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Gait classification of stroke survivors - An analytical study

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Abstract

Gait of post-stroke patients have been analyzed and classified in this paper. Data pertaining to gait of both post-stroke patients and healthy people of the same age group were obtained and analyzed. Xsens motion capture system was used for obtaining this data from 40 people belonging to both categories. Advanced modern machine learning techniques such as Logistic Regression, Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) were employed for classifying the data obtained. Accurate spatiotemporal parameters values for gait were obtained. Amongst the different machine learning techniques, XGBoost gave the most accurate classification result of about 96%. The walking patterns of the patients who had undergone a stroke attack were analyzed. severity of abnormal gait patterns was a key factor that was taken into consideration and points were given accordingly. The data presented in this paper can be used to develop diagnostic tools for gait rehabilitation of stroke survivors, to evaluate and estimate their way of walking in order to understand their progress. It can be used to understand the different types of walking disorders post-stroke and thereafter select the right kind of treatment that needs to be implemented for proper recovery.

Subject Classification: *62P10, 92B05, 92C50.*

Keywords: *Gait classification, Machine learning algorithms, Stroke patients, Neurological diseases, Sensors.*

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I. Introduction

A stroke is a neurological disorder which is caused due to either reduction or complete blockage in the blood supply to any part of the brain. This in turn causes shortage of oxygen supplied to the brain cells which may result in the death of those cells [1]. Depending upon the severity of the stroke, the patient may or may not survive with or without severe after effects. Even when the patient survives, it usually causes different levels of disability. A stroke survivor may be affected by partial or complete paralysis of the limbs depending upon the extent of damage occurred to the brain. The rehabilitation of such patients is a tough process and recovery is difficult. It might require multiple therapies and lots of efforts from the patient himself. Yet it has been noticed that the survivor usually ends up with some amount of abnormality in walking.

Various types of abnormalities in gait are encountered in a post-stroke patient. The abnormalities may be differences in step length between the two limbs, asymmetry in the gait interval of the two limbs, longer time duration and overload experienced by the healthy limb, difference in other spatiotemporal values and cadence in gait [2]. A large number of post-stroke patients experience various difficulties in walking. Hence it is of utmost importance that these changes in gait are detected as soon as possible so that the right kind of rehabilitation process can be estimated and decided for different individuals depending upon their needs [3].

Much research has been conducted in this field in order to analyze the gait characteristics of post-stroke patients. Many kinds of classifications have been brought out. Begg & Kamruzzaman (2005) classified the gait parameters for both young and old people. Peak motion analysis systems were employed to determine the kinetic and kinematic gait parameters as well as the spatiotemporal parameters. Those parameters were then compared through SVM application and it was found to be 91.7% accurate [4].

Classification of pathological gaits of post-stroke and Huntington's disease patients was done by Manini et al (2016) by again using the SVM application (on similar lines as Begg & Kamruzzaman) and then paired with the Hidden Markov Model (HMM). IMU sensors (inertial measurement unit) were attached on the gait pressure mat as well as on both the shanks in order to obtain the data. The classification obtained through this study was found to be 90.5% accurate [5].

KINECT sensors have been used widely to determine the gait characteristics and orientation of the ankles, knees, hips and the spine.

Obembe et al. (2014) used this concept and concluded that cadence and velocity were the most important features while evaluating the balance in a person who is walking [6]. On the other hand Dolatabadi et al (2017) concluded that velocity or acceleration were the least important features while classifying gait patterns [7].

Various neuromuscular and neurological diseases as well as Juvenile Idiopathic Arthritis (JIA) needs to be first identified before treatment for which the gait data of the patient has to be obtained and studied. For this purpose, various machine learning programs like multilayer perceptron (MLP), boosting and Random Forest (RF) were employed. Accurate analysis was established by these methods by using the spatiotemporal parameters of the patient's gait as inputs to the models. RF and MLP gave a 100% accuracy whereas 96.4% accuracy was established by SVM classifiers [8].

Papavasileou et al. (2017) fixed four barometric sensors as well as pressure sensors on the patient's shoes during their gait in order to capture the various features during walking. In this study the focus was to classify the important features which segregate patients of Parkinson's disease and stroke. For this, the prime gait characteristics of both the diseases were classified separately using multi-task feature learning. The features that were studied were cadence, symmetry during swing phases, imbalance as well as double support. With respect to the area beneath the curve, the results of classification maintained a score of about 0.96 [9].

It has been noticed that patient's with neurological diseases specially the Parkinson's disease sometimes cannot move, and that state is called as the 'freezing of gait' or FOG. This phase of the patient was studied by Camps et al. (2018) by employing deep learning methods. A lone IMU sensor was attached to the patient's waist in an attempt to obtain all the parameters related to walking [10]. The SVM algorithm and ANN or artificial neural networks have been tested against each other to classify the gait of both healthy as well as people affected by Parkinson's disease. The parameters taken into consideration were spatiotemporal characteristics such as cadence, speed, ground reaction forces etc. SVM algorithms performed better than ANN as they gave more accurate results and the best feature for gait classification was found to be the spatiotemporal characteristics [11].

Various machine learning algorithms [12] like SVM algorithm, Naïve Bayes, decision tree, k-NN and linear Discriminant Analysis (LDA) were employed to tabulate and compare the walking patterns of healthy and Parkinson's disease patients using an IMU sensor by Caramia et al. (2018).

The mean accuracy obtained from the results varied between 63% to 83% [13]. Neural network, decision tree and MLP were also employed by other researchers while using IMUs for obtaining the walking features of patients of neurological diseases including stroke patients. 84.78% accuracy was obtained while classifying the gait of neurologically diseased patients by employing MLP by Hsu et al. (2018) [14]. During experiments or clinical practices, IMU based methods were employed by Yang et al. (2011) and their performance was found to be good. For obtaining the temporal parameters during gait, inertial sensors were employed [15].

The results of the literature survey confirm that IMU sensors are most commonly used for measuring the gait patterns of patients affected by different types of neurological disorders. Optitrack, KINECT and VICON are the other camera based sensors which were used for analyzing gait patterns. Optitrack Certus is an advanced system. The accuracy of KINECT was cross checked by Xu et al (2015) by obtaining the gait data from healthy people using KINECT and comparing it with the data obtained through Optitrack [16]. Through Turkey post-hoc and one way ANOVA it was proven that though the KINECT sensor recorded the gait parameters, its accuracy level varied among various parameters. The KINECT sensor was also employed to check for lower body characteristics by Nizam et al. (2017) and it resulted in accurate measurements although some errors were observed in the gait spatiotemporal characteristics as they were measured manually [17]. Various kinds of experimental setups were used to test the efficiency of KINECT sensors to obtain various gait parameters from healthy people, for example while simply walking, climbing up and down the stairs. But it can be said that the gait of neuro patients hasn't been very widely worked upon and analyzed using too many camera based sensors [18-22].

Finally, from the literature survey it can be conveniently concluded that among all machine learning methods employed for gait analysis, the SVM method is most popular. In most cases it is observed to have attained very high classification rates. On the other hand, IMUs were found to be very good for extraction of data from the patient's gait.

Therefore, the aim of this study is to apply a few machine learning techniques to collect and understand the different mobility levels of the entire group comprising of patients of varying levels of the disease. The next step is to check whether those techniques are able to differentiate between sick and healthy people based upon the gait analysis. Emphasis is also to understand which of the features contribute maximum towards differentiating the gait. It can be conveniently concluded that this study has been performed in order to understand and monitor the rehabilitation progress amongst stroke patients of varying degrees of mobility during the treatment process.

The strategy is to employ IMU based sensors to analyze the gait data of the patients using various machine learning techniques that have been picked from the literature survey. The various ML techniques which have been discussed include logistic regression, MLP, SVM and XGBoost algorithms. They will be used to identify as well as differentiate between stroke patients and healthy people.

II. Methodology and materials used

1. *Participants*

The experiments were conducted on 40 post-stroke patients as well as 40 healthy people simultaneously. The participants were in the age bracket of 43 to 61 with a B.M.I less than 29. In consultation with a therapist, patients from the Stroke center and Department of Early Rehabilitation of city Hospital №1 in Nur-Sultan (Astana), Kazakhstan were chosen to participate in the project. The criteria was that none of the patients had to have any mental or physical ailment other than any abnormality caused due to stroke. The other important point under consideration was that the patients were to use only crutches or assistive devices if necessary, for walking a minimum of 60 meters but strictly without any human support or wheelchair. Declaration of Helsinki was maintained, and approval was taken from the local Institutional of Research Ethics committee. Besides this, each participant was also asked to sign a consent form before beginning the experiment.

2. *Equipment*

Xsens Motion Capture System consisting of 17 motion trackers with its MVN Studio software was used to capture the gait parameters. The motion trackers imitate the small IMU sensor which also contains 3D magnetometers, 3D linear accelerometers and also 3D gyroscopes. The system provides the kinematic updates from all parts of the body at a rate of 120 Hz. The power for activating the motion trackers are derived from the Xbus Master module which synchronizes the data obtained from various sensors to transmit it via a wireless receiver to a computer. The MVN studio software was then used to process the data for skeleton simulation. The implementation of this entire set up can be done very quickly and easily.

3. *Procedure*

In order to track the motions developed, 17 body sensors attached with MVN mounting straps which can be fastened with Velcro were placed strategically on various parts of the body. The entire set up of how the Xsens motion capture system with 17 IMU sensors are strategically placed on a patient is illustrated in Fig. 1. Since the patient would have to be around the system for affective measurements during walking, it was obvious that after a while he would need to stop walking and turn around which would adversely affect the measurements. Hence the patients were asked to walk counterclockwise in a particular area whose dimensions were 850 cm by 540 cm for 3 whole cycles.

4. *Feature Extraction*

The spatiotemporal parameters which were chosen for gait classification in this study are as follows:

1. ***Step count:*** Total number of steps taken to complete the entire 3 cycles.
2. ***Step length****:* The distance between the point where the first foot's heel strikes to the point where the other foot's heel strikes.
3. ***Step width:*** The perpendicular distance between two feet with respect to the direction of walking.

Fig. 1

Front and back view placements of sensor's on various points on the participant's body

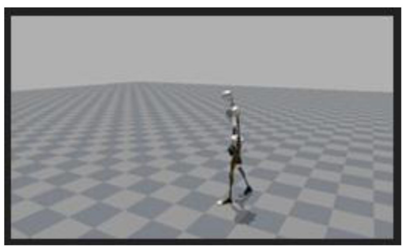

Fig. 2

Participant's movement being simulated live by MVN software

4. ***Step frequency:*** Measured as the number of steps taken in one second.
5. ***Velocity:*** The speed in which the patient covers the stipulated distance.
6. ***Gait cycle:*** Time taken between the strike of one foot and the next consecutive strike of the same foot on the walking surface.
7. ***Double support phase:*** Measured as the time during which both the feet touch the ground simultaneously during a single gait cycle.

All the above features except for the ***'step count'*** have been obtained from BVH i.e., the Bio-vision hierarchy format by using MATLAB. For that the BVH file was loaded into the MATLAB memory after which all the kinematics were calculated, and the output was stored. The step count was then determined. The peak values for both the feet were obtained and only the peak values which were larger than 21cms were plotted on the z-axis. 21cms was fixed as an index for measurement assuming that it would take a person a minimum of 21cms to lift his leg in order to perform the stepping action. Now by summing up the total number of times both the legs have crossed 21cms, the ***'step count'*** could be easily determined. The following figure shows the right heel action with respect to the z-axis.

For determining the step length, the changes of both the heels along with both the x and y axis have been considered and the Euclidean distance [23] between the two feet was determined using the following formula:

Euclidean distance between the heels of either feet

$$= \sqrt{\begin{array}{l}(left\_heel\_x - right\_heel\_x)^2 \\ +(left\_heel\_y - right\_heel\_y)^2\end{array}} \quad (1)$$

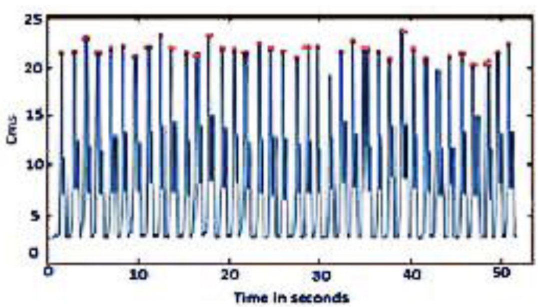

Fig. 3

Right heel action on z-axis

Where the $(left\_heel\_x)$ and $(right\_heel\_x)$ is the change experienced by the left foot and right foot along the x-axis respectively. Similarly $(left\_heel\_y)$ and $(right\_heel\_y)$ is the change experienced by the left foot and right foot along the y-axis respectively. For finding the step length, a loop is used to determine the amplitude points with respect to time. The total sum of the amplitude point values of Euclidean distance thus obtained is then divided by the total number of step counts in order to obtain the average step length. For frequency and velocity calculations, it is necessary to determine the total time that a participant has spent to cover the whole cycle. The time can be determined by the max (time) function. Step frequency is obtained by dividing the total number of steps taken by the time taken. Velocity is determined by dividing the entire sum of absolute values of Euclidean distance by the time taken and multiplying the result obtained by 0.01.

5. *Classification*

In gait analysis the usual statistical method of analysis has some drawbacks when compared to machine learning techniques. Machine learning techniques allows the model to learn continuously when more data is provided besides discovering hidden details [24]. Although the procedure to experiment on gait pattern recognition has got many tasks as shown in the flow diagram (fig. 4). The tasks include collection of data, extracting the features, data training, classification of data, accuracy assessment and then finally the results were obtained.

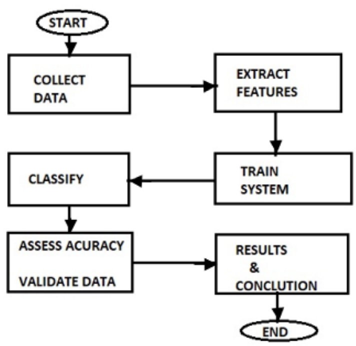

Fig. 4

Block diagram - Gait pattern recognition. Data collected through Xsens and analyzed by machine learning techniques

Four machine learning algorithms were implemented for classifying data [25]. They are Extreme Gradient boosting (XGBoost), Support Vector Machine, Logistic Regression (LR) and Multi-layer Perceptron (MLP). For effective analysis of data, 'scikit-learn' from python was used to implement machine learning [26]. For splitting X and Y into training and testing sets during the implementation itself train/test was used. Xsens motion capture system was used to collect the data which was then split into 60 training and 24 testing sets.

$$Training\, set = \{(x_1, y_1),\ (x_2, y_2), \ldots (x_i, y_i)\}$$

$$where\ i = 1, 2, 3 \ldots m$$

$$Testing\, set = \{(x_1, y_1),\ (x_2, y_2), \ldots (x_i, y_i)\}$$

$$where\ i = 1, 2, 3 \ldots n$$

$$Total\, number\, in\, dataset\, is\ Z = m + n$$

Sigmoid function whose values lie between 0 and 1 is the basis of Logistic Regression algorithm in machine learning and it stems from the statistics discipline. An example for Logistic Regression is given in Equation 2

$$y = \frac{e^{a_0 + a_1 * x}}{1 + e^{a_0 + a_1 * x}} \tag{2}$$

Where a_0 is the intercept point and a_1 signifies the co-efficient of the input value of x which can be obtained from the training dataset. Another algorithm, 'Extreme Gradient Boosting (XGBoost)' which is a scalable tree boosting system is applied vastly these days for data classification problems [27] as its performance in solving machine learning problems is commendable.

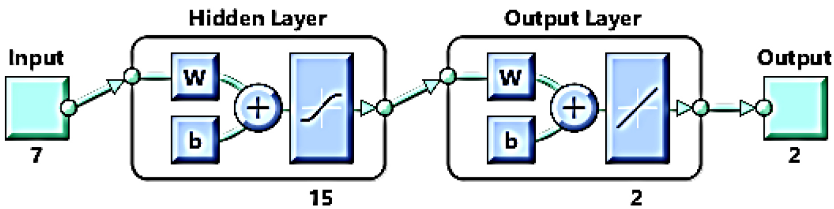

Fig. 5

Multilayer perceptron ANN with 15 hidden layer nodes.

Artificial Neural Networks (ANN) [28] have been inspired from the way a human brain functions, the signals developed and its interaction. One of the supervised learning algorithms of ANN is MLP [29] which is very popular as a classifier algorithm as it can be used to recognize data which cannot be linearly separated (Fig. 5). The corresponding input and output sets are connected. A median value of 15 is set as the size of the hidden layer so as to eliminate any problems, i.e., a larger hidden layer size will cause overfitting problems and a lower hidden layer size might cause inaccuracy in the results of classification.

The sigmoid function was applied by the hidden layer nodes in order to map the inputs to their appropriate outputs. Although SVM is comparatively a new machine learning algorithm, it is used very well not only to model data but also to solve problems related to binary classifications. 'Softmax' function was utilized by the nodes present in the output layer. Vapnik's statistical learning theory gave rise to the SVM algorithm [30]. This is a supervised learning method, so it needs to be trained. It can be used to extract the best hyperplane which segregates the data and helps in maximizing the training data margins. Here the 'sklearn' library which is based on the 'libsvm' tool (which means a one to one method) is used to implement the SVM classifier.

III. Results

The participants were divided into two groups. First a group of healthy people and the second a group of stroke patients who were healthy enough to walk and who were not confined to bed. It has been observed that stroke patients have a smaller step length and walk more slowly than normal people, hence increasing their gait cycle and decreasing their step frequency.

Table 1 shows the results of classifying the logistic regression model.

Table 1

Logistic regression classification report

	Precision	Recall	F1 score	Support
Healthy person	0.92	0.92	0.92	12
Stroke patient	0.92	0.92	0.92	12
Average/total	0.92	0.92	0.92	12

Table 2

XGBoost classification report

	Precision	Recall	F1 score	Support
Healthy person	0.92	1.00	0.96	11
Stroke patient	1.00	0.92	0.96	13
Average/total	0.96	0.96	0.96	24

Precision refers to the ratio between the positive predicted observations to the total number of predicted observations. In this study the average precision score of stroke being 0.92 translates to the fact that the results of the stroke group were actually theirs. Similarly, a recall score of 0.92 translates to every data point from a stroke being rightly so. A 0.92 score for precision and recall is a particularly good value to be obtained. F1score pertains to the weighted average of both the precision as well as the recall scores. A classifier's overall accuracy is defined by its F1 score. Support value of a particular class refers to the number of times a correct response was obtained. In other words, it can be stated that the model has managed to classify the data of both the stroke as well as the healthy group with a precision of 92% each.

So it can be pronounced that this logistic regression classifier has an overall accuracy of 92%. Table 2. shows the results of classifying the XGBoost. Here too the average precision and recall values of 0.96 show that the results are perfectly accurate. 24 test observations were made, and

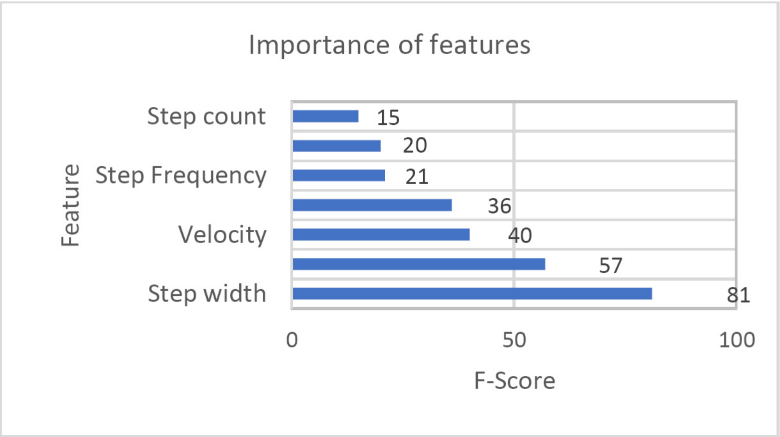

Fig. 6

XGBoost-Feature importance

Table 3

Multilayer perceptron classification report

	Precision	Recall	F1 score	Support
Healthy person	0.83	0.91	0.87	11
Stroke patient	0.92	0.85	0.88	13
Average/total	0.88	0.88	0.88	24

Table 4

SVM classification report

	Precision	Recall	F1 score	Support
Healthy person	0.50	0.86	0.63	7
Stroke patient	0.92	0.65	0.76	17
Average/total	0.80	0.71	0.72	24

a 96% accuracy has been obtained which proves that the classifier has a 96% accuracy which is commendable.

Table 3. shows the classification results of the multilayer perceptron. The average accuracy of this model is fouund to be only 88% which is lesser than the other models. By iteratively tuning, 15 hidden layers were considered. The healthy group and stroke group had a precision score of 83% and 92% respectively. For classifying data, a support vector machine was used and the classification results for the same has been compiled in table 4. The gait-temporal data of both the healthy as well as stroke groups have been compiled using this model.

IV. Discussion

In this report, four types of machine learning techniques such as logistic regression algorithm, extreme gradient boosting algorithm, multi-layer perceptron algorithm and support vector machine algorithm (SVM) were employed for the purpose of classification. 40 data samples each were recorded from the healthy people's group and from the stroke patient's group making it a total of 80 data samples. With the use of machine learning algorithms, the gait data of both healthy people as well as stroke patients were classified successfully so it can be of substantial use in both clinical as well as rehabilitation purposes as it will be quite easy to determine abnormal gait patterns as well as to monitor the progress during

Table 5

F1-Score values of machine learning algorithms

Name	%
Logistic Regression	92
XGBoost	96
Multilayer Perceptron	88
Support Vector Machine	72

gait rehabilitation. There is a clear cut difference in the results of both the groups which helps in understanding the groups functioning better. The research has also helped to recognize the features which contributes the most to differentiate between the two groups clearly.

Table. 5 gives the average F1-score values which have been obtained from the classification results of various machine learning algorithms. The results of classification based on gait data of both healthy as well as stoke patients have been established. The other aim of this study was to study the medical history as well as the gait of patients in order to determine the extent of their disability.

Fig.7 shows the time elapsed between the stroke attack to when the analysis was made. From the ongoing analysis it is safe to conclude that men between 50 and 60 years of age were more susceptible to stroke . The chart shows that 25% of the patients underwent a stroke more than a year before the survey was conducted, 35% more than 6 months prior to the survey etc. The study also showed that the probability of falling sick

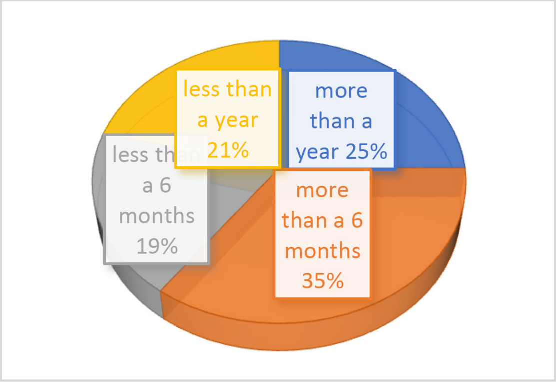

Fig. 7

Patient chart with respect to disease duration

above the age of 60 is high and it increases exponentially thereafter [31]. This relation can be estimated by the following equation

$$y = 0.47831 * e^{0.08461x} \tag{3}$$

Where 'y' stands for the probability of getting a stroke and x is the patient's age. This equation which shows the relation between age and stroke was determined from the number of participants in the conducted survey.

The various deficiencies in gait performance as well as their medical history was studied during the survey. Motor deficiency was one of the prime reasons contributing to improper gait. For example, cases who exhibited inability to have proper limb control had the root cause lying in the muscles. Muscles spasticity is a condition which causes continuous contraction of muscles which in turn can makes the muscles sore, causing it to become tight and stiff. This muscle stiffness will hinder their day to day activities such as body movements, walking or even the person's speech. Spasticity occurs due to any form of damage occurring anywhere in the brain or spinal cord and it in turn causes different pathological poses in the body. The brain and the spinal cord are the centers which controls the entire human body. So, if any portion the brain or spinal cord gets damaged then it directly affects the body part which it is connected to and hinders its normal functioning thereafter. The severity of the damage in the body depends upon the amount of damage occurred in the brain or spinal cord. This can cause various pathological poses like the Wernicke-Mann pose which was found in about 38% of patients. This caused the patient's arm to flex and leg to extend resulting in stooping shoulders, bent forearms, bent and stretched wrists, unbent tibia and hips and lastly the foot is flexed because the legs are elongated. Therefore, the patient formed a semi-circular pattern while walking as he was forced to drag his leg across the side [32]. In most of the patients, a highly rigid form of hypertension in muscles was found along with a dominant spastic component. For studying the motor disorders in detail, the pathological movements of 40 stroke victims were determined and tabulated in table 6. This procedure was influenced by the work performed by Shevchenko [33].

The classification presented in table 6 is presented in terms of a bar graph in Fig. 8 which clearly shows that the majority of the patients who were tested were not people who had undergone any severe stroke attack and they belonged to group C and group D.

Table 6

Motor disorders-A clinical classification

Weight	Group	Level of motor Deficiency
5 Points	A	No abnormal mobility disorders present
4 Points	B	Pathological posture is fine. Slight difficulty and defect observed in random movements hence causing a slight limp while walking. Although slow but can walk without any external aid.
3 Points	C	Slight disorientation found in pathological posture making random movements slightly difficult and defective which in turn makes walking a difficult task. Self-support is slightly tough and one might need partial assistance of both hands.
2 Points	D	Mildly defective pathological posture making random movements difficult and defective. Walking is tough but can be accomplished with the help of a healthy hand.
1 Points	E	Bad pathological posture observed making random movements highly difficult and abnormal. Walking without any external help is impossible. Independent walking is almost impossible or maybe accomplished with the help of a healthy hand.
0 Points	F	Limb-plegia

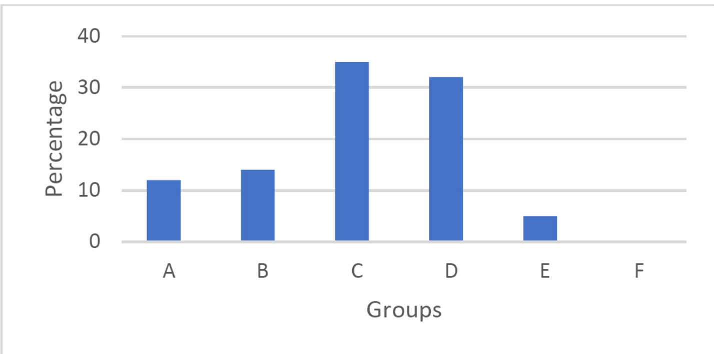

Fig. 8

The effect of various motor disorders in stroke patients

V. Conclution

It can be concluded that the study has generated and implemented tools very effectively. The tools used were able to clearly differentiate between stroke patients and healthy people very well despite the fact that the people enrolled for the study were not very severely affected by stroke. The machine learning tools employed were still very effective in classifying healthy people and the stroke patients with a high amount of accuracy. The research work conducted used an extreme gradient approach for classifying the participants based on the F1-score which resulted in a remarkably high amount of accuracy. Specific spatiotemporal characteristics were selected to be worked upon and the information obtained was helpful in classifying gait.

The other aspect that was worked upon was understanding the general walking process of stroke victims. The motor skill deficiency and the acute lack of mobility in participants were studied and then these two parameters were combined. Statistically, the results of the entire group of participants were examined to conclude that mostly stroke affected people were between 50 and 60 years of age. It was also derived that the probability of a person undergoing a stroke begins to increase after the age of 40. Men are at a higher risk and the risk amount can be mathematically defined by the equation $y = 0.4783 \times e^{0.0846x}$. The condition of the disease is at its peak during the first three to four months and its best to start the rehabilitation process as early as possible to facilitate maximum recovery. For this purpose, proper diagnosis is essential and that can be done by using gait analysis tools which depends upon machine learning tools which of course has to be performed in consultation with specialized doctors. The models that have been achieved here can be effectively used to classify as well as to detect changes in gait patterns.

The research done here can be used to develop tools for gait diagnosis which can be utilized by clinicians to categorize different gait disorders as well as to monitor the improvement in the condition of the patient. Therefore, this study will contribute largely to understand the different types of disorders and to finalize the best possible treatment needed by each individual patient.

References

[1] What is Stroke? The National Heart, Lung, and Blood Institute (NHLBI), www.nhlbi.nih.gov.

[2] Guzik, A., et al., Validity of the gait variability index for individuals after a stroke in a chronic stage of recovery. Gait Posture, 2019. 68: p. 63-67.

[3] Guzik, A., et al., Assessment of test-retest reliability and internal consistency of the Wisconsin Gait Scale in hemiparetic post-stroke patients. Advances in Rehabilitation, 2016. 30.

[4] Begg, R. and J. Kamruzzaman, A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. *J Biomech*, 2005. 38(3): p. 401-8.

[5] Mannini, A., et al., A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients. Sensors (Basel), 2016. 16(1).

[6] Obembe, A.O., M.O. Olaogun, and R. Adedoyin, Gait and balance performance of stroke survivors in South-Western Nigeria--a cross-sectional study. *The Pan African medical journal*, 2014. 17 Suppl 1(Suppl 1): p. 6-6.

[7] Dolatabadi, E., B. Taati, and A. Mihailidis, An Automated Classification of Pathological Gait Using Unobtrusive Sensing Technology. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2017. PP: p. 1-1.

[8] Joyseeree, R., R. Sabha, and H. Müller, Applying Machine Learning to Gait Analysis Data for Disease Identification. Studies in health technology and informatics, 2015. 210: p. 850-4.

[9] Papavasileiou, I., et al., Classification of Neurological Gait Disorders Using Multi-task Feature Learning. 2016.

[10] Camps, J., et al., Deep learning for freezing of gait detection in Parkinson's disease patients in their homes using a waist-worn inertial measurement unit. Knowledge-Based Systems, 2018. 139: p. 119-131.

[11] Tahir, N. and H. Manap, Parkinson Disease Gait Classification based on Machine Learning Approach. *Journal of Applied Sciences*, 2012. 12: p. 180-185.

[12] Prajapati, P. and A. Thakkar, Extreme multi-label learning : A large scale classification approach in machine learning. *Journal of Information and Optimization Sciences,* 2019. 40(4): p. 983-1001.

[13] Caramia, C., et al., IMU-Based Classification of Parkinson's Disease From Gait: A Sensitivity Analysis on Sensor Location and Feature Selection. *IEEE J Biomed Health Inform*, 2018. 22(6): p. 1765-1774.

[14] Hsu, W.-C., et al., Multiple-Wearable-Sensor-Based Gait Classification and Analysis in Patients with Neurological Disorders. Sensors (Basel, Switzerland), 2018. 18(10): p. 3397.

[15] Yang, C.-C., et al., Real-time gait cycle parameter recognition using a wearable accelerometry system. Sensors (Basel, Switzerland), 2011. 11(8): p. 7314-7326.

[16] Xu, X., et al., Accuracy of the Microsoft Kinect™ for measuring gait parameters during treadmill walking. Gait & Posture, 2015. 42(2): p. 145-151.

[17] Nizam, Y., M.N. Mohd, and M. Mahadi Abdul Jamil, Biomechanical application: Exploitation of kinect sensor for gait analysis. *ARPN Journal of Engineering and Applied Sciences,* 2017. 12(10): p. 3183-3188.

[18] Gabel, M., et al., Full body gait analysis with Kinect. Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. *IEEE Engineering in Medicine and Biology Society. Annual Conference*, 2012. 2012: p. 1964-1967.

[19] Muller, B., et al., Validation of enhanced kinect sensor based motion capturing for gait assessment. PLoS One, 2017. 12(4): p. e0175813.

[20] Oh, J., et al., Validity of the Microsoft Kinect™ in assessing spatiotemporal and lower extremity kinematics during stair ascent and descent in healthy young individuals. *Medical Engineering & Physics,* 2018. 60: p. 70-76.

[21] Souza, A.d.M.e. and M.R. Stemmer, Extraction and Classification of Human Body Parameters for Gait Analysis. *Journal of Control, Automation and Electrical Systems,* 2018. 29(5): p. 586-604.

[22] Sun, B., et al. Human gait modeling and gait analysis based on Kinect. in 2014 IEEE International Conference on Robotics and Automation (ICRA). 2014.

[23] Chen, P.Y. and H.M. Yu, Euclidean distance-based method for variable selection and its application in geological data. *Journal of Interdisciplinary Mathematics*, 2016. 19(2): p. 215-232.

[24] Mitchell, T.M., Machine Learning. McGraw-Hill, Inc. 432., 1997.

[25] Singh, R.M., et al., Comparative analysis of SVM and ANN classifier based on surface EMG signals for elbow movement classification. *Journal of Interdisciplinary Mathematics*, 2020. 23(1): p. 153-161.

[26] Pedregosa, A.F., et al., Scikit-learn: Machine Learning in Python. *J. Mach. Learn. Res.*, 2011. 12(null): p. 2825–2830.

[27] Chen, T. and C. Guestrin, XGBoost: A Scalable Tree Boosting System, in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016, Association for Computing Machinery: San Francisco, California, USA. p. 785–794.

[28] Shalu and D. Singh, Artificial neural network-based virtual machine allocation in cloud computing. *Journal of Discrete Mathematical Sciences and Cryptography*, 2021: p. 1-12.

[29] Kriesel, D., A Brief Introduction to Neural Networks. http://www.dkriesel.com, 2007.

[30] Vapnik, V.N., The nature of statistical learning theory. Springer-Verlag, 1995.

[31] Wolf, P.A., et al., Probability of stroke: a risk profile from the Framingham Study. Stroke, 1991. 22(3): p. 312-8.

[32] Pirker, W. and R. Katzenschlager, Gait disorders in adults and the elderly : A clinical guide. Wien Klin Wochenschr, 2017. 129(3-4): p. 81-95.

[33] Shevchenko, L., Movement disorders in patients with cerebral hemispheric stroke, and their therapeutic correction. Moscow, 1999.