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Framework for early detection and classification of balance pathologies using posturography and anthropometric variables

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ABSTRACT

Background: Early detection of balance-related pathologies in adults using Posturography, anthropometric and personal data is limited. Our goal is to address this issue. It will enable us to identify adults in early stages of balance disorders using easily accessible and measurable data.
Methods: Open-source data of 163 subjects (47 males and 116 females) is used to train and test classification algorithms. Features include mean and standard deviation of the center of pressure displacement, obtained through posturography, the anthropometric and personal variables (age, sex, body mass index, foot length), and Trail Making Test scores. 75% of the data is employed for training and 25% of the data is used for testing. It is then validated using an indigenously collected dataset of healthy individuals.
Findings: Accuracy and Sensitivity, both, increases when anthropometric and personal variables are included alongside center of pressure features for classification. Specificity decreases slightly with the addition of anthropometric and personal variables with center of pressure displacement feature, which also affects the classification algorithms' performance. Standard deviation of the center of pressure displacement is found to be more effective than the mean value. A similar trend of the increased performance is observed during validation, except when neural networks were used for the classification.
Interpretation: Posturography data, Anthropometric measurements, personal data and self-assessment scales can identify balance issues in adults, making it suitable for community health centers with limited resources. Early detection prompts timely medical care, improving the management of disorders and thus enhancing the quality of life through rehabilitation.

1. Introduction

The stability of a body is its resistance to changes in acceleration and equilibrium, while balance refers to the ability to control the equilibrium(Egoyan and Moistsrapishvili, 2013). Balancing involves maintaining posture, aiding movement, and regaining stability using three sensory systems: vision, the vestibular system and somatosensory system (Winter, 1995). Postural control, influenced by age and musculoskeletal issues, affects the risk of falls, disabilities, and healthcare costs, impacting independence and quality of life. Injuries due to falls have been reported to be a major worldwide health hazard. As per reports from World Health Organization (2008), falls are experienced by about 28–35% of the people older than 64 years, every year(Chen et al., 2021). Various qualitative tests such as the Berg Balance Test (BBS), the Tinetti Performance Oriented Mobility Assessment (POMA), the Clinical test for sensory interaction in Balance (CTSIB), balance error scoring system (BESS) and the Mini Balance Evaluation Test (Mini-BESTest)(Chen et al., 2021)(Mancini and Horak, 2010) assess balance, but they are disorder-specific, lack sensitivity, and require physician expertise for conducting. Hence, they aren't suitable for large-scale screening due to diverse balance deficit causes. Quantitative posturography, which measures ground reaction forces (GRF) and COP location, can address

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this need and has been used to identify balance-related pathologies. Posturography data under different conditions have been employed to classify normal and pathological subjects with an accuracy of 82.7%, with foam/rubber surface and eyes closed condition being the most distinguishing feature(Ahmadi et al., 2019). Gait data under different conditions have been successfully employed to classify Parkinson's disorder (PD) subject(E et al., 2021). Postural Sway Ratio (SR) analysis have also been employed to assess PD patients and age-matched healthy participants under quiet standing with eyes open and eyes closed condition which recommends Sway Ratio and force plate posturography to be reliable measure for studying postural impairments(Błaszczyk and Orawiec, 2011). Mean COP position in A/P direction is reported to be an individual-specific feature associated with the biomechanics of a subject (Yamamoto et al., 2015). Consideration of several anthropometric variables during balance studies is important as balancing cannot be explained by any single anthropometric variable(Kejonen et al., 2003). Fall risk due to postural instability is reported to increase with old age (Chen et al., 2021) and higher body weight(Greve et al., 2013)(Hue et al., 2007). Additionally, there is a direct correlation between sex and balance ability(Kejonen et al., 2003) as the effect of body mass on balance is stronger in males than in females(Greve et al., 2013). In most of the cases, a single dataset with the same experimental setup is considered which might raise its applicability in other datasets universally or its usage in the field. Therefore, there is a crucial need for a simple quantitative method to identify individuals with compromised balance control and promote specialist intervention using easily measurable data that can be collected by semi-skilled medical workers in the field. Thus, our aim is the early-detection of balance-related pathologies in adults using Posturography, anthropometric measurements and personal data. The subject with balance-related pathologies have been classified using COP values (mean and SD), surface support conditions (Firm Ground and Foam), Vision (Eyes Open and Closed), age, body mass index (BMI), and Trail Making Test (TMT) scores. TMT score is considered as a self-assessment feature and it provides us with the complex attention of the subject(Pellerito, 2010). Three models are trained and tested using an open-source database(Santos and Duarte, 2016), and then validating their universality and applicability with an indigenously developed dataset. This approach enables it to screen adults with balance-related disorders in a large scale which can be implemented through community health centers.

2. Methods

Fig. 1 gives us an overview of the various steps undertaken during

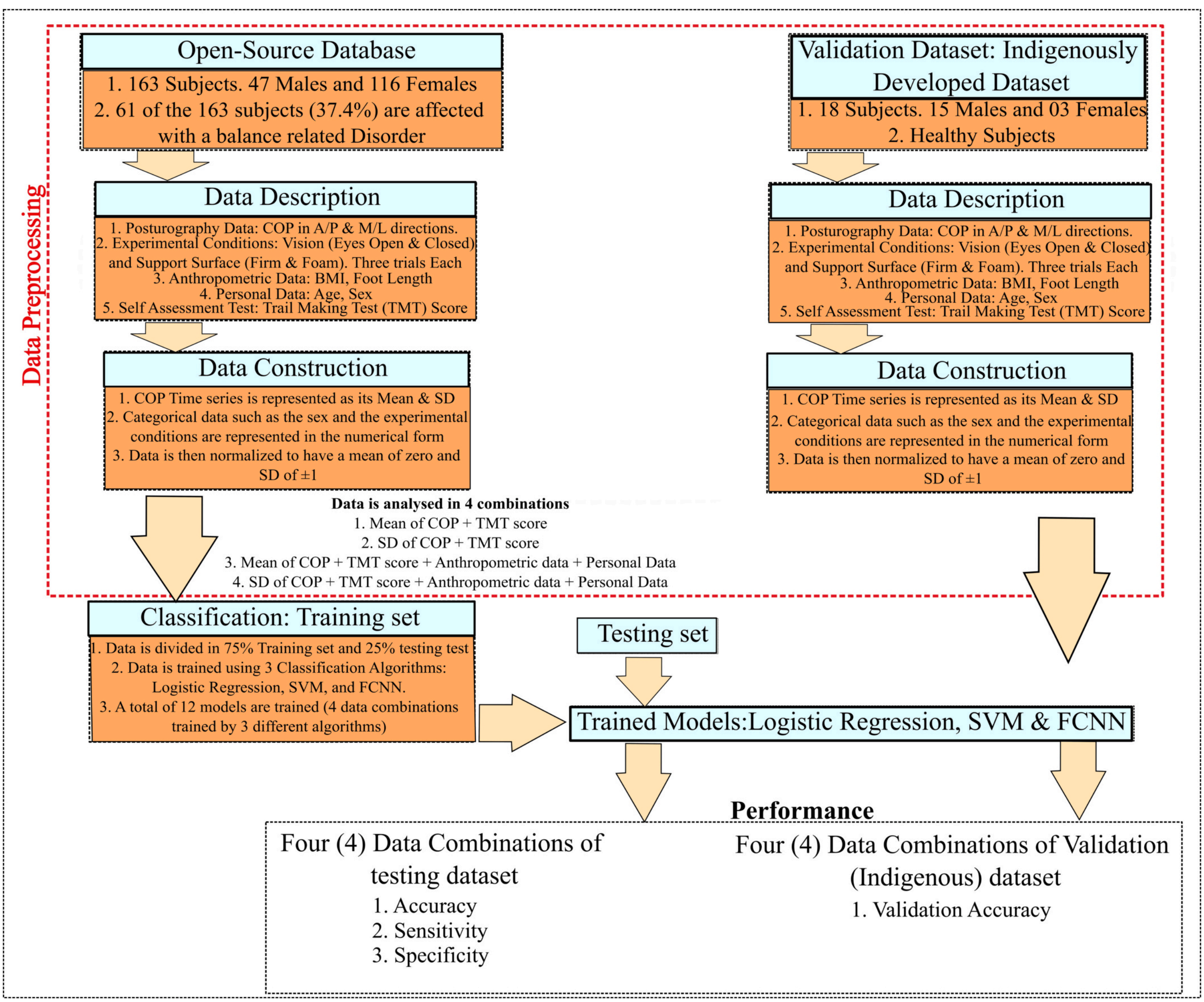

Fig. 1. Flowchart of the Methodology.

the study. It includes Pre-processing of the data, Training and Testing the data, and finally validating the classification models using the Indigenously Developed Dataset in Gait and Motion Analysis Lab, IIT Guwahati.

2.1. Open-source data

The classification algorithm is proposed using the dataset developed by Santos and Duarte(Santos and Duarte, 2016) and made available online through Physionet.org(Goldberger et al., 2000). The dataset comprises of 163 subjects with 47 males and 116 females. The subjects have an average weight of 62.21 ± 8.06 kg, average height of 162.34 ± 9.64 cm, average BMI of 23.71 ± 3.28 kg/m^2 and an average age of 47.84 ± 22.88 years. 61 of the total 163 subjects (37.4%) are classified to have a disorder affecting his/her balance. Five are affected with Labyrinthitis which causes balance disorder through vestibular problems, one is affected with PD, and the rest were affected with various musculoskeletal disorders such as Osteopenia, Herniated Lumbar, Arthrosis, Heel Spurs, Poliomyelitis, Osteoporosis and Scoliosis. The data are collected following an experimental protocol with four experimental conditions. According to the protocol, the subject is asked to stand still for 60 s on a rigid surface with eyes open for one condition and closed for another; and on an unstable surface with eyes open for one condition and closed for another. The unstable condition is emulated using a 6 cm height foam block from Airex AG, Sins, Switzerland. The data acquisition is started once the subject finds a stable and comfortable posture. The subjects' feet are placed at an angle of 20 degrees with the heels kept 10 cm apart. The data acquisition is done using a commercial force platform by OPT400600–1000; AMTI, Watertown, MA, USA at a sampling frequency of 100 Hz. The force and moment of the forces in all 3 directions and the COP position in X and Y direction are recorded. The anterior direction is the positive x-direction, the right side of the subject is positive y-direction and the z-positive is downwards in the ground. The clinical evaluation of the subjects is also done and is reported on a self-assessment scale called Trail Making Test (Set A and B) scale which evaluates the complex attention ability of the subject. The COP data is smoothened with a 10 Hz 4th Order zero lag low-pass Butterworth filter. The smoothening was done using MATLAB ver. 2022a.

2.2. Data construction

The COP values in X and Y direction are provided as time-series data by Santos and Duarte(Santos and Duarte, 2016). The data are recorded at 100 Hz frequency for about 60 s and hence has around 6000 data points for each subject. The mean and standard deviation of the COP values in X and Y direction are considered as relevant features. This reduces the dimensionality of the dataset and hence reduces computational complexity. The mean and standard deviation of the COP values are evaluated as per eq. (1) and (2) respectively, which gives us one value of COP in X and one for COP in Y-direction for each subject.

$$\mathrm{COP}_{\mathrm{mean}} = \frac{\sum(COP_i)}{N} \tag{1}$$

$$COP_{stddev} = \sqrt{\frac{\sum(COP_i - COP_{mean})^2}{N-1}} \tag{2}$$

where,

COP_i= COP values at each interval.

N = Total Number of time interval.

In addition to the mean and standard deviation of $\mathrm{COP_x}$ and $\mathrm{COP_Y}$ in two surface support conditions (firm or foam) and two visual condition (open or closed), four anthropometric and personal data features are considered which include age, sex, BMI, and foot length of the subject. The TMT (A&B) scores is also used as features. Any rows containing null values are removed. To apply any classification model, the entire dataset is converted into numerical type. The parameters such as the surface support condition, vision, sex of a person and pathology of a person are categorical data, which are then converted into numerical data. This causes an increase in the number of unique features, for example now a categorical input feature like sex gets split into two features i.e., male and female. Subsequently, one feature gets divided into two independent features in the dataset. This technique is known as one-hot encoding. After the implementation of one-hot encoding, one of the independent features is to be dropped from each of the categorical features to avoid redundancy. In addition, Height and weight were not considered as BMI is included. Skin colour and footwear are not considered for the analysis. The data is normalized to have mean zero and a unit standard deviation using the standardscaler function of Python's scikit-learn library.

2.3. Classification

Posturography under four different experimental conditions (Eyes Open and Closed; and Firm and Foam Surface Support), anthropometric and personal data along with TMT scores are used to classify subjects with balance-related pathologies. Each subject is subjected to three trials of the four experimental conditions. COP with respect to time is obtained for each trials and experimental condition in anterior-posterior (A/P) and medio-lateral (M/L) directions from posturography. Mean and SD of the COP are calculated for all the 12 measurements (three trials in four conditions) for each subject. They are employed along with the other features to perform the classification. The dataset consists of 10 features namely Age, Vision (Open or Closed), Surface Support Condition (Firm or Foam), sex, BMI, Foot Length, COP (A/P direction), COP (M/L direction) and the TMT A & B score. The models considered for classification are Logistic Regression, Support Vector Machine (SVM) with linear kernel and a fully connected neural network. Logistic regression helps us to understand the available data and explains the correlation between the dependent binary variable (Illness) and the remaining input independent features (sex, foot length, BMI, Age, Vision, Surface, and COP values). The probability threshold used for classification using logistic regression is $\geq$ 0.5. Support Vector Machine (SVM) is another machine learning algorithm that tries to find a hyperplane in an N-dimensional space that can classify the data points with most accuracy. Several hyperplanes are developed and the 'best' hyperplane is chosen by an algorithm that has the maximum margin. Here margin is the distance between the data points of the divided classes. Once the 'best' hyperplane is established, the data points on either side are attributed to a different class and any unknown data point will be attributed to the respective class depending on its position relative to the hyperplane. Fully connected neural networks is an algorithm, where all the nodes are in one hidden layer are connected to all the nodes in the next layer. Here, a fully connected neural network with three hidden layers has been used. In the output layer, two neurons are passed through a SoftMax function converting them into probabilities for classifying the unknown data. All the models are trained with 75% of the data as training set and the other 25% as test set. The logistic regression and SVM were implemented using Python's scikit-learn library and the Fully Connected Neural Network was implemented using PyTorch. The classification is performed in four combinations using only COP features (mean and SD) and TMT score; and using COP features (mean and SD), TMT score, anthropometric measurements and personal data.

2.4. Performance assessment

The performance of the different classifiers is evaluated by calculating accuracy, sensitivity, and specificity. True Positive (TP) is a situation when the classifier output agrees with the clinical condition of the pathology considered as positive. The successful exclusion of a pathology by the classifier is similarly considered as True Negative (TN). The classification of healthy person as pathological by the classifier results in a false positive (FP) and similarly the incorrect identification of a pathological subject as a healthy subject result in a false negative (FN). The classification accuracy is evaluated as: -

$$\text{Accuracy} = (\text{TP} + \text{TN})/\text{TCT},$$

Where, TCT (TP + TN + FP + TN) is the total number of classification tests. Sensitivity (true positive rate) and specificity (true negative rate) are evaluated as: -

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}), \text{ and}$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}).$$

Accuracy provides us the overall performance of the model. Sensitivity gives the accuracy at which the model detects pathological subjects and Specificity gives the authenticity of the negative outcome i.e., the accuracy of identifying healthy subjects. The performance of the algorithms is evaluated in four combinations: COP mean with TMT score, COP SD with TMT score, COP mean with TMT score, Anthropometric and personal data, and COP SD with TMT score, Anthropometric and personal data.

2.5. Validation of the model

The trained and tested model is also applied to classify an indigenously developed dataset to evaluate the model's sensitivity to experimental setting and demography. The data is collected in Gait & Motion Analysis Lab, IIT Guwahati, Assam, India. A total of 18 healthy subjects' data is collected, out of which 15 are male and 03 are female. The subject participation is voluntary and informed consent is taken from the subjects. They are enlisted through informal organizations and word of mouth. The data collection is approved by Institute Human Ethical Committee (IHEC) of IIT Guwahati, Assam, India. The clinical assessment of the subjects is scored on the TMT test (set A and set B). Then, the stabilography evaluation of the subject is done. The subject is asked to stand barefoot in a self-selected comfortable posture over the force plates for a period of 60s. The data is collected in four experimental setting, namely firm ground with eyes open and closed and foam surface with eyes open and closed, which are shown in Fig. 2. The foam surface is emulated using a balance pad of 6 cm thickness from Airex which has been employed in the study by Santos and Duarte(Santos and Duarte, 2016). The stabilography data is collected using two Portable Force Plates by Kistler Systems, Type No. 9286BA, of dimension 600*400*35 mm with a maximum measuring limit of 10 kN and sensing area of 600*400 mm for each plate. The right leg is placed on one force plate and the left leg is placed on the other force plate. The COP position is obtained in the A/P and M/L direction at a frequency of 200 Hz. In addition, the subject's details such as age, sex, BMI, and foot length are collected. The COP displacement values are smoothened with a 10 Hz 4th Order zero lag low-pass Butterworth filter using MATLAB ver. 2022a. Mean and SD of the COP are then calculated for all the 12 trials for each subject. The models trained and tested using the open-source data are then used to classify the data collected in Gait & motion analysis Laboratory, IIT Guwahati. The performance of the models in an untrained dataset collected in a different experimental setting gives an insight into the universal applicability of the models making it independent of experimental setup, demography of the subjects and only dependent on the data features. In addition, it will help us to reaffirm the relationship between classification accuracy and the efficient selection of classification metrics. This will greatly increase its potential to be applied in real world applications and identify the key feature combinations that can give the best results.

3. Results

The accuracy, sensitivity, and specificity of the models are shown in Fig. 3, Fig. 4, and Fig. 5 respectively where (i) COP features with TMT scores and (ii) COP features with TMT scores anthropometric and personal data are considered. It is observed that accuracy remains almost same or slightly increases with the addition of anthropometric and personal data. It is increased by 5.4% with the addition of anthropometric and personal data to SD of the COP and TMT score using Logistic regression. The accuracy performance remained unchanged at 74% using SVM for the all the cases. When FCNN is explored, the accuracy is increased to 98% and 99% when anthropometric and personal data are

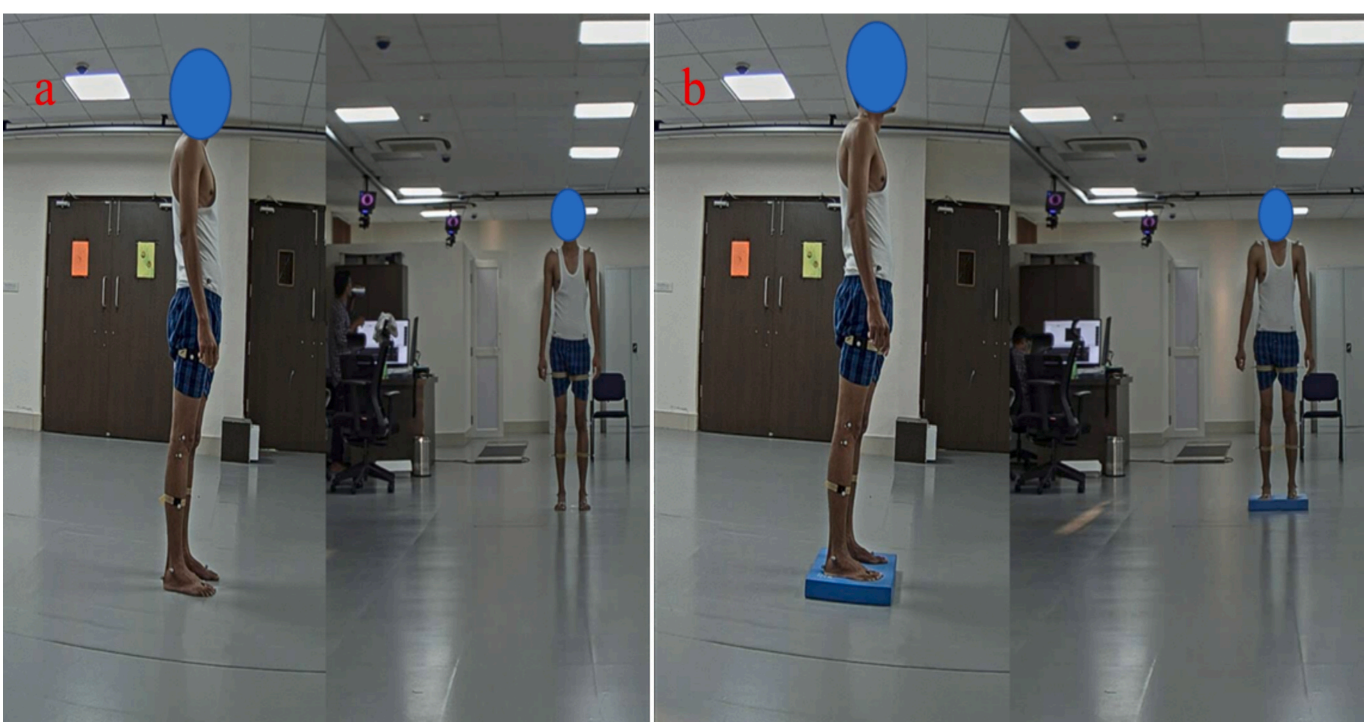

Fig. 2. Standing data collected in (a) Firm Surface, and (b) Foam Surface.

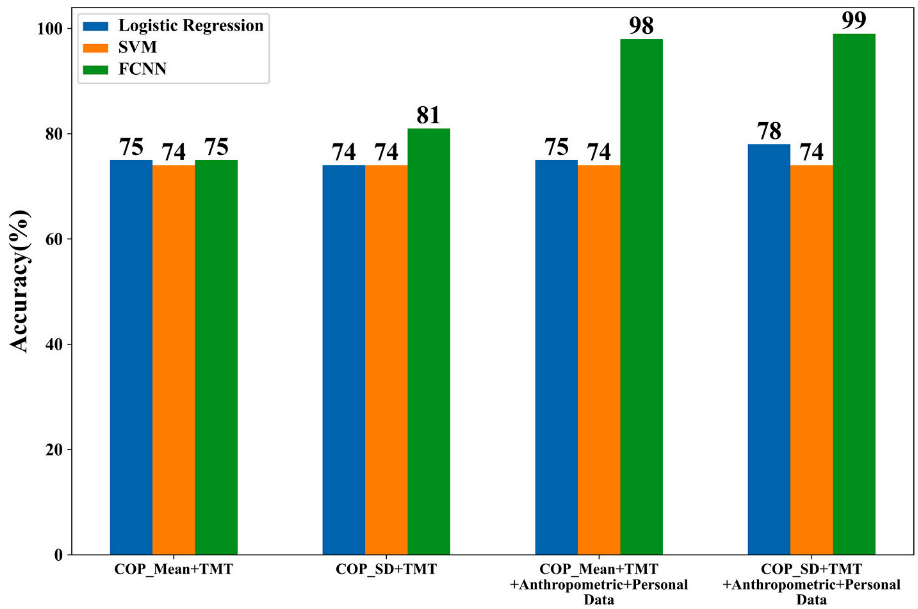

Fig. 3. Accuracy of the three models under the 4 different conditions with Open-source Data.

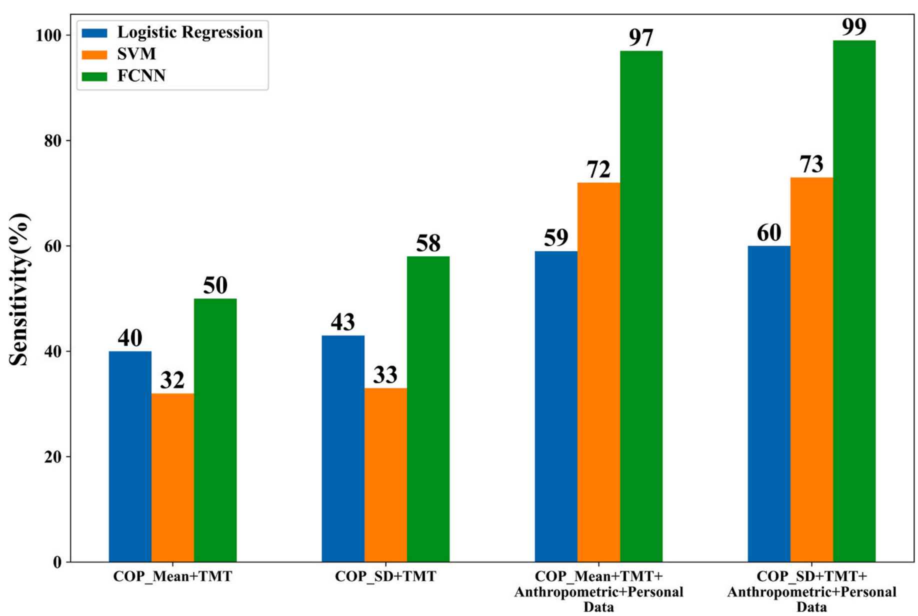

Fig. 4. Sensitivity of the three models under the 4 different conditions with Open-source Data.

added to the mean and SD of the COP respectively. The sensitivity, which is the parameter for detecting pathological subjects, greatly improves when anthropometric and personal data are included along with the COP features for classification in all the models. The sensitivity is increased by 47.5%, 125% and 94% for Logistic regression, SVM and FCNN, respectively, when the anthropometric and personal data are added to COP (mean) and TMT score for classification. When SD of the COP is used instead of COP (mean), the increase in sensitivity is limited to 39.5%, 121.2% and 70.6% for Logistic regression, SVN and FCNN respectively. Although the improvement of the sensitivity metric is higher in case of the mean of the COP than the SD, COP SD is the overall better performer with the highest sensitivity among all which is shown in Fig. 4. However, the specificity i.e., the accuracy of detecting healthy subjects, is decreased with the addition of anthropometric and personal data in the classification algorithms except FCNN. It is decreased by 8.7% and 20.2% in case of Logistic regression and SVM respectively, but increased by 13.8% for FCNN with the addition of anthropometric and personal data to COP (mean) and TMT score. Considering SD of COP, the specificity is increased by 7.6% for FCNN, and decreased by 3.4% and 20.2% for Logistic Regression and SVM respectively which are shown in Fig. 5. In addition to the incorporation of anthropometric and personal data, the selection of COP feature also influences the classification accuracy, especially on the sensitivity metric, which essentially gives the accuracy of detecting pathological subjects. The standard deviation of the COP values is found to be the most effective in increasing the sensitivity in all the models. The best performing classification parameters are the standard deviation of the COP values, the TMT scores of the subjects and their anthropometric and personal data. To validate the model and test the universal applicability of the model, it is then tested on an indigenous dataset of 18 healthy individuals with 15 male and 3 female subjects. Classification performance is evaluated using the COP features and the TMT scores of the subjects alone and along with the

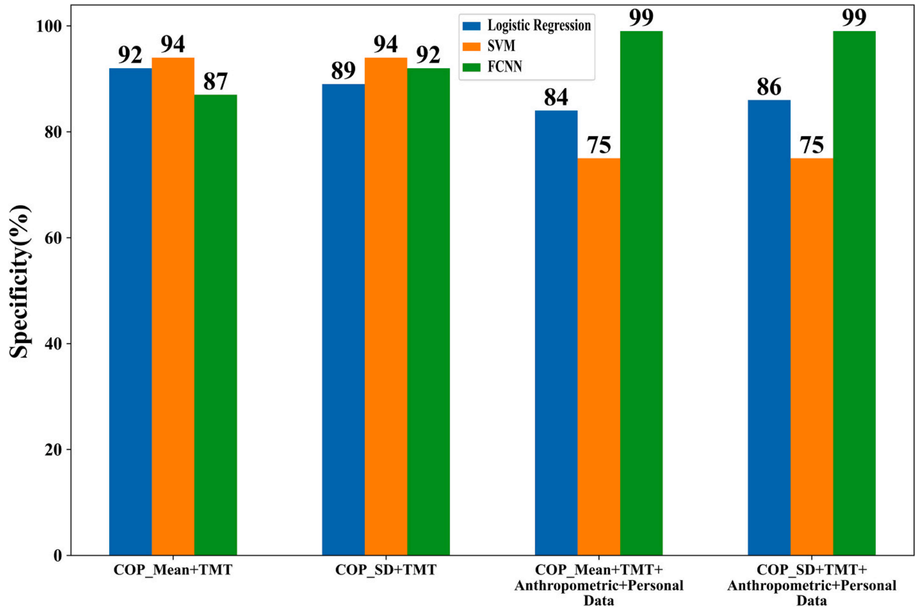

Fig. 5. Specificity of the three models under the 4 different conditions with Open-source Data.

subject's anthropometric and personal data. Since the dataset consists of healthy individuals, only accuracy is to be employed for assessing the performance of the model validation. The classification accuracy is increased with the addition of anthropometric and personal data of the subject along with the COP features and TMT scores of the subject for Logistic regression and SVM but decreased for FCNN which are shown in Fig. 6. It is increased by 12.3% for both logistic regression and SVM when anthropometric and personal data are added to COP (mean) and TMT score. Accuracy of FCNN is decreased by 10.34%, when anthropometric and personal data are added. Considering SD of the COP instead of the mean also results in the same trend. The accuracy is increased by 8.1% for both logistic regression and SVM and decreased by 12.7% when anthropometric and personal data are added. The classification performance is better when mean of the COP is used instead of SD during validation. Also, FCNN performed poorly with the indigenously developed dataset. The best classification parameter for the validation set is the mean of the COP values, the TMT score, and the anthropometric and personal data of the subject, obtaining an accuracy of 82% for both logistic regression and SVM, and 52% for FCNN as shown in Fig. 6.

4. Discussion

As fall risk and its related injuries have increased resulting in significant consequences to the quality of life of people, there is a greater need for early identification of such balance-related complications. Early identification will result in early intervention by a specialist depending upon the disorder. Since, a variety of underlying causes can result in balance disorder, thus, usage of biomechanical markers can eliminate the effect of causes and identify based only on the impact. This will greatly increase the preliminary diagnostic capabilities for balance-related disorders and encourage individuals with minimal symptoms to seek specialist medical intervention. Thus, identification of factors that influence balance is of utmost importance for the detection of balance-

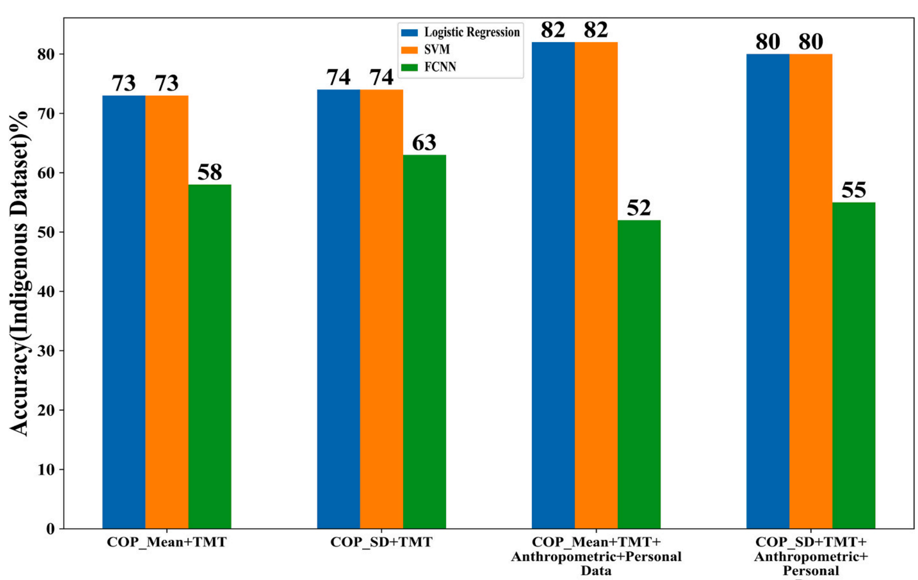

Fig. 6. Accuracy (Validation) of the three models under the 4 different conditions with Indigenously developed dataset.

related disorder. COP displacement has been employed to understand balance ability, neural mechanisms of postural control and to classify subjects based on age, sex, and pathology(Abrahamová and Hlavacka, 2008). COP displacement in the form of mean and standard deviation along with TMT score have been able to classify subjects with an accuracy of around 75% for Logistic regression and SVM. The accuracy is a little higher for FCNN with SD of COP and TMT score of 81%.

The accuracy is increased to 78% with the addition of anthropometric and personal data to the SD of the COP respectively using Logistic regression. The positive influence of the addition of the anthropometric and personal features is even more prominent on the sensitivity metric, which is increased from 40% to 59%, 32% to 72% and 50% to 97% for logistic regression, SVM and FCNN respectively with mean of COP. The performance improvement on the addition of anthropometric and personal features is similar when SD of the COP is considered instead of the mean. The sensitivity is increased from 43% to 60%, 33% to 73%, and 58% to 99% for logistic regression, SVM and FCNN respectively. The positive influence on the performance of the classification algorithm due to the addition of the anthropometric and personal data to the COP features reinforces the results of the studies which highlights the effect of different anthropometric variables like age(Chen et al., 2021), sex (Kejonen et al., 2003), BMI(Greve et al., 2013)(Hue et al., 2007) on the balance control and hence enhances the performance of the model. The increased accuracy and specificity with the addition of the anthropometric and personal data along with the COP features and TMT scores is attributed to the dynamic characteristics of COP features and TMT scores and hence are affected by the subject's physical movement and condition. In addition, standard deviation is found to be a better feature for classifying the pathological subjects. As the individuals affected by balance-related pathologies inherently suffer from higher sway during standing and hence results to have greater standard deviation. These characteristics are very much required to be translated when models are to classify an untrained dataset. Thus, the trained model is validated using the indigenously collected dataset under the same experimental conditions. It is found to follow similar trends in performance metric. Since, the indigenously developed dataset comprised of only healthy subjects, thus, accuracy is obtained. The accuracy is increased from 73% to 82% with the addition of anthropometric and personal data to the mean of COP using both Logistic Regression and SVM. Considering the SD of the COP instead of the mean, the increase is observed from 74% to 80%. It can be noted that, instead of the standard deviation feature of the COP, mean value of the COP was the most effective feature for classification when applied together with the anthropometric and personal data for the validation set. It is because the validation dataset does not contain any pathological subjects, which is a limitation of the study, who are expected to experience larger postural sway and hence have a greater standard deviation. The performance, however reduced for the fully connected neural network when employed with the validation set. An accuracy of 63% was obtained when classified using standard deviation values of the COP displacement. This suggests the importance of the applicability of the conventional algorithms over neural networks in case of untrained new or less amount of data. Such datasets can be classified on an algorithm already trained on a different dataset.

5. Conclusion

This study establishes that Posturography data along with Anthropometric measurements, personal data and self-assessment scale like the TMT score can be used to classify balance-related disorders. The classification is most effective when Posturography data is considered as the SD of the COP. Balance-related disorders often result in a more pronounced postural sway in affected adults, leading to increased SD of the COP position displacement. It is observed that the Neural Network, FCNN, excelled over conventional machine learning algorithms; however, they are sensitive to new data. When the testing dataset is experimentally different from the training dataset, machine learning algorithms are better suited. It is of importance because the ability to be used even with different experimental conditions opens up the possibility of its applicability in the real world.

Moreover, as the data used for classification are either self-reporting in nature or performed under simple conditions, it allows the data collection to be performed by general healthcare staff. This provides the opportunity for its application in mass scale health camps with high rural population and limited or expensive access to medical facilities needed to detect such disorders. Thus, persons with the possibility of being affected by such disorders can be identified and thus can be encouraged to seek further medical consultation. This will help to manage the onset of balance-related disorders, increase user compliance outside the clinic and improve the quality of life of the people through early rehabilitation.

CRediT authorship contribution statement

Arnab Sarmah: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Visualization. **Raghav Aggarwal:** Formal analysis, Investigation, Methodology. **Sarth Sameer Vitekar:** Formal analysis, Investigation, Methodology. **Shunsuke Katao:** Formal analysis, Investigation, Methodology. **Lipika Boruah:** Data curation, Investigation, Methodology, Software, Validation. **Satoshi Ito:** Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Subramani Kanagaraj:** Funding acquisition, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors have no financial and personal relationships with other people or organizations that could inappropriately influence (bias) their work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clinbiomech.2024.106214.

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