DIAGNOSE FLAT FOOT FROM FOOT PRINT IMAGE USING COMBINE INDEXES BASED ON NEURAL NETWORK

WANLOP ARUNTAMMANAK

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……………………………………
Mr. Wanlop Aruntammanak
Candidate

……………………………………
Asst. Prof. Supaporn Kiattisin,
Ph.D. (Electrical and Computer Engineering)
Major advisor

……………………………………
Asst. Prof. Adison Leelasatitham,
Ph.D. (Electrical Engineering)
Co-advisor

……………………………………
Lect. Waranyu Wongseree,
Ph.D. (Electrical Engineering)
Co-advisor

……………………………………
Prof. Banchong Mahaisavariya,
M.D., Dip Thai Board of Orthopedics
Dean
Faculty of Graduate Studies
Mahidol University

……………………………………
Asst. Prof. Supaporn Kiattisin,
Ph.D. (Electrical and Computer Engineering)
Program Director
Master of Science Program in Technology of Information System Management
Faculty of Engineering
Mahidol University

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on
March 10, 2014

……………………………………
Mr. Wanlop Aruntammanak
Candidate

……………………………………
Lect. Sotarat Thammaboosadee,
Ph.D. (Information Technology)
Chair

……………………………………
Lect. Surapong Pongyupinpanich,
Ph.D. (Electronic and Informatic Engineering)
Member

……………………………………
Asst. Prof. Supaporn Kiattisin,
Ph.D. (Electrical and Computer Engineering)
Member

……………………………………
Lect. Waranyu Wongseree,
Ph.D. (Electrical Engineering)
Member

……………………………………
Asst. Prof. Adison Leelasantitham,
Ph.D. (Electrical Engineering)
Member

……………………………………
Prof. Banchong Mahaisavariya,
M.D., Dip Thai Board of Orthopedics
Dean
Faculty of Graduate Studies
Mahidol University

……………………………………
Lect. Worawit Isarangkul
M.S. (Technical Management)
Dean
Faculty of Engineering
Mahidol university

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Wanlop Aruntammanak

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WANLOP ARUNTAMMANAK 5438247 EGTI/M

M.Sc. (TECHNOLOGY OF INFORMATION SYSTEM MANAGEMENT)

THESIS ADVISORY COMMITTEE: SUPAPORN KIATTISIN, Ph.D., ADISON LEELASATITHEM, Ph.D., WARANYU WONGSEREE, Ph.D.

ABSTACT

Until now, there have been many methods used to diagnose of flatfoot. Each method uses different indicators, e.g. the Staheli arch index, Clark's angle, the Chippaux-Smirak index. However, the results from such indicators vary for each method. Therefore, this paper proposes a classification of flatfoot by combining multiple indicators with the neural network process. It can improve the accuracy of classification more than the use of only one indicator. This study used 132 images of footprints (left and right) consisting of a normal foot or flatfoot. The experimental results using a combination of indicators show that the result is up to 93% more accurate than using a single index, i.e., the Staheli arch index at 43%, Clark's angle at 68%, the Chippaux-Smirak index at 80%. It can more precisely diagnose flatfoot.

KEY WORDS: FLATFOOT/ FOOT PRINT/ COMBINE INDEX/ NEURAL NETWORK/ STAHELI ARCH INDEX/ CLARK'S ANGLE/ CHIPPAUX-SMIRAK INDEX

58 pages

การวินิจฉัยโรคเท้าแบนจากภาพรอยพิมพ์ฝ่าเท้า โดยการผสมผสานดัชนีชี้วัดบนโครงข่ายประสาทเทียม
DIAGNOSE FLAT FOOT FROM FOOT PRINT IMAGE USING COMBINE INDEXES BASED ON NEURAL NETWORK

วัลลภ อรุณธรรมนาค 5438247 EGTI/M

วท.ม. (เทคโนโลยีการจัดการระบบสารสนเทศ)

คณะกรรมการที่ปรึกษาวิทยานิพนธ์ : สุภาภรณ์ เกียรติสิน, Ph.D., อดิศร ลีลาสันติธรรม, Ph.D., วรัญญู วงษ์เสรี, Ph.D.

บทคัดย่อ

ปกติการวินิจฉัยโรคเท้าแบนมีหลายวิธี ซึ่งแต่ละวิธีใช้ตัวชี้วัดของวิธีต่างกัน บางครั้งในการวินิจฉัยของหลายวิธีมีคำตอบของการวินิจฉัยต่างกัน ดังนั้นงานวิจัยนี้จึงได้เสนอวิธีการจำแนกโรคเท้าแบน โดยเป็นการผสมผสานดัชนีชี้วัดหลายตัวร่วมกัน ด้วยกระบวนการโครงข่ายประสาทเทียม (Neural network) ซึ่งผลการจำแนกนั้นมีความแม่นยำกว่าการใช้ดัชนีชี้วัดเพียงตัวเดียว ในจำนวน 132 ภาพรอยพิมพ์ฝ่าเท้า ประกอบด้วยเท้าซ้ายและเท้าขวาของบุคคลที่มีลักษณะเท้าที่ปกติ และลักษณะเท้าแบน ซึ่งได้ผลการทดลองโดยวิธีการผสมผสานดัชนีชี้วัดมีผลลัพธ์ความแม่นยำร้อยละ 93 ซึ่งมากกว่าดัชนีชี้วัดแบบเดี่ยว คือ Staheli arch index ร้อยละ 43, Clark’s angle ร้อยละ 68, Chippaux-Smirak index ร้อยละ 80 ทำให้สามารถวินิจฉัยโรคเท้าแบนได้แม่นยำยิ่งขึ้น

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CHAPTER I
INTRODUCTION

1.1 Background and significance of the problems

Foot is the heaviest organ in the body commissioned. The weight of the body to move in to take over and become the nerve center of the body. So what do the feet that would affect other organs as well as foot care is very important part of human life. At present, most individuals do not realize they have a foot wrong. May be caused by congenital or birth. Changes in childhood which may be a problem with the foot. And can be caused by wearing the wrong shape.

Flat foot may be the result of hereditary caused by a torn ankle ligament or the diseases related to the brain or spinal cord. However, most patients are not aware as a result of suffering a foot ligament inflammation (Plantar Fasciitis and Corn). There are no more patients who go to see a doctor to treat them because most people will pay attention to take care of their foot less than as expected. A regular basis of the disease is characterized by weight while standing, the talon is lost. But while sitting or sleeping, talon is back to normal. If you would like to see a clear talon, notice by standing on tiptoe will make it clearer.

The medical diagnosis is to identify the disease of flat foot. There are many ways such as inspection, ultrasonography and analysis of the footprints. In this research, sample images (footprint) are from the basic medical device (Podoscope) used for storing the data. The result is a digital image which each variable is measured by the size of the individual indicators in order to test the accuracy of the individual indicators. By measuring the plane f 1st Metatarsal head and Medial Calcaneal, perpendicular from the plane is to measure the widest of the talon. A line shows both the muscle of mid foot and the muscle of hide foot, 5th Metatarsal head and Lateral Calcaneal. It also shows the muscle of fore foot and the arches degree of the foot. This research will analyze the data by using mathematical calculations. Finally, the results show that dataset has been characterized as a normal foot or flat foot.

The results of combining three indicators indicate that are accurate and precise as follows. Firstly, Staheli arch index is a relative ratio of midfoot and forefoot. Secondly, Clark's angle is a measure of the degree of arch (Arch). Thirdly, Chippaux-Smirak index is a relative ratio the hindfoot and midfoot. Each index is specificity in the measurement and interpretation which are different to interpreter the meaning. Process variable is the indicator calculated mathematically combined to provide the results that are more accurate. Such the three mathematical models are different kinds to provide more accurate results using an integration of them which is used to determine more accuracy than measuring with a single index.

1.2 Research objectives

1.2.1 Study of treatment physician-based diagnosis.

1.2.2 To improve the way to find the disease by flat feet using the footprint.

1.2.3 To create the model for abnormalities classification of foot.

1.3 Delimitation of the research

1.3.1 Use footprint from 66 persons that have flat feet and normal feet.

1.3.2 Use Staheli arch index, Clark's angle and Chippaux-Smirak index in this thesis.

1.3.3 Use combine the result to classify by neural network, C4.5 decision tree, Logistic regression and Bayesian.

1.3.4 Compare result from classify and choose the best result.

1.4 Expected outcomes and benefits

1.4.1 Learning the characteristics of the flat feet.

1.4.2 Can use the result of the thesis to be tool to help diagnosis of flat feet with accuracy and efficiency.

1.4.3 Engineering knowledge to practical application

1.4.4 To publish the knowledge that obtained from analysis and creating a model to the researchers in related fields.

CHAPTER II
REVIEW OF RELATED LITERATURE AND RESEARCH

2.1 Foot

Figure 2.1 Feet

The foot (plural feet) is an anatomical structure found in many vertebrates. It is the terminal portion of a limb which bears weight and allows locomotion. In many animals with feet, the foot is a separate organ at the terminal part of the leg made up of one or more segments or bones, generally including claws or nails.

2.1.1 Structure

The human foot and ankle is a strong and complex mechanical structure containing exactly 26 bones, 33 joints (20 of which are actively articulated), and more than a hundred muscles, tendons, and ligaments.

An anthropometric study of 1197 North American adult Caucasian males (mean age 35.5 years) found that a man's foot length was 26.3 cm with a standard deviation of 1.2 cm.

The foot can be subdivided into the hind foot, the mid foot, and the fore foot:

The hind foot is composed of the talus (or ankle bone) and the calcaneus (or heel bone). The two long bones of the lower leg, the tibia and fibula, are connected to the top of the talus to form the ankle. Connected to the talus at the subtalar joint, the calcaneus, the largest bone of the foot, is cushioned inferiorly by a layer of fat.

The five irregular bones of the mid foot, the cuboid, navicular, and three cuneiform bones, form the arches of the foot which serves as a shock absorber. The mid foot is connected to the hind- and fore-foot by muscles and the plantar fascia.

The fore foot is composed of five toes and the corresponding five proximal long bones forming the metatarsus. Similar to the fingers of the hand, the bones of the toes are called phalanges and the big toe has two phalanges while the other four toes have three phalanges. The joints between the phalanges are called interphalangeal and those between the metatarsus and phalanges are called metatarsophalangeal (MTP).

Both the mid foot and forefoot constitute the dorsum (the area facing upwards while standing) and the planum (the area facing downwards while standing).

The instep is the arched part of the top of the foot between the toes and the ankle.

Figure 2.2 Medial aspect And Lateral aspect of Skeleton of foot

2.1.2 Arches of the foot

The arches of the foot are formed by the tarsal and metatarsal bones and, strengthened by ligaments and tendons, allows the foot to support the weight of the body in the erect posture with the least weight.

The arches are categorized as transverse and longitudinal arches of the foot.

The longitudinal arches of the foot can be broken down into several smaller arches, medial and lateral. In collapse of longitudinal arches, there is a resulting flat feet which causes problems with stability and pain on walking long distances.

2.1.2.1 Medial arch

The medial arch is higher than the lateral longitudinal arch. It is made up by the calcaneus, the talus, the navicular, the three cuneiforms, and the first, second, and third metatarsals.

Its summit is at the superior articular surface of the talus, and its two extremities or piers, on which it rests in standing, are the tuberosity on the plantar surface of the calcaneus posteriorly and the heads of the first, second, and third metatarsal bones anteriorly. The chief characteristic of this arch is its elasticity, due to its height and to the number of small joints between its component parts.

Its weakest part (i.e., the part most liable to yield from overpressure) is the joint between the talus and navicular, but this portion is braced by the plantar calcaneonavicular ligament a.k.a. spring ligament, which is elastic and is thus able to quickly restore the arch to its pristine condition when the disturbing force is removed. The ligament is strengthened medially by blending with the deltoid ligament of the ankle-joint, and is supported inferiorly by the tendon of the Tibialis posterior, which is spread out in a fanshaped insertion and prevents undue tension of the ligament or such an amount of stretching as would permanently elongate it.

The arch is further supported by the plantar aponeurosis, by the small muscles in the sole of the foot, by the tendons of the Tibialis anterior and posterior and Peronæus longus, and by the ligaments of all the articulations involved.

2.1.2.2 Lateral arch

The lateral arch is composed of the calcaneus, the cuboid, and the fourth and fifth metatarsals.

Two notable features of this arch are its solidity and its slight elevation. Two strong ligaments, the long plantar and the plantar calcaneocuboid, together with the Extensor tendons and the short muscles of the little toe, preserve its integrity.

2.1.2.3 Fundamental longitudinal arch

While these medial and lateral arches may be readily demonstrated as the component antero-posterior arches of the foot, yet the fundamental longitudinal arch is contributed to by both, and consists of the calcaneus, cuboid, third cuneiform, and third metatarsal: all the other bones of the foot may be removed without destroying this arch.

The human foot has two longitudinal arches and a transverse arch maintained by the interlocking shapes of the foot bones, strong ligaments, and pulling muscles during activity. The slight mobility of these arches when weight is applied to and removed from the foot makes walking and running more economical in terms of energy. As can be examined in a footprint, the medial longitudinal arch curves above the ground. This arch stretches from the heel bone over the "keystone" ankle bone to the three medial metatarsals. In contrast, the lateral longitudinal arch is very low. With the cuboid serving as its keystone, it redistributes part of the weight to the calcaneus and the distal end of the fifth metatarsal. The two longitudinal arches serve as pillars for the transverse arch which run obliquely across the tarsometatarsal joints. Excessive strain on the tendons and ligaments of the feet can result in fallen arches or flat feet.

2.2 Flat feet

Flat feet (also called pes planus or fallen arches) is a postural deformity in which the arch of the foot collapses, with the entire sole of the foot coming into complete or near-complete contact with the ground. In some individuals (an estimated 20–30% of the general population) the arch simply never develops in one foot (unilaterally) or both feet (bilaterally).

There is a functional relationship between the structure of the arch of the foot and the biomechanics of the lower leg. The arch provides an elastic, springy connection between the forefoot and the hindfoot. This association safeguards that a majority of the forces incurred during weight bearing of the foot can be dissipated before the force reaches the long bones of the leg and thigh.

In pes planus, the head of the talus bone is displaced medially and distal from the navicular. As a result, the spring ligament and the tendon of the tibialis posterior muscle are stretched, so much so that the individual with pes planus loses the function of the medial longitudinal arch (MLA). If the MLA is absent or nonfunctional in both the seated and standing positions, the individuals has “rigid” flatfoot. If the MLA is present and function while the individual is sitting or standing up on their toes, but this arch disappear when a foot-flat stance, the individual has “supple” flatfoot. This latter condition can be correctable with well-fitting arch supports.

Three studies (see citations below in military section) of military recruits have shown no evidence of later increased injury, or foot problems, due to flat feet, in a population of people who reach military service age without prior foot problems. However, these studies cannot be used to judge possible future damage from this condition when diagnosed at younger ages. They also cannot be applied to persons whose flat feet are associated with foot symptoms, or certain symptoms in other parts of the body (such as the leg or back) possibly referable to the foot.

2.2.1 Flat feet in adults

Figure 2.3 Flat foot

Flat feet can also develop as an adult ("adult acquired flatfoot") due to injury, illness, unusual or prolonged stress to the foot, faulty biomechanics, or as part of the normal aging process. This is most common in women over 40 years of age. Known risk factors include obesity, hypertension and diabetes. Flat feet can also occur in pregnant women as a result of temporary changes, due to increased elastin (elasticity) during pregnancy. However, if developed by adulthood, flat feet generally remain flat permanently.

If a youth or adult appears flatfooted while standing in a full weight bearing position, but an arch appears when the person dorsiflexes (stands on heel or pulls the toes back with the rest of the foot flat on the floor), this condition is called flexible flatfoot. This is not a true collapsed arch, as the medial longitudinal arch is still present and the Windlass mechanism still operates; this presentation is actually due to excessive pronation of the foot (rolling inwards), although the term 'flat foot' is still applicable as it is a somewhat generic term. Muscular training of the feet, while generally helpful, will usually not result in increased arch height in adults, because the muscles in the human foot are so short that exercise will generally not make much difference, regardless of the variety or amount of exercise. However, as long as the foot is still growing, it may be possible that a lasting arch can be created.

2.2.1.1 Pathophysiology

Research has shown that tendon specimens from people who suffer from adult acquired flat feet show evidence of increased activity of proteolytic enzymes. These enzymes can break down the constituents of the involved tendons and cause the foot arch to fall. In the future, these enzymes may become targets for new drug therapies.

2.2.1.2 Diagnosis

Many medical professionals can diagnose a flat foot by examining the patient standing or just looking at them. On going up onto tip toe the deformity will correct when this is a flexible flat foot in a child with lax joints. Such correction is not seen in the adult with a rigid flat foot.

Figure 2.4 Footprint

An easy and traditional home diagnosis is the "wet footprint" test, performed by wetting the feet in water and then standing on a smooth, level surface such as smooth concrete or thin cardboard or heavy paper. Usually, the more the sole of the foot that makes contact (leaves a footprint), the flatter the foot. In more extreme cases, known as a kinked flatfoot, the entire inner edge of the footprint may actually bulge outward, where in a normal to high arch this part of the sole of the foot does not make contact with the ground at all.

2.2.1.3 Treatment

Most flexible flat feet are asymptomatic, and do not cause pain. In these cases, there is usually no cause for concern, and the condition may be considered a normal human variant. Flat feet were formerly a physical-health reason for service-rejection in many militaries. However, three military studies on asymptomatic adults (see section below), suggest that persons with asymptomatic flat feet are at least as tolerant of foot stress as the population with various grades of arch. Asymptomatic flat feet are no longer a service disqualification in the U.S. military.

In a study performed to analyze the activation of the tibialis posterior muscle in adults with pes planus, it was noted that the tendon of this muscle may be dysfunctional and lead to disabling weightbearing symptoms associated with acquired flat foot deformity. The results of the study indicated that while barefoot, subjects activated additional lower-leg muscles to complete an exercise that resisted foot adduction. However, when the same subjects performed the exercise while wearing arch supporting orthotics and shoes, the tibialis posterior was selectively activated. Such discoveries suggest that the use of shoes with properly fitting, arch-supporting orthics will enhance selective activation of the tibialis posterior muscle thus, acting as an adequate treatment for the undesirable symptoms of pes planus.

Rigid flatfoot, a condition where the sole of the foot is rigidly flat even when a person is not standing, often indicates a significant problem in the bones of the affected feet, and can cause pain in about a quarter of those affected. Other flatfoot-related conditions, such as various forms of tarsal coalition (two or more bones in the midfoot or hindfoot abnormally joined) or an accessory navicular (extra bone on the inner side of the foot) should be treated promptly, usually by the very early teen years, before a child's bone structure firms up permanently as a young adult. Both tarsal coalition and an accessory navicular can be confirmed by x-ray. Rheumatoid Arthritis can destroy tendons in the foot (or both feet) which can cause this condition, and untreated can result in deformity and early onset of Osteoarthritis of the joint. Such a condition can cause severe pain and considerably reduced ability to walk, even with orthoses. Ankle fusion is usually recommended.

Treatment of flat feet may also be appropriate if there is associated foot or lower leg pain, or if the condition affects the knees or the lower back. Treatment may include using Orthoses such as an arch support, foot gymnastics or other exercises as recommended by a podiatrist/orthotist or physical therapist. In cases of severe flat feet, orthoses should be used through a gradual process to lessen discomfort. Over several weeks, slightly more material is added to the orthosis to raise the arch. These small changes allow the foot structure to adjust gradually, as well as giving the patient time to acclimatise to the sensation of wearing orthoses. Once prescribed, orthoses are generally worn for the rest of the patient's life. In some cases, surgery can provide lasting relief, and even create an arch where none existed before; it should be considered a last resort, as it is usually very time consuming and costly.

2.3 Classify of flatfoot

Generally, three index is used for analyzing the footprints i.e. Staheli arch index (SI), Clarke's angle (CA) and Chippaux-Smirak index (CSI).

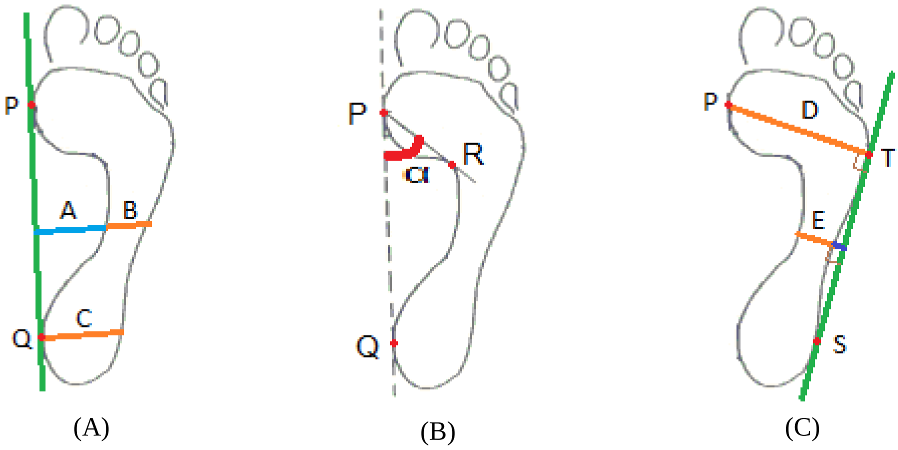

Figure 2.5 Footprint analysis: (A) Staheli arch index=B/C; (B)Clarke's angle=α; (C)Chippaux-Smirak index=E/Dx100

2.3.1 Staheli arch index

Staheli arch index is used to compare the ratio of midfoot and forefoot. Line B is the narrowest of midfoot and line C is the widest of hindfoot. The perpendicular to the plane of the line PQ is the 1st Metatarsal head and the Medial Calcaneal. The index of the papers has been reported for a case of the flat foot in the condition of higher than 0.9 and the normal foot of lower than 0.89. In this case study, if the value is less than 0.8125, it will be a normal foot whilst if the value is higher than 0.8125, it will be a flat foot.

2.3.2 Clarke's angle

Clarke's angle is the corner to find a different foot. The angle is a result of the third point where P is the 1st Metatarsal head at 1, Q is the Medial Calcaneal, and R is the narrowest of midfoot with P as vertex angle. The index of the papers has been reported for a case of the flat foot in the condition of lower than 41o and the normal foot to be higher than 42o. In this case study, if the value is less than 46o, it will be a flat foot whilst if the value is higher than 46o, it will be a normal foot.

2.3.3 Chippaux-Smirak index

Chippaux-Smirak index compared to the percentage of hindfoot and midfoot. Line E is narrowest of midfoot and line D is the widest of forefoot. Must be perpendicular to the line. TS Lines plane of the 5th Metatarsal head and the Lateral Calcaneal on the outside. The index of the papers have been reported for a case of the flat foot in the condition of higher than 40% and the normal foot to be lower than 39.9%. In this case study, if the value is less than 37.5, it will be a normal foot whilst if the value is higher than 37.5, it will be a flat foot.

2.4 Algorithm for create modal

2.4.1 Neural network

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

2.4.1.1 Activation function

If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model (see perceptron). What makes a multilayer perceptron different is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain. This function is modeled in several ways.

The two main activation functions used in current applications are both sigmoids, and are described by

$$\emptyset(y_i) = \tanh(v_i) \ and \ \emptyset\,(v_i) = (\,1 + \ e^{-v_i})^{-1}$$

In which the former function is a hyperbolic tangent which ranges from -1 to 1, and the latter, the logistic function, is similar in shape but ranges from 0 to 1. Here y_i is the output of the i^{th} node (neuron) and v_i is the weighted sum of the input synapses. Alternative activation functions have been proposed, including the rectifier and softplus functions. More specialized activation functions include radial basis functions which are used in another class of supervised neural network models.

2.4.1.2 Layers

The multilayer perceptron consists of three or more layers (an input and an output layer with one or more hidden layers) of nonlinearly-activating nodes. Each node in one layer connects with a certain weight w_{ij} to every node in the following layer. Some people do not include the input layer when counting the number of layers and there is disagreement about whether w_{ij} should be interpreted as the weight from i to j or the other way around.

2.4.1.3 Learning through backpropagation

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron.

We represent the error in output node j in the n^{th} data point by $e_j(n) = d_j(n) - y_i(n)$, where d is the target value and y is the value produced by the perceptron. We then make corrections to the weights of the nodes based on those corrections which minimize the error in the entire output, given by

$$\varepsilon(n) = \frac{1}{2}\sum_{j} e_j^2(n)$$

Using gradient descent, we find our change in each weight to be

$$\Delta w_{ji}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial v_i(n)} y_i(n)$$

Where y_i is the output of the previous neuron and η is the learning rate, which is carefully selected to ensure that the weights converge to a response fast enough, without producing oscillations. In programming applications, this parameter typically ranges from 0.2 to 0.8.

The derivative to be calculated depends on the induced local field v_j, which itself varies. It is easy to prove that for an output node this derivative can be simplified to

$$-\frac{\partial \varepsilon(n)}{\partial v_j(n)} = e_j(n)\emptyset'(v_j(n))$$

Where $\emptyset'$ is the derivative of the activation function described above, which itself does not vary. The analysis is more difficult for the change in weights to a hidden node, but it can be shown that the relevant derivative is

$$-\frac{\partial \varepsilon(n)}{\partial v_j(n)} = \emptyset'\left(v_j(n)\right) \sum_k -\frac{\partial \varepsilon(n)}{\partial v_k(n)} w_{kj}(n)$$

This depends on the change in weights of the k^{th} nodes, which represent the output layer. So to change the hidden layer weights, we must first change the output layer weights according to the derivative of the activation function, and so this algorithm represents a backpropagation of the activation function.

2.4.2 C4.5 decision tree

Algorithm J48 decision tree or C4.5 algorithm is used to create a decision tree developed by Ross Quinlan. C.45 extension that is added to the algorithm ID3 decision tree. This structure could be used for C4.5 classification and this reason it is called frequently for the statistical classifier in the C4.5 algorithm to build decision trees from the same training data ID3 principle of information entropy. The C4.5 uses an accuracy of each list of attributes data for decision to split the data into sub-groups which will review the C4.5 normalized information gain (the difference in entropy). Results from the selected distribution list for the group data by feature with the highest normalized information gain is one of a decision.

Decision tree is created by done recursively in splitting the data set on the independent variables. Each possible split is evaluated by calculating the resulting purity gain if it was used to divide the data set D into the new subsets {D_1,...,D_n}. The purity gain Δ is the difference in impurity between the original data set and the subsets as defined as follow

$$\Delta = I(D) - \sum_{i=1}^{n} P(D_i) \cdot I(D_i)$$

Where I (·) is impurity measure of a given node and P(D_i) is the proportion of D that is placed in D_i. The split resulting in the highest purity gain is selected, and repeat recursively for each subset in this split.

Different decision tree algorithms apply different impurity measures. C4.5 uses entropy as impurity measures as follow.

$$Entropy(t) = -\sum_{i=0}^{c-1} p(i|t) log_2 p(i|t)$$

Where, c is the number of classes and $p(i|t)$ is the the fraction of instances belonging to class i at the current node t.

2.4.3 Logistic regression

In statistics, logistic regression or logit regression is a type of probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor, used for predicting the outcome of a categorical dependent variable (i.e., a class label) based on one or more predictor variables (features). That is, it is used in estimating empirical values of the parameters in a qualitative response model. The probabilities describing the possible outcomes of a single trial are modeled, as a function of the explanatory (predictor) variables, using a logistic function. Frequently (and subsequently in this article) "logistic regression" is used to refer specifically to the problem in which the dependent variable is binary—that is, the number of available categories is two—and problems with more than two categories are referred to as multinomial logistic regression or, if the multiple categories are ordered, as ordered logistic regression.

Logistic regression measures the relationship between a categorical dependent variable and one or more independent variables, which are usually (but not necessarily) continuous, by using probability scores as the predicted values of the dependent variable. As such it treats the same set of problems as does probit regression using similar techniques.

2.4.3.1 Basics

Logistic regression can be binomial or multinomial. Binomial or binary logistic regression deals with situations in which the observed outcome for a dependent variable can have only two possible types (for example, "dead" vs. "alive"). Multinomial logistic regression deals with situations where the outcome can have three or more possible types (e.g., "disease A" vs. "disease B" vs. "disease C"). In binary logistic regression, the outcome is usually coded as "0" or "1", as this leads to the most straightforward interpretation. If a particular observed outcome for the dependent variable is the noteworthy possible outcome (referred to as a "success" or a "case") it is usually coded as "1" and the contrary outcome (referred to as a "failure" or a "noncase") as "0". Logistic regression is used to predict the odds of being a case based on the values of the independent variables (predictors). The odds are defined as the probability that a particular outcome is a case divided by the probability that it is a noncase.

Like other forms of regression analysis, logistic regression makes use of one or more predictor variables that may be either continuous or categorical data. Unlike ordinary linear regression, however, logistic regression is used for predicting binary outcomes of the dependent variable (treating the dependent variable as the outcome of a Bernoulli trial) rather than continuous outcomes. Given this difference, it is necessary that logistic regression take the natural logarithm of the odds of the dependent variable being a case (referred to as the logit or log-odds) to create a continuous criterion as a transformed version of the dependent variable. Thus the logit transformation is referred to as the link function in logistic regression—although the dependent variable in logistic regression is binomial, the logit is the continuous criterion upon which linear regression is conducted.

The logit of success is then fit to the predictors using linear regression analysis. The predicted value of the logit is converted back into predicted odds via the inverse of the natural logarithm, namely the exponential function. Therefore, although the observed dependent variable in logistic regression is a zero-or-one variable, the logistic regression estimates the odds, as a continuous variable, that the dependent variable is a success (a case). In some applications the odds are all that is needed. In others, a specific yes-or-no prediction is needed for whether the dependent variable is or is not a case; this categorical prediction can be based on the computed odds of a success, with predicted odds above some chosen cut-off value being translated into a prediction of a success.

2.4.3.2 Logistic function, odds ratio, and logit

An explanation of logistic regression begins with an explanation of the logistic function, which always takes on values between zero and one:

$$F(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}}$$

And viewing t as a linear function of an explanatory variable x (or of a linear combination of explanatory variables), the logistic function can be written as:

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

This will be interpreted as the probability of the dependent variable equalling a "success" or "case" rather than a failure or non-case. We also define the inverse of the logistic function, the logit:

$$g(x) = \ln \frac{F(x)}{1 - F(x)} = \beta_0 + \beta_1 x$$

And equivalently:

$$\frac{F(x)}{1 - F(x)} = e^{\beta_0 + \beta_1 x}$$

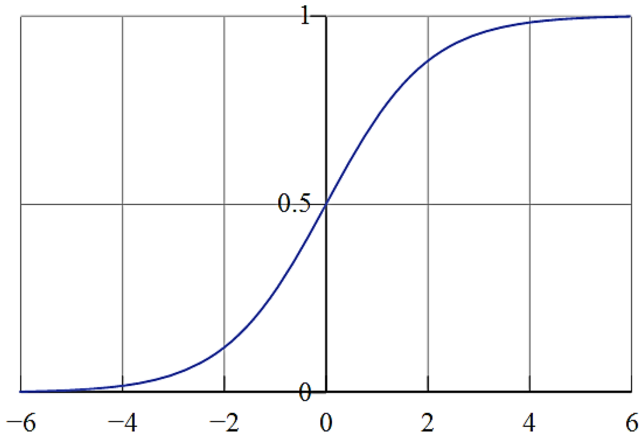

Figure 2.6 The logistic function, with $\beta_0 + \beta_1 x$ on the horizontal axis and $F(x)$ on the vertical axis

A graph of the logistic function $F(x)$ is shown in Figure 2.6. The input is the value of $\beta_0 + \beta_1 x$ and the output is $F(x)$. The logistic function is useful because it can take an input with any value from negative infinity to positive infinity, whereas the output $F(x)$ is confined to values between 0 and 1 and hence is interpretable as a probability. In the above equations, $g(x)$ refers to the logit function of some given linear combination x of the predictors, 'ln' denotes the natural logarithm, $F(x)$ is the probability that the dependent variable equals a case, β_0 is the intercept from the linear regression equation (the value of the criterion when the predictor is equal to zero), $\beta_1 x$ is the regression coefficient multiplied by some value of the predictor, and base e denotes the exponential function.

The formula for $F(x)$ illustrates that the probability of the dependent variable equaling a case is equal to the value of the logistic function of the linear regression expression. This is important in that it shows that the value of the linear regression expression can vary from negative to positive infinity and yet, after transformation, the resulting expression for the probability $F(x)$ ranges between 0 and 1. The equation for $g(x)$ illustrates that the logit (i.e., log-odds or natural logarithm of the odds) is equivalent to the linear regression expression. Likewise, the next equation illustrates that the odds of the dependent variable equaling a case is equivalent to the exponential function of the linear regression expression. This illustrates how the logit serves as a link function between the probability and the linear regression expression. Given that the logit ranges between minus infinity and infinity, it provides an adequate criterion upon which to conduct linear regression and the logit is easily converted back into the odds.

2.4.3.3 Multiple explanatory variables

If there are multiple explanatory variables, then the above expression $\beta_0 + \beta_1 x$ can be revised to $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m$. Then when this is used in the equation relating the logged odds of a success to the values of the predictors, the linear regression will be a multiple regression with m explanators; the parameters β_j for all j = 0, 1, 2, ..., m are all estimated.

2.4.4 Bayesian

A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model". An overview of statistical classifiers is given in the article on Pattern recognition.

In simple terms, a naive Bayes classifier assumes that the presence or absence of a particular feature is unrelated to the presence or absence of any other feature, given the class variable. For example, a fruit may be considered to be an apple if it is red, round, and about 3" in diameter. A naive Bayes classifier considers each of these features to contribute independently to the probability that this fruit is an apple, regardless of the presence or absence of the other features.

For some types of probability models, naive Bayes classifiers can be trained very efficiently in a supervised learning setting. In many practical applications, parameter estimation for naive Bayes models uses the method of maximum likelihood; in other words, one can work with the naive Bayes model without accepting Bayesian probability or using any Bayesian methods.

Despite their naive design and apparently oversimplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations. In 2004, an analysis of the Bayesian classification problem showed that there are sound theoretical reasons for the apparently implausible efficacy of naive Bayes classifiers.[1] Still, a comprehensive comparison with other classification algorithms in 2006 showed that Bayes classification is outperformed by other approaches, such as boosted trees or random forests.

An advantage of naive Bayes is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix.

2.4.4.1 Probabilistic model

Abstractly, the probability model for a classifier is a conditional model.

$p(C|F_1, \dots, F_n)$ over a dependent class variable C with a small number of outcomes or classes, conditional on several feature variables F_1 through F_n. The problem is that if the number of features n is large or when a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable.

Using Bayes' theorem, this can be written

$$p(C|F_1, \dots, F_n) = \frac{p(C)\, p(F_1, \dots, F_n|C)}{p(F_1, \dots, F_n)}$$

In plain English the above equation can be written as

$$posterior = \frac{prior\ x\ likelihood}{evidence}$$

In practice, there is interest only in the numerator of that fraction, because the denominator does not depend on C and the values of the features F_i are given, so that the denominator is effectively constant. The numerator is equivalent to the joint probability model $p(C, F_1, \dots, F_n)$ which can be rewritten as follows, using the chain rule for repeated applications of the definition of conditional probability:

$$
\begin{aligned}
p(C, F_1, \dots, F_n) &= p(C)\, p(F_1, \dots, F_n | C) \\
&= p(C)\, p(F_1|C)\, p(F_2, \dots, F_n | C, F_1) \\
&= p(C)\, p(F_1|C)\, p(F_2|C, F_1)\, p(F_3, \dots, F_n | C, F_1, F_2) \\
&= p(C)\, p(F_1|C)\, p(F_2|C, F_1) \dots p(F_n | C, F_1, F_2, F_3, \dots, F_{n-1})
\end{aligned}
$$

Now the "naive" conditional independence assumptions come into play: assume that each feature F_i is conditionally independent of every other feature F_j for $j \neq i$ given the category C. This means that $\left(F_n|C, F_j\right) = p(F_i|C)$, $p\left(F_i|C, F_j, F_k\right) = p(F_i|C)$, $p\left(F_i|C, F_j, F_k, F_l\right) = p(F_i|C)$, and so on, for $i \neq j, k, l$, and so the joint model can be expressed as

$$
\begin{aligned}
p(C|F_1, \dots, F_n) &\propto p(C, F_1, \dots, F_n) \\
&\propto p(C)\, p(F_1|C)\, p(F_2|C)\, p(F_3|C) \dots \\
&\propto p(C) \prod_{i=1}^{n} p(F_i|C)
\end{aligned}
$$

This means that under the above independence assumptions, the conditional distribution over the class variable C is:

$$
p(C|F_1, \dots, F_n) = \frac{1}{Z} p(C) \prod_{i=1}^{n} p(F_i|C)
$$

Where Z (the evidence) is a scaling factor dependent only on $F_1, \dots, F_n$, that is, a constant if the values of the feature variables are known.

Models of this form are much more manageable, because they factor into a so-called class prior $p(C)$ and independent probability distributions $p(F_i|C)$. If there are k classes and if a model for each $p(F_i|C) = c$ can be expressed in terms of r parameters, then the corresponding naive Bayes model has (k − 1) + n r k parameters. In practice, often $k = 2$ (binary classification) and $r = 1$ (Bernoulli variables as features) are common, and so the total number of parameters of the naive Bayes model is $2n + 1$, where n is the number of binary features used for classification.

2.5 Valuation

2.5.1 Sensitivity and specificity

Sensitivity and specificity are statistical methods to test the efficiency of the categories classification. The Statistical function, which is commonly used in the medical community.

Sensitivity values of detection are the ratio of patients which are testing results were positive divide by all patients. In practice, we should choose the detection with high sensitivity in screening patients for diseases that are more serious but it can be treated. If the patient has not been diagnosed with the diseases, they will lose the benefits. It is also suitable for initial screening processes to reduce the number of patients who were determined specifically for the diagnosis further. The results in a way that has a high sensitivity value will more meaningful in case of result is negative. Because it means that patients has less likely to be diseased with this method.

The detection with high specificity value means that patients with a positive test result has the high opportunity to be a disease. Therefore, it is useful to confirm the diagnosis in case of the data from other detection that the patient likely to be sick with the disease. This feature is very useful in case of positive results to cause effect to patients both the mind and the treatment of vulnerable. Therefore, detection with high specificity is very useful in case of a positive result.

In general, we usually expect the diagnostic method that developed with highest sensitivity and specificity but it is impossible. When increasing higher sensitivity, the specificity value of detection usually decreased. On the contrary, if the specificity value is higher, sensitivity value will lower typically. The cut - off point appropriate to classify between normal and abnormal in case of result with continuous data depends on the appropriate of high sensitivity or high specificity.

Screening for classifying and diagnosis in experiments, the test result is positive means predicted to be diseased or the test result is negative means predicted to normal. The results of the experiment might not be correspond to results of the medical diagnosis.

In that setting:

- True positive: Sick people correctly diagnosed as sick

- False positive: Healthy people incorrectly identified as sick
- True negative: Healthy people correctly identified as healthy
- False negative: Sick people incorrectly identified as healthy

In general, Positive = identified and negative = rejected. Therefore:

- True positive = correctly identified
- False positive = incorrectly identified
- True negative = correctly rejected
- False negative = incorrectly rejected

Let us define an experiment from P positive instances and N negative instances for some condition. The four outcomes can be formulated in a 2×2 contingency table or confusion matrix, as follows:

		Condition (as determined by "Gold standard")		
		Condition positive	Condition negative	
Test outcome	Test outcome positive	True positive	False positive (Type I error)	Precision = Σ True positive / Σ Test outcome positive
	Test outcome negative	False negative (Type II error)	True negative	Negative predictive value = Σ True negative / Σ Test outcome negative
		Sensitivity = Σ True positive / Σ Condition positive	Specificity = Σ True negative / Σ Condition negative	Accuracy

Figure 2.7 Contingency table or confusion matrix

2.5.1.1 Sensitivity

Sensitivity relates to the test's ability to identify positive results. The sensitivity of a test is the proportion of people that are known to have the disease who test positive for it. This can also be written as:

$$sensitivity = \frac{number\ of\ true\ positives}{number\ of\ true\ positives + number\ of\ false\ negatives}$$

Sensitivity is not the same as the precision or positive predictive value (ratio of true positives to combined true and false positives), which is as much a statement about the proportion of actual positives in the population being tested as it is about the test.

2.5.1.2 Specificity

Specificity relates to the test's ability to identify negative results. Consider the example of the medical test used to identify a disease. The specificity of a test is defined as the proportion of patients that are known not to have the disease who will test negative for it. This can also be written as:

$$specificity = \frac{number\ of\ true\ negatives}{number\ of\ true\ negatives + number\ of\ false\ positives}$$

However, highly specific tests rarely miss negative outcomes, so they can be considered reliable when their result is positive. Therefore, a positive result from a test with high specificity means a high probability of the presence of disease.

Another method that can be used to select the appropriate the cut-off point is creating a Receiver Operator Characteristic (ROC) curve. To create a relationship graph between the true positive rate (Sensitivity) and false positive rate (1 - Specificity) by changing the cut - off point. In addition, creating a ROC curve also helps in comparison the efficiency of the diagnosis by comparing the area under the lines of each test. The area under curve represents the higher performance.

2.5.2 Receiver Operating Characteristic (ROC)

Receiver operating characteristic (ROC) or ROC curve is creating a graph that shows the performance of the algorithm which will change according to the Threshold setting. It is created from the plot of the Sensitivity and Specificity values so it shows the tradeoff between the sensitivity and specificity.

If a sensitivity value is increased, a specificity value will be increased respectively. Therefore, if the algorithm is better, the error will rise as well. We can see that the researchers around the world are trying to solve this problem and seek to maximize or minimize values of specificity.

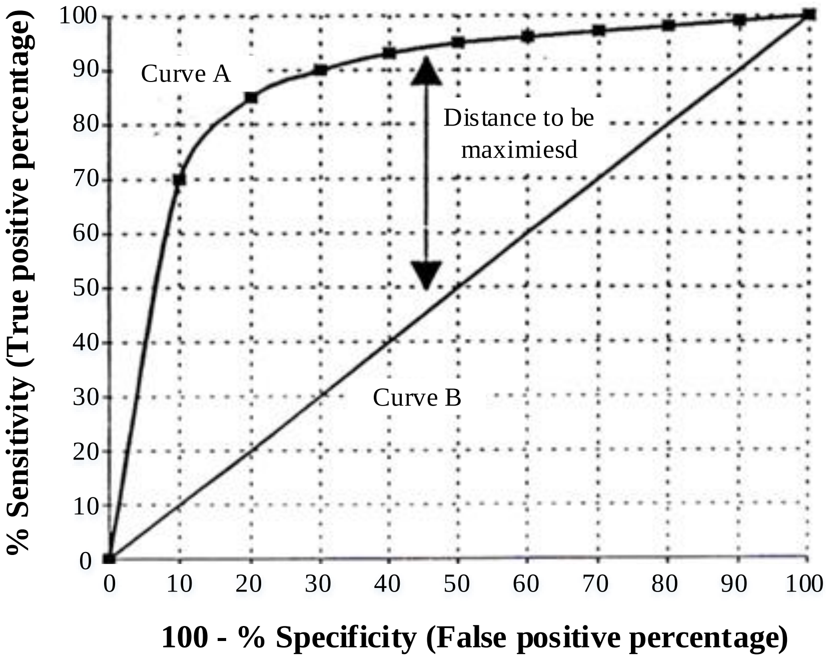

Figure 2.8 ROC curve: Illustrates the relationship between Sensitivity and Specificity

Figure 2. if a graph curve approaches the point that is on the left corner, the slope graph is high and area under the curve is greater. It means that algorithm has a good performance.

CHAPTER III
MATERIALS AND METHODS

3.1 Materials and Schedule

3.1.1 Schedule

Schedule of this research has start at July and use 4 months for thesis with any topic in table 3.1

Table 3.1 Schedule of research

Task\Month	November	December	January	February
Planning and collecting data				
Data analysis				
Result evaluation				
Result of Classify analysis				
Documentation				

3.1.2 Tools

List of tools for process Diagnose Flat Foot from Foot Print Image Using Combine Indexes Based on Neural Network.

3.1.2.1 Hardware

Computer Name	:	Macbook
Processor	:	Intel Core 2 2.5 GHz
RAM	:	DDR III 2 GB
Hard Drive	:	250 GB

3.1.2.2 Software

Classify Tools	:	Weka 3.7.5
Operating Systems	:	Microsoft Windows 7

3.1.3 Data

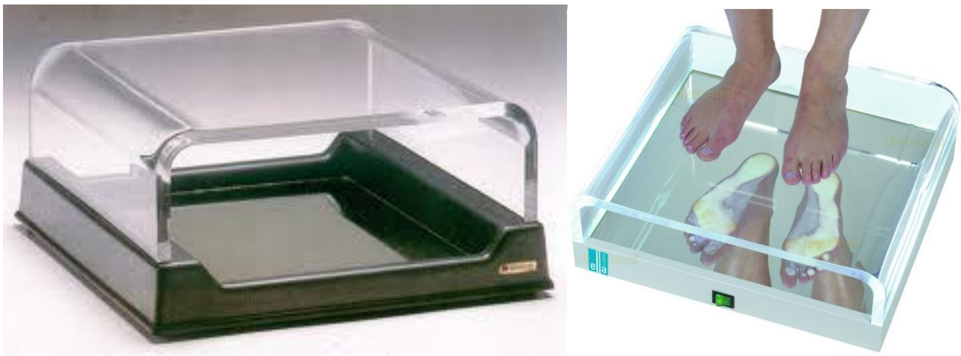

Figure 3.1 Podoscope

Podoscope is equipment for footprint on shooting glass, but the problem is the light which is reflected from the photos that have no clear safety glass required to control the amount of incident light from the top and bottom of the machine. For the trial application of the light source, the result is a light source which LED light is green leading to the most clear picture of Figure 2 [16].

Figure 3.2 Foot Print

The data is used in this research derived from the study of patients with foot with diagnosis by using 66 tracks, In Podoscope, aged between 18-58 years, the total foot print are 132 images (on the left side of 66 images and the right side of 66 images). The averages are 165 cm and 67 kg for the height and weight, respectively.

3.2 Method

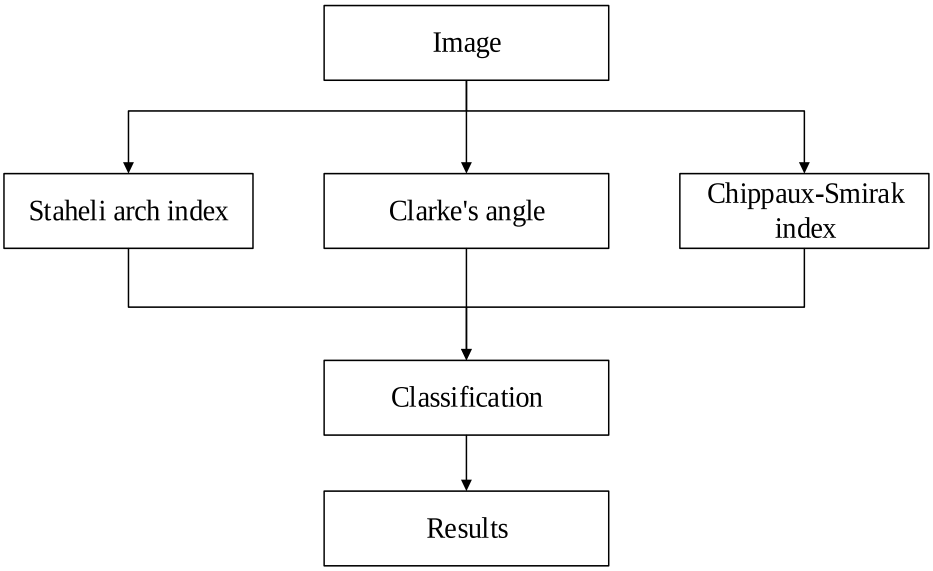

Figure 3.3 Flow process diagram

Step 1: To measure the size of each variable indicators from foot print images by normal people and flat feet people.

Step 2: To calculate indicators for each of the indicators with variables from step 1.

Step 3: To create model by using data from step1 and step2 for classify foot print. There are 4 algorithms: 1) Neural network 2) C4.5 decision tree 3) Logistic regression and 4) Bayesian. There are 7 variables set as input and 1 variable set as output. If the result is equal to 1, it will be classified to flat feet. But if the result is equal to 0, it means normal or not flat feet.

Step 4: To execute results from each algorithms by comparing the performance that used in the classification.

1. Accuracy of the degree of conformity of a measured or calculated quantity to its actual (true) value.

2. Area under curve (AUC) Curve showing the sensitivity and specificity of SN.

3. Sensitivity related to the test's ability to identify positive results.

4. Specificity related to the test's ability to identify negative results.

In flat foot screening, data is divided into four sets by using 4 indicators for comparing the performance of each algorithm: neural network, decision tree, logistic regression and Bayesian (pair T-Test).

CHAPTER IV
ANALYSIS AND RESULTS

In classification of flat foot data into three sets are right foot, left foot and both sides of foot by using algorithm Neural Network, C4.5 decision tree, Logistic regression and Bayesian. The result will be an average of all the tests by compare with a baseline classifier (here it is the Neural Network),

4.1 Analysis

Footprint find parameter by Staheli arch index, Clarke's angle and Chippaux-Smirak index. (Can see in AppendicesA)

B = Line B is the narrowest of midfoot

C = line C is the widest of hindfoot

The Staheli index = B/C

D = line D is the widest of forefoot

E = Line E is narrowest of midfoot

CSI - Chippaux-Smirak Index = D/E

FPA-archangle = The angle is a result of the third point where P is the 1st Metatarsal head at 1, Q is the Medial Calcaneal, and R is the narrowest of midfoot with P as vertex angle

ANS = foot’s Expert

And then using Algorithm to create modal by neural network, C4.5 decision tree, Logistic regression and Bayesian

4.2 Results

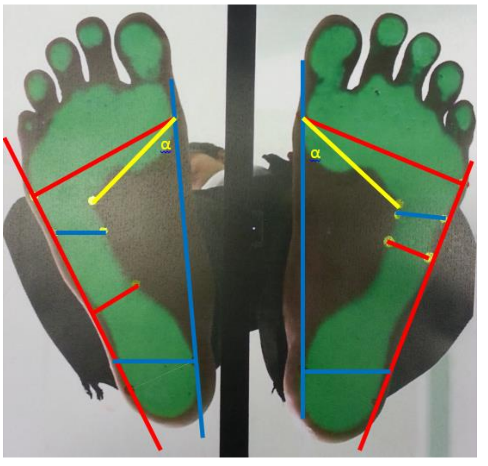

Figure 4.1 Calculate feet of three index

From figure 4.1 calculate feet of the Staheli arch index, Clark's angle, the Chippaux-Smirak index to find parameters by semi-automatic process. The point was mark on structure of foot by handwrite and distance from point to point process with computer measurement by screen divider program in centimeter units.

Table 4.1 Staheli arch index compare with Gold standard

Staheli arch index		Gold standard	
Normalfoot	Flatfoot	Normalfoot	Flatfoot
97	25	65	57

From table 4.1 Staheli arch index was calculate flatfoot 25 subjects and gold standard was calculate flatfoot 57 subjects from 122 subjects. The Staheli arch index calculate with line B (median = 2.2± 0.488197162) and line C (median = 2.8± 0.261619263)

Table 4.2 Clark's angle compare with Gold standard

Clark's angle		Gold standard	
Normalfoot	Flatfoot	Normalfoot	Flatfoot
80	42	65	57

From Table 4.2 Clark's angle was calculate flatfoot 42 subjects and gold standard was calculate flatfoot 57 subjects from 122 subjects. Clark's angle calculate with angle (45± 9.578391436)

Table 4.3 Chippaux-Smirak index compare with Gold standard

Chippaux-Smirak index		Gold standard	
Normalfoot	Flatfoot	Normalfoot	Flatfoot
83	39	65	57

From Table 4.3 the Chippaux-Smirak index was calculate flatfoot 39 subjects and gold standard was calculate flatfoot 57 subjects from 122 subjects. The Staheli arch index calculate with line D (median = 5.2± 0.427155363) and line E (median = 1.825± 0.45195758)

Table 4.4 Three index compare with Gold standard

Staheli arch index	Clark's angle	Chippaux-Smirak index	Gold standard
43.8596%	73.68421%	68%	100%

From Table 4.4 when the results of the three index compare with the gold standard. The percent accuracy in calculations was the Staheli arch index was 43.8596%, Clark's angle was 73.68421%, the Chippaux-Smirak index was 68%.

This research study shows the results from 4 main algorithms as follows: 1) Neural network 2) C4.5 decision tree 3) Logistic regression and 4) Bayesian.

Table 4.5 Summary performance of the classification from dataset right foot 66 images (numbers in parentheses are standard deviations.)

Algorithm	Accuracy	AUC	Sensitivity	Specificity
Neural Network	89 (12.12)	0.96* (0.09)	0.93 (0.14)	0.86 (0.22)
C4.5 decision tree	86 (13.79)	0.86 (0.15)	0.85 (0.21)	0.89 (0.19)
logistic regression	85 (14.29)	0.93 (0.11)	0.87 (0.19)	0.82 (0.22)
Bayesian	85 (14.15)	0.95 (0.10)	0.89 (0.17)	0.82 (0.24)

Table 4.6 Summary performance of the classification from dataset left foot 66 images (numbers in parentheses are standard deviations.)

Algorithm	Accuracy	AUC	Sensitivity	Specificity
Neural Network	89 (12.12)	0.96* (0.08)	0.87 (0.18)	0.86 (0.23)
C4.5 decision tree	84 (13.14)	0.86 (0.14)	0.86 (0.18)	0.83 (0.24)
logistic regression	86 (13.03)	0.95 (0.09)	0.89 (0.17)	0.83 (0.26)
Bayesian	88 (12.64)	0.97 (0.07)	0.91 (0.15)	0.85 (0.22)

Table 4.7 Summary performance of the classification from dataset both sides of foot 132 images (numbers in parentheses are standard deviations.)

Algorithm	Accuracy	AUC	Sensitivity	Specificity
Neural Network	93 (7.37)	0.98* (0.04)	0.95 (0.09)	0.90 (0.14)
C4.5 decision tree	90 (8.62)	0.90 (0.10)	0.91 (0.11)	0.89 (0.14)
logistic regression	89 (8.04)	0.92 (0.06)	0.92 (0.11)	0.87 (0.14)
Bayesian	88 (8.11)	0.90 (0.10)	0.91 (0.12)	0.85 (0.15)

Table 4.5-4.6 shows the best efficiency classification algorithm of neural network and when test dataset (Both sides) from Table 4.7 shown AUC 0.98 (standard deviations 0.04) and the sensitivity of 0.95 and specificity of 0.90.

Table 4.8 Compare all algorithm advantages and disadvantages.

Algorithm	Advantages	Disadvantages
Neural Network	-This foot parameter was nonlinear. This algorithm was support nonlinear parameter	This algorithm was complex
C4.5 decision tree	-This algorithm was easy to understand	This foot data was not distribution. Tree function can not divided.
logistic regression	-Logistic regression very popular in the medical field. -Independent variable can be both numerical and nominal.	-Have limitation for large data set applications.
Bayesian	– Easy to use – Handles discrete data.	– Available to the independent attribute only.

From Table 4.7-4.8 the highest accuracy of model was neural network algorithm 93% with AUC 0.98 significant because of neural network compute nonlinear parameter. This foot parameter was nonlinear is worked on neural network, But this algorithm was complexity. The lower accuracy of all model was Bayesian algorithm

89% AUC 0.90 wasn’t significant. Bayesian was work in available to the independent attribute only and handles discrete data only. C4.5 decision tree was model easy to understand but this foot data was not distribution, because tree function can’t divided. The logistic regression is very popular in medical field but the accuracy is not the best of all algorithm and limitation for large data set application.

CHAPTER V
CONCLUSION AND DISCUSSION

The results showed that the classification is more accuracy after learning by neural network using multiple index to show the characteristic of flat feet. For the left feet, the accuracies for the classification of Staheli arch index (SI), Clarke's angle (CA) and Chippaux-Smirak index (CSI) are increased from single index to 41%, 20% and 9%, respectively. For the right feet, the accuracies for SI, CA and CSI are increased from single index to 50%, 21% and 9%, respectively. Finally, the accuracies of both sides for SI, CA and CSI are increased from single index to 50%, 25% and 13%, respectively. These algorithms are suitable for classification and able to apply in screening process of flat feet effectively.

The last this model make from data 122 samples, you can will add samples more than this model to instead Thailand population and model was stronger and reliability. In the future work can be develop to application classification foot type for patient in hospital and clinic. Development mobile application for measurement foot type in baby for prevention flat foot.

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APPENDICES

APPENDIX A
DATA USED IN CREATE MODAL

Data used in create modal

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
2.7	3	0.9	5.9	1.5	25.42372881	47.5	0
2.5	3.1	0.806451613	5.65	2.3	40.7079646	41.5	1
2.7	3	0.9	5.75	2.2	38.26086957	52	1
2.8	3.4	0.823529412	6.3	1.95	30.95238095	56	0
1.8	2.8	0.642857143	5.6	1.3	23.21428571	50	0
2.3	3	0.766666667	5.35	1.9	35.51401869	49	0
2.5	3.2	0.78125	5.4	2.4	44.44444444	46	1
2.6	3	0.866666667	5.7	2.4	42.10526316	39	1
3	2.7	1.111111111	5.7	2.5	43.85964912	18	1
2.3	3	0.766666667	5.65	2.05	36.28318584	45	0
3.1	2.5	1.24	4.9	2.55	52.04081633	12	1
2.5	3	0.833333333	5.4	2.35	43.51851852	37.5	1
3.4	2.7	1.259259259	6.05	2.6	42.97520661	23	1
2.5	3.2	0.78125	5.4	2.3	42.59259259	24	1
1.5	3.1	0.483870968	4.9	1.6	32.65306122	53	0
2.2	3.2	0.6875	5.45	1.9	34.86238532	52	0

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
2.7	3	0.9	5.45	2.6	47.70642202	39	1
2.3	2.5	0.92	5	1.8	36	41.5	1
1.2	2.9	0.413793103	4.9	1.2	24.48979592	35	0
1.9	2.6	0.730769231	5	1.5	30	47	0
2.2	3	0.733333333	4.8	2.3	47.91666667	30	1
1.6	2.5	0.64	5.15	1.35	26.21359223	51.5	0
3.3	3.1	1.064516129	5.95	2.6	43.69747899	34.5	1
2.4	3	0.8	5.5	1.9	34.54545455	49	0
2.2	3	0.733333333	5.4	0.85	15.74074074	49	0
2.2	2.6	0.846153846	5.55	1.65	29.72972973	44.5	0
1.3	2.8	0.464285714	5.2	0.8	15.38461538	53	0
2.2	2.8	0.785714286	5.1	2.1	41.17647059	42	1
1.9	2.8	0.678571429	5.1	1.65	32.35294118	45	0
2.3	2.5	0.92	5.4	1.8	33.33333333	48	1
2.6	3.3	0.787878788	6.2	1.9	30.64516129	47	0
2.1	3	0.7	5	1.55	31	48	0
2.3	3	0.766666667	5.3	1.7	32.0754717	39	0
3	3.4	0.882352941	5.4	2.75	50.92592593	31	1
2	2.7	0.740740741	4.8	1.8	37.5	55	0
2.4	3	0.8	5.8	2	34.48275862	47.5	0
1.7	2.8	0.607142857	5	1.5	30	49	0

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
2.2	2.5	0.88	4.8	1.9	39.58333333	50	0
2.4	3	0.8	5.15	2	38.83495146	37.5	1
2.2	2.8	0.785714286	5.2	1.7	32.69230769	42	0
1.4	2.8	0.5	4.7	1.2	25.53191489	53	0
1.5	2.9	0.517241379	5.1	1.4	27.45098039	48	0
1.8	2.9	0.620689655	4.9	1.4	28.57142857	43	0
2.1	2.8	0.75	4.9	2	40.81632653	47	1
2	2.9	0.689655172	5	1.9	38	53	1
1.2	2.8	0.428571429	4.5	1.7	37.77777778	36	0
2.4	2.6	0.923076923	5.2	2	38.46153846	39	1
1.7	2.7	0.62962963	4.8	1.3	27.08333333	50	0
2.4	2.8	0.857142857	5	2.1	42	50	1
2.2	2.4	0.916666667	4.5	2.15	47.77777778	32	1
2.1	2.3	0.913043478	4.6	1.6	34.7826087	47	0
2	3	0.666666667	5.3	1.95	36.79245283	39	0
1.9	2.7	0.703703704	4.85	1.7	35.05154639	37.5	0
2.5	2.9	0.862068966	5.6	2.2	39.28571429	47	1
1.4	2.2	0.636363636	4.5	0.8	17.77777778	43.5	0
2.5	3	0.833333333	5.4	1.65	30.55555556	31.5	1
2.4	2.5	0.96	5.6	1.7	30.35714286	43.5	1
2.5	3	0.833333333	6	2.4	40	50	1

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
2.6	2.9	0.896551724	5.5	2.4	43.63636364	34	1
1.8	2.4	0.75	4.6	1.6	34.7826087	48	0
2.5	3.2	0.78125	5.75	1.5	26.08695652	47	0
2.4	3.1	0.774193548	5.3	2	37.73584906	40	1
2.3	3.1	0.741935484	5.6	2	35.71428571	51	0
2.6	3.5	0.742857143	6.1	1.8	29.50819672	50	0
1.6	2.8	0.571428571	4.9	1.2	24.48979592	55	0
2.3	2.7	0.851851852	5.2	1.75	33.65384615	51.5	0
2.3	2.9	0.793103448	4.9	2	40.81632653	49	1
2.6	3.1	0.838709677	5.5	2.3	41.81818182	40	1
4.1	2.8	1.464286	5.3	3.3	62.26415	5	1
2.4	3	0.8	5.35	2	37.38318	45	0
2.2	2.8	0.785714	4.85	2.15	44.3299	36	1
2.7	2.8	0.964286	5.2	2.4	46.15385	41	1
2.9	2.7	1.074074	5.8	2.3	39.65517	41	1
2.9	3	0.966667	5	2.3	46	20	1
1.6	2.8	0.571429	4.85	1.4	28.86598	51.5	0
2.2	3.2	0.6875	5.3	1.9	35.84906	50	0
2.7	3.1	0.870968	5.8	2.3	39.65517	38.5	1
2.3	2.3	1	4.9	1.8	36.73469	42	1
0.8	2.9	0.275862	5.2	0.8	15.38462	37	0

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
1.9	2.9	0.655172	4.9	1.5	30.61224	43	0
1.8	2.6	0.692308	4.6	1.2	26.08696	51.5	0
2.7	3	0.9	4.6	2.9	63.04348	17	1
1.7	2.5	0.68	5.05	1.4	27.72277	49	0
2.6	2.8	0.928571	5.75	2.4	41.73913	31.5	1
1.9	2.9	0.655172	5.25	1.7	32.38095	50	0
2.1	2.9	0.724138	5.45	1.4	25.68807	47	0
1.9	2.6	0.730769	5.2	1.6	30.76923	46	0
1.6	2.6	0.615385	4.8	1.1	22.91667	54	0
2.3	2.5	0.92	5.2	2.15	41.34615	40	1
1.9	2.6	0.730769	5.15	1.65	32.03883	39	0
2.2	2.5	0.88	5.4	1.3	24.07407	53	0
2.6	3.2	0.8125	6	1.85	30.83333	45	0
1.9	2.9	0.655172	4.9	1.45	29.59184	44.5	0
2	3	0.666667	5	1.6	32	34	0
2.2	3.2	0.6875	5.5	2.1	38.18182	31	1
1.5	2.5	0.6	4.5	1.9	42.22222	45	0
1.8	2.8	0.642857	5.5	1.5	27.27273	48.5	0
1.6	2.8	0.571429	4.8	1.5	31.25	42	0
2.1	2.2	0.954545	4.8	1.9	39.58333	48.5	0
2	2.9	0.689655	4.8	2	41.66667	36.5	1

B	C	The Staheli index B/C	D	E	CSI - Chippaux-Smirak IndexD/E	FPA-archangle	ANS
2	2.7	0.740741	5	1.6	32	43	0
3.3	2.5	1.32	4.4	2.5	56.81818	5.5	1
1.6	2.5	0.64	4.7	1.4	29.78723	48	0
2.3	2.8	0.821429	5.2	1.8	34.61538	46	1
1.6	2.7	0.592593	4.8	1.2	25	45	0
1.8	2.9	0.62069	4.8	1.3	27.08333	50	0
2.1	2.5	0.84	4.6	2.2	47.82609	23	1
2.3	3	0.766667	5.25	2.2	41.90476	46	1
1.6	2.9	0.551724	4.4	1.4	31.81818	42	0
2.4	2.8	0.857143	5.3	2.3	43.39623	42.5	1
1.7	2.5	0.68	4.4	1.5	34.09091	46	0
2.3	2.7	0.851852	4.9	2	40.81633	43.5	1
2.1	2.4	0.875	4.4	1.7	38.63636	39	0
2.1	3.1	0.677419	5.2	1.9	36.53846	33	0
1.8	2.8	0.642857	4.9	1.4	28.57143	43	0
2.4	3	0.8	5.4	2.05	37.96296	47	1
1.6	2.2	0.727273	4.65	1	21.50538	47.5	0
2.5	3	0.833333	5.3	1.7	32.07547	44	1
2.3	2.6	0.884615	5.1	1.75	34.31373	43.5	1
2.6	2.8	0.928571	5.9	2.05	34.74576	46	1
2.4	2.9	0.827586	5.25	2.1	40	36	1

APPENDIX B
EXPERIMENTAL OUTPUT

Multilayer Perceptron output

Sigmoid Node 0
Inputs Weights
Threshold -3.134320843537483
Node 2 -6.542368972353043
Node 3 10.88769706857216
Node 4 8.427600035175043
Node 5 -0.002608390321050413
Sigmoid Node 1
Inputs Weights
Threshold 3.1346353322824827
Node 2 6.542577688198934
Node 3 -10.887861097195882
Node 4 -8.427672657428998
Node 5 0.0017151061689646614
Sigmoid Node 2
Inputs Weights
Threshold 2.865155793991978
Attrib B 5.155902180316246
Attrib C -0.5628077150817373
Attrib TheStaheliindexB/C 5.15218531053527
Attrib D 1.1886307805612268
Attrib E 1.4632740722940896
Attrib CSI - Chippaux-Smirak IndexD/E 0.7492794618628058
Attrib FPA-archangle -4.441237719221777

Sigmoid Node 3

Inputs Weights

Threshold -5.964094727899289

Attrib B -8.735489893691708

Attrib C 1.6812454559891226

Attrib TheStaheliindexB/C -8.955078460322966

Attrib D 4.2784815367193465

Attrib E -4.831275068517828

Attrib CSI - Chippaux-Smirak IndexD/E -5.634755523684348

Attrib FPA-archangle 3.339742051193793

Sigmoid Node 4

Inputs Weights

Threshold -8.27652327323856

Attrib B -3.78357299275067

Attrib C -5.052551694952838

Attrib TheStaheliindexB/C -1.9763999610401868

Attrib D -3.661698458537083

Attrib E -3.769024685762044

Attrib CSI - Chippaux-Smirak IndexD/E -2.3223580766400946

Attrib FPA-archangle 4.407417997313882

Sigmoid Node 5

Inputs Weights

Threshold -0.8118567819797936

Attrib B -0.21434276812863776

Attrib C -0.17848792595291652

Attrib TheStaheliindexB/C -0.14837465495736296

Attrib D -0.07674972185090519

Attrib E -0.3170054446956526

Attrib CSI - Chippaux-Smirak IndexD/E -0.3180346139859391

Attrib FPA-archangle -0.0024888515624194134

Class 0

Input

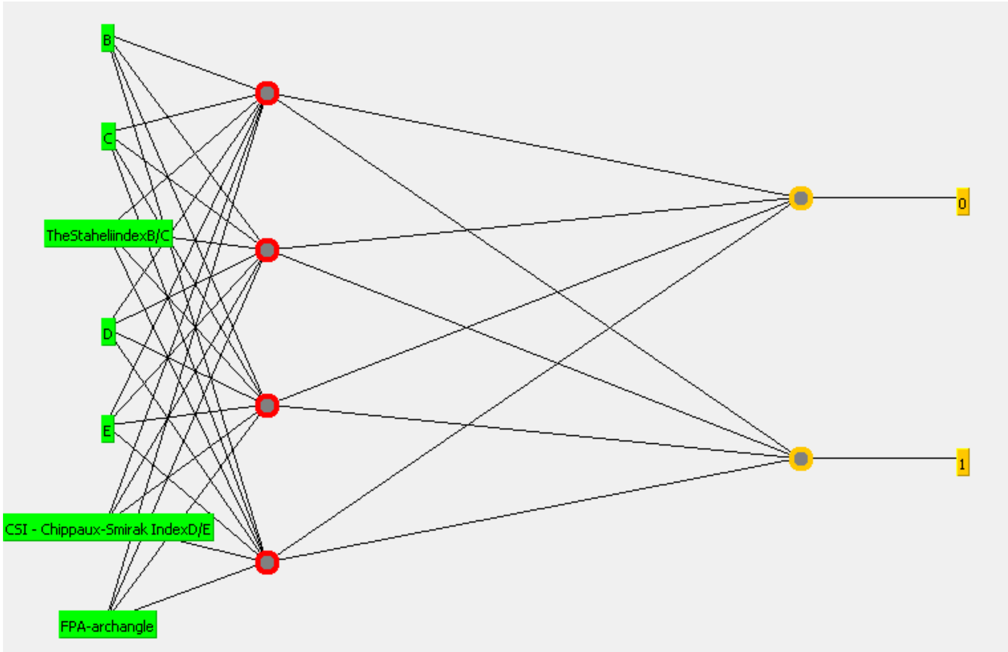
Node 0

Class 1

Input

Node 1

Multilayer Perceptron Visualizer



Multilayer Perceptron Stratified cross-validation

Correctly Classified Instances	114	93.4426 %
Incorrectly Classified Instances	8	6.5574 %
Kappa statistic	0.866	
Mean absolute error	0.0808	
Root mean squared error	0.2324	
Relative absolute error	16.4066 %	
Root relative squared error	46.8086 %	
Total Number of Instances	122	

C4.5 decision tree output

Number of Leaves : 6

Size of the tree : 11

E <= 1.95

| B <= 2.2: 0 (56.0/1.0)

| B > 2.2

| | FPA-archangle <= 46

| | | TheStaheliindexB/C <= 0.8125: 0 (2.0)

| | | TheStaheliindexB/C > 0.8125: 1 (7.0)

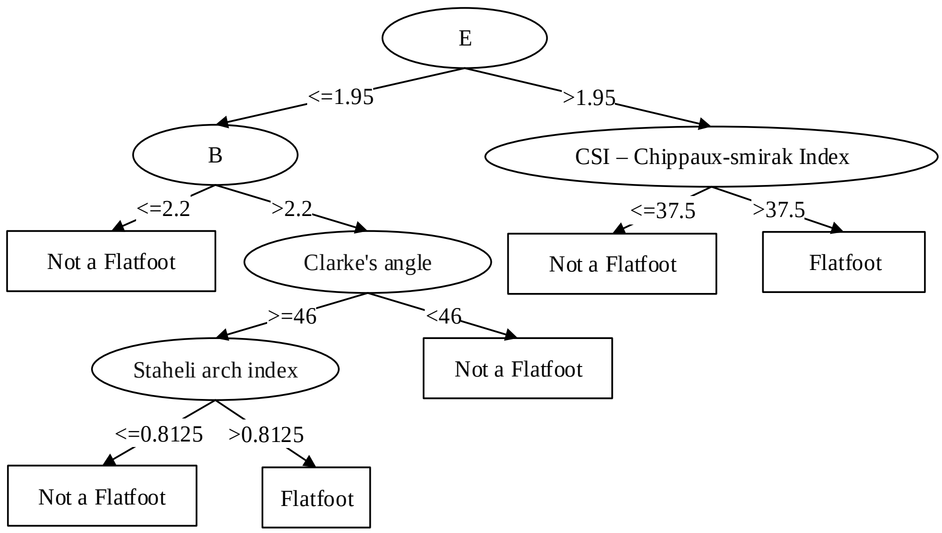
| | FPA-archangle > 46: 0 (9.0/1.0)

E > 1.95

| CSI - Chippaux-Smirak IndexD/E <= 37.5: 0 (5.0/1.0)

| CSI - Chippaux-Smirak IndexD/E > 37.5: 1 (43.0)

Tree Visualizer



C4.5 decision tree Stratified cross-validation

Correctly Classified Instances	113	92.623 %
Incorrectly Classified Instances	9	7.377 %
Kappa statistic	0.8502	
Mean absolute error	0.0965	
Root mean squared error	0.2682	

Relative absolute error	19.6046 %
Root relative squared error	54.0289 %
Total Number of Instances	122

Logistic Stratified cross-validation

Correctly Classified Instances	109	89.3443 %
Incorrectly Classified Instances	13	10.6557 %
Kappa statistic	0.7827	
Mean absolute error	0.1246	
Root mean squared error	0.272	
Relative absolute error	25.3159 %	
Root relative squared error	54.7881 %	
Total Number of Instances	122	

Bayes NaiveBayes Stratified cross-validation

Correctly Classified Instances	108	88.5246 %
Incorrectly Classified Instances	14	11.4754 %
Kappa statistic	0.7654	
Mean absolute error	0.1336	
Root mean squared error	0.2873	
Relative absolute error	27.1493 %	
Root relative squared error	57.8834 %	
Total Number of Instances	122	

APPENDIX C
DIAGNOSE FLAT FOOT FROM FOOT PRINT IMAGE BASED ON NEURAL NETWORK

Wanlop Aruntammanak, Yuttapong Aunhathaweesup, Waranyu Wongseree,
Adisorn Leelasantitham and Supaporn Kiattisin
Technology of Information System Management Program, Faculty of Engineering, Mahidol University
25/25 Puttamonthon, Nakorn Pathom 73170, Thailand
wanlop_5@hotmail.com, pentagon.ou@gmail.com, waranyu1979@hotmail.com,
ladisorn@hotmail.com and tom_kiattisin@hotmail.com

Abstract*—Normally, there have been many methods to diagnosis of flat foot. Each method is different to use indicators e.g. Staheli arch index, Clark’s angle and Chippaux-Smirak index. However, the results from such indicators are still varied in each method. Therefore, this paper proposes a classification of the flat foot by combining of multiple indicators with neural network process. It can improve an accuracy of classification more than the use of only one indicator. There are 132 images of footprints (left and right foot) consisting of normal foot or flat foot. The experimental results using a combination of indicators show that an accuracy of the result is up to 93% more than the single index i.e. Staheli arch index 43%, Clark's angle 68%, Chippaux-Smirak index 80%. It can make more precisely diagnose of flat foot.

Keywords*— Nasal cross sectional area; Acoustic Rhinometry; Classification; Ripper Rule; C4.5 decision tree; K-Nearest neighbor;

I. INTRODUCTION

Flat foot [1] may be the result of hereditary caused by a torn ankle ligament or the diseases related to the brain or spinal cord. However, most patients are not aware as a result of suffering a foot ligament inflammation (Plantar Fasciitis and Corn). There are no more patients who go to see a doctor to treat them because most people will pay attention to take care of their foot less than as expected. A regular basis of the disease is characterized by weight while standing, the talon is lost [2]. But while sitting or sleeping, talon is back to normal. If you would like to see a clear talon, notice by standing on tiptoe will make it clearer.

The medical diagnosis is to identify the disease of flat foot. There are many ways such as inspection, ultrasonography and analysis of the footprints [1, 3]. In this research, sample images (footprint) are from the basic medical device (Podoscope) used for storing the data. The result is a digital image which each variable is measured by the size of the individual indicators in order to test the accuracy of the individual indicators. By measuring the plane f 1st Metatarsal head and Medial Calcaneal [4], perpendicular from the plane is to measure the widest of the talon. A line shows both the muscle of mid foot and the muscle of hide foot, 5th Metatarsal head and Lateral Calcaneal. It also shows the muscle of fore foot and the arches degree of the foot. This research will analyze the data by using mathematical calculations. Finally, the results show that dataset has been characterized as a normal foot or flat foot.

The results of combining three indicators indicate that are accurate and precise as follows. Firstly, Staheli arch index is a relative ratio of midfoot and forefoot. Secondly, Clark's angle [5, 6] is a measure of the degree of arch (Arch) [7]. Thirdly, Chippaux-Smirak index is a relative ratio the hindfoot and midfoot [8, 9]. Each index is specificity in the measurement and interpretation which are different to interpreter the meaning. Process variable is the indicator calculated mathematically combined to provide the results that are more accurate. Such the three mathematical models are different kinds to provide more accurate results using an integration of them which is used to determine more accuracy than measuring with a single index [10]

II. LITERATURE REVIEW

Generally, three index is used for analyzing the footprints i.e. Staheli arch index (SI), Clarke's angle (CA) and Chippaux-Smirak index (CSI).

(A) (B) (C)

Figure 1 Footprint analysis: (A) Staheli arch index=B/C; Clarke's angle=α; Chippaux-Smirak index=E/Dx100

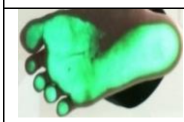
Staheli arch index is used to compare the ratio of midfoot and forefoot. Line B is the narrowest of midfoot and line C is the widest of forefoot. The perpendicular to the plane of the line PQ is the 1st Metatarsal head and the Medial Calcaneal. The index of the papers [5, 6] has been reported for a case of the flat foot in the condition of higher than 0.9 and the normal foot of lower than 0.89. In this case study, if the value is less than 0.8125, it will be a normal foot whilst if the value is higher than 0.8125, it will be a flat foot.

Clarke's angle is the corner to find a different foot. The angle is a result of the third point where P is the 1st Metatarsal head at 1, Q is the Medial Calcaneal, and R is the narrowest of midfoot with P as vertex angle. The index of the papers [7, 11, 12] has been reported for a case of the flat foot in the condition of lower than 41o and the normal foot to be higher than 42o. In this case study, if the value is less than 46o, it will be a flat foot whilst if the value is higher than 46o, it will be a normal foot.

Chippaux-Smirak index compared to the percentage of hindfoot and midfoot. Line E is narrowest of midfoot and D is the widest of hindfoot. Must be perpendicular to the line. TS Lines plane of the 5th Metatarsal head and the Lateral Calcaneal on the outside. The index of the papers [8, 11] have been reported for a case of the flat foot in the condition of higher than 40% and the normal foot to be lower than 39.9%. In this case study, if the value is less than 37.5, it will be a normal foot whilst if the value is higher than 37.5, it will be a flat foot.

A calculation of the methods mentioned above shows the development of the medial longitudinal arch. It is a popular tool used in the screening of a flatfoot, as summarized in Table I.

TABLE I COMPARISON OF THE RESULTS INDICATORS FOR EACH INDEX.

	Staheli arch index	Chippaux-Smirak index	Clarke's angle
	normal	flat foot	normal
	normal	flat foot	normal
	normal	flat foot	flat foot

It can be seen from Table I that the use of all three index to find the flatfoot is a problem because of different results in each index. The results are compared with medical expert i.e. Staheli arch index is 43 percent, the left foot is 48 percent and right foot is 39 percent. Chippaux-Smirak index is 68 percent, the left foot is 69 percent and right foot is 68 percent. Clarke's angle index is 80 percent, the left foot is 80 percent and right foot is 80 percent.

This research proposes methods to determine the combination of flat foot which is a disease primarily of the above three methods i.e. 1) Staheli arch index, 2) Chippaux-Smirak index and 3) Clarke’s angle index.

Neural network consisting of input and output by emulation to each input has a weight that weight determines of the input by neurons. Each unit has a threshold value determines the total weight of the input. The artificial neural units are to work together. This work is in a logical way, it is like a chemical reaction that occurs in the brain [3]. When the process is input into the network, the input is multiplied by the weight of the line network. The results of the neural are inputted to put together and are taken from a defined threshold. If the sum is greater than the threshold then it sends output to the neurons. If the value is less than the threshold then it will not be output. This output will be sent to the input of other neurons in the network.

Decision tree is the process of mining data. It is to help in the work and decisions. The rules are in the form "if conditions then the results" such as "If degree (α)> 41o = normal foot, else = Flatfoot". For the nature of the decision tree, this tree is similar to a tree upside down by the first node being the root node, then they are connected by branches to each node display features. Each branch will show the results of the test, and leaf nodes [13] is defined as shown in Figure 2.

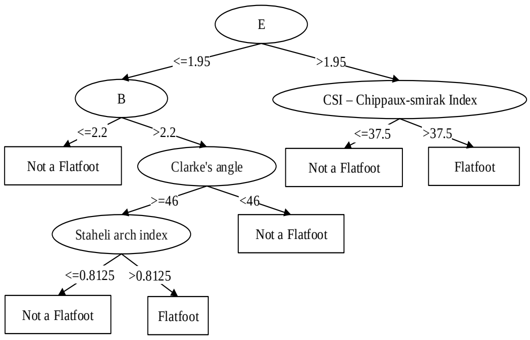


Figure 2 example Decision tree

Logistic regression analysis designs to predict the probability of an event of interest. The logistic equation is generated from the data set of predictive variables and is also generated from the set of predictive variables. A variable contains data in the least. The predictor variables are related to low logistic regression analysis. Relationship between the predictor variables and the criterion variable is not a linear relationship in the analysis which will be adjusted in a linear relationship [14].

$$logistic(P) = \alpha + \beta_1 x_{1+} \beta_2 x_{2+} \dots + \beta_k x_k + \varepsilon \quad (1)$$

P is the probability or chance of an event study.

α is the intercept Y (intercept) or the value of Y when X equals 0.

βk is constant or the slope (slope) of the line represents the rate of change of Y on Xk to one unit of the other X variables constant.

ε is the error of the forecast.

Bayesian theory can be applied for the conditional decision by the principle that the sample space S is the common n Events A1 ,A2 ,A3 ,..., An if B is entitled to one event in a sample. MySpace and a part of Ai (i = 1,2,3,…,n) by P (B)> 0 is

$$P(A_i|B) = \frac{P(B|A_i)\cdot P(A)}{\sum_{n=1}^{n} P(B|A_i)\cdot P(A_i)} \quad (2)$$

From the equation P(Ai|B), we can determine the probability of the event B to cause the event A. This means is any of the event B happens, A will have the opportunity to apply any classification by selecting any event A according to the highest probability [15].

Four Algorithms are represented by a nonlinear, linear and non-parametric. To the new rules of composition, how to determine a diagnosis of flat feet.

III. MATERIALS AND METHODS

Podoscope is equipment for footprint on shooting glass, but the problem is the light which is reflected from the photos that have no clear safety glass required to control the amount of incident light from the top and bottom of the machine. For the trial application of the light source, the result is a light source which LED light is green leading to the most clear picture of Figure 2 [16].

Figure 2 foot prints

The data is used in this research derived from the study of patients with foot with diagnosis by using 66 tracks, In Podoscope, aged between 18-58 years, the total foot print are 132 images (on the left side of 66 images and the right side of 66 images). The averages are 165 cm and 67 kg for the height and weight, respectively.

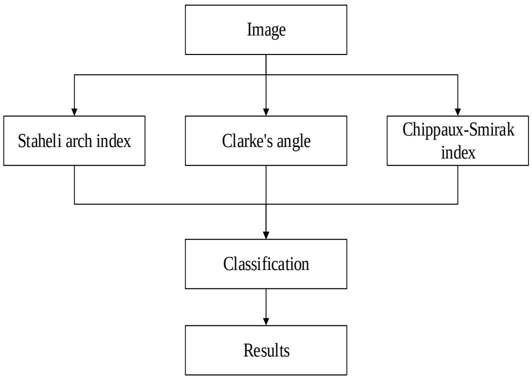


Figure 3 functional flow combine index

Step 1 To measure the size of each variable indicators from foot print images.

Step 2 To calculate indicators for each of the indicators with variables from step 1.

Step 3 To create model by using data from step1 and step2 for classify foot print. There are 4 algorithms: 1) Neural network 2) C4.5 decision tree 3) Logistic regression and 4) Bayesian. There are 7 variables set as input and 1 variable set as output. If the result is equal to 1, it will be classified to flat feet. But if the result is equal to 0, it means normal or not flat feet.

Step 4 To execute results from each algorithms by comparing the performance that used in the classification. There are 4 indicators as below:

1. Accuracy of the degree of conformity of a measured or calculated quantity to its actual (true) value.

2. Receiver Operating Characteristic (ROC) Curve showing the sensitivity and specificity of SN.

3. Sensitivity related to the test's ability to identify positive results.

4. Specificity related to the test's ability to identify negative results.

In flat foot screening, data is divided into four sets by using 4 indicators for comparing the performance of each algorithm: neural network, decision tree, logistic regression and Bayesian (pair T-Test).

IV. EXPERIMENTAL RESULT

This research study shows the results from 4 main algorithms as follows: 1) Neural network 2) C4.5 decision tree 3) Logistic regression and 4) Bayesian.

TABLE II SUMMARY PERFORMANCE OF THE CLASSIFICATION FROM DATASET (RIGHT FOOT 66 IMAGES) AND THE VALUES IN PARENTHESES ARE STANDARD DEVIATIONS.

Algorithm	Accuracy	ROC	Sensitivity	Specificity
Neural Network	89 (12.12)	0.96 (0.09)	0.93 (0.14)	0.86 (0.22)
C4.5 decision tree	86 (13.79)	0.86 (0.15)	0.85 (0.21)	0.89 (0.19)
logistic regression	85 (14.29)	0.93 (0.11)	0.87 (0.19)	0.82 (0.22)
Bayesian	85 (14.15)	0.95 (0.10)	0.89 (0.17)	0.82 (0.24)

TABLE III SUMMARY PERFORMANCE OF THE CLASSIFICATION FROM DATASET (LEFT FOOT 66 IMAGES) AND THE VALUES IN PARENTHESES ARE STANDARD DEVIATIONS.

Algorithm	Accuracy	ROC	Sensitivity	Specificity
Neural Network	89 (12.12)	0.96 (0.08)	0.87 (0.18)	0.86 (0.23)
C4.5 decision tree	84 (13.14)	0.86 (0.14)	0.86 (0.18)	0.83 (0.24)
logistic regression	86 (13.03)	0.95 (0.09)	0.89 (0.17)	0.83 (0.26)
Bayesian	88 (12.64)	0.97 (0.07)	0.91 (0.15)	0.85 (0.22)

TABLE IV SUMMARY PERFORMANCE OF THE CLASSIFICATION FROM DATASET (BOTH SIDES OF FOOT 132 IMAGES) AND THE VALUES IN PARENTHESES ARE STANDARD DEVIATIONS.

Algorithm	Accuracy	ROC	Sensitivity	Specificity
Neural Network	93 (7.37)	0.98 (0.04)	0.95 (0.09)	0.90 (0.14)
C4.5 decision tree	90 (8.62)	0.90 (0.10)	0.91 (0.11)	0.89 (0.14)
logistic regression	89 (8.04)	0.92 (0.06)	0.92 (0.11)	0.87 (0.14)
Bayesian	88 (8.11)	0.90 (0.10)	0.91 (0.12)	0.85 (0.15)

Table II-III shows the best efficiency classification algorithm of neural network and when test dataset (Both sides) from Table IV shown ROC 0.98 (standard deviations 0.04) and the sensitivity of 0.95 and specificity of 0.90.

V. CONCLUSION

The results showed that the classification is more accuracy after learning by neural network using multiple index to show the characteristic of flat feet. For the left feet, the accuracies for the classification of Staheli arch index (SI), Clarke's angle (CA) and Chippaux-Smirak index (CSI) are increased from single index to 41%, 20% and 9%, respectively. For the right feet, the accuracies for SI, CA and CSI are increased from single index to 50%, 21% and 9%, respectively. Finally, the accuracies of both sides for SI, CA and CSI are increased from single index to 50%, 25% and 13%, respectively. These algorithms are suitable for classification and able to apply in screening process of flat feet effectively.

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BIOGRAPHY

NAME	Mr. Wanlop Aruntammanak
DATE OF BIRTH	31 August 1988
PLACE OF BIRTH	Bangkok, Thailand
INSTITUTIONS ATTENDED	University of Thai Chamber of Commerce, 2007-2011 Bachelor of Engineering (Computer Engineering) Mahidol University, 2011-2013 Master of Science (Technology of Information System Management)
RESEARCH GRANTS	Grant to Support Graduate Students in Academic Presentations in Thailand Academic Year 2013
HOME ADDRESS	82/18 Suk Sawat Road, Bang Phueng, Phra Pradaeng, Samut Prakan, Thailand, 10130 Tel. 089-446-2521 E-mail : wanlop_5@hotmail.com
PUBLICATION / PRESENTATION	BMEiCON-2013 (October 23-25, 2013) (Diagnose Flat Foot from Foot Print Image Based on Neural Network)