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RESEARCH

# Classification of dementia risk in the elderly through gait analysis with machine learning algorithms

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**Abstract**

The irreversible and progressive decline of physiological functions is known as aging. Among these changes is brain aging, which leads to cognitive decline and the onset of dementia. This directly affects memory, learning, and motor skills, reducing gait efficiency. This study aimed to investigate the feasibility of identifying and classifying the risk of dementia based on the analysis of kinematic variables related to gait in older adults using machine learning algorithms. This cross-sectional observational study examined a sample of 59 individuals aged 60 ± 8 years, divided into two groups: 26 institutionalized older adults (GI) and 33 non-institutionalized older adults (GNI), all residing in Bragança, Portugal. Gait data were collected during a 10-m walk, recorded on video, and analyzed using Kinovea software. Cognitive status was assessed using the Mini-Mental State Examination (MMSE). Python™ was used for statistical analysis and to develop machine learning models to classify dementia risk based on gait variables. The results showed that the algorithmic models achieved an overall accuracy of 74.6%, with the AdaBoost algorithm performing best at 83.5%. Cross-validation revealed an overall accuracy of 72%, with the Support Vector Machine (SVM) classifier achieving the highest individual performance at 80%, correctly classifying 80% of cases across different data subsets. In conclusion, gait analysis combined with machine learning algorithms demonstrated a strong relationship between gait variables and dementia, proving to be a safe and efficient technique for dementia classification. This approach offers a low-cost and accessible early identification and intervention method, with potential applications in clinical and public health settings.

**Keywords** Aging · Dementia · Gait analysis · Machine learning · Cognitive decline · Kinematic variables

## Introduction

Aging is a biological process characterized by the progressive and irreversible decline of physiological functions, often associated with age-related diseases [1]. Among these changes, cognitive decline stands out, particularly affecting learning, memory, and executive functions [2]. These alterations are linked to structural and functional modifications in key brain regions such as the hippocampus and prefrontal cortex [3, 4]. Reduced neuroplasticity in the aging brain impairs the formation of new neural connections, increasing vulnerability to neurodegenerative conditions [5, 6].

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Dementia, a clinical syndrome characterized by progressive cognitive deficits such as memory loss, language impairments, and executive dysfunction [7], poses a major challenge to the independence and quality of life of older adults [8, 9]. Globally, dementia affects millions, with projections estimating an increase from 78 million cases in 2019 to 139 million by 2050, alongside associated economic costs reaching $2.8 trillion annually by 2030 [10]. Early identification of dementia is therefore critical to allow timely interventions that may slow cognitive decline and improve outcomes [11, 12].

The relationship between cognitive function and locomotor abilities has been widely studied, revealing that gait is not merely a mechanical activity but also a cognitive process involving brain regions, such as the frontal and prefrontal cortices [4]. Declines in the volume and functionality of these areas, commonly observed with aging, are associated with both deteriorations in cognitive abilities and impairments in gait control [5]. Subtle changes in gait patterns—such as reduced speed, increased variability, and postural instability—have been identified as early markers of cognitive decline and predictors of dementia [13, 14].

Despite the growing understanding of the link between gait and cognition, early diagnosis of dementia remains challenging. Conventional cognitive assessments often detect dementia only at later stages, limiting the effectiveness of intervention strategies. There is a clear need for accessible, objective, and cost-effective tools that can support the early identification of individuals at risk for cognitive decline [11, 12].

In this context, gait analysis combined with artificial intelligence (AI) and machine learning algorithms has emerged as a promising solution. Recent studies have demonstrated that gait features, extracted through video-based techniques and processed with machine learning models, can successfully distinguish between cognitively healthy individuals and those at risk for dementia [15, 16]. Machine learning is particularly suited for this application due to its ability to detect complex, multidimensional patterns that traditional statistical methods might overlook [17]. Furthermore, video analysis offers a low-cost, accessible, and non-invasive alternative for large-scale screening.

Although promising, the current literature is still limited by certain gaps. Many studies focus predominantly on individuals over the age of 65, potentially missing earlier signs of cognitive decline that may emerge as early as the mid-50s [18–20]. Additionally, a few investigations have integrated low-cost video-based gait analysis with machine learning techniques to predict dementia risk in community-dwelling and institutionalized older adults.

Previous evidence suggests that institutionalized older adults often present lower cognitive function and reduced gait performance compared to community-dwelling individuals, likely due to differences in physical activity levels, environmental stimulation, and health status [21]. Exploring this comparison can provide important insights into contextual influences on dementia risk.

Addressing these gaps, the present study includes participants starting at 55 years of age, aiming to detect early functional and cognitive changes that precede clinical diagnosis.

Therefore, this study aimed to investigate the feasibility of identifying and classifying the risk of dementia based on the analysis of kinematic gait variables in older adults—including both cognitively healthy individuals and those with varying degrees of cognitive impairment—using machine learning algorithms. The specific objectives were to (1) identify the best gait kinematic variables for dementia classification; (2) compare cognitive and gait-related differences between institutionalized and non-institutionalized participants; (3) validate the machine learning models through cross-validation; and (4) evaluate model performance metrics. We hypothesized that kinematic gait variables could accurately predict the risk of dementia, with the developed machine learning models achieving an error rate below 30% and an accuracy above 70%, supporting their applicability in clinical and public health contexts.

## Methodology

### Study design

This is an observational, cross-sectional study to identify the most relevant gait kinematics variables for classifying dementia in the elderly. The methodological approach combines gait analysis captured by video with machine learning algorithms to identify data patterns and assess the model's accuracy and replicability in real clinical contexts.

The study was conducted in accordance with international ethical guidelines, and all participants signed an informed consent form. The project was approved by the IPB Ethics Committee under case number 501020.

### Sample

The study was approved by the Ethics Committee of the Polytechnic Institute of Bragança (IPB), under process number 501020, and is part of a larger research project entitled "Effects of Multicomponent Training on the Risk of Alzheimer's Disease, Functional Aptitude and Well-Being of Physically Active Elderly Women", which began in 2023.

To participate in the current study, the following inclusion criteria were defined: being aged 55 or over; absence of psychological or physical disorders that could compromise performance during the tests; absence of critical visual or hearing impairments affecting gait; no use of walking aids;

ability to perform tasks of daily living without obvious difficulties. Additionally, the following criteria were defined as of exclusion: age under 55; presence of psychological or physical disorders that impair performance of the tests; use of assistive devices during the gait assessment; obvious difficulties in performing tasks of daily living.

The sample consisted of 59 participants, with an average age of 76 ± 6 years (56 participants aged 65 or over), an average body mass of 60 ± 10 kg, 17 men and 42 women. The participants were divided into two groups: (i) The Non-Institutionalized Group (NIG): 33 elderly people taking part in a community social project called "MAIS IDADE MAIS SAÚDE" (MORE AGE MORE HEALTH), held at the IPB. (ii) Institutionalized Group (IG): 26 elderly residents of the Santa Casa da Misericórdia de Bragança. Although the original inclusion criteria allowed individuals aged 55 and above, the recruitment was conducted within ongoing programs predominantly targeting older adults (65 +), which explains the limited representation of participants aged 55–65. All participants were informed of the potential risks and discomforts of the study and signed an informed consent form.

## Procedures

### Cognitive assessment: Mini-Mental State Examination (MMSE)

The cognitive state of the participants was assessed using the Mini-Mental State Examination (MMSE), in the version validated for Portuguese [22]. The MMSE is one of the most widely used instruments for screening cognitive impairment in elderly populations due to its practicality, low cost, and ease of application [23, 24]. Previous studies have shown that the MMSE has high validity and reliability, with internal consistency coefficients of over 0.80 and good discriminative capacity to identify different levels of cognitive impairment [25, 26]. Furthermore, its application in the Portuguese population has been previously validated, ensuring that the results obtained are representative and comparable to other studies carried out in Portugal [22]. The choice of this instrument is justified by the fact that it is widely accepted in scientific literature, with a strong methodological basis and recommendations for use by international organizations in dementia studies [27–29]. The MMSE consists of 11 items that assess cognitive abilities, such as spatial and temporal orientation, retention, attention and calculation, recall, language, and constructive capacity. The maximum score is 30 points, with classifications of 24–30 points indicating normal cognition, 18–23 points suggesting mild cognitive impairment, and 0–17 points indicating moderate-to-severe cognitive impairment.

To estimate the mechanical powers (WINT, WEXT, and WTOT) and metabolic power (EMET), the models were proposed by Minetti and Saibene [30] and Kram and Taylor [31]. These models, although predictive, have been validated in various studies, such as those by Minetti et al. [30] and Roberts et al. [32], which confirmed their effectiveness in estimating biomechanical and metabolic parameters during gait. The application of these models in our study allowed for a robust analysis of kinematic variables, although without direct measurements of physiological parameters.

### Biomechanical analysis of gait

The gait video recordings and cognitive assessments were conducted by two trained evaluators experienced in biomechanical and cognitive evaluation. During gait data analysis, evaluators were blinded to the participants' cognitive status and group assignment (institutionalized or non-institutionalized) to minimize bias. To ensure data reliability, a subset of ten randomly selected gait videos was independently analyzed by both evaluators. The intraclass correlation coefficient (ICC) for key gait variables was calculated, yielding an ICC greater than 0.90, indicating excellent inter-rater reliability.

Gait data were collected in a flat, regular space. Participants were instructed to walk at a naturally selected speed, similar to their daily speed, for a distance of 10 m, with the central 5 m used for analysis. The gait was recorded in high-definition video (120 FPS) using an iPhone 12, and the videos were processed in Kinovea software to extract the kinematic variables of the gait, such as flight time, contact time, stride frequency, and speed [33].

The camera was positioned perpendicular to the walking path at a height of 1.20 m and a distance of approximately 3 m from the participants to ensure a complete lateral view. In Kinovea software, manual marking was performed by identifying anatomical landmarks, such as the greater trochanter and lateral malleolus. Stride length was estimated based on the known walking distance and the number of strides observed.

### Estimation of mechanical and metabolic powers

To estimate the mechanical powers (WINT, WEXT, and WTOT) and metabolic power (EMET), the models were proposed by Minetti and Saibene [30] and Kram and Taylor [31]. These models, although predictive, have been validated in various studies, such as those by Minetti and Saibene [30] and Roberts et al. [32], which confirmed their effectiveness in estimating biomechanical and metabolic parameters during gait. The application of these models in our study allowed for a robust analysis of kinematic variables, although without direct measurements of physiological parameters.

The internal mechanical power (WINT) was determined using the equation $\mathrm{WINT} = \frac{\sum m\cdot v_i^2}{2\cdot t}$, where $m$ represents the body mass, $v_i$ is the internal velocity of the body segments. This equation estimates the energy expenditure related to the movement of the body segments relative to the center of mass. The external mechanical power (WEXT) was calculated using the equation $\text{WEXT} = \frac{m \cdot g \cdot h}{t}$, where $h$ is the vertical displacement of the center of mass, and $t$ is the time. This equation reflects the energy required to move the center of mass against gravity during gait. The total mechanical power (WTOT) was obtained by summing the internal and external mechanical powers, as expressed by the equation $\text{WTOT} = \text{WINT} + \text{WEXT}$. This variable provides a comprehensive measure of the mechanical energy used during walking, combining the energy for moving body segments and the energy for moving the center of mass.

Gait efficiency was calculated as described by Cavagna and Kaneko [34], using the ratio between total mechanical power and metabolic power, following the equation $\text{Efficiency} = \frac{\text{WTOT}}{E_{\text{met}}}$, where $E_{\text{met}}$ represents the metabolic power estimated based on the models proposed by Minetti and Saibene [30]. This calculation allows the assessment of how effectively mechanical energy is converted relative to the metabolic energy expended, providing insights into the energy efficiency of gait.

## Variables under study

The variables analyzed were divided into three categories: Anthropometric Data Cognitive Function and Gait Kinematic Variables (Table 1). Anthropometric variables analyzed in this study included age and body mass, providing a general characterization of the sample. These are summarized in the section “Results”.

Table 1 displays the kinematic variables of gait, encompassing measurements like speed, stride frequency, and various power outputs, which are essential for analyzing gait efficiency and performance.

## Data analysis

### Statistical procedures

The analyses were carried out using the Python™ programming language [35]. The normality of the data was tested using the Shapiro–Wilk test [36], and comparisons between groups were made using the Student’s *T* test for parametric data [37] and the Mann–Whitney–Wilcoxon test for non-parametric data [38]. For both tests, the significance level was set at a 95% confidence interval ($p < 0.05$) [39] and the effect size was calculated using Cohen’s *d* [40], with thresholds of 0.20 (small), 0.50 (moderate), and 0.80 (large).

### Correlation analysis

A correlation matrix was used to identify the most relevant independent variables for classifying dementia. Only variables with moderate or high correlation coefficients ($\geq 0.50$) were considered, including age, total mechanical power, external mechanical power, internal mechanical power, 5-m walk time, gait speed, and gait efficiency.

### Implementation of machine learning algorithms

The following classification algorithms were implemented to assess the risk of dementia based on gait kinematic variables. The methodological approach was based on previous studies that demonstrated the effectiveness of machine learning techniques for gait data classification in cognitive disorders [41–43].

Each algorithm was chosen for its specific strengths in handling binary classification problems and enhancing model accuracy. The implementation process involved data preprocessing, normalization, and model training

**Table 1** Kinematic variables of gait

| Variable | Unit | Description |
|---|---|---|
| Time in 5 m | s | Time taken to walk a distance of 5 m |
| Speed | m/s | Linear displacement rate, calculated as distance divided by time |
| Contact time | s | Duration in which the foot is in contact with the ground |
| Flight time | s | Duration in which the foot is off the ground |
| Stride frequency | Hz | Number of steps taken per unit of time |
| Metabolic power | W | Rate of energy consumption to sustain gait |
| Internal mechanical power | W | Energy generated to move body parts relative to the center of mass |
| External mechanical power | W | Energy generated to move the center of mass relative to the external environment |
| Total mechanical power | W | Sum of internal and external mechanical power |
| Gait efficiency | Dimensionless | Ratio between total mechanical power and metabolic power measures energy efficiency |

using a cross-validation approach to ensure reliability and minimize bias. The algorithms include Naive Bayes, which applies probabilistic classification methods; Logistic Regression, suited for binary outcomes; Random Forest, an ensemble technique leveraging multiple decision trees; and Support Vector Machine (SVM), designed to maximize class separation. Additionally, K-Nearest Neighbors (KNN) was used for proximity-based classification, Decision Tree for a hierarchical division of features, and Gradient Boosting for sequentially combining weak models. Advanced techniques, such as AdaBoost and XGBoost, were also utilized to improve model performance by focusing on misclassified instances [44]. A summary of these algorithms is presented in Table 2.

All machine learning models were applied to the total sample, without stratification by institutionalization status. This decision was made due to the limited sample size, which would not allow for reliable training and testing of models within each subgroup. Moreover, the primary aim of the modeling phase was to explore the feasibility of gait-based dementia classification across a heterogeneous older adult population, rather than to draw subgroup-specific conclusions.

The data were divided into training (70%) and test (30%) sets, with a random seed (seed = 0) to ensure reproducibility [45, 46]. Cross-validation was carried out using the K-folds method, dividing the data set into K subsets for training and testing iteratively [47]. Performance metrics were calculated for each fold, including average accuracy and standard deviation [47].

It is important to note that the same dataset was used for both the initial variable selection and the model training/testing process. Although this approach is consistent with prior exploratory studies in similar contexts [41–43], it may introduce a risk of overfitting. To mitigate this, we employed K-fold cross-validation and used independent test sets (30% of the data) to estimate model performance and reduce bias.

### Evaluation metrics

The model performance metrics included accuracy, sensitivity (recall), precision, F1-score, and the ROC/AUC curve. Accuracy was calculated as the proportion of correctly classified instances using the equation: $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$. Here, TP represents true positives, TN represents true negatives, FP denotes false positives, and FN indicates false negatives.

Sensitivity (recall) was determined as the proportion of true positives correctly identified, using the following equation: $\text{Sensitivity} = \frac{TP}{TP+FN}$.

Precision was defined as the proportion of positive instances that were correctly predicted, calculated by $F1 - \text{score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision}+\text{Sensitivity}}$..

Additionally, the ROC/AUC curve was used to assess the model's ability to discriminate between classes. This included evaluating the true positive rate (sensitivity): $\text{True - positive rate} = \frac{TP}{TP+FN}$.

And the false-positive rate: $\text{False - positive rate} = \frac{FP}{FP+TN}$.

These metrics provided a comprehensive assessment of the model's performance, ensuring a balanced evaluation between sensitivity, precision, and the ability to discriminate between classes.

## Results

### Parametric and non-parametric statistics

Table 3 shows the descriptive statistics for the two groups involved in the study. Statistically significant differences were observed, indicating superiority with large effect sizes, of the non-institutionalized group (NIG) in relation to the institutionalized group (IG) in the variables age, 5-m time, gait speed, internal mechanical power, external mechanical power, total mechanical power, gait efficiency, and MMSE score, as well as in contact time, but with small-effect sizes.

**Table 2** Summary of classification algorithms

| Algorithm | Purpose | Key feature |
|---|---|---|
| Naive Bayes | Probabilistic classification | Assumes independence between features |
| Logistic Regression | Binary classification | Uses sigmoid function for probability estimation |
| Random Forest | Ensemble classification | Aggregates multiple decision trees |
| Support Vector Machine (SVM) | Maximizing margin between classes | Uses kernel functions for complex data separation |
| K-Nearest Neighbors (KNN) | Proximity-based classification | Considers the nearest neighbors for class prediction |
| Decision Tree | Hierarchical classification | Divides data using decision nodes |
| Gradient Boosting | Sequential model improvement | Minimizes loss function iteratively |
| AdaBoost | Weighted ensemble classification | Focuses on misclassified instances |
| XGBoost | Optimized gradient boosting | Enhances speed and accuracy with regularization |

**Table 3** Sample characteristics

| Variable | IG (*n* = 26) Mean ± SD (95%IC) | NIG (*n* = 33) Mean ± SD (95%IC) | *t*-stat | *p* value | *U*-stat | pU | Cohen's *d* |
|---|---|---|---|---|---|---|---|
| Age (years) | **82.19 ± 7.86** (79.17–85.21) | **71.66 ± 4.78** (70.03–73.29) | **6.34** | **< 0.001** | **NA** | **NA** | **1.62** |
| Body mass (kg) | 65.05 ± 9.57 (61.37–68.73) | 64.84 ± 11.65 (60.87–68.82) | 0.07 | 0.93 | NA | NA | 0.02 |
| Body weight (N) | 638.21 ± 93.93 (602.10–674.31) | 636.10 ± 114.34 (597.09–675.11) | 0.07 | 0.94 | NA | NA | 0.02 |
| Time over 5 m (s) | **5.59 ± 1.15** (5.15–6.03) | **3.97 ± 0.32** (3.86–4.08) | **7.70** | **< 0.001** | **NA** | **NA** | **1.92** |
| Speed (m/s) | **0.93 ± 0.20** (0.85–1.01) | **1.26 ± 0.10** (1.23–1.29) | **8.35** | **< 0.001** | **NA** | **NA** | **−2.09** |
| Contact time (s) | **0.66 ± 0.08** (0.63–0.69) | **0.63 ± 0.05** (0.61–0.65) | **2.11** | **0.03** | **NA** | **NA** | **0.45** |
| Flight time (s) | 0.35 ± 0.039 (0.335–0.365) | 0.35 ± 0.031 (0.34–0.36) | NA | NA | 435 | 0.93 | 0 |
| Stride frequency (Hz) | 0.99 ± 0.12 (0.94–1.04) | 1.02 ± 0.08 (0.99–1.05) | NA | NA | 308 | 0.06 | −0.29 |
| Metabolic power (W) | 176.67 ± 31.5 (164.56–188.78) | 185.35 ± 32.65 (174.21–196.49) | NA | NA | 375 | 0.41 | −0.27 |
| Internal mechanical power (W) | **19.51 ± 9.20** (15.97–23.05) | **35.79 ± 6.55** (33.56–38.03) | **NA** | **NA** | **69** | **< 0.001** | **−2.04** |
| External mechanical power (W) | **10.16 ± 10.10** (6.28–14.04) | **26.67 ± 7.85** (23.99–29.35) | **NA** | **NA** | **76** | **< 0.001** | **−1.83** |
| Total mechanical power (W) | **29.67 ± 18.9** (22.41–36.94) | **62.46 ± 13.57** (57.83–67.09) | **NA** | **NA** | **77** | **< 0.001** | **−1.99** |
| Gait efficiency (dimensionless) | **0.1661 ± 0.0848** (0.134–0.199) | **0.3396 ± 0.0516** (0.322–0.357) | **NA** | **NA** | **48.5** | **< 0.001** | **−2.47** |
| MMSE (a.u.) | **18.53 ± 5.17** (16.54–20.52) | **26.18 ± 2.83** (25.21–27.15) | **NA** | **NA** | **63** | **< 0.001** | **−1.84** |

Bold values indicate statistically significant differences between groups ($p < 0.05$)

*IG* institutionalized group, *NIG* non-institutionalized group, *t-stat* statistic for the independent *t* test, *pt p* value for the independent *t* test, *U-stat* statistic for the Mann–Whitney–Wilcoxon test, *pU p* value for the Mann–Whitney–Wilcoxon test, *NA* not applicable, *Cohen's d* effect size

The full correlation matrix is provided in Supplementary Fig. 1, illustrating the relationships between all independent variables and dementia status. Among these, the most relevant correlations with dementia risk were observed for reductions in internal mechanical power ($r = -0.62$), external mechanical power ($r = -0.61$), total mechanical power ($r = -0.63$), gait speed ($r = -0.62$), and gait efficiency ($r = -0.59$), as well as increases in age ($r = 0.51$) and 5-m walk time ($r = 0.59$).

Although several variables exceeded the $r = 0.50$ threshold, only five were selected for inclusion in the final classification model: age, internal mechanical power, time spent walking 5 m, external mechanical power, and gait efficiency. These variables were chosen not only for their statistical correlation but also based on their established clinical relevance in gait and aging research, their interpretability, and their contribution to avoiding multicollinearity. Variables with overlapping information or high inter-correlation (e.g., total

**Table 4** Performance metrics of the machine learning algorithms implemented

| Algorithm | Accuracy (%) | Precision (%) | Sensitivity (%) | F-1 score (%) | AUC | Average ($\bar{x}$) | VN | FP | FN | VP |
|---|---|---|---|---|---|---|---|---|---|---|
| Naive Bayes | 72.2 | 77.7 | 70 | 73.6 | 88.7 | 76.4 | 6 | 2 | 3 | 7 |
| Logistic Regression | 72.2 | 77.7 | 70 | 73.6 | 91.2 | 76.9 | 6 | 2 | 3 | 7 |
| Random Forest | 66.6 | 75 | 60 | 66.6 | 87.5 | 71.1 | 6 | 2 | 4 | 6 |
| Support Vector Classifier | 72.2 | 77.7 | 70 | 73.6 | 81.2 | 74.9 | 6 | 2 | 3 | 7 |
| K-Nearest Neighbors classifier | 77.7 | 80 | 80 | 80 | 83.7 | 80.2 | 6 | 2 | 2 | 8 |
| Decision Tree | 72.2 | 77.7 | 70 | 73.6 | 72.5 | 73.2 | 6 | 2 | 3 | 7 |
| Gradient Boosting classifier | 72.2 | 75.9 | 72.2 | 71.9 | 73.7 | 73 | 7 | 1 | 4 | 6 |
| Ada Boost classifier | 83.3 | 83.9 | 83.3 | 83.3 | 83.7 | 83.5 | 7 | 1 | 2 | 8 |
| Xgboost classifier | 77.7 | 79.7 | 77.7 | 78.7 | 78.5 | 78.5 | 7 | 1 | 3 | 7 |
| General metrics ($\bar{x}$) | 75.1 | 76 | 72.5 | 74.9 | 82.2 | 74.6 | NA | NA | NA | NA |

*AUC* area under the curve, $\bar{x}$ arithmetic mean, *VN* true negatives, *FP* false positives, *FN* false negatives, *VP* true positives, *NA* not applicable

Best classification panel: age, internal mechanical power, 5-m walk time, external mechanical power, and gait efficiency mechanical power or gait speed) were excluded to ensure a parsimonious and stable model.

## Machine learning algorithms

Table 4 shows the results of applying the nine machine learning algorithms. The results showed good overall performance (74.6%) for classifying dementia based on age, 5-m walk time, internal and external mechanical power, and gait efficiency. The best algorithm was the Ada Boost classifier (83.5%). In addition, the algorithms showed accuracy (76%) and sensitivity (72.5), showing that they, respectively, had balanced performances for differentiating true positives from false positives, and for identifying the proportion of true positives in relation to participants who were actually positive. The F-1 score showed a good balance between the accuracy and sensitivity of the analyses, reporting a harmonic percentage (74.9%).

Figure 1 is a graphical representation illustrating the relationship between the rate of true positives and false positives, two important metrics for evaluating a classification model, in which Logistic Regression stood

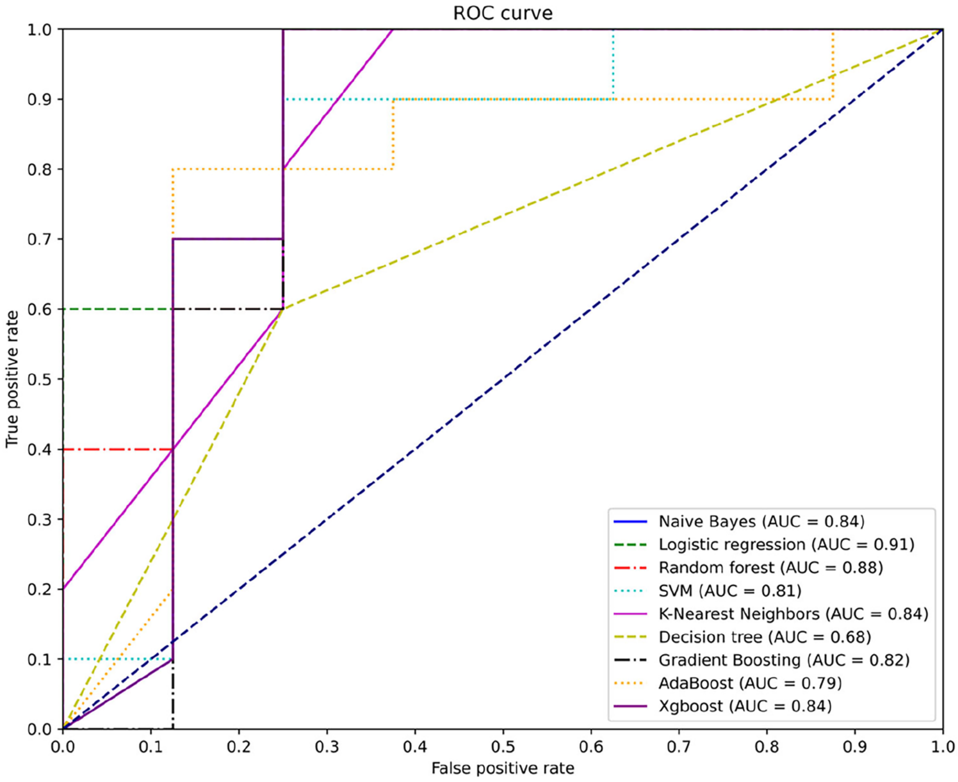

**Fig. 1** Area above the ROC curve for the nine machine learning algorithms

**Table 5** Cross-validation performance metrics of the machine learning algorithms

| Algorithm | Accuracy (%) | Accuracy (Sub.1) | Accuracy (Sub.2) | Accuracy (Sub.3) | Accuracy (Sub.4) | Accuracy (Sub.5) | SD |
|---|---|---|---|---|---|---|---|
| Naive Bayes | 0.80 | 0.66 | 0.83 | 0.83 | 0.75 | 0.90 | 0.08 |
| Logistic Regression | 0.78 | 0.66 | 0.83 | 0.83 | 0.83 | 0.72 | 0.06 |
| Random Forest | 0.67 | 0.58 | 0.75 | 0.66 | 0.75 | 0.63 | 0.06 |
| Support Vector Classifier | 0.80 | 0.66 | 0.83 | 0.83 | 0.83 | 0.81 | 0.06 |
| K-Nearest Neighbors classifier | 0.71 | 0.75 | 0.75 | 0.75 | 0.75 | 0.54 | 0.08 |
| Decision Tree | 0.64 | 0.58 | 0.83 | 0.41 | 0.75 | 0.63 | 0.14 |
| Gradient Boosting classifier | 0.69 | 0.75 | 0.83 | 0.58 | 0.75 | 0.54 | 0.11 |
| Ada Boost classifier | 0.71 | 0.75 | 0.83 | 0.66 | 0.58 | 0.72 | 0.08 |
| Xgboost classifier | 0.69 | 0.66 | 0.83 | 0.58 | 0.75 | 0.63 | 0.08 |
| General metrics ($\bar{x}$) | 0.72 | 0.67 | 0.81 | 0.68 | 0.75 | 0.81 | 0.05 |

Sub: subsets of the data set used to test the algorithms. The best model is highlighted in bold. SD: standard deviation of the accuracy over the subsets out compared to the other algorithms, being closest to the decision limit during the data test set (AUC = 0.91). However, the overall average AUC for all the algorithms reached 82.2%, showing a high probability of correct classifications during the execution of the algorithms.

### Cross-validation of the algorithms

Table 5 shows the results of the cross-validation of the data set used in the analyses, where an overall accuracy of 72% was observed considering all the algorithms. The cross-validation process was not only used to validate the model performance but also to assess the model's ability to correctly identify **true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)**. This approach ensured a comprehensive evaluation of the model's discriminative capacity and robustness. The **Support Vector Classifier** showed the best individual performance, with an accuracy of 80%, demonstrating superior ability in minimizing false positives and false negatives while maximizing true positives and true negatives. Additionally, both the Support Vector Classifier and **Naive Bayes** models presented the best accuracies for validation, indicating their reliability in distinguishing between correct and incorrect classifications across different subsets of the data.

## Discussion

The main objective of this study was to classify the risk of dementia based on kinematic gait variables using machine learning algorithms. The results indicated that gait variables, such as efficiency, mechanical power, and speed, are effective predictors for identifying dementia. The non-institutionalized elderly group (NIG) showed superior performance in all the variables analyzed, with statistically significant differences compared to the institutionalized group (IG). These findings align with the previous studies, such as those by Chiaramonte and Cioni [48] and Cedervall et al. [49], who highlighted the relationship between cognitive decline and changes in the spatial–temporal parameters of gait.

The selected predictors—age, 5-m walk time, internal mechanical power, external mechanical power, and gait efficiency—each reflect critical aspects of cognitive-motor decline. Increasing age and longer walking time are associated with slower gait and reduced cognitive processing speed, as supported by the literature [49, 50]. In this study, the IG group had a significantly higher average age (82.19 ± 7.86 years) compared to the NIG (71.66 ± 4.78 years), with a large effect size (Cohen's $d = 1.62$). The 5-m walk time was also longer in the IG (5.59 ± 1.15 s) versus the NIG (3.97 ± 0.32 s, $p < 0.001$, $d = 1.92$), indicating reduced gait efficiency and motor control. Decreased internal (19.51 ± 9.20 W in IG vs. 35.79 ± 6.55 W in NIG, $d = 2.04$) and external mechanical powers (10.16 ± 10.10 W in IG vs. 26.67 ± 7.85 W in NIG, $d = 1.83$) suggest diminished muscle performance and biomechanical capacity in institutionalized participants.

The efficiency of the gait was one of the most relevant indicators, with the NIG group showing significantly higher values (0.3396 ± 0.0516) compared to the IG group (0.1661 ± 0.0848), representing a very large effect size (Cohen's $d = 2.47$). These results are consistent with the findings of Mian et al. [50], who observed gait efficiency values ranging from 17 to 25% in older adults. In addition, Kuan et al. [51] emphasized that even in early stages of cognitive dysfunction, balance and gait are negatively affected—which may partially explain the stark differences between institutionalized and non-institutionalized participants observed here.

These differences were particularly notable when comparing institutionalized and non-institutionalized participants. The NIG group not only walked faster but also exhibited significantly greater mechanical power and gait efficiency, which may be attributed to differences in physical activity levels, autonomy, and environmental stimulation—all factors known to influence cognitive and motor health in older adults.

The machine learning algorithms demonstrated an overall accuracy of 74.6% in the classification of dementia, with the AdaBoost algorithm achieving the best performance (83.5%). These results align with previous studies, such as that of Cabitza et al. [52], who considered performances between 70 and 90% indicators of robust models. Furthermore, gait analysis as a predictor of cognitive disturbances has been validated in studies such as that of Park et al. [17], who found AUC values close to 80%, similar to our results (82.2%).

AdaBoost's superior performance can be attributed to its iterative learning process, which emphasizes difficult-to-classify cases and combines multiple weak classifiers into a strong predictive model. Its ability to handle non-linear relationships and potential class imbalance makes it particularly suitable for clinical data with complex patterns. In our case, AdaBoost worked well, because the dataset presented good quality in the point division in the multidimensional space of features [53].

The cross-validation of the algorithms revealed an overall accuracy of 72%, with the Support Vector Classifier (SVM) showing the best individual performance (80%). These results reinforce the effectiveness of machine learning models in classifying dementia, especially when combined with variables, such as age, internal mechanical power, walking time, external mechanical power, and walking efficiency. These variables proved robust predictors, corroborating studies like Mc Ardle et al. [54] and Fritz et al. [55], who highlighted the relationship between walking speed and variability with cognitive decline.

These results reinforce the growing body of evidence supporting the use of gait parameters as early indicators of cognitive decline, as demonstrated in recent studies that highlight strong associations between gait alterations and cognitive impairment in aging populations [56–59].

The results of this study have significant implications for clinical practice and public health. Using machine learning algorithms to classify the risk of dementia based on gait analysis can be a valuable tool for early identification and personalized intervention. This low-cost and widely accessible approach can be implemented in health systems, nursing homes, and clinics, allowing for continuous monitoring of patients' cognitive status. The implementation of this system would require the collaboration of health professionals for the regular collection of gait data and the application of the Mini-Mental State Examination (MMSE). These data could be integrated into an electronic medical record, where pre-trained machine learning algorithms would generate automated reports to assist clinical decision-making. This approach would allow for quick and personalized interventions, improving the quality of life for the elderly and reducing the burden on healthcare systems.

Furthermore, this methodology can be used for the development of public policies for the prevention and early treatment of dementia, as well as for the promotion of awareness campaigns and exercise programs aimed at at-risk elderly individuals.

This study presented some limitations, including the sample size and the predominance of women (69.57%), which may limit the generalization of the results. Future studies should aim for more balanced samples in terms of gender and include an analysis of the effect of sex on the classification models. Moreover, additional variables, such as medical history, dietary habits, lifestyle, and sociodemographic factors, could improve the accuracy of the models. Validating the results in different populations, considering geographic, cultural, and socioeconomic factors, is also essential to ensure the global applicability of the methodology. Additionally, it is important to acknowledge that the sample included participants from two distinct settings—community-dwelling and institutionalized—which may introduce variability due to differences in environmental context, social interaction, and health status. This heterogeneity could affect the internal validity of the findings and should be considered when interpreting the results.

Furthermore, although the inclusion criteria allowed participants aged 55 and over, the sample was overwhelmingly composed of individuals aged 65 or older (56 out of 59 participants). This imbalance was primarily due to the recruitment process, which relied on pre-existing programs that primarily targeted older adults. Consequently, the results may not fully capture early locomotor and cognitive changes that may occur in the 55–65 age group, limiting the generalizability to this younger segment of the older adult population.

Finally, a methodological limitation of this study is that the same dataset was used to select input variables and to train and test the machine learning models. Although cross-validation techniques were applied to reduce overfitting, the absence of an external validation cohort limits the generalizability and scientific strength of the findings. Future studies should consider using independent datasets for variable selection and model evaluation to enhance the robustness of the results.

## Conclusion

This study investigated the feasibility of identifying and classifying the risk of Dementia based on the analysis of kinematic variables related to the gait of the elderly using machine learning algorithms. Based on video analysis, the methodology used demonstrated that increased walking time reduced internal and external mechanical power, and walking efficiency correlated with dementia, enabling the classification of dementia risk. The developed algorithmic models, particularly the Ada Boost Classifier and the Support Vector Classifier, have proven to be very effective in classifying cognitive disturbances, suggesting that gait analysis, combined with machine learning algorithms, is a reliable and effective method for classifying dementia. This reports a promising perspective for the early detection and monitoring of cognitive disturbances in the elderly for early interventions and improvement of the quality of life for seniors.

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**Author contributions** R.B.C. (Raí Braz Costa) conceptualized, designed the study, performed the data collection, and processed the video-based gait analysis using Kinovea software. S.E. (Samuel Encarnação) conceptualized, conducted the statistical analysis, implemented the machine learning models, including AdaBoost and Support Vector Machine (SVM), and prepared figures and tables illustrating the kinematic variables and model performance. A.S. (André Schneider) conceptualized and prepared figures and tables illustrating the kinematic variables and model performance and drafted the main manuscript text. J.E.T. (José Eduardo Teixeira) and P.F. (Pedro Forte) conducted the designed the study and drafted the main manuscript text. P.F. and A.M.M. (António Miguel Monteiro) interpreted the results and drafted the main manuscript text. A.M.M. (António Miguel Monteiro) and T.M.B. (Tiago M. Barbosa) performed the data collection and processed the video-based gait analysis using Kinovea software. All authors reviewed and approved the final version of the manuscript.

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**Data availability** The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Declarations

**Ethical approval** This study was approved by the Ethics Committee of the Polytechnic Institute of Bragança (approval number: 501020).

**Informed consent** All participants provided written informed consent prior to participation in the study.

**Competing interests** The authors declare no competing interests.

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