ISSN 2007-9737

Automatic Detection of Social Isolation Based on Human Behavior Analysis

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Abstract. Social isolation is a problem that is accentuated in the stage of old age. This condition puts the physical and mental integrity of older adults at risk. This paper presents a predictive model for the automatic detection of social isolation in older adults. The predictive model was implemented in a mobile application that monitors communication and mobility activities performed by an older adult. The mobile application was also generated for a caregiver who is responsible for receiving notifications about the specific level of social isolation of the older adult. The predictive model was evaluated using an experimental group of older adults.

Keywords. Older adult, social isolation, predictive model, mobile application.

1 Introduction

At the present time, growth in the number of older persons is a global phenomenon: it is expected that between 2017 and 2050, virtually every country in the world will experience a substantial increase in the size of the population aged 60 years or over [1]. This has led to greater attention being paid to the particular needs of the elderly and the problems faced by many of them.

The United Nations Organization (UN) establishes the age of 60 for considering that a person is an older adult. This criterion is used by the National Institute of Older Adults and other instances such as the Ministry of Health in Mexico, such as the National Women's Institute [2].

The aging of society has aroused the interest of health institutions and related areas to improve the well-being of older adults. In this context, finding effective ways to provide care for older adults has become one of the greatest challenges for the scientific community [3].

Social isolation is defined as the lack of contact and interaction with others [4]. Social isolation is one of the issues that are exacerbated in older adults due to factors such as labor retirement, children living in different places, or loss of a spouse. An early diagnosis of this condition significantly reduces the risk of depression, cognitive impairment, decreased food intake, reduced physical exercise, or impoverishment of the social network [5]. This risk underscores the importance of knowing at all times when an older adult stop socializing in order to carry out interventions that allow him/her to overcome this condition and be kept in a socially active state.

Currently, there are several psychological instruments, called scales, which assess the level of social isolation in older adults. Some of these psychological instruments are: a) the Friendship Scale, which consists of six Likert questions about perceived social support from family and friends [6]; b) the, which identifies social support satisfaction, social participation, and material aid [7]; c) the Inventory of Socially Supportive Behaviors, which assesses instrumental, informational and social support [8], and d) the Lubben Social Network Scale, which measures the social support felt from friends and family in older adults. These instruments share the common objective of assessing the level of social isolation with diagnose s based on sets of questions from the social support felt [9].

Unfortunately, the application of these instruments is tedious because older adults need to go to assistance centers or specialized professionals in order to be assessed. This has motivated the development of novel approaches that enable the automatic monitoring of significant changes in their social interactions and that also generate alerts or notifications for relatives to provide support to the older adult.

The aim of this paper is to present the implementation of a predictive model that permits the automatic detection of the level of social isolation in older adults. To achieve this objective, a software application was developed that monitors the daily activities of an older adult, which are mapped with the predictive model that is defined in this research work. The software application allows family members, friends, or caregivers of the elderly to be informed when the older adult presents a pattern of isolation based on the predictive model.

The paper is structured as follows: Section 2 describes the background and related works of this research. Section 3 presents an overview of the proposed solution. Section 4 presents our predictive model for automatically detecting social isolation. Section 5 presents the results obtained from the tests applied to an experimental group. Finally, Section 6 presents the conclusions and future work.

2 Background and Related Work

This section presents works that are closely related to the research presented in this paper. In works of [3], a statistical analysis was performed to identify social interaction activities that have a statistically significant correlation with the degree of social isolation of an older adult. The main difference between our previous work and the research presented in this paper is that, in [3], we only focused on the statistical analysis, and, in this work, we address the predictive model, its implementation, and the evaluation of the predictive model proposed in this work, we address the predictive model, its implementation, and the evaluation of the predictive model proposed in a software application, which automatically collects the relevant attributes for the predictive model.

The framework presented by Tang [10] introduces a human-friendly partner that is able to have natural communication with elderly people using relevance theory. According to the results of the research work, elderly people can check their living conditions using a visualization system that is built by using life-log data in an information structured space. This information can also be shared and used by the elderly person’s family and caregivers as a remote monitor. The objective of the system is to determine unusual life patterns or unusual behavior of elderly people in order to provide immediate assistance. That research work is therefore focused on determining general daily activities, while our research work is centered on social isolation.

The research work of Castillo & Fernandez [11] proposes a gerontechnological framework, which enables real-time and continuous monitoring of the emotional states of an older adult. Based on the detected emotion, an action can be performed to be able to change the emotional state of that older adult. The framework recognizes emotions through physiological signals, facial expression, and voice. In contrast to our proposed approach, which analyzes communication, mobility, and demographic variables, that research work is focused only on communication.

In the work of Rodriguez [12], a system that is based on mobile technology is presented. It is focused on sup- porting the relationship between older adults living alone in Mexico and their relatives living abroad. The system proposes a communications system that allows elderly people to maintain close social ties by sharing information, personal reminiscences, and stories. This work can complement our proposed approach in order to provide support to the elderly when social

ISSN 2007-9737

isolation is detected.In the works of Dasgupta [13], a mobile platform for elder care was developed that permits daily to be tracked and that provides support to daily activities, such as social engagement and medication scheduling.

In the works of Ten [14], an indoor monitoring system for the elderly was developed that uses a Fitbit Flex wristband and active RFID to determine areas with activity. In that research work, the activity level of the elderly is evaluated via a dissimilarity measurement by using an activity density map with a high level of accuracy. Finally, in the works of Silva [15], a framework for assisting elderly people was developed that has the following components: a) a fall detection mobile application; b) a biofeedback monitoring system through wearable sensors; c) an outdoor location service through a shoe equipped with a Global Positioning System (GPS); and d) a mobile application for caregivers who take care of several older adults confined to a home environment.

In all of the studies presented in the related work section, the authors emphasize the importance of addressing the management of chronic diseases and the maintenance of the physical and mental health of the elderly. The differences with our approach are the types of variables that are used to monitor the activity of the older adult, the automatic approach used to obtain activity data about the older adult using smartphones and sensors, and the use of medical scales, such as: friendship Scale [6], Social Support Questionnaire [7], the Inventory of Socially Supportive Behaviors [8], The Medical Outcomes Study Social Support Survey [16], Lubben Social Network Scale [9]. on which to base the prediction of the isolation level.

3 Overview of the Proposed Solution

In this section, we present an overview of the proposed solution for the implementation of a predictive model for the automatic detection of social isolation in elderly people. Figure 1**¡Error! No se encuentra el origen de la referencia.** presents an overview of the proposed solution, which includes four steps for building the proposed predictive model. This model was implemented in two applications: The Older Adults app and Caregivers app.

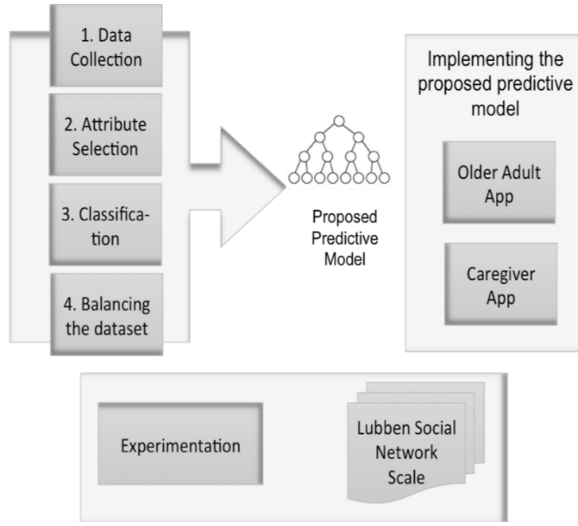

Fig. 1. Overview of the proposed solution

In addition, a phase of experimentation was carried out to evaluate our proposed predictive model.

This information was the input for the process to obtain a predictive model to determine social isolation in elderly people. The predictive model allows the behavior of older adults to be analyzed in order to determine their level of social isolation. The evaluation phase consisted of a protocol to evaluate (in practice) the proposed model with real older people in Mexico. The evaluation of social isolation was compared with the results of a clinical test for isolation.

4 Proposed Predictive Model for Detecting Social Isolation

In this research work, a predictive model examines the behavior of a set of individuals and determines the behavior pattern using a model allocating the individuals into classes in order to predict the class to which a new individual will belong based on his/her behavior pattern. In this sense, a predictive model examines an attribute set and produces an outcome class. Our research work focuses on identifying attributes that have a correlation with social isolation. These attributes correspond to social activities performed by older adults.

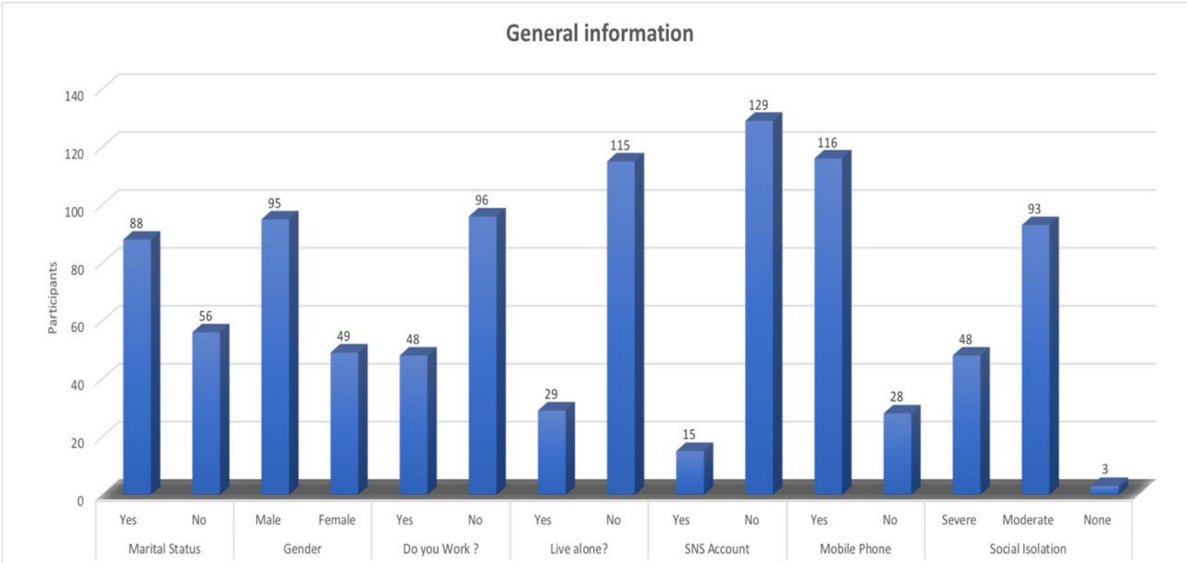

Fig. 2. Summary of the sample´s general information

The creation of the predictive model is composed of the following stages: the data collection process, the selection of relevant attributes, the classification of the attributes, and the generation of the proposed predictive model.

4.1 Data Collection

The data collection consisted of carrying out a non-probability sampling through a questionnaire that was applied to 144 older adults. The sample included both men and women between 60 and 89 years of age (68.2 ±8.9) with full physical and cognitive abilities, without mobility impairment, who own a mobile phone and have the ability to use it to make calls or send text messages. In addition, these subjects had no difficulty understanding the questions, and they signed an informed consent form indicating that they were willing to take part in the research.

The older adults were surveyed about their social interactions over the last 30 days. The sample was collected in the city of Cuernavaca, Mexico. The interviews took place in public parks and malls. The questionnaire is comprised of two parts. The first one is the Spanish version of the Lubben Social Network Scale (LSNS-6) [9], which was used to determine the level of social isolation of older adults. The second part of the questionnaire collected data concerning demographic information as well as social interaction activities. The questions formulated by the LSNS-6 request information about the frequency of social interactions during one month prior to the interview, which is often difficult to remember accurately.

Figure 2 shows a summary of the sample's general information. This chart shows 48 severe cases of social isolation, 93 moderate cases of isolation, and 3 cases where no social isolation was detected.

4.2 Attribute Selection

Attribute selection is the process of identifying and removing irrelevant and redundant information. Most machine-learning algorithms were designed to identify the most appropriate attributes for classification. Decision-tree methods choose the most promising attribute to split at each point and should, in theory, never select irrelevant or unhelpful attributes [17]. In order to obtain the first subset of relevant attributes, the J48 classification algorithm was applied to the full dataset. Then, the subset obtained was assessed using Chi-Squared and InfoGain methods [18] with the Ranker method for the corresponding evaluation of attributes.

ISSN 2007-9737

Table 1. Relevant variables

Interaction Type	**Relevant Variables**
Communication	Average incoming calls from family (Min.)
	Average duration of incoming calls from family (Min.)
	Average incoming calls from friends
	Average duration of outgoing calls to family (Min.).
	Average outgoing messages sent to friends.
	Average incoming messages received from family.
Mobility	Average time in the bedroom (Hrs.).
	Average time in the living room (Hrs.).
	Average time in the dining room (Hrs.).
	Average time in the garden (Hrs.).
	Average time in other areas in home (Hrs.).
	Number of places visited
Demographic	Gender

The correlation-based Feature Selection method was used with BestFirst and Greedy Stepwise [19] for the evaluation of the sets of attributes. All of the tests were performed with 10-fold cross validation ten times as the standard evaluation technique [17]. The detected relevant variables were grouped into three groups: communication, mobility, and demographic variables (Table 1).

The first group of variables was obtained from the older adult´s communication using her/his mobile phone: the number of incoming family calls, the average duration of incoming family calls (Min.), the number of incoming calls from friends, average duration of outgoing calls to the family (Min.), the number of messages sent to friends, and the number of messages received from the family.

The second group is oriented to the mobility of older adults inside and outside of their home: the number of places where older adults stay during the day, and the time they stay in each area of the home. Finally, the third group uses gender as a demographic variable that is relevant in determining social isolation.

Table 1 shows a summary of social interaction activities grouped by technological resources and the location where the activity is performed. Previous studies have demonstrated that these groups of activities are highly correlated with subjective social isolation (loneliness), for instance, time spent at home [15], time spent away home [20], and communication through mobile phones [21]. For this reason, such activities were considered as the attribute set for the development of the predictive model.

4.3 Classification

In order to develop the most suitable model for predicting social isolation, a range of classifier algorithms were assessed [22]. This process was carried out using WEKA [23]. The ZeroR (ZR) algorithm was used as a baseline. The other classifier algorithms used were NaiveBayes (NB), Simple Logistic (SL), Support Vector Machine (SVM), kNearest-Neighbor (kNN), AdaBoost (AB), OneR (OR), J48, and SimpleCart (SC). The stratified ten times ten-fold cross-validation technique was used because it is the standard evaluation technique in situations where only limited data is available in (Witten et all, 2011).

4.4 Balancing the Dataset

The data provided by the surveys needs to be balanced; therefore, the synthetic minority oversampling technique SMOTE [24], [25], which

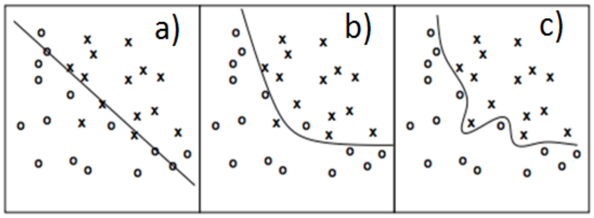

Fig. 3. a) underfitting, b) correct learning, c) overfitting

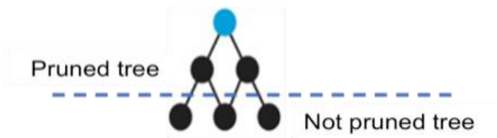

Fig. 4. Pruned and not pruned decision tree

Table 2. Dataset before and after applying balancing

Risk of social isolation	Low	Medium	High	Total
Before applying SMOTE	3	93	48	144
After applying SMOTE	192	186	192	570

is included in the WEKA data mining tool was applied to balance the data of three categories. A set of data is unbalanced if the classification categories are not represented equally.

The unbalance among categories could have an impact on the classification, generating algorithms that better predict the classes with larger datasets.

SMOTE is a statistical technique that is used to increase the number of cases in the data set in a balanced manner, generating new instances from existing cases that are provided as input. The new instances are created by taking samples of the characteristic space for each Class of destination and their closest neighbors and generating new examples that combine characteristics of the destination case with characteristics of its neighbors [24]. Table 2 shows the dataset before and after applying SMOTE.

4.5 Resultant Predictive Model

Overfitting is the effect of overtraining a learning algorithm with data where the results are well known. The learning algorithm must reach a state in which it is able to predict the expected result using the training data as the basis for solving situations that are different from those defined in the training data.

However, when a system is overtrained the learning algorithm has poor predictive performance. Overfitting occurs when a model begins to "memorize" training data rather than "learning" to generalize from a trend. Figure 3 shows the different types of machine learning levels.

The predictive model for social isolation is based on a decision tree. Therefore, to avoid overfitting, the tree is pruned to eliminate leaves of the tree (Figure 4).

The binary tree must be the representation generated by the WEKA application, which is used to guide the automatic detection of social isolation.

We have found a match between the average value of the data from the survey and the average values obtained from the algorithm with the training data. The average of the values for each of the attributes is obtained from the training data (144 records of surveys) that are introduced as the input of WEKA. For example, 192.82 is the average value of the number of incoming calls from family, and this value indicates which branch of the tree must be followed based on the real data obtained for the mobile application. Figure 5 presents the pseudocode of the proposed predictive model.

4.6 Implementing the Proposed Predictive Model

The predictive model for detecting social isolation in older adults proposed in this research was implemented in a software application that considers the data collection regarding activities of the elderly and the monitoring of the level of social isolation based on the predictive model.

We implemented the predictive model in a smartphone that allows the values of the relevant variables of older adults to be collected.

The mobile app of the older adult is responsible for obtaining the resources of the smartphone, and the sensors embedded in the home are responsible for capturing relevant variables, such as communication patterns, average times in different areas in the house/outside the house, etc. (Table 1). As a result, the app determines the level

ISSN 2007-9737

Pseudocode of predictive model proposal

```
if Average incoming calls from family > 192.82
  then Level of social isolation == NULL
    if not if Average incoming calls from family <= 192.82 then
      if Average incoming calls from friends <= 7.37
        if Average time in the living room (Hrs.) <= 114.34
          If Average time in other area in the home (Hrs.). <=0
        If number of places visited <=3
          If Average outgoing messages sent to friends <= 0.01
            if Average duration of incoming calls from family (Min.) <= 28.54
              If Average incoming calls from friends <= 0.21
                If Gender == Male
                  If Average duration of outgoing calls to family (Min.) <= 0.43
                    If Average incoming calls from family <= 0.05
                      then level of social isolation == Low
                    if not then level of social isolation == Low
                  If not level of social isolation == High
                If not then level of social isolation == Low
                if not Gender == Female
                  if Number of places visited <= 1.49
                    then level of social isolation == High
                      If not level of social isolation == Low
                        If not then level of social isolation == High
                          If not Average duration of incoming calls from family (Min.) >28.54
                if not Gender == Male
                  If Average timein the garden (Hrs.) >= 65.88
                    then level of social isolation == Low
                  If not
                    then level of social isolation == High
                      If Gender == Female
                        If Average timein the garden (Hrs.) >=21.85
                          If Average time in dinning room (Hrs.) <=60
                            then level social isolation == High
                          if not then level of social isolation == Low
                      If not level of social isolation == Low
                    If not if average incoming calls from family (Min.) <= 1287.21
                  then level social isolation == High
                if not
              then Level social isolation == High
            If not
              then level social isolation == Low
          If not if Number of places visited <= 1.60
            If Average time in the dinning room hrs. <= 1.20
              then level social isolation == High
            If not Average incoming calls from family (Min.) <= 202.29
              then Level of social isolation == Low
        If not Level of social isolation == High
    If not average outgoing messages sentto friends <= 0.003
        then Level of social isolation == High
  If not average incoming calls from family (Min.) <= 80
        then Level social isolation == Low
    If not Level of social isolation = High
        if not
          then level of social isolation == Low
            If not If average outgoing messages sento to friends <= 0.037
              If average time in the bedroom (hrs.) <= 72.46
                then level of social isolation == Low
              If not if average time in the bedroom (Hrs.) <= 104.64
                then level of social isolation == High
              If not
                then level of social isolation == Low
            If not if average timein the living room (Hrs.) <= 32.67
          If average incoming calls from family (Min.) <= 120
        If Average time in the living room (Hrs.). <=4.21
          then level of social isolation == Low
```

Fig. 5. Pseudocode of the predictive model

of social isolation establishing the relation of data captured from the smartphone and the patterns determined in the predictive model.

The app will be used to help the caregiver provide support to the older adult in risk situations.

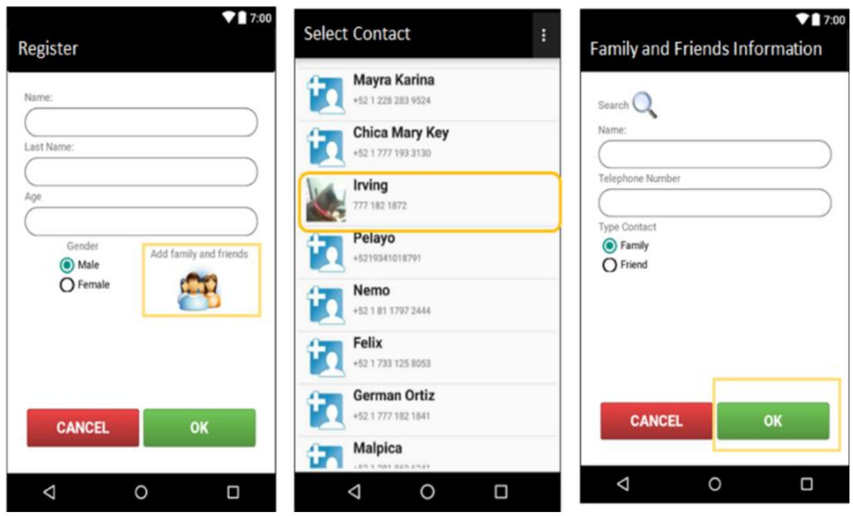

Fig. 6. Screenshot of: (a) register an Adult older; (b) register contacts; (c) register relatives and friends. The only intervention of the older adult with the software app was made at this point, when they used the app interface to register their data and information about their smartphone contacts, indicating their contacts with family and friends

Four main modules compose the smartphone application:

– The Registration Module: This module requests demographic information from the older adult, such as age, gender and name. The configuration module allows the user to manually indicates the phone numbers of family members and friends that the user older usually contacts using the smartphone. The smartphone app contains a window showing if the contacts entered into the app are family members or friends. The step takes approximately 5 minutes.

– Message Retrieval Module: This module retrieves the information of messages from the smartphone of the older adult. The relevant variables that are extracted in this module are: outgoing messages sent to friends, and incoming messages received from family.

– The Call Pickup Module: This module retrieves information of calls from the older adult's smartphone. The relevant variables that are obtained in this module are: average incoming calls from family, average duration of incoming calls from family (Min.), average incoming calls from friends, average duration of outgoing calls to family (Min.).

– The Home Monitoring Module: This module captures information on the amount of time (measured in hours) that the older adult stays in each area of his/her house. The relevant variables that are obtained from this module are: average time in the bedroom (Hrs.), average time in the living room (Hrs.), Average time in the dining room (Hrs.), average time in the garden (Hrs.), average time in other areas at home (Hrs.). We used Bluetooth devices, called Beacons, to obtain this information automatically.

Following, the functionalities of the app of the older adult are presented in Figure 6.The app provides a specific interface (Figure 6a) to register the data of the older adult, an interface to select the contact numbers (Figure 6b) and an interface to register whether a contact is a relative or a friend (Figure 6c). The application also offers an interface to present the results of the monitoring activity.

4.7 Experimentation

In order to evaluate our proposed predictive model, an experiment was conducted with real data from elderly people in Mexico. A comparison of the model's results with the real condition of the older adults was carried out.

ISSN 2007-9737

Table 3. List of activities of the participants

Demographic variable		Communicates variables						Mobility variables						
Gender	*Age*	*Average incoming calls from family*	*Average duration of incoming calls from family (Min.)*	*Average incoming calls from friends,*	*Average duration of outgoing calls to family (Min.).*	*Outgoing messages sent to friends.*	*Incoming messages received from family*	*Average time in the bedroom (Hrs.)*	*Average time in the living room (Hrs.)*	*Average time in the dinning room (Hrs.)*	*Average time in the garden (Hrs.)*	*Average time in another area in the home (Hrs.)*	*Number of places visited*	**Level of social isolation**
Female	74	128	256	64	40	0	0	182	111.87	150.40	36.80	149.80	84	Low
Male	75	4	120	24	24	0	0	410.8	60.20	177.27	44.13	1.47	156	Low
Female	67	12	60	64	24	0	0	364.93	68.20	21.47	1.93	0.00	100	Low
Female	68	20	260	44	0	68	48	48.25	0.72	7.20	0.65	3.92	164	Low
Female	60	8	12	4	20	0	0	601.04	24.80	36.80	12.56	129.80	4	High
Male	69	56	560	4	0	0	0	275.07	79.33	36.27	63.33	242.27	8	High
Female	70	24	270	16	48	12	32	214.4	53.93	8.27	109.27	57.40	64	Low

The participants of the experiment: 7 older adults (5 women and 2 men) composed the experimental group. The participants had the following profile: (i) 60 years old and older; (ii) older adults without cognitive and motor issues, and (iii) older adults using a smartphone. These older adults were between 60 and 74 years old.

Data Collection: Participants' mobile phones, beacon information, and printed forms were used to collect the information for the evaluation.

The procedure of the experiment: First, the participants were asked to sign the informed consent form where they agreed to participate in the experiment. The monitoring apps were installed on their smartphones.

The user usually spent 5-6 minutes to complete the registration. In addition, a set of presence sensors (beacons) was installed in different areas at the participants' homes, later on the daily activities of each participant were monitored for one week. In order to obtain the data, the older adults needed to carry the smartphone during their normal daily activities in the evaluation period.

No further interventions were needed between the older adult and the software app because the activity monitoring was performed automatically by the app taking the information directly from the smartphone resources.

The objective of the sensors was to determine the amount of time that the older adults spent in each home area, which is information that is very relevant to the prediction model. It is important to point out that the participants were notified that the sensors used did not register audio or video.

In the data collection phase, a set of checkpoints was considered by the person responsible for carrying out the evaluation: The sensors (Beacons) were installed in the following rooms: the bedroom, living room, dining room, garden and other home areas such as the studio, garage, kitchen, and cellar. Each sensor was labeled with the name of the room in which the sensor was installed. To avoid signal interference from the Beacons, the sensors were placed more than two meters apart from each other.

The participants were given recommendations about the use of the smartphone. The first recommendation for them was that they needed to use the smartphone in all daily activities, and, at the end of the day, they needed to connect the smartphone to a power source so that the device was ready to collect information the next day.

4.8 Applying the Lubben Social Network

The Lubben Social Network Scale [9] was used as a psychological instrument in order to obtain the social isolation level of the older adult. This scale has 6 Likert-type questions with a score range of 0 to 30, where a score of 30 points indicates the absence of social isolation, a score of 12 points or more indicates a low risk of social isolation, and a score of less than 12 points indicates a high risk of social isolation

ISSN 2007-9737

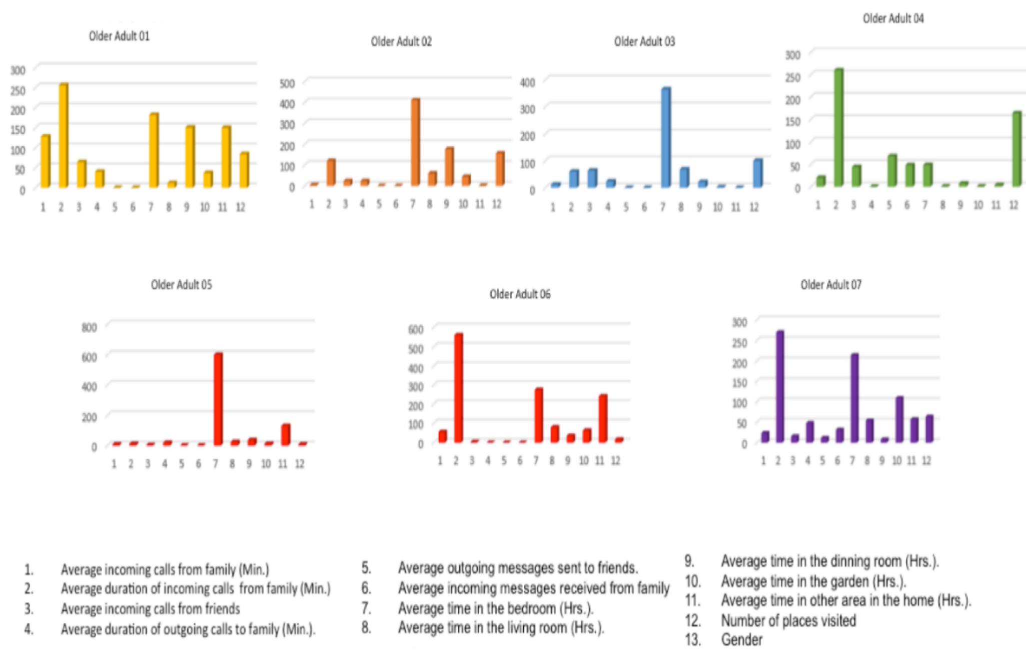

Fig. 7. List of activities of each participant of the experimental group

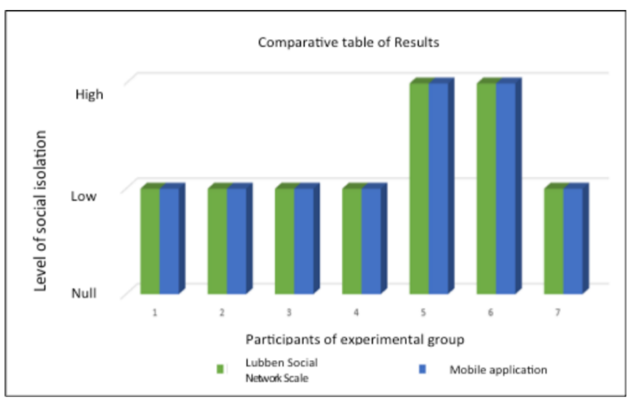

Fig. 8: List of activities of each participant of the experimental group

In addition, this scale has a Spanish version, which was suitable for the profile of the study group. In this phase, after the monitoring, the Lubben Social Network Scale was applied to the experimental group to obtain the level of social isolation.

5 Results of the Experimentation

The tests carried out on the experimental group (7 older adults) consisted of two phases: 1) monitoring the activities of the older adults through a smartphone, and 2) applying the Lubben scale to the data captured by the sensors and the smartphone. The results of the first phase were compared with the results indicated by the Lubben Social Network Scale in the second phase.

As stated above, each participant was evaluated for one week. All of the levels of social isolation detected by our mobile application were the same as the results obtained by the Lubben Social Network Scale. Therefore, the precision of our predictive model in these tests was 100%.

This means that the social isolation detection model implemented in the mobile application correctly classified seven of the seven participants belonging to the experimental group (see Figure 8).

6 Conclusions and Future Work

The population of older adults is constantly increasing. Statistical prediction indicates that in 2050 approximately one quarter of the Mexican population will be older adults, increasing the demand for medical services that are related to physical and mental health. This emphasizes the importance of social, family, and health support systems.

A timely diagnosis of social isolation in elderly people can significantly reduce the risk of depression or cognitive impairment in this specific segment of the population. This situation motivates the development of computer systems that can be able to identify automatically situations of risk in the social interactions of older adults.

In this research, a social isolation detection model was implemented. We developed a mobile application that automatically detects the level of social isolation of an older adult. A mobile application was also developed so that the caregiver of the older adult can be informed of the degree of social isolation that the older adult is having.

The initial evaluation of the proposed approach with seven older adults has shown that the implementation of the system is 100% accurate in determining social isolation.

However, more extensive evaluations need to be implemented to determine the effectiveness of the approach with precision.

Acknowledgments

The research work presented in the paper has been funded by the institutions participants in the research work: TECNM/CENIDET, Tecnologico de Monterrey and TECNM/I.T.Chilpancingo.

References

1. **United Nations. (2017)**. *World Population Ageing*. https://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2017_Highlights.pdf
2. **National Women's Institute. (2015).** *Situation of the elderly in Mexico.* http://cedoc.inmujeres.gob.mx/documentos_download/101243_1.pdf .
3. **Martinez, A. & Campos, W. (2015)**. Correlation between social interaction activities registered with new technologies and level of social isolation in older adults in Spanish. *Biomedical Engineering Mexican Journal*, Vol. 36, No. 3, pp. 181–190.
4. **Townsend, P. (1955)**. The family life of old people: an investigation in east London. *The Sociological Review*, Vol. 3, No. 2, pp. 175–195. DOI:10.1111/j.1467-954X.1955.tb01052.x.
5. **Cornwell, E.Y. & Waite, L.J. (2009)**. Measuring Social Isolation Among Older Adults Using Multiple Indicators From the NSHAP Study. *Journals of Gerontology*, Vol. 64B, pp. i38-i46. DOI:10.1093/geronb/gbp037.
6. **Hawthorne, G. (2006)**. Measuring Social Isolation in Older Adults: Development and Initial Validation of the Friendship Scale. *Social Indicators Research*, 77(3), pp. 521−548. DOI:10.1007/s11205-005-7746-y.
7. **Sarason, I., Levine H., Basham R., & Sarason, B. (1983)**. Assessing social support: the social support questionnaire. *Journal of Personality and Social Psychology*, Vol. 44, No. 1, pp. 127–139. DOI:10.1037/0022-3514.44.1.127.
8. **Stokes, J. & Wilson D. (1984)**. The inventory of socially supportive behaviors: Dimensionality, prediction, and gender differences. *American Journal of Community Psychology*, Vol. 12, No. 1, pp. 53–69. DOI:10.1007/BF00896928.
9. **Lubben, J. & Gironda, M. (2017)**. *Measuring Social Networks and Assessing their Benefits.* Social Networks and Social Exclusion: Sociological and Policy Perspectives, Taylor & Francis.
10. **Tang, D., Yusuf, B., Botzheim, J., Kubota, N., & Chan, C. (2015)**. A novel multimodal communication framework using robot partner for aging population. *Expert Systems with Applications*, Vol. 42, No. 9, pp. 4540–4555. DOI:10.1016/j.eswa.2015.01.016.
11. **Castillo, J. & Fernandez, A. (2014)**. A framework for recognizing and regulating emotions in the elderly. *Proceedings of the International Workshop on Ambient Assisted Living IWAAL´14.* Lecture Notes in Computer Science, pp. 320–327.

12. **Rodriguez, M., Gonzalez, V., Favela, J., & Santana P. (2009)**. Home-based communication system for older adults and their remote family. *Computers in Human Behavior*, 25(3), pp. 609–618. DOI:10.1016/j.chb.2008.08.017.
13. **Dasgupta, D., Feldman, K., Waghray, D., Mikels-Carrasco, W.W., Willaert, P., Raybold, D., & Chawla, N. (2014)**. An integrated and digitized care framework for successful aging. *Proceedings of the International Conference on Biomedical and Health Informatics (BHI),* pp. 440–443. DOI:10.1109/BHI.2014.6864397
14. **Tan, T., Gochoo, M., Chen, K., Jean, F., Chen, Y., Shih, F., & Ho, C. (2014)**. Indoor activity monitoring system for elderly using RFID and Fitbit Flex wristband. *Proceedings of the International Conference on Biomedical and Health Informatics (BHI)*, pp. 41–44. DOI:10.1109/BHI.2014.6864299.
15. **Silva, B.M.C., Rodrigues, J.J.P., Simões, T M.C., Sendra, S., & Lloret, J. (2014).** An ambient assisted living framework for mobile environments. *Proceedings of the International Conference on Biomedical and Health Informatics (BHI)*, pp. 448–451. DOI:10.1109/BHI.2014.6864399.
16. **Giangraso, B. & Casale, S. (2014)**. Psychometric Properties of the Medical Outcome Study Social Support Survey with a General Population Sample of Undergraduate Students. *Social Indicator Research*, Vol. 116, No. 1, pp. 185–197. DOI:10.1007/s11205-013-0277-z.
17. **Witten, I., Frank, E., & Hall, M. (2011)**. *Mining: Practical Machine Learning Tools and Techniques*. Elsevier. DOI:10.1016/C2009-0-19715-5.
18. **Moore, D. (2015).** *Applied Statistics.* Barcelona: Purdue University.
19. **Mark, A.H (1999).** *Correlation-based Feature Selection for Machine Learning.* (Doctoral dissertation, Waikato University These), Waikato University Theses and Dissertations Archive. https://www.cs.waikato.ac.nz/~mhall/thesis.pdf
20. **Petersen, J., Austin, D., & Kaye, J. (2014).** Unobtrusive in-home detection of time spent out-of-home with applications to loneliness and physical activity. *IEEE Journal Biomed Health Informatics*, Vol. 18, No, 5, pp. 1590–1596. DOI:10.1109/JBHI.2013.2294276.
21. **Tan, C., Pamuk, M., & Dönder, A. (2013).** Loneliness and Mobile Phone. *Procedia- Social and Behavioral Sciences*, Vol. 103, pp. 606–611. DOI:10.1016/j.sbspro.2013.10.378.
22. **Chapman, H. (2009)**. *The Top Ten Algorithms in Data Mining*. Taylor & Francis.
23. **Hall, M., Frank, E., & Holmes, G. (2009)**. The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter*, Vol. 11, No. 1, pp. 10–18. DOI:10.1145/1656274.1656278.
24. **Microsoft, Azure. (2019)**. *SMOTE, 2019.* https://docs.microsoft.com/en-us/azure/machine-learning/studio-module-reference/smote?redirectedfrom=MSDN.
25. **Chawla, N.V., Bowyer, K.W., Hall, L.O., & Kegelmeyer, W.P. (2002)**. SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, Vol. 16, pp. 321–357. DOI:10.1613/jair.953.

Article received on 26/06/2020; accepted on 01/09/2020.
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