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Measurement of users' well-being through domotic sensors and machine learning algorithms

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Abstract— This paper proposes a specific domotic sensor network to measure the well-being of elderly people in private home environments through Machine Learning (ML) algorithms trained with daily surveys. The tests have been conducted in 5 apartments lived by 8 older people where the non-obtrusive sensor network is installed. Two ML algorithms are compared, Random Forest (RF) and Regression Tree (RT), such that to verify whether the users' well-being is encoded in behavioural patterns obtained from the domotic data. These data are used to measure users' well-being and compared with three reference indices obtained through a daily survey: a physical (Phy), a mental (Mind) and a general health index (Avg). The extracted indices from the daily survey are used to train ML algorithms in the estimation of user's well-being for users that live alone (single-resident) or with others (multi-resident). Single-house and multi-house procedures are tested, both to extract a user-specific behaviour, and assess whether the model is able to generalise across different users and environments. Results show that the RF algorithm provides better performance than the RT algorithm in predicting the level of well-being with a Mean Absolute Error in the multi-house procedure of 32%, 13% and 17% for the Avg, Mind and Phy indices, respectively.

Index Terms— aging, sensors, smart home, machine learning, measurement uncertainty.

I. INTRODUCTION

OVER the last years, with the fast increase in the aged population, in the healthcare industry there has been a considerable growth in the demand for an artificial intelligence system of monitoring of people's well-being status. The ability of measuring and monitoring the behaviour of people in their home environment using sensors has become an important aspect for the obtainment of information about people's health and well-being [1]. In fact, monitoring people's well-being in the residence of their own choice can help to increase people's quality of life by promoting their independence as well as to give the opportunity to detect a possible decline in both their cognitive and physical functionalities, which could result in the outbreak of aging diseases [2]–[4].

The monitoring of human activity at home is generally made through many technologies largely relying on the Information and Communication Technologies (ICTs) and Internet of Things (IoT) solutions, whose main scope is to obtain information about users' daily activity, typically without

contact and neglecting, however, the subjective aspect of their well-being [5], [6].

In current literature, in fact, human behaviour is studied in terms of sequence of Activities of Daily Living (ADLs): each ADL is individuated as a sequence of sensor activation patterns that characterise human behaviour but do not provide any information about users' self-perception and well-being.

In related works, the behaviour of persons in the home environment using domotic sensors is correlated with health events, e.g. falls, sleep disorders [7], [8]. In fact, smart home-detected behaviour data occurs as a result of health events and mental disorder changes. This could be analysed measuring the variability of the home data that could be associated with the onset of pathology but also with a behaviour occurring after the prescription of a new therapy [9]. Considering that, most of the time the correlation between the home data collected from domotic and unobtrusive sensors installed in the home environment and the user's health and mental conditions is non-linear. In this case, Machine Learning (ML) techniques and appropriate algorithms are used to extract health status condition of older users and behaviour changes [8], but also to detect onset and monitor progression of some age-related diseases and disorders [10], [11].

Therefore, most of the related works evaluate the changes in mental, e.g. Mild Cognitive Impairment, Alzheimer, Dementia disease, etc. and health conditions, e.g. sleep disorders, falls, etc., through the variations in the behaviour of the user using a domotic sensor network and using as a reference, for example, the opinion of a physician. In contrast with them, in this work, the authors propose a methodology to quantitatively measure the well-being of older users living alone or in couple through the deployment of a non-obtrusive domotic sensor network installed at home analysed through ML algorithms trained with daily self-evaluation surveys as a reference (see Fig. 1). In fact, changes in the behavioural patterns measured with domotic sensors could be associated with the variation of the user's well-being [12]. With the term well-being, the authors considered the health and mental status of older users based on their personal feeling/perception and daily physical activities. From the literature, well-being and happiness, also said positive psychology, characterise the process of evaluating people in terms of being satisfied with their life [13]. Moreover, well-being and happiness depend on health and economy that include

physical activities, personal behaviour, nutrition and lifestyle [14]. In this work, the only reference system to evaluate the well-being of the older users is provided by a daily survey that, currently, is a reliable measurement of human well-being, as described in [15]. Users have been required to fill in questionnaires to report about their status. From the survey, the authors extracted numerical indices representing the self-evaluation of users' physical and mental states. The proposed research is aimed at demonstrating how human well-being can be assessed by measuring the activity of users during their daily routine in their home environment. Another innovative aspect, with respect to the state of the art, is that in this paper the daily survey to train ML algorithms is used for single-resident and multi-resident apartments. The estimation of well-being through the survey provides the possibility to measure the well-being not just for a single user, but also in a multi-resident condition. In fact, the survey is used to train the ML algorithms and to estimate the well-being of the user that lives alone or in a multi-resident context. In this way, this insight can be used to provide services and advices to the older user at home to improve their life-quality.

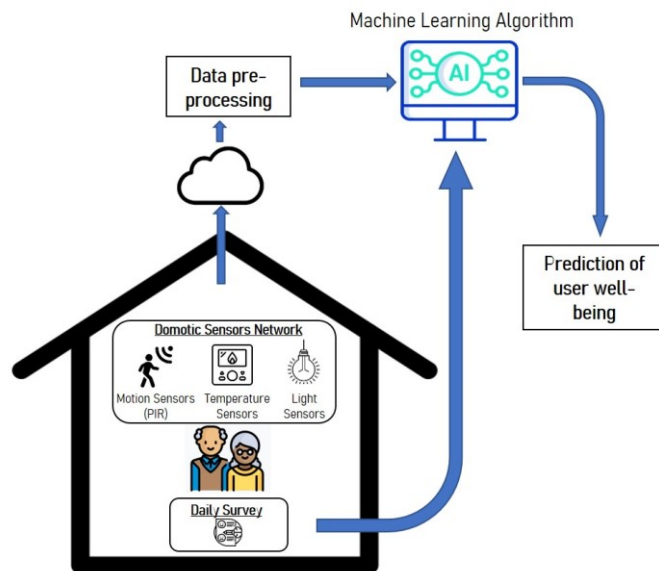


Fig. 1. Scheme of the system architecture used to collect and train the ML algorithm.

The experimental set-up implies the continuous monitoring and collection of data related to users' behaviour. Thus, Machine Learning algorithms are applied to the preprocessed data to extract unknown and non-trivial patterns which cannot always be detected by rule-based approaches [16], [17]. In this phase, the daily survey is used as output of the ML algorithm that has to be trained.

ML, neural networks and deep learning solutions are becoming part of the measurement chain process in the field of human behaviour, since the multitude of devices that can be installed in the home environment can generate a great amount of information that cannot always be interpreted through traditional techniques [18], [19]. Moreover, the ML approach can maximise the efficiency of datasets that cannot be processed by common techniques because they come from

complex and nonlinear measurements [20]–[22]. Recent studies have demonstrated how the use of ML techniques can give positive results in predicting human behaviour from a domestic sensor network, as reported in [23] and [24]. After the training, the prediction of human well-being derived from the trained algorithm, just using the domestic sensor data, can provide services to improve the life-quality of the users at home (see Fig. 2).

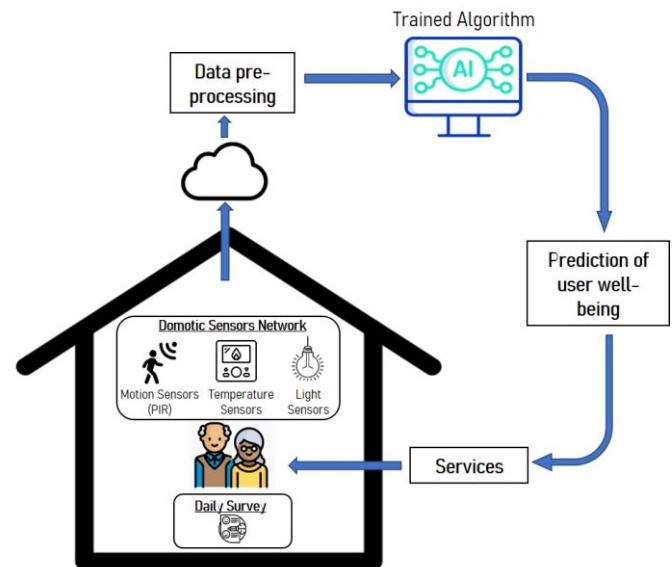


Fig. 2. Use of trained data.

This work could therefore provide the basis for making a first step in the complex field of the well-being measurement, which includes subjective quantities.

II. MATERIALS AND METHODS

In this work, Five apartments in the same building with eight older users have been monitored for a period of one year [26], [27]. The validation reported in this paper was performed considering a two months period.

A. Domestic Sensor Network

The hardware and software involved in the data collection make use of sensors to monitor users' behaviour and the home environment. The sensor network, named "Home Automation Kit", is described in [26]–[29]. For the analysis presented in this work, to monitor users' behaviour and the home environment, the following systems were used:

- light status, which can detect the switching on/off of lights;
- a thermostat which monitors and controls the air temperature inside the apartment;
- Passive InfraRed sensors (PIR), used to monitor the presence of users in the volume covered by the sensor.

In each apartment two PIR sensors were installed close to the door entrance of the living room (PIR 1) and the bedroom (PIR 2), while light sensors were positioned in the living room (Light 1), kitchen (Light 2), hallway (Light 3), bathroom (Light 4), bedroom (Light 5) and bathroom mirror (Light 6). The thermostat in all the apartments is placed in the living room far from external sources that can alter the air temperature

measurement (e.g., open windows, cookers).

Due to the similarity of the planimetries (see Fig. 3), the equipment installation in the five apartments is comparable. In this way, a homogeneous distribution of data is obtained, which makes it possible to reproduce the methodology proposed for each of the monitored flats.

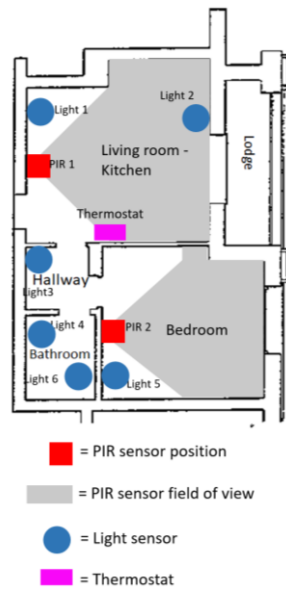


Fig. 3. Schematic plan of one of the apartments with installed domotic sensors. All the involved flats are characterised by this type of configuration.

B. Participants

In this work, eight participants, both males and females, spread out over the five apartments, have been involved: age between 68-82, no particular pathologies. This group of participants was living alone or in couple, with normal social status, no psychological disease and able to perform everyday activities. Moreover, apartments 1, 3 and 4 were inhabited by married couples, while apartments 2 and 5 by single users. In literature, domotic sensor networks (PIR, lights, door sensors, etc.) are usually installed in single-resident apartments [8], [9], [11] to measure changes in behaviours, ADLs and well-being. In this paper, single-resident but also multi-resident apartments are included in the analysis in order to evaluate the possibility in identify the well-being of the older user that lives alone or with other residents using ML techniques trained by surveys. In case of a single-resident apartment, the ML algorithms are trained using the daily survey of the resident on his/her sensor network dataset. When in the apartment there are two residents A and B, the ML algorithms are trained for the resident A with the survey of resident A and for the resident B with the survey of resident B but using as input the common sensor network dataset of the apartment.

C. Survey

A crucial step was to study a possible correlation between environmental data and users' general status, called in this paper well-being. The survey provided by the users every day for 60 days is used as a predictor of the well-being of the user, considering that the user's well-being influences the human behaviour patterns acquired from the domotic sensor network

[12]. For this reason, the authors created a daily survey as a subset of the MOS Short-Form-36 (SF36) questionnaire [30] to be answered by the older adults for a period of 2 months at the end of the overall one year test period.

The number of items was reduced to make the survey easier and quicker to be completed, reduce the daily effort to fill it in and improve the acceptability. The survey consisted of ten multiple-choice items asking to rank general health perception, functional status (i.e., housekeeping activity, physical activity, role limitation due to physical issues, general physical perception), mental wellness (i.e., mental health, role limitations due to mental problems) and guests' presence (Table I).

TABLE I
SURVEY

N°	Question
1	In general, how would you describe your health today?
2	Have you performed moderate activities (e.g. housecleaning, cooking, washing up, etc.) today?
3	Has your health status limited you in carrying out these moderate activities?
4	Have you carried out physical activities (e.g. walking, climbing stairs, etc.) today?
5	Has your health status limited you in carrying out these physical activities?
6	In general, how would you describe your mental health today?
7	Has your mental status affected your daily routine today?
8	Have you felt well physically (e.g. no aches, pains, etc.) today?
9	Have pains limited you in carrying out your daily activities today?
10	Have you received visits today?

For each question, older users could answer using an ordinal scale ranging from 1 to 3, where a rank of 3 meant that users were able to perform a great amount of activities during the day and no limitations due to mental or physical conditions occurred, therefore they had a positive self-perception, while a rank of 1 meant that they performed no activities during the day or that limitations due to mental or physical conditions prevented them from carrying out everyday tasks, which resulted in a negative self-perception.

D. Data Analysis

In the following paragraphs, a description of the methodology adopted to analyse the measured data is given.

1) Domotic Data

The data provided by the sensors were collected using a Cloud-based architecture and catalogued as described in [16]. Previous studies, for example [17] and [31], have shown the possibility to introduce ML approaches for discovering unseen patterns in the raw data collected from sensor networks in order to predict an activity profile and alert condition.

A preliminary processing phase assumes an important role when data must be input into the ML algorithm. In [16], the so-called Garbage-In-Garbage-Out principle states that poor

quality of information could be the main reason for wrong results and low performance of the ML algorithm. Therefore, it was crucial to identify and classify any source of noise that could reduce the quality of information.

Since the purpose of the work was to track the users' behaviour from the activation pattern of the sensor network, the data provided to the ML algorithms were exclusively referred to the behaviour of the considered specific family units. From this assumption, it is possible to deduce that the quality of the information increases with the removal of the outliers, e.g., data generated by a source of noise like external guests (external visitors, caregivers, etc.), malfunctioning of the system or of a single sensor (e.g., out-of-range or missing values) that can lead to possible misleading results. The external visitors are monitored by the authors using the survey. In fact, the tenth question of the survey "Have you received visits today?" is used to delete data from days during which the user received visitors.

Specifically, the pre-processing of collected data was based on the removal of outlier values considering these as the data out of the interval defined as ± 3 standard deviations in the dataset. Outliers can be generated by a momentary malfunctioning of the sensor network or of a single sensor (i.e., low batteries, cable disconnections, out-of-range or missing values for a day, etc.).

List wise deletion was adopted by removing from the dataset all the information associated with those days in which data were missing for at least one sensor [32].

After pre-processing, the information provided by each sensor was then processed as follows. It was assumed that PIR sensors indicated whether the user had entered the room and/or was moving within the room, therefore data were analysed by counting the number of times that each sensor switched on. PIR activations were counted daily, therefore the information was processed by aggregating the total number of activations during the whole day. The same approach was adopted to process light sensor data. Also, in this case, the data were analysed considering the total daily activations of the sensors.

Fig. 4 shows, the typical daily activations of the PIR sensor, after outliers removal, installed in the living room (PIR 1) of one apartment during 60 days of monitoring.

The air temperature coming from the thermostat is processed to obtain a mean value for each day.

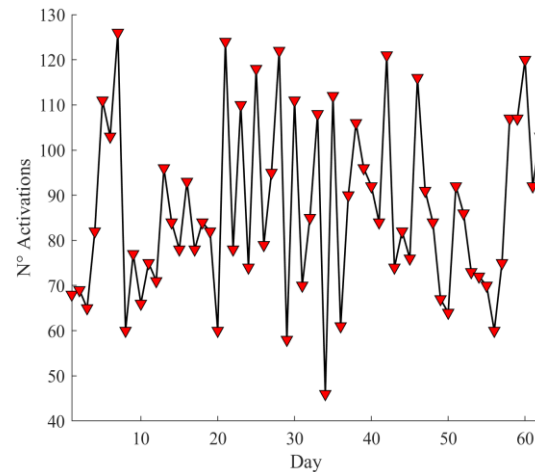


Fig. 4. Example of the trend of the PIR sensor installed in the living room of one of the apartments.

2) Survey analysis and environmental data correlation

The survey provided a quantitative representation of the older users' well-being from a mental and physical perspective. In order to obtain a specific description of their mental and physical status, authors computed three indices derived from specific items of the survey: a "physical" index, a "mental" index and a "general health impact" or "average" (Avg) index. The Physical index (Phy) was obtained by aggregating the ranks of the items regarding the functional status, whereas the Mental index (Mind) was computed by combining the scores of the items related to Mental wellness. The "general health impact" expresses a balance between the activity performed (i.e., housekeeping and physical activity) and the level of impairment due to physical or mental issues and it was computed by averaging (Avg) the two above-mentioned indices, Phy and Mind. Thus, the indices were computed by summing the values of the responses related to them. To provide a uniform reading of the data, the indices were normalised within the range 0 to 1. Fig. 5 shows an example of the trend of the indices obtained for one of the older users. These three indices constitute a quantitative way to interpret the self-reported vote provided daily by the older users.

The baseline analysis aimed to compute a linear correlation (i.e., Pearson correlation) between the older users' self-reported well-being condition and the pre-processed data (i.e., number of daily activations) collected by the sensors. The level of significance was set at 0.05 for all statistical comparisons.

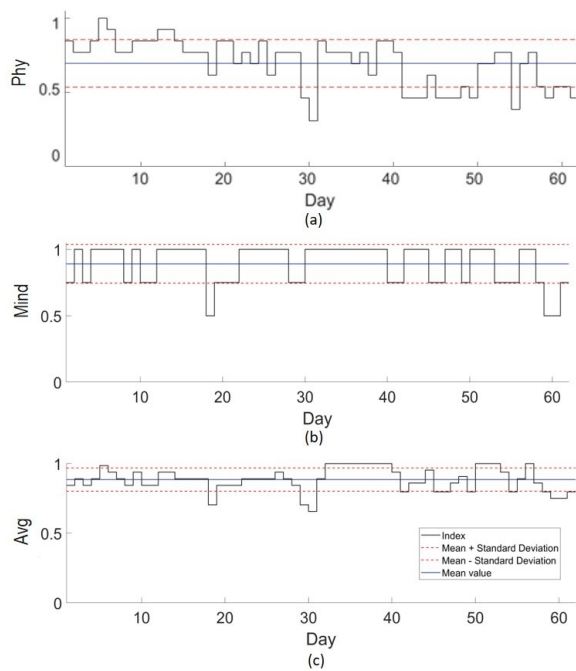


Fig. 5. Example of the trend of each index for one of the occupants: a) physical index; b) mental index; c) average index.

3) Machine Learning algorithms

The main analysis was conducted by using ML algorithms on different subsets of the dataset (processed sensors activations and survey indexes). Two main techniques were tested: the Regression Tree (RT) [33] and the Regression Forest (RF) techniques [34]. The main goal of this kind of analysis was to discover the multivariate pattern in the sensor data that can be discriminative to predict users' self-reported health status. The user responses represent the output of ML models while the domestic data gathered in the home environment represent the input.

The primary reason behind the application of the RT and RF techniques is the interpretability of the model. In this context, the authors aimed to know not only the occupants' predicted self-reported health status, but also why and how the prediction was made. The RT allows learning a non-linear/complex decision boundary while ensuring at the same time interpretability and moderate computation effort. Although the RT often relies on an intuitive notion of interpretability, the degree of interpretability depends on the model size (i.e., number of nodes and depth of the tree) [35]. Hence, we constraint the maximum depth of the tree (i.e., maximum size) to be at most 10 in the performed grid-search. This approach allows increasing both the discriminative power and the interpretability (i.e., the maximum number of tests regression rules required for a single estimation step < 10).

The RT model was built through binary recursive partitioning of the dataset, by iteratively splitting the data into partitions or branches. The split criterion was selected so as to decrease the Mean Squared Error (MSE) and the Mean Absolute Error (MAE) in the two separate partitions. MAE and MSE were estimated according to the following equations:

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n} \quad (1)$$

$$MSE = \frac{\sum_{i=1}^n (y_i - x_i)^2}{n} \quad (2)$$

where y_i is the prediction obtained from the model and x_i is the true value.

This splitting rule was applied to each new branch until each node reached a specified minimum node size and became a terminal node. The model is a variant of a bagging tree model and consists of an ensemble of RTs generated by independent identically distributed random vectors.

The RF algorithm has proven to be useful for the extraction of discriminative information in a relatively small dataset by generating an artificial dataset. More specifically, the strength of the methodology lies in its use of deep trees randomly generated by using a bootstrapping sample of the data combined with the node split that is made by using the candidate from a randomly selected subset of features that provides the best results [34].

In fact, the RF algorithm was built by sampling from the observation and from the features set (i.e., number of features to be selected) and by varying two tree-parameters (i.e., maximum number of splits and maximum size). The RT hyper parameters and the RF hyper parameter were optimised by performing nested cross-validation based grid search within the training set [36]. The RF model is known to have a superior generalization performance, at the expense of losing interpretability [37]. To overcome this issue, the importance of a feature in identifying the self-reported health status was measured according to permutation of out-of-bag feature observations [38].

The permutation approach offers a reliable solution to interpret the most discriminative features while building a high-complex model (i.e. huge number of ensemble RT). According to the permutation approach, if a feature is significant for the identification of the self-reported health status index, then permuting its responses should affect the model error. Accordingly, if a feature is not significant, then permuting its responses should not considerably affect the model error. The permutation approach offers an almost unbiased importance measure and is more consistent compared to other approaches (e.g., Gini index) [38]. The importance of a feature in the RT model was instead evaluated by summing changes in the MSE for each split of the predictor considered and dividing the sum by the number of the branch nodes.

Both RT and RF disclose a moderate computation effort for the training phase (also for a shallow tree) [39]. In particular, the training time for a RT is usually much faster than black-box model such as neural-network models [40].

Additionally, for the solution of this regression task, the models selected (i.e., the RT and RF models) performed favorably against other competitors (i.e., linear Support Vector Machine, Gaussian Support Vector Machine and Boosting algorithm).

4) Data analysis for well-being measurement

Two configurations were considered:

- single-house: the analysis focused on a single house;
- multi-house: all the houses were considered in the analysis.

In the single-house procedure, the ML algorithms were tested independently for each house using measured data collected during 59 days for the training phase and one day for the testing phase, iteratively. In the multi-house procedure, the data collected from all the houses were aggregated in a total dataset. Hence, the RT and RF algorithms models were tested using a leave one observation out procedure. The multi-house procedure made it possible to increase the sample size of the dataset and the ML models should be able to generalise across different users and houses. This setting was exploited by taking into account the similar planimetry across the different houses.

III. RESULTS

This section discusses the results obtained by adopting the methodology described in the previous section. The results refer to the two months taken into consideration for the analysis. The baseline analysis was performed by computing the linear correlation between the raw sensor data and the indices derived from the survey. Subsequently, the ML results were obtained. In particular, the features acquired by the home automation equipment (domotic features) were used as predictors of the machine learning model.

The aim of this analysis was to investigate whether domotic data can be interpreted as predictors of users' general health status. The attention focused on how to process and combine such data through ML techniques, so as to derive useful and high-level information related to the users' self-reported health status for each house independently as well as for all the houses considered.

The results would be to generate a chain for well-being measurement composed of a domotic sensor network and a trained ML predictor.

A. Baseline: correlation analysis

A first inspection of the data trend was performed by assessing the Pearson linear correlation coefficient (R) between each domotic sensor data and the corresponding average, mental and physical indexes. The correlation analysis was made considering the processed dataset.

The baseline analysis does not report satisfying results for this study. The R values are not significant for most of the correlated data and are low for the others. This means that the correlation between each domotic sensor data and indexes does not provide information regarding the well-being of the user. In addition, it confirms the non-linearity of the problem. For this reason, the ML technique is adopted not considering the single sensors but the whole domotic dataset.

B. Machine Learning

1) Single-house procedure

In the experiments, the authors used classification approaches (i.e., supervised learning techniques) according to

the acquired data. First of all, the single-house analysis was performed. This investigation refers to a "user-specific" model that trains itself on the behaviour patterns of each user to estimate the user's average, mental and physical indices. The data of a single house (i.e., domotic data collected) were provided to the ML algorithms in order to predict the user's self-perception.

More in detail, the most relevant results were obtained for the Phy index and the Avg index. In fact, as it can be observed in Table II, the RT method made it possible to obtain a significant correlation both for the Phy and the Avg indices in house 1 and house 3. On the other hand, the RF algorithm confirmed that the Phy index can be estimated from domotic data. However, the performance of the ML algorithms changed across the different houses.

TABLE II
PEARSON COEFFICIENT BETWEEN THE PREDICTED INDICES OF ML OUTPUT AND THE SELF-REPORTED INDICES

ML algorithms	RF			RT		
	Avg	Mind	Phy	Avg	Mind	Phy
Home 1(u1)	0.5*	n.s.	0.4*	0.5*	0.4*	n.s.
Home 1(u2)	n.s.	n.s.	n.s.	n.s.	n.s.	0.4*
Home 2	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Home 3(u1)	n.s.	n.s.	n.s.	0.4*	n.s.	n.s.
Home 3(u2)	n.s.	n.s.	0.4*	n.s.	n.s.	0.5*
Home 4(u1)	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Home 4(u2)	n.s.	n.s.	n.s.	n.s.	n.s.	0.4*
Home 5	n.s.	n.s.	n.s.	0.4*	n.s.	n.s.

*pval<0.05

2) Multi-house procedure

The multi-house procedure refers to a model trained on a dataset created by aggregating the domotic data collected from all the houses involved in the single-house procedure. The main purpose was to capture the behaviour patterns of the different users in order to estimate the self-reported physical, emotional and Avg indices.

The results of the multi-house procedure are shown in Table III. The Pearson coefficient computed for the RF algorithm was higher than the one computed with the RT algorithm, which indicates the better performance of the RF method. This assumption is confirmed when considering the MSE and the MAE, since their values decreased when applying the RF technique.

Moreover, in contrast to the single-house procedure, the

mental index achieved the best results for both the RT and the RF methods.

TABLE III
PEARSON COEFFICIENT CONSIDERING THE MULTI-HOUSE PROCEDURE

ML algorithms	RF			RT		
	Index	Avg	Mind	Phy	Avg	Mind
Pearson's coefficient		0.52*	0.62	0.44*	0.30*	0.50*
MSE		0.17	0.02	0.05	0.27	0.03
MAE		0.32	0.13	0.17	0.40	0.15

*pval<0.05

Fig. 6 reports an example of results for two users, in which the predicted indices of the RF methods against the real trend of the self-reported indices are presented. To provide this analysis, during the training, the daily activations of the whole domotic sensors dataset are used as input together with the average, physical and mental indices. The dashed line indicates the real survey and the red line the predicted survey. For this analysis, the authors removed all the days from the dataset where some domotic sensors data are missed, the survey is missed, and the users received visits. To perform the analysis, the authors have chosen to process the output data coming from the algorithm adopting a moving average technique (both for the real and the predicted data) to extract the trend of the indices over time, Figure 6.

As shown, the RF model is able to understand when a variation of the rank is happening, but, in certain situations, the model decreases accuracy in estimating the real rank, probably also due to the presence of multi-inhabitants in the same apartment, which makes it difficult to distinguish the pattern of each single user.

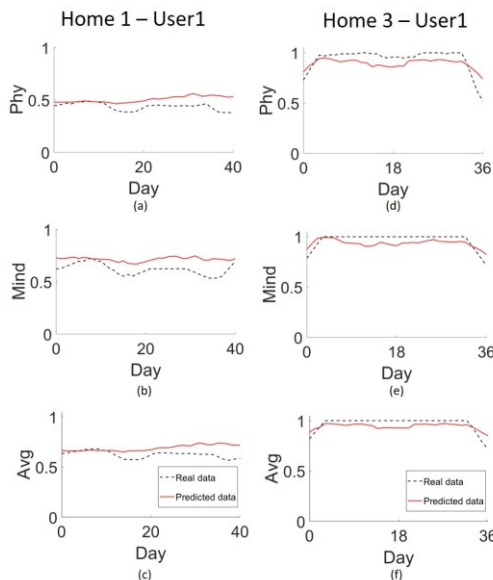


Fig. 6. Example of the trend of the predicted data (red line) against the real trend (dashed line) for two users resulting from the RF algorithm and using the moving average technique to extract the trend of the users behaviour over time for: a) Home 1 user 1 physical index; b) Home 1 user 1 mental index; c) Home

1 user 1 average index; d) Home 3 user 1 physical index; e) Home 3 user 1 mental index; f) Home 3 user 1 average index.

C. Pattern Localisation

The last step useful for the analysis was focused on the sensors that mostly contributed to train the prediction model. By estimating predictor importance, it was possible to highlight the relative influence of each variable in the model. The analysis was performed considering only the average index, since it represents a condition of the users' general well-being (i.e., physical and mental indices).

Fig. 7 illustrates the color matrix which expresses the relevance of each sensor activation over each fold of the leave one day out procedure for the RF model. The average index seems to be best predicted from the information provided by the light sensor installed in the bathroom and the PIR sensor in the bedroom.

Predictor importance is stable across the different experiments. A possible explanation for these results could be the fact that, in a typical home environment, the bathroom and the bedroom are the busiest rooms in everyday situations, which results in a well-defined pattern of activation. For example, the light sensor is usually predominantly activated during nighttime and less frequently during daylight hours.

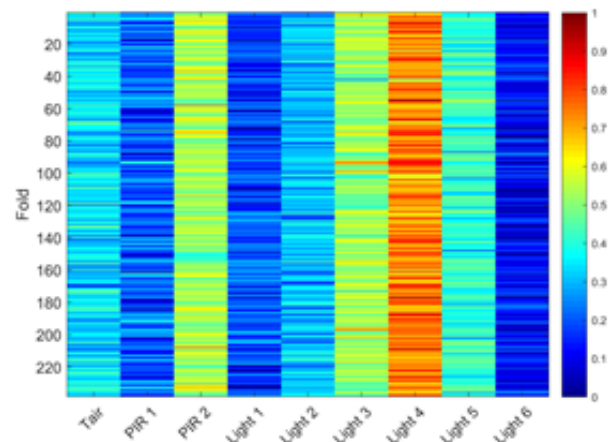


Fig. 7. The color matrix of the average index. It expresses the relevance of each sensor activation over each fold of the leave-one day out procedure for the RF model.

IV. CONCLUSION

The study aimed at estimating elderly people's well-being using non-intrusive sensors and a machine learning approach trained with daily surveys. The authors aim to demonstrate the feasibility of the approach for both the cases of multi-resident and single-resident apartments [41]. A preliminary analysis (i.e., baseline analysis) suggests that no information can be deduced from the correlation between the each domotic sensor data and the corresponding indices. Therefore, as a main contribution, ML techniques were applied to extract high-level information from the dataset to predict the users' self-reported status. Two ML methods were compared (i.e., the RF and the RT algorithms) and tested in two different procedures: a single-house procedure and a multi-house procedure. The former

refers to a “user-specific” model which is able to predict the physical, mental and general health status indexes by generalising across the unseen samples of the same user within the same house. The latter consists of a trained model on a dataset created by aggregating the environmental data collected from all the houses involved in the single-house procedure to predict the indices.

The single-house procedure suggests that the Phy index and the Avg index can be significantly predicted in more than one house using the RT algorithm. On the contrary, the RF algorithm makes it possible to identify only the Phy index.

The multi-house procedure provides higher performance in terms of Pearson correlation coefficient compared to the single-house analysis. In particular, an improvement is obtained with the RF algorithm, which makes it possible to estimate the self-reported indices with a MAE of 32%, 13% and 17% for the Avg, Mind and Phy indices, respectively.

These results state that the RF algorithm applied to domestic data provides a robust methodology for predicting the well-being of a user living in an apartment equipped with environmental sensors in a non-intrusive manner. More in detail, with regards to the average index, a predictor importance analysis led to establishing that the bathroom light and the bedroom PIR sensors seem to be the best predictors for the Avg index.

In conclusion, the results of the paper show that integrating in the same dataset the all data from the all users living in the building (multi-house procedure) where the same domotic sensor network is installed in each apartment, the uncertainty in the prediction of the well-being decreases. Hence, the ML algorithms are able to generalize across different users living in different houses in the building. This event could be explained by the increasing amount of data available for the ML algorithms which may lead to better model both the intra-subject variability (i.e. the variability of the survey responses of a specific user) and the inter-subject variability (i.e. the variability among the survey responses of different users).

In conclusion, the main contributions of the work are summarized below:

- The accurate estimation of users' well-being using as predictors the human behaviour patterns obtained from domotic data gathered in the home environment. The users' well-being is estimated in terms of users' self-reported status.
- The robustness of the proposed methodology to estimate user-specific well-being and to generalize across different users and home-environments.
- The application of machine learning methodology for solving this task. The employed models represent the best trade-off between the model interpretability, computation effort and performance prediction;
- The multi-resident evaluation without adding additional sensors to the domotic sensor network.

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