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ASSESSING THE EFFECT OF AGE-RELATED SENSORY INPUT CHANGES ON POSTURAL SWAY IRREGULARITY

YAŞA BAĞLI DUYUSAL DEĞİŞİKLİKLERİN POSTURAL SALINIM DÜZENSİZLİĞİ ÜZERİNDEKİ ETKİSİNİN DEĞERLENDİRİLMESİ

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ABSTRACT

Age-related decline in sensory inputs in elderly people leads to postural instability that increases irregularity of postural sway. This study aimed to examine the effect of visual or somatosensory inputs on postural sway irregularity in the elderly by using machine learning (ML). The feature set was extracted from entropy measurements including sample, fuzzy, distribution, conditional, and permutation. Then, the variables were classified by ML including support vector machines (SVM), k-nearest neighbors (k-NN), and linear discriminant analysis (LDA) algorithms. Classification performances were compared with the confusion matrix. For the elderly, in the eyes closed condition on an unstable surface, the SVM algorithm achieved higher accuracy (77%), sensitivity (72%), specificity (85%), and precision (83%) for the cv dataset. For young, SVM also achieved high accuracy (86%), sensitivity (87%), specificity (84%), and precision (84%). For the elderly, under the eyes open on unstable surface conditions, the SVM exhibited an accuracy of 79%, sensitivity of 75%, specificity of 72%, and precision of 75%. However, for young, it did not reveal good results for both surfaces. In conclusion, the findings suggest that older people adapt their postural control mechanisms, relying more on somatosensory inputs. ML algorithms with entropy-based features can give insights into age-related differences in postural control.

Keywords: Older people, balance, postural sway, entropy, machine learning

ÖZET

Yaşlılarda duyusal girdilerde yaşa bağlı azalma, postüral dengesizliğe yol açarak postüral salınımın düzensizliğini artırır. Bu çalışma, makine öğrenimi (ML) kullanarak görsel veya somatosensoriyel girdilerin yaşlılarda postural salınım düzensizliği üzerindeki etkisini incelemeyi amaçladı. Özellik seti örnek, bulanık, dağıtım, koşullu ve permütasyon dâhil Entropi ölçümlerinden çıkarıldı. Daha sonra değişkenler, destek vektör makineleri (SVM), k-en yakın komşular (k-NN) ve doğrusal diskriminant analizi (LDA) algoritmalarını içeren ML modelleri ile sınıflandırıldı. Modellerin sınıflandırma performansları hata matrisi ile karşılaştırıldı. Yaşlılar için, stabil olmayan bir yüzeyde gözleri kapalı durumda SVM algoritması test veri seti için daha yüksek doğruluk (%77), duyarlılık (%72), özgüllük (%85) ve kesinlik (%83) elde etti. Gençler içinde SVM yüksek doğruluk (%86), duyarlılık (%87), özgüllük (%84) ve kesinlik (%84) elde etti. Kararsız yüzey koşullarında gözleri açık olan yaşlılar için SVM %79 doğruluk, %75 duyarlılık, %72 özgüllük ve %75 kesinlik sergiledi. Ancak gençler için her iki yüzeyde de iyi sonuçlar ortaya çıkmadı. Sonuç olarak, bulgular yaşlı insanların postüral kontrol mekanizmalarını somatosensör girdilere daha fazla güvenerek uyarladıklarını göstermektedir. Entropi tabanlı özellik setine sahip ML algoritmaları, yaşlılarda postüral salınım dinamiklerini yöneten temel mekanizmalar hakkında fikir verebilir.

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Anahtar Kelimeler: Yaşlı insanlar, denge, postüral salınım, entropi, makine öğrenimi

INTRODUCTION

The human body's ability to maintain an upright stance and navigate through its environment is facilitated by a sophisticated balance system, which plays a fundamental role in performing daily activities. To achieve and sustain postural stability, the human body relies on the intricate interplay of three key sensory systems including the visual, vestibular, and proprioceptive systems (Peterka, 2018). These systems converge their sensory inputs, and through a highly coordinated motor output, form a feedback mechanism essential for maintaining precise balance control. Each of these systems possesses unique anatomical and functional features, collectively contributing to the body's perception of spatial orientation and movement. The visual system, encompassing the eyes as the primary sensory organs, along with relevant parts of the central nervous system, plays a pivotal role in postural stability (Maurer et al., 2006). The vestibular system consists of the semicircular canals and otolith organs, which are mainly responsible for detecting angular accelerations and linear accelerations, respectively. The somatosensory system, encompassing various sensory receptors, plays a vital role in providing the body with information about its position and movement in space (Mergner et al., 2005). This intricate system includes cutaneous receptors, joint receptors, muscle spindles, and Golgi tendon organs, each serving unique functions. Understanding the integration and interactions of these sensory inputs is of paramount importance in comprehending the mechanisms underlying postural sway and balance control, particularly in the context of aging populations and related issues such as fall risk in the elderly because the aging process is an inevitable facet of the human life cycle, bringing with it a myriad of physiological, sensorial, and functional changes (Horak et al., 1989). Decrease or deterioration in sensory inputs in elderly people leads to balance problems that increase the risk of falling, which can have severe consequences for the health and independence of older individuals (Qiu et al., 2012). Analysis of postural sway, defined as the involuntary movement of the body while maintaining an upright stance, has been a critical indicator of balance and postural control.

In literature, many studies have revealed an in-depth investigation into the interplay of visual, vestibular, and somatosensory inputs in postural sway dynamics (Horak et al., 1989; Mergner et al., 2005; Qiu et al., 2012; Wang et al., 2010). Qui et al. (2012) examined the integration of visual and somatosensory inputs affects postural sway and balance, with reliance on somatosensory information increasing when visual input was limited. They suggested that textured insole surfaces could reduce postural sway in older people, particularly during more challenging balance tasks, providing an important intervention in fall prevention. They found clear differences in postural sway based on age, insole surface, and standing surface and significant interaction for various postural sway measures. Wang et al. (2010) found that visual inputs significantly affected postural sway and balance, particularly when combined with an unstable base of support. Their results revealed that visual information impacted postural reactions and sway responses. Postural response amplitudes depended on visual field velocity. Tanaka & Uetake (2005) found that older adults had increased postural sway on a foam surface compared to a firm surface, regardless of age. The findings of their study revealed that among older adults, there is an increased dependence on visual cues for correcting M-L postural sway. Moreover, the deterioration in visual acuity associated with aging could potentially heighten the susceptibility to sideways falls, especially in demanding conditions, such as when standing on unstable surfaces. This underscores the significance of visual function assessment in the context of fall prevention strategies for the elderly. Garbus et al. (2019) investigated how visual and somatosensory inputs interact to improve postural sway and balance. They suggested that providing explicit visual feedback of the center of pressure does not increase the light touch effects on the postural sway, and the importance of the implicit somatosensory information on postural control is discussed. Ito et al. (2020) reported that elderly individuals were more dependent on somatosensory signals for balance control than adults.

Previous studies indicate that there is no consensus on the dominant effects of visual and/or somatosensory inputs on postural control and balance due to aging. Moreover, postural sway has been traditionally assessed through simple biomechanical metrics, such as center of pressure (COP) displacement and velocity, in particular using linear or statistical signal analysis approaches. However, these conventional measures may not fully capture the complexity of postural control mechanisms, especially in dynamic real-life situations. Instability or irregularity of postural sway could be associated with an increased risk of falls (Seigle et al., 2009). The irregularity can be measured by nonlinear methods rather than linear or statistical approaches. Employing a nonlinear approach, it can integrate findings from neurophysiology, biomechanics, and machine learning (ML) to gain comprehensive insights into the complexity of human balance control. In recent years, entropy measurements have been used as a very popular method for measuring irregularity and complexity in time series (Alcan, 2022). By leveraging advancements in nonlinear signal analysis capabilities, it is needed to shed further light on the mechanisms governing postural stability in older people. Furthermore, advancements in ML algorithms have been considered useful clinical decision support tools for investigating postural sway dynamics and analyzing intricate patterns within large datasets. Therefore, this study aimed to present the results of an in-depth investigation into the impact of sensory inputs on the entropy of postural sway in the elderly, utilizing ML techniques. Specifically, the study focused on various entropy algorithms and the application of support machine vectors (SVM), k-nearest neighbors (k-NN), and partial least squares discriminant analysis (PLS-DA) algorithms to decipher the complex interactions between sensory inputs and postural sway patterns in older people

METHODS

Data

The present study used a public dataset that recruited a cohort of elderly participants, who underwent comprehensive assessments of postural sway under four sensory conditions including eyes-open, eyes-closed, stable surface, and unstable surface (Santos & Duarte, 2016). Postural sway data were collected using advanced force plate technology in anterior-posterior (A-P) and medial–lateral (M-L) directions, allowing for precise measurements of COP displacement in response to sensory perturbations.

Entropy Algorithms

Based on entropy algorithms, the feature set was built with six well-known entropy algorithms to conduct postural sway changes of older people in A-P and M-L directions.

Sample entropy (SampEn):

SampEn is a measure used to quantify the complexity or irregularity of time series data. It compares the likelihood of repeated patterns of a certain length in the data. Sample entropy builds upon approximate entropy and involves counting matches of templates in the time series data (Richman & Moorman, 2000). The mathematical equations and backgrounds for SamEn are explained in Equation 1.

$$SampEn\ (m,\tau,r) = -\ln\frac{\sum_{i=1}^{N-m\tau} A_i^{(m+1)}(d,r)}{\sum_{i=1}^{N-m\tau} A_i^{(m)}(d,r)} \tag{1}$$

Fuzzy Entropy (FuzzyEn)

FuzzyEn measures the spread or dispersion of membership degrees within the fuzzy set (Chen et al., 2009). Unlike SampEn, the average number of vectors Xm(j) that are within "r" of Xm(i) is used with the average degree of membership. The specific mathematical equations for the membership function and FuzzyEn are calculated in Equation 2 and Equation 3.

$$A_i^{(m)}(d,r) = \sum_{j=1,j\neq i}^{N-m\tau} e^{-\ln(2)\left({d_{i,j}}/{r}\right)^2} \tag{2}$$
$$membership\ function = e^{-\ln 2\left({x}/{r}\right)^2} \tag{3}$$

Conditional Entropy (CE)

CE is a measure of the amount of uncertainty or information content in a random variable given the knowledge of another random variable. It quantifies the remaining uncertainty in one variable after the other variable is observed (Porta et al., 1998). CE is calculated as the average entropy of the conditional probability distribution of the first variable given the second variable. Mathematically, for two discrete random variables, CE is calculated by Equation 4.

$$CE(m,\tau) = SE\left(z_j\right) - SE(w_i) + perc(m)SE \tag{4}$$

where the summation is performed over all possible values of X and Y.

Distribution Entropy (DistEn)

DistEn is a measure that quantifies the diversity or variability in the probability distribution of a random variable (Li et al., 2016). It captures the dispersion of the probability density function of the distance matrix by the histogram approach with a fixed bin number of B. The mathematical equations for DistEn are calculated by Equation 5.

$$DistEn\ (m,\tau,B) = -\frac{1}{log_2(B)}\sum_{t=1}^{B} p_t \log_2(p_t) \tag{5}$$

where p_t is the probability of each bin

Permutation Entropy (PermEn)

PermEn is based on the idea of permuting the values of a time series and analyzing the resulting patterns (Bandt & Pompe, 2002). It quantifies the probability distribution of ordinal patterns (sequences of values' ranks) within the time series as follows:

$$PermEn\ (m,\tau) = -\frac{1}{log_2 m!}\sum_{j=1}^{m!} p_t(m,\tau)\log_2[(p_j(m,\tau)] \tag{6}$$

Machine Learning Algorithms

To investigate the intricate relationship between sensory inputs and postural sway patterns, the most common ML algorithms including SVM, k-NN, and LDA were applied to model the complex interactions within the data. These supervised ML algorithms were chosen for classification tasks and their ability to handle high-dimensional data and nonlinear relationships, makes them well-suited for the analysis of postural sway dynamics. Samples were usually divided into training dataset and cross-validation (CV) as a testing dataset based on the Venetian blinds approach. A 5-fold CV value was used for internal validation of all models.

Support Vector Machines (SVM)

SVMs aim to find an optimal hyperplane that separates the data points of different classes with the largest margin. The mathematical foundation of SVM relies on the concept of a maximum-margin hyperplane and the use of kernel functions for handling nonlinearly separable data. The basic idea is to transform the input data into a higher-dimensional space using a kernel function and then find the hyperplane that maximizes the margin between classes. The optimization problem in SVM involves finding the hyperplane parameters that minimize the classification error and maximize the margin. Popular kernel functions used in SVM include linear, polynomial, gaussian, and sigmoid kernels.

K-Nearest Neighbor (k-NN)

In k-NN, the class or value of an unknown sample is determined based on the majority vote or averaging of the values of its k nearest neighbors in the training data. The mathematical background of k-NN involves computing the distances between data points to identify the k-nearest neighbors. The choice of distance metric, such as Euclidean distance or Manhattan distance, plays a crucial role in the k-NN algorithm. For classification tasks, k-NN assigns the class label based on the majority class among the k nearest neighbors. For regression tasks, k-NN takes the average or weighted average of the target values of the k nearest neighbors to estimate the unknown sample's value.

Linear Discriminant Analysis (LDA)

LDA is a supervised classification and dimensionality reduction technique that seeks to find linear discriminants to maximize the separability between classes. It can be used for classification tasks when the class structure is important and is a useful tool for feature extraction and dimensionality reduction in supervised learning scenarios. Concerning principal component analysis, LDA can provide a two-step approach to first reduce dimensionality and then maximize class separability for improved classification performance.

Classification Performance of ML Algorithms

To evaluate the classification performances (in training and cross-validation test sets of samples), a confusion matrix was provided. From the confusion matrix, several important metrics were calculated, including precision, sensitivity (recall), and specificity. A confusion matrix is a square matrix with dimensions “NxN+1”, where N is the number of classes. It summarizes the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions made by a classification model, where TP is the number of correctly predicted positive samples, FP is the number of samples wrongly predicted as positive (actually negative), TN is the number of correctly predicted negative samples, and FN is the number of samples wrongly predicted as negative (actually positive). Precision indicates the proportion of correctly predicted positive samples among all samples predicted as positive by Precision = TP/(TP+FP). Sensitivity (recall) measures the proportion of correctly predicted positive samples among all actual positive samples. It assesses positive samples correctly by sensitivity = TP/(TP+FN). Specificity measures the proportion of correctly predicted negative samples among all actual negative samples. It assesses negative samples correctly by specificity = TN/(TN+FP). Accuracy measures the overall proportion of correct predictions made by the model, considering both positive and negative instances by accuracy = (TP+TN)/(TP+TN+FP+FN).

RESULTS

The classification performance of the SVM, k-NN, and LDA algorithms was evaluated by using a confusion matrix. Table 1 shows the overall accuracy of the models for older subjects.

Table 1. The overall accuracy of the ML algorithms for older subjects

Overall Accuracy for Older Subject							
		SVM		**k-NN**		**LDA**	
Eyes Condition	**Class**	**Training (%)**	**CV (%)**	**Training (%)**	**CV (%)**	**Training (%)**	**CV (%)**
Eyes Open	**Stable Surface** / **Unstable Surface**	82	79	78	73	83	79
Eyes Closed	**Stable Surface** / **Unstable Surface**	82	77	70	72	79	77

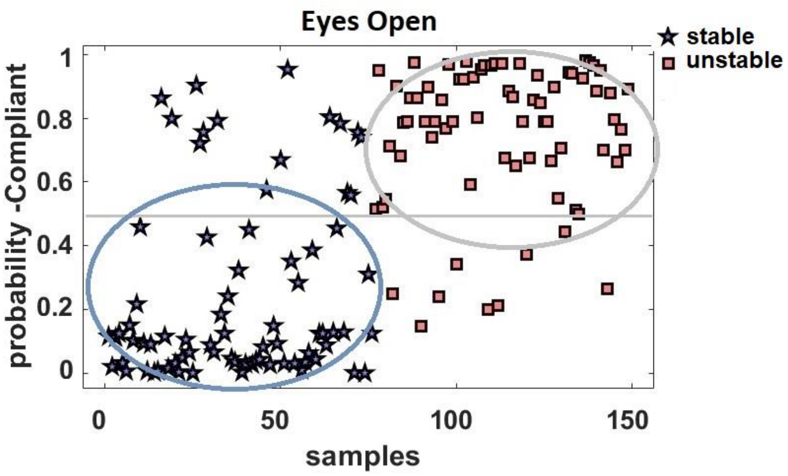
Concerning the older subjects, the overall accuracy of the SVM model was 82% and 79% for training and CV data, respectively, under eyes-open conditions while 82% and 77% for training and CV data under eyes-closed conditions, respectively. The overall accuracy of the k-NN model was 78% and 73% for training and CV data respectively, under eyes-open conditions while 70% and 72% for training and CV data under eyes-closed conditions, respectively. For the LDA algorithm, the overall accuracy was 83% and 79% for training and CV data respectively, under the eyes-open condition while 79% and 77% for training and CV data under the eyes-closed condition, respectively. These results indicated that the SVM model revealed a better performance than k-NN and LDA models in overall predictive accuracy. Table 2 shows the overall accuracy of the models for young subjects.

Table 2. The overall accuracy of the ML algorithms for young subjects.

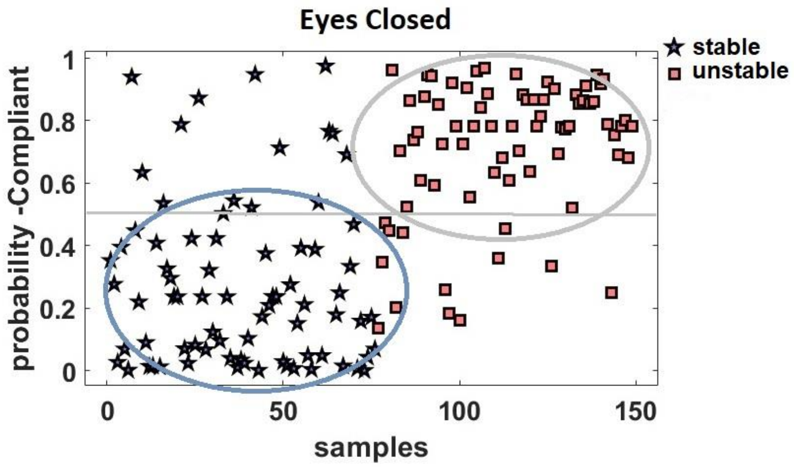
Overall Accuracy for Young Subject							
		SVM		**kNN**		**LDA**	
Eyes Condition	**Class**	**Training (%)**	**CV (%)**	**Training (%)**	**CV (%)**	**Training (%)**	**CV (%)**
Eyes Open	**Stable Surface** / **Unstable Surface**	70	64	66	71	80	74
Eyes Closed	**Stable Surface** / **Unstable Surface**	88	86	87	86	85	86

In Table 2, the overall accuracy of the SVM model was 70% and 64% for training and CV data, respectively, under eyes-open conditions while 88% and 86% for training and CV data under eyes-closed conditions, respectively. The overall accuracy of the k-NN model was 66% and 71% for training and CV data under eyes-open conditions, respectively. On the other hand, it was 87% and 86% for training and CV data under eyes-closed conditions, respectively. For the LDA algorithm, the overall accuracy was 80% and 74% for training and CV data, respectively, under eyes-open conditions while 85% and 86% for training and CV data under eyes-closed conditions, respectively. These results indicated that the SVM model also revealed a better performance than k-NN and LDA models in overall predictive accuracy.

To understand the classifier's confidence in its predictions and assess its performance, the probability graphs were produced by SVM algorithms shown in Figure 1 and Figure 2. Each point on the graph represents a sample, and its corresponding probability estimate is on the y-axis. These graphs are often used in binary classification tasks, where the SVM model assigns labels +1 and -1 to the two classes and tries to maximize the margin between the support vectors (data points closest to the decision boundary). Figure 1 shows the probability graphs for older subjects.



a)



b)

Figure 1. The Probability Graphs For Older Subjects. The Relationship Between The SVM's Probability Estimates And The Samples Used In Stable Vs Unstable Evaluation Under a) Eyes-Open Condition b) Eyes-Closed Condition.

In Figure 1a, most samples of the unstable class have high probabilities (close to 1), while samples of the stable class have low probabilities (close to 0), which indicates that the SVM is effectively distinguishing between the classes. A tight cluster of probabilities around 0.5 for the samples indicates that the SVM is uncertain about their classification. On the other hand, Figure 1b indicates that SVM does not perfectly distinguish between the classes. Fewer samples of unstable and stable classes have high and low probabilities (close to 1 or 0), respectively. Figure 2 shows the probability graphs for young subjects.

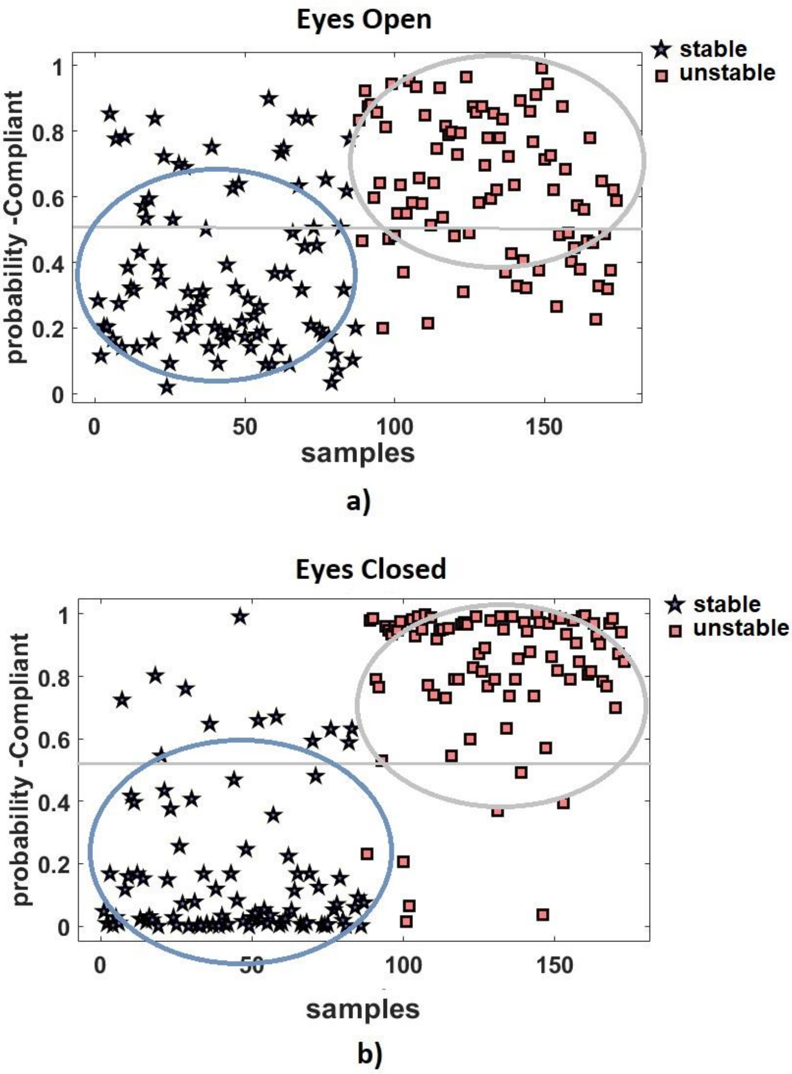


Figure 2. The Probability Graphs For Young Subject. The Relationship Between The SVM's Probability Estimates And The Samples Used In Stable Vs Unstable Evaluation Under a) Eyes-Open Condition b) Eyes-Closed Condition.

In Figure 2a, a larger cluster of probabilities around “0.5” for the samples indicates that the SVM is uncertain about their classification. Fewer samples of the unstable class have high probabilities (close to 1), while fewer samples of the stable class have low probabilities (close to 0). In Figure 2b, most samples of unstable and stable classes have a high and low probability, respectively. The graph results indicate that the SVM better distinguished between stable and unstable classes under eyes-closed condition compared to eyes-open condition.

Table 3 shows confusion matrix metrics for older subjects. When compared to the ML models, the SVM model exhibited also better sensitivity (recall), specificity, and precision values than k-NN and LDA models, indicating its capability to correctly identify true positive samples for both training and CV data sets.

Table 3. Confusion Matrix Metrics For Evaluating The Performance Of Classification ML Algorithms For Older Subjects

			SVM			k-NN			LDA		
		Class	**Sens %**	**Spec %**	**Prec %**	**Sens %**	**Spec %**	**Prec %**	**Sens %**	**Spec %**	**Prec %**
Training	Eyes Open	Stable	75	89	88	64	92	89	78	90	89
		Unstable	89	75	77	92	64	71	90	78	80
	Eyes Closed	Stable	82	82	83	55	86	81	68	86	84
		Unstable	82	82	81	86	55	65	86	68	72
CV	Eyes Open	Stable	72	85	83	55	92	88	76	88	87
		Unstable	85	72	75	92	55	66	88	76	78
	Eyes Closed	Stable	76	77	77	66	66	66	67	84	81
		Unstable	77	76	76	66	66	66	84	67	71

CV=cross-validation; SVM=support vector mechines; k-NN=k-nearest neighbors; LDA=linear discriminant analysis; Sens= sensitivity; Spec= specificity; Prec=precision

Concerning older subjects, under eyes-open conditions, the SVM algorithm generally achieved higher sensitivity (89% and 85%), specificity (75% and 72%), and precision (77% and 75%) for unstable surfaces in both training and CV datasets, respectively. For stable surfaces, the SVM algorithm revealed high sensitivity (75% and 72%), specificity (89% and 85%), and precision (88% and 83%) in training and CV datasets, respectively. SVM revealed also similarly good results for the eyes-closed condition in both stable and unstable surfaces. Table 4 shows confusion matrix metrics for young subjects.

Table 4. Confusion Matrix Metrics For Evaluating The Performance Of Classification ML Algorithms For Young Subjects

			SVM			k-NN			LDA		
		Class	**Sens %**	**Spec %**	**Prec %**	**Sens %**	**Spec %**	**Prec %**	**Sens %**	**Spec %**	**Prec %**
Training	Eyes Open	Stable	74	67	69	48	84	75	75	85	83
		Unstable	67	74	72	84	48	62	85	75	77
	Eyes Closed	Stable	84	92	91	86	87	87	82	88	88
		Unstable	92	84	85	87	86	86	88	82	83
CV	Eyes Open	Stable	68	61	63	53	90	84	70	77	75
		Unstable	61	68	65	90	53	66	77	70	72
	Eyes Closed	Stable	84	87	87	84	87	87	84	87	87
		Unstable	87	84	84	87	84	84	87	84	84

CV=cross-validation; SVM=support vector mechines; K-NN=k-nearest neighbors; LDA=linear discriminant analysis; Sens= sensitivity; Spec= specificity; Prec=precision

Concerning young subjects, under eyes-closed conditions, the SVM algorithm achieved higher sensitivity (92% and 87%), specificity (84% and 84%), and precision (85% and 84%) for unstable surfaces in both training and CV datasets, respectively. For stable surfaces, the SVM algorithm revealed high sensitivity (84% and 84%), specificity (92% and 87%), and precision (91% and 87%) in training and CV datasets, respectively. However, it did not reveal good results for eyes-open conditions in both stable and unstable surfaces.

DISCUSSION

The primary objective of this study was to evaluate the relationship between visual and somatosensory inputs and the entropy of postural sway in elderly individuals. Secondly, it was aimed to assess the efficacy of ML algorithms (SVM k-NN, and LDA) in analyzing postural sway patterns and identifying potential predictors of postural stability. Four sensory conditions involved altered visual inputs (eyes open and eyes closed) and somatosensory manipulations (stable and unstable surfaces) to simulate real-life scenarios where sensory challenges may lead to balance disturbances. In the present study, the results of the classification of postural sway entropy features suggested valuable insights into the effects of age on postural control.

Age-Related Visual And Somatosensory Effect On Postural Sway

The young subjects indicated a high rate of classification accuracy, sensitivity, specificity, and precision, particularly in conditions with eyes closed and on unstable surfaces. However, they exhibited a lower rate of performance when their eyes were open, suggesting that visual input and stable surface significantly contributed to decreased irregularity of postural sway in young or vice versa. In contrast, the older subjects exhibited similar rates of accuracy, sensitivity, specificity, and precision in postural sway classification on both stable and unstable surfaces, regardless of whether their eyes were open or closed. This suggests that the postural control mechanisms in the elderly remain relatively consistent across different sensory conditions. The observed differences in classification performance between the older and the young subjects can be attributed to changes in sensory processing with age. Age-related physiological changes can affect the sensory systems of older people, including the visual and somatosensory systems. The lower classification performance in young subjects with their eyes open could indicate that reliance on visual input decreases with age. This could be due to age-related declines in visual acuity and processing speed. As a result, young individuals might experience difficulty maintaining balance solely with visual input, especially in challenging conditions like standing on unstable surfaces. On the other hand, the consistent performance of older people across different sensory conditions suggests that they might rely more on somatosensory inputs for postural control. The somatosensory system, which includes sensory information from the feet and proprioceptive receptors, plays a crucial role in balance maintenance. The results showed that stability gains were observed with increasing sensory information, but the nature of these gains was modulated by somatosensory (proprioceptive) information and the reliability of the haptic support surface. Additionally, the perception of somatosensation was influenced by congruent and incongruent visual inputs and body posture, with better localization observed when visual inputs and body posture were congruent with somatosensation. With aging, the somatosensory system might become more important in compensating for visual deficits and maintaining postural stability. These findings suggest that somatosensory inputs play important roles in postural control and can affect balance (Wiesmeier et al., 2015). It was found that older subjects favor proprioceptive than younger subjects do, and parameter differences between young and old may result from both deficits and compensation strategies in the elderly. The main reason can be related to impairments of the motor system in older people who can have difficulties in sensory reweighting, which is the process of scaling the relative importance of sensory cues (visual, vestibular, and proprioceptive) for motor control (Horak et al., 1989). In this study, standing on an unstable surface reduced the reliability of somatosensory information and increased the entropy of postural sway. With aging, older subjects can have a lower sensitivity to the plantar surface of the foot than younger subjects, which can increase postural sway. These age-related effects may be further magnified in conditions where visual input is eliminated, leading to heightened dependence on somatosensory information (Lord et al., 1991; Patel et al., 2011).

Entropy and ML Algorithms

Age-related differences in spontaneous sway mainly concern an increased postural sway (mean velocity, sway, mean frequency, etc.) by using traditional CoP analysis (Barela et al. 2018). However, in this study, measures of postural control were segregated into spontaneous sway entropy measures of motor behavior induced by surface perturbations. While removing visual feedback affects postural control in young people leading to changes in the dynamics of postural oscillations by increased entropy, it did not affect older people. On the contrary, for older subjects, manipulating somatosensory feedback led to changes in the dynamics of postural oscillations by increased entropy suggesting somatosensory had a dominant effect on the postural sway oscillations. Concerning unstable surface conditions under both eyes open-and-closed conditions, the results showed that the irregularity of postural sway was higher in older subjects than in young subjects. For older subjects, the balance was less stable with absent somatosensory information. Sensory inputs to the somatic system can decrease with age, which can contribute to increased irregularity (entropy) postural sway in older subjects compared to young (Shiota, 2015).

In previous studies, Alcan (2023) calculated entropy measurements including SampEn, FuzzyEn, DistEn, CE, PermEn, and sparse density entropy from CoP data. SVM and k-NN ML algorithms were used to investigate the effect of visual or somatosensory inputs on CoP signal in solely the elderly. This study found that the measurement of CoP irregularity or nonlinear dynamics in balance assessments in the elderly was more sensitive to somatosensory inputs than visual inputs. Similarly, Hansen et al. (2017) found that entropy measures were more sensitive in analyzing postural sway compared to traditional measures. They used SampEn, multi-scale sample entropy (MSE), and multivariate multi-scale entropy and compared them to traditional measures of COP variability. Their results suggested that non-linear methods appear to be an additional valuable tool for analysis of the dynamics of posture especially when applied to incremental time series when compared to the classical parameters and entropy measures of the original time series. Giovanini et al. categorized age groups using different CoP time series. They used the same data as the dataset. However, they calculated large feature sets including temporal, spatial, spectral, and nonlinear features including mean distance, root mean square (RMS) distance, mean velocity, RMS velocity, standard deviation (SD) of velocity), sway path, length of COP path, excursion area, total mean velocity, mean frequency, median frequency, spectral power with 95%), SampEn, MSE, scaling exponent, Hurst exponent of distance. They used SVMs, k-NN, NB MLP, RF, and decision tree (DT) ML models and found that a 60 s sampling duration provided the most discriminative information. The overall classification accuracy of all ML models was 61.3% for dataset 1 and 67.8% for dataset 2. The mean values of all ML models were smaller for a 30 s duration, affecting the CoP time series duration in different age groups. Çetin & Bilgin (2019) distinguished between young and aged groups using the same dataset. Unlike our feature set, they extracted features from time-dependent variables including CoP and force change. They used various classifiers and found that force signals were more successful than COP signals. The SVM model had the highest accuracy (81.67%) in separating the young and older groups. Seigle et al. (2009) concluded that classical stabilometric variables and Recurrence Quantification Analysis (RQA) outputs provided complementary information for the characterization of aging effects on postural sway. They found that COP displacement was affected by vision in both young and elderly adults. The RQA method was able to discriminate COP displacement in elderly subjects. Ojle et al. (2021) investigated the effects of visual and somatosensory input on postural sway using entropy and ML algorithms. They used the k-NN model to investigate the effects of the visual, proprioceptive, and vestibular systems using the postural sway information in the M-L and A-P directions. They found that the visual system affected M-L sway, and proprioceptive and vestibular systems affected A-P sway. A-P sway was more affected by sensory systems than M-L sway. Sun et al. (2019) implemented an ML approach to assess the accuracy and feature importance of various postural sway metrics to differentiate individuals with Multiple Sclerosis (MS) from healthy controls as a function of physiological fall risk and M-L sway amplitude was identified as the strongest predictor for fall risk groupings. The feature set used in this study consisted of 20 common postural sway metrics derived from static posturography assessment. The ML algorithm used in this study was random forest (RF) with 10-fold cross-validation. The sway-metric-based RF classifier had high accuracy in discriminating controls from MS individuals (>86%). Sway sample entropy was identified as the strongest feature for the classification of low-risk MS individuals from healthy controls. Whereas for all other comparisons, mediolateral sway amplitude was identified as the strongest predictor for fall risk groupings. They found that posturography was beneficial for balance impairment and fall risk assessment in individuals with MS. Sample entropy and M-L sway amplitude were strong predictors for fall risk in MS individuals. Lee et al. (2020) found that using logistic regression analysis with sensor data and entropy analysis provided an accurate classification of fall risk in elderly people. Their results showed that logistic regression analysis predicted fall risk in the elderly and PerEn and statistical features provided accurate classification.

Consequently, the findings of the present study are consistent with previous research on age-related changes in postural sway and suggest the use of such entropy indices from nonlinear domains extracted from CoP signals and its complex components as potential markers for postural instability and fall risk in older adults. ML algorithms also provided complementary information and very good classification performance for the characterization of aging effects on postural sway. From a clinical perspective, the ML approach of applying entropy analysis to CoP data on a fall-risk scale can allow medical practitioners to predict risk and can provide decision-makers with a more accurate way to classify fall risk in elderly people.

CONCLUSION

This study found how visual and somatosensory information significantly affects the postural sway irregularity (balance ability) of older people, as measured by nonlinear dynamics by entropy. The findings suggest that older people adapt their postural control mechanisms, relying more on somatosensory inputs, to maintain stability. Meanwhile, young individuals heavily rely on visual input, particularly in challenging situations. Findings suggest the loss of somatosensory function may explain much of the age-related increase in the irregularity of postural sway, with different entropy algorithms measured with eyes closed then eyes open on foam, and then a firm surface. For clinical decision support systems, the SVM algorithms can give insights into the underlying mechanisms that govern postural sway dynamics in the elderly population, shedding light on the role of sensory inputs in maintaining balance. The findings of this study have the potential to enhance preventive measures and interventions aimed at improving postural stability and reducing fall-related incidents, thereby contributing to the well-being and quality of life of the elderly population and society at large.

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