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A Mobile Clinical DSS based on Augmented Reality and Deep Learning for the home cares of patients afflicted by bedsores

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Abstract

A bedsore, also known as pressure sore, pressure ulcer or decubitus ulcer, is the result of constant pressure on skin occurring in bedridden patients and paraplegics continuously sitting in chair. All patients who are immobile for a long time due to any cause are likely to get bedsores. Effective and efficient management of processes related to the treatment of bedsores is an important issue for healthcare organizations as it heavily affects the quality of life of patients and the costs for such organizations. Therefore organizations need and look for more and more to provide their field workforce with smart mobile tools able to support such processes. In such a context, this paper proposes a mobile app implementing a Clinical Decision Support System (CDSS) to help field operators to measure the bedsore, classify its status, trace its evolution along the timeline and making correct decisions about the course of actions to effectively treat it. The mobile app is mostly based on Augmented Reality supported by Deep Learning, thus it requires an adequate system architecture to be effectively deployed, adopted and used. From the conceptual viewpoint, the defined CDSS model lays on three important considerations: providing automatic support to classify the status of a bedsore does not do all the work but help operators to improve the quality of their decisions, augmented reality allows to build a situated environment for decision-making supporting the operators' cognitive processes, operators should use only one tool to execute all their tasks in order to be more focused on the real problem which is to improve the quality of life of their patients.

Keywords: Mobile Decision Support System; Healthcare; Deep Learning; Augmented Reality

1. Introduction and related works

When a patient is stuck in a chair or in bed and is immobile for long time, a continuous pressure over bony prominences is produced by her body weight over the mattress or chair. Hence, an ulcer develops over this pressure area which can involve the muscle and bone also. It may be covered by black colour dead skin. This ulcer is frequently

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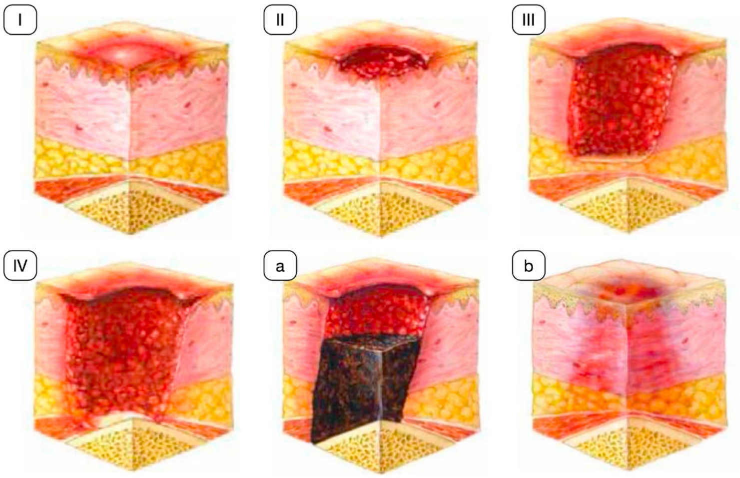

Fig. 1. Categories/stages for EPUAP/NPUAP (source: italian version of [12])

infected. The infection can spread rapidly in musculofascial planes producing deep seated abscesses. This type of spread produces life threatening septicaemia and mortality in old fragile patients. These could be the tremendous physical effects of bedsores but their management is often not limited to clinical decisions, it also affects emotional, psychological, social, financial aspects of the family. Although, bedsores are common in intensive care units, surgical units and neurology units of a tertiary care hospital, also the inmates of old age homes or assisted living homes and nursing homes as well as patients in their private houses are likely to develop bedsores. Extensive wound care is needed to prevent that the bedsore leaves the early stage to reach an advanced stage [3]. Typically, skilled professionals use consolidated approaches and obtain very promising results. The challenge is to support less-experienced field operators to reduce errors and to develop skills faster. Having success in using less-experienced field operators by keeping acceptable results will impact also on costs, which is one of the main goals of healthcare organizations. The specialized literature provides strategies, guidelines and mostly scales to support operators to assess the situation related to a bedsore and act accordingly. In particular, EPUAP (NPUAP for USA) [8, 15] classification is based on the identification of the stage in which the bedsore currently is. Being aware of the correct bedsore stage is fundamental to understand how to act directly or asking for the surgical consultation. More in detail, the EPUAP scale consists of four stages: I) non-blanchable erythema, II) partial thickness skin loss, III) full thickness skin loss, and IV) full thickness tissue loss. Two additional stages have been added (unstageable: depth unknown and suspected deep tissue injury: depth unknown) [12]. Fig. 1 graphically reports such stages. In this context, the idea underlying this work is twofold: defining the model of a Clinical Decision Support System (CDSS) targeted to the field workforce facing helping the patients with bedsores, and designing and implementing an adequate architecture allowing such workforce to use only low-cost devices (smartphones or tablets). In other terms, the technological enablers for the implementation of the CDSS model (first objective), which are Deep Learning and Augmented Reality, are the main triggers of the second objective.

The idea to use Artificial Intelligence for handling bedsores-related processes is not new, in fact it is possible to recognize numerous works from the specialized literature. In particular, many of such works focus on predicting the risk of bedsore occurrence like [1] that uses a system of force sensors and sends an alarm to the nurses or caretakers if there is a variation in the pressure exerted on a specific area. The same approach is proposed by the authors of [14] who developed a wireless, autonomously site-specific powered sensor system that sends alerts to medical personnel to inform about the possibility of a pressure ulcer for the monitored patients. The system is based also on machine learning algorithms. Other works propose models to analyse structured for identifying high-risk (for pressure ulcers) patients like [7] that focuses on the study of observational data from electronic health records and use specialized scores like that of Barden. The same scale is exploited by the authors of [11] who uses multiple logistic regression to develop a prediction model with significant predictor variables from the bivariate analyses. Lastly, further solutions based on Machine Learning algorithms have been proposed by two papers. The first one [2] uses transfer learning technique where pre-trained deep Convolutional Neural Networks are employed for extracting discriminatory features from the images and subsequently these features are fed into a Support Vector Machine for classification. The approach aims at discriminating burns and pressure ulcers. The second one [6] uses machine learning approaches to train a model with data collected by monitoring the positions of a set of patients during their period of hospitalization.

With respect to the aforementioned related works, this proposal is based on the use of Deep Learning approaches to classify a bedsore according to four classes (one of this is represented by the NPUAP stage in which the ulcer is) supporting the field operators to analyse the bedsore and act consequently. Such approach is part of a set functionalities focused on supporting decision-making (measuring tool, time evolution visualization and next action recommender system) and is included in an AR-based App that allows the operator to execute all tasks in a situated way.

The paper is structured as follows. Section 2 describes the Clinical Decision Support System model and motivates the adopted design solutions. Section 3 describes the system architecture, explain how the components work together to support mobile low-cost scenarios and describe the core parts of the application: Deep Learning and Augmented Reality. Section 4 shows the early evaluation of the implemented AR-based app realized by involving end users. Conclusions and future works are provided in Section 5.

2. The underline model: Clinical Decision Support System

The Clinical Decision Support System for bedsore assessment has been defined by starting from the analysis of the decision making process which the field operators are involved in. In particular, the field operator is the decision maker and has to solve a decision problem related to the selection of a *suitable course of actions* related to the bedsore treatment. In this scenario, the final decision should be made only when a set of abstract information has been correctly inferred from (raw) data. The abstract information are: i) the stage (NPUAP/EPUAP) in which the bedsore is, ii) additional attributes of the bedsore (skin conditions in the lesion area, extension of deep tissue damage, presence of necrosis), iii) dimension of the bedsore and iv) temporal evolution of the bedsore. Typically (without using the proposed CDSS) the above information are derived from the field operators by means of their skills and experience in analysing raw data like the observation of the bedsore, textual description included in reports of past examinations and by interviewing the patients. Starting from these considerations, a hierarchy has been constructed.

The hierarchy composed of three main levels (goal/decision, sub-goals/information and input/data) summarizes the cognitive process executed by the field operator and is graphically depicted in Fig. 2. The adopted analysis technique is the so-called GDTA (Goal-Directed Task Analysis) [5] widely used for designing systems supporting the operators' situation awareness. GDTA has been already used for increasing situation awareness in paramedics' tasks [10]. Hence, Fig. 2 shows a schematized decision-making process (blocks n.1) and also role and components of the proposed CDSS (block n.2). In particular, the CDSS is functionally decomposed in three main components: *bedsore classifiers*, *bedsore measurement tool* and *bedsore time machine*. More in detail, the first one is a set of four classifiers able to determine the NPUAP/EPUAP stage and the further three attributes of the bedsore whose image is captured by the smartphone/tablet camera. The automatic classification results (produced by applying Deep Learning approaches) are graphically registered and attached on the bedsore image by means of Augmented Reality. Through this component, the field operator can receive a first support for her assessment task without switching on other tools or system, in a situated way. The second component is a tool that supports the operator in making one or more measures of the bedsore dimensions. Such component does not force the operator to use additional devices or changing the main screen of the application. Also in this case, Augmented Reality is the key enabler. The third component allows the operator to travel along the timeline to get past examination results in terms of measurements and classification results to sustain her comprehension regarding the evolution of the bedsore. All the three component functionalities sustain the decision-making process of the field operator without replacing her but helping her to better focus on the task and avoiding inattention (situated work) and to make high quality decisions by trying to foster the objectivity of the decisions (suggestions from the automatic classifiers and reasoning on the temporal evolution).

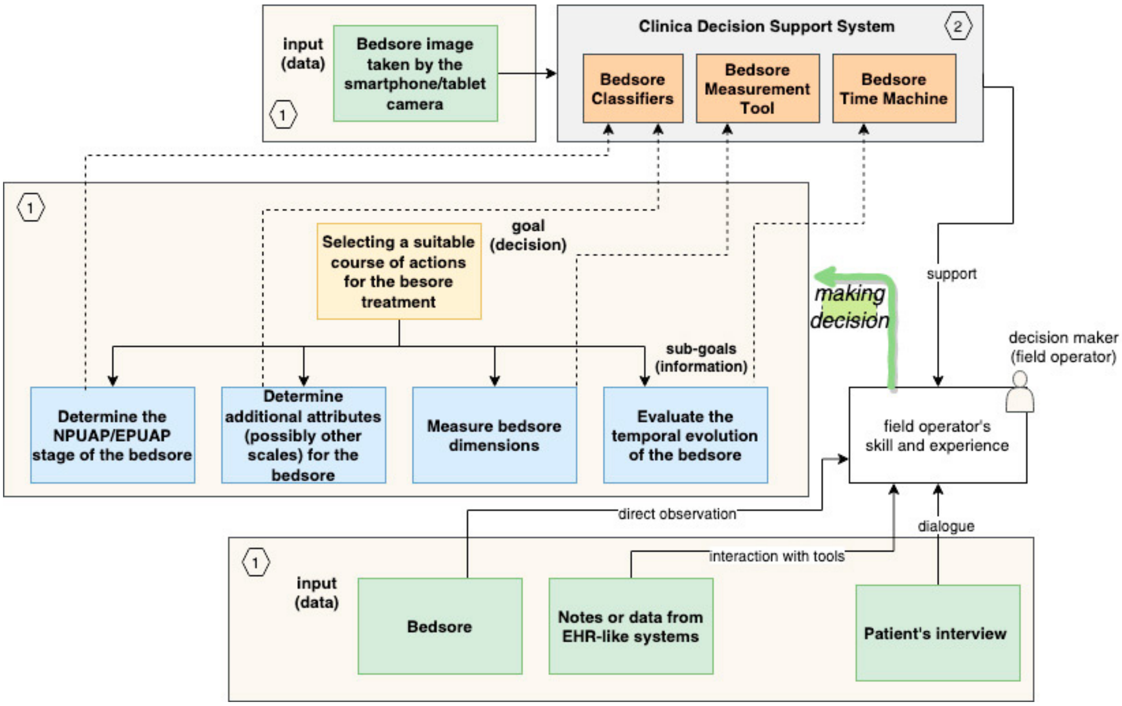

Fig. 2. Conceptual model of the CDSS

3. Architecture and component design

The CDSS model described in the previous Section has been implemented as an Android AR-based App whose overall architecture is sketched in Fig. 3. The sketch shows that Unity3D[1] (with C# as scripting language) and EasyAR[2] are the technologies adopted for the implementation of the App front-end, the local storage and the *Time Machine* inner component (namely Bedsore Time Machine). PyTorch[3] is the Deep Learning technology used to implement the *Classifiers* remote component, i.e., to train the classification models (namely Bedsores Classifiers) and Open CV[4] is the Computer Vision technology exploited to realize the *Measurement Tool* remote component (namely Bedsore Measurement Tool). Remote components live within Web Services realized through Python Flask[5] and exchange data with the main App by using JSON[6] portable format. It is also the possibility to plug further services in order to connect the App with external systems like, for instance, electronic health records (EHR), patient relationship management (PRM), and so on. The Web Service invocations within the App are realized through HTTP requests made by using C# scripts.

The main idea underlying the design and implementation of such component is to train four models (one for each decisional attribute on which it is needed to classify) by using a training set of bedsore photos through the use of a Deep Neural Network. First of all, the whole bedsore image set[7] has been divided into the training set (75%) and the test set (25%) only after having pre-processed the whole image set to obtain PNG images of 192x192 pixels. Pixel values have been also normalized. Moreover, the training set has been enriched to provide more images by which train the model. The Image Data Augmentation technique has been used to generate more variants of the same

[1] https://unity.com/
[2] https://www.easyar.com/
[3] https://pytorch.org/
[4] https://opencv.org/
[5] https://palletsprojects.com/p/flask/
[6] https://www.json.org/json-it.html
[7] Provided by INNOVA

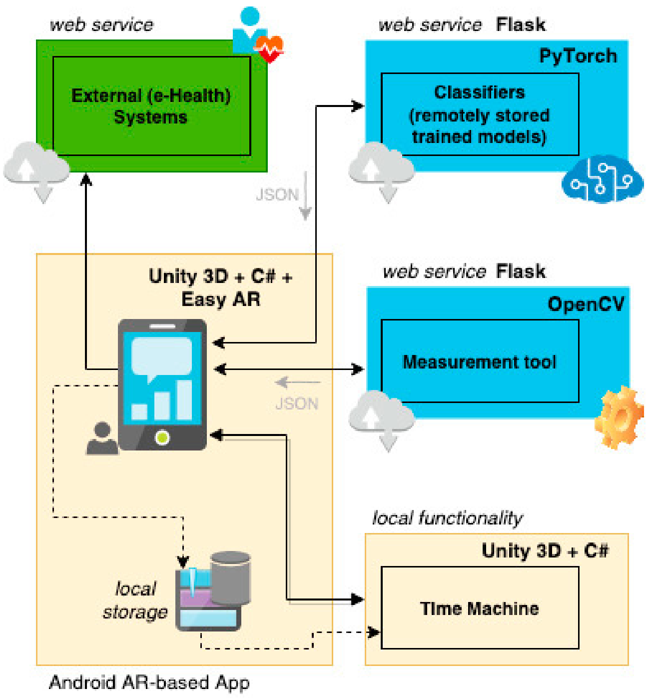

Fig. 3. Overall Architecture for the AR-based App implementing the CDSS

Fig. 4. Some samples belonging to the training set

bedsore image. The aim is providing the training algorithm with several conditions in which the same bedsore could be photographed. Such technique is useful to increase la variety in the training set, extract more solid features and allow the generalization of the mode. More in detail, image variants have been generated by both horizontally and vertically flipping the original image, rotating it, changing its scale, adding noise, changing brightness and contrast, etc. Fig. 4 reports few images included in the pre-enriched training set. With respect to the Deep Neural Network architecture, in order to deal with a poor training set, the idea was to start from a pre-trained network. Therefore, MobileNet V2[8] is used to define the backbone of the deep neural network architecture. MobileNet V2 is a convolutional neural network that can be customised and fine tuned enabling the training of classifier starting from low resolution images, using low-cost hardware and providing results high levels of accuracy. The main idea behind MobileNet models is to replace expensive convolutional layers with depthwise separable convolutional blocks where each block consists of a 3x3 depthwise convolutional layer that filters the input, followed by a 1x1 pointwise convolutional layer that combines these filtered values to create a new feature. It is much faster than the regular convolution with approximately same result. Each layer of MobileNet V2 has batch normalization and the ReLU6 as the activation function. However, the output of the projection layer does not have an activation function [13]. The proposed approach employs four MobileNet V2 networks (one for each bedsore attribute to consider for the classification task) and replaces, for each network, only the last layer (a classifier with 1000 classes supported) with a classifier supporting only the number of classes needed to handle the specific bedsore attribute. For instance, in the network for the classification related to the attribute *NPUAP/EUPAP stage* the classifier supports four classes (stage I, stage II, stage III, stage IV). Once defined the architecture for the four deep neural networks, the approach foresees a step based on transfer learning, a machine learning method used to adjust an original model trained to accomplish an original task in order to execute a second different task. The transfer learning method is particularly useful to train a model starting from a pre-trained model and by not an untrained network. This method allows to avoid wasting huge resources. More in detail, for the Bedsore Classifiers, only the last layer of each network has been trained by using the bedsore training set. The remaining layers

[8] https://machinethink.net/blog/mobilenet-v2/

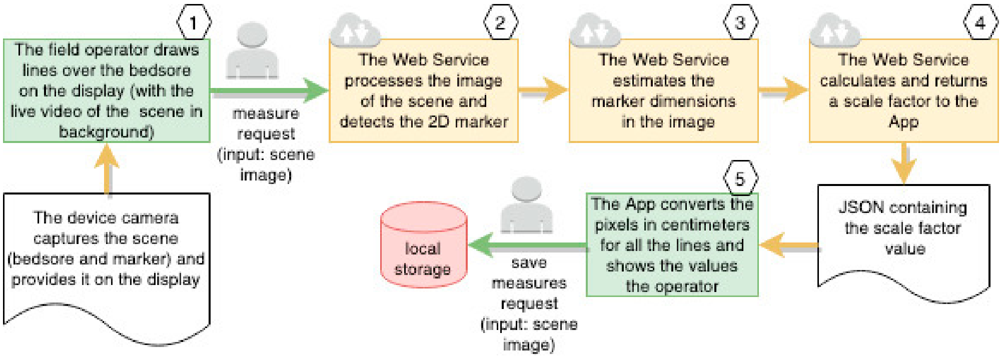

Fig. 5. Workflow of the Measurement Tool

of all networks have been pre-trained by using ImageNet[9], i.e., an image database organized according to the WordNet hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images. Lastly, the fine tuning step has been accomplished by means of the trial-and-error practice.

The main idea behind the Bedsore Measurement Tool is to allow the field operator to measure the dimensions of the ulcer by using the same device and the same App exploited for the lesion classification and the other functionalities during the same working situation. In general, a bedsore has not a regular shape so there could be the need to allow and store several measures (diagonal, height, width, etc.). The field operator can use a simple graphical tool to draw lines, in Augmented Reality mode, directly on the bedsore image (captured by the device camera) and measure the length of each line. The issue to face is to convert the above measures from pixels to centimeters (or other conventional units) but this operation depends on the position and rotation of the camera with respect to the bedsore. The proposed approach, depicted in Fig. 5, consists in using a small 2D marker to obtain a scale factor for converting pixels in centimeters. In particular, the adopted marker, namely *ArUco Marker* [9], must be printed and positioned near the bedsore in a way that it is possible, for the device camera, to capture a scene in which the bedsore is shown together with the marker and provide it to the device display. The field operator can draw more lines over the bedsore on the display (step 1). Each line represents a dimension to measure. Now, the field operator asks for measurements and the Web Service is invoked. The Web Service receives the image of the scene on which the lines have been drawn and detects the 2D marker in such a scene (step 2). The detection process returns the position of the four corners of the marker in the image and the *id* of the marker (previously the marker has been stored into a dictionary in order to enable the identification). To detect the marker it is needed to analyse the image in order to find square shapes that are candidates to be markers, apply an adaptive thresholding to segment the markers, extract contours from the thresholded image, discard the candidates that are not convex or do not approximate to a square shape. Extra filtering is applied and lastly the inner patterns of the remaining candidates have to be determined in order to match the candidate with the models stored into the dictionary. Once the corners of the detected marker have been calculated, it is possible to approximate the dimensions of the marker in the image, measured in pixels (step 3). Knowing the real dimensions of the physical 2D marker (near the bedsore) it is possible to calculate a scale factor and bring it back to the App (step 4). The App converts line dimensions measures from pixels to centimenters by using the scale factor (step 5). Lastly, the field operator can save the measures and the corresponding lines to make them available for the *Bedsore Timeline*.

4. Case Study

For the evaluation aim, a laboratory experiment has been designed and executed. In particular, the objective is to evaluate the effectiveness and the efficiency of the CDSS by measuring both decision making outcome and process (experience). For this early prototype, the bedores classifiers have been trained by using a training set of 62 images (augmented dynamically during the training process). The training results have been provided in Fig. 7. Honestly,

[9] http://www.image-net.org/

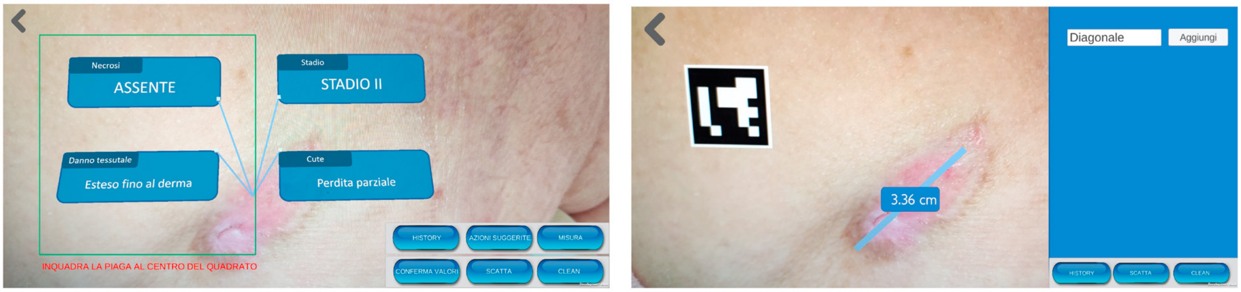

Fig. 6. Two screenshots of the prototype

Class	Precision	Recall	F-score
stage I	1.0	0.43	0.6
stage II	0.83	0.88	0.86
stage III	0.74	0.89	0.81
stage IV	0.89	0.84	0.86

Fig. 7. Training quality results

such training set must be largely extended in the next prototypes in order to have better results when we use trained models for classification of new images. The first prototype of the AR-based has been released in order to execute the early experimentation phase. The user interface (UI) of the App has to be replaced with a complete one (respecting the Android look and feel) but in Fig. 6 it is possible to see part of the current UI. In particular, the screenshot on the left shows the bedsore augmented with the results coming from the classifiers. Moreover, the screenshot on the right shows the *Bedsore Measurement Tool*. An early experimentation activity has been carried out by means of the prototype of the AR-based App. Such experimentation has been designed [4] with the aim of evaluating the quality of both decisions and decision-making processes supported by the proposed CDSS. In particular, the idea is to prepare and execute a laboratory test in which three field operators with different experience levels (very low, low and medium) use the App (installed on a 6-inches display smartphone) to be supported in making a decision related to a bedsore treatment. In particular, the experimentation is focused on three bedridden patients with pressure ulcers. The history of the three patients is pre-loaded into the App in order to enable also the *Bedsore Time Machine* functionality. Each history is constructed along three time points. For each point, bedsore photo, measurements and classification data have been provided through the aforementioned functionality. Furthermore, a new photo of the last evolution step of the ulcer for all patients has been provided. The three operators were asked to use the App and the photo and provide their assessment results and the choosed course of actions for the bedsore treatment. Lastly, operators' decisions and results have been compared to those of a third high-experienced operator to rate their quality. Moreover, the first three operators were also asked to answer a questionnaire to evaluate the whole decision-making processes. With respect to the evaluation of the decision quality, over a total of 12 classification results (4 attributes for 3 patients) for each field operator, the percentage of correct results (validated by the high-experienced operator) was around 80%. More in detail, the percentage for the operators with very low and medium experience was around 83% (10 correct values over a total of 12). The operator with low experience achieved the 75% (9 correct values over a total of 12) of correct classification values. With respect to the evaluation of the decision-making process quality, the answers from the field operators underlined three important aspect: i) the usefulness of the App to support their work and guide the decision-making process, ii) the usefulness of using only one tool to accomplish all the tasks, iii) the need to provide a better navigation guide across the different functionalities, and iv) the need to use a greater display. Furthermore, all the three operators evaluate as `good` (possible values: `excellent`, `good`, `fair`, `poor`, `bad`) their experience with the App. Lastly, the operator with very low experience affirms to have accepted (without changes) `(always)` the App advices. The operator with low experience affirms to have accepted (without changes) `(sometimes)` the App advices. The operator with medium experience affirms to have accepted (without changes) `(very often)` the App advices.

5. Final remarks

This paper proposes a Clinical Decision Support System model, for assessing bedsores status, implemented as a Mobile App for low-cost devices. The App leverages on Augmented Reality and Deep Learning to support field operators in their decision-making process related to the bedsore treatment. The App has been early experimented with laboratory tests. The experimentation results show promising results. For the future activities the authors are planning more significant experimentation/validation especially with respect to the results of the classifiers based on Deep Neural Networks. More in detail, the idea is to use the same training methodology for such networks but with more samples to improve the quality of the results.

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