OPEN ACCESS
International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-6 Issue-4, April 2017

Foot Classification and Influence of Pattern Recognition

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Abstract*: The article presents the application of neural network and decision tree techniques to investigating barometric data got with instruments measuring the weight of the human plantar onto contact surface while strolling. The examination was completed on a gathering of plantar foot photo taken while the subject remained on the reflected photograph box. We gather 35 understanding, 30 of them are male and 5 female with various ages. Numerical qualities for foot examination for every patient foot part get measuring 12 property. Some foot plant pathologies, similar to buckle and level foot, are ordinarily identified by a human master by method for impression pictures. All things considered, the absence of prepared individual to finish such huge first screening discovery endeavors blocks the routinely analytic of the previously mentioned pathologies. In this work an imaginative programmed framework for foot plant pathologies in view of neural systems (NN) and Decision Tree (DT) are introduced. The outcomes accomplished with this framework confirm the attainability of setting up programmed conclusion frameworks in light of the impression and example acknowledgment. The order settled on by the resultant choice tree was right for all the more than 94% steps. This permits to point the parameters which are the best discriminators between the explored sorts of human walk.

***Index Terms*: Foot Deformities, Photography, Pattern Recognition, Neural Network, Decision Trees.**

I. INTRODUCTION

Data mining is the arrangement of techniques which empowers to deal with an immense and multidimensional arrangement of measured Data [1]. Data digging accommodates quick and proficient dissecting of the information and finding new, infrequently unforeseen, associations between different parameters [2]. Biomedical building is an exceptionally specific and essential field of information mining application. Above all else, biomedical designing aides in enhancing the nature of human life. Second, biomedical information have uncommon elements, for example, high between and intrasubject changeability, high nonlinear reliance between a few parameters, multidimensionality and so on, which cause troubles in dissecting instances of specific subjects with routine strategies [3]. One of the imperative issues in biomedical building is a programmed instrumented human step investigation. Walk is a fundamental human movement. It empowers us to move our body. Stride is additionally an exceptionally complex human movement. It is depicted by tremendous number of parameters which include:

- Kinematics;
- Kinetics;
- Anthropometrics;
- Electromyography's;
- Others.

The estimation of some of those parameters is important to play out the quantitative human step appraisal. The appraisal of human stride is an imperative errand to for example, assess the level of ailment and measuring the impacts of recovery process or surgical mediation. The achievement of adopting the traditional strategy to human step by clinician is emphatically restricted by his capacity. Great clinician ought to be acquainted with the specialized and therapeutic side of the examination. He ought to likewise have the capacity to handle substantial arrangements of information and to make legitimate aptitude in light of his insight and experience. These days, the techniques for programmed human step examination are exceptionally prevalent, in light of the fact that they break the impediments of manual assessment of the information concerning walk [3, 4, 5, 6, 7, 8, 9]. The manmade brainpower techniques for programmed step examination are as per the following: neural systems [9], fluffy rationales [10] and others [5, 11]. Numerous potential and proven benefits of pattern recognition to clinical biomechanics data analysis and prosthesis control mislead most often to their application by neglecting some key issues. A key issue is related to the pre- and post-processing of data. A combination of experience and trial and error will be necessary for appropriate pre- and post-processing data. Pre-processing covers the selection of input data, techniques like scaling, normalization, Fourier or wavelet transformation, rectification and averaging [12] which all will significantly affect the performance. Especially under consideration of an adequate relationship of the number of input variables and number of adjustable weights with an ANN these issues are of specific interest. Although formal feature selection methods from statistical pattern recognition are offered [13], they have not been widely applied in clinical biomechanical data analysis. A further and closely related issue to the first one is the issue in developing ANNs concerning generalization. This is identified with the nature of the forecasts for cases that are not in the preparation set. Like in other adaptable non-straight estimation techniques, over-fitting and under fitting is a basic issue to manage. Under-fitting can come about because of a not adequately complex ANN that neglects to recognize the flag in a muddled information set. Over-fitting may come about because of an ANN that is excessively mind boggling and drives,

Manuscript published on 30 April 2017.
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Making it impossible to fit the commotion, not only the flag. [14] Consider over-fitting particularly hazardous with a hefty portion of the normal sorts of neural systems since it effectively can prompt forecasts that are past the scope of the preparation information. [15]Recommends the utilization of expansive measure of preparing information with a specific end goal to stay away from over-fitting. Over-fitting is by all accounts improbable, if there are no less than 30 times the same number of preparing cases as there are weights in the system.

A standout amongst the most encouraging procedures of information mining is choice tree. Choice trees empower to separate the information covered up in the information and showing it in an exceptionally clear manner. They give extremely straightforward conditions in the tree hubs and prompt conclusion (class) on the least level of the tree. It is critical that the outcomes are simple for translation and could be utilized by the staff with neither scientific nor building foundation. This settles on choice trees helpful device for clinical applications. A standout amongst the most intriguing properties of choice trees is no from the earlier presumptions. Also, to work legitimately, the choice trees don't require as much information as neural systems. It is particularly vital in biomedical applications, where the quantity of subjects is exceptionally restricted. Obviously, a greater arrangement of information give more exact and more dependable results. Choice trees have as of now been effectively utilized as a part of the human walk examination in clinical applications [16, 17]. Be that as it may, in late papers the fundamental fate of choice trees is an order assignment.

At the point when the foot is planted, not all the sole is in contact with the ground, the impression is the surface of the foot plant in contact with the ground. The give in foot and the level foot are pathologies exhibited. On the off chance that these foot deformities are not distinguished and treated on time, they turn out to be most noticeably awful amid adulthood creating a few aggravations, agony and stance related disarranges [20].

Shape and zones of the impression are appeared in figure 1. Zones 1, 2 and 3 relate to locales in contact with the surface when the foot is planted, these are called foremost heel, back heel and isthmus separately. Zone 4 does not form part of the surface in contact and is called impression vault [21]. A basic strategy to acquire impressions is specifically venturing the inked foot onto a paper on the floor. Subsequent to acquiring the impressions, a specialist breaks down them and surveys in the event that they show pathologies. More often than not, in the conclusion of these pathologies an instrument known as podoscope is utilized to catch the impressions. A straightforward computerized rendition of the podoscope in light of a scanner has been proposed in [22]. Another essential instrument to get impressions is the pedobarograph. Present day variations of the pedobarograph are proposed in [23, 24]. A technique to fragment impressions in optical shading pictures of the sole by utilizing neural systems is proposed as a part of [25].

As of now, a specialist characterizes if a patient has an ordinary, surrender or level foot by a manual exam called photopodogram. A photopodogram is a compound photograph of the foot part supporting the heap. The master decides the position for the two separations, sizes them, computes the proportion and groups the foot. Indeed, even intense the criteria for arranging impressions appears to be exceptionally straightforward, the utilization of a classifier in light of pattern recognition offers the accompanying points of interest contrasted and more conventional methodologies: (1) it is not easy to build up a calculation to decide with exactness the right position to quantify the separations, and (2) it can be prepared to perceive different pathologies or to enhance their execution as more cases are accessible.

We will probably think about between example acknowledgment methods as Neural Network and Decision Tree ordering a gigantic information sent out from screening for the recognition of pathologies as level foot and give in foot. These information were arranged by a specialist.

This paper portrays contrast of a programmed characterizing information with analyze foot plant pathologies. We define analyze of foot plant pathologies as an example acknowledgment issue. This paper is sorted out as takes after. Area 2 present the foot plant pathologies. Segment 3 depicts material and methods used. Segment 4 introduces result and discussion of use classifiers. Area 5 demonstrates conclusion of using classifier.

II. MATERIAL AND METHOD

A. Material

Electronic systems for recording and evaluating pressure distribution under the foot in static and dynamic conditions. The platforms provide accurate, reliable information for the analysis of foot function and diagnosis of foot pathologies. Foot deformities and malfunction can be detected during analysis of the barefoot pressure data. The Technical specification of emed®-xl platform, dimension (mm) is 1,529 x 504 x 21, Sensor area (mm) is 1,440 x 440, number of sensors 25,344, resolution (sensor/cm^2) is 4 and with 100 Hz frequency. Foot type was determined by obtaining arch index values. We collect 35 patient, 30 of them are male and 5 female with different ages. numerical values for foot as Total Object, Hind foot, Mid foot, Fore foot, MH1, MH2, MH3, MH4, MH5, Toes, Big toe, Second toe, Toes 345 and Toes 2345 for each patient foot part get measuring the following 12 attribute; [Force Time Integral, Max Force (N), Peak Pressure (Kpa), Contact Area (cm^2), Contact Time] mean and standard deviation, Arch Index and grade. We use WEKA 3.6.9 platform for classification step. Waikato Environment for knowledge Analysis (Weka) is a popular suite of machine learning software written in java, developed at the University of Waikato, New Zealand.

B. METHOD

A "highest quality level" technique for deciding foot sort has yet to be set up, and clinical perception remains the strategy frequently depended upon. [29] Measures showed poor to great dependability in supporting clinical judgments of foot sort, [30] yet the unwavering quality of these estimations in grouping foot sort has not been researched.

Curve record values have been utilized to decide foot sort.

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[31] Arch record values ascertained by impression examination have been acquired from compel plate, [31] carbon impression paper, [34] and photos brought with a reflected glass box. [32] [33]. [34] Arch list ascertained [35] solid for figuring curve list values, [32] and ok for both people of typical weight and those with stoutness. [36] Arch list additionally shifts with age, falling into the typical grown-up range by age [32] [37] Whether among corpulent or non-hefty individuals, [36] school-matured kids or grown-ups, [37] or men or ladies from various nations, [38] curve record values fall into the distinctive scopes of curve list values proposed and utilized as a potential technique to arrange high-angled, ordinary, and low-angled foot sorts. [38] The unwavering quality of grouping foot sort by this technique has not been examined, be that as it may. Foot plant pathologies and pattern recognition diagnosis; It is conceivable to characterize a foot by its impression shape and measurements as an: ordinary, level or give in foot. Figure 1b demonstrates a picture of a level foot, figure 1c demonstrates a picture of a typical foot, and figure 1d demonstrates a picture of a give in foot.

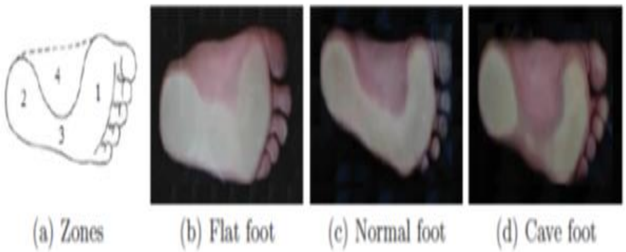

Figure 1 Images of The Foot

Before characterization, the impression is confined from whatever remains of the segments of the sole picture by utilizing the technique proposed as a part of [1]. Figures 2a, 2b and 3c demonstrated the division of a level, a typical foot, and a give in foot individually.

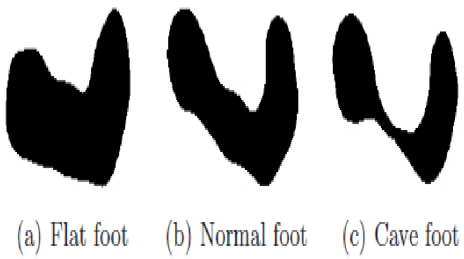

Figure 2 Segmentation of Footprint

Subsequent to playing out the division, the impression is spoken to by a vector containing the width in pixels of the divided impression, without toes, by every segment in the level course. Since each picture has a width vector with various length, the vectors were standardized to have similar length. Likewise the estimation of every component was standardized to an esteem in the scope of 0 to 1.Figures 2a, 2b and 2c demonstrate the standardized vectors of a level, a typical and a surrender foot.

The absence of a dependable characterization standard for foot sort makes making inferences from existing exploration and clinical choices troublesome, since various foot sorts may move and react to treatment in an unexpected way. The motivation behind this study was to decide interrater assention for foot-sort arrangement. Strategy: Arch list was ascertained from impression photos acquired through reflected photograph box. Grouping as high-angled, typical, or low-curved foot sort depended on curve list values. Unwavering quality of the curve file was resolved with intra-class relationships; concurrence by walking sort arrangement was resolved utilizing quadratic weighted kappa (kw).

III. RESULTS AND DISCUSSION

We will use data of foot measurements to compare which classifier will be more suitable for automatic classification of the foot. We will use two type of classifiers as Decision Tree and Neural Network. Compare between them to detect which of them are more accurate in the ability of differentiation of foot categories from our dataset. We use 10-fold cross validation technique.

- Neural Network using weka classifiers functions Multilayer Perceptron as shown in figure 3.

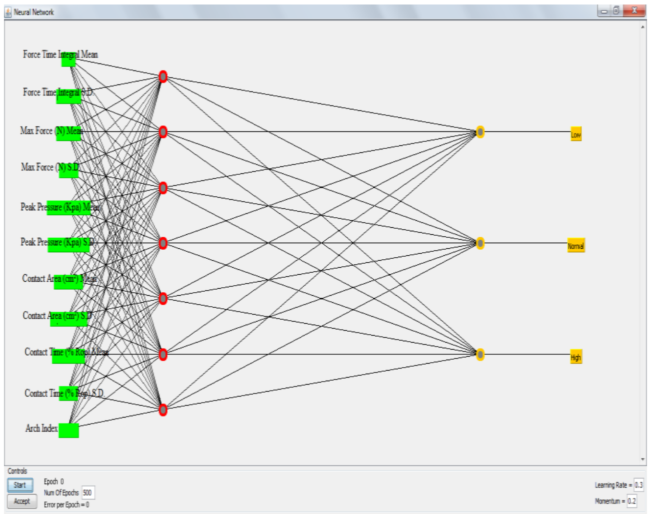

Figure 3 Neural Network for 12 Attribute Classified to Get Three Different Grade of Foot.

- Decision Tree using weka classifiers trees J48 figure 4 present decision tree configuration.

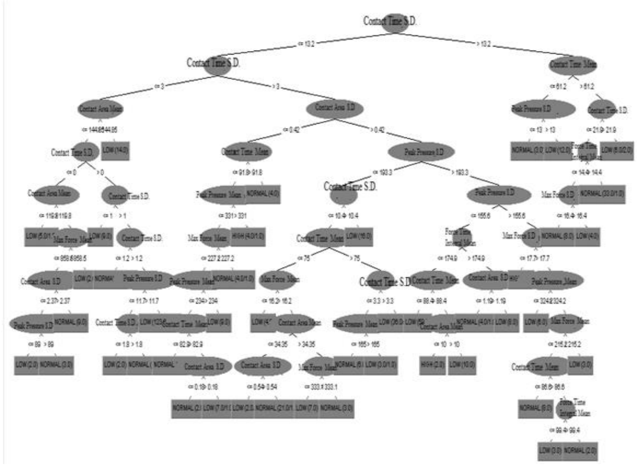

Figure 4 Decision Tree Example for Classify Data.

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We will apply the sensitivity test in order to determine the sensitivity of each classifier in order to distinguish between foot categories. Sensitivity and specificity are widely used statistics to describe a diagnostic test. In particular, they are used to quantify how good and reliable a test is. Sensitivity evaluates how good the test is at detecting a positive disease. Specificity estimates how likely patients without disease can be correctly ruled out.

The ROC curve is a graphic representation of the relationship between both sensitivity and specificity, and it helps to decide the optimal model. Accuracy measures how correct a diagnostic test identifies and excludes a given condition. The accuracy of a diagnostic test can be determined from sensitivity and specificity with the presence of prevalence [51]. There are several terms that are commonly used along with the description of sensitivity, specificity and accuracy. They are true positive (TP), true negative (TN), false negative (FN), and false positive (FP).

Sensitivity = TP/ (TP + FN) (1)

Specificity = TN/ (TN + FP) (2)

Accuracey = (TP+TN)/ (TP+TN+FP+FN) (3)

Positive predicted value = TP/ (TP+FP) (4)

Negative predicted value = TN/ (TN+FN) (5)

False Discover Rate = FP/ (FP+TP) (6)

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. In the field of artificial intelligence, a confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class [51].

- Classification for 12 attribute.
  a. Neural Network function Multilayer Perceptron for patients left leg data, building model time taken is 80.55 sec, confusion matrix in table 1 followed by ROC Curve in figure 5 clarify model output numbers. Correctly Classified Instances is 452 with 92.4335 % and Incorrectly Classified Instances are 37 with 7.5665 %.

Table 1 Confusion Matrix represent left leg classification with Neural Network Model for 12 attribute.

Classified as	*LOW*	*NORMAL*	*HIGH*
LOW	*279*	*0*	*0*
NORMAL	*28*	*154*	*0*
HIGH	*0*	*9*	*19*

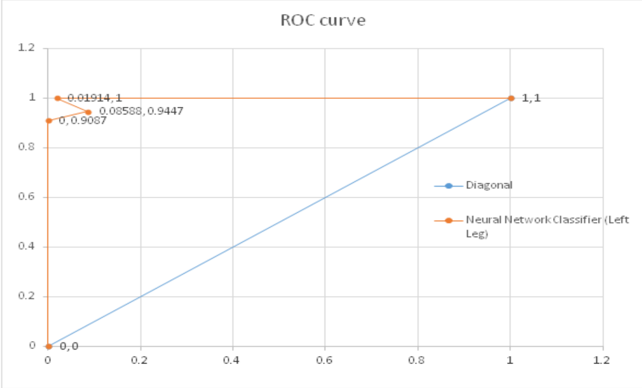

Figure 5 ROC curve of Neural Network classifier for Left Leg Data

The model has different pattern for each categories we have Low categories Sensitivity = 90.87%, Specificity = 100%, Accuracy= 94.27%, Positive predictive value = 100%, Negative predicted value = 86.66% and false rate Discover = 0%; Normal categories Sensitivity = 94.47%, Specificity = 91.41%, Accuracy= 92.43%, Positive predictive value = 84.61%, Negative predicted value = 97.06% and false rate Discover = 15.388%.; and High categories Sensitivity = 100%, Specificity = 98.08%, Accuracy= 98.159%, Positive predictive value = 84.615%, Negative predicted value = 97.06% and false rate Discover = 32.14%

  b. Decision Tree function J48 for patients left leg data, building model time taken is 0.02 seconds, confusion matrix in table 2 followed by ROC Curve in figure 6 clarify model output numbers. Correctly Classified Instances are 461 with 94.274 % and Incorrectly Classified Instances are 28 with 5.726 %

Table 2 Confusion Matrix represent left leg classification with Decision Tree Model for 12 attribute.

Classified as	**LOW**	**NORMAL**	**HIGH**
LOW	279	0	0
NORMAL	28	154	0
HIGH	0	9	19

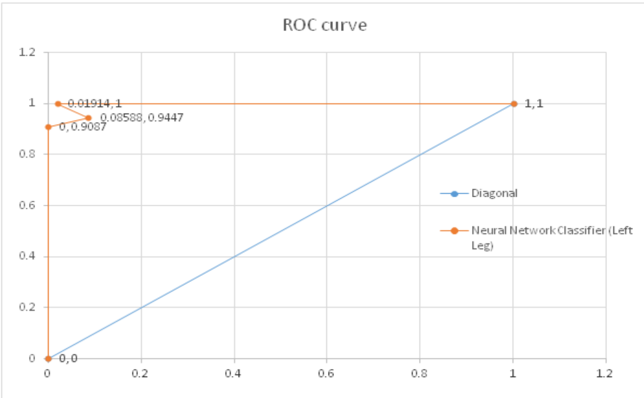

Figure 6 ROC curve of Neural Network classifier for Left Leg Data

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The model has different pattern for each categories we have Low categories Sensitivity = 90.87%, Specificity = 100%, Accuracy= 94.27%, Positive predictive value = 100%, Negative predicted value = 86.66% and false rate Discover = 0%; Normal categories Sensitivity = 94.47%, Specificity = 91.41%, Accuracy= 92.43%, Positive predictive value = 84.61%, Negative predicted value = 97.06% and false rate Discover = 15.388%.; and High categories Sensitivity = 100%, Specificity = 98.08%, Accuracy= 98.159%, Positive predictive value = 84.615%, Negative predicted value = 97.06% and false rate Discover = 32.14%

c. Decision Tree function J48 for patients left leg data, building model time taken is 0.02 seconds, confusion matrix in table 2 followed by ROC Curve in figure 6 clarify model output numbers. Correctly Classified Instances are 461 with 94.274 % and Incorrectly Classified Instances are 28 with 5.726 %

Table 3 Confusion Matrix represent left leg classification with Decision Tree Model for 12 attribute.

classified as	LOW	NORMAL	HIGH
LOW	279	0	0
NORMAL	28	154	0
HIGH	0	0	28

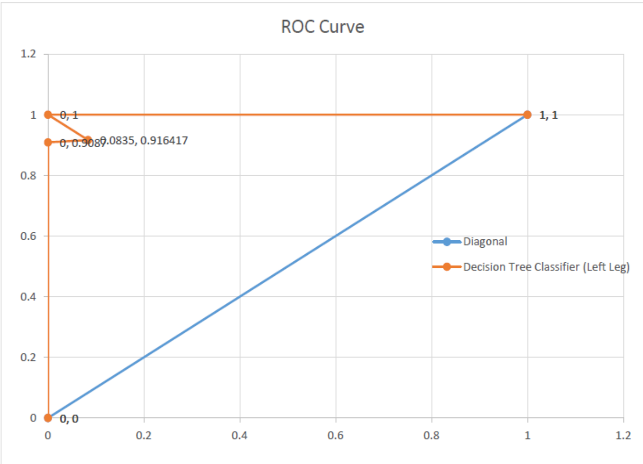

Figure 7 ROC curve of Decision Tree classifier for Left Leg Data

The model has different pattern for each categories we have Low with Sensitivity = 90.87%, Specificity = 100%, Accuracy= 94.27%, Positive predictive value = 100%, Negative predicted value = 86.66% and false rate Discover = 0%; Normal with Sensitivity = 100%, Specificity = 91.64%, Accuracy= 96.93%, Positive predictive value = 94.27%, Negative predicted value = 84.615% and false rate Discover = 15.38%. And High categories Sensitivity = 100%, Specificity = 100%, Accuracy= 100%, Positive predictive value = 100%, Negative predicted value = 100% and false rate Discover = 0%.

d. Neural Network function Multilayer Perceptron for patients Right leg data, building model time taken is 0.63 sec, confusion matrix in table 3 followed by ROC Curve in figure 7 clarify model output numbers. Correctly Classified Instances is 475 with 96.9388 % and Incorrectly Classified Instances are 15 with 3.0612 %.

Table 4 Confusion Matrix represent Right leg classification with Neural Network Model for 12 attribute.

classified as	LOW	NORMAL	HIGH
LOW	308	0	0
NORMAL	1	167	0
HIGH	0	14	0

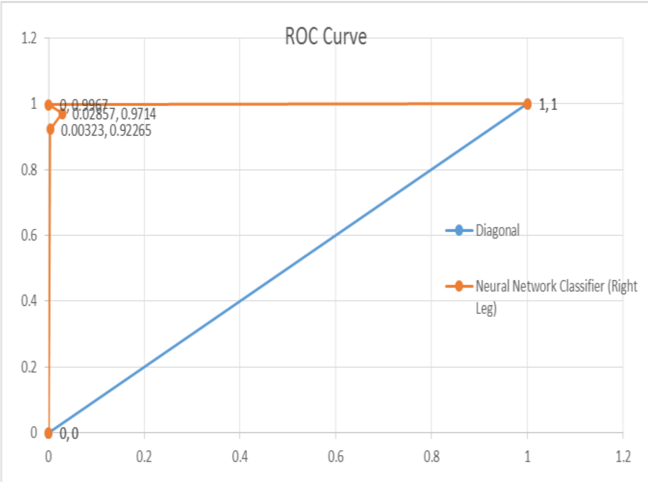

Figure 8 ROC curve of Neural Network classifier for Right Leg Data

The model has different pattern for each categories we have. Low information Sensitivity = 99.67%, Specificity = 100%, Accuracy= 99.79%, Positive predictive value = 100%, Negative predicted value = 99% and false rate Discover = 0%, Normal with Sensitivity = 92.265%, Specificity = 99.67%, Accuracy= 96.93%, Positive predictive value = 99.4%, Negative predicted value = 9565% and false rate Discover = 0.59%. And High data Sensitivity = 0%, Specificity = 97.14%, Accuracy= 100%, Positive predictive value = 0%, Negative predicted value = 100% and false rate Discover = 100%.

e. Decision Tree function J48 for patients Right leg data, building model time taken is 0.03 seconds, confusion matrix in table 4 followed by ROC Curve in figure 8 clarify model output numbers. Correctly Classified Instances are with 100 % and Incorrectly Classified Instances are 0 %

Table 5 Confusion Matrix represent Right leg classification with Decision Tree Model for 12 attribute

classified as	LOW	NORMAL	HIGH
LOW	308	0	0
NORMAL	0	168	0
HIGH	0	0	14

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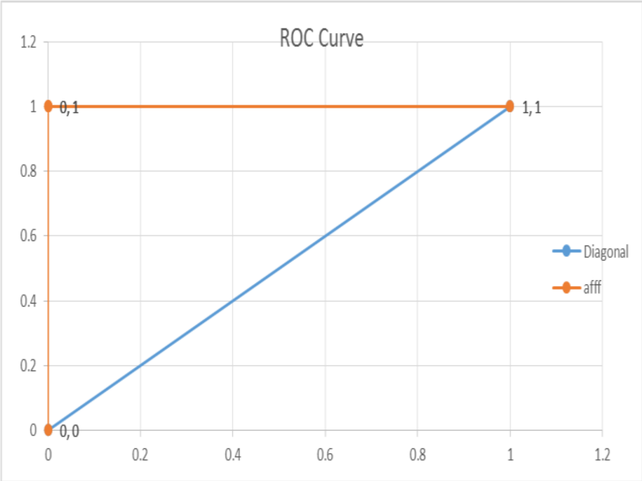

Figure 9 ROC curve of Decision Tree classifier for Right Leg Data

The model has different pattern for each categories we have. Low information data Sensitivity = 100%, Specificity = 100%, Accuracy= 100%, Positive predictive value = 100%, Negative predicted value = 100% and false rate Discover = 0%; Normal Sensitivity = 100%, Specificity = 100%, Accuracy= 100%, Positive predictive value = 100%, Negative predicted value = 100% and false rate Discover = 0%. And High Sensitivity = 100%, Specificity = 100%, Accuracy= 100%, Positive predictive value = 100%, Negative predicted value = 100% and false rate Discover = 0%. Applying both model of pattern recognition Neural Network and Decision Tree to our data which consist from 12 attribute shows that decision tree gives an impressive result in identifying each category of the foot classification for both legs information. These result encourage us to find out the importance of arch index attribute and test if it has influence to the degree of classification or not. So we will exclude this attribute from our data and repeat the previous test.

- Classification for 11 attribute.

We Repeat the previous test but without identification of Arch Index information and observe deviation in the classifier result.

f. Neural Network function Multilayer Perceptron for patients left leg data, building model time taken is 0.45 sec, confusion matrix in table 5 clarify model output numbers. Correctly Classified Instances is 261with 53.3742 % and Incorrectly Classified Instances are 228 with 46.6258 %

Table 6 Confusion Matrix represent left leg classification with Neural network Model for 11 attribute.

classified as	LOW	NORMAL	HIGH
LOW	223	54	2
NORMAL	144	37	1
HIGH	19	8	1

g. Decision Tree function J48 for patients left leg data, building model time taken is 0.03 seconds, confusion matrix in table 6 clarify model output numbers. Correctly Classified Instances are 317 with 64.8262 % and Incorrectly Classified Instances are 172 with 35.1738 %

Table 7 Confusion Matrix represent left leg classification with Decision Tree Model for 11 attribute.

classified as	LOW	NORMAL	HIGH
LOW	218	57	4
NORMAL	83	96	3
HIGH	15	10	3

h. Neural Network function Multilayer Perceptron for patients Right leg data, building model time taken is 0.61 sec, confusion matrix in table 7 clarify model output numbers. Correctly Classified Instances is 336 with 68.5714 % and Incorrectly Classified Instances are 154 with 31.4286 %

Table 8 Confusion Matrix represent Right leg classification with Neural Network Model for 11 attribute

Classified as	LOW	NORMAL	HIGH
LOW	294	14	0
NORMAL	126	42	0
HIGH	12	2	0

i. Decision Tree function J48 for patients Right leg data, building model time taken is 0.03 seconds, confusion matrix in table 8 clarify model output numbers. Correctly Classified Instances are 363 with 74.0816 % and Incorrectly Classified Instances are 127 with 25.9184 %

Table 9 Confusion Matrix represent Right leg classification with Decision Tree Model for 11 attribute.

classified as	LOW	NORMAL	HIGH
LOW	279	28	1
NORMAL	82	81	5
HIGH	8	3	3

The results shows that Decision tree classifier still is the best choice in classifying the foot categories but there are a big drop for accuracy of each classifier by 25% to 30% in both Decision Tree even in Neural Network. This drop give arch index importance indication, this also prove that arch index is critical attribute and its affect the classification.

IV. CONCLUSION

Using arch index values obtained from digital photography using a photo-box to classify foot type as high arched, normal, or low-arched, based on defined ranges, proved to be a reliable method that led to excellent agreement between raters. Classifying feet to subdivide sample populations may help differentiate mobility, gait, or treatment effects among foot types in future research and clinical practice. What is already known on this topic a variety of foot measures, including arch index,

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Have been shown to be reliable and related to other static measures. Yet static measures have not correlated strongly with motion in gait, in part because some study samples have included mixed foot types.

What this study adds Classification of foot type based on arch index values rather than clinical judgments demonstrated excellent agreement. Standardized foot-type classifications allow sample subdivisions that may further our understanding of different mobility characteristics or treatment effects among high-arched, normal, and low-arched foot types in future research and clinical practice.

The approach to automatic human gait analysis demonstrates that decision trees are a powerful technique which could be successfully applied in biomechanics. A decision tree could manage vector of a many numbers of real parameters as an input and point the values which are main discriminators. The advantage of employing decision trees is the easiness of interpretation so it could be applied successfully to clinics. Moreover, decision trees could improve the understanding of human gait phenomena and could lead to the selection of more suitable methods for human gait improvement. It is really important that the same procedure could be used in any data describing a human activity independent of the clinical problem.

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Biography

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Publications:

- Saleh S. Altayyar. "The Importance of Plantar Pressure Measurements and Appropriate Footwear for Diabetic Patients" Journal of Analytical & Pharmaceutical Research. Volume 3 Issue 3. October18, 2016
- Saleh S. Altayyar. "Medical Devices and Patient Safety" Journal of Analytical & Pharmaceutical Research. Volume 2 Issue 5. July 5, 2016
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- S.Tayyar, P.S.Weinhold, R.A.Butler, J.C.Woodara, L.D Zaadiackas, K.R.ST.JOHN, J.M.Bledsoe, J.A.Gilbert. **"Computer Simulation of** Trabecular Bone Remodeling Using A Simplified Structural Model". Bone Vol. 25, No.6 Dec.1999 733-739.

Invited lectures & conference proceedings:

- **Saleh S. Altayyar. "Impact of Physical Activities (Walking) On the Plantar Pressure of Diabetic And Non-Diabetic Subjects" Accepted for presentation at** ESM 2016. Lisbon in July 27-30.
- Saleh S. Altayyar, Medical Devices & Patient Safety. 24th World Congress on Medical Physics & Biomedical Engineering (IUPESM 2015). 7-12 June 2015. Toronto Canada.
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Achievements:

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- Established a state of the art medical devices regulatory system in Saudi Arabia that achieved the respect and recognition of the international regulatory arena.
- Chair, Asian Harmonization Working Party (AHWP), an organization of more than 23 member economies working toward harmonization of medical devices in Asia, Africa, Middle East, and Latin America for three years,
- Chair, Riyadh Biomedical Engineering Club.
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Board Memberships:

- Board of Saudi Standard, Metrology and Quality Organization (SASO).
- The Scientific Board for Applied Medical Sciences (SBAMS), Saudi Commission for Health Specialties.
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- Member of the advisory board of many colleges and universities in Saudi Arabia.

Refereed and co-authored innovation in healthcare, diabetic foot, and clinical engineering management.

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- Participate in "**Automatic Segmentation of Acute Leukemia Cells International"** Journal of Computer Applications (0975 – 8887) Volume 133 – No.10, January 2016.
- Participate in **"Decision support system in lymphoma classification",** Current Medical Imaging Reviews Journal, Volume. 12, No. 4, pp. 1-10, 2016.
- Participate in **"A Decision Support System for Acute Leukemia Classification Based on Digital Microscopic Images",** Alexandria Engineering journal AEJ, 2017 in publication.
- Participate in **"Classifiers comparison in Acute Myeloid Leukemia Classification of Digital Microscopic Images",** Journal of Engineering and Applied Science, 2017 in publication.
- Participated in 3D Medical Printing Special Session in BUILDING HEALTHCARE MIDDLE EAST Exhibition &Conference at 30th May 2016.
- Participated in Medical Equipment Planning in BUILDING HEALTHCARE MIDDLE EAST Exhibition &Conference at 30th, 31st May 2016.
- Participated in Healthcare Management Conference in BUILDING HEALTHCARE MIDDLE EAST Exhibition &Conference at 1st June 2016.
- Participated in Lab Management & Mega Project Investment Session in BUILDING HEALTHCARE MIDDLE EAST Exhibition &Conference at 1st June 2016.
- Participated in PROMOTING THE QUALITY CULTURE: NEAR MISS MONITORING AS A HARBINGER OF BIGGER ISSUES Session in BUILDING HEALTHCARE MIDDLE EAST Exhibition &Conference at 1st June 2016.
- Attend ICME Workshop "The Importance of Design in Creating a Functional and Efficient Hospital" – Building Healthcare 2016, Dubai, 30th May 2016
- Attend ICME Workshop "The role of project management and site supervision in delivering a project on time and budget" – Building Healthcare 2016, Dubai, 31st May 2016
- Attend in CIBEC the 6th Cairo International Biomedical Engineering Conference Dec 20-22, 2012.
- Attend the 6th Cairo International Biomedical Engineering Conference workshop entitled CLINICAL ENGINEER on December 2012.
- Attend workshop and conference about OLYMPUS technologies and products of telepathology in August 2009.
- Attend the 2nd Oncology Conference on "Lymphoma Updating, Diagnosis & Management" at International Medical Center from 24th-25th December 2008.
- Attend First construction of telepathological experiment at International Medical Center July 2007.
- Attend in the 3rd Cairo International Biomedical Engineering Conference and workshops 2006:
- Visualization. Medical Equipment Specifications. Attend workshop on Electron-Microscope at Central Medical Labs of Military of Defense 2006.
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