Emotional condition in the Health Smart Homes environment: emotion recognition using ensemble of classifiers

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Abstract—The fraction of elderly people in the population has increased significantly in most developed countries in recent years. Embedded computing enables the deployment of Health Smart Homes that can enhance nurses or caregivers to assist patients in need of timely help, and the implementation of this application can be extremely easy and cheap when aided by Internet of Things technologies. In addition, there are few studies that take into account the patient’s emotional state, which is crucial for them to be able to recover from a disease. This article discusses the use of images and emotional detection to assist patients and elderly people within an in-home healthcare context and sets out a model for the classification of emotions based on the facial expressions of the users. Finally, the results described in this article show that the Ensemble Classification that is put forward can achieve greater rates of accuracy, average of 82.53%, in classifying feelings than what can be obtained by using a single classifier.

Keywords—Internet of Things; Health Smart Homes; Emotions Classification; Facial Mapping; Human-Computer Interaction.

I. INTRODUCTION

The number of elderly people is large increasingly in several countries, highlighting countries in Europe, the USA, Japan and Brazil. These people tend to live alone and are prone to have more diseases than young people. In view of this, the use of Health Smart Homes (HSH) is extremely important [1], [2]. The concept of HSH has emerged from a combination of telemedicine, domotics products and information systems; it can be defined as a Smart Home that is equipped with specialized devices for remote healthcare. These devices are mainly sensors and actuators that can take action whenever a critical situation is detected. The aim is to allow the technology to be used to monitor patients and elderly people and issue alerts to nurses and/or relatives whenever necessary while they are recovering at home, in addition to providing some independence so that they can live their lives in a more self-reliant manner.

Apparently, most current and recent research focuses on improving the daily lives of patients by providing them with specific gadgets, such as alert alarms; however, it cannot recognize any type of emotional response which is a crucial factor during the treatment at home to determine the emotional health of an individual in turn, can be used as an important symptom for the diagnosis of various diseases [3]–[5] such as: schizophrenia, depression, autism and bipolar disorder. We highlight that the above mentioned diseases may be symptoms caused by the excessive time on negative emotions, lack of emotional expressions or the instability of expressed emotions [3]–[5]. In addition to the use of emotional health to diagnose diseases, emotional states can influence social interaction and also help us in making decisions/measures if he/she is stressed.

This paper offers an in-home healthcare solution by making use of images and facial expressions to monitor patients and elderly people that have special needs. Hence, this article proposes a solution to intelligently detects user emotions. In our approach, the emotional classification is carried out through the use of Machine Learning (ML) techniques, so that emotions can be detected and classified. Capturing facial expressions over a certain period of time can give an idea of to what extent the elderly/patient is feeling pain and can enable a nurse/relative to decide whether help is required or not. Similarly, the patients face can register his/her emotional state, which is also a crucial factor during the treatment. Emotion plays an important role in recovery from disease [6], [7]. The purpose of our approach is to detect any new feature in the house through the use of cameras and facial expressions. It should also be stressed that there is no need to have someone watching the whole video stream all day long as the detection of new features is carried out automatically without any human intervention.

While having a camera in the home raises problems about privacy, we believe these can be overcome since they can be turned off whenever a resident wishes. It should be noted that the use of cameras and image processing can be less intrusive as there is no need for people to be fitted with any special item (such as wireless-based emergency buttons) to ask for special help.

This article is structured as follows. Section II, there is a review of the literature with regard to the issues discussed
in this article and how these studies can be drawn on to form an emotion recognition and classification system in HSH. Section III examines some important concepts that are needed to understand the use of the face to identify emotions, we describe how the face mapping is performed, we set out the emotion classification module and our approach for monitoring emotional aspect in HSH. In Section IV, there is an assessment of the emotion classification system that was conducted to validate our approach. Finally, Section V concludes this work and some suggestions are made for future investigations.

II. RELATED WORK FOR HEALTH CARE CONSIDERING EMOTIONS

This section examines the advances made in HSH based on Internet of Things (IoT) technologies with a view to describing and explaining the main challenges of this research study. The authors of [8] review the emerging concept of Health “Smart” Home and picture potential applications of these systems, such as social alarm systems and remote monitoring. The paper also discusses prominent technologies that are being deployed and reports pilot projects of e-care systems already in use by hospitals and residences. The advances of in-home healthcare are also due to the application of Ambient Intelligence and Artificial Intelligence. The combination of modern sensing equipments, with advanced data processing techniques and wireless networks culminates in the creation of digital environments that improves the daily life of residents.

The study of [9] used cameras for improving the analysis of the environment, e.g. detecting possible hazardous situations, while providing a system that is non-intrusive. Different from this work that argues that the use of a camera-based approach enables the emotional state of the patients to be analyzed and can provide a non-intrusive system that is not heavily dependent on attached sensors, unlike most of the current solutions. The proposed solution differs from the other systems and introduces new features for treating patients.

The authors of [1] propose a wireless architecture for Personal Area Network (WPAN) that takes advantage of the benefits offered by an intelligent environment by using information from sensors. The system is based on image processing and can provide solutions that are integrated with other control devices. This enables the detection of movements and patterns of the activities of a resident, such as speed and direction. It should be noted, however, that no attempt is made to analyze the emotional state of the residents in order to assess the state of their health.

Another important work is being developed by the University of Florida’s Mobile and Pervasive Computing Laboratory, creating the Gator Tech Smart House (GTSH) [10], an experimental laboratory and a real environment aimed at validating smart home technologies and systems. The goal of GTSH is to create supportive environments, such as homes, that can help its residents and is able of mapping the physical world with remote monitoring and intervention services, conducting research and development activities designed to assist elderly and people with special needs in maximizing independence and maintaining a high quality of life. Similarly, researches from the Georgia Institute of Technology developed the Aware Home Research Initiative (AHRI) [11]. The Aware Home has enabled research in many areas, such as: provision of data to the house, innovative sensing and control infrastructure, and a variety of applications to assist residents. The health and well-being of residents is one area of research that has received significant efforts focusing on technologies that enable a better aging, and help caregivers of children with disabilities such as autism. The Aware Home is a residential laboratory and such studies have achieved satisfactory results enabling real residents to use the developed prototypes. However, in none of the two approaches, an attempt is made analyze the emotional state of the residents in order to assess the state of their health.

Table I summarizes the related literature is made providing the following comparison items to ensure that an overall view is given: (i) use of IoT sensors while monitoring patients/elderly people; (ii) adoption of image processing techniques as a way of monitoring people, and; (iii) employment of user’s emotions for identifying patient’s well-being.

<table>
<thead>
<tr>
<th>Related work references</th>
<th>Use of IoT sensors</th>
<th>Image processing</th>
<th>Consider emotions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Romero et al., 2009 [1]</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Augusto et al., 2007 [9]</td>
<td>X</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Helal et al., 2005 [10]</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Kientz et al., 2008 [11]</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Our system</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</table>

To the best of our knowledge, none of the proposals in the literature take into account the patient’s emotional side and hence they fail to exploit a considerable amount of “rich” information available in facial expressions and body language. This includes detecting pains and other emotional related issues, as depression and autism.

III. OUR SMART IN-HOME HEALTHCARE SYSTEM CONSIDERING EMOTIONS

This work adopts a generic approach to construct adaptive applications on computing devices, making use of facial expressions to monitor patients and elderly people that have special needs. Thus, this section we describe how the face mapping is performed by the image, we set out the emotion classification module based on ML algorithms and our approach for monitoring emotional aspect in the environment HSH.

A. Study of Emotions and Facial Mapping

Motor Expressions which are also known as Expressive Reactions are responsible for communicating the behavioral tendencies of an individual [12]–[15]. This emotional feature involves the changes in facial expression that register the emotional experience of the users.

Basic emotions are represented by distinct and universal facial expressions. The word universal suggests that the same
muscular movements are involved in carrying out facial expressions. Within the discrete models, the most widespread is [16], which states that there are the following basic emotions: joy, disgust, fear, a neutral state, anger, surprise and sadness - as can be seen in Fig. 1. All the other emotional categories can then be built on combinations of these basic emotions. The main advantage of using this model is that people tend to describe emotional demonstrations observed in their day-to-day life very similarly. Thus, these models facilitate the association of emotions with the facial expressions that represent them.

As shown by [17], the task of analyzing automatic facial expressions can be divided into three key stages: i) face detection, ii) facial feature extraction and iii) emotion classification. Face detection is a processing stage to automatically find the facial region on the input images. Detecting a face in a complex scene is a non-trivial problem: head movements, occlusion, changing the illumination settings, and the presence of hair or glasses, are examples of possible complications that can occur to the system [17]. After the face detection, it is possible to extract and represent the facial changes produced by expressions, because several types of perceptual cues to emotional states, are displayed in the face. The extraction approach for face identification and expression analysis adopted here, is based on geometric features. Methods based on geometric features are used in facial modelling (motor expressions) with a view to adopting an approach which resembles the way that human beings interpret the different parts of the face. Thus, the use of different facial representations (a neutral state, joy, disgust, sadness, fear, anger and surprise) is a recommended way for the identification and classification of feelings, since they are able to encode the facial configuration of the individual [12], [16], [18]. Thus, it is possible to model the shape and locations of facial components (including the mouth, eyes, eyebrows and nose) through the use of geometric elements such as angles, distances or areas used to represent the geometry of the face. The classification of facial expressions is the last stage where techniques based on ML are employed to tackle this problem.

In this paper, FaceTracker [19] is used for facial mapping, being a tool of computer vision that is used to obtain information about facial features. It uses an optimization strategy which employs a linear approximation by adjusting the reference points in consistent locations to record a model designed to work within fixed parameters; moreover, the algorithm seeks to align the elements of the face being analyzed with the feature points of the reference model. To reduce the computational cost while at the same time being able to classify emotions, we considered thirty-three important facial points that are crucial to this end [20]. Let us mention that this is supported by the theories of the psychologists [16]). As such, we considered i) eight points that map the mouth, ii) six for each individual eye, iii) three for each eyebrow; iv) three for the chin, v) two for the nostrils. We also considered vi) two for delineating the lateral extremities of the face near the eyes. Figure 2 provides an example of the mapping of a face carried out by FaceTracker that was used in our model.

To compute the number of features, we considered the distances between two distinct points and the angles made by the line connecting them with the horizontal axis. These are obtained at all possible combinations of the points. As a result, it creates a dimensionality representation of 1,130 features. These features are used for the training of our model for emotion classification.

B. Approach to classification of emotions

Despite their extensive use, the classifiers generated by means of ML methods rarely achieve a 100% degree of accuracy [21]. This is because the performance of each method depends on several parameter settings, how representative are the data from the training set and the degree of difficulty associated with particular problem. Selecting a single classifier involves rejecting a significant amount of potentially useful information. For this reason, the concept of Ensemble of Classifiers (EC) has been regarded as a possible solution for the development of high-performance systems in the area of pattern recognition [22]. This is based on the assumption that the combination of classifiers can lead to an improved performance in terms of generalization and/or increased accuracy.
The classifiers that compose an EC are assumed to be different from each other if they have uncorrelated errors. Thus, for an ensemble to achieve an acceptable performance, it must avoid making coincidence errors, so that the errors of a classifier can be corrected by the choices made by all the other components [21], [22]. For this reason, for our proposal classification techniques were used that have been increasingly employed to analyze the user’s emotional responses, such as:

- **k-Nearest Neighbor (kNN)** - The kNN, used in some studies [23], [24] is a non-parametric classification approach, which assumes no prior probability distribution for the data. The kNN algorithm is a set of k objects in the training set that are closer to the test object, and can be classified as the predominant class of its k-neighbors [25].

- **Support Vector Machine (SVM)** - The SVM algorithm used by [26]–[28] for emotion recognition is one of the most robust and accurate methods of the known algorithms. According to [25], the goal of SVM is to find the best function to distinguish two classes of training data. It ensures that the best function is achieved because it maximizes the margin between the classes by offering a better generalization ability [27], [28].

- **Logic Fuzzy** - Logic Fuzzy, which is adopted and used in [26], [29], is capable of processing incomplete data and providing approximate solutions to problems that other methods are not able to solve [29].

- **Decision or Regression Tree** - The Decision or Regression Tree applied by [23], [26] uses a tree to perform the classification or value estimation of a given test. One of the most well-known algorithms that generates these trees is C4.5. This algorithm grows the tree through a divide-conquer approach; the tree is branched by using the attribute that obtains the best information gain [30].

- **Bayesian Networks** - Bayesian Network is a probabilistic graph model, which was applied by [26], [27], [31] and represents a set of random variables and their conditional dependencies as a directed acyclic graph [25]. For example, a Bayesian network may represent the relationship between symptoms and diseases. Once the the symptoms are known, one can infer the probability of the outbreak of a disease.

On the basis of this assumption, Figure 3 shows the module structure for face which is classified by means of the EC approach. This model aims to use a facial mapping and, through a combination of response values of classification algorithms, identify and categorize the user’s emotion, so that computing systems can interact more assertively with the user’s emotional state.

The first processing layer (layer 1 of Figure 3) receives, as input, the results of the facial mapping. This layer consists of individual classifiers that may have different architectures, but outputs a common form, such as the ranking of candidate classes. The second processing layer (layer 2 of Figure 3) consists of a decision-making process which operates on the outputs of the previous layer to generate the general decision of the EC (see Figure 3). Equation 1 was used for the weighting process and assigned proportional weights for each algorithm in accordance with its rate of accuracy [20]. In the equation, $W$ is the weighted average of accuracy for each algorithm; $AR$ matches the average rate of accuracy for the algorithm. Thus, each algorithm will be assigned a weight that is proportional to its degree of accuracy.

$$Wx_i = \frac{ARx_i}{\sum_j ARx_j}$$  \hspace{1cm} (1)

**C. Generic Approach for Emotional Aspect**

With this in mind, a system called FlexEmotion was designed that is based on the OpenCom model [32], which has the following characteristics: i) a generic software constructing system; ii) flexible and extensible architecture; iii) it is a language-independent platform; iv) it is based on a microkernel, where the features are deployed whenever required.

*FlexEmotion* is a framework that supports the development of systems that are able to classify to the emotional state of the users during the interaction [32]. Figure 4 illustrates the FlexEmotion architecture, in which the microkernel entity loads and interconnects the components needed for the interaction with the user. In the case of this work, FlexEmotion instantiates and connects a camera (on the right of Figure 4), but it can also be used for other sensors, e.g. video, temperature or sound.
We propose a system based on the use of IoT for smart and individualized monitoring of elderly patients in their homes. Having as main features the scalability of its components and the ability to infer the emotions or feelings that patients experience (such as pain or the onset of depression).

The system is based on the Smart Architecture for In-Home Healthcare (SAHHc) [18], composed of two elements: (i) Sensors; and (ii) the Decision Maker. The sensor elements are devices distributed in the environment; they can be found in large numbers and their purpose is to collect information (for instance, capture images) on the patient’s health and send this to the Decision Maker element. Furthermore, the Decision Maker serves as an interface between the patient and the helper. Figure 5 shows the elements in a scenario where the proposed system is used.

Given the features of the environment where this type of application has to be implemented, all the devices must run on the power supply of the household and use battery as a backup source. In addition, it is assumed that the residence has an internal communication network that can be used by the system. Although wireless networks ensure that the system can be implemented with ease and mobility, a wired network can also be used. The structure consists of simple and dedicated devices that act as sensors and collect the information about the patient’s emotion. The sensor elements are able to detect the presence of people and also capture their images and the information is processed to classify the person’s facial characteristics and detect his/her emotional state. Figure 6 depicts the structure of the interactions between FlexEmotion and the user. This framework includes a recognition module, which extracts the user’s facial features, and the classification algorithm, that classifies an emotion based on the features processed in the identification of the user’s face.

**IV. EVALUATION AND DISCUSSION**

For training/evaluating our model, we used pictures of facial expressions with different emotions to assess the Ensemble of Classifiers; the databases used are Radboud Faces (RaFD) [33], Extended Cohn-Kanade (CK+) [34], IMPA-FACE3D [35] and FACES [36], all with open access to the public. The RaFD database provides examples of the facial expressions of 67 participants (adults and children, male and female), of American and Moroccan nationality. CK+ database only has facial expressions of adults, 69% female and 31% male, 81% are Europeans or Americans, 13% African-Americans and 6% belong to other ethnic groups. CK+ has 593 facial expressions of 123 different participants. IMPA-FACE3D database includes pictures of 38 individuals, with samples of the six universal facial expressions and neutral expression. It consists of 22 men and 16 women, most aged between 20 and 50. Finally, the FACES database consists of images of the faces of 171 subjects, 58 young, 56 middle-aged and 56 elderly men and women, showing each of the seven facial expressions analyzed in this work.

Only the subsets of these databases are used in the experiments. We selected all the images in which the participants were facing forward and expressing the following emotions: joy, disgust, fear, anger, surprise, sadness or in a neutral state. Thus, 67 examples of each emotion are obtained from the RaFD database, 38 from IMPA-FACE3D and 171 from FACES, including children, adults and elderly people. The selected subset from the CK+ database, includes all the existing expressions from the different participants, for each of the evaluated facial expressions. Thus, we used a total of 3,115 images in our experiment, divided into 445 images for each emotion group, to achieve an optimal balance between the training images used for the tests. It is worth noting that the combination of the selected images, provided a set of heterogeneous tests, consisting of images from different regions and a model that can be applied to any computing device regardless of the ethnicity of the individual who uses it.

Our approach used the WEKA Framework [37] to facilitate the implementation of the selected algorithms. This is widely employed by researchers in the area of ML and Data Mining. This framework is also suitable for the development of new ML systems [37]. Table II shows the parameters used for the individual tests as well as for the development of the proposed Ensemble model.

In this context, we implemented the algorithms to assess the accuracy of the classification module. As mentioned earlier, the approach were adopted to set the weights that make up the EC: weighted average. As a result, we were able to collect data on the behavior and evaluation of the classification module as
TABLE II
PARAMETERS USED IN THE SELECTED CLASSIFIERS OF WEKA.

<table>
<thead>
<tr>
<th>Implementation</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bayesian (NaiveBayes)</td>
<td>displayModelInOldFormat = false, useKernelEstimator = false, useSupervisedDiscretization = false</td>
</tr>
<tr>
<td>Decision Tree (J48)</td>
<td>binarySplits = false, collapseTree = true, confidenceFactor = 0.25, debug = false, minNumObj = 2, reducedErrorPruning = false, numFolds = 3, saveInstanceData = false, seed = 1, subtreeRaising = true, unpruned = false, useLaplace = false, useMDLcorrection = true</td>
</tr>
<tr>
<td>Fuzzy (FuzzyNN)</td>
<td>KNN = 10, debug = false, fuzzifier = 3.0, similarity = SimilarityFNN -R first-last -T weka.fuzzy.tnorm.TNormLukasiewicz -C 0.0</td>
</tr>
<tr>
<td>kNN (IBk)</td>
<td>KNN = 1, crossValidate = false, debug = false, distanceWeighting = No distance weighting, nearestNeighbourSearchAlgorithm = LinearNNSearch -A “weka.core.EuclideanDistance -R first-last”, meanSquared = false, windowSize = 0</td>
</tr>
<tr>
<td>SVM (SMO)</td>
<td>buildLogisticModels = false, c = 1.0, checksTurnedOff = false, debug = false, filterType = Normalize training data, kernel = PolyKernel -C 250007 -E 1.0, numFolds = -1, randomSeed = 1, epsilon = 1.0E-12, toleranceParameter = 0.001</td>
</tr>
</tbody>
</table>

A. Evaluation of the Emotion Classification

Initially, we analyzed the performance of the algorithms separately through the Experimental Planning and Evaluation technique; in this case, we employed k-fold cross-validation with $k = 10$, with $k - 1$ for training and the rest for testing. Thus, it is possible to measure error estimation more accurately, as the mean value tends to the true zero error rate as $n$ increases, which is generally the case with small example sets. In this way, it was possible to obtain the average rate of accuracy for each algorithm, which was used for weighting the final decision for EC.

The results demonstrated that the EC provides a more precise classification than the use of individual classifiers. This can be seen in Figure 7, which shows Boxplots for each type of classifier employed. The right-hand box plot refers to the results of the EC and displays a higher median accuracy than the other classifiers (the median values can be seen in Table III). Moreover, a smaller dispersion of the results obtained by the EC can be detected, which shows a greater stability in its execution. This is noticeable from the interquartile range of the Boxplot.

We conducted a few statistical analyses to validate the results. Initially, we used the Shapiro-Wilk method to check their suitability for normality hypothesis and hence, this led to parametric or non-parametric tests. As not all the $p$-values obtained are greater than 0.05 (see Table III), we rejected the normality hypothesis with 95% reliability. This means that the non-parametric test is the most suitable for the next analysis.

The pairwise comparisons made with the aid of the Wilcoxon Rank Sum test are shown in Table IV. The $p$-values obtained by means of the Wilcoxon technique indicate that Naive Bayes classifiers, J48, FuzzyNN and IBk do not show a statistically significant difference in the rating of emotions. However, the classification performed by SMO (in addition to the higher accuracy shown in Figure 7) shows a statistically significant difference from the other individual classifiers. Finally, it is clear that the results obtained with the EC have a statistically significant difference from all the other individual classifiers.

These results demonstrate that, of all the individual classifiers employed, SMO is the technique that achieves the greatest accuracy in emotion rating. However, it is outperformed when the Ensemble of Classifiers is used, since this approach...
achieves a greater degree of accuracy than the others, which is evidence of its efficiency in identifying emotions. Finally, Figure 8 shows the error matrix, also known as the confusion matrix, in which the columns represent the reference data, while the rows represent the classification generated by the EC.

<table>
<thead>
<tr>
<th>Class</th>
<th>TP Rate</th>
<th>FP Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Happy</td>
<td>0.957</td>
<td>0.012</td>
</tr>
<tr>
<td>Disgust</td>
<td>0.822</td>
<td>0.029</td>
</tr>
<tr>
<td>Fear</td>
<td>0.764</td>
<td>0.028</td>
</tr>
<tr>
<td>Neutral</td>
<td>0.732</td>
<td>0.038</td>
</tr>
<tr>
<td>Anger</td>
<td>0.701</td>
<td>0.028</td>
</tr>
<tr>
<td>Surprise</td>
<td>0.950</td>
<td>0.008</td>
</tr>
<tr>
<td>Sad</td>
<td>0.710</td>
<td>0.048</td>
</tr>
</tbody>
</table>

It is worth noting that the model based on the Ensemble provides a better classification of the emotions “Joy”, “Disgust” and “Surprise”. However, despite achieving a lower degree of accuracy than the other emotions, the Ensemble model classifies the other emotions as having the lower computational cost, and the model has a better rate of accuracy for classification than the models that are based on individual classifiers.

V. CONCLUSION

According to psychologists, emotions play a crucial role while a patient is trying to recover from a wide range of diseases. Hence, we believe that this is an important feature to measure while monitoring patients. As a result, we adopted an approach that took into consideration all these features and conducted experiments to validate the whole idea in terms of performance, accuracy and statistical analysis.

This paper discussed the use of images and emotions for helping the healthcare in smart home environments in an automatic way through an IoT infrastructure (i.e. without the need for human intervention to detect new features). We made use of images to identify the emotional state of each person. The rate of accuracy was around 82% and there was a good convergence obtained through our proposed Ensemble model.

As future research in this area, we plan to explore evolutionary mechanisms to ensure that the classification algorithms of facial expression can make progress while taking into account advances in the treatment of certain ailments like Parkinson disease. This can be again a good challenge for our model as it will require processing cycles and communications along with evolutionary approaches in a heterogeneous environment. Furthermore, it is worthwhile to mention that we plan to improve our emotion recognition system by taking into account different components, such as voice analysis and home environment.

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