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Medication dispenser with touch screen and consumption authenticator for monitoring adherence to medication in the elderly

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ABSTRACT

The elderly population continues to grow, this population has many chronic conditions, which is why they take multiple pills at the same time, this situation makes it difficult for them to take their medications at the appropriate time, which can cause health complications and even death. death. The objective of this research is to improve medication adherence using a medication dispenser that allows authenticating medication consumption accurately with a high level of usability. To do this, we implemented a dispenser with an alarm system that can be configured from a graphical interface, with internet of things (IoT) to remotely monitor the intake of pills and authenticate their consumption through artificial vision that will use the instant messaging system to inform the caregiver about the situation and finally measure the dispenser usability.

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1. INTRODUCTION

End-of-life care needs are increasing due to growing age-related challenges [1]. One of the side effects of population aging is the widespread impact of many chronic diseases and conditions [2]. On average, people over 65 years of age suffer from three chronic diseases and more than 70% take five or more medications per day [3]. Lack of medication adherence has a major impact on people's health because it leads to an increase in chronic diseases [4]; it is critical to ensure that the right medication is consumed at the right time. However, due to cognitive impairment, older people tend to forget or take medication at the wrong time, which increases the number of hospitalizations or the risk of premature death [5].

Due to the aforementioned problems due to inappropriate use of medications, commercially available pill dispensers are constantly being upgraded [6]. Recently, computer vision based systems have been developed for automated pill identification and counting that are based on image analysis such as the one developed [7] that used a classifier model for drug container recognition using deep learning. Combining and organizing previously annotated image data with you only look once v4 (YOLOv4)-tiny framework obtaining mean average precision (mAP) of 98.33% or in that of [8] where it used three object detection models to identify pills among them RetinaNet, single shot multi-box detector (SSD) and YOLOv3 in which they obtained mAP of 82.89%, 82.71% and 80.69% respectively. Other pillboxes such as developed the authentication of drug consumption as developed by [9] which detected drug consumption using locally on Raspberry Pi object detection employing a YOLOv3 model in the captured images, trained to detect human hands using bounding box coordinates in the image frame authenticating drug consumption and internet of things (IoT) technologies, to develop monitoring systems [10] from the cloud. However, most dispensers focus only on the recognition of medications to support the patient when selecting the correct container or pill at the time of consumption, but leave aside the authentication of medication consumption, which means that it is not possible to know if the patient has consumed the medication as the first antecedent or only takes into account the position of the hand to determine the consumption of the medication, which can generate low accuracy, since there are several activities with which the intake of medication can be confused, such as yawning, stretching or waving [11] and there is also no system for sending photos to the caregiver or family member so that they can verify whether the intake was performed correctly, as in the second antecedent. In addition, both antecedents do not have an interactive system in the same dispenser that allows them to stimulate the memory of patients [12], so the mentioned limitations can be reduced by adding a system of authentication of medication consumption that is based on the recognition of postures using OpenPose and super vector machine (SVM) for the capture of the posture and subsequent sending of the captured image by WhatsApp message to the caregiver so that he can evaluate the information regarding the consumption of the medication.

This research is subdivided as follows: section 2, which deals with methods and materials, is focused on explaining the setup and operation of the drug dispenser in conjunction with the use of system programming for the use of machine vision, messaging and IoT all in conjunction. Section 3 presents and discusses the results obtained by using the ingestion authentication system with the experimental procedure and the use of the instant messaging system, as well as the posture recognition accuracy of the system. Section 4 is the conclusions of the main findings of this study, then there are the acknowledgements and finally the references.

2. MATERIAL AND METHOD

2.1. Materials

The hardware layer uses a Raspberry Pi 4B with 8 GB RAM, 4 core processor and a default Intel GeForce GT 730M graphics card which is of German origin [13]. A V2 camera module for Raspberry that has a fixed focus lens, an 8Mpx Sony IMX219 sensor and a maximum photo resolution of 3280×2464 and a frame rate of 30 fps [14] of Chinese origin. A 7 inch thin film transistor liquid crystal display (TFT LCD) screen that produces images that are 1024×600 pixels in size with a file size of about 190 to 210 kB [15] from China, a ULN2003 stepper motor driver from China that is a monolithic array of high-voltage, high-current Darlington transistors that can amplify the output current of the computer from a few mA to a 500 mA input to the stepper motor [16]. Five 28BYJ-48 stepper motors that have a 5 V direct current (DC) supply voltage; phase number 4; speed variation ratio 1/64; Stride angle 5.6250/64; frequency 100 Hz; DC resistance 50 Ω ± 7% (250 C) of Chinese origin [17]; and a speaker for the alarm.

The software layer utilized a combination of tools and libraries, including Python (version 3.8, Python Software Foundation, Wilmington, DE, USA) with the Anaconda distribution, TensorFlow (version 2.4.0, Google, Mountain View, CA, USA) [18] for deep learning development. Pycocotools is used for tasks related to mask region-based convolutional neural networks (R-CNN), OpenPose for keypoint detection, OpenCV-Python for image display and storage, Tkinter for creating the graphical interface, Firebase for cloud-based data storage, and PyWhatKit for sending information via WhatsApp [19]. The general operation of the artificial vision system in posture recognition considering the joint work of the materials used in the hardware layer and the software layer is shown in Figure 1.

2.2. Medicine dispenser circuit design

This section explains the parts of the electronic circuit of the medicine dispenser and explains the functionality they fulfill within the system. The general circuit is shown in Figure 2 where its components are bounded by Figures 2(a)-(g). In Figure 2(a) you can see 5 stepper motors which will allow each compartment to be opened to dispense the corresponding medications. Figure 2(b) shows commercial batteries with a battery charger module and an ignition switch. Figure 2(c) shows a speaker that will be activated when it is time to take the medicines. Figure 2(d) shows an infrared sensor that is located near the common compartment that, when taking the medicines from the common compartment, will activate the camera shown in Figure 2(e). Figure 2(f) shows a touchscreen where data can be entered in the graphical interface. Figure 2(g) shows a Raspberry Pi 4B which will carry out the entire computational process of programming.

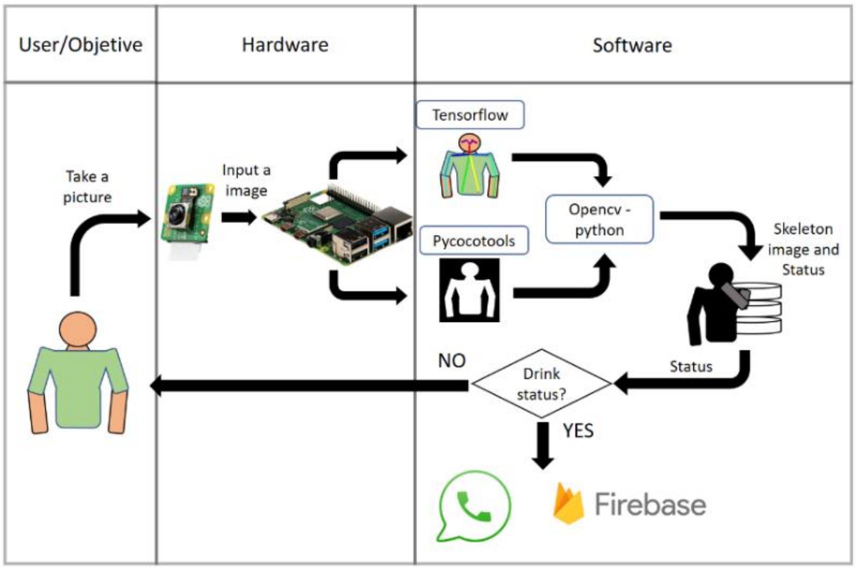

Figure 1. Predicting pill intake posture system flowchart

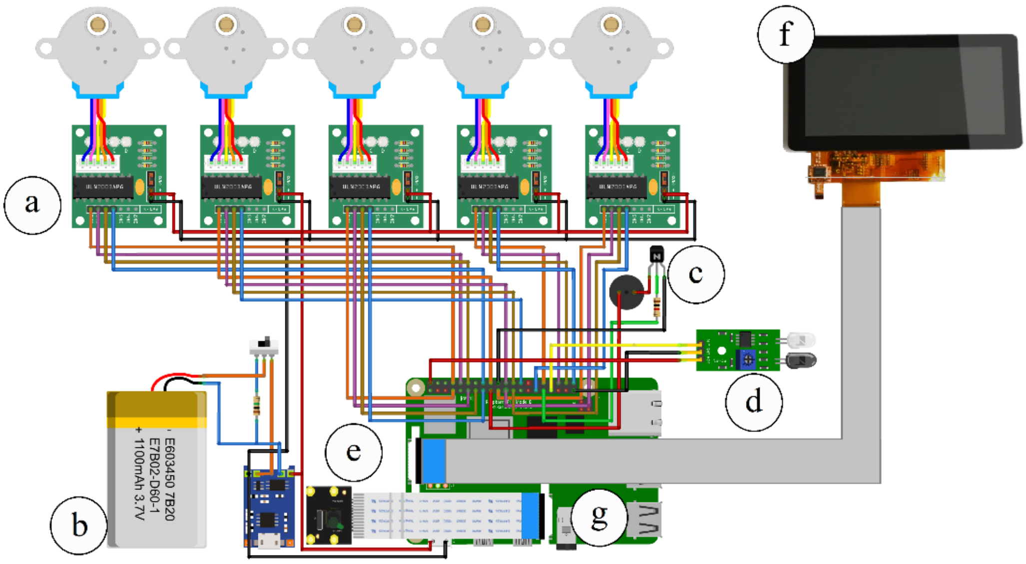

Figure 2. Medicine dispenser circuit design: (a) 5 stepper motors, (b) commercial batteries, (c) alarm speaker, (d) infrared sensor, (e) Raspberry camera, (f) touchscreen TFT LCD, and (g) Raspberry Pi 4B

2.3. Medication dispenser mechanical design

The medicine dispenser has a 7-inch TFT LCD at the top, which is part of the lid. This lid is responsible for covering the compartments, which are 6 and are located internally, in these compartments the medications that will be dispensed by the motors will be placed when it is time to consume the medication. The dispenser is shaped like a parallelepiped, 20.5 cm long, 13 cm wide and 14 cm high. Additionally, to provide durability and stability, the external chassis of the medication dispenser is made of polylactic acid. The physical layout of the medication dispensing system is illustrated in Figure 3 where its components are bounded by Figures 3(a)-(f). In Figure 3(a) you can see the touchscreen with which the patient can interact and verify the time of taking the medication. Figure 3(b) shows the camera with which the image analysis for posture detection will be carried out. Figure 3(c) shows the common compartment that will be where the pills will accumulate. Figure 3(d) shows the lid that serves to cover the compartments of the dispenser where the pills are stored, which can be seen in Figure 3(e), and finally Figure 3(f) shows the motor that will activate the mechanism responsible for allowing the passage of the medication.

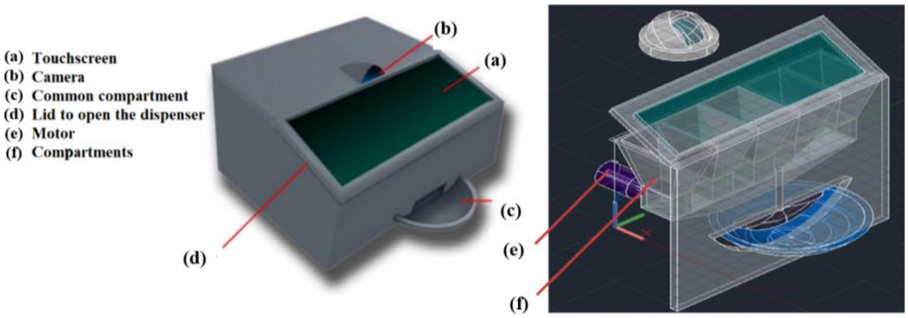

Figure 3. Design of the external mechanical system

2.4. Machine vision programming

TensorFlow (Google's deep learning library) was used to create the action recognition classifier model and OpenPose [20] for human pose estimation using TensorFlow. OpenPose is based on a convolutional neural network with supervised learning in the Caffe deep learning framework that takes a color image as input and produces the 2D locations of anatomical landmarks for each person in the image as output [21]. The database used by the OpenPose [8] algorithm is based on a model trained on the common objects in context (COCO) dataset using an 18-point skeleton.

The system employed a multistage convolutional neural network (CNN) [21] for image processing, featuring an initial stage for creating feature maps and a subsequent stage for predicting trust maps and Affinity fields. In the first stage, it extracts and encodes visual features from input images, providing a foundation for pattern recognition and object identification. The second stage utilizes these feature maps to evaluate the reliability of detected objects through trust maps and establish spatial relationships between elements via Affinity fields. This comprehensive approach enhances the system's ability to extract valuable information, make informed decisions, and accurately interpret complex visual data, making it a potent tool for various image-related tasks and applications.

2.4.1. Step 0

This step is for creating feature maps F for each input image. Visual geometry group 19 (VGG-19) is a new generation of convolutional neural networks developed by visual geometry group and Googled DeepMind. The network extracts features and information from the acquired image through 10 layers of convolutional neural network and then completes point acquisition key, the connection of keypoints and the recognition of the pose of a person in 6 steps as shown in Figure 4 [22].

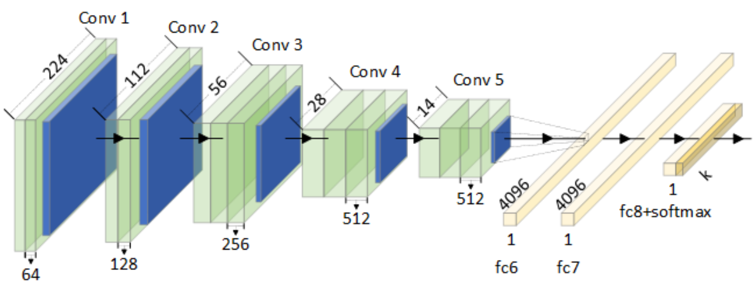

Figure 4. Basic structure of VGG-19

2.4.2. Step 1

This stage uses 2-branch CNN. The first branch is in charge of predicting the set of vector fields for the respective partial affinity fields (PAFs) [23] which is represented by a 2D vector that stores the orientation and position of the limb. At each stage, the PAF mapping with the input feature layer and keypoint heatmap is taken into account and known as L^t and S^t shown in (1) and (2). The acquired heatmap and PAFs of the prediction stages provide the position information and the direction vector of all connected articulation points [20]. At each subsequent stage, the predictions from the previous stage and the original image F-features are concatenated and used to produce refined predictions.

$$L^t = \phi^t(F, L^{t-1}), \forall 2 \leq t \leq T_P \quad (1)$$

where ϕ^t refers to the CNNs for the inference in stage t. T_P refers to the total number of PAF stages. After the T_P iterations the other branch is used to predict the body parts 2-D confidence map matrix set which is a grayscale image starting at the most up-to-date PAF prediction [24].

$$S^{T_P} = p^t(F, L^{T_P}), \forall t = T_P \quad (2)$$

$$S^t = p^t(F, L^{T_P}, S^{t-1}), \forall T_P < t \leq T_P + T_C \quad (3)$$

where p^t refers to the CNNs for the inference at stage t. T_C refers to the number of stages of the total confidence map. After classifying the actions using the keypoints of the pose obtained as input, the classification algorithm was performed with the support vector machine (SVM) machine learning classifier and the cubic epsilon loss-insensitive optimization technique was used, where the Gaussian kernel bandwidth should be set, along with the Lagrangian multipliers (statistical learning theory; Wiley: New York,). The objective of this method is to find the cubic function (4)

$$f(x) = (x^T \cdot \beta + b)^3 \quad (4)$$

This function is obtained by formulating a convex optimization problem to find $f(x)$ with minimum value for $\|\beta^T \cdot \beta\|$, with the following stopping criteria for the residuals: $\forall_n : |y_n - (x^T \cdot \beta + b)^3| \leq \varepsilon$. The objective is to minimize the following Lagrange equation, where non-negative multipliers α_k and α_k^* were introduced for each data sample *k*, from the *N* available [25].

$$L(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)x_i^T \cdot x_j + \varepsilon\sum_{i=1}^{N}(\alpha_i - \alpha_i^*)x_i^T \cdot x_j + \sum_{i=1}^{N} y_i(\alpha_i^* - \alpha_i) \quad (5)$$

$$\sum_{i=1}^{N}(\alpha_n - \alpha_n^*) = 0 \quad (6)$$

$$\forall_n = 0 \leq \alpha_k \leq C \quad (7)$$

$$\forall_n = 0 \leq \alpha_k^* \leq C \quad (8)$$

These keypoints are then used to generate a skeletal representation of the pose. Then, the network processes the sequence of poses and recognizes the type of pose [26] for taking medication. For this purpose, the movement of the left or right arm in the medication intake position is detected, taking into account the keypoints from the upper torso and the position of the hands, as shown in Figure 5. In Figure 5(a) detecting the human body and tracking each part of the body is observed. Figure 5(b) shows the movement of the right arm in the pill-taking position, point "0" being the head and point "4" the right hand. Figure 5(c) shows the movement of the left arm in the pickup position, "7" the left hand.

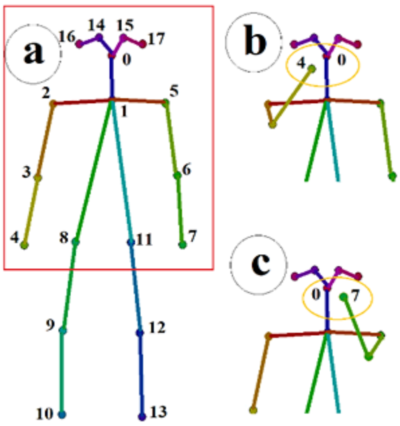

Figure 5. Detection of the human body through artificial vision thanks to the TensorFlow pose estimator library: (a) full body detection with upper torso priority, (b) right hand drug intake detection, and (c) left hand drug intake detection

Below is the test carried out to verify the computer vision algorithm. It can be seen the process of analyzing and drawing the lines in each joint of the patient's upper body because the TensorFlow library allows you to estimate the posture in real time and constantly. In this case, the person picked up the medicine, causing the sensor to send a signal that activated the camera monitoring the patient's posture, as shown in Figure 6.

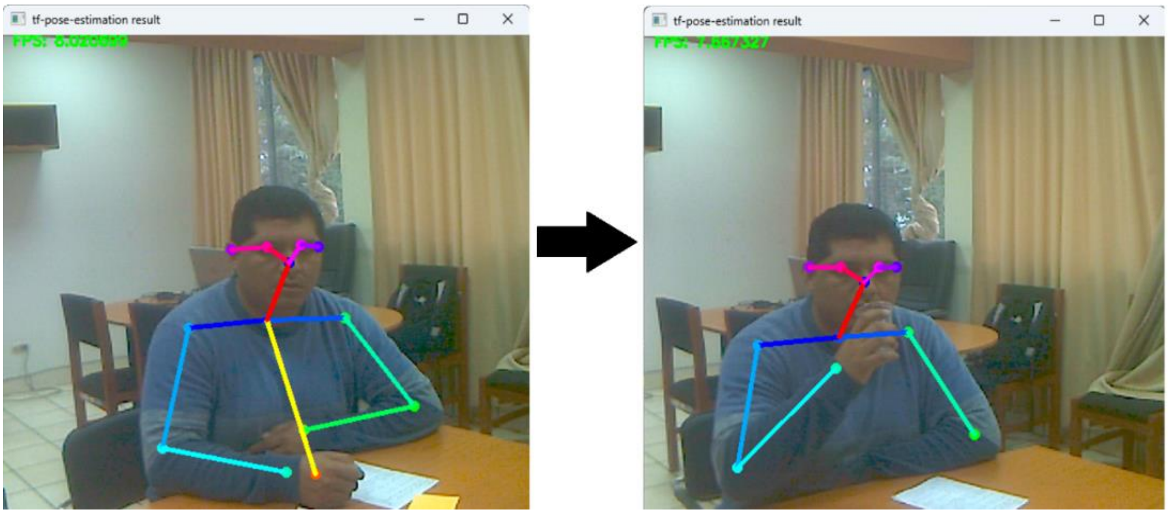

Figure 6. Tf-pose-estimation result when the person picked up the pill

2.5. Interface programming

2.5.1. Data register

The 'tkinter' library is imported to enable the use of labels, inputs, and buttons in the user interface, as illustrated in Figure 7. This iterative algorithm generates a dynamic set of buttons and textboxes, allowing users to input their personal data [12], medication information, caregiver's cell phone number, intake start time, and intake intervals. This user-friendly interface enhances the system's versatility and ease of customization, making it a valuable tool for individualized data management.

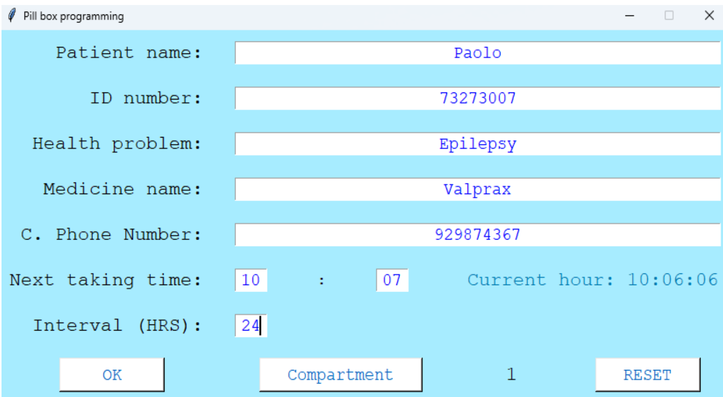

Figure 7. Interface for entering patient and medication data

Then we can select in the graphic interface the number of the compartment in which the pill will be located in the dispenser so that the pills can be counted properly. In addition, the number of pills being placed can be selected, so that when there are three or fewer pills left, an alert signal is sent so that the number of pills can be increased. Finally, once all the information is placed, it will be stored when press the "confirm" button and we can continue registering more medications or register another user [27] as can be seen in Figure 8.

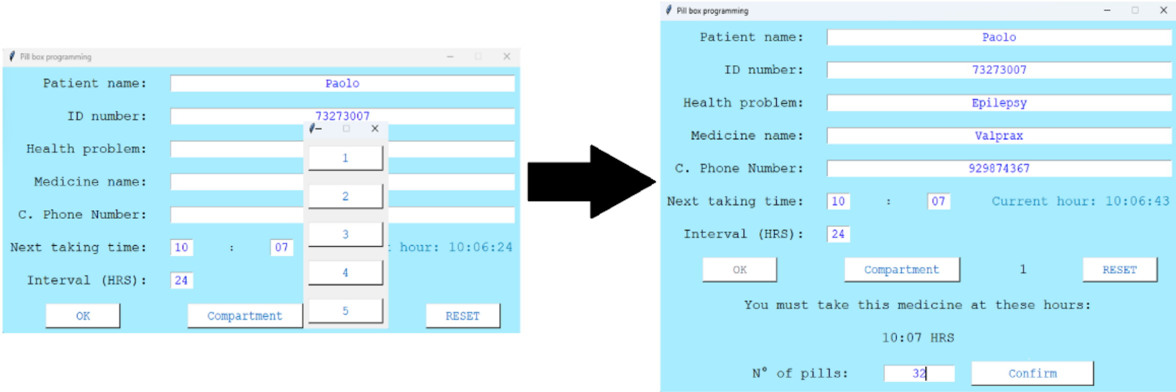

Figure 8. Selection of the compartment where the medicine will be placed with its respective quantity of medicines to enter

2.5.2. Data information

When it is time to take medication, an interactive graphical interface is displayed on the 7-inch TFT LCD screen to serve as a reminder for patients. This interface dynamically displays the specific medications to be taken, the number of pills remaining for each medication, medication intervals, pill names, and the current time. In addition, it has a button called "More information" that provides additional information about how the medication should be taken and what beneficial properties it has. To ensure that the patient can clearly understand the information provided by the dispenser, the information is presented in different colors and font types, as shown in Figure 9.

Figure 9. Checking the inserted data in the user interface

2.6. Flow chart of the general programming

The program is initialized once all the information requested by the graphical interface about the patient and the medication has been completed. Firstly, the system waits for the time to take the medication for the first dose according to the programmed time. Once it is time to take the medication, both the alarm is activated to alert the patient, the motor to dispense the medication and the graphical interface to guide the patient. From this moment on, the system analyzes two main scenarios: The first scenario involves the intake of medication during or after the designated intake time, while the second scenario refers to the intake of medication when the next dose is activated and the medication from the previous intake has not yet been consumed [2]. The maximum time window to alert about taking medication is 10 minutes after the time indicated for taking the medication, which will be divided into 2 alarms of 4 minutes and a 2-minute interval of silence.

2.6.1. Within the hour of taking medication

In the first scenario, an evaluation is performed to determine if the individual has taken the pill. If the person picks up the pill at any time within the first 10 minutes after the alarm, the alarm is deactivated and the camera is activated, which uses artificial vision to check whether the person has actually swallowed the pill. If the medication has not been recovered within the first 10 minutes, the chamber remains inactive, and the alarm is deactivated. If the sensor detects that someone picked up the pill before or after the established 10 minutes, the camera will be activated, and the image evaluation will be carried out. If the images do not detect the medication-taking posture, a notification is sent to the caregiver. This notification serves as an alert, prompting the caregiver to contact the senior and aid if necessary. If the medication-taking posture is detected, a photo is captured and sent via WhatsApp to the caregiver with information about the pill consumed.

2.6.2. Out of time of taking medication

If the person has not taken their medications and it is time for the next dose, the system will evaluate whether the next pill is the same as the one found in the "pill accumulation compartment". If it is the same, the engine will remain off. However, if the pill for the next dose is different, the motors will be activated to dispense it. In both cases, a graphical interface will be displayed with a message that will communicate the accumulation of doses so that the patient can take it into account. If the person recovers all the pills when there is more than one dose in the common compartment, the camera will be activated and the conditions mentioned in the first scenario will be applied again, these conditions will be repeated a number of times equal to the number of pills accumulated in the common compartment and the pill schedule will be changed, informing the caregiver in this case.

All activities that take place inside the pill dispenser, as described in the two aforementioned cases, are evaluated, activating and deactivating the alarms, sensors and camera transmitting the obtained information to the Firebase cloud, as shown in Figure 10. This data is continuously monitored, allowing reports to be generated that help measure and verify medication adherence in real time [28]. This system not only facilitates adherence monitoring, but also provides control over medication intake by caregivers.

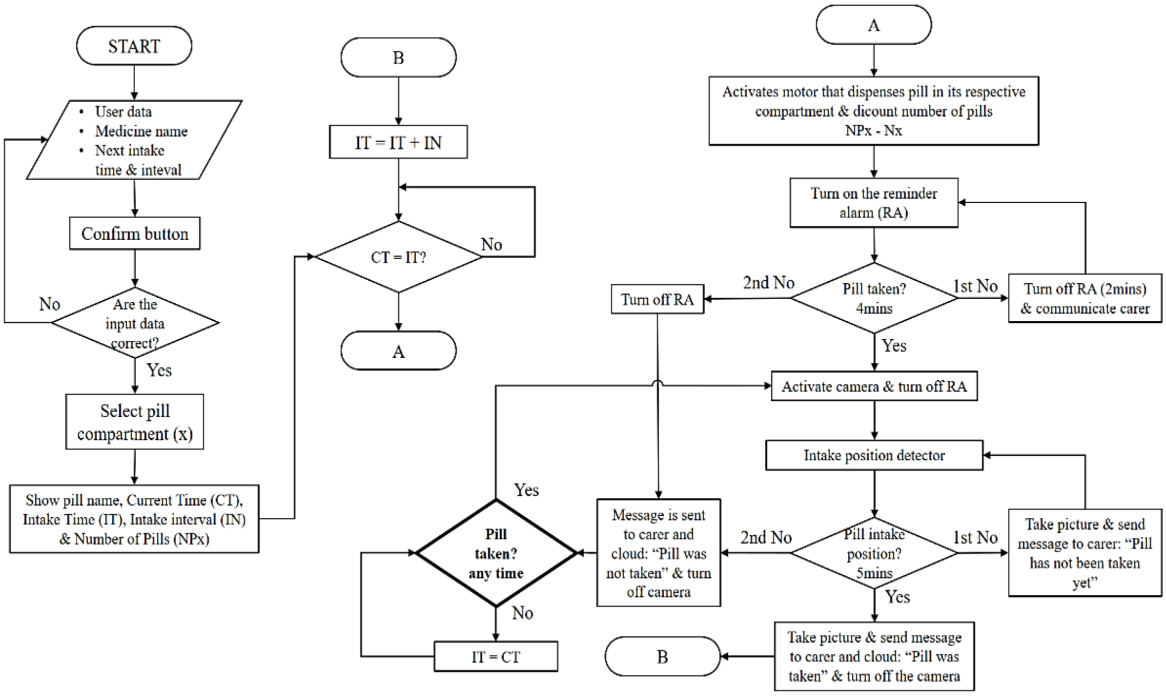

Figure 10. General flowchart of the program

3. RESULTS

During the operation of the medicine dispenser, the different operating conditions were evaluated, and the results obtained were stored in the Firebase database from where real-time monitoring of the situation can be carried out, as can be seen in Figure 11. Firebase can provide information related to the date, time of taking, the name of each medication with the respective name of the disease that is being controlled or recovered from and the status of taking the medication. This information is available so that the caregiver or family member can access it remotely at any time from a mobile phone or laptop.

In [28], as in this study, Firebase, a cloud computing-associated platform, was employed. The study verified that it provides a platform that allows managing medication consumption due to the data that can be easily stored and interpreted. Accessible in real time and remotely from web applications and operating systems such as iOS, OS X and ANDROID with a user who logs in from a Google or Facebook account, maintaining their privacy with email authentication.

The tests were carried out to verify the sending of information through instant messaging via WhatsApp about the status of taking the medication. Figure 12 shows a photo of the position in which the person is located and information about the medication sent from the dispenser. This photo is sent once the medication taking time has ended or at the moment in which the medication taking posture is detected. If more than one medication has to be taken, the pill box will take the same number of photos as the pills dispensed.

Figure 11. Data storage in Firebase

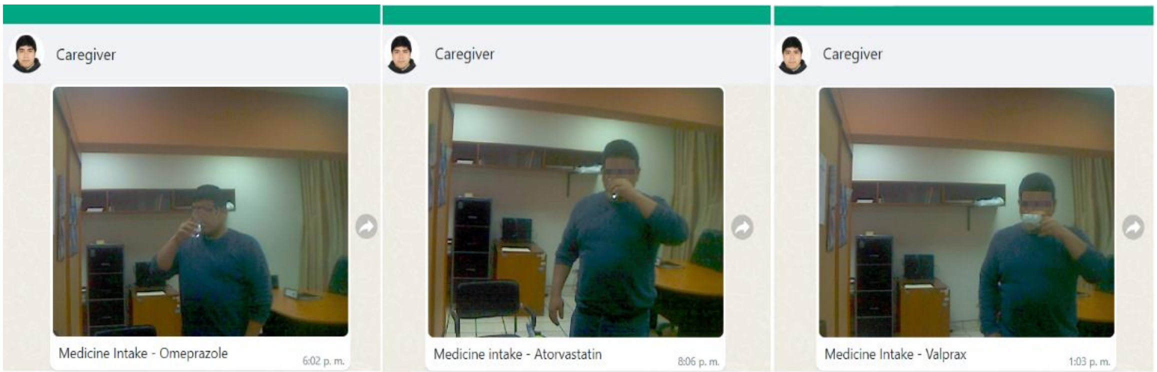

Figure 12. Sending photos of medication intake via WhatsApp

In the study carried out by [9], a text message alert system was installed in the pill box which could notify the caregiver of the status of taking the medication, being an imprecise system, since it does not allow authenticating the taking of medication. That is why WhatsApp was used in this study because it is most used as an instant messaging system by doctors [29] and its platform allows the sending of photos that have been captured by the dispenser's camera at the time of taking the medication. With these photos the caregiver can verify in a more realistic way if the medication was taken and have a history of photos on their WhatsApp. The execution time that the dispenser takes from capturing the photo when the medication-taking posture is detected to sending the photo to the caregiver's WhatsApp is recorded. The experimental tests of the proposed system are carried out ten times at different times and each result can be seen in Figure 13 where the time it takes to execute the procedure on the Raspberry Pi 4+ with 8 GB of RAM is recorded, which averaged a time of 93.979 seconds.

In the study carried out by [19] it is seen that the execution time of the device is on average 69.24 seconds using a Raspberry Pi 4+ with Google's Coral USB accelerator which compared to the tests carried out in this study, which obtained an execution time of 93.973 seconds, has a longer delay, although it is within an acceptable time to speak of real-time monitoring. The additional delay in this dispenser is caused by the greater weight of the information, since the first uses only messages while in this project a message with photos of the patient is sent through WhatsApp. To perform the classification of actions, 1,000 images were collected for each class, using the COCO human poses dataset. For each image, the keypoints were normalized to 128×128 pixels. The SVM classifier model has been used to classify the three categories of actions of the human body. The model results in considerable precision in the prediction of the three classes of human action as shown in the confusion matrix that appears in Figure 14 where the precision reached 97.69%.

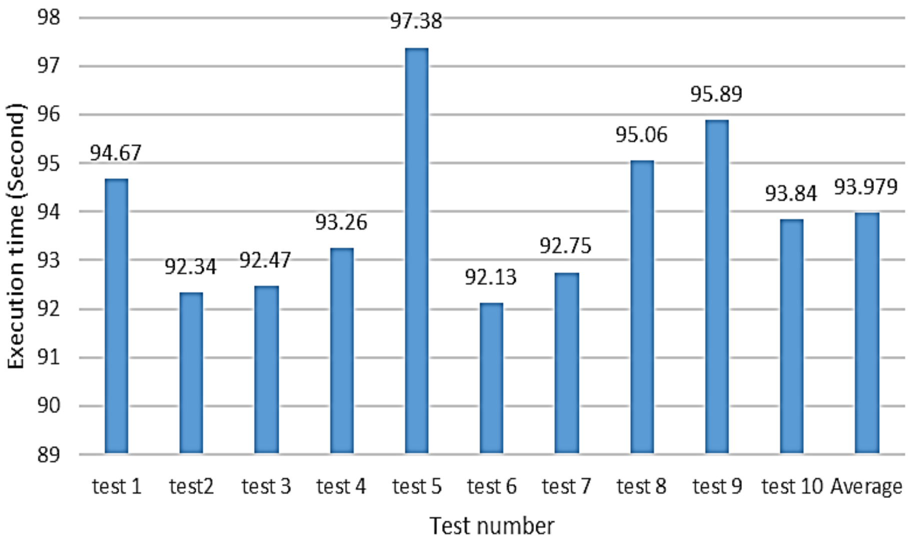

Figure 13. Runtime analysis

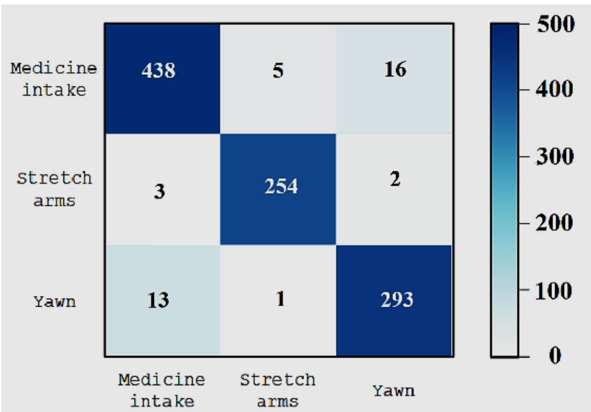

Figure 14. Confusion matrix of medicine intake, stretch arms and yawn actions

When comparing the accuracy percentages for posture detection using the OpenPose and SVM algorithm of this system with that developed by [20], it can be seen that the accuracy of this dispenser is better, since 97.69% accuracy was obtained while in the other obtained 87%. This improvement is attributed to the dispenser's focus on detecting a specific posture, while in the other system, it is used to detect 4 different types of actions which require further analysis. In addition, the optimization technique insensitive to cubic epsilon loss was used in the dispenser, considering the preliminary results obtained from the collected data, which allows a more precise analysis. The data was normalized and divided into 80% for training and 20% for validation. Then cross-validation was performed 5 times, that is, the data was divided randomly. During the training and for the assessment of the results obtained, two complementary indices were used, that is, the R^2 index and the root mean square (RMSE). The results are shown in Table 1.

Table 1. General results for the estimation of the human pose

Method	R^2	RMSE	Time [msec]
Cubic SVM	0.9921	0.1384	1.632

In the study carried out by [25], the Cubic SVM was used and as a result an R^2 close to 1 and an RMSE close to zero were obtained. These findings indicate that the model employed in both studies exhibits a high level of accuracy in its responses. Notably, the dispenser has a higher elapsed time to monitor human pose using the camera where the margin of difference is approximately 0.32 seconds compared to the mentioned study.

4. CONCLUSION

The medication intake authentication system worked efficiently in real time through posture analysis with the OpenPose algorithm and SVM. This authentication system used materials that allow the portability of the medication dispenser, including the Raspberry Pi 4+ microcomputer, the TFT LCD and the V2 camera through which the recordings for posture detection were made. The system was able to detect the medication-taking posture by efficiently taking advantage of the computational resources of the Raspberry Pi 4+, being a functional system with high precision when processing the video sequence.

The integration of a graphical interface in this system helps the patient by reminding him which pills to take and when. By providing an automated process, it is suitable for patients with memory problems to keep track of their treatment. In addition, with the availability of a database, it allows constant monitoring to see the evolution of the patient.

In relation to the IoT, the use of WhatsApp to inform the caregiver about taking medication through a photo and a confirmation message allows the situation to be better verified, being more effective than the use of text messages where the information ends up being limited. The sending of this photo is done with minimal delay on the part of the dispenser, which will facilitate decision making on the part of the caregiver. In addition, Firebase allows you to store and access information on previous doses remotely and securely.

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