Impaired Balance Assessment in Older Adults with Muscle Weakness Caused by Stroke

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ABSTRACT

Stroke causes a severe impact on movement in daily life. It affects static balance in the human who has impaired movement control. Assessing balance using evaluation criteria or a check-list can be replaced by movement monitoring. For example, one can use the Berg Balance Scale, which is the gold standard in clinical assessment. This tool can also be supplemented by electronic motion detector sensors. To analyze the balance assessment results, the physiotherapist uses statistical methods to interpret the data. This research studies the suitable classification algorithms for evaluating balance control in stroke patients who have muscle weakness. After finetuning, the proposed methodology will improve the algorithm's accuracy of data prediction for measuring the validity of regaining balance while standing. The dataset consists of three main factors: personal information, a diagnostic result from a physiotherapist, and the balance control performance while standing still on the Nintendo Wii Fit Balance Board. By evaluating various scenarios with different combinations of attributes, the dataset with three attributes has the highest accuracy rate. The clinical assessment is used as ground truth for assessing the prediction on how to regain a patient's balance control during standing. Among four algorithms: Support Vectors Machine, Decision Tree, Naive Bayesian, and Artificial Neural Network, the most accurate classification model is the Artificial Neural Network with 93% accuracy of prediction.

Keywords: Stroke, Balance Assessment, Artificial Neural Network, Nintendo Wii Fit Balance Board, Machine Learning

1. INTRODUCTION

The elderly population in Thailand, surveyed in 2014, is about 10 million, or 15% of the total population [1]. The Public Health Statistics Report by the Ministry of Public Health revealed that the mortality rate of Thai strokes per hundred thousand people in 2012-2016 is 31.7, 35.9, 38.7, 43.3, and 48.7, respectively [2]. Moreover, the rate of Thai stroke patients per hundred thousand in 2007-2011 is 330.60, 354.54, 366.81, 352.30, and 425.24, respectively [3]. These figures confirm that the rate of Thai stroke patients is increasing every year. The report of Disease and Injury in Thai People states that stroke is the first critical cause of death in both 30,402 Thai men and 31,044 Thai women [2]. Furthermore, stroke is the primary cause of premature death of Thai women, and is the second most common cause of death for Thai men.

The World Health Organization (WHO) reported that 15 million people suffer from stroke [4]. High blood pressure contributes to more than 12.7 million strokes worldwide. In Europe, on average approximately 650,000 patients die from strokes each year. In the 2017 annual report of the World Stroke Organization (WSO) [5], the situation of stroke around the world confirms that more than 17 million people are stroke patients, and more than 6.5 million of the patients die every year.

In general, stroke disease is a condition of stenosis of cerebral vascular aneurysms caused by clogging or high blood pressure. The effect of a stroke is to reduce the brain's ability to control muscles in the body. Therefore, the muscles in body parts that link to brain's cerebral vascular region will suffer from the side effects which will be manifested in weakness of their balance during doing activities. These symptoms of the brain disease cause problems of muscle weakness in the left side body, reduced visibility, and reduced mobility. In other words, the effects of a

Manuscript received on July 1, 2019 ; revised on September 4, 2019.

Final manuscript received on November 3, 2019.

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DOI 10.37936/ecti-cit.2020142.200323

stroke that has occurred in the left hemisphere will have an impact of weakening the muscles in the right-side of the body. These effects lead to slow conversation and movement of the patients.

This research work is proposed as a new tool to measure the balance performance of stroke patients who have the problem of muscle weakness. It applies the Nintendo Wii Fit Balance Board to measure the patient balancing control data during two experiments which are Open-eye biofeedback and Closed-eye biofeedback.

2. LITERATURE REVIEW

2.1 Balance Impairment

A stroke occurs when a blood vessel bringing blood and oxygen to the brain gets blocked or ruptures. Brain cells do not get the blood and its oxygen, and nerve cells stop working and die within minutes. The WHO has defined the term "stroke" as rapidly developing clinical signs of focal disturbance and cerebral function. This symptom can lead to be death within only 24 hours after its occurrence [6-7].

Two significant categories of the pathology of stroke are ischemia and hemorrhage. Ischemic stroke accounts for approximately 80% of strokes, whereas hemorrhagic stroke accounts for the remaining 20% [8]. Ischemia is a lack of blood flow, causing brain tissue to have a shortage of needed fuel and oxygen.

It can be further divided into two types: embolic and thrombotic stroke. An abrupt onset characterizes embolic stroke, and material formed elsewhere within the vascular system lodges into a vessel and blocks the blood flow. Most embolic strokes are secondary to emboli that are cardiac in origin. These can come from primary entries such as the aorta, carotid, vertebral arteries, systemic veins, and occasionally smaller arteries. The second most common sources of emboli are atherothrombotic lesions that result in artery-to-artery embolisms. Artery-to-artery emboli are composed of a clot, platelet clumps, and fragments of plaque that break off from the vessels. Cardiac sources of embolic include the heart valves, endocardium, and clots or tumors within the atrial or ventricular cavities [9-10].

The incidence of new cases of first-time strokes, standardized for age and sex, is about 200 cases per 100,000 medical cases in a year, or about 0.2% of the population [11-15]. Stroke is the third most common cause of death in the United States [16]. The prevalence of stroke increases with age: 8.1% of respondents aged 65 years reported a history of stroke, compared with 0.8% of persons aged 18-44 years. The prevalence of stroke among men (2.7%) and women (2.5%) were similar [17]. Stroke has been identified as the most prevalent diagnosis among adults who fall [18].

In Thailand, Public Health statistics show that the number of strokes has been on the increase [19]. It is one of the major health problems and the tenth most common cause of death.

Balance is defined as the ability to maintain or move the center of pressure (COP) within the base of support [20-22]. Balance can further be broken down into three aspects: steadiness, symmetry, and dynamic stability [23]. Steadiness refers to the ability to maintain a given posture with minimal extraneous movement (sway). The term symmetry is used to describe equal weight distribution between the weight-bearing components (e.g., the feet in a standing position, the buttocks in a sitting position), and dynamic stability is the ability to move within a given posture without loss of balance [23]. All these components of balance (steadiness, symmetry, and dynamic stability) are disturbed following stroke [20-22]. Balance testing of patients with hemiparesis secondary to stroke has revealed a greater amount of postural sway during static stance. Thus, a principal construct within physical therapy practice is the reestablishment of balance function in patients following stroke [23].

In this study, the main point of interest is in measuring the natural balance of older people who have muscle weakness caused by stroke. This is necessary to assess the condition of balancing and classify into groups those who are more susceptible to collapsing. This classification will help physiotherapists make plans that are beneficial to help future patients regain balance.

2.2 Stroke Identification using Decision Support System

A Decision Support System (DSS) is an Information System used by many organizations to manage their business, clinical tests, education, and factory. Typically, these pattern reports are discovered by traditional data exploration because the relationships are too complicated or have too much data. In clinical data, DSS is used for processing information for the diagnosis using images from brain surgery [24]. DSS is widely used in the field of nursing in Singapore [25]. The DSS is used to support the stipulations in the treatment of patients in hospitals [26]. The classification technique they use is one of the famous ones used to develop DSS. It is an algorithm that learns from a training set, containing a set of attributes and a particular outcome, usually called a goal or prediction attribute. There are several DSS which have applied the concept of classification to their development.

This study has adopted a decision support system to assess the balance in older people who have muscle weakness from stroke together with the equipment and tools such as sensors. This proposed system can be deployed in rural areas where hospitals cannot obtain the expensive equipment.

Table 1: *Statistics of Participants.*

Gentle	%	Age	%	Weight	%	Height	%	Disease	%
Male	56.25	75-80	10	40-50	25	140-150	18.75	Healthy	37.5
Female	43.75	71-75	10	51-60	31.25	151-160	37.5	Ischemic stroke	43.75
		66-70	42.5	61-70	31.25	161-170	31.25	Hemorrhage stroke	18.75
		61-65	37.5	71-80	12.5	171-180	12.5		

3. MATERIALS AND METHODS

This research develops a tool for measure the balancing performance of stroke patients who have a problem of myasthenia gravis or muscle weakness, which is caused by ischemic stroke and hemorrhagic stroke.

3.1 Population and Sample

The population of the sample in this research was from three districts: Wiang Chai, Phayamengrai, and Muang, in Chiang Rai, Thailand. These participants were stroke patients that have the problem of muscle weakness of some parts in their body. These patients all had at least three months of treatment history. Another group of participants was made up of healthy people invited to participate in the research. The statistical details of participants are shown in Table 1.

3.2 Sampling Data

This research selects the sampling data by using the technique of purposive sampling by choosing only the population that has the same characteristics as the study objective mentioned in section 3.1.

Furthermore, the people must be willing and be cooperating in this study. The criteria for selecting patients to be involved in this research are as follows:

step 1: The patients are diagnosed as stroke patients and have the problem of muscle weakness in some parts of the body for at least three months.

step 2: These stroke patients have to pass the Berg Balance test with at least 45 points.

step 3: These stroke patients have to pass the SittoStand test with the evaluated result of 5 times in 15 seconds.

step 4: These stroke patients have to pass the Time up and Go test with the evaluated result of the 6-meters round trips walking in less than 6 seconds.

step 5: These stroke patients have to pass the Comfortable Gait Speed test with the evaluated result of the 10-meters walking in less than 9 seconds.

step 6: These stroke patients have to pass the Speed Gait test with the evaluated result of the 10-metres quick walking in less than 7 seconds.

The protocol of selecting these stroke patients to participate in the research has been approved by the MFU research ethics committee according to REH 59068.

3.3 Proposed Measurement Device

The ability to maintain a center of pressure can be measured three different ways. The steadiness is the simplest and easiest performance metric to use to observe abnormal balance control. By standing still on the platform, the human brain controls the muscles to balance the human body, so-called static balance. Therefore, any sway that occurs during balancing the body can be monitored as a predictor of falling accidents in everyone's life.

Many pieces of research have tested and proved the Nintendo Wii Fit Balance Board (WBB) as an appropriate low-cost device that meets medical standards in both validity and reliability [27- 29]. Additionally, the device also has the special characteristic that it is easy to move to different areas.

Consequently, this WBB was adopted to measure the human balance while standing still.

"The svelte Wii Balance Board weighs at about 8 pounds (roughly 3.5 kilograms) and can support up to 330 pounds (about 150 kilograms) for in-game functionality. It runs on four AA batteries, which the maker says can provide up to 60 hours of playtime depending on the settings used. The board shuts off automatically to conserve power when not in use after a short time. It has built-in wireless capabilities and communicates with the Wii using the same Bluetooth technology found in the Wii Remote.

Four load sensors sit snugly at the bottom of each of the board's squat cylindrical-shaped legs. It determines the position of the center of gravity to track the movements as the shift of the weight from one part of the board to another. Each is a small strip of metal with a sensor, known as a strain gauge, attached to its surface [34]."

In static balance testing, the participant will stand on the Nintendo Wii Fit Balance Board. The device will measure a COP to analyze path length, sway area, and velocity.

In this study, two courses of static balance, which are closed eyes and open eyes biofeedback, were conducted for the balance testing. The experimental results were collected using static balance test software to record the values of several parameters obtained by the computation of weight transfer changing from standing to compare with COP. The parameters of the software can be explained as follows:

1. Path Length is the length of trajectory in weight transferring to both feet of the experimental patients

that have been tested for 30 seconds. These parameter values are in millimeter units.

2. Sway area is the area that is computed from the boundary of trajectory in the weight transferring of the patients. These parameter values are rectangle areas in square-millimeter units.

3. Velocity is the speed-changing of COP during a weight transferring along with the trajectory line of the patients. These parameter values are in millimeters/second units.

3.4 Data Collection Process

This research selected the participants and divided them into two groups.

The first group contained the stroke patients who have the problem of muscle weakness, which is caused by ischemic stroke and hemorrhagic stroke using the purposive sampling. These stroke patients were still able to walk alone without any assistant person or walking stick while they have been testing. Fifty stroke patients were invited from the Wiang Chai and Phayamengrai hospitals in Chiang Rai, Thailand.

The second group contained healthy people. These thirty healthy persons were invited from two sub-districts which are Nang Lae and Thasud, both in Chiang Rai, Thailand.

The processes for measuring balance control performance can be explained as follows:

step 1: Collect personal profile, education details, daily life activities, and fill in an evaluation form of movement balancing performance.

step 2: Describe the testing process of balancing performance measurement on the Nintendo Wii Fit Balance Board and collect the testing data using the Static Balance Test software (SBT).

step 3: Evaluate the static balance measure while standing for 30 seconds by testing with two biofeedback types: open eye and closed eye testing.

step 4: Record the evaluated result from the Health Evaluation form and the result of balancing performance measurement. This dataset is fed into

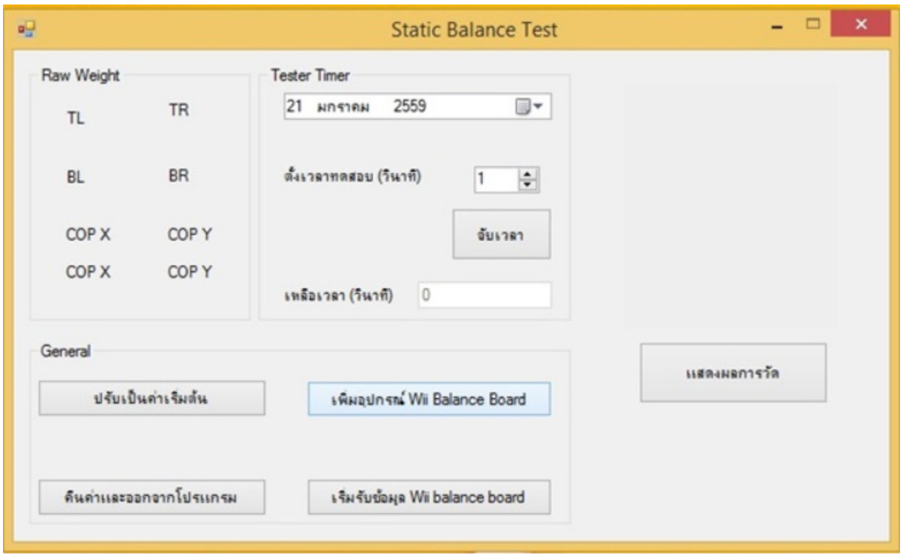

Fig.1: *Static Balance Test Software.*

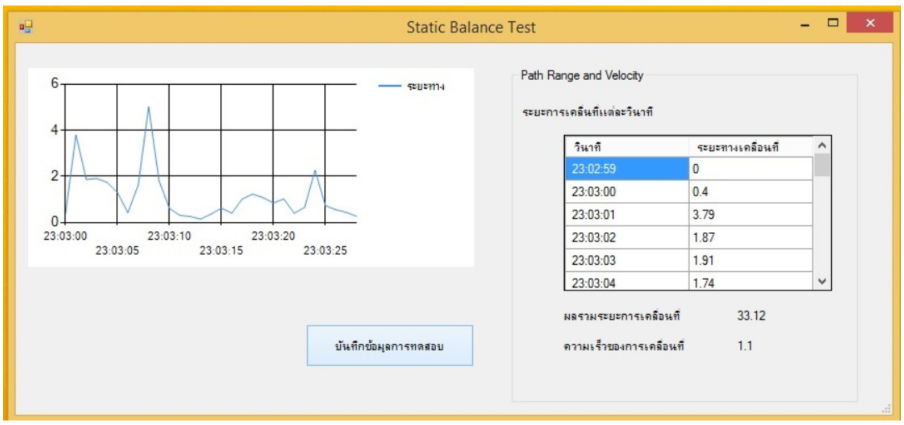

Fig.2: *Balance Parameters Computed from Static Balance Test Software.*

the classification process.

step 5: Classify the dataset using four classification techniques, which are Artificial Neural Network (ANN), Support Vector Machine (SVM), Naïve Bayesian Classification (NB), and Decision Tree (DT).

step 6: Validate the classification accuracy and classification error for each algorithm to find the best model to identify impaired balance in stroke patients.

3.5 Static Balance Measurement Process

Participants had their balance control performance measured by two types of biofeedback on the static balance test.

For open–eye biofeedback, the participants were asked to open their eyes while standing on the Nintendo Wii Fit Balance Board and keep looking forward without any disturbances for 30 seconds, as shown in Figure 3.

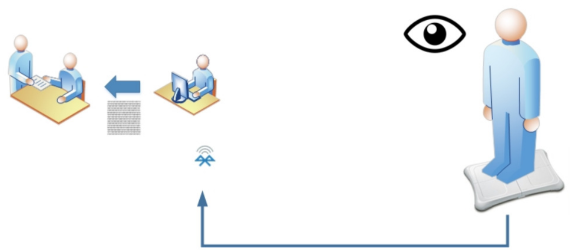

Fig.3: *The Route Representation.*

For closed–eye biofeedback, the participants were asked to close their eyes while standing on the Nintendo Wii Fit Balance Board for observing the behaviour with their eyes closed for a 30 second period, as shown in Figure 4.

Fig.4: *Closed–Eye Biofeedback for Static Balance Measurement.*

Table 2 shows the list of factors and their descriptions used for analyzing the difference in stroke patients when comparing them to healthy people. These factors were elicited from the static balance parameters by computing within the proposed software.

Table 2: *Static Balance Parameters.*

Dataset	Description
Path length	Length of COP transferring to both feet of the participant during testing for 30 seconds.
Velocity	Speed in changing the length of COP transferring by the participant.
Sway Area	Area of the COP's length transferring during the experiment by the participant.

The descriptions and information on patient profile factors and clinical tests' factors are presented in Tables 3 and 4.

Table 3: *Patient Profile Factors.*

Dataset	Description
Age	Participant's age
Weight	Participant's weight
Height	Participant's height
Gender	Participant's sex
Ischemic stroke	History of Ischemic disease
Hemorrhage stroke	History of Hemorrhage disease
Weakness	The weakness of body, left and right
Walk 200 meters	Interviewed data from the participant about walking a 200m straight path
Waking stick	Interviewed data from the participant about any assistants used to stabilize his balance
Assistant Bar	Interviewed data from the participant about any assistants used to stabilize his balance
Assistant Person	Interviewed data from the participant about any assistants used to stabilize his balance
Falling in a month	Falling history within a month, by interviewing the participant
Falling in six months	Falling history within six months, by interviewing the participant
Falling in twelve months	Falling history within a year, by interviewing the participant

Table 4: *Clinical Test's Factors.*

Dataset	Description
Impairment	Decision made by the physiotherapist about balance disorder
5 Times Sit to Stand	Clinical Test for selecting the participant based on the times (seconds) to sit on a chair
3 Meter Time Up and Go	Clinical Test for selecting the participant based on the times (seconds) to stand up from a chair and walk through the walkway for 3 meters
10 Meter Walk Test Normal Pace	Clinical Test for selecting the participant based on the times (seconds) to walk on 10 meter walkway
10 Meter Walk Test Speedup	Clinical Test for selecting the participant based on the times (seconds) to walk quickly on 10 meter walkway

Patient records include the personal profiles including gender, age, weight, height, and the symptoms of stroke disease within the last 3, 6, and 12 months.

3.6 Data Classification

To identify impairment in balance control, this study adopted four active data classification algorithms [30-34]. The ANN, SVM, DT, and NB were selected to construct the decision support system model. The classification algorithms in which their accuracy is more than 80% would be considered for analyzing the balanced dataset received from the Nintendo Wii Fit Balance Board® device. The values of factors received from the Static balance test combined with the personal profiles and the values of clinical balance tests were fed into the model to train and test its predicting performance.

Additionally, there are three scenarios for measuring the classification performance and the accuracy of the predicted result.

Scenario 1: Classify 50 stroke patients and 30 healthy people in two types of balance assessment, open − eye versus closed − eye biofeedback on 22 collected factors. The static balance parameters (from Table 1), the patient's profile (from Table 2), and clinical test results (from Table 3) are fed to the model. This model construction is illustrated in Figure 5.

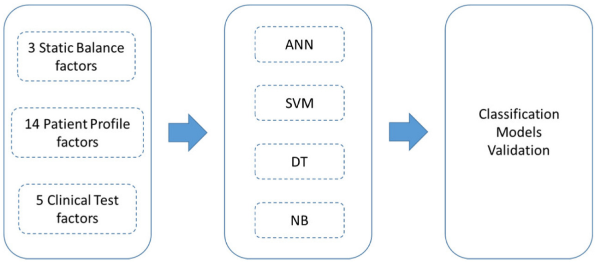

Fig.5: *Classification Model for 22 Factors.*

Scenario 2: Classify 50 stroke patients and 30 healthy people in two types of balance assessment, open–eye versus closed–eye biofeedback on 11 collected factors. These factors are the combination of all factors from static balance measurement, the first-seven factors (listed in Table 3) of the patient's profile, and impairment status from the clinical test. The classification model construction is illustrated in Figure 6.

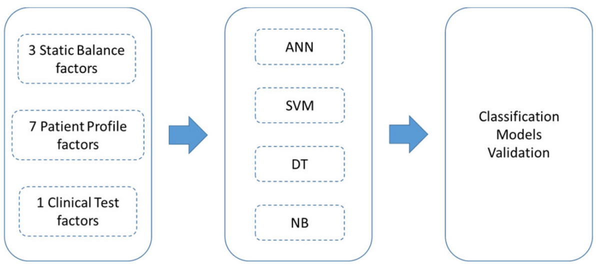

Fig.6: *Classification Model for 11 Factors.*

Scenario 3: Classify 50 stroke patients and 30 healthy people in two types of balance assessment, open–eye versus closed–eye biofeedback on only three collected factors. The training dataset consists of only parameters from static balance measuring with the WBB device. These parameters are path length, velocity, and length area. The classification model of static balance factors elicited from SBT software is illustrated in Figure 7.

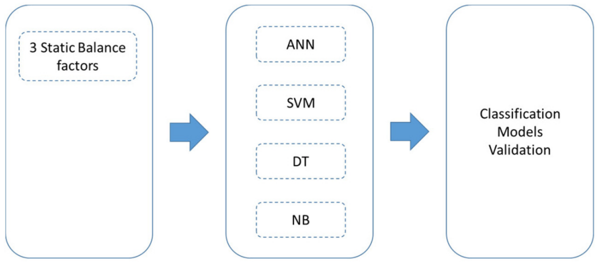

Fig.7: *Classification Model for 3 Factors.*

3.7 Evaluation

This research applied the following methods to evaluate the classification models.

1. An experiment in 10-fold cross-validation to compare the accuracy of classification algorithms. The experimental dataset in this validation is the stratified samples. 10% of the data has been selected from each category of data, resulting in so-called stratification. The stratified samples from this method must not be duplicated across the primary experimental dataset.

2. Additional comparison validates the static balancing performance in two types of biofeedback which are open-eye biofeedback and closed-eye biofeedback.

3. Classification accuracy of four algorithms which are ANN, SVM, DT, and NB was gathered. This research use ten-fold cross-validation for evaluating the accuracy of all four classification algorithms. The best performance was selected to construct the final model.

4. RESULTS AND DISCUSSION

This research proposes using a classification model to identify the static balance performance of stroke patients. The classification model is built upon the following dataset: the static balance measured by WBB, the patient's profile, and the clinical test result.

The experiment in this research evaluated the classification model in three scenarios for analyzing and finding the relationships among factors in each scenario. The validation of the four purposed classification algorithms in each scenario was used to classify the stroke patients and the healthy older people into categories by using 22 factors. The experimental result shows that ANN gives the best performance for all scenarios in this testing. All of the classification results of these scenarios as well as other classifiers, such as DT, SVM, and NB, are shown in Table 5.

Table 5: *Classification Results for Distinguishing Between Stroke Patients and Healthy Older People Based on 22 Factors.*

Biofeedback	Classifiers							
	ANN		SVM		Decision Tree		Naïve Bay	
	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)
Open-eye	83.3	8.5	79.5	8.2	72	8.4	74	8.5
Closed-eye	86.7	6.4	80	12.4	66.2	7.2	71	8.7

These results show that the ANN algorithm gives the best accuracy in Open-eye and Closed-eye biofeedback testing. ANN yields 83.3% and 86.7% accuracy, and the error rates are 8.5% and 6.4%, respectively.

The SVM algorithm gives the best performance in Close-eye biofeedback testing, which is 80% accuracy and 12.4% error. The DT algorithm gives its best performance in Open-eye biofeedback with 72% accuracy and 8.4% error. The Naïve Bay algorithm gives its best performance of 74% accuracy and 8.5% error in Open-eye biofeedback testing.

Furthermore, the classification using a different combination of factors shows that ANN classified on 11 factors gives higher accuracy than the 22 factor classification. The classification results of the second scenario are shown in Table 6.

Table 6: *Classification Results for Distinguishing Between Stroke Patients and Healthy Older People Based on 11 Factors.*

Biofeedback	Classifiers							
	ANN		SVM		Decision Tree		Naïve Bay	
	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)
Open-eye	92.5	7.4	91.2	8.3	86.4	9.2	88.2	8.4
Closed-eye	92	7.6	87.7	9.2	82.3	9.4	86	7.9

Table 7: *Classification Results for Distinguishing Between Stroke Patients and Healthy Older People Based on 3 Factors.*

Biofeedback	Classifiers							
	ANN		SVM		Decision Tree		Naïve Bay	
	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)	Accuracy (%)	Error (%)
Open-eye	93	6.4	91	9.5	87.2	9.8	88.4	9.4
Closed-eye	92.5	7.5	88.1	9.3	83.2	9.2	86.5	8.5

Table 7 shows the accuracy of classifiers on the three factor dataset which was elicited from the participants' physical balance when standing still on the WBB (scenario 3). The results show that ANN can perform better than others with 93% accuracy on the open-eye biofeedback. The decision tree only achieves 87.2% on the open-eye biofeedback.

Table 8: *Performance of Classification Algorithms using different numbers of features.*

No. of factors	**Open eyes**	**Close eyes**
22	*ANN* 83.3%	*ANN* 83.3%
11	*ANN* 92.5%	*ANN* 92%
3	*ANN* 93%	*ANN* 92.5%

In Table 8, the classification results to distinguish between stroke patients and healthy people are shown. By evaluating the classifiers with different numbers of features, e.g. 22, 11, and 3 factors, the ANN is outperforming the others with the best accuracy at 93% of the time within the Open-eye scenario using only three computed COP parameters collected from WBB.

5. CONCLUSIONS

Blocked blood vessels that lead to the brain can lead to stroke or stenosis. Those in turn can cause weakness in the muscles on one side of the body. Patients suffering from these problems may need equipment or an assistant to help balance themselves while doing daily activities to prevent collapsing or even death. Numbness and weakness in the muscles needs to be evaluated appropriately. It can be treated even though the patient has undergone operations to heal a stroke.

There are two main ways to evaluate and help patients recovering from a stroke that primarily focus on maintaining balance. The Dynamic Balance Assessment utilizes the Berg Balance Scale to evaluate the patient. The Static Balance Assessment uses a center of pressure where the patient stands on the Force Plate to measure their balance. This method can require expensive equipment. Lastly, analyzing the patient's balance in a hospital would be quite tricky as there is no detailed assessment guideline.

Therefore, this research is aimed at improving algorithms in which the performance of balance control in stroke patients who have muscle weakness is measured. After verifying the proposed algorithm's accuracy, it can be used to predict impairment by examining the ability to regain balance while standing. This is done by repurposing equipment used along with a console to examine the subject's ability to regain balance. A variable of this examination is a balance assessment. When data is brought from measuring the center of pressure (COP), attributes are placed in the dataset. The dataset has three main categories of factors: patient profile, clinical test by the physiotherapist, and the physical balance while standing still on the Nintendo Wii Fit Balance Board® (WBB). Each dataset has varying numbers of attributes. The best dataset is the combination of only three attributes from COP measured when standing still on the WBB. After constructing the classification model, the three attribute dataset had the highest accuracy rate on classifying data with Artificial Neural Network (ANN). The ANN's capabilities in predicting abnormal balance control are accurate 93% of the time when measuring the open-eye biofeedback. Therefore, by using the ANN with the physical body features computed from the low-cost WBB, this proposed tool can help the physiotherapist to easily diagnose stroke patients who have balance impairment.

ACKNOWLEDGEMENTS

This research article is the memorial contribution to Mr. Kitchana Kaewkaen, who passed away, for his motivation and direction of the research. This research was also supported by Mae Fah Luang University. The authors also would like to thank all participants for contributing to the research.

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