An Intelligent Ecosystem to improve Patient Monitoring using Wearables and Artificial Intelligence*

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Abstract
Our work describes a smart-ecosystem able to monitor patients' health condition, even at home or at work, by exploiting a creative blend of Medical Wearables, Intelligent Agents, Complex Event Processing and Image Processing. With the help of a smart application, that links together the Wearables and the power of Artificial Intelligence, patients will be continuously and actively supervised during their daily activities. This can even save their lives, in case sudden or gradual issues should occur. Thanks to our system, patients with non-severe though potentially unstable chronic diseases will no longer overburden first aid services. This is also useful for containing the spread of COVID-19. Specifically, in this paper we focus on automated vitals monitoring, electrocardiogram (ECG) analysis, and Psoriasis detection.

Keywords
Artificial Intelligence, Wearables, Intelligent Agents, Complex Event Processing, Image Processing

1. Introduction

The Coronavirus pandemic has highlighted telehealth as a crucial component of modern and sustainable treatment. In fact, telemedicine's primary purpose is to virtually erase the distance between patient and physician, as well as to reduce time and expense involved in healthcare access. Furthermore, during the COVID-19 pandemic, the growing usage of telehealth has often reduced the danger of providers and patients being exposed to the virus [1]. However, despite recent efforts, telemedicine is still in its early stages for a variety of reasons; as a result, one of the most significant consequences is that First Aid departments are frequently overburdened by people who do not require immediate assistance; this could be avoided by allowing patients to use telehealth applications to monitor their vitals either at home or even at work. Thus, in order to cope with these issues, in our approach we joined together Wearables (such as portable ECG devices and Pulsoximeters), Intelligent Agents, Complex Event Processing (CEP), and Image Processing algorithms in an integrated framework able to follow the patient wherever (s)he

CILC 2022: 37th Italian Conference on Computational Logic, June 29 – July 1, 2022, Bologna, Italy
*Research partially supported by project INDAM GNCS-2022 InSANE (CUP_E55F22000270001).
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is. This paper improves our previous work in the E-Health field [2, 3], by adding new features, algorithms and devices, in order to create a complete ecosystem.

Specifically, our ecosystem is composed by a number of devices (both hardware and software) allowing users to monitor their health status constantly. We have sensors measuring oxygen saturation, hearth rate, and all the heart parameters (by performing an ECG); sensors communicate with the developed Android application, that forwards the acquired data to a server. Such data will be immediately analyzed by the main components of our system, that, through sophisticated algorithms, are able to assess the patient's health status. The assessment is provided to him/her, and, in case of severe detected problems, a doctor is immediately informed, and, if necessary, first aid services are alerted.

In the literature, in [4] and [5] specific systems are described that can be used to detect Atrial Fibrillation and hearth anomalies in patients, via wearable devices, such as an Arduino linked to a Bitalino Board or smart sensors embedded in dresses.

In our work, instead, we exploit medical-grade more precise ECG sensors, allowing the user to autonomously perform a professional ECG with very accurate outcomes; additionally, these are ready-to-use devices that the user does not need to assemble.

In [6], the authors describe a Multi-Agent system for E-Health that can be used to read and analyze sensor values, and alert an administrator if health issues are detected. Our system improves their work by adding wearable technology, thus providing the patient with the possibility to monitor his/her health status in every situation, not only at home.

Moreover, in [7] the authors describe a method that can be adopted in order to detect the Psoriasis on the patient's skin, using k-means clustering, segmentation and bounding box strategies. In our work, differently from them, we detected Psoriasis using AVG color detection, image segmentation and clustering, obtaining, in addition, even the severity value of the psoriasis detected on the hand.

In the majority of these works, even if they may appear similar to ours, they implement stand-alone solutions with a single "brain", monitoring a limited number of situations; in our work, instead, we created a smart-ecosystem, with more "brain-sectors" linked together, each one specifically needed for some kind of calculations, that, together, have a very strong computational power.

In summary, our contributions are listed in the following:

- We present a wearable smart-ecosystem, that can follow users wherever they go, even to their job;
- We integrate Intelligent Agents, Complex Event Processing and Wearables in a joint mobile application, leaving the computational power to the Server-side;
- We define a specific Image Processing algorithm, able to detect whether the user has Psoriasis or not, which will be also extended to other pathologies in the near future.

2. System Architecture

Our system consists of six main components: User and Doctor Interfaces - Android App, Database and Web interface, Hardware, Intelligent agents, Complex Event Processing and Image Processing.

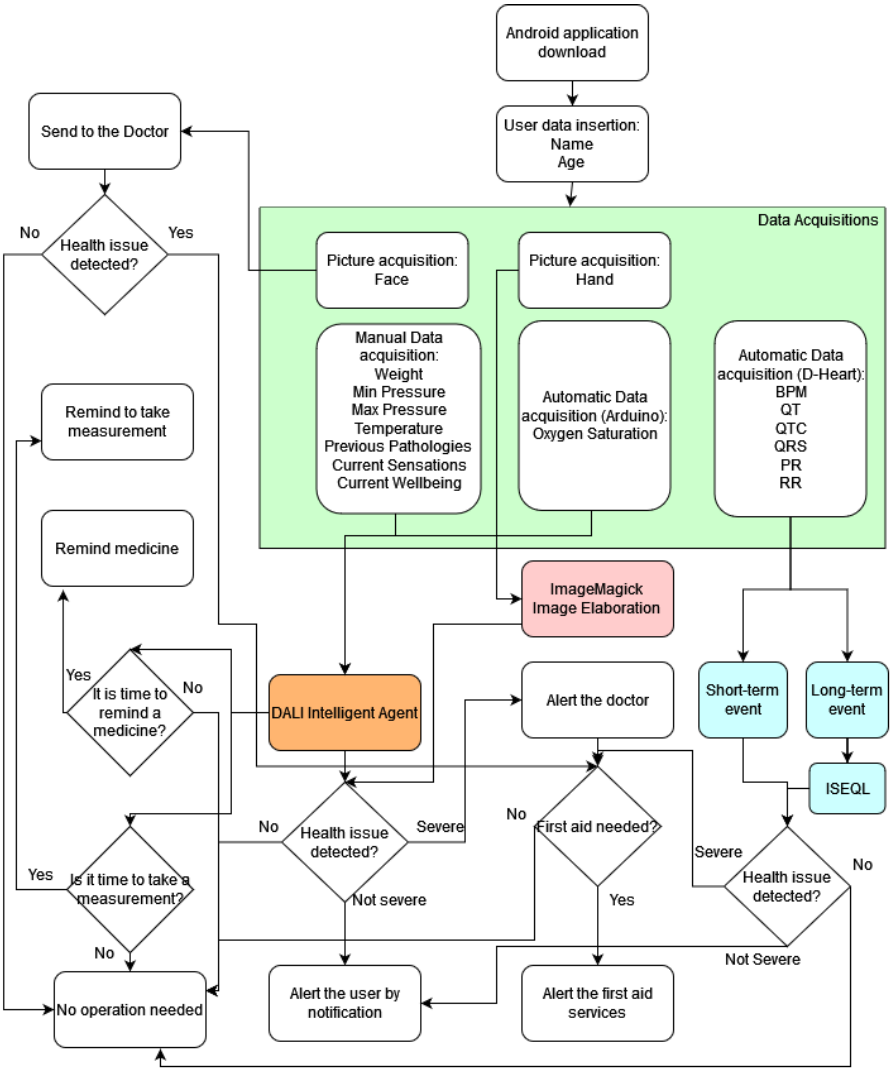

Figure 1: Whole system workflow

The user and doctor interfaces consist in a mobile application, which is currently released only for android devices, but that we are planning to customize for Apple devices too. Our system's "core" is the database, that, in our case, is a MySQL one. A web interface that runs the main algorithm which acts as an effective "hub" linking together the Android Applications, Intelligent agents, CEP, Image processing and the Database.

Our ecosystem encompasses a number of hardware devices (medical wearables), with the advantage of being modular. In fact, being also equipped an Arduino, we can attach a number of sensors that are very effective for our goals; we have already used Arduino with other medical-related and wearable-related projects [8, 9], obtaining interesting results that improved our awareness to use wearables in the medical field. We currently have one sensor attached to

Arduino (the pulse oximeter), and one sensor that is a single block (the ECG device), but we are going to expand this collection in the near future. They both communicate to the mobile app via Bluetooth.

Additionally, after an accurate search for an appropriate ECG device, supported by qualified medical advice, we selected *D-Heart*[1]. Specifically, D-Heart is the first ECG device for smartphone that is simple to use, clinically reliable, portable and affordable. To sum up, Fig. 1 depicts the entire workflow of our system.

2.1. Intelligent Agents

In our work, we use DALI in order to implement a system composed by intelligent agents. DALI is an agent-oriented logical language derived from Prolog, and, similarly to it, is based on the logic programming paradigm. DALI has been fully implemented, on the basis of a fully logical semantics [10]. By analyzing data, our intelligent system is able to recognize the patient's state of well-being or discomfort in both short and long term; therefore, the system is able to assess the seriousness of the situation and, if necessary, alert a human doctor or even call the Emergency Service. Using DALI, we created two intelligent agents: the *Patient_agent* and the *Doctor_agent*. The Patient_agent analyses the patient's vital parameters (heart rate, saturation, minimum and maximum pressure, temperature, weight) taken by wearable devices or by the patient, and returns immediate feedback on each of them.

It also acts as an Ehealth-companion, reminding the user to take pills at the correct time, sending a reminder for temperature, blood pressure and weight measurements. The Doctor_agent receives messages from the Patient_agent, analyzes the communicated problem, e.g., fever or tachycardia, and responds by suggesting a medication to take or, in case of serious danger, it suggests going to the Emergency Room. Events currently detected by our DALI intelligent agents are *Angina Pectoris*, *Tachicardia*, *Bradhicardia*, *Hypoxia*, *Hypertension* and *Fever*.

2.2. Complex Event Processing

The specific language that we use in order to carry out Complex Event Processing tasks extends relational algebra [11] and the well-known Allen's interval relationships [12]; specifically it is named ISEQL [13], standing for Interval-based Surveillance Event Query Language. We exploit this language so as to easily define the medical events we are interested in. Using ISEQL, we are able to detect short-term and long-term events in patient's ECGs.

2.2.1. Short-term event detection

A *Short-term Event* is an event to be detected within the context of a single ECG measurement. To detect such events, we must analyze the ECG signal in depth using specific criteria stored in the knowledge base and complying with the guidelines found in the literature [14]. As a result, the events automatically discovered in this stage thanks to the *D-Heart* device[2] are the *QT interval*, the *QTC interval*, the *RR interval*, the *QRS interval* and the *PR interval*.

[1]https://www.d-heartcare.com/it/
[2]https://www.d-heartcare.com

Moreover, on top of such events, we define specific additional event models in ISEQL, aimed at identifying possible anomalies in ECGs, thus extending the literature in the context of their automatic analysis. More specifically, the events are modeled in ISEQL and associated with their severities on a scale from 0 (lowest severity) to 3 (highest severity - in such a case, a medical doctor is automatically alerted).

2.2.2. Long-term event detection

Working on aggregated data at a different resolution, such as examining the results of several ECG measurements taken in specified wider temporal windows, allows a detailed long-term analysis of the patient's clinical history. In this paper, we focus on the detection of different categories of long-term events; in fact, on the one hand we identify some possible long-term anomalies exploiting ISEQL, and on the other hand we implement specific algorithms for detecting the *Atrial Fibrillation (AF)* and the *Wolff-Parkinson-White (WPW)* syndromes.

As regards the *Atrial Fibrillation* detection, we use the data that have been previously stored in our ECG measurements, such as RR intervals and heart-rate.

To sum up, we obtain the HR values and the standard deviation of the RR intervals in 5 ECGs, and, after applying our specific algorithm, we detect an AF disorder in case the obtained parameters are greater than a Threshold value[3]. The defined algorithm extends the one in [4], that encodes useful information on how to diagnose early Atrial Fibrillation (AF) using ECG measurements, with custom improvements and adaptations, via exploiting the full power of ISEQL on interval data.

As regards the Wolff-Parkinson-White syndrome detection, we exploit the information previously inferred from the ECG measurements, such as PR intervals and QRS complexes. For this kind of study, we have partially used and adjusted the algorithm obtained from [15], that contains useful information on how to diagnose Wolff-Parkinson-White syndrome (WPW) using ECG measurements. To sum up, we extract the PR intervals and the QRS complexes of 5 ECGs, then we apply an interval detection strategy on these events, and, if the conditions are met, we detect a WPW syndrome.

Additionally, exploiting the right cardinality constraint of ISEQL [16], the system is also able to alert patient and medical doctors in case anomalies are identified in several measurements in a relatively short temporal interval.

2.3. Image Processing

We also define an Image Processing algorithm in order to elaborate and extract features from images. We used image processing in order to evaluate the condition of the patient's hand, and possibly diagnose the presence of Psoriasis. In order to correctly elaborate the image of a person's hand, and make it “visible" to the computer, we exploit one of the most used software for Image elaboration, that is named ImageMagick[4].

[3]Both the number of measurements and threshold values were suggested by medical doctors; clearly, we can easily update them in case requirements will change.

[4]https://imagemagick.org

Our computer vision algorithm consists of three main steps. In the first one, we are going to detect the presence of the AVG colour of the Psoriasis on the hand of the patient, with a percentage of fuzzyness. In the second step, we fill the whole image with Black and White colours, through the technique of image segmentation, depending on the presence of the Psoriasis or not. In the third step, we cluster all the detected Psoriasis spots with a particular area threshold, using the technique of Clustering. After applying this algorithm, we obtain a certain number of psoriasis clusters detected; then, we are going to count their number and their size, and provide a response to the user according to the resulting data.

3. Experimental Results

After developing the prototype, we made a set of tests to validate its correctness and validity. So, we asked a doctor for assistance, asking for four patients with the following characteristics, that should be doing our tests:

1. The first patient should be a person who suffered from none of the below pathologies, nor other special or particular ones, being a “healthy" one. He should be a 45 years old male.
2. The second patient should be a person who suffered from Atrial Fibrillation, without other special or particular pathologies, in order to allow us to correctly detect his pathology, without being influenced by other factors. He should be a 45 years old male.
3. The third patient should be a person who suffered from Wolff-Parkinson-White syndrome, without other special or particular pathologies, in order to allow us to correctly detect his pathology, without being influenced by other factors. He should be a 45 years old male.
4. The fourth patient should be a female patient aged over 80, suffering from severe heart failures and occasional angina, with comorbidities.

We also asked the doctor for pictures of a hand with Psoriasis and a hand without Psoriasis, in order to test our image processing algorithm.

In order to get more precise results, we decided that a “blind" test would be more appropriate, in order to really understand the potentialities of our newborn system. So, we performed the first three tests like blind tests, the fourth one as a regular test, and the fifth one (the Psoriasis test) as a regular image test. In our blind tests, the operator of the device does not know the pathology of the person (s)he is examining, thus avoiding results contamination. In the regular test, the operator of the device knows the pathologies of the person (s)he is examining because those results are less “scientifically related" but more “development-related", so we decided to have a regular test instead. In the Psoriasis test, 10 hand pictures are given to the machine, some with psoriasis, some with no psoriasis, thus validating the capability of our machine to correctly discover the disease.

3.1. Healty Patient Case Study

In the first case, the patient that the operator examined was the healthy one, without any particular pathologies. He gave the patient the D-Heart device, the Arduino device, a pressure measurement device, a thermometer, and the Android smartphone used for testing.

In this test the patient did five ECGs, one every 45 minutes; the collected data related to all the ECGs were stored in the database. After running all the tests, the system was queried for results. The tests resulted as expected, being the patient the healthy one, and in fact the system did not discover any dangerous short-term or long-term events.

3.2. Atrial Fibrillation Case Study

In the second case, the patient that the operator examined was the one who suffers from Atrial Fibrillation, without any other particular pathologies. He gave the patient the same testing tools as the first patient. Also in this test the patient did five ECGs, one every 45 minutes.

Also in this case, the system confirmed that the patient suffers from Atrial Fibrillation, since it detected the related short-term and long-term events. The detected short-term events are listed in Table 1; as a result, there are a lot of "warnings", whose severity is 1, some dangerous situations, indicated with severity 2, and only one very severe situation, indicated with severity 3, with the id 233. Since an event of high severity is detected, immediately after the ECG data processing, the doctor is alerted. The long-term event detected, in this case, is the following: "An Atrial Fibrillation was discovered. The AVG BPM is 118.2 and the STD RR is 300.66". The system correctly detected all the short-term events, and, using ISEQL, it understood that the patient suffers from Atrial Fibrillation.

3.3. Wolff-Parkinson-White syndrome Case Study

In the third case study, the patient that the operator examined was the one who suffers from Wolff-Parkinson-White syndrome, without any other particular pathologies. He gave the patient the same testing tools as the other patients. Also within this test, the patient did five ECGs, one every 45 minutes.

In this case, the system, instead of detecting the WPW syndrome, discovered a "possible" WPW syndrome. The short-term events detected are listed in Table 2; as a result, there are a lot of "warnings", whose severity is 1, but no more severe situations detected; in this case, the doctor is not alerted, being the situation not "urgent". The long-term event detected, in this case, is the following: "A Potential Wolff-Parkinson-White syndrome was discovered. The AVG PR is 108.4, the AVG QRS is 125.8 and the STD QRS is 2.31". The system correctly detected all the short-term events, and, using ISEQL, it understood that the patient suffers from a possible Wolff-Parkinson-White syndrome, not fully understanding the problem, but going very close to detecting it.

3.4. Intelligent Agent Case Study

In the fourth case study, the patient that the operator examined was a female patient aged 85, suffering from severe heart failures and occasional angina, with comorbidities. In this case, differently from the previous ones, we are not going to do a precise diagnosis, but we are just testing the system, with particular interest to DALI and the related Intelligent Agent. In particular, we covered:

- The therapies (which medications at which time of the day).

Table 1
Atrial Fibrillation Case Study - short-term events detected

Ecg	ID	Name	Type	Value	Description	Severity
Ecg 1	212	Y	hr	105	low tachycardia	1
	213	Y	qt	435	slightly long	1
	214	Y	qtc	450	long	2
	215	Y	rr	850	regular	0
	216	Y	qrs	123	slightly long	1
	217	Y	pr	201	slightly long	1
Ecg 2	218	Y	hr	120	severe tachycardia	2
	219	Y	qt	350	regular	0
	220	Y	qtc	360	regular	0
	221	Y	rr	1450	slightly long	1
	222	Y	qrs	112	regular	0
	223	Y	pr	194	regular	0
Ecg 3	224	Y	hr	122	severe tachycardia	2
	225	Y	qt	340	regular	0
	226	Y	qtc	350	regular	0
	227	Y	rr	1150	regular	0
	228	Y	qrs	114	regular	0
	229	Y	pr	195	regular	0
Ecg 4	230	Y	hr	126	severe tachycardia	2
	231	Y	qt	346	regular	0
	232	Y	qtc	355	regular	0
	233	Y	rr	1650	too long	3
	234	Y	qrs	110	regular	0
	235	Y	pr	190	regular	0
Ecg 5	236	Y	hr	118	low tachycardia	1
	237	Y	qt	345	regular	0
	238	Y	qtc	356	regular	0
	239	Y	rr	950	regular	0
	240	Y	qrs	111	regular	0
	241	Y	pr	180	regular	0

- The symptoms that can be treated by readjusting the therapies.
- The situations of danger/alarm that require immediate intervention of a doctor, or urgent transportation to the hospital.

As a first step, the patient, aided by an assistant, since she is impractical with the use of smartphones, inserted all the data into the system, using the Android application.

The data the patients inserted, are listed in Table 3.

As a result, the patient has two parameters that can indicate health problems, i.e., the QT and the QTC intervals, which are slightly longer than normal ones. Then, the Intelligent Agent started doing its elaborations and reminding features. As first reasoning, the intelligent agent understood that the minimum pressure is too high, sending a notification to the patient's smartphone. After that, it continued with its reasonings, since it did not find anything else relevant.

At the beginning of the next day, the system began sending notifications to the patient's smartphone. The first notification, which arrived at 7, had the following text: "You should take Eutirox 50, quantity 1 capsule"; it means that the patient should take 1 pill of Eutirox 50, at 7:00. Later, it continued sending notifications to the patient, to remind her of the other

Table 2
Wolff-Parkinson-White syndrome Case Study - short-term events detected

Ecg	ID	Name	Type	Value	Description	Severity
Ecg 1	242	Z	hr	70	regular	0
	243	Z	qt	345	regular	0
	244	Z	qtc	355	regular	0
	245	Z	rr	650	regular	0
	246	Z	qrs	123	slightly long	1
	247	Z	pr	110	slightly short	1
Ecg 2	248	Z	hr	70	regular	0
	249	Z	qt	349	regular	0
	250	Z	qtc	350	regular	0
	251	Z	rr	654	regular	0
	252	Z	qrs	125	slightly long	1
	253	Z	pr	114	slightly short	1
Ecg 3	254	Z	hr	70	regular	0
	255	Z	qt	349	regular	0
	256	Z	qtc	350	regular	0
	257	Z	rr	654	regular	0
	258	Z	qrs	129	slightly long	1
	259	Z	pr	110	slightly short	1
Ecg 4	260	Z	hr	80	regular	0
	261	Z	qt	329	regular	0
	262	Z	qtc	350	regular	0
	263	Z	rr	640	regular	0
	264	Z	qrs	124	slightly long	1
	265	Z	pr	108	slightly short	1
Ecg 5	266	Z	hr	80	regular	0
	267	Z	qt	345	regular	0
	268	Z	qtc	355	regular	0
	269	Z	rr	620	regular	0
	270	Z	qrs	128	slightly long	1
	271	Z	pr	100	slightly short	1

medicines that she should take. At 14:00, the system reminded the patient that she should take the weight measurement, pressure measurement and temperature measurement. This time, the measurements were “perfect", and the system did not detect any event. At 17:45, the patient did not feel very well, and took the related measurements, registering a low minimum pressure, with a value of 55, and low maximum pressure, with a value of 89. At this point, the intelligent agent, following its rules, noticed that the patient suffers from Hypertension, and, when both min and max pressures are low, a dangerous situation may happen, so, after displaying a warning to the patient, the system also alerted the doctor. The doctor briefly read the alert on the application, and called the patient, telling her that an ECG is required. The patient, at this point, with the help of an assistant, attached D-Heart and did an ECG, sending the values to the system. At this point, the doctor read the ECG values, noting that were normal, with no particular issues, and called the patient to reassure him, because it was just a low-pressure situation. As we can detect from this last example, the intelligent agent acted as previsioned, helping the patient into the home monitoring, with minimum effort needed by both patient and doctor.

Table 3
Elderly patient case study

Parameter	Value
Name	W
Weight	67
Age	85
Temperature	37
Max Pressure	130
Min Pressure	91
Saturation	97
Pathology	Hypertension
Pathology	Angina
BPM	87
QT	435
QTC	445
QRS	112
PR	192
RR	720

3.5. Hand Psoriasis Case Study

In the fifth case study, differently from the others, we examined ten pictures of the back of the hands, given to us by the doctor. In 8 out of 10 cases, the pictures represented a hand with Psoriasis, the other 2 pictures represented a hand with no psoriasis. In these test cases, we are giving a diagnosis, thus detecting the hands in which psoriasis is present.

As a first step, we entered our Android application and began inserting the pictures of the hand given by the doctor, one per time, in order to let the system do its elaborations. Later, we exported and elaborated the database, in order to have a human-readable result, in the form of a table; in this table, we can see the picture identifier, the number of clusters detected, the diagnosis made by our system and the real diagnosis made from the doctor. The data are visible in Table 4.

As we can see from Table 4, our system correctly detected 8 out of 8 cases of psoriasis. In one of these, it detected possible psoriasis, since there were fewer clusters because the disease was in an initial state, and, in another case, it detected Severe Psoriasis, being the disease in a Severe situation. In the other 2 cases, the system correctly recognized that the hand is in a regular stage, detecting 0 and 1 clusters for such cases.

3.6. Precision and Recall

In order to calculate precision for our experiments, we used the well-known *Precision* and *Recall* formulas.

In the Healthy Patient test, reasoning with short-term events, we have 30 TruePositives results (considering as TruePositive all the “regular" values), and 0 FalsePositives (irregular values, because a healthy patient should not have those values far from normal ranges). Since we do not

Table 4
Psioriasis hand test

ID	Clusters	Machine Diagnosis	Severity	Real Diagnosis
1	29	Psoriasis	2	Psoriasis
2	45	Psoriasis	2	Psoriasis
3	33	Psoriasis	2	Psoriasis
4	19	Possible Psoriasis	1	Psoriasis
5	0	Regular	0	Regular
6	55	Severe Psoriasis	3	Psoriasis
7	39	Psoriasis	2	Psoriasis
8	1	Regular	0	Regular
9	23	Psoriasis	2	Psoriasis
10	43	Psoriasis	2	Psoriasis

have short-term events detected, we obtained a precision of 1, which is the maximum precision possible. We also have a recall of 1, having also 0 FalseNegatives, which is the maximum recall possible.

In the Atrial Fibrillation Patient test, reasoning with short-term events, following the algorithm for the atrial fibrillation discovery previously mentioned, we should consider as TruePositives results all the BPM values that are greater than 100. We cannot consider RR values as TruePositives, FalsePositives or FalseNegatives, because we use the Standard Deviation in order to detect AF. We should consider FalseNegatives all the BPM values that are smaller than 100. We do not have FalsePositives values at all. To sum up, also referring to Table 1, we have 5 TruePositives results, 0 FalseNegatives and 0 FalsePositives, thus obtaining a precision of 1, that is the maximum precision possible. We also get a recall of 1, having also 0 FalseNegatives.

In the Wolff-Parkinson-White Patient test, reasoning with short-term events, following the algorithm for the WPW discovery previously mentioned, we should consider as TruePositives results all the PR values that are smaller than 120 and all the QRS complexes that are greater than 120. We cannot consider QRS values as TruePositives, FalsePositives or FalseNegatives, because we use the Standard Deviation in order to detect WPW. We should consider FalseNegatives all the PR values that are greater than 120 and all the QRS complexes that are smaller than 120. We do not have FalsePositives values at all. To sum up, also referring to Table 2, we have 10 TruePositives results, 0 FalseNegatives and 0 FalsePositives, thus obtaining a precision of 1. We also get a recall of 1, having also 0 FalseNegatives.

In the Psoriasis test, reasoning with short-term events, following the algorithm for the Psoriasis discovery previously exposed, we should consider as TruePositives results all the events that have a machine-diagnosis of Psoriasis (Psoriasis, Severe Psoriasis) and the patient is currently affected by psoriasis. We should consider FalsePositives all the cases detected by the machine as Psoriasis (Psoriasis, Severe Psoriasis), but the patient has not psoriasis. We should consider FalseNegatives all the cases detected by the machine as Regular or Possible Psoriasis, but the patient does have Psoriasis. To sum up, also referring to Table 4, we have 7 TruePositives results, 1 FalseNegatives and 0 FalsePositives, thus obtaining a precision of 1. We

Table 5
All tests summary

	Healthy	Atrial	WPW	Psoriasis
True Positives	30	5	10	7
False Positives	0	0	0	0
False Negatives	0	0	0	1
Precision	1	1	1	1
Recall	1	1	1	0.875

have a recall of 0.875, having 1 FalseNegatives element, that is the row with ID 4 on the Table 4.

Eventually, In Table 5, we can see a brief summary of all our experiments, summarizing all the results of our tests, showing True Positives, False Positives, False Negatives, Precision and Recall for each test. All the tests obtained a precision of 1, indicating the maximum proportion of positive identifications is actually correct. Three out of four tests obtained a recall of 1, indicating that, for these three tests the maximum proportion of actual positives was identified correctly. For the other test, the Psoriasis detection one, we have a recall of 0.875, that, even being a high value, it is not the maximum value available, thus, we can improve our algorithm to obtain a higher recall value in the future.

4. Conclusion

In this paper, we have proposed an integrated framework aimed at actively supporting patient monitoring by exploiting an innovative combination of wearables, DALI intelligent agents and Complex Event Processing. Additionally, we also defined an effective image processing algorithm for psoriasis detection. Experiments conducted on real patients confirm the validity of the proposed approach.

The reader should notice that the health conditions and the case studies that we have discussed (all of them discussed with medical doctors) have been selected only to the aim to develop and test the system on solid ground. In the future, the system will be, again in concert with the doctors, extended in many ways. The intelligent agent will become able to cope with many other health issues; additional work will be also carried out to broaden the set of short-term and long-term events detectable via ISEQL. Addtionally, our Psoriasis detection algorithm will be able to automatically detect other skin diseases.

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