Intelligent Sitting Posture Classifier for Wheelchair Users

Patrick Vermander, Aitziber Mancisidor, Itziar Cabanes, *Member, IEEE*, Nerea Perez, and Jon Torres-Unda

***Abstract*—In recent years, there has been growing interest in postural monitoring while seated, thus preventing the appearance of ulcers and musculoskeletal problems in the long term. To date, postural control has been carried out by means of subjective questionnaires that do not provide continuous and quantitative information. For this reason, it is necessary to carry out a monitoring that allows to determine not only the postural status of wheelchair users, but also to infer the evolution or anomalies associated with a specific disease. Therefore, this paper proposes an intelligent classifier based on a multilayer neural network for the classification of sitting postures of wheelchair users. The posture database was generated based on data collected by a novel monitoring device composed of force resistive sensors. A training and hyperparameter selection methodology has been used based on the idea of using a stratified K-Fold in weight groups strategy. This allows the neural network to acquire a greater capacity for generalization, thus allowing, unlike other proposed models, to achieve higher success rates not only in familiar subjects but also in subjects with physical complexions outside the standard. In this way, the system can be used to support wheelchair users and healthcare professionals, helping them to automatically monitor their posture, regardless physical complexions.**

***Index Terms*—Artificial neural network, sitting posture classification, wheelchair, force sensors.**

I. Introduction

TODAY, 20% of the elderly population and 10% of people with disabilities, such as stroke or paraplegia, need to use a wheelchair in their daily lives [1]. Therefore, approximately 75 million people around the world are in a situation of low mobility, in which the use of a mobility aid becomes an essential necessity to lead a seemingly normal life. Currently, there are other devices that are intended to serve as a support [2]. However, this technology is still more expensive and complex than the use of a wheelchair, so this second option stands out.

Autonomous sitting is a fundamental ability for people's health and well-being, even more if they are affected by a neurodegenerative disease, e.g. multiple sclerosis. As these people present a reduced mobility, they spend a large part of the day in a seated position. Imbalance due to a sedentary lifestyle and age, as well as a consequence of the disease itself, affect the skeleton, deforming it and making it difficult to adopt a correct posture in the long term [3].

Adopting a sedestation posture is essential to both, prevent musculoskeletal problems in the long term as well as to prevent the development of ulcers in people who spend long periods of time seated. The appearance of ulcers leads to a deterioration in the health-related quality of life of those who suffer from them [4]. Moreover, inappropriate sedestation causes the appearance of muscular tension both in the cervical and shoulder area [5] and in the lumbar area [6]. Above-mentioned muscle problems cause chronic low back pain (LBP) or some neuropathies like sciatica [6], [7]. It is therefore necessary to continuously monitor the postural status of people.

At present, given the difficulty of continuous monitoring by health specialists, postural monitoring and diagnosis is carried out by means of specific questionnaires [8]. However, these questionnaires are composed of a certain subjective character, and they are not suitable to monitor posture on a continuous basis. In an attempt to eliminate the subjective component characteristic of these questionnaires, the interest in the development of postural monitoring devices that allow objective quantification of a patient's postural status has grown in recent years. These devices can be quantified depending on how invasive the technology used for the measurement is: wearable sensors, vision sensors and pressure or force sensors.

The first group of sensors used for sitting posture monitoring are the so-called wearable sensors [3], [9], [10]. The main advantage of this type of sensors is that they are small in size. This allows them to be easily implemented in clothing, providing great portability to the data acquisition system. However, they are intrusive sensors, which sometimes cause discomfort to the user, having also drifts that have to be

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corrected during use. For this reason, other types of monitoring technologies have been developed.

The second group of sensors used for postural monitoring are sensors based on vision technologies. Within this group, the Kinect camera stands out, which uses depth sensor technology [11], [12], [13], [14]. With the cameras being placed in the environment, the intrusiveness problem of wearable sensors is eliminated. However, it is necessary to place them in controlled environments, with constant lighting conditions, as well as to avoid the appearance of occlusions that interfere with the image. For this, vision sensors are not very portable and are not suitable for wheelchair users.

The last group is made up of pressure or force sensors. These sensors, either conductive in textile format [15], [16], [17], or resistive [18], [19], [20], [21], are arranged along the seat and back of a chair, allowing the force exerted on them to be measured. In this way, the intrusiveness of wearable sensors is avoided and portability is gained with respect to vision sensors.

The pressure sensors can be arranged as a mat or in a distributed manner. Currently, there are both commercially available solutions [22], [23], [24], and custom-made solutions [15], [25]. However, due to the very fabrication of these meshes, they have an excessive number of sensors, which makes them expensive and of limited usage time. In addition, as the number of data collected increases, the difficulty and computational cost of the subsequent processing of the data increases.

For this reason, some authors use Force Sensitive Resistors (FSR) distributed in the form of a mesh [26], [27]. One of the advantages of FSR resistive sensors is that, as it acts as a variable resistor, it does not require large electronics for its proper implementation. Another advantage of this type of sensor is its low price and availability. However, prior calibration is necessary to ensure the suitability of the measured data. In addition, the portability of these sensors is associated with the portability of the wheelchair to which they are attached [19], [22].

Once the postural data acquisition method has been selected, highlighting above the rest the use of sparse pressure sensors due to their portability and low cost, a second block of machine learning techniques is used for postural identification. This second block is carried out in two stages. A first one in which a selection of the most relevant features is made, and a subsequent training stage of the classifier based on the selected features.

For the first stage, in the case of discretely located sensors, in addition to using information collected from the sensors directly [19], [22], [28], statistical indicators such as mean or standard deviation are taken among others [18], [20]. The calculation of the center of pressures (COP) in seat and backrest has also been proposed [20], [24]. However, there is no standardized methodology for the selection of features for seated classification, as is the case in other health care settings [29].

For the second stage of training a classifier, statistical methods such as Naive-Bayes [11] have been used. However, Machine Learning (ML) based classification models are the ones that have stood out above the rest. Specifically, the use of supervised learning models has become popular, where the model is able to learn to predict an output class from features provided as input. In this way, classification models based on K-nearest neighbors (KNN) [20], [21], Support Vector Machines (SVM) [28], [30], [31] and Artificial Neural Networks (ANN) [19], [27], [32] have been developed.

However, all models have a number of constraints. First, much of the previous work is oriented to office work [19], [30], [31], [32]. Since this is a different approach, the postures to be monitored are different, taking into consideration, for example, leg crossing, which does not occur in wheelchair users. Likewise, portability and adaptation of these devices to different types of wheelchairs is not taken into account [21], [30]. Furthermore, the varied physical complexion of these people, with an obesity rate higher than that of the general population [33], is not considered. Few of the papers focus on wheelchair users [27], but the number of subjects in the trials is low or authors do not detail the methodology proposed to guarantee the robustness of the classifier. Thus, results could be affected by the diversity of physical complexions of the participants. Considering that variance between subjects is greater than between postures [34] and the intrinsic dependence of the models on the physical complexion, results may be inferior if validated with subjects who have not participated in training [19], [28], [35].

The aim of this paper is to present a robust sitting posture classification model, focused on wheelchair users, able to distinguish between the common improper sitting postures adopted by disabled users regardless their physical complexion. The classification model, based on a ANN structure, uses as input the information collected using a postural monitoring system developed ad hoc, which has been called i-KuXin. This device is based on the use of FSR sensors located in a distributed way in a portable cushion in both the seat and the backrest. This allows the device to be inexpensive, have a longer battery autonomy and simplify the subsequent data processing. This device is designed to be portable and independent of the wheelchair used.

In order to make the system simple, robust and independent of physical complexions, a methodology based on a K-fold stratified in weight groups has been designed. In this way, in contrast to other studies, it is possible to obtain high accuracy results in new subjects without being affected by their physical complexion. The robustness of the classifier, validated with a large number of subjects, allows to extend and generalize the advantages of postural monitoring as well as provide great flexibility to healthcare specialists.

The rest of this article is structured as follows. In Section II the design of the monitoring system is presented as well as the method followed in the data acquisition and trials. In Section III, the methodology used for the intelligent classifier based in ANN is explained. Then, in Section IV, an analysis and discussion of the results is provided. Finally, in Section V the main conclusions are extracted and the future work is defined.

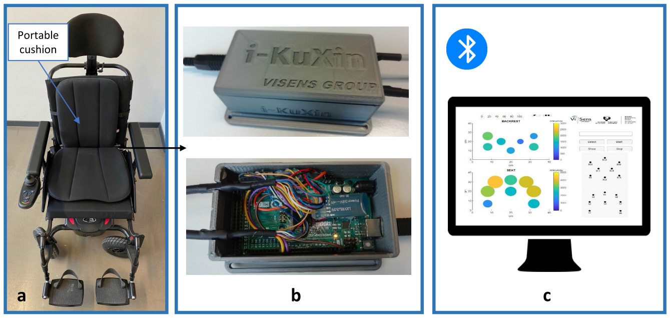

Fig. 1. i-KuXin postural monitoring device modules. The three modules that make it up are: a-Sensing module (portable cushion). b-Acquisition system. c-User interface. Currently, this design is patent pending (P210811ES).

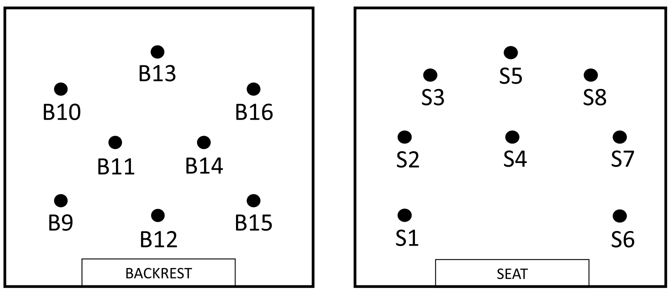

Fig. 2. Optimal distribution of FSR sensors for postural monitoring. On the left: Distribution of the sensors on the backrest. Right: Distribution of the sensors on the seat.

II. Data Base for Sitting Posture Classifier

This section describes the monitoring device developed for data collection (Section II-A), as well as the methodology used during the experiments conducted for postural data base generation (Section II-B).

A. Postural Monitoring Device: i-KuXin

The postural monitoring device, which has been named i-KuXin, is divided in 3 modules: a sensing module, the acquisition system and user interface (Figure 1).

The sensing module consists of a set of 16 FSR sensors distributed along the rest and backrest of a cushion. Given the lack of precision of these sensors, they have been subjected to a previous calibration process with weights within their range of action. These sensors have a linear relationship between weight and voltage on the logarithmic scale.

A preliminary study has been carried out for the selection of the best sensor distribution [36]. In this study, commercial pressure mats (Seating Dev Kit from Sensing Tex S.L. [37]) were used to identify the most relevant pressure points of both the seat and the backrest in order to identify the most common sitting postures. The results of this study show as the most relevant points those represented in Figure 2.

The seat sensors are distributed as follows: S3 and S8 sensors are responsible for monitoring the ischium area, S1, S2, S6 and S7 sensors are responsible for monitoring the thighs at different heights, and S5 and S4 sensors monitor frontal displacements. On the other hand, the backrest sensors are distributed as follows: B15, B16, B9 and B10 sensors monitor lateral displacements in both the lumbar and dorsal areas. Sensors B11, B12, B13 and B14 monitor spinal pressure at different heights. The sensors have been covered with a padded cushion to protect them, as well as to add more comfort to the user. The system has been designed to be portable and independent of the type of chair used, so that, in addition to wheelchair users, it can be used in desk chairs, office chairs or student chairs, among others.

Sensor data acquisition is performed through an Arduino MEGA 2560 board. It is a board with an ATmega2560 processor and the capacity to connect 16 analog inputs, one for each FSR sensor used. The sampling frequency used is 4 Hz. In addition, a wireless connection module HC-05 has been used, which allows the board to transmit data via Bluetooth to a remote computer. The Arduino board is powered by an external 10000 mAh battery that allows the system to collect data for more than 24 hours. The data is transmitted in real time with a sample frequency of 4 Hz to a remote computer on which a graphical interface based on Matlab software has been designed.

This interface has been developed with the idea of facilitating, on the one hand, the real-time display of sensor measurements. For this purpose, the value of the sensors are shown intuitively, varying their size and color depending on the measured force, as shown in Figure 3. On the other hand, an analysis tab has been designed, in which the most relevant information for the subsequent study of the historical data by a health specialist is represented in an orderly manner.

Therefore, the i-KuXin system developed, composed of the three modules described above, allows real-time monitoring of the postural status of wheelchair users, and transmits the information to the health specialist. Thanks to the limited number of sensors, an autonomy of more than 24 hours is achieved at a low cost.

B. Test Procedure for the Generation of a Seating Posture Database

To develop a sitting posture classifier, it is first necessary to have a good database. For this, the first step is to decide which sitting postures to be classified, which are relevant to know the functional status of wheelchair users.

As discussed in Section I, wheelchair users tend to have a trunk control problem, mainly due to muscle and bone weakness. It is therefore necessary to monitor spinal displacements. For this reason, lateral tilts and frontal tilt are selected as relevant postures. Lateral tilt is defined as the displacement of the back to one side by 15-20 degrees, with the back resting on the backrest (Posture 02 and 03). On the other hand, in the forward tilt (Posture 05), the back is moved forward by approximately 40 degrees, so that it no longer makes contact with the backrest. In both positions, the buttocks remain fixed on the seat, but the weight distribution is modified. Feet resting on the floor.

In addition, wheelchair users have, to a large extent, thoracic kyphosis, so this will be another posture to be taken into account (Posture 04). Therefore, they are instructed to hunch their shoulders slightly forward, maintaining contact with the

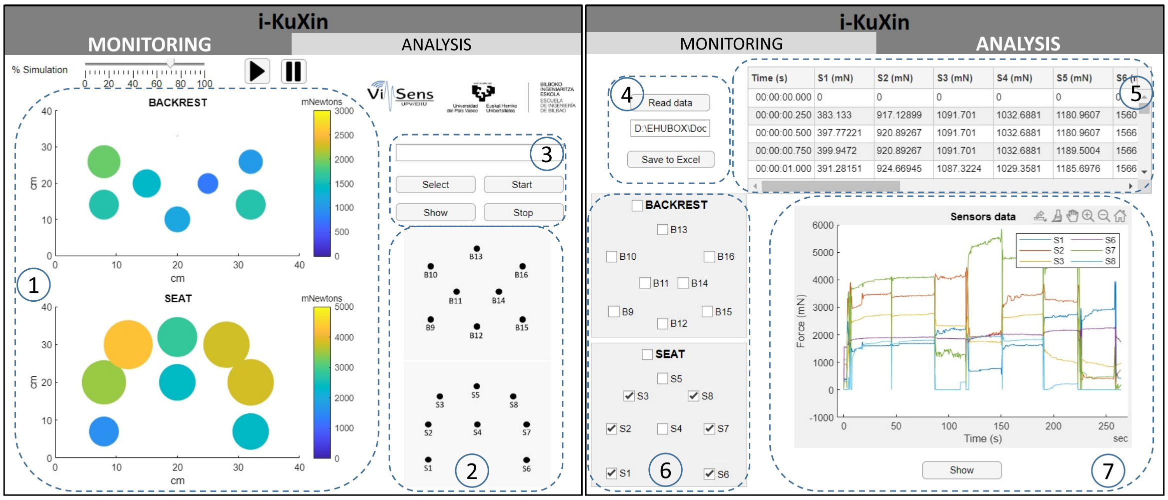

Fig. 3. Graphical interface of the developed i-KuXin postural monitoring system. On the left: Monitoring tab. Right: Analysis tab. Description of components: 1- Real-time display of sensors. 2- i-KuXin sensors distribution scheme. 3- Monitoring tab user interaction buttons. 4- Analysis tab user interaction buttons. 5- Table of representation of previously saved data. 6- Selection panel of sensors to visualize. 7- Time representation of selected sensors.

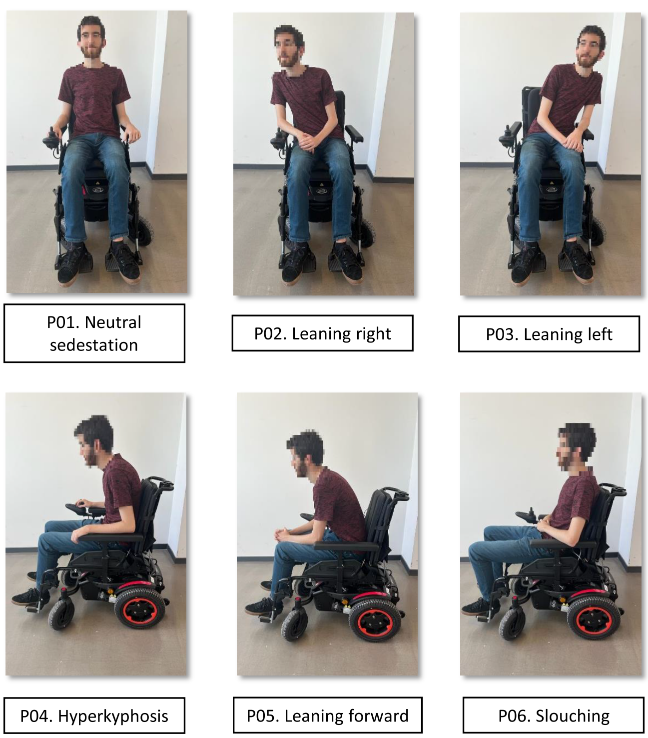

Fig. 4. Wheelchair users common postures: P01 - Neutral sedestation, P02 - Leaning right, P03 - Leaning left, P04 - Hyperkyphosis, P05 - Leaning forward, P06 - Slouching posture. The person in the image consents to the use of his image.

backrest in the lumbar area. Finally, possible frontal sliding that can lead to falls is considered as a relevant posture (Posture 06). The complete list of positions is shown in Figure 4.

The test subjects maintain each of the postures for a total of 30 seconds. Between postures, the subjects had to return to the neutral sedestation, which was considered the reference posture and from which the rest of the postures began. The instructions on how to perform each of the postures, as well as the supervision of the correct performance of each posture, were supervised by a specialist in physiotherapy. This specialist also performed the different postures in front of the participants, so that they could replicate them in as a mirror. In this way, the degree of inclination they had to perform in the lateral movements was also limited and it has been possible to standardize the different postures for all subjects. Furthermore, the physiotherapist is responsible of taking anthropometric measurements of the subjects as well as ensuring that the footrests are individually adjusted to the correct height. Anthropometric measurements include height, weight, leg length and shoulder width, among others. For each user, the process has been repeated twice, to monitor the differences of the same posture and user. The total duration of the trials for each participant was about 30 minutes.

The trials were conducted with a total of 37 healthy subjects belonging to the University of the Basque Country (UPV/EHU), 25 male and 12 female between 20 and 49 years of age. These subjects have been instructed by health specialists regarding the usual postures of wheelchair users. It has been sought to have a high number of healthy subjects, in order to cover the largest number of physical complexions, before transferring this system to people who use wheelchairs on a daily basis. Therefore, attention was paid to height and weight, among others, when selecting test subjects. A more detailed description of the physical characteristics of the test subjects is given in Table I.

The tests have been carried out in the facilities of the University of Basque Country. The tests were carried out on a wheelchair on which the i-KuXin monitoring device was placed. The tests were performed on a Sunrise Medical QUICKIE Q200 R wheelchair, on which the i-KuXin monitoring device was placed. To validate the tests, the pressure mats used in previous studies have been used and placed over the

TABLE I
PHYSICAL CHARACTERISTICS OF TRIAL PARTICIPANTS

	Total (n = 37)					
	Q1	Median	Q3	Min	Mean	Max
Age (years)	23,0	25,0	27,0	20,0	26,9	49,0
Weight (kg)	63,3	68,6	75,7	49,9	71,5	121,5
Height (cm)	164,7	173,0	177,4	152,6	172,3	192,0
BMI (kg/m^2)	21,2	23,5	24,9	17,8	24,5	47,4

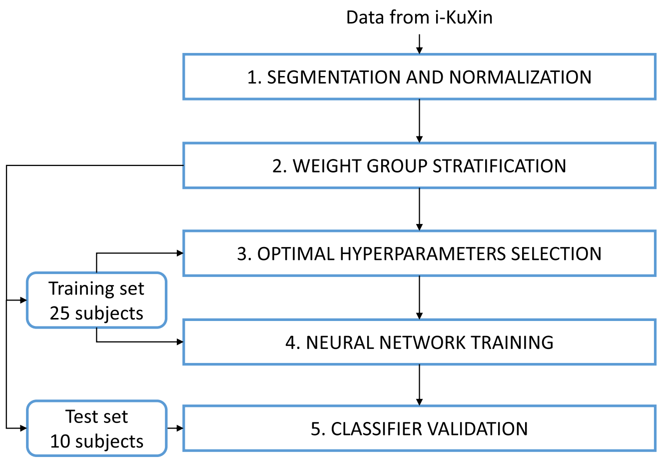

Fig. 5. Methodology followed for the development of the neural network-based posture classifier. This methodology is divided into five phases: data segmentation and normalization, stratification in different groups, selection of the optimal hyperparameters, training and evaluation and analysis of the results.

i-KuXin, allowing measurements to be taken simultaneously with both devices.

Prior to conducting the trials, subjects have signed a consent form agreeing to participate in the trials. At the end, they have completed a usability test to provide feedback on different aspects of their experience. The trials were conducted under the authorization of the ethics committee of the University of the Basque Country (M10_2022_007).

III. METHODOLOGY FOR THE DEVELOPMENT OF THE INTELLIGENT CLASSIFIER

A multilayer perceptron neural network has been selected for the sitting postural classifier. This selection has been made on the basis of their good performance in other health care fields [29]. In order to eliminate the dependence on weight in the classification, while maintaining the high percentage of success, the methodology explained below has been carried out and is shown in Figure 5.

The methodology can be divided into five main steps: A first step of segmentation, normalization and conditioning of the classifier input data (Section III-A). Subsequently, a second step is carried out in which segmented data is stratified into groups based on the subjects' weight (Section III-B). Then, an analysis and selection of optimal hyperparameters is performed in Section III-C. Finally, the fourth step of training and the fifth step of validation are presented in Section IV.

It should be noted that of the 37 subjects who participated in the trials, 2 of them have a physical build outside the norm, both in weight and body mass index (BMI), defined as the quotient between weight and height squared. To be exact, these two subjects were above the 97th percentile for BMI corresponding to their age. The remaining 35 subjects were uniformly between 50 and 90 kg, achieving an acceptable representation in this range. For this reason, it was decided at first not to use the data from these two subjects for the design of the classifier. However, the data from these subjects are not kept aside, since they are used later for the validation and analysis of the robustness of the proposed methodology.

A. Segmentation and Normalization of Input Data

In order to create the classifier, and for a correct differentiation of the postures, a window segmentation process has been followed. In order to eliminate the transient between postures, the initial 30-second windows have been shortened to 20-second windows, cutting 7 seconds from the beginning and 3 seconds from the end. This is because the transient between postures is mostly concentrated at the beginning of each window. In addition, given the time of the windows and the sampling frequency being 4 Hz, 81 samples are taken from each window. For each person and posture there are a total of 162 samples, given that each person repeats each posture twice.

Therefore, a balanced database is available for all postures, with a representative number of samples for each posture. Taking into account the total number of postures and subjects that participate, there are a total of 35964 samples to be used for classifier training and validation.

Once the data has been segmented into windows, the normalization process continues, with the idea of achieving two purposes. The first is the elimination of the user weight-dependent component in the sensors' amplitude. The weight of the users greatly influences the measurement collected by the sensors, especially the seat sensors, by interaction with gravity. The second purpose is the conditioning of the data at the input of the classifier. In this case, being a multilayer perceptron neural network, input data ranges between 0 and 1 or between -1 and 1 are commonly used.

As discussed in Section I, there is no standardized feature selection methodology. Therefore, for simplicity, each of the already segmented window samples is selected as input features. However, these data, by themselves, do not comply with the independence of the weight of the users and range of input to the networks. Therefore, instead of using the raw force data as input, it is decided to use the weight distribution at each time instant as input data. That is, for each of the sensors, at a time instant t, its force value is divided by the total sum of the force on the seat and on the backrest, as represented in Equation 1.

$$x_i(t) = \frac{F_i(t)}{\sum_{k=1}^{16} F_k(t)}; \quad i \in \{1, 2, 3, \ldots, 16\} \tag{1}$$

where $x_i(t)$ is the percentage in percent of the total weight measured by sensor i at time t and F_i is the force measured

TABLE II
DISTRIBUTION OF GROUPS BY WEIGHT

Group	Weight (kg)		
	Min	Mean	Max
1	49.95	56.03	61.8
2	62.1	63.85	65.45
3	66	68.68	72
4	72.25	74.33	75.3
5	77	84.59	91.65

by sensor i at a specific time t. The denominator corresponds to the sum total of the force measured by the 16 sensors at an instant t.

Consideration has been given to the possibility of calculating the weight distribution independently for seat and backrest. However, in this way the existing seat-back ratio is lost.

B. Stratification of Subjects by Weight

Once the data have been normalized, the next step is the selection of optimal neural network hyperparameters. It is a matter of choosing those hyperparameters that allow to achieve, on the one hand, high classification percentages. On the other hand, the network must have an optimal generalization capacity, allowing it to perform efficiently regardless of the subjects used for training and validation.

Furthermore, despite having eliminated the weight component in the input sensor amplitude to the classifier, the distribution of forces used is still conditioned to the different physical complexions of the users who participated in the tests. For this reason, an additional approach is proposed based on stratifying the data into groups according to weight. Specifically, the subjects are divided into 5 groups, each consisting of 7 subjects. The criterion used for the creation of these groups is that each group should include subjects with a similar weight range. The distribution of weights is shown in Table II.

Thus, the final set composed of the data from the 35 subjects, and 6 relevant postures, is divided into two balanced data sets, the training set and the test set.

The training set will be used both for the selection of optimal hyperparameters of the neural network and for the subsequent training of the neural network. This set is balanced for the 6 postures, so that a similar relative importance is given to each of the postures when training the classifier. The test set is used only for the analysis and validation of the neural network once trained. It has also been balanced for the 6 postures, so that representative results can be obtained for all of them. It is also important to note that the test set has not been used in the optimal hyperparameter selection block, to ensure that the results obtained correspond to subjects who have not participated at any time in the training.

This division has been made in a proportion of 71.5% of the data for the training set and the remaining 28.5% for the test set. In addition, it is added as an additional requirement that data from the same subject cannot be part of both sets simultaneously. This requirement is added to help to know in greater detail the degree of generalization of the model, thus avoiding that the known data of a subject influence the percentage of success of the model. Following this criterion, the data from 25 subjects are included in the training set and the remaining 10 in the test set. The selection of test and training subjects was randomized by adding a single condition.

This condition is based on the idea that in order to analyze the real influence of weight on the classification model, it is necessary that among the test subjects there is a broad representation of all physical complexions. Therefore, a condition is imposed, that among the 10 test subjects, 2 are from each group formed and represented in Table II.

For the posterior selection of the optimal hyperparameters, a K-Fold cross-validation with K = 5 was performed, using only the training set data. Therefore, the 25 subjects that make up this data set are divided into 5 groups of 5 subjects each, imposing a single requirement. The requirement is that each group must consist of one person from each weight range previously selected. The process of separating the dataset into training and test sets, as well as the stratification of the groups, was performed automatically and randomly.

Thus, there is a test set of 10 subjects (2 from each weight group) on the one hand and a training set of 25 subjects in 5 groups of 5 persons each on the other hand. By stratifying, it is ensured that there is a wide representation of physical complexions in both training and validation.

C. Optimal Neural Network Hyperparameters Selection for Sitting Posture Classification

With the 25 training subjects, the optimal hyperparameter selection step is performed. A multilayer perceptron neural network is considered as classifier. The network is composed of an output layer with 6 neurons, one for each posture to be classified and an input layer composed of 16 neurons matching the input features, i.e., signals from the 16 S_i and B_i normalized sensors. Moreover, it has been considered to make use of a network with a single hidden layer. The hyperbolic tangent sigmoid is chosen as the activation function of the neurons that compose this hidden layer. Therefore, the hyperparameter to be optimized is the number of neurons in this hidden layer.

As mentioned, for the selection of the optimal number of neurons in the hidden layer, a K-fold was performed with K = 5. Thus, in each iteration the model is trained with 4 of the training groups (20 subjects) and validated with the remaining group (5 subjects). Between iterations, the group used for validation is modified. With the training and validation sets created, samples were randomly shuffled within each group to prevent spurious results. In addition, in each iteration the study was performed for a range between 1 and 20 neurons. This range has been chosen in order to minimize computational cost and in view of the good results obtained in previous experimental studies [27].

Moreover, to add a further degree of randomness to the training, this K-fold is performed up to 3 times. For each of them, the previous step of stratification by weight groups has been performed independently. In this way, both the training and validation sets are modified, as well as the distribution of K-fold groups. This is intended to eliminate the possibility

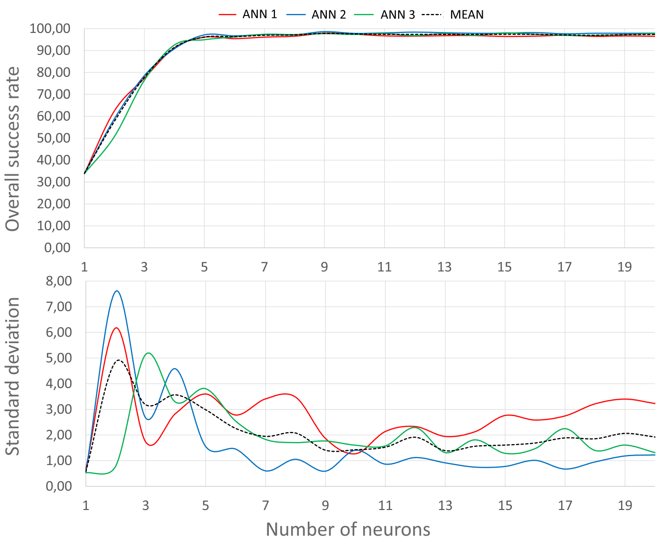

Fig. 6. Analysis of the results obtained in the 5-Fold. Top: Average success rate as a function of the number of neurons in the hidden layer. Bottom: Standard deviation as a function of the number of neurons in the hidden layer.

that the selection of the optimal number of neurons may be conditioned to a specific selection of the training and test sets.

For the analysis of the selection of the optimal hyperparameters, two statistical indicators, the mean and the standard deviation, have been taken into account. In this way, the mean of the success percentages of each of the K-fold iterations and each number of neurons of the hidden layer is calculated. In this way, it is possible to obtain a degree of knowledge of the effectiveness of the classifier. On the other hand, the standard deviation of the success percentages is calculated. This allows us to know the degree of uncertainty offered by the model for a given number of neurons in the face of changes in the training and test subjects.

The results for this 5-Fold are plotted in the graph in Figure 6. This graph shows the mean and standard deviation as a function of the number of neurons for the 5-fold performed. In addition, the mean value of all 5-folds is represented in dashed lines.

In view of the results obtained in the K-fold, it can be seen that with a low number of neurons in the hidden layer a good result in postural classification prediction can be obtained. To be exact, with a number of 5 neurons, the percentage of success is already around 95%, stabilizing around this value for a higher number of neurons. It can be thought that the best option is to choose this number of neurons, since this value allows to achieve a good performance while reducing the computational cost. However, for this number of neurons, the standard deviation has not yet stabilized. This may distort the results for new, unknown subjects. This is why a more conservative approach is adopted, choosing the number of neurons that minimizes the standard deviation. To be exact, a total of 9 neurons are chosen in the hidden layer. In addition, using this number of neurons allows minimizing the difference in standard deviation between the different 5-folds. This indicates that for this number of neurons the system offers a lower uncertainty in the face of changes in the training and test subjects.

TABLE III

CONFUSION MATRIX OF THE SUCCESS RATE OBTAINED BY CLASSIFYING TEST SET'S POSTURES USING THE ANN TRAINED. P01 - NEUTRAL SEDESTATION, P02 - LEANING RIGHT, P03 - LEANING LEFT, P04 - HYPERKYPHOSIS, P05 - LEANING FORWARD, P06 - SLOUCHING

		Predicted					
		P01	P02	P03	P04	P05	P06
Real	P01	**90%**	0%	0%	10%	0%	0%
	P02	0%	**100%**	0%	0%	0%	0%
	P03	0%	0%	**95%**	5%	0%	0%
	P04	3,2%	1%	0%	**96,7%**	0%	0%
	P05	0%	0%	0%	0%	**100%**	0%
	P06	5%	0%	0%	0%	0%	**95%**

TABLE IV

SUMMARY TABLE OF METRICS FOR EVALUATION OF THE CLASSIFICATION MODEL: ACCURACY, PRECISION, RECALL, SPECIFICITY AND F1-SCORE

Posture	Accuracy	Precision	Recall	Specificity	F1-Score
P01	0,9697	0,9164	0,9000	0,9836	0,9081
P02	1,0000	1,0000	1,0000	1,0000	1,0000
P03	0,9917	1,0000	0,9500	1,0000	0,9744
P04	0,9697	0,8658	0,9670	0,9700	0,9136
P05	1,0000	1,0000	1,0000	1,0000	1,0000
P06	0,9917	1,0000	0,9500	1,0000	0,9744

IV. RESULTS AND DISCUSSION

Based on the methodology explained in the previous section, we proceed to analyze the results obtained after its application (Section IV-A). On the other hand, a discussion of these results is made, analyzing the influence of the weight in the classifier, as well as the training model of the neural network (Section IV-B).

A. Training and Validation of the Sitting Posture Classifier

Once the optimal structure of the neural network has been defined, it is trained using an algorithm based on Bayesian Regularization.

These results correspond to test subjects that were initially excluded and were not part of the hyperparameter optimization process. Using subjects who have not participated in the training allows us to know the degree of generalization of the postural classifier.

The results of this training are reflected in the confusion matrix in Table III and metrics such as accuracy or precision provided in Table IV. The percentages in the table represent the number of samples that are classified in a posture by the network, with respect to the total number of samples of a given real posture. Thus, the sum of the percentages for each row adds up to 100%. Thus, the percentages located on the main diagonal correspond to the success rate for each posture, i.e., the correctly classified postures.

For this particular example, the overall success rate is 95.5%. In general, a good percentage of postures classified correctly is achieved for all postures, being Posture 01

(Neutral sedestation) the one with the lowest percentage of success, confusing some samples with the Posture 04. This may be due to the fact that this is the posture with the greatest variability per person, not being as well defined as the rest.

Looking at the table, it can be seen that for most of the postures, the failures are due to missclassifications with another particular posture. Moreover, these failures correspond to the same subject. This highlights the generalization capability of the trained neural network. This indicates that for the vast majority of users, the classifier is able to correctly predict their postural state, and if it does, the percentage is close to 100%. The failures are concentrated for a specific person and a specific posture. Therefore, despite achieving more than acceptable results, in order to improve them even further, the option of adopting a more individualized strategy could be considered. Especially considering that the trials were conducted in a controlled environment. However, this does not change the fact that the classifier shows a high degree of accuracy for the general population, and the failures detected are more related to the individual particularities of each subject at the time of sitting.

Based on the results, the performance of the classifier is high. This performance is even more acceptable considering that subjects who have not been used in any of the previous phases of the methodology, and are therefore unfamiliar to the model, were used for validation. It is difficult to compare these results with those of other studies, given that there are different cases, both in terms of postures, number of subjects and the measurement system used. Results for other similar works where it is clearly specified that validation has been performed on unfamiliar subjects generally show worse results, compared to the near 100% success rate of the approach proposed here. Thus, in [28] a success rate of 90.4% is obtained and in [19] of 81%, both using MLP networks.

Few studies have focused on analyzing the difference in results obtained when validating the model with familiar or unfamiliar subjects. Thus, in [35], results for classifying driver postures go from 85.5% to 71.6% when they are validated with familiar and unfamiliar subjects, respectively. It can be thought that the generalization of the classifier is due to the fact that it is being validated with subjects of similar physical complexions to those of the training, even if they are new for the model, and not to the proposed methodology. To check this, it was decided to use the two subjects who were initially discarded because they weighed more than 100 kg. For this purpose, the network trained following the proposed methodology is used to validate the hypothesis that the classifier is able to generalize to subjects with physical complexions not included in the training. The overall results in terms of success rate for these subjects with a high body mass index is 94.65%. In general, the results are slightly lower. This is not surprising, given that the two subjects being studied are in a range of weights totally different from the training weights.

To make sure that the results are due to the proposed methodology, and not to the specific characteristics of these subjects, a neural network has been trained following a traditional 5-fold. The results for this network do not exceed 70% accuracy in people with high BMI, thus it can be affirmed that the methodology followed allows to achieve good results regardless of the physical constitution of the subjects. Other works obtain results close to 92% using both MLP [31], [38] and KNN [21]. These works obtain a slightly lower success rate than the one obtained in this work, but these results have been obtained with a general population and without specifically analysing the results for people with a BMI outside the average.

Finally, a comparative analysis has been carried out using 3 ML techniques commonly used for sitting classification, SVM, KNN and ANN. Based on the results of this analysis, it can be seen that the success rates obtained for subjects with normative bodies are similar in all models (94,14% SVM, 91,49% KNN and 95,5% ANN). However, for non-normative bodies this difference is increased, with success rates of 65,6% for SVM, 69,9% for KNN and 94,7% for ANN. This analysis reinforces the fact that the methodology based on neural networks is the best performer when it comes to sitting postural classification of people with an BMI outside the norm.

In this way, as much importance is given to the fact of having a large database, with subjects of diverse complexion, as to the fact of employing an effective training and hyperparameter selection methodology. Based on the results, it is proved that the proposed methodology is effective to classify postures of users of different physical complexions, increasing the generalization of the trained neural network. This is important, since physical complexion independence has been achieved, it allows to transfer the advantages of postural monitoring to a wider range of wheelchair users, while providing a greater flexibility to healthcare professionals.

B. Sensor Relevance Analysis Based on Neural Network Results

Finally, in order to analyze not only the results, but also the methodology proposed, the relative relevance that the neural network gives to each of the sensors is studied. Knowing the relevance that the network brings to the sensors, it is possible to know to some extent the learning process that it carries out, and compare it with the experience of a physiotherapist.

In order to calculate the relative influence of the sensors, Garson's formula is used, already applied in other fields for the same purpose [39]. This algorithm allows estimating the relative importance of each feature based on the weights of the input layer and the hidden layer once the neural network has been trained. This estimation is represented by the following formula:

$$Relevance_j = \frac{|\mathbb{W}_j|}{\sum_{j=1}^{16} |\mathbb{W}_j|} \tag{2}$$

where $\mathbb{W}_j$ refers to the network weights associated with an input feature j.

The algorithm returns values between 0 and 1 for each input, which have been translated into percentages for better understanding. The higher the value, the greater the contribution of a feature in the network. To eliminate the variability of the

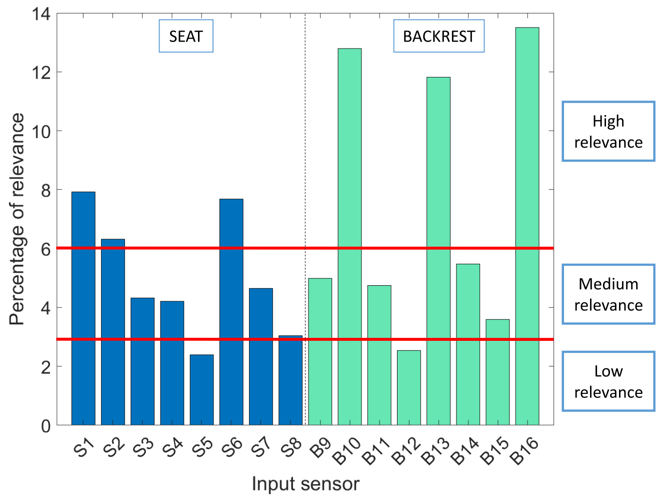

Fig. 7. Bar diagram of the percentage of relevance of the sensors based on the results obtained using Garson's formula. In blue, relevance of seat sensors are represented. In green, relevance of back sensors are represented.

weights when training different neural networks, this process has been applied to the three trained neural networks, and the average of the three has been obtained. The results are represented in Figure 7 by a bar graph.

In view of the results, the sensors can be classified into 3 groups according to their relevance for classification: sensors of high relevance, sensors of medium relevance and sensors of low relevance. In general, a slight asymmetry is observed between sensors located at the same height. However, this asymmetry does not affect their relevance. This asymmetry may be due, in addition to the variability inherent to the training of the networks, to the fact that the subjects do not feel centered at any time. In the event that two symmetrical sensors are in two different relevance groups, the sensor with the higher relevance is taken into account to classify them both within the same group.

In the backrest, the most relevant sensors for classification are B10, B13 and B16. These sensors are located in the upper part of the backrest, at the level of the dorsal region. In contrast, the lumbar area, with sensor B12, is the least relevant. This may be due to the fact that the tests were carried out with healthy subjects, who have a natural lumbar lordosis. The results when testing with regular wheelchair users may vary, giving it a higher relevance than the current one. The rest of the sensors have a medium relevance, in the case of sensors B11 and B14 because, being located in the central area of the spine, they do not present great variations. In the case of sensors B9 and B15, these are intended for monitoring acute lateral displacements. Their average relevance may be due to the fact that these tests were performed in a controlled manner and excessive lateral displacement was not required.

As for the seat, the difference in relevance between the sensors is not as noticeable as in the backrest. The most relevant sensors in this case are those located on the thighs, i.e. sensors S2, S7, S1 and S6, the latter two being of particular relevance. On the other hand, the least relevant sensors is sensor S5, located in the back area of the buttocks. In the zone of medium relevance are sensors S3 and S8, located around the ischia. Despite being the area around which most force is exerted, is one with less relevance with respect to other sensors. This may be due to the fact that at all times, regardless of posture, force is exerted around this area, so that variations in force are minimal. Therefore, they provide little information on the postural state compared to other sensors. However, these sensors are of great importance, among others, for the prevention of ulcers, so there are no plans to eliminate them. Finally, sensor S4, despite not having a high overall relevance, is of great importance for monitoring slouching posture.

Backrest sensors are more relevant than the seat sensors, despite the fact that most of the force is collected in the seat. The backrest is precisely where the greatest variability of force between postures occurs, while a lighter weight redistribution occurs in the seat.

In general, considering that the classifier gives greater importance to force variations, however small they may be, rather than to the measured force, the results are coherent. The sensor relevance results are in line with medical experience for classifying wheelchair users' relevant postures. Thus, it can be concluded that the presented classifier, together with the training methodology, not only obtains good results for subjects of different body shapes, but also follows an intuitive learning process interpretable by healthcare experts.

V. Conclusion

The use of wheelchair during long term as in the case of people with disabilities or functional problems is related to several health problems and loss of quality of life. Therefore, monitoring is essential to prevent these disorders. Given the need to quantify in an objective way the postural condition of wheelchair users, in this paper, an intelligent sitting posture classifier for wheelchair users is presented. This intelligent classifier has the ability to generalise to new users and is independent of the users' weight.

The innovative i-KuXin postural monitoring device was used to generate the database. The monitoring system developed consists of 16 FSR sensors allowing prolonged monitoring, at low cost, while maintaining portability and wheelchair independence. For the generation of the database, tests were carried out on a wheelchair with 37 subjects of varying physical complexions, under the supervision of a physiotherapist.

With the generated postural database, a neural network training strategy has been followed, based on a K-Fold strategy stratified in groups of people according to their weight. The methodology based on K-Fold stratified allows high success rates to be obtained, regardless of the user's physical complexion. Based on the results obtained, with 9 neurons in the hidden layer, success rates of over 95% are achieved. On the other hand, an analysis of the relative relevance of each of the sensors has been carried out using Garson's formula. This analysis confirms that the classifier not only obtains good results for subjects of varying physical build, but also follows a training process that is intuitive and consistent with medical experience.

However, this study has some limitations. This study was carried out in a controlled environment, with healthy subjects. Since this is a development oriented to wheelchair users, the classifiers should be tested in the future on people with low mobility. In addition, these tests should be performed on an older population, over a longer period of time, thus allowing the results obtained to be consolidated. Furthermore, during this testing, it is necessary to use the wheelchairs of the users themselves, thus also verifying that the results obtained are independent of the assistive device used.

In this way, and once the results have been validated, i-KuXin can be used to support patients and healthcare professionals, helping them to automatically monitor their posture and prevent the development of ulcers thanks to the feedback obtained from the system. In addition, as a future work, historical data obtained from i-KuXin can be used to associate changes in postural patterns with changes in the functional status of users.

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