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Predicting Fall Risk in Elderly Individuals: A Comparative Analysis of Machine Learning Models Using Patient Characteristics, Functional Balance Tests, and Computerized Dynamic Posturography

Running Head: Predicting the fall risk of elderly individuals in machine learning

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Summary

- Fall risk can be assessed using a range of both simple balance tests and advanced balance platforms
- Balance test results can sometimes be contradictory, making it challenging to determine which results to trust.
- Also, falls are multidimensional and can result from various factors, including sensory disorders, inattention, diseases, and medications.
- Therefore, simpler methods are needed to estimate fall risk by evaluating multiple factors and providing a single result (there is a risk of falling or not).
- In this study, machine learning was used to develop models that predict fall risk with high accuracy, based on individuals' comorbidities, balance tests, and physical characteristics.

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Abstract

Objective: This study aimed to predict the risk of falling using patient characteristics, computerized dynamic posturography, and functional balance tests (FBTs) in machine learning.

Methods: One hundred twenty elderly individuals were included in this study. The fall status, physical characteristics, and medical history of individuals were investigated. Pure tone audiometry test, simple FBTs and sensory organization test (SOT) were applied to the individuals.

Results: The machine learning model that incorporated comorbidities, physical characteristics, and functional balance tests achieved a 100% accuracy in predicting fall risk. Models using only comorbidities and physical characteristics, functional balance tests, or the SOT had accuracies of 87.5%, 83.34%, and 91.66%, respectively.

Conclusion: Advanced balance systems are not always necessary to assess fall risk. Instead, fall risk can be effectively determined using simple balance tests, comorbidities, and patient characteristics in machine learning.

Keywords: Elderly Individuals, Fall Risk, Machine Learning, Balance, Posturography

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Introduction

Aging, which causes biological, physical and functional changes, directly or indirectly causes deterioration in individuals. Approximately one-third of those aged 65 and above experience a fall once a year. This rate reaches 50% in individuals aged 80 and over.[1] Falls in elderly individuals can cause superficial injuries or severe injuries, functional disabilities and deaths. 90% of hip fractures occur as a result of falls, and 25% of elderly individuals who experience hip fractures die shortly after the accident.[2] Even if injuries resulting from falls do not cause severe disabilities, they can cause fear of falling again, self-restraint, and anxiety. Thus, it may reduce the quality of life in elderly individuals.

In order to maintain posture and maintain balance, signals from the visual, proprioceptive and vestibular systems must be quickly processed by the central nervous system, and the processed information must be accurately transferred to the musculoskeletal system via efferent pathways. Disruptions in any of these systems can cause imbalance, gait disturbance, dizziness, vertigo and falls in individuals. Whether it is a natural process due to ageing or diseases, deteriorations in balance systems are more common in older individuals.[3] The best method to prevent undesirable consequences of imbalance (falls) is considered to be a multi-component exercise program that includes strength, endurance and balance training.[4] In addition, systematic fall risk assessment is crucial to reduce the prevalence of falls in older individuals.[5] Various tests and scales, both with and without instruments, are generally used in these evaluations. The most well-known of these tests is computerized dynamic posturography (CDP), which evaluates all three balance systems. CDP is very sensitive for determining the risk of falling in elderly individuals, but it is difficult to obtain due to its cost.[6] Functional tests such as the functional reach test (FRT), timed up and go test (TUG), and one-leg stand test (TADT) can be used to assess fall risk without the need for any equipment. However, these tests can give contradictory findings in some cases, and the sensitivity or specificity of some

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tests is relatively low.[7] Therefore, there is a need for more accurate and more accessible methods to assess fall risk.

Artificial intelligence simulates human behaviour using computers and innovative technologies.[8] Artificial intelligence (machine learning) has recently been used to diagnose diseases and determine disease prognosis.[9] Large data sets regarding diseases or prognoses are provided to the system, and the effect of the data on diagnosis or prognosis is taught to the system. While machine learning algorithms process the inputs, they weigh the effect of the data on the output, which is insufficient to predict the result alone, and a model is created. Models are expected to predict the outcome based on the following inputs provided later with this weighted algorithm. Similarly, machine learning can be used to predict falls due to intrinsic and extrinsic factors. To our knowledge, there is no comprehensive literature study investigating the risk of falls in machine learning using CDP and functional balance tests.

This study aims to predict the risk of falling by using patient characteristics, computerized dynamic posturography and functional balance tests in machine learning.

Material and Method

Ethical Situation and Participants

This study was conducted on elderly individuals aged 65-79. Individuals who underwent neuro-otological examination and were referred to the hearing, balance and speech disorders unit were included in the study. Approval for the study was received from the XXXX University Faculty of Medicine Human Research Ethics Committee (2022000648-2022/648). Verbal and written permission was obtained from all individuals included in the study.

One hundred twenty elderly individuals were included in the study. They were divided into two groups according to their fall status. 65 individuals without a history of falling were included in group I. Fifty-five elderly individuals who had a history of falling at least once within a year, regardless of any loss of consciousness or an identifiable cause (orthopaedic diseases, stroke, seizure or substance/alcohol use), were included in group II. Falls were defined as events in which the individual lost balance and came into contact with the ground.

Criteria for Inclusion of Individuals in the Study

- Age is between 65-79,
- No history of head trauma,
- Patients do not have complaints/history of vertigo due to diagnosed causes such as Meniere's disease, vestibular neuritis, BPPV,
- Absence of musculoskeletal disorders, vision loss and neurological disease,
- Mini-Mental State Examination score (MMSE)> 24.[10]

Measurements and Procedure

Medical history was taken from the participants, and the individual's demographic information, comorbidities, imbalance and fall conditions were questioned. A patient information form was applied to all individuals, including the medications used. MMSE, audiological evaluation, Romberg test, FRT, TADT, TUG, visual analogue scale (VAS), Tinetti Balance and Gait Test (TBGT) and CDP were applied to all participants.

Audiological Evaluation

A pure tone audiometry test was performed on all individuals included in the study with an AC-40 clinical audiometer (Interacoustics, Denmark) in a quiet cabin. Air conduction hearing thresholds of the participants were determined between 125-8000 Hz bilaterally using TDH 39 supra-aural headphones, and bone conduction hearing thresholds were determined between 500-4000 Hz bilaterally using radio ear B71 bone vibrator. Pure tone average (PTA) was calculated using the 500, 1000, 2000 and 4000 Hz averages. Hearing was considered normal if PTA was less than 20 dB. PTA between 20-40 dB is mild hearing loss, 41-55 dB is moderate hearing loss, 56-70 dB is moderate-severe hearing loss, 71-90 dB is severe hearing loss and > 90 dB was considered profound hearing loss.[11] A more than 15 dB difference between right and left ear PTAs was considered asymmetric hearing loss.[12] Tympanometric measurements of the elderly individuals included in the study were performed with the GSI Tympstar Version 2 (Grason Stadler Inc., MN, USA) device at 226 Hz probe tone. Participants' bilateral ipsilateral and contralateral acoustic reflex thresholds were determined in the 500-4000 Hz range.

Evaluation of Functional Balance

For the Romberg test, participants are asked to take off their shoes, put their feet together, close their eyes and stand in the desired position with their hands at the sides for 30 seconds (sec). The time individuals could stand was recorded with a stopwatch. The test was applied in 3 different combinations: traditional romberg, foam pad romberg and tandem romberg.[13]

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For the OLST, participants were asked to remove their shoes and raise their non-dominant leg. The test was repeated with eyes open and closed. Individuals were expected to stand in the desired position (eyes open/closed) for 30 seconds without losing balance. The time to stay in balance was recorded with a stopwatch.[14]

For FRT, participants were asked to stand with their feet shoulder-width apart and stand parallel to the wall where a tape measure was placed, not touching the wall. Individuals were asked to flex their shoulders on the side of the tape measure to 90 degrees and make a fist with their hands. The individual's 3rd inter-phalanx joint level was marked on the tape measure, and they were asked to lie forward as far as they could without moving their feet. The maximum distance the individual could reach was marked again on the tape measure. The difference between the first distance and the second distance was calculated.[15]

For TUG, participants were asked to sit on a chair with a height of approximately 50 cm, stand up with the "start" command, walk the 3-meter walking track quickly, return from the endpoint and quickly sit on the chair again. The individuals' time to complete the course was measured with a stopwatch.[16]

TBGT was developed by Mary Tinnetti and consists of two parts.[17] The first part consists of 13 items and includes balance; The second part consists of 9 items and evaluates walking. The total score is calculated out of 35

Visual Analog Scale (VAS)

The participants' imbalance severity was evaluated with VAS. The endpoints of a 10 cm line drawn on paper were numbered 0 (no imbalance) and 10 (extreme imbalance). Individuals were asked to mark a point on this line appropriate to their imbalance's severity.[18]

Computerized Dynamic Posturography

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CDP testing was performed with Smart Equitest Dynamic Posturography (NeuroCom Balance Manager Systems, Natus, USA). Participants were asked to wear safety vests to prevent falls, and the Sensory Organization Test (SOT) was applied to the individuals taken to the platform. SOT, each condition lasting 20 seconds; It evaluates six different situations, and three consecutive repetitions are made for each situation.[19]

SOT 1: Eyes open, platform and surface stable.

SOT 2: Eyes closed, platform and surface stable.

SOT 3: Eyes open, platform moving and surface stationary.

SOT 4: Eyes open, platform stationary and surface moving.

SOT 5: Eyes closed, platform stationary and surface moving.

SOT 6: Eyes open, platform and surface moving.

Machine Learning and Feature Selection

Python (Version 3.7) programming language was used for machine learning. Our study used supervised learning algorithms k-nearest neighbors (KNN), naive Bayes, decision trees, random forest, SVM, logistic regression, XGBoost and artificial neural networks (ANN). While modelling the algorithms, 96 (80%) of the data were used in the training process, and the remaining 24 (20%) were used in the testing process. Individuals' ages, demographic information, comorbidities, and balance tests were defined as input attributes. The patients' fall status was defined as output. A hyperparameter selection Grid Search method was used. A statistical analysis method was used to determine the study's input features. In statistical analysis, data with a significance level of $p<0.05$ were defined as attributes (variables with no significant difference between groups were not used in machine learning). Statistical analysis was performed with IBM SPSS 21. Student's T-test is used to compare groups when normality assumptions are met. In cases where the assumptions were not met, the Mann-Whitney U test was used. The performances of the algorithms were evaluated with their success rates in the testing phase. The area under the ROC curve (AUC) was considered if the success rate was equal between the algorithms. In our study, five different models were created using five different feature groups. These models were MODEL-1 (anamnesis, diseases and physical characteristics data), MODEL-2 (functional balance tests data), MODEL-3 (MODEL-1 and MODEL-2), MODEL-4 (sensory organization test data) and total-MODEL (all features). The flow chart of the procedures and models applied to the participants is presented in Figure 1.

Results

Of the individuals in Group I, 33 were female, 32 were male, and the average age was 69.13±4.58. Of the individuals in Group II, 37 were female, 18 were male, and the average age was 70.20±4.70. There was no difference between the groups in terms of age and gender ($p=0.175$, 0.068, respectively).

Individuals in Group II were shorter in height and had a higher BMI than those in Group I ($p<0.05$). Additionally, complaints of imbalance, severity of hearing loss, and the prevalence of diabetes mellitus and hypertension were higher in Group II than in Group I ($p<0.05$). Additionally, the severity and duration of imbalance in individuals in group II were greater than in individuals in group I ($p<0.001$). Eyes open and closed OLST, foam Romberg test, tandem Romberg test, FRT, TUG and all SOT scores of individuals in Group II were worse than those in Group I ($p<0.001$). The physical characteristics, comorbidities, functional balance tests and SOT scores of the participants according to the groups are presented in Table 1. According to SOT, the somatosensory, visual, vestibular and composite scores of individuals in Group II were worse than those in Group I ($p<0.05$). However, there was no difference between the groups in terms of visual preference ($p>0.05$). Somatosensory, visual, vestibular, composite and visual preference scores according to groups are presented in Figure 2.

In MODEL-1, created using medical history and physical features, KNN, naive bayes, random forest, XGBoost and ANN reached the highest accuracy rate with 87.5%. The naive Bayes algorithm had the highest AUC-ROC value of 0.979 among the five algorithms. In MODEL-2, created using functional balance tests, naive bayes, KNN, SVM, ANN and logistic regression reached the highest accuracy rate of 83.5%. The logistic regression algorithm had the highest AUC-ROC value of 0.944 among the four algorithms. The SVM algorithm reached the highest accuracy rate with 100% in MODEL-3, created using the features used to develop MODEL-1 and MODEL-2 together. In MODEL-4, created using SOT values, XGBoost reached the highest accuracy rate with 91.6%. In the total-MODEL created using all attributes, naive Bayes reached the highest accuracy rate with 100%. The test successes of the models are presented in Table 2. Confusion matrices and ROC curves of the best-performing algorithms according to the models are presented in Figure 3.

Discussion

This study aimed to predict the risk of falling using patient characteristics, computerized dynamic posturography, and functional balance tests in machine learning. For this purpose, we created five different machine-learning models using different parameters. The model built using SOT data predicted fall risk with 91.6% accuracy (XGBoost/MODEL-4). The model created using individuals' comorbidities and physical characteristics predicted the risk of falling with 87.5% accuracy (Naive Bayes /MODEL-1). The model created using individuals' functional balance scores predicted the risk of falling with 83.3% accuracy (Logistic regression/MODEL-2). The model created using individuals' diseases, physical characteristics and functional balance scores predicted the risk of falling with 100% accuracy (SVM/MODEL-3).

It is known that the risk and prevalence of falls increase with ageing. Deterioration in the visual system, hearing loss, cognitive decline, and decreased muscle tone and reflexes caused by ageing increase the risk of falling. Approximately 30% of individuals over the age of sixty-five fall each year, and approximately half of these individuals experience relapses.[20] We included individuals aged 65-79 in our study and did not detect any difference in age between elderly individuals who fell and those who did not fall. This finding shows that the risk of falling does not change significantly between the ages of 65-79.

It is known that women fall more than men and that women suffer from more fractures due to falls. Although the reason for this difference is not fully understood, various opinions have been put forward.[21,22] Bone mineral density decreases in women due to menopause. Reduced bone mineral density may cause women to fall more frequently and cause more fractures due to falls.[21] Similarly, our study found that women fell more than men (67.3% vs. 50.4%), but this difference was not statistically significant.

Obesity and its complications cause many diseases and affect the daily lives of individuals. Moreover, obesity may increase the risk of falling in older individuals. Mijangos et al.[23] reported that gait and balance deteriorate and falls increase as BMI increases. Similarly, in our study, the BMI of older people who fell was higher than that of those who did not. Increasing BMI can affect individuals' musculoskeletal systems and change the body's centre of gravity (geometry). Additionally, Son[24] reported that the feet of obese individuals are exposed to too much force, and accordingly, the proprioceptive inputs in the feet become desensitized (plantar desensitization). However, in our study, there was no difference in weight between individuals who fell and those who did not. The difference in BMI between the groups was due to height, meaning that shorter ones had a higher risk of falling. Therefore, plantar desensitization cannot explain the observed falls in individuals with high BMI in our study. In our study, the possible reason for the higher risk of falling in individuals with high BMI was interpreted as changes in body geometry and gait.

Risk factors for falls in older individuals are complex. In addition to known risk factors such as vertigo, musculoskeletal disorders and visual disorders, medications used or diseases that seem unrelated to falls can also cause falls. A combination of these risk factors often causes an individual's fall. Some diseases, such as arthritis, diabetes mellitus, hypertension, and chronic obstructive pulmonary disease, may increase the risk of falls in older individuals.[25] In the literature, it has been stated that the use of certain medicines (opioids, benzodiazepines, diuretics, vasodilators, etc.) and the use of more than five (number of) medicines cause gait and balance disorders and increase the rate of repeated falls.[26] Similar to the literature, our study determined that imbalance symptoms, hypertension, diabetes mellitus and hearing loss were risk factors for falls. However, there was no difference between the groups in terms of the total number of medications used, hyperlipidemia, depression, cardiovascular diseases, thyroid and prostate. The fact that the number of medicines used in our study did not pose a risk of falling

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can be explained by our criteria for including individuals in the study. Our study included those who fell at least once in the last year. It is known that the total number of medicines used causes repeated falls, not single falls.[26]

Studies on machine learning and falls in the literature generally focus on detecting falls (video cameras, etc.).[27] In machine learning studies aiming to predict the risk of falling, electronic health records, surveys, scales, hospital admission evaluations, TUG and sit-to-stand tests were generally used.[28] In a retrospective study by Thapa et al.[29] using electronic health records, data from 2785 individuals were used. The fall risk of these individuals was estimated using machine learning with 68 attributes such as age, gender, diseases, and medications used. The study reported that Extreme Gradient Boosting predicted the risk of falling with 84.8% sensitivity and 70.6% specificity. However, it was reported that incomplete and unevenly distributed data limited the study. Ikeda et al.[30] predicted fall risk with XGBoost and random forest algorithms using 14 attributes such as depressive symptoms, age, health status, and urinary incontinence. The authors reported that the XGBoost algorithm predicted falls with 88% accuracy. Fahimi et al.[31] applied three functional tests (force production, postural sway and gait evaluation) to 80 elderly individuals and created machine learning models using the data of these tests. The authors reached the highest accuracy rate of 74.50% with the KNN algorithm. Ziegl et al.[32] used TUG data of elderly individuals living in nursing homes in the random forest algorithm and stated that the model could predict falls with an ROC-AUC rate of 96.9%. In another study, Tongterm et al.[33] used functional fitness tests in machine learning and aimed to predict the risk of falling with the decision tree. The authors determined the model's accuracy to be 0.95 and the specificity to be 0.55. To the best of our knowledge, no study in the literature detects fall risk using SOT data in machine learning. Unlike other studies, we used the features individually (SOT, functional balance and medical/physical features) and in combination when creating machine learning models. XGBoost, one of the algorithms created with SOT,

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considered the gold standard test for evaluating balance, predicted the risk of falling with 91.6% accuracy (MODEL-4). SVM, one of the algorithms created using individuals' comorbidities, physical characteristics and simple, functional balance tests, predicted the risk of falling with 100% accuracy (MODEL-3). Similarly, naive bayes, one of the algorithms in which all features (23 features) were used in machine learning (total-MODEL), predicted the risk of falling with 100% accuracy.

Falls in elderly individuals occur due to physical, perceptual and cognitive changes combined with diseases and an environment unsuitable for the safety of the elderly. Our study found that SOT administered with CDP is the most reliable test that can be used alone to predict fall risk. CDP is objective and evaluates all balance parameters. However, in addition to being a complex and expensive test, it also takes time. Moreover, our study found that the machine learning model (MODEL-3) created with simple, functional balance tests and comorbidities/physical characteristics detected the risk of falling at a higher rate than CDP. This shows that although balance tests used to assess fall risk are reliable, individuals' diseases and physical characteristics should also be taken into account. By using functional balance tests, individuals' comorbidities and physical characteristics in machine learning, the fall risk of elderly individuals can be predicted quickly and cheaply. This way, individuals at risk of falling can be identified early, and fall prevention strategies (exercise, awareness raising and ergonomics) can be recommended.

There are several limitations to this study. First, the sample size included in the study is limited to 120 elderly individuals. The prospective nature of the research and the long duration of the tests limited the sample size. In future studies, larger sample groups can be examined with retrospective data. In addition, despite the success of MODEL-3 and its potential to be applied without requiring a special device, this study was tested on a limited sample. Studies with larger sample groups will allow a better assessment of the general applicability and effectiveness of MODEL-3. Thus, an essential first step may have been taken in developing applicable methods to determine the global fall risk in elderly individuals.

Conclusion

Although balance tests to assess fall risk are reliable, individuals' diseases and physical characteristics should also be considered. Fall risk can be successfully predicted using simple, functional balance tests, comorbidities, and individuals' physical characteristics in the SVM algorithm. Moreover, machine learning-based websites or mobile applications can be developed with these models. In this way, elderly individuals can detect the risk of falling with online counselling without resorting to clinics. Similarly, online fall prevention strategies can be recommended to these individuals.

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Tables

Table 1. Physical characteristics, comorbidities, functional balance tests and sensory organization test scores of the participants according to groups.

	Group I, n=65 Mean±SD or Median (Min-Max)	Group II, n=55 Mean±SD or Median (Min-Max)	p
Physical Properties			
Weight, kg	73.81±11.67	72.23±12.51	0.476[d]
Height, cm	165.29±8.73	156 (143-182)	**<0.001**[a]
Body mass index (BMI)	27.10±4.50	29.04±4.97	**0.027**[d]
Comorbidities and Medication			
Number of medications	0 (0-5)	1 (0-10)	0.144[a]
Imbalance symptom, n (%)	15 (%23.1)	44 (%80.0)	**<0.001**[b]
Imbalance Severity	0 (0-5)	4 (0-8)	**<0.001**[a]
Duration of Imbalance (months)	0 (0-36)	10 (0-120)	**<0.001**[a]
Diseases, n (%)			
Hypertension, n (%)	25 (%38.5)	32 (%58.2)	**0.031**[b]

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Diabetes Mellitus, n (%)	10 (%15.4)	18 (%32.7)	**0.025**[b]
Hyperlipidemia, n (%)	11 (%16.9)	12 (%21.8)	0.497[b]
Cardiovascular Diseases, n (%)	8 (%12.3)	5 (%9.1)	0.572[b]
Thyroid, n (%)	2 (%3.1)	2 (%3.6)	0.625[c]
Major Depression Disorder, n (%)	2 (%3.1)	1 (%1.8)	0.660[c]
Prostate, n (%)	1 (%1.5)	1 (%1.8)	0.709[c]
Right Ear PTA (dB)	40 (12.5-75)	57.48±24.60	<0.001[a]
Left Ear PTA (dB)	41.25 (8.75-98.75)	53.85±22.61	<0.001[a]
Number of individuals with hearing loss n, (%)	51 (%78.5)	50 (%90.9)	<0.001[b]
Mild	35 (%53.8)	13 (%23.6)	
Moderate	18 (%27.6)	12 (%21.8)	
Moderately severe	3 (%4.6)	19 (%34.5)	
Severe	0 (%0)	5 (%9.1)	
Profound	0 (%0)	1 (%1.8)	
Asymmetric Hearing Loss (n)	14 (%21.5)	18 (%32.7)	0.167[b]
Functional Balance Tests			

Romberg Test (sec)	30.00 (25.67-30.00)	30.00 (15.05-30.00)	0.287[a]
Foam Romberg (sec)	30.00 (5.42-30.00)	11 (1.63-30.00)	<0.001[a]
Tandem Romberg Test (sec)	13.54 (2.37-30.00)	5.67 (1.11-30.00)	<0.001[a]
One Leg Standing Test (sec)			
Open Eyes	16.82 (4.21-30.00)	4.85 (1.52-30)	<0.001[a]
Closed Eyes	5.74 (1.34-30.00)	2.76 (0.30-16.15)	<0.001[a]
Tine up and FO (sec)	8.34±1.36	10.08 (7.27-17.56)	<0.001[a]
Functional Reach Test (cm)	29.32±5.08	22.71±5.32	<0.001[d]
Tinetti Balance and Gait Test	35 (33-35)	33 (27-35)	<0.001[a]
Sensory Organization Test			
SOT1	94.00 (88.34-96.67)	91.33 (60.66-97.00)	<0.001
SOT2	93.67 (85.67-96.67)	89.34 (58.00-96.67)	<0.001

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SOT3	92.00 (81.34-97.34)	87.00 (0.00-95.67)	<0.001
SOT4	79.07±7.45	68.00 (0.00-97.00)	<0.001
SOT5	68.67 (39.34-86.34)	44.36±24.04	<0.001
SOT6	66.03±10.94	43.00 (0.00-93.00)	<0.001

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Table 2. Test success of the models.

Algorithms	Precision	Recall	F1-score	Accuracy	ROC-AUC
MODEL-1					
KNN	0.90	0.82	0.86	0.8750	0.933
Naive Bayes	**0.83**	**0.91**	**0.87**	**0.8750**	**0.979**
Decision Tree	0.73	0.73	0.73	0.7550	0.748
Random Forest	0.91	0.91	0.91	0.8750	0.951
SVM	0.82	0.82	0.82	0.8334	0.972
Logistic Regression	0.82	0.82	0.82	0.8334	0.972
XGBoost	0.90	0.82	0.86	0.8750	0.937
Artificial neural networks	0.82	0.82	0.82	0.8334	0.832
MODEL-2					
KNN	0.82	0.82	0.82	0.8334	0.898
Naive Bayes	0.77	0.91	0.83	0.8334	0.937
Decision Tree	0.78	0.64	0.70	0.7500	0.842
Random Forest	0.75	0.82	0.78	0.7916	0.951
SVM	0.82	0.82	0.82	0.8334	0.930
Logistic Regression	**0.82**	**0.82**	**0.82**	**0.8334**	**0.944**
XGBoost	0.82	0.82	0.82	0.8334	0.881

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Artificial neural networks	0.80	0.73	0.76	0.7916	0.786
MODEL-3					
KNN	1.00	0.82	0.90	0.9166	0.979
Naive Bayes	0.85	1.00	0.92	0.9166	0.986
Decision Tree	0.82	0.82	0.82	0.8334	0.832
Random Forest	0.91	0.91	0.91	0.9166	0.972
SVM	**1.00**	**1.00**	**1.00**	**1.0000**	**1.000**
Logistic Regression	0.77	0.91	0.83	0.8334	0.965
XGBoost	0.91	0.91	0.91	0.9166	0.940
Artificial neural networks	0.85	1.00	0.92	0.9166	0.923
MODEL-4					
KNN	0.89	0.73	0.80	0.8334	0.825
Naive Bayes	1.00	0.73	0.84	0.8750	0.930
Decision Tree	0.89	0.73	0.80	0.8334	0.814
Random Forest	0.89	0.73	0.80	0.8334	0.888
SVM	0.88	0.64	0.74	0.7916	0.867
Logistic Regression	0.88	0.64	0.74	0.7916	0.867
XGBoost	**1.00**	**0.82**	**0.90**	**0.9166**	**0.895**
Artificial neural networks	0.90	0.82	0.86	0.8750	0.871

MODEL-5					
KNN	1.00	0.82	0.90	0.9166	0.909
Naive Bayes	**1.00**	**1.00**	**1.00**	**1.0000**	**1.000**
Decision Tree	1.00	0.91	0.95	0.9583	0.975
Random Forest	0.90	0.82	0.86	0.8750	0.972
SVM	0.89	0.73	0.80	0.8334	0.937
Logistic Regression	0.78	0.64	0.70	0.7500	0.881
XGBoost	0.91	0.91	0.91	0.9166	0.993
Artificial neural networks	1.00	0.73	0.84	0.8750	0.863

Bold text: Algorithm with best success, KNN: K-nearest neighbor, SVM: Support vector machine, AUC-ROC: Area under the receiver operating characteristic curve

Figure 1. The flow chart of the procedures and models applied to the participants.

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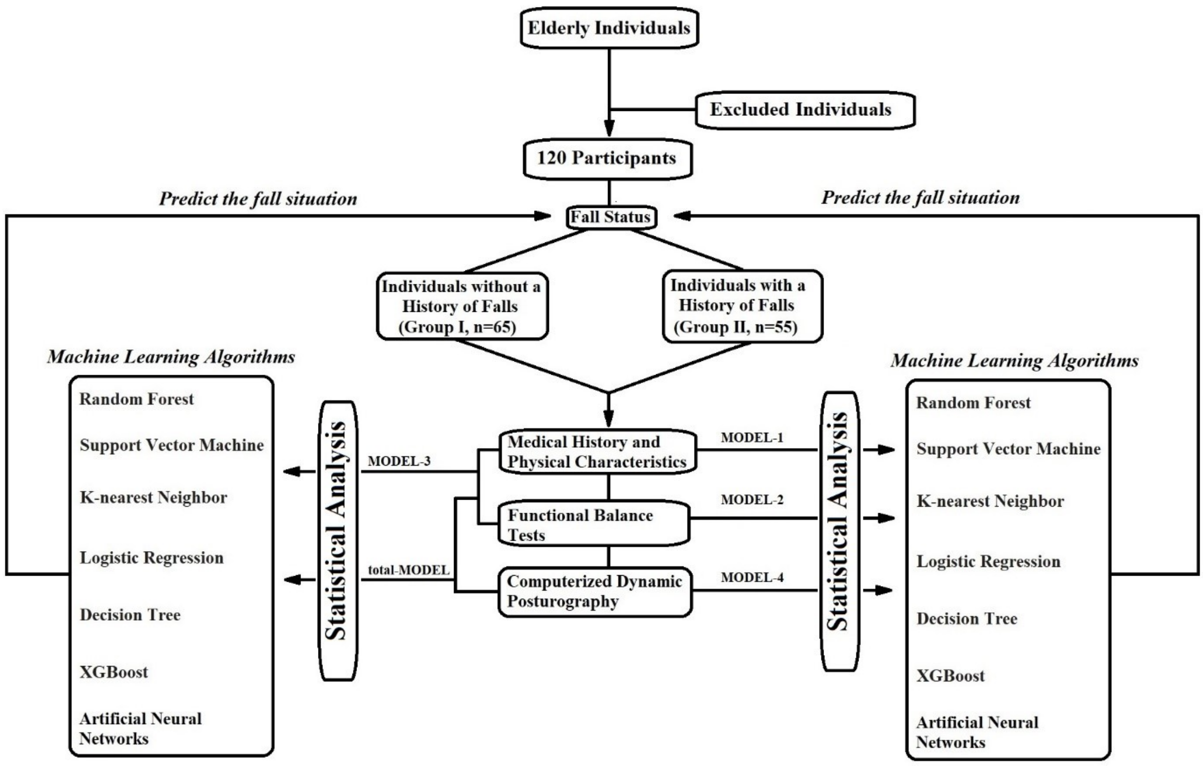

Figure 2. Somatosensory, visual, vestibular, composite and visual preference scores according to groups.

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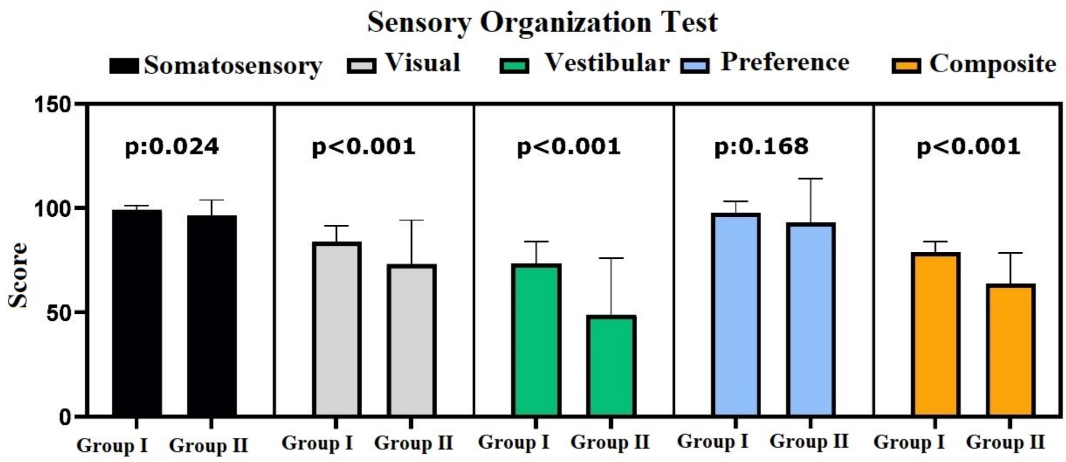
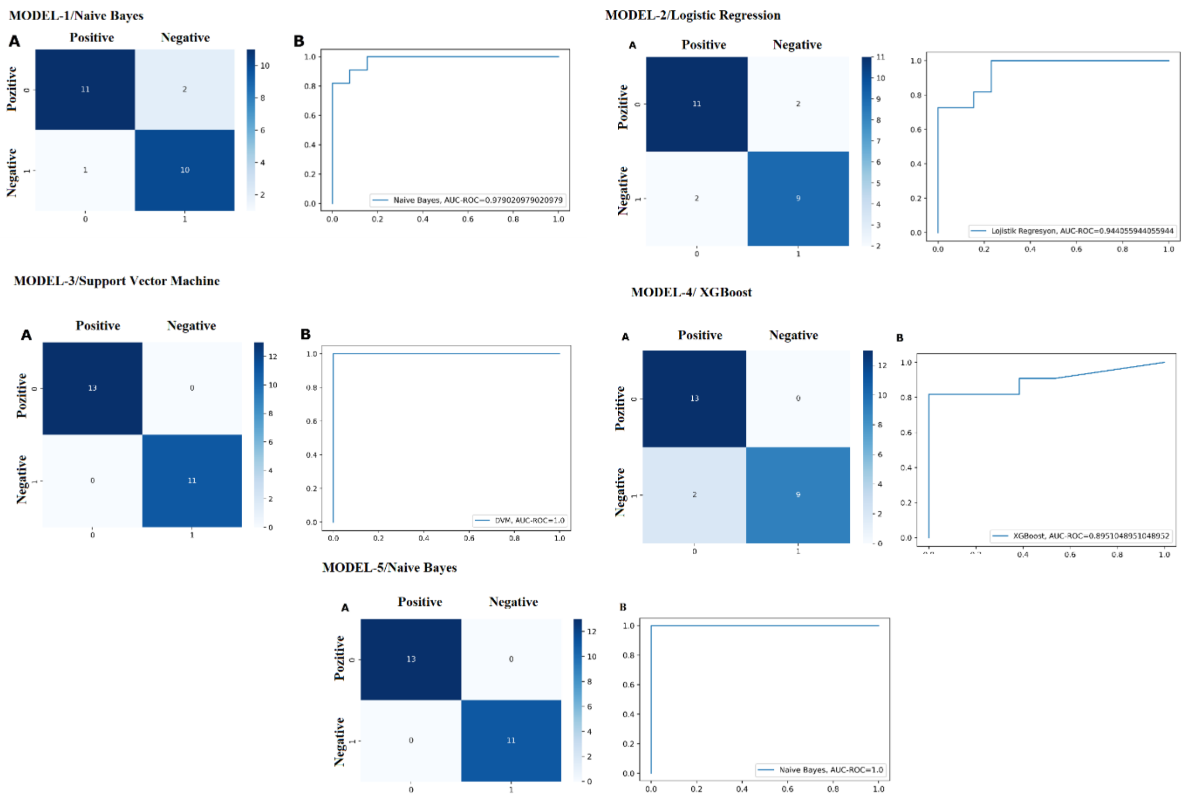


Figure 3. Confusion matrices and ROC curves of the best-performing algorithms according to the models.



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