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Review article

Machine learning approaches for frailty detection, prediction and classification in elderly people: A systematic review

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ABSTRACT

Background: Frailty in older people is a syndrome related to aging that is becoming increasingly common and problematic as the average age of the world population increases. Detecting frailty in its early stages or, even better, predicting its appearance can greatly benefit health in later years of life and save the healthcare system from high costs. Machine Learning models fit the need to develop a tool for supporting medical decision-making in detecting or predicting frailty.
Methods: In this review, we followed the PRISMA methodology to conduct a systematic search of the most relevant Machine Learning models that have been developed so far in the context of frailty. We selected 41 publications and compared them according to their purpose, the type of dataset used, the target variables, and the results they obtained, highlighting their shortcomings and strengths.
Results: The variety of frailty definitions allows many problems to fall into this field, and it is often challenging to compare results due to the differences in target variables. The data types can be divided into gait data, usually collected with sensors, and medical records, often in the context of aging studies. The most common algorithms are well-known models available from every Machine Learning library. Only one study developed a new framework for frailty classification, and only two considered Explainability.
Conclusions: This review highlights some gaps in the field of Machine Learning applied to the assessment and prediction of frailty, such as the need for a universal quantitative definition. It emphasizes the need for close collaboration between medical professionals and data scientists to unlock the potential of data collected in hospital and clinical settings. As a suggestion for future work, the area of Explainability, which is crucial for models in medicine and health care, was considered in very few studies.

1. Introduction

According to the 2020 report of the UN on aging [1], in 2019, 703 million persons were aged 65 years or over, around 9% of the global population. This number is projected to double to 1.5 billion in 2050, representing 16% of the total. This increase in life expectancy in the rapidly growing global population is one of the main reasons why *frailty in older people* is a trending topic in research. Despite all recent studies and publications, frailty has no precise universal clinical definition other than an age-related syndrome consisting of a state of vulnerability that affects multiple physiological systems [2]. However, some criteria for defining and detecting frailty are more widely accepted and used than others. In particular, in 2001, Fried et al. [3] presented the definition of the Fried's Frailty Phenotype (FFP) to classify patients as frail, pre-frail, and robust. It assesses five measurable criteria: weight loss, exhaustion, low physical activity, slowness, and weakness. FFP is one of the most widely used definitions in the medical field and data-driven studies. In 2005, Rockwood et al. proposed the Clinical Frailty Scale (CFS) [4], based on the Frailty Index (FI), which is defined by deficits accumulation, sometimes including cognitive aspects and the patient's medical history. This definition relies on the percentage of selected deficits that indicate frailty and classifies patients into seven categories, from *very fit* to *severely frail*. By the same principle, in 2016, Clegg et al. [5] presented the electronic Frailty Index (eFI), a definition of frailty that uses the cumulative deficit percentage extracted from Electronic Health Records (EHR). In 2017, Gleason et al. [6] proposed a screening tool in the form of a short questionnaire to detect frailty in elderly patients with fractures. Although it was developed and tested to avoid adverse postoperative outcomes, it proved to be a sound detection system, and some studies in the review decided to adopt it. Another operational

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definition based on a questionnaire and medical records was presented by García-García et al. [7] in 2014, the Frailty Trait Scale (FTS). It relies on 12 items representing the frailty-related categories of energy balance–nutrition, physical activity, nervous system, vascular system, strength, endurance, and gait speed. The variety of clinical definitions of frailty and related diagnosis methods (questionnaires, medical examinations, clinical records) reflects the uncertainty about this syndrome. This uncertainty likely represents the biggest challenge for non-medical scientists developing decision-support tools based on data.

Taking care of older adults is becoming increasingly important, not only to improve the population's quality of life but also because of the large amount of resources needed to support frail individuals. These resources must then be spread over potential recovery cases for often costly rehabilitation practices. Additionally, early detection of frailty is vital for effective treatment, and it is often challenging for healthcare personnel to detect it in its early stages due to a lack of training [8]. Furthermore, frailty is a reversible syndrome [9], another major factor promoting research in its early detection. In fact, a tool capable of detecting frailty in its early stages, or even better, predicting it, could greatly assist medical personnel in decision-making and resource allocation problems. Machine Learning (ML) is one of the most promising approaches to developing such a tool, thanks to the increasing amount of data available in health care. Such data can be gathered from hospitals and clinics, or using sensors to study gait movement or physical activity in general. However, the lack of a universal quantitative definition of frailty sometimes makes it difficult even to compare the results. In addition, the sources of data used to detect or predict frailty can vary widely. This paper systematically compares the principal attempts to apply data-driven models to detect, predict, and classify frailty.

The remainder of the paper is organized as follows. Sect. 2 documents the research questions and the review protocol. Sect. 3 illustrates the main findings and insights of the systematic review. Finally, Sect. 4 concludes this paper and outlines possible future improvements.

2. Methods

In this Section, the selection process for the publications is described, divided into three phases: search, screening, and study, following the PRISMA methodology [10]. The search phase consists of a query run on relevant publications' databases, followed by the screening phase in which issues are excluded by title and abstract reading. The inclusion/exclusion criteria applied in the study phase consist of eight relevant questions to which each issue must provide an answer to be included. During the study phase, relevant data extraction and analysis are performed on the included issues.

2.1. Systematic selection process

The records reviewed in this paper have been selected through the systematic process of PRISMA [10]. Initially, on the 19th of April 2023, the results of the query

"Frailty" AND *"Machine Learning"* AND *"Elderly"*

were collected from the most relevant issues databases (Google Scholar, Elsevier, PubMed, Web of Science, Scopus) for a total of 549 records. After eliminating duplicates and presentation posters, 427 remained, which went through a screening phase consisting of reading the title and abstract. Of these, 43 were selected for in-depth study, guided by the following questions, to which each article must be able to provide an answer to be included in the review:

1. What is the primary goal of the study? (frailty Prediction/Detection/Classification)
   Relevance: see how many studies attempt to predict the appearance of frailty in the future (prediction) and how many aim to detect frailty that is already affecting the patient, using multiclass (classification) or binary classification (detection).

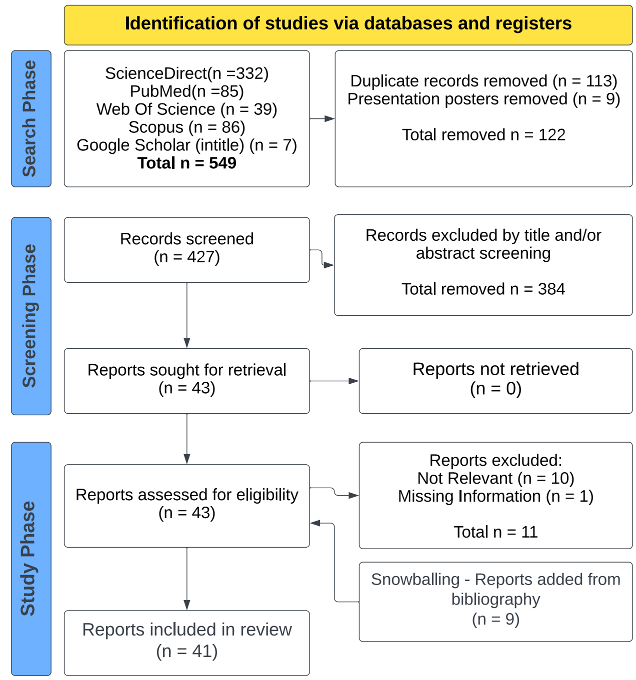

Fig. 1. PRISMA systematic review process.

2. What is the definition of frailty used in the study?
   Relevance: check how many different definitions are used for the target variables, which is the most common, and how it affects the study and the results.
3. What type of data is used in the study, and how were they collected?
   Relevance: check the variety of data sources and what models are the most common with which data types. See how the data was collected and whether the collection was carried out within the study.
4. Are the data available?
   Relevance: reproducibility of results.
5. What type of ML algorithms is used in the study?
   Relevance: Check which models are the most common in the field and which obtained the best results, paired with which type of data.
6. Is the code repository public?
   Relevance: reproducibility of results.
7. Is the aim of the study to develop a decision-support tool?
   Relevance: check how easy it would be for medical personnel to use the results of the study.
8. Does the study consider Explainability/Interpretability at any time?
   Relevance: see how many studies consider Explainability/Interpretability a critical factor in developing a functional support tool for healthcare professionals.

Of the 43 articles considered, 11 did not pass this stage because they could not satisfactorily answer to all the questions listed above. However, during the study phase, 9 more reports were identified through the bibliography and retrieved (snowball effect). Thus, a total of 41 studies were included in the review, as shown in Fig. 1, describing the whole process.

2.2. Extraction

The study phase consisted of a thorough reading of the issues, necessarily but not exclusively, looking for answers to the eight relevant questions. Once all the answers to the research questions have been retrieved, the publication is included in the review, and the information collected is shown in Table 1.

Table 1
Sum up a table of the publications. *Goal*:{P = Prediction, D = Detection, C = Classification}; *Self-Collected (SC)* = Self-Collected:{Y = Yes, N = No}; *Avail* = Availability of the datasets:{Y = Yes, N = No, R = Request}; *Repo*Availability of the repository:{Y = Yes, N = No, R = Request}; *Expl* = Explainability was considered:{Y = Yes, N = No}.

Ref	Author	Goal	Target var	Data	SC	Avail	Models	Repo	Expl
[12]	Abbas et al.	C	Gait speed	Gait sensors [13]	Y/N	Y	DT, LR, MLP, RF, SVM	N	N
[14]	Abbas et al.	P	Physical weakening	Clinical + gait [15]	N	Y	Ada, MLP, GBM, kNN, SVM	N	N
[16]	Akbari et al.	D	Fried	Kinect movement sensor	Y	R	BC, kNN, MLP, SVM, VC	N	N
[17]	Ambagtsheer et al.	D	eFI	Residential care records	N	N	DT, kNN, SVM	N	N
[18]	Aponte-Hao et al.	D	FI	Primary care data [19]	N	R	CaRT, GNB, kNN, LR, MLP, RF, SVM, XGB	R	N
[20]	Arshad et al.	D	FRAIL Scale	Gait images	Y	N	Deep CNN	N	N
[21]	Bertini et al.	C,P	Hospitalization/death	Socioclinical DBs	N	N	LR	N	N
[22]	Blanes-Selva	P	FI	Hospital records	N	N	DNN, GBM	N	N
[23]	da Cunha Leme et al.	D	Fried	Aging study [24]	N	R	BN	N	N
[25]	Eskandari et al.	D	Fried	Heart Rate	Y	N	LSTM	N	N
[26]	Garcia-Moreno et al.	D	Fried	Wearable sensors movement	Y	N	GNB, kNN, RF, SVM	N	N
[27]	Gomez-Cabrero et al.	C	Fried	Clinical/aging [28–30]	N	R	ML framework	N	N
[31]	Goonawardene et al.	D	FI	Home sensors	Y	N	GNB, LDA, LR	N	N
[11]	Greene et al.	D	Fried	Sensors gait tests	Y	N	SVM	N	N
[32]	Hassler et al.	P	Fried	Aging study [28]	N	R	C5.0, CaRT, bCaRT, GNB, LDA, RF, SVM	N	Y
[33]	Idris et al.	C	MoCA + Fried	Blood samples [34]	N	R	CaRT, GNB, kNN, LDA, LR, RF, SVM	N	N
[35]	Jung et al.	D	FRAIL scale	Gyroscope gait test	Y	N	LSTM	N	N
[36]	Kim K. et al.	D	Fried	Smart Meter Consumption	Y	N	LightGBM, MLP, XGB	N	N
[37]	Kim B. et al.	D	Fried	Wearable sensors habits	Y	N	LR	N	N
[38]	Koo et al.	D	Fried	Aging study [39]	N	R	GBM, RF, SVM	N	N
[40]	Kraus et al.	P	SPPB ≤ 8	Clinical + Gait tests	Y	N	kNN, RF	Y	N
[41]	Kumar et al.	C	TUG & SPPB	Cognitive clinical [42]	N	R	LR	N	N
[43]	Kuo et al.	D	LSNS-6	Demographic and physical	Y	N	BaggedCaRT, C5.0, MLP, RF, XGB	N	N
[44]	Le Pogam et al.	P	Fried	Hospital discharge data [45]	N	R	best-subsets-LR, Lasso-LR, RF, SVM	N	N
[46]	Liu et al.	D	Fried	Gait from Machine Vision	Y	R	AlexNet (CNN), VGG16 (CNN)	N	N
[47]	Minici et al.	D	Fried	Wrist + lower back sensors	Y	N	GNB, LR, MLP, RF, SVM	N	N
[48]	Moguilner et al.	P	8-year mortality	Aging study [49]	N	R	LDA	N	N
[50]	Oates et al.	D	FI	EHR and administrative [51]	N	R	GP to optimizeDT, LR, RF, SVM	N	N
[52]	Park et al.	D	Fried	Pendant sensor activity	Y	R	LR	N	N
[53]	Park et al.	D	Fried	Sit-to-Stand tests	Y	N	LR	N	N
[54]	Peng et al.	P	FI	EHR [55]	N	R	RF	N	N
[56]	Pérez et al.	D	VIG	Grip strength test	Y	N	MLP	N	N
[57]	Razjouyan et al.	C	Fried	Pendant sensor habits	Y	N	DT	N	N
[58]	Razjouyan et al.	D	CF	Pendant sensor habits	Y	N	DT	N	N
[59]	Sajeev et al.	D	Fried & CFS	Health questionnaire	Y	R	LDA, LR, RF, SVM	N	N
[60]	Sargent et el.	P	CF & Fried	Aging study [30]	N	R	XGB	N	N
[61]	Tarekegn et al.	P	6 variables	EHR and administrative	N	N	GP	N	N
[62]	Tarekegn et al.	P	6 variables	EHR and administrative	N	N	DT, GP, LR, MLP, RF, SVM	N	N
[63]	Tsipouras et al.	D	Fried	Bluetooth sensors	Y	N	DT, GNB, kNN, MLP, RF	N	N
[64]	Tyrovolas et al.	D	FI	Aging study [65]	N	R	LR	N	N
[66]	Wu et al.	P	FI	Aging study [67]	N	Y	DT, GNB, LR, MLP, RF, SVM, XGB	N	Y

However, the study phase does not stop once the questions are answered. On the contrary, the inclusion of an issue in the review is a symptom that the content of such an issue needs to be further investigated. Some of the conclusions and findings of the study phase, which are not collected in the table, are included in Section 3.

In addition to content studies, we calculated some interesting statistics using data contained in Table 1 and the bibliography. Although the topic of frailty is of increasing importance, among the selected issues, not one is from 2023, and the year of the highest production is 2021, as shown in Fig. 2. Publications began in 2018, with one exception in 2014 (Greene et al. [11]).

All publications are well distributed between North America, Europe, and Asia, with only a few from Australia and South America, as shown in Fig. 2.

3. Results

In this section, we collect the main results and findings of the review, focusing on three main aspects: the definition of frailty selected by the research group, the type of data used, and the models developed, with the relative results.

3.1. Target variables

As all reviewed studies focus on the prediction, detection, or classification of frailty, the target variables depend exclusively on the definition of frailty chosen by the authors. As shown in Fig. 3, the most common definition of frailty is the FFP [3], which was adopted by 18 studies. Among these 18 examples, 9 used gait data to train their algorithms ([16,26,11,37,46,47,52,53,57]), 7 used EHR ([23,27,32,38,44,59,60]), and the remaining two used electric consumption ([36]) and Bluetooth sensors ([63]). This distribution is reasonably similar to the general distribution of data sources shown in Fig. 4, therefore, there is no correlation between using FFP as a frailty definition and the type of data used in the study.

The second most common definition of frailty is the use of a FI, first introduced by Rockwood et al. [4], defined as the percentage of deficits present in a patient among those selected that denote frailty. The selec-

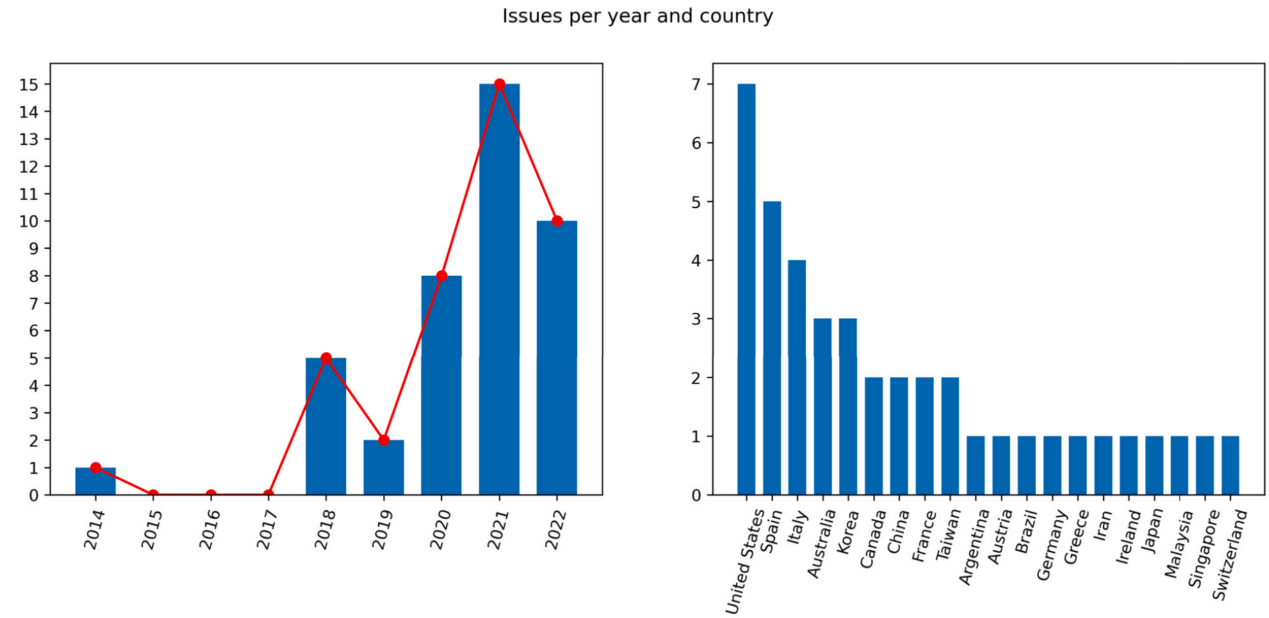

Fig. 2. Bar charts grouping the issues per publication year on the left, and country of the organization of the first author on the right.

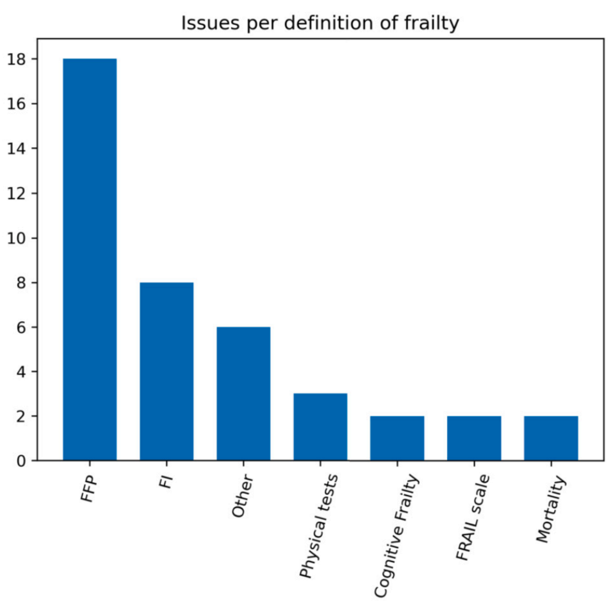

Fig. 3. Definitions of frailty used in the studies.

tion of these deficit features can vary depending on the available data; hence the frailty definition changes. The task of selecting which features define the FI is not trivial. Two groups specifically worked on it: Oates et al. [50] used partial genetic algorithms to optimize four classifiers to select the most relevant features among administrative and medical data; Peng et al. [54], with a similar procedure, defined a multimorbidity-FI using Random Forest (RF) for feature selection on medical records. It is notable the case of Sajeev et al. [59], who focused on the detection of pre-frailty using the definitions of both FFP and CFS.

Within the "*Other*" category of Fig. 3, two studies from Tarekegn et al. are included [62,61], in which six target variables that indicate frailty were determined from an administrative health database (mortality, urgent hospitalization, preventable hospitalization, disability, fracture, and admission to the emergency department), and supervised learning models were developed to predict their appearance separately. Two more studies used single variables, such as hospitalization or mortality in a certain time interval, as a definition of frailty [21,48].

Razoujan et al. [58] used data collected from pendant sensors to detect FFP and Cognitive Frailty (CF), defined as underperforming in one of the Fried criteria categories and scoring less than 27 in Mini-Mental State Examination (MMSE). In the same category, we included Abbas et al. [12], who used gait speed as an indicator of frailty; Kuo et al. [43], who defined "social frailty" using the Lubben Social Network Scale (LSNS-6) and then used demographic and physical data to detect it among the older population in Taiwan; and Pérez et al. [56], who are the only ones who used a comprehensive geriatric assessment called VIG [68] to define frailty. They trained an Artificial Neural Network (ANN) with the scope of frailty detection using only grip strength data.

Some groups incorporated CF in their studies, defining it in different ways: Idris et al. [33] used FFP and Montreal Cognitive Assessment test (MoCA) to divide patients into seven CF categories and then trained seven classifying models with blood samples data; Sargent et al. [60] developed two distinct models, one for FFP, and one for CF (defined by MMSE + Trail Making Tests (TMT)) prediction. On the contrary, Kumar et al. [41] started from cognitive data and developed regression models to determine the physical frailty of patients, defined using Timed Up-and-Go Test (TUG) or Short Physical Performance Battery (SPPB) tests.

3.2. Datasets

ML-based tools developed in the studies can be roughly divided into two groups based on the data source that was used to train the models. As shown in Fig. 4, slightly more than half of the studies (22 exactly) use EHR, which can come from hospital records, private clinics, residential facilities, or, in most cases, from aging-specific studies that are concerned with collecting interesting data from a cohort of older people over several years. Depending on the source of the data, they can also include age-specific questionnaires and financial and social information. Studies in this review using this type of enriched EHR data usually select FFP [23,27,38,44] or a FI [17,18,22,64] as target variables.

The second group is formed by gait data or physical activity data in general. These data are collected, in most cases, through motion sensors, which are often wearable by patients. Three exceptions to wearables are Goonwardene et al. [31] and Tsipouras et al. [63], who use motion sensors installed in patients' homes, to detect patterns of behavior that may be indicators of frailty, and Akbari et al. [16], who used a Kinect sensor to collect data from gait test performed by patients in front of the sensor. Wearable sensors are one of the main ways to collect data

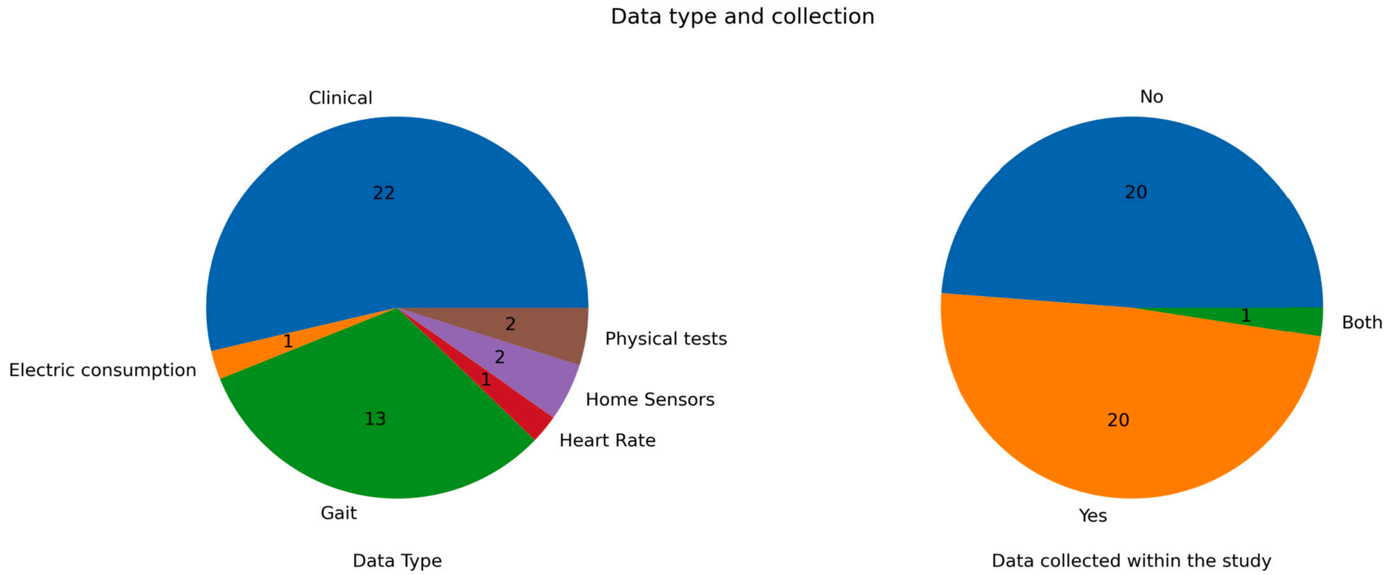

Fig. 4. Pie charts indicating the type of data used in the studies and whether they were collected within the study or not.

Table 2
Collection of the most relevant Databases used within the studies.

Ref	Name	Subj	Vars	Longit	Open	Data type	#Studies
[13]	WWBS Metrics	30	20× timestep	N	Y	Gait from wearable sensors	1
[15]	AVPMD	117	58	N	Y	EHR + gait	1
[19]	CPCSSN	> 400,000	-	N	R	EHR	1
[24]	ELSI-Brasil	9,949	-	Y	R	EHR and aging questionnaire	1
[28]	TSHA-Toledo	2,488	-	Y	R	EHR and aging questionnaire	2
[29]	The AMI cohort	1002	-	Y	R	EHR and aging questionnaire	1
[30]	InCHIANTI	1,167	-	Y	R	EHR and aging questionnaire	2
[34]	MELoR	1,123	712	Y	R	EHR	1
[39]	KFACS	3,014	-	Y	R	EHR and aging questionnaire	1
[42]	Dilip V. Jeste	112	-	Y	R	Cognitive, physical, and mental health	1
[49]	TILDA	8504	-	Y	R	EHR and aging questionnaire	1
[51]	ACFI	592	-	N	R	EHR and administrative care facilities data	1
[55]	NHIRD	23.5 M	-	N	R	EHR	1
[65]	COURAGE	10,800	-	Y	R	EHR and aging questionnaire	1
[67]	CLHLS	113,000	-	Y	Y	EHR and aging questionnaire	1

related to frailty and constitute a distinct trend among the studies in this review. Sensors can be of various types, from wrist worn [26,37], to wrist plus lower back [47], to pendant [52,53], to insole [40], and finally, a combination of legs, waist, and chest sensors, depending on the test the patient has to take [11].

The study by Kim K. et al. [36] is the only one that falls outside of the two categories mentioned above since it proposes using electricity consumption data collected through Smart Meters to detect frailty.

The second pie chart in Fig. 4 shows how about half of the research groups collected their data within the study, while the other half used available databases, mainly from previous aging studies. The only exception is the study by Abbas et al. [12], in which both self-collected data and publicly available datasets were used.

We collected the most relevant databases in Table 2, and it is interesting to note that not one of them was used in more than two studies, indicating the large variety of available data.

The number of subjects per database varies widely, from 30 [13] to over 23 millions [55]. On the other hand, it was hard to determine the number of variables in each dataset since most are only accessible upon request. Most of the databases in Table 2 contain EHR, with the notable exception of WWBS Metrics [13], which is a collection of gait data recorded from sensors and is open access.

Ten out of the collected fifteen Databases come from aging longitudinal studies [24,28–30,34,39,42,49,65,67], and two of the five remaining are complete administrative health databases of Canada [19] and Taiwan [55]. Only three of the fifteen databases are open to download, while the rest are available upon request.

3.3. Algorithms and models

Table 1 shows that ML models applied to frailty can be divided by their objective. In this review, we differentiated between prediction (only if the model is developed using temporal data and the task is to predict the appearance of frailty), detection (binary classification problem with target classes being *frail* and *non-frail* or *robust*), and classification (multi-class classification problem; typically the target classes are *frail*, *pre-frail* and *non-frail* or *robust*, but there could be more). Detection is the most common task, being the goal of about 57% of the studies, prediction follows with about 29%, and finally classification at 14%. Multiclass problems are the less common because patients are often divided between *robust* and *non-robust* to compensate for data imbalances by grouping all individuals showing signs of *pre-frailty* with the frail ones.

As shown in the bar chart in Fig. 5, the three most common algorithms are Linear Regression (LR), Support Vector Machine (SVM), and RF, used in 17, 16, and 15 studies, respectively, and are independent of the goal of the model (prediction/detection/classification). They are followed by Multi Layer Perceptron (MLP), Decision Tree (DT), Gradient Boosted Machine (GBM), and Gaussian Naive Bayes

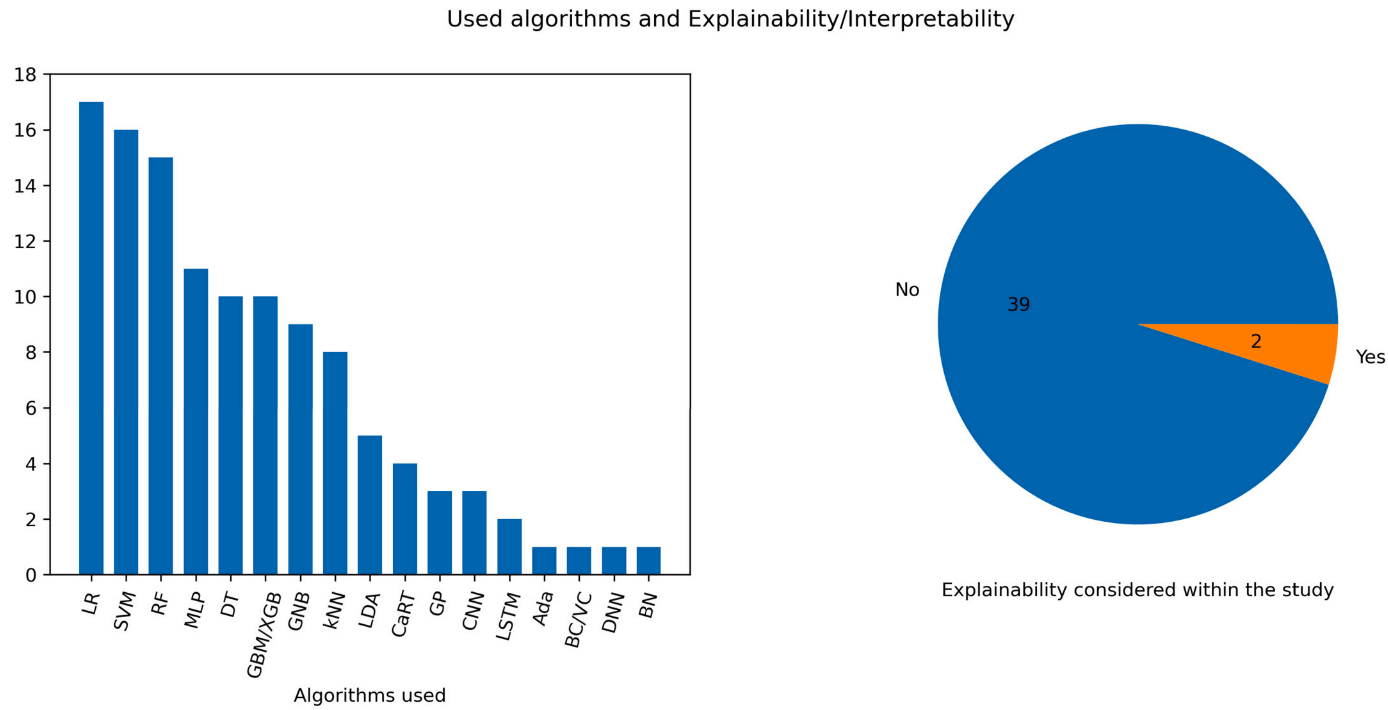

Fig. 5. Types of algorithms used in the studies, and how many of them considered explainability/interpretability.

(GNB), all with around ten applications. Linear Discriminant Analysis (LDA) follows this group with five applications, including aging study data ([32,48,59]), blood samples data ([33]), and home movement sensor data ([31]). It should be noted, however, that if we group up GBM/EXtreme Gradient Boosting (XGB) and Classification and Regression Tree (CaRT) in the DT category, it becomes the most popular algorithm, with 24 appearances.

Arshad et al. [20] and Liu et al. [46] were the only groups that used Convolutional Neural Network (CNN), both applied to images. The first collected gait data and converted them to images to exploit the potential of CNN with single and multi-image input. The second applied machine vision to extract gait parameters from walking test recordings and then trained two CNN intending to detect FFP.

An interesting approach was adopted by Jung et al. [35], who collected gait data from gyroscope sensors attached to patients' feet and used said data to train a Long Short-Term Memory (LSTM) network for frailty detection, achieving an F1-score of 0.931. The only other study that uses LSTM models is by Eskandari et al. [25], who collected data on heart rate during a walking test in a cohort of older adults to detect FFP. Apart from these studies, only two more publications use deep learning: the first is the gait images study by Arshad et al. [20], and the second is by Blanes Selva et al. [22], who used hospital records to predict the appearance of frailty, defined by a FI, and obtained approximately the same precision using a Deep Neural Network (DNN) and a GBM, improving the scores of a LR model baseline.

Genetic Programming (GP) techniques have only been applied by Tarekegn et al. [62,61] and Oates et al. [50], who used them to optimize the hyperparameters of their instances of DT, LR, RF, and SVM models.

After a thorough data cleaning and feature selection process, Hassler et al. [32] trained seven different ML models for frailty prediction (FFP) and concluded that SVM with Radial Basis Function (RBF) as kernel has the overall best performance. However, the downside of nonlinear kernels such as RBF is that they cannot be interpreted from a human perspective, a factor that very few studies in this review considered, as shown by the pie chart in Fig. 5. The only publication that uses explainability methods is Wu et al. [66], who applied SHapley Additive exPlanations (SHAP) to the results of their supervised model to provide clinicians with an interpretation of the most relevant features on which the prediction is based.

Finally, a few algorithms have been used only in one study, such as Adaboost (Ada) by Abbas et al. [14], Bagging Classifier (BC) and Voting Classifier (VC) by Akbari et al. [16], and Bayesian Network (BN) by da Cunha Leme et al. [23], and only one publications proposed a new specific ML framework for frailty classification [27].

4. Conclusions

Although we started our research by focusing on studies specifically on frailty, we immediately found the topic's first big issue: the need for a proper definition of *frailty*. Some definitions are used more than others, but single-variable definitions, such as mortality or hospitalization, have also been shown to be accepted. To make the review consistent from a data-oriented perspective, we should have also included studies that detect or predict those individual variables, even if they did not specifically mention *frailty* (e.g., mortality prediction studies). However, we decided not to extend the search nor exclude those publications from the review to point out this discrepancy and the need for a standard definition to make data approaches effective and comparable. Despite the uncertainties about the models' target variables, the studies in this review generally aim to facilitate and complement the medical personnel's work. Most of the studies' goal is to develop a decision-support tool to help clinicians in the early detection of frailty. Moreover, data-based models could identify crucial variables or patterns in EHR related to frailty, which might be overlooked or not evident to medical personnel, as shown by Sajeev et al. [59].

Another interesting fact emerging is the quantity and variety of data used in these studies. Especially all the different datasets used, and hence the variety of approaches, make the problem of tackling frailty through Artificial Intelligence (AI) exciting. No dataset has been used more than twice in the included studies, making comparing results even more complicated. Replicating the results is another crucial step for researchers to compare and improve current results; however, only one study gave public access to the code repository, and only another explicitly said that the code would be available upon request (see Table 1).

The review shows that the most widely used ML techniques to detect, classify, and predict frailty are very well-known supervised models, provided by almost any ML library. The three most popular algorithms are LR, SVM, and RF, followed by slightly less-used models, such as MLP, DT, GBM or XGB, GNB, and k-Nearest Neighbor (kNN). These statistics show no clear trend in frailty models, and an algorithm that outperforms others has yet to be identified. We believe it is due to the wide variety of problems that fall under the *frailty* umbrella, as discussed in Sect. 1 and Sect. 3.

One of the most significant open issues in this field is the integration of the data models into the healthcare systems, which is the final step to developing functional decision-support tools for clinicians. Most of the studies used either data from aging studies questionnaires or gait data collected from sensors. In both cases, integrating with the electronic systems clinicians are used to is a challenging task that, to our knowledge, has yet to be tackled. It is the only way to develop a virtually real-time decision-support system that helps medical personnel and makes a real difference. To achieve this core goal, close collaboration between data science groups and practitioners should be a priority in future research.

Another important topic for future work is Interpretability or Explainability, which is essential when models are applied to delicate tasks such as clinical assessments [69]. As discussed in Section 3, only two of the 41 research groups mentioned the topic in their publication, and only one of the two provided clinical personnel with an explanation of the results of the models. It is vital to explain model results so that the practitioner can trust them and the decision-support systems are effective.

In conclusion, frailty prediction, detection, and classification are vast problems that have been interpreted and tackled in many different ways using ML. Thanks to the interest in this topic and the number of publications that increased in recent years, a solid baseline has been created through the studies in this review. We believe that future results in ML could benefit significantly from working closely with medical personnel and defining effective target variables, which would improve the medical use of the models and the comparability of the results. We also believe that it is crucial to consider the replicability of results and Explainability in all future work.

Summary table

- The wide variety of frailty definitions and types of data used in the models makes it challenging to compare results.
- Machine learning models fit the need for a detection and prediction tool for frailty in older populations.
- Many well-known algorithms have been applied to the task, but very few frailty-specific ones have been developed.
- In future work, Explainability and Interpretability need to be considered for the medical community to accept data-based assessments.

List of acronyms

Ada	Adaboost
AI	Artificial Intelligence
ANN	Artificial Neural Network
BC	Bagging Classifier
BN	Bayesian Network
CaRT	Classification and Regression Tree
CF	Cognitive Frailty
CFS	Clinical Frailty Scale
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DT	Decision Tree
eFI	electronic Frailty Index
EHR	Electronic Health Records
FI	Frailty Index
FFP	Fried's Frailty Phenotype
FTS	Frailty Trait Scale
GBM	Gradient Boosted Machine
GNB	Gaussian Naive Bayes
GP	Genetic Programming
kNN	k-Nearest Neighbor
LDA	Linear Discriminant Analysis
LR	Linear Regression
LSNS-6	Lubben Social Network Scale
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi Layer Perceptron
MMSE	Mini-Mental State Examination
MoCA	Montreal Cognitive Assessment test
RBF	Radial Basis Function
SC	Self-Collected
RF	Random Forest
SHAP	SHapley Additive exPlanations
SPPB	Short Physical Performance Battery
SVM	Support Vector Machine
TUG	Timed Up-and-Go Test
TMT	Trail Making Tests
VC	Voting Classifier
XGB	EXtreme Gradient Boosting

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Matteo Leghissa: Conceptualization, Methodology, Formal analysis, Data Curation, Writing - Original Draft, Visualization. **Álvaro Carrera:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration, Funding acquisition. **Carlos A. Iglesias:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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