIAL VISION

The evolutional of computers and image acquisition technology has allowed to greatly improve the capabilities of artificial vision systems. The most common architecture for such systems, as depicted in Figure 2, will be covered in detail in the next sub-sections.

Figure 2. Generic Artificial Vision Pipeline



Computational vision is understood as the transformation of data from a photo or video camera into a decision or a new representation. All these transformations are done to achieve a specific goal. A decision can mean a conclusion about what is presented in the image, while a new representation can mean, for example, transforming a color image into a grayscale image, or translating camera movement into a sequence of images. A computer vision system typically presents the architecture shown in

Figure 2, being composed of the stages of image acquisition, preprocessing, and final processing (Parker, 2010).

Image Acquisition

This first step in a computer vision system is to analyze lighting conditions. A careful observation and preparation of these aspects can drastically reduce problems in later stages (e.g. shadows, overexposed areas). Regarding image acquisition, depending on the sensor used, it is possible to obtain several types of images, which can be two-dimensional, three-dimensional or sequences of images, where each pixel represents the value responsible for a light intensity in one or more color bands. It is also possible to use infrared sensors, that provide temperature information, or even depth cameras, who give information about the distance of each pixel in relation to the camera. (Burke, 1996)

Pre-Processing

In the pre-processing phase, it is necessary to verify whether the image satisfies the required conditions for further processing and, if not, apply the necessary operations to achieve this. To do so, several techniques are used, such as a) remapping, to ensure a coordinate system, b) filtering, to ensure that unwanted/incorrect information is minimized, c) contrast enhancement, to ensure that relevant information is detected. The segmentation of the region of interest if also performed when required. For feature extraction, it is common to use mathematical features that can be obtained in an image (Meyer-Baese & Schmid, 2014).

Camera Calibration

To use a camera as a trustworthy visual sensor, it is fundamental to know and define its intrinsic parameters. Sensor characteristics or lens geometry are some of the aspects that vary with the device. Calibrating a camera makes it possible to determine an accurate relationship between a 3D point in the real world and its corresponding 2D projection in the image captured by the calibrated camera. There are three main known calibration methods: pattern calibration, geometric tracks, and deep learning based. The pattern calibration method is common when there is full control over the imaging process, and the best way to perform the calibration is to capture several images of an object or pattern of known dimensions from different perspectives. The method of geometric tracks is advised when there are other geometric tracks in the scene, such as straight lines and vanishing points of known dimensions, which can be used as reference in the calibration task. Finally, when there is little control over the image configuration, the deep learning method is used, making it possible to obtain camera calibration information (Huo et al., 2022). The calibration stage is usually performed only once for a specific setup.

Filtering

This is an unavoidable step in computer vision processes, and it is responsible for removing noise due to the image acquisition process. Noise can originate from sources such as the type of sensor, weather conditions, or the relative position between the objects of interest and the camera. Thus, it is possible to state that noise can be either an interference in the image capture signal, or interferences that can influence the interpretation and recognition of objects. To circumvent noise, two types of filters are used, spatial and frequency filters. The spatial filters act directly on the image, while the frequency filters initially require that the image be transformed to the frequency domain using the Fourier transform, being subsequently filtered in this domain, and finally, transformed back to the space domain (Gonzalez & Woods, 2017).

Region of Interest Extraction

In this stage, we select specific regions of interest for posterior processing. Usually, a structured image section is the region of interest, which must be identified and extracted from an unstructured background. With this operation, the posterior processing operation can focus on a previously selected area where the required analysis conditions are met. The used techniques can vary from simple image cropping or basic segmentation algorithms to complex deep learning-based approaches. The selection of the best strategy will always depend on the application (Farhan et al., 2021; Yeum et al., 2019).

Feature Selection and Extraction

The objective of the feature extraction process is to obtain the relevant and non-redundant information from the original data and translate it in a lower dimensionality space. This is a useful operation when it is not feasible or practical to process the totality of input data. A feature selection process is conducted before in order to find the smallest feature set but with higher representation/discrimination power. The selection process can be made manually, but when a large number of features can be extracted, an automated method is preferable. As stated in (Kumar & Bhatia, 2014): "Features should contain information required to distinguish between classes, be insensitive to irrelevant variability in the input, and also be limited in number, to permit, efficient computation of discriminant functions and to limit the amount of training data required". A set of simple but commonly used features are presented in Figure 3. These are widely used and their application can lead to good results in many cases, showing potential for the development of a baseline system or for a prototype. Nevertheless, many other features exist, adaptable to different objectives and image contexts: Binary robust independent elementary features (BRIEF), Contour profiles, Deformable templates, Features from accelerated segment test (FAST), Fourier based descriptors, Gabor features, Geometric moment invariants, Gradient feature, Graph description, Harris corner detection, Oriented fast and rotated brief (ORB), Projection histograms, Scale-invariant feature transform (SIFT), Shi-Tomasi corner detector, Speeded-up robust features (SURF), Spline curve approximation, Template matching, Unitary image transforms, Zernike moments or Zoning, are some examples, among others (Mutlag et al., 2020). Modern deep-learning based techniques are also arising, such as: Superpoints (DeTone et al., 2018), LF-Net (Ono et al., 2018), (Y. Liu et al., 2018) or (Huo et al., 2022). The later have the advantage of being obtained as part of the training process, eliminating the need for manual selection. The downside is that these "deep- features" don't always have a meaningful representation or are explainable.

Figure 3. Examples of commonly used image features, grouped by type

Color			Texture	Statistical	Geometry
Color Histogram	Color Space	Color Moment	• Gray Level Co-Occurrence Matrix (GLCM): Entropy, Correlation, Energy, Contrast, Homogeneity • Tamura: Roughness, Line-like, Contrast, Coarseness, Direction, Regularity • Histogram of Oriented Gradients (HOG) • Local Binary Patterns (LBP)	• Contrast • Correlation • Entropy • Energy • Kurtosis • Mean • Moments • Smoothness • Variance • RMS	• Area • Centroid • Convexity • Diameter • Regularity • Perimeter • Slope
• Distribution • Flatness • Entropy	• Channel analysis • Range limitation	• Mean • Std. Dev. • Skewness			

Image Processing

The final stage in the artificial vision pipeline is the heavy image processing. Here, after image preparation the desired outputs are obtained.

Segmentation

Image segmentation focuses on partitioning an image into different parts according to their features or properties. This can be a finality per se or a simplifying step for later easier analysis. These techniques can be used to split or group specific pixels in an image. In addition, elements can be added to the image as markers for the segmentation process, if required. It is possible to draw lines, sharpen boundaries, or outline objects. There are several possible approaches for image segmentation, with some examples shown in Figure 4. These can be grouped into three major types: a) Discontinuity-based (the first three columns of Figure 4); b) Similarity based (forth column) and c) Other techniques. The last type has a growing number of promising machine-learning algorithms where very successful results can be obtained (Minaee et al., 2022; Wang et al., 2022).

Figure 4. Most common Image segmentation techniques, organized by type of approach

Edge Based	Clustering-based	Thresholding	Region-based	Others
• Canny edge detector • Laplacian of Gaussian • Gradient: Sobel, Robert, Prewitt • LOG • Zero-Cross	• K-means • Fuzzy C-means	• Otsu's • Mean shift • (Local or Global)	• Region growing • Split and merge • Graph-cut	• Watershed • Artificial neural networks • Partial differential equations

Classification

Object recognition is one of the main functions inherent to computer vision systems and is directly related to pattern recognition. An object can be defined by one or more patterns, such as texture, shape, color, and dimension, and the individual recognition of each of these patterns can facilitate the recognition of the object as a whole.

In classification/recognition process, a vision system needs to have knowledge about the objects to be recognized. This information can be directly implemented, through, for example, a rule-based system, or it can be ensured by a database of previously selected samples, which will support a model, using machine learning techniques. This process can be achieved by structural type techniques, where patterns are described in a symbolic way and the structure is the relation between these patterns, or based on decision theory techniques, where quantitative properties are used to describe patterns and then to decide whether the object has certain properties.

Tracking

Additionally, we can mention a tracking stage, when sequences of images or videos are the source data. The process of tracking is similar to the process of recognizing pattern, thus, this process also needs a knowledge base about the motion of the object being tracked in order to minimize the search among the images of a sequence. For the implementation of this process there are several techniques that can be addressed, such as: corner finding, subpixel corners, optical flow, mean-shift and camshift, and estimators.

ROBOTICS

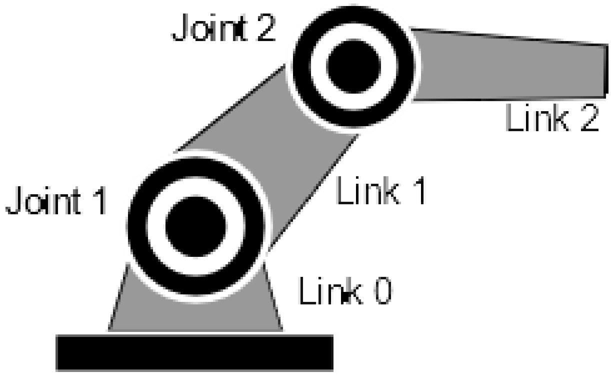
Robotics plays a key role in supporting medicine. In this section, we aim at framing the theme of collaborative robotics as a resource in the performance of daily tasks, with a view to improving the working conditions of health professionals.

Definition and Classification

According to the International Organization for Standardization (ISO), in its ISO 8373:2021 standard, a robot is a programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning (ISO, 2022a). According to this same standard, robots can be classified in one of three categories: industrial robots, service robots, and medical robots. A medical robot is a robot intended to be used as medical electrical equipment or medical electrical systems.

Mechanically, robots are constituted by sequences of rigid bodies called links that are coupled to each other by articulations called joints, as described in Figure 5. This demands the study of the spatial relationships between these same links and their movements and allow them to perform a series of actions automatically, especially if programmed by a computer. Robot manipulators have many characteristics but, most often, they are specified by their a) payload, which corresponds to the weight they can carry; b) working space, the region they can cover; c) range, distance that can be reached by the handle; and d) maximum speed, and repeatability, the ability to repeatedly reposition itself on the same programmed point.

Figure 5. Diagram illustrating the mechanical constitution of a robotic arm: links and joints



Robot manipulators are classified by their mechanical structure, being essentially divided into seven types: rectangular or Cartesian, cylindrical, polar or spherical, pendular, articulated, Selective Compliance Assembly Robot Arm (SCARA), and parallel (ISO, 2022a). An articulated robot is a manipulator which has three or more rotary joints.

Robots usually work in cells. A robotic cell is composed of a manipulator used to perform the desired task, a controller responsible for controlling the manipulator, and a programming console to program and control the tasks. In addition, it is constituted by a set of peripherals that may be needed, such as security elements or sensors needed to perform the tasks. Regarding the tool attached to the manipulator, this varies according to the application that the robot will perform.

Due to the risks that these machines pose to humans, mostly derived from their high moving speeds and the masses in motion, most applications of industrial robots' demand that these work inside closed cells, typically by fences, to safeguard the operators working with it. Recently, have been introduced into the market robots that are adequate to work in the vicinity of humans, without requiring the physical separation between both.

Collaborative Robotics

Robotic applications are called collaborative when robots interact directly with people in a shared space, and cooperative when there are information and action exchanges between multiple robots to ensure that their motions work effectively together to accomplish the task. Collaborative robotics results from the evolution of "traditional" robotics and are associated with applications on which robots work in the vicinity of, and collaborate with, humans without the need for fencing. They are safe as they make it possible to share the same space with humans without the need for fences, since they integrate safety features that, for example, limit force and power in accordance with ISO-10218 and TS-15066 guidelines regarding risk assessment for collaborative applications (ISO, 2022b).

Regarding its characteristics, and when compared to "traditional" industrial robots, collaborative robots (usually called cobots) present rounded shapes and soft materials so as not to hurt the human in situations of occasional collisions (Matthias et al., 2011). On the other hand, they are considered lighter when compared to industrial robots, since they are made of materials that give them a low weight, compact, since they can be easily transported and moved between work areas within the factory, and flexible, since they can be installed in any orientation or on any mobile platform - as in the case of lift systems, Automated Guided Vehicles (AGV) and linear axes. Finally, unlike industrial robots, which require a lot of space on the factory floor to be isolated by means of protective systems, collaborative robots can be installed in tight spaces, and depending on the application can dispense with the use of protective systems (El Zaatari, 2019).

Human-robot collaboration has manifested itself in several areas, such as assembly, logistics and consumer-oriented service industries. The underlying reason for adopting collaborative robotics is usually the issue of safety, particularly in situations where the human works in proximity, or directly, with the robot. To this end, it is common to use sensors to control force, avoid collisions, and detect the presence of obstacles.

Safety Aspects

According to ISO 10218-2 and ISO/TS 15066 it is possible to name four collaborative modes of operation that, depending on the requirements of the respective application and the design of the robotic system, can be used individually or in combination. These four modes of operation are "Safety-rated monitored stop", "Hand guiding", "Power and force limiting by design or control", and "Speed and separation monitoring" (ISO, 2022b), which are illustrated in Figure 6.

Figure 6. Collaborative modes of operation: "Safety-rated monitored stop", "Hand guiding", "Power and force limiting by design or control", and "Speed and separation monitoring"

In "Safety-rated monitored stop" mode, the robot is stopped in the collaborative space during interaction with the operator. This state is monitored, and the drive can remain on. In "Hand guiding" mode, the safety of the human/machine collaboration is guaranteed by the fact that the robot can be consciously guided manually, at a reduced and safe speed. In the "*Power and force limiting by design or control*" mode, physical contact between the robotic system and the operator can occur intentionally or inadvertently. The necessary safety is achieved by limiting the power and force to values considered safe to avoid injury or threat. The technical specification ISO/TS 15066 includes maximum values, which cannot be exceeded in the collision of the robot with body members. Finally, in "Speed and separation monitoring", the speed and trajectory of the robot are monitored and adapted according to the speed and position of the operator in the protected space (ISO, 2022b).

However, it should be noted that there are no safe robotic applications. Although the robot, *per se*, can be considered safe, the application may not. This means that, although with cobots the security requirements have adapted, an adequate and careful risk assessment is always necessary in each robot application. Considering the scenario in which the robot's task consists in handling a knife or a blade, no matter how well it can perform what is intended, it is automatically no longer considered collaborative. Thus, manufacturers, integrators, and cobots' users should realize the importance of considering both the application and the collaborative environment when assessing their security level.

For a complete risk assessment, it is mandatory that the system conforms to what is prescribed in the standards developed for this purpose, which are guidelines created at the European level to comply with European legislation (European Parliament and European Council, 2006). Besides the compliance with the Machinery Directive, and as far as the robot is concerned, two standards should be highlighted and differentiated: ISO 10218-1 and ISO 10218-2. ISO 10218-1 refers to the standards that are recommended to be followed in an evaluation of the safety level of the robot in isolation. IS0 10218-2 refers to a complete safety assessment of the robot cell and the integrated system. It also deserves attention the existence of the ISO/TS 15066 guidelines, which specify the risk assessment criteria oriented to collaborative robots.

Finally, and concerning collaborative robots, it deserves a mention the fact that the KUKA LBR Med collaborative robot has been certified for medical applications (KUKA, 2017), which will, in the authors' opinion, allow the increase of the number of medical robotic applications.

Healthcare Applications

The use of robotics can be useful in several tasks intrinsic to medicine. In the following, are presented several examples of robotic applications to support surgical interventions, radiotherapy treatments, physical therapy and rehabilitation, nursing assistance, and also to perform COVID-19 tests, a task in demand during the pandemic period.

Surgical Assisted Intervention

When referring to the use of robots to support surgical interventions, the most prominent name is the da Vinci robot, developed by Intuitive. It is a robot remotely controlled by a physician. The architecture of this robotic system presents a compact design allowing a higher degree of movement of the instruments, when compared to the movements performed by a surgeon in a conventional intervention. As far as the patient is concerned, it allows for less invasive and, therefore, less traumatic surgeries, allowing for a better recovery (Won *et al.*, 2020). This robot is used by physicians to perform several surgeries, such as gastrectomies for partial or total removal of the stomach (Aktas *et al.*, 2020), robotic myomectomies to remove fibroids (Won *et al.*, 2020), and thyroidectomies to remove all or part of the thyroid gland (Tunca *et al.*, 2020).

Robotic Device for Radiotherapy

The CyberKnife, manufactured by Accuray Incorporated, is the first fully robotic radiotherapy device for the treatment of benign tumors and malignant tumors (CyberKnife, 2022). It uses a system called stereotactic body radiation therapy through real-time image guidance, which is based on delivering radiation doses in a localized manner and with a higher accuracy than that obtained with conventional radiotherapy (Pishvaian *et al.*, 2006). Its flexibility in the robotic arm allows radiation beams to be focused in all directions, focusing high doses of radiation on the tumor and simultaneously minimizing the dose to adjacent healthy tissues (CyberKnife, 2022).

Nursing Assistant in Patient Transport

Transporting a patient unable to move by himself from a bed to a wheelchair, or vice versa, is one of the most physically challenging tasks in nursing care (Mukai *et al.*, 2010). The Robot for Interactive Body Assistance (RIBA) is a nursing assistant robot developed by a Japanese partnership between the RIKEN collaboration center and Tokai Rubber Industries, Ltd. This robot is used to lift and transfer a patient between a bed and a wheelchair by means of instructions sent by a healthcare professional via haptic sensors. The contact between the robot and the human body is controlled by sensors that aim to avoid the possibility of causing pain sensation in patients (Mukai *et al.*, 2010).

Exoskeleton in Locomotive Rehabilitation

Exoskeletons are robotic structures intended to aid in the rehabilitation of patients who suffer locomotion problems (Bogue, 2022). Marsi Bionics is a Spanish company of exoskeletons for gait rehabilitation, customized for each patient. They have developed two models of exoskeletons, the MB Active Knee (MAK) and the Atlas Pediatric Exo (ATLAS) (Marsi Bionics, 2022).

The MAKs are robotic knees with a stiffness adaptable to the needs of each patient. They provide the strength, mobility and stability necessary for locomotion and are supported by sensors to analyze the patient's gait in order to improve it (Marsi Bionics, 2022). ATLAS is an exoskeleton developed for the physiotherapy of children with neurological diseases, such as cerebral palsy, and neuromuscular diseases, such as spinal muscular atrophy and myopathies. Its function is to support a child from the trunk to the feet and is composed of eight active joints that provide total mobility on the ground (Marsi Bionics, 2022).

Another example is a robotic structure controlled by the brain through which a quadriplegic patient was able to control his movement again (Benabid, 2019). To control this exoskeleton, a surgery was performed in which two implants were placed on the surface of the brain, covering the parts of the brain responsible for movement control. These implants are used to read the brain activity and transmit instructions to a computer. Afterwards, by means of software, the brain waves received by the computer are transformed into instructions that serve to control the exoskeleton placed on the patient. Thus, when the patient thinks about walking, a chain of movements in the robotic exoskeleton is initiated, resulting in the movement of his legs (Benabid, 2019).

Assisted Passive and Active Mobilization

The use of devices to perform rehabilitation and physiotherapy exercises is widely used by therapists nowadays (Bélanger-Barrette, 2019). Examples of devices are arthromotors and elastic devices for ankle resistance (Bertelsen *et al.*, 2020).

Passive mobility is associated with exercises in which movement is restricted to the range of motion and is produced solely by an external force, with little or no voluntary muscle contraction. The external force can originate from the force of gravity, a machine, a therapist, or the person himself who uses the force of another body segment (Bertelsen *et al.*, 2020). One example of such a robotic device is the ROBERT© robot, based on a collaborative manipulator arm, from the Danish company Life Science Robotics.

Assisted active mobilization consists of the action of an external force, manual or mechanical, that assists the performance of a movement when a patient has decreased mobility in some body segments. Typically, the patient can initiate the movement, but is not able to reach its maximum amplitude (Padilla-Castañeda *et al.*, 2018).

COVID-19 Test Performance

During the COVID-19 pandemic period, the unprecedented need for medical testing resulted in an initiative by the well-known Universal Robots, which directed its energies toward the development of an autonomous robot capable of performing COVID-19 testing. This robot was first launched in Denmark by the company Lifeline Robotics in March 2020 (Universal Robots, 2022). Developed in collaboration with robotics researchers at the University of Southern Denmark, the system starts by scanning the patient's identification card, prepares a sample kit consisting of a container with an identification label, and collects the sample on a swab. When collecting the sample, he uses a vision system to identify the right spots to be reached in the throat of the patient. Then, he places the sample in the container that is screwed and sent to a laboratory for analysis (Universal Robots, 2022).

Summary

In this section the reader was introduced to the subject of robotics, describing its main characteristics. It was explained what is meant by application and collaborative robotics, to justify the choice of using a collaborative robot in the implementation phase of this project. In addition, were presented a set of practical examples where the use of robotics, in some cases collaborative ones, shows advantages in supporting activities related to human health. Relevant examples are the ROBERT© system for physiotherapy assistance and the Universal Robots robotic arms applied to perform COVID-19 tests.

CLOUD TECHNOLOGY

In the healthcare area, there is an increasing demand to improve results, both clinically and economically, while not forgetting the general well-being of the population. To tackle these challenges, in the last few years several technological advances in computing, sensing, networking, and communications, have been introduced with the objective of improving the cost-effectiveness of services and raise their quality.

The healthcare system landscape is extensive, diverse, and encloses high complexity systems and software. The ecosystem encompasses healthcare providers, clinical personnel and patients but also includes health insurance companies, laboratories, pharmacies, and other stakeholders, each with specific requirements and expectations. These, combined with the available digital technologies make health related services an increasingly data-intensive community with a high demand for computational resources.

The use of storage and computing capacity in the cloud thus arises naturally, allowing distributed access to dynamic and scalable resources, also allowing software as a service (SaaS) or Platform as a Service (PaaS) models. Technologies like the electronic health records (EHR), the Internet of Things (IoT) and Ambient Assisted Living (AAL) require a strong level of integration and computation, only possible with robust cloud systems. For example, cloud computing helps healthcare organizations share information such as EHR, medical certificates, prescriptions, insurance information, and gather results stored in various information systems. Additionally, the use of machine learning approaches, where data is the main source of knowledge, further increases the need of cloud resources, especially when it is possible to scale the use of such systems. The construction of an appropriate infrastructure should follow the industry priorities, which, by order of relevance, as addressed in (Ratnam & Dominic, 2014), are: scalability, privacy, security and fast access.

The universal access to cloud resources can also be used to gather healthcare data, when required, from in a mass scale. Crowdsourcing, a new emerging field, refers to the possibility of a large number of people who contribute together to solve an individual or organizational problem or complete a task. This is a widespread approach in many business areas, but it is still underexplored in the healthcare perspective, especially in the field of global health. It can be easily adapted to multiple situations, it is unexpensive when compared with similar purpose solutions, and allows to effectively collect large amounts of information from a large geographically distributed targeted group. Eight major areas where crowdsourcing of healthcare is used have been defined: Monitoring; Nutrition; Public Health and Environment; Education; Genetics; Psychology; and General Internal Medicine / Others (Wazny, 2018).

Concerning robotics, there is a consistent increase on its use in the healthcare area. According with the International Federation of Robotics, the medical robot's area, that represents 11.3 billion USD market worldwide in 2022, has been growing and is expected to grow at a two digits rate, with similar growing numbers for logistic robots. Its applications are growing in the healthcare area, having evolved from simple repetition-oriented tasks to highly flexible and environment-aware functionalities, where devices are capable of working side by side with humans.

The application can be broadly classified as receptionist robot area, nurse robots in hospital area, ambulance robot area, telemedicine robot area, hospital serving robot area, cleaning robot area, spraying/disinfestation robot area, surgical robot area, radiologist robot area, rehabilitation robot area, food robot area, and outdoor delivery robot area (Khan et al., 2020). The use of robots for the automation of tasks where they operate alone is already widely accepted, unlike situations where they must interact with humans, where their use has yet to be further promoted. Based on a series of interviews in a Catalunya hospital during the first and second waves of COVID-19, citizens' opinions and perceptions about automation were wittingly related with the high demand context of the medical system. The survey analysis found that the patient's view of health care robots was ambiguous and consistent with other welfare technology surveys. On the other hand, they thought it was very positive to introduce robots that would take care of people, support them, and replace nurses and medical staff when needed (Vallès-Peris et al., 2021). Despite the technical complexity, robot agents can undoubtedly increase the effectiveness and efficiency of services. Afterwards, advanced Human-Robot Interaction (HRI) that make use of natural communication strategies (such as voice and gestures, which are very mature technologies), mimicking human-to-human interactions, can improve the user experience and enhance the systems' acceptability.

In this context, cloud and robotic system integration is essential. Cloud Robotics explores the possibility of robots relying on remote shared data or code to support operations, rather than consolidating all computation, storage, and sensing capabilities into a single stand-alone station. Partially supporting operation on the cloud allows to reduce computational requirements and to use a larger robotic knowledge base while guaranteeing a minimum guaranteed QoS, scalability and flexibility. This, paves the road to a more flexible operation, allowing to manage complex or unexpected situations with reusable libraries, skills, or actions (Fosch-Villaronga et al., 2018). Cloud robotics is expected to influence the adoption of robot services and enable a new generation of robots that are smarter and cheaper than traditional stand-alone and connected robots.

Nevertheless, the acceptance of new technologies and services depends heavily on their usefulness, effectiveness, efficiency, reliability, and ease of use, as the end user recognizes. some open challenges must be overcome to achieve an optimal service. Technological issues that temporarily limit the use of such systems or difficulties on the access to the resources can frustrate customer expectations. Another concern is interoperability between systems, which can create unreachable infrastructural islands or that imply additional middleware services, making it harder to achieve the desired universal access. Security and privacy are also a major concern since centralized resources can easily become a target for malicious purposes or for unwanted data access.

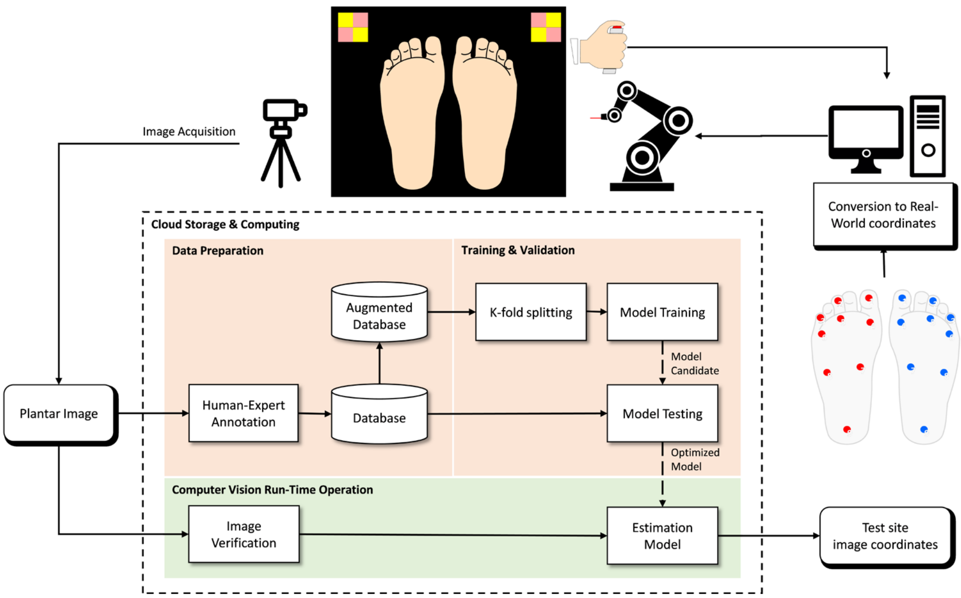
APPLICATION CASES

One of the objectives of this chapter was to observe the example of the diabetic foot assessment process, as an application case where robotics and cloud systems work together, towards an improved healthcare service. This is a barely covered application, whose existing studies will now be briefly presented.

In order to automate the testing of SWMT, a group of researchers (Wilasrusmee et al., 2010) reported the development of a prototype robotic systems for the screening of diabetic neuropathy. In this system we highlight essentially the development of software, a controller, and a robotic monofilament testing system. A dedicated control software was created to manage the action of the robotic system and to activate the movements of the monofilament, with the respective commands being sent by the interfacing hardware controller. The software is also capable of storing the patient's data, as well as the respective test results, in a database. The location of the database is not specified but the doctor operates the robotic system remotely, which allows to have a cloud interface. The electronic controller is also responsible for receiving the response of patient through a joystick, as feedback to the monofilament touch. The robotic monofilament testing system consists of a machine responsible for controlling the monofilament movement, performing the operation of touching the patient's foot, when it receives the command sent by the controller. To direct and position the robotic monofilament at the respective predefined plantar points for the SWMT evaluation, the physician has the possibility to control the necessary movements around the xx and yy axes remotely. One of the limitations of the system is the fact that only three of the ten pre-defined plantar points recommended in the method were tested, as well as the need to adjust the shape and surface of the robotic monofilament in order to better fit the different patients. However, it is worth noting its achievement with respect to its framework in telemedicine and remote data transmission.

A more recent system explores the use of an artificial vision system and a collaborative robot to perform the SWMT, as depicted in Figure 7. The artificial vision system (Costa et al., 2022) uses a three stages pipeline to estimate the location of the testing sites. For the automatic segmentation of the testing sites, a set of algorithms is described, consisting of a) background segmentation, b) hallux segmentation, and c) plantar and heel segmentation. As an alternative, a segmentation oriented deep-learning algorithm, such as U-Net can be used.

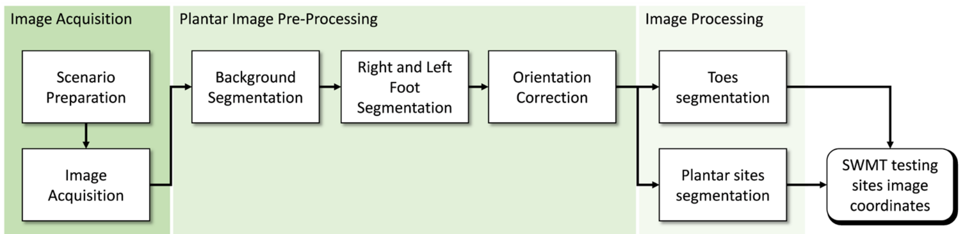
Figure 7. Diagram of an automated plantar sensitivity exam considering supported by a deep-learning based artificial vision system, representing both training and run-time stages



For the development of the system the authors have created a novel plantar images database. For the image acquisition process, a simple photographic scenario was prepared in order to obtain more stable conditions. It consisted of two black pieces of paperboard, one for background and another for floor area below the feet, connected in a L-shaped format. The background cardboard had two reference targets, created with yellow and pink sticky notes, with known dimensions, positioned on the top left and right corners. The use of this scenario setup allows to: (a) Create a common setup for image acquisition while hiding external elements or image disturbance sources; (b) It allows to easily identify image elements, with known physical dimensions, all with explicit, facilitating the creation of conversion bases between digital pixel distances with real world coordinates. (c) It creates a visual barrier between the patient and its feet, preventing the observation of the SWMT, minimizing induced false feedback.

The pipeline depicted in Figure 8 represent the image processing stages. Unlike the deep-learning approach, a manual combination of processing blocks allows to have full control of the processing operation. For each plantar image presented at the input, the first step is to perform background segmentation, by identifying the feet area, and to find the calibration markers, located on the top left and right corners of the background. Next, after cropping the region of interest, its orientation is estimated and the image is rotated to a vertical orientation. This guarantees that all feet will follow with a known orientation to the next step. Two sub images are then generated: one containing the toes area and another for the central plantar region and heel. For each of these new images, specific processing algorithms were developed exploring the known anatomic features of the foot. All information is finally combined and referenced as coordinates in the original image.

Figure 8. Artificial vision pipeline for SWMT, adapted from (Costa et al., 2022)



The image coordinates are the transformed to real-world coordinates, using the known references markers dimensions. Robotic trajectories are then calculated to randomly reach each of the testing points, while waiting for the patient's feedback using a hand gripped button. The force that the robot applies is limited to 10gf, as recommended by the international SWMT guidelines.

After image acquisition, the storage and processing operations can be performed using cloud systems. The robotic system is also controlled over a wireless network, been able to receive coordinates or trajectories from a cloud-based controller. The cloud-based patients' database allows to store the SWMT results and, later provides to clinical personnel the latest values as well as the evolution of the disease. Considering additional cloud-based information it is possible to develop a prognostic for the disease and create a personalized therapy plan.

CONCLUSION

In this chapter we have shown how artificial vision, robotics, artificial intelligence and cloud systems can be integrated to bring an increase quality to healthcare organization along with a more cost-effective operation. To explore the topic we have focused on diabetes, a growing disease worldwide that can highly reduce the patients' quality of life and a major economic impact, with several direct and indirect costs. After describing the disease and its implications we have centered our attention on how technology can be used in such cases and what benefits it can bring. Initially we describe artificial vision and the main stages of a typical processing pipeline and then we have provided an overview of each individual step. The use of hard-coded algorithms vs machine-learning algorithms is covered, as well as the advantages and disadvantages of each approach. Robotics in healthcare, an important and growing area, was also introduced, with a thorough perspective of distinct application cases. Users' perspective, ethical and security questions were especially addressed in the context of collaborative robotics. Finally, the use of cloud technology as an operational pillar of such systems was described and the possibilities of having a highly reliable and always accessible computational infrastructure were enhanced. The integration of these technologies in a single application is showcased in the final section where the automation of the diabetic foot monofilament examination presented.

Technological evolution has created immense possibilities that were previously unimaginable. The rapid adaptation of organizations, particularly in healthcare, has allowed a significant improvement of services accompanied by greater efficiency and effectiveness in the use of resources, both human and material. In parallel, new ethical questions arise along with the need for humans to adapt to an increasingly digital world. So far, the benefits of technology have far outweighed the risks, and it is expected that, in a near future, health will be an increasingly universal good.

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