

Article

Handgrip Strength Time Profile and Frailty: An Exploratory Study

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Abstract: This study aims to explore the use of force vs. time data obtained from an isometric handgrip test to match a frailty state based on the TFI score. BodyGrip, a novel prototype system, is used for handgrip strength over 10 s time interval tests. A cross-sectional study with a non-probabilistic sample of community-dwelling elderly women was conducted. The force/time data collected from the dominant handgrip strength test, together with the Tilburg Frailty Indicator (TFI) test results, were used to train artificial neural networks. Different models were tested, and the frailty matching of TFI scores reached a minimum accuracy of 75%. Despite the small sample size, the BodyGrip system appears to be a promising tool for exploring new frailty-related features. The adopted strategy foresees ultimately configuring the system to be used as an expedite mode for identifying individuals at risk, allowing an easy, quick, and frequent person-centered care approach. Additionally, it is suitable for following up of the elderly in particular, and it may assume a relevant role in the mitigation of the increase in frailty evolution during and after the imposed isolation of the COVID-19 pandemic. Further use of the system will improve the robustness of the artificial neural network algorithm.

Keywords: artificial neural networks; frailty; handgrip strength time profile; occupational health; smart systems



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1. Introduction

Population aging is a global phenomenon caused by a decline in fertility and an increase in life expectancy. As the number of elderly people grows, so does the prevalence of chronic diseases and frailty, challenging health and social services all over the world [1,2]. Frailty is a state of high vulnerability in which minor stressors may lead to negative outcomes, such as hospitalization, disability, institutionalization or death [3]. It is caused by physiological age-related changes, by comorbidity, and, in some instances, by life-course determinants [4]. Although there is no consensus regarding the clinical presentation of frailty, the vast majority of researchers and clinicians agree that this condition may be prevented, reduced, or reversed [2,5]. Consequently, the screening of frailty is crucial to ensure the dignity and quality of life of older populations.

The present COVID-19 pandemic, with the imposed physical and social isolation, is contributing to an increase in frailty, in particular, among the elderly population, with an impact that will remain even after the pandemic crisis. As referred by Abbatecola [6], “the irreversible spiral of the Frailty Syndrome” needs to be prevented, fighting effects such as lack of activity, psychological stress, and physical distancing. Those features disturbing the emotional and affections balance will affect the elderly, who are especially vulnerable

to social isolation and loneliness, which is accelerating and rising significantly worldwide during and will remain after the pandemic [7].

Therefore, detecting possible frailty states not only becomes highly important but also for following its evolution in the elderly. The use of an easy and quick screening system can be valuable. Having signaled an elderly person is more likely to enter a frail state, social or health care organizations can plan timely interventions or/and treatments, thus avoiding or slowing down the health deterioration process [8].

A common assessment of frailty is the biological model developed by Fried [9]. It comprises the measurement of five physical components that compose the frailty phenotype: unintentional weight loss, exhaustion, low physical activity (self-report), slow walking speed (timed test), and decreased maximum value of handgrip strength (dynamometer measurement). In this operationalization, a person is considered frail if three or more components are positive. However, this approach is often contested for several reasons. First, the feasibility of measuring the components of the frailty phenotype in a busy daily routine is debatable [10,11]. Consequently, measurements with fewer variables have been developed, such as the Study of Osteoporotic Fracture Criteria for Frailty (SOF) index [12], or measurements based only on self-report, such as the FRAIL scale [13]. Second, some authors argue that other measurements and adjusted score calculations can present a higher predictive validity considering the main outcomes of frailty (e.g., SHARE-FI [14]). Lastly, the unidimensional (i.e., entirely physical) approach to frailty is criticized for not considering that psychological and social factors can increase one's vulnerability. Consequently, biopsychosocial measures have been developed, such as the Tilburg Frailty Indicator (TFI) [4,15].

Maximum value of handgrip strength (HGS) is considered an important biomarker [16]. In fact, it is associated with overall health status, physical function decline, malnutrition and is a relevant predictor of all-cause mortality [17]. Several studies show that low HGS is associated with various indicators of frailty [18,19] since it is a sign of overall muscle weakness and sarcopenia [20,21], an age-related decline in muscle mass that leads to the loss of muscle fibers [22].

HGS offers numerous advantages over other nutritional, functional, and health indicators as it is simply evaluated based on dynamometry, an inexpensive, easy, quick, and reliable method, exhibiting low intra- and between-variability and does not require specialized professionals [23].

In most studies found in the literature, handgrip strength is defined as the maximum value of strength, typically assessed using an isometric test with a handgrip dynamometer, according to a given protocol. With the availability of a few dynamometers capable of measuring the exerted force during a test time interval continuously, other force parameters related to muscle condition have been studied and proposed, such as the rate of force development and sustainability of maximum force. Such parameters depend on the ability to produce energy at the mitochondrial level, which is crucial to several daily tasks that require repetition or a continuous hold [24–27].

The hand dynamometer most frequently reported and accepted as the gold standard is the JAMAR (from Patterson Medical). The original design of JAMAR using a hydraulic system is only able to measure the maximum value of handgrip strength. The JAMAR® Smart Hand Dynamometer uses a load cell and electronics for wireless communications, with a mobile app that allows accessing other handgrip strength vs. time parameters. Although these new functionalities are quite helpful, accessing the raw data and implementing other data processes is not possible. Moreover, the test time intervals are quite short, nor selectable, and therefore not suitable for the investigations, such as the one here described. Similar limitations arise when considering the use of other commercialized handgrip dynamometers, such as the one from Biometrics and the one from JTECH Medical™ Commander Echo Grip and software (USA). The proprietary nature of the communications and available software for these devices limit their use if other test configurations and data analysis are required.

In this work, measurements of handgrip strength time profile were performed using BodyGrip, a patented digital system based on a novel dynamometer [28], allowing the exploitation of the raw data coming from the recorded handgrip test, also permitting the suitable time interval to be defined and adjusted. Adding to its new functionalities, the device is very light, a great advantage for testing among the elderly.

Very little research has focused on the relationship between frailty and the parameters obtained from the force *vs.* time profile, such as rate of force development and sustainability of maximum force, etc. Furthermore, universal definitions of these parameters are not found in the literature.

The present study aims at exploring HGSt data obtained from an isometric handgrip test and to match it with a frailty state based on the TFI score. A universal set of descriptors is proposed inspired by the response of a first-order system to a step stimulus. In fact, this type of response is similar to that obtained when an individual is incited to apply a sudden maximum grip force to the handgrip and sustain it for a given time period.

In this exploratory work, the BodyGrip system was used to measure the dominant handgrip strength profile during a ten-second duration test performed in a group of community-dwelling elderly women. The TFI questionnaire data were also collected. Different sets of descriptors from the force *vs.* time curves were applied to train ANN models to match the TFI test results. This approach envisages ultimately configuring the handgrip prototype system [23] as a tool for supporting frailty screening that can be utilized in ambulatory care, with the test conducted and results obtained in a short time, and performed by any health care professional, such as occupational therapists, after an informed short training. Moreover, such a quick test is more likely to be performed over time, allowing for longitudinal assessments, which can be important, for instance, in illness recovery phases or as an evaluation of an intervention strategy. Ultimately, the broad goal is to provide a tool that can support decision-making by caretakers and doctors.

Models based on Machine Learning (ML) algorithms, such as artificial neural networks, can be of major importance to predict health-related conditions, therefore guiding the caretakers and doctors in decision making [29]. In reference [30], several ML models are compared on their ability to predict frailty conditions in elderly people based on clinical and social-economic characteristics.

In summary, the novel aspects of this work can be outlined as:

- Exploring the relationship between the HGSt data obtained from an isometric handgrip and the frailty state based on the TFI score;
- Using a novel technology transfer patented system, validated against the gold standard, to measure handgrip strength profile during a pre-defined and adjustable time interval;
- Using ANN models that predict a TFI frailty score based on the HGSt data;
- Suggesting a very easy and quick to perform procedure that can be of great use to support decision-making by caretakers and doctors.

The current pandemic situation prevented further data collection. However, the expected effect on the health and well-being of the elderly triggers the need to find solutions that can be quick and easy to implement and explore, such as the one proposed here.

The paper is organized as follows. In Section 2, the design of the study is described including, the prototype system for handgrip strength measurement, the participants, the collected data and its analysis. Results are presented in Section 3 and a discussion and conclusions in Section 4.

2. Materials and Methods

2.1. The Prototype System

To measure the HGSt, the BodyGrip dynamometer developed in the Integrated System and Automation Processes Research Unit of the Institute of Mechanical Engineering of the Faculty of Engineering of the University of Porto was used.

The smart multifunction device allows measuring the compressive or traction force and the estimation of the energy and power used by a particular body muscle or of a group of muscles by just adapting accessories. Together with a software application developed for a PC, the BodyGrip system permits performing different calculations from measuring data provided by the device to recording them in a local or remote database, to processing the data and offering digital monitoring of all features. The system also shows in real-time on the user interface the respective force–time profile. The test elapsed time duration can be adjusted through the user interface to the protocol defined for the study. The prototype device has been used for handgrip evaluation in different fields and was initially validated against the gold standard JAMAR [28].

During its mechanical design, features, such as portability, good sensitivity, force range, and ergonomics, were considered. The device is small, light, and easily portable, although robust. The novel design of its mechanical sensing element (load cell), sensorized with electrical strain gauges, avoids the need for specially designed handles. The bending-type cells, both cantilevered from the center, receive the load on both free ends. This arrangement, and the load sensorization with strain gauges, contribute to the calculation of non-uniformly distributed loads applied to the handle and to provide the free end displacement for partial estimation of the muscle energy.

Its electronics include strain sensors, signal conditioning, and basic processing, which incorporates an IMU for the identification of device orientation, offering Bluetooth connection and USB connection for battery charging.

The BodyGrip system, presenting good sensitivity and resolution, offers a compact device with wireless communication with a software application (10 ms sampling rate) for data registration and monitoring.

The prototype dimensions (114 mm × 22 mm × 45 mm) and weight (0.250 Kg) make it a pocket device for a clinical trial, convenient to the diverse functions presently open to its use, Figure 1.



Figure 1. BodyGrip prototype.

Adding to these features, the BodyGrip allows the measurement of low-level forces without handling effort, in a suitable size where the current large and heavy devices are no longer adequate, which makes it suitable for the elderly, children, and young adults. Further, it offers good characteristics in sensitivity and range.

Currently, the software application runs on a PC or a mobile device. This application provides data monitoring and patient registration, with access to a local or cloud database. Other functionalities include the possibility to access other patient data, such as hand circumference, hand length. A current implementation under development is to provide frailty screening based on handgrip force–time data, building on the experience that this work describes.

The current development is under a Technology Transfer process by the UPorto spin-off named GripWise (<https://gripwisetech.com/>; accessed May 2021), and about 15 systems in a further development stage, named GripWise, are already being used in different health and health care institutions.

2.2. Participants

A cross-sectional study with a non-probabilistic sample of 61 community-dwelling elderly women aged from 66 to 91 years old (averaging 76.6 ± 6.3) from the north of Portugal, who volunteered after information regarding the study was disclosed in social, recreation, and daycare centers. The exclusion criteria consisted of physical impairment or pain in the upper limb, severe cognitive impairment screened by the Mini Mental State Examination (MMSE), using 10 points as the cut-off point [31], and the inability to speak Portuguese.

All assessments took place in the local institutions where the participants were recruited. The studies were performed under a protocol established between the Health School of Polytechnic of Porto and the review boards of the “Private Institution for Social Solidarity of Paços de Ferreira” and the “Social and Parish Centre of Ferreira”. Written informed consent, according to the Helsinki Declaration, was obtained from all participants, and their anonymity has been preserved.

2.3. Data Collection

The data collected from all participants included sociodemographic characteristics (age, sex, hand dominance, and level of education) and, as referred above, cognitive performance (assessed with MMSE). In the present analysis, valid tests from the dominant hand of 61 female participants were considered, with an average age and standard deviation of 76.6 ± 6.33 , the minimum age being 70 and the maximum 91. The number of valid tests from male participants was below 20, and the decision was not to include them. The level of education data was incomplete, and it was decided to discard it in the analysis.

A TFI test was conducted to classify all the participants as frail or not frail. The TFI [15] is a questionnaire used to assess frailty in three domains: physical (8-items), psychological (4-items), and social (3-items). The components of the physical domain are overall physical health, unexplained weight loss, difficulty in walking, difficulty in maintaining balance, hearing problems, vision problems, lack of strength in hands, and physical tiredness. The psychological domain includes questions about memory, mood, anxiety, and coping, while the social domain refers to living alone, social relations, and social support.

Based on a study developed under a Ph.D. thesis [18], a cut-off value of 6 was found as a better classifying indicator for the Portuguese elderly individuals as frail (TFI < 6 – non-frail; TFI \geq 6 – frail).

During the handgrip strength assessment with the BodyGrip, the patient was instructed to hold the device with the dominant hand to be tested, give maximum effort, and to keep exerting force during a ten second test time, by convenient voice incitement. The person who conducted the assessment registered the force–time profile automatically in a computer database and had access to a graphical view of HGSt. Figure 2 shows a typical HGSt curve obtained during the test.

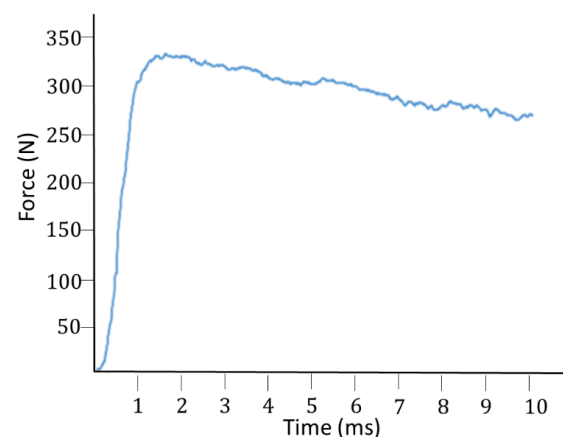


Figure 2. Typical force vs. time curve.

The participant performed the test in a comfortable seated position, with the shoulder adducted and neutrally rotated, with the elbow close to the body and flexed at 90 degrees, and the forearm and wrist in a neutral position, supported on a table. The dominant hand was tested twice, allowing one minute to rest between tests.

All assessments took place in the local institutions where the participants were recruited.

2.4. The ANN Model

Artificial neural networks (ANN) can be seen as an algorithmic approach capable of combining multiple types of information in the process of finding a solution for a given problem [32–34]. ANN have the ability to find the best fitting model by learning which relationships are present in the data and are able to deal both with linear and non-linear relationships. Besides being used in regression analysis and estimations, they are also very well suited for classification problems. As such, they fit naturally into the problem of using the multiple elements of the force profile, as well as complementary information from each individual, for frailty screening. As ANN learn by example, they are very suited to work through real-time events. Therefore, one can build an embedded system that measures handgrip strength and immediately flags a possible frailty state.

The proposed approach is based on the development of an ANN model that uses data from the force profile obtained with BodyGrip, to provide an indication of the frailty level.

Due to the characteristics of the ANN output functions, a threshold, or cut-off level, was subsequently applied to the ANN output values in order to classify frailty, as described in Figure 3.

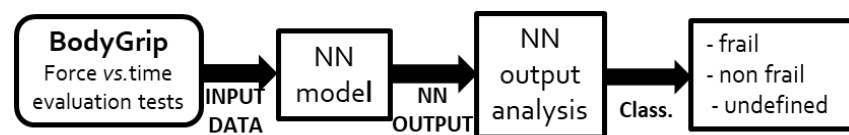


Figure 3. Global system architecture for frailty matching.

The implementation of an ANN was based on the availability of data, which consisted of identified frailty and non-frailty cases, to adjust a mathematical model of the problem, see Figure 4.

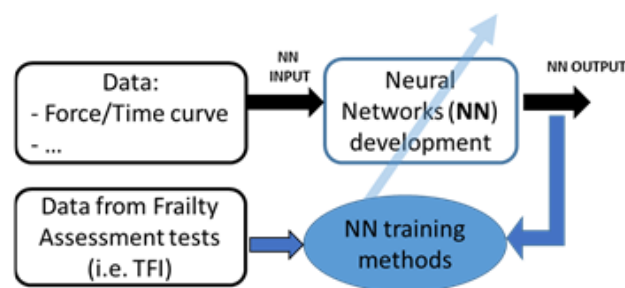


Figure 4. ANN model development process.

Once trained, this model can be used to classify new individuals. The integration of ANN in the developed handgrip system prototype was also straightforward.

Modeling the frailty problem into an ANN included first defining which information was given to the ANN, and how it was encoded in its input, together with the information wanted from the ANN and the respective encoding in its output. The selection of the number of elements, respective functions, and interconnections defined the structure of the ANN model.

The parameters of this model can be adjusted through an iterative process (training phase) in order to minimize the error obtained when comparing the ANN output with the known solutions from the available cases.

In the experiments to develop the ANN model, different ANN structures, data from the force profile, and the results from a frailty test that identified an individual as frail or not were used.

2.5. ANN, Input and Output Features

In a typical handgrip force vs. time profile assessment, obtained with the described protocol during 10 s, there was an initial sharp increase in force until the maximum value was reached, followed by a slower decrease until the end of the trial. This change in the force with time suggests the use as the following variables shown in Figure 5: maximum force, F_{MAX} , 67% of the maximum force, F_1 , and respective times, T_2 and T_1 , the force at the end of tests, F_2 , and the angle α .

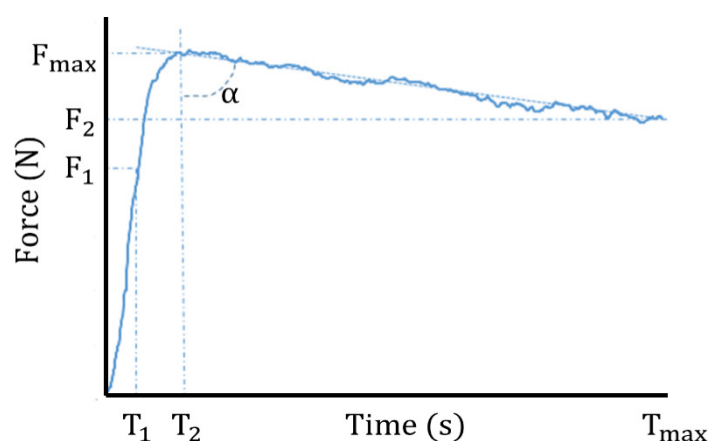


Figure 5. Features from force profile from a typical force vs. time curve.

In this study, different sets of ANN input features were explored. Set 1 included F_{MAX} , F_1 , F_2 , T_1 , T_2 , and α . Another set of features, Set 2, included F_{MAX} , the rate of force development until F_{MAX} was reached, Rate 1, given by (F_{MAX}/T_2) , and the subsequent decay rate until the end of the trial, Rate 2, defined as $(F_{MAX}-F_2)/(T_{MAX}-T_2)$. These two sets of features were an attempt to describe not only the strength of each individual but also the ability to develop strength and the ability to maintain it, which can be associated with power and endurance, respectively.

The ANN was developed using normalized values of the input elements and a structure based on a conventional multilayer feedforward organization of its elements. The Levenberg–Maquardt adjustment algorithm was used due to its suitability for training small-sized problems.

Two output elements of the ANN were tried out: Output 1 was the dichotomous variable indicating frailty state, either 0 (non-frail) or 1 (frail), obtained from the Tilburg test by considering that a TFI result of 6 or higher corresponded to a frail state and lower than 6 to a non-frail state. The other output considered, Output 2, was the variable of the TFI test, ranging from 0 to 15. For each output, several ANN configurations were explored, with a different number of hidden layers.

The data included 61 cases of female individuals and was randomly divided into three sets: training (77.0%), validation (11.5%), testing (11.5%). The training set was used to adjust the parameters of the ANN in an iterative way, using the performance on the validation set as the adjustment stop criterion. The validation set serves to tune the ANN parameters, namely the number of hidden layers. The performance on the test set measures the generalization capability of the algorithm after the adjustment (i.e., training) phase.

3. Results

Multiple experiments were performed with different ANN architectures, the different sets of input features, and the two output variables. Comparing the accuracies obtained

with the different ANN and analyzing the behavior of the square root of mean square error values (SQR(MSE)) in the training, test, and validation samples, it was possible to conclude that better results were obtained with the input features of Set 1. The configurations leading to better performance had six inputs, two hidden layers, in the case of Output 1, and 3 hidden layers in the case of Output 2. Tables 1 and 2 present, respectively, the results obtained for two different models, Model 1, with Output 1 and Model 2, with Output 2.

Table 1. Results obtained with Model 1.

Data Set (n° of Cases)	ANN Performance			ANN Classification Performance (Output Cut-Off 0.5)	
	SQR (MSE)	Max Error	Min Error	[%]	N°
Training (47)	0.3966	1.0142	−0.6537	81	38
Validation (7)	0.4910	0.4205	−0.6440	57	4
Test (7)	0.4539	0.4279	−0.6247	71	5

Table 2. Results obtained with Model 2.

Data Set (n° of Cases)	ANN Performance			ANN Classification Performance (Output Cut-Off 0.5)	
	SQR (MSE)	Max Error	Min Error	[%]	N°
Training (47)	1.6337	5.2768	−3.6216	77	36
Validation (7)	3.7178	5.7762	−4.3075	57	4
Test (7)	3.2971	5.4062	−4.1098	71	5

The tables include SQR(MSE) values, the extreme error values (positive and negative), and the classification performance on frailty screening based on a cut-off value to interpret the ANN output. In the case of Table 1 (Output 1), values bigger or equal to 0.5 were considered to be a frail state, and in the case of Table 2 (Output 2), values bigger or equal to 6 were considered to be a frail state. The last columns of the tables show the percentage of correctly and the number of cases classified.

Regarding ANN performance related to the difference between the correct classification and the result from the ANN, it could be observed that, in general, the average errors and extreme values were significant. This can be associated with the difficulty of the ANN in directly classifying each case into two levels of frailty (0/1) (Model 1) or in a value ranging from 0 to 15 (Model 2), as the outputs were values from a continuous function approaching those binary or ordinal levels, respectively, Figures 6 and 7.

The frailty classification was obtained by assigning as frail states (1) cases for which the output value of Model 1 was bigger or equal to 0.5 and as non-frail states (0) cases for which the output value was lower than 0.5. As for Model 2, an output value equal or bigger than 6 corresponded to a frail state (1) and lower than 6 to a non-frail state (0).

Figures 8 and 9 compare the classifications obtained with the two models when matching the outputs with those from the TFI frailty assessment.

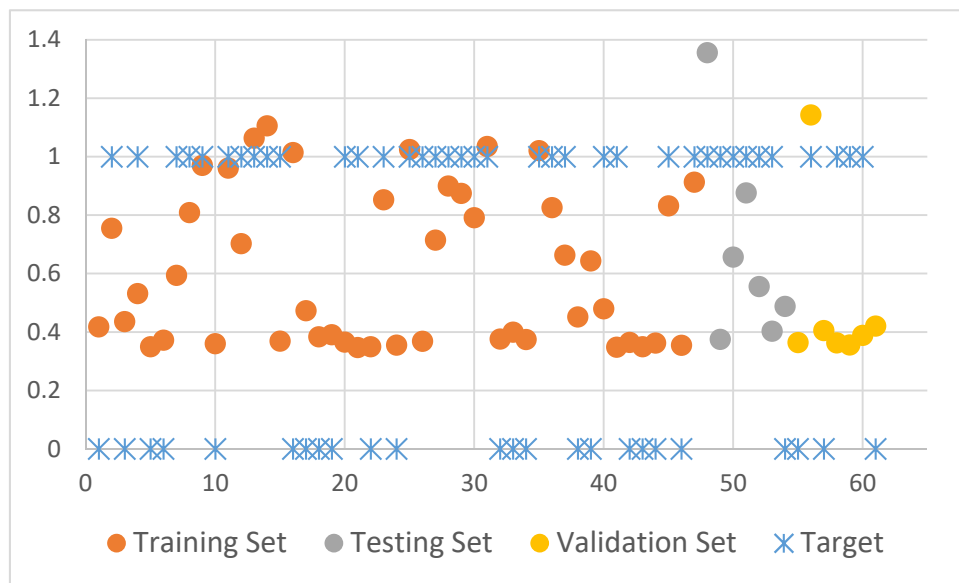


Figure 6. ANN results and known frailty dichotomous classification (target) for Output 1.

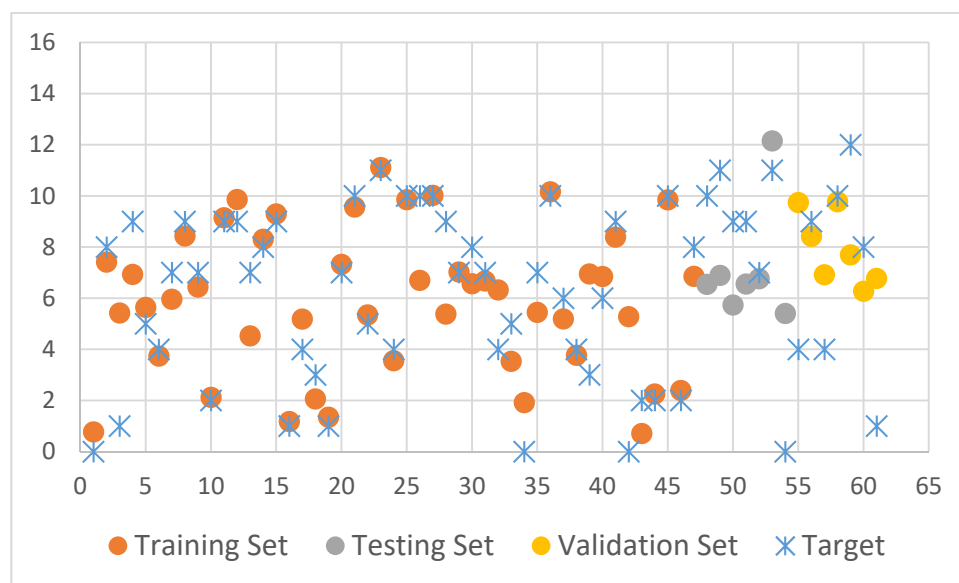


Figure 7. ANN results and known TFI classification (target) for Output 2.

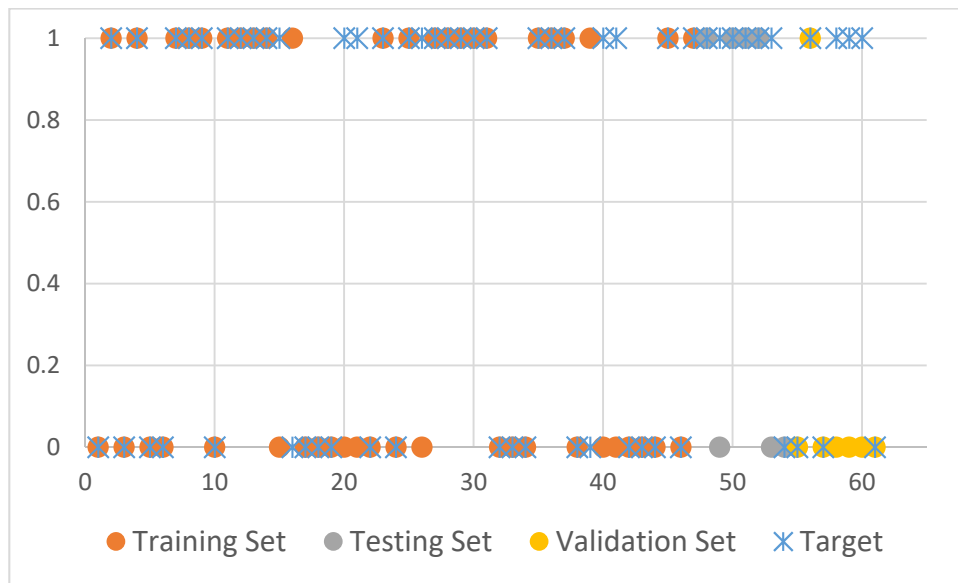


Figure 8. ANN results and known frailty state classification (target) for Output 1.

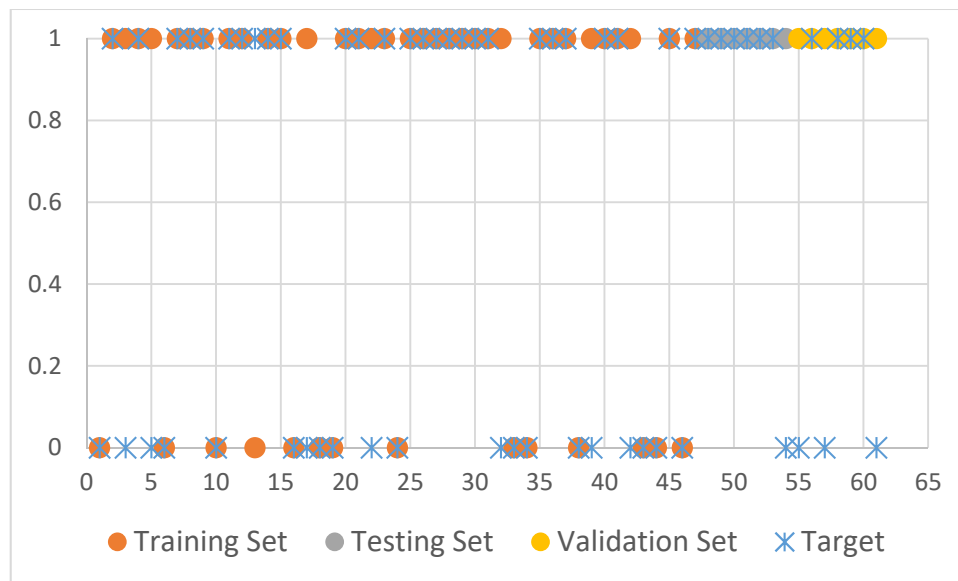


Figure 9. ANN results and known TFI classification (target) for Output 2.

When analyzing the results for each data set, in both models, the performance on the training set was better on average error values because those cases were used to adjust the ANN parameters and they included more cases than the other two data sets. These other sets were used as a stop criterion for the algorithm adjustment (validation data set) and as new cases to evaluate the generalization ability of the ANN (test data set). It can therefore be expected that with a larger data set, the ANN performance will improve significantly.

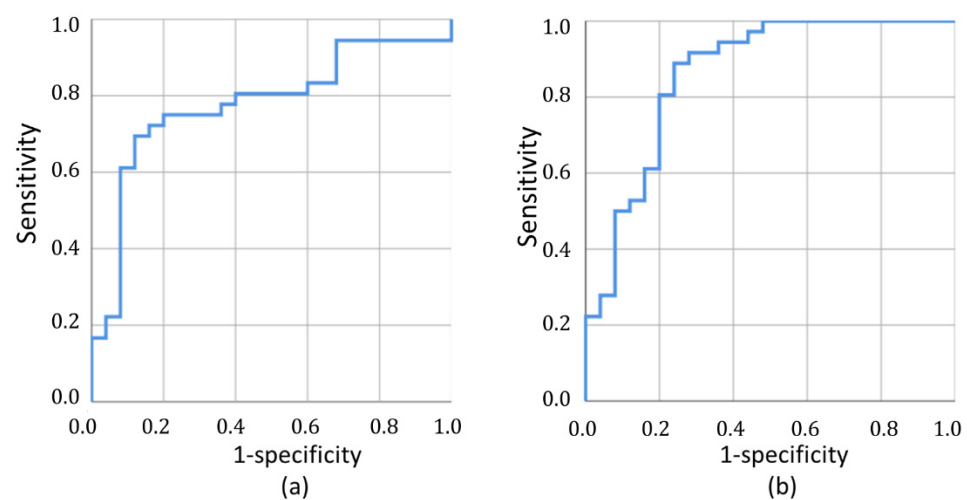
Table 3 shows the classification for frail and non-frail states obtained with the two different models, the values for true positive rate (TPR) or sensitivity, true negative rate (TNR) or specificity, and overall accuracy.

Both models identified better frail cases than non-frail cases, as the TPR and TNR values confirmed. The second model performed under 50% in identifying non-frail states. The accuracy in both cases was above 75%.

Table 3. Frailty classification obtained with the different output functions.

ANN Results–Classification Table						
		Model 1		Model 2		
Frailty Test		1	0	1	0	
assessment	1	26	2	36	1	
	0	11	22	13	11	
	True Positive Rate		70%		97%	
	True Negative Rate		92%		47%	
	Accuracy		79%		77%	

Figure 10 depicts the receiver operating characteristic curves (ROC) [35] obtained with the results of the two models.

**Figure 10.** ROC curves for the different models: (a) Output 1 (b) Output 2.

The area under the curves (AUC) was, respectively, 0.79 and 0.78, indicating clearly a non-random classification. In spite of the reduced number of cases available, this exploratory study shows that developing an ANN model to map force-profile information into frailty according to TFI tests is possible. With a larger set of data, the algorithm can be developed to include additional information, which it can be envisaged will help in this characterization.

4. Discussion and Conclusions

The researchers are aware of the various dimensions of frailty and the small sample. However, this very preliminary study shows that with this approach, different ANN models can match a frailty state obtained in a TFI test with an accuracy of 75%.

This work has several limitations, most of which relate to data availability. First, the data were obtained in community-dwelling elderly people, where women are always in higher number than men. There were also men in the sample, but the small number made it difficult to draw any conclusions, even in the context of a preliminary study. Moreover, since men have a significantly higher handgrip strength than women, those cases could interfere in the classification. In the future, recruitment will be performed aiming at balanced samples in gender and age classes. Second, the informed consent obtained from the participants did not include asking other relevant characteristics, such as anthropometric data or health-related issues, such as traditional objective physical activity tests. This type of data will also be considered in a new version of the system software.

Other limitations concern the evaluation of the ANN model performance. For frailty classification, it might be advisable to take into account the unbalanced sample and look at the performance of the model for specific groups of participants, as suggested in [36].

In addition, with larger samples, the models can be improved by performing a k-fold cross-validation procedure [37].

As soon as the pandemic situation will allow, new tests will be performed, and larger samples will allow refining the models. For instance, including other participants' characteristics will allow investigating feature importance and, in particular, assessing the importance the HGSt parameters in predicting the frailty condition as compared with other individual characteristics.

A commercialized upgraded version of the system, named Lipowise (Lipowise Tech), will be used for future measurements of handgrip strength. A specific protocol will be implemented that can be easily followed by any caretaker or therapist. A recorded incitement will be available within the system, contributing to testing in the same conditions. This is a very important component in order to conduct a typical meaningful curve for comparing and study purposes.

Loss of muscle strength associated with aging may hinder daily activities, contributing to a decrease in general well-being. It is known that the maximum value of handgrip strength is associated with aged-related health conditions, and in particular to frailty. However, not much research has been reported relating frailty with other indicators of muscle condition, such as rate of force development and force maintenance. In this work, that relationship is explored by analyzing how parameters of the handgrip force vs. time profile, HGSt, match TFI test scores. Measurements were performed among a small number of elderly women, using BodyGrip, a system based on a portable, sensitive, and light device and a software application that offers the possibility to record the handgrip force profile, in a few seconds test (adjustable), and permits a post algorithm data processing.

Given the population aging, the prevalence of frailty in this population, and the frailty consequences, it is important to develop an easy and fast screening tool for frailty. In fact, the majority of frailty assessment tools (e.g., TFI) conducted by specialized professionals are very time-consuming. This innovative system performs a test in just 10 s and immediately processes the data providing a quick result. Thus, this system can easily be used in community and primary health care facilities not only as an evaluation instrument but as a tool to identify and alert for frailty risk. This may be of importance for health care planning, as it can aid in determining priority groups to be targeted for comprehensive geriatric assessments and interventions. In a busy daily routine, characteristic of health care professionals working in geriatrics, such as occupational therapists, such a tool can help use time more efficiently and consequently improve the quality of life and well-being of the elderly.

It is important to note that ANN are compatible to including other types of information that can be associated with this problem, and the overall approach can be continuously improved as new data is collected.

Due to the current pandemic situation, it has not been possible to gather additional data. This work is still very preliminary, but it might be useful to give an insight into the relationship between indicators of muscle condition obtained in a very quick and easy-to-do test and a frailty test score. Further use of the system, complemented by other assessments, such as the Fried phenotype assessment, can improve the robustness of the artificial neural network algorithm and increasing its accuracy.

This approach to frailty screening can be particularly relevant during and after the imposed isolation to mitigate the COVID-19 pandemic.

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