Skeleton Bone Assessment Using Region of Interest and Ann Methods

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Abstract- In this project work we present a tool for automatic assessment of skeletal bone age according to a modified version of the Tanner and Whitehouse (TW2) clinical method. Tanner Whitehouse (TW2, TW3), Eklof and Ringertz methods. A bone age assessment study helps doctors to calculate the maturity of a child's skeletal system. The BAA estimation is usually done through a single X-ray of the left hand, wrist, and fingers. It is very simple, safe and painless that uses a small amount of radiation. The bone age is measured in years. The fingers and wrist of the child's radiographic images contain growth plates in growth zoning at both ends. The special cells in growth plates will determine the growth of the finger. Because of fewer minerals in radiograph images the growth plates can be finding easily in x-rays. As a person grows the growth plate of the radiograph will change in appearance on the X-ray images and become thinner, eventually the growth plates are closed. The tool is able to provide an accurate bone age assessment in the range 0–6 years by processing epiphytical/metaphysical ROIs with image-processing techniques, and assigning TW2 stage to each ROI by means of artificial neural network algorithms. The system was evaluated on a set of 360 X-rays (180 for males and 180 for females)achieving a high success rate in bone age evaluation (mean error rate of 0.41 ± 0.33 years comparable to human error) as well as outperforming other effective methods. In this project work aim that to define the best method using ANN (Artificial Neural Network) for estimating bones age based on comparisons of these four methods with their accuracy and efficiency.

Keywords *– Bone Age Assessment, Region of Interest, TW2 (Tanner and Whitehouse) clinical method and ANN (Artificial Neural Network).*

I. INTRODUCTION

The science and designing behind the sensors, instrumentation and programming used to get biomedical imaging have been developed ceaselessly since the x-beam was first concocted in 1895. Present day x-beams utilizing strong state gadgets require only milliseconds of presentation time, definitely diminishing the x-beam dosage initially required for recording to film tapes. The picture quality likewise enhanced, with upgraded determination and complexity, detail, giving most dependable and precise conclusions. Biomedical imaging focuses on the catch of pictures for both indicative and helpful purposes. Previews of in vivo physiology and physiological procedures can be accumulated through cutting edge sensors and PC innovation. Biomedical imaging advances uses either x-beams (CT filters), sound (ultrasound), attraction (X-ray), radioactive pharmaceuticals (atomic prescription: SPECT, PET) or light (endoscopy, OCT) to overview the current situation with an organ or tissue and can screen a patient after some time after some time for investigative and treatment appraisal.

Bone age assessment is to estimate the degree of maturity of a child's bone. A human growth as childhood, puberty, young adult, middle adult, and senior citizen. These changes can be seen by x-ray. There are 206 different bones in human body. In paediatric radiology Bone Age Assessment is clinical procedure to estimate the growth rate of the children.BAA uses Left hand wrist radiograph (x-ray) image is taken as input and the bone age of a children will be estimated. There are several methods are available to estimate the skeletal maturity of a children. Paediatric radiology mainly uses Greulich and Pyle which involves visual inspections and comparison of bone of hand based on the digital atlas.

Tanner Whitehouse (TW2, TW3), Eklof and Ringertz methods. A bone age assessment study helps doctors to calculate the maturity of a child's skeletal system. The BAA estimation is usually done through a single X-ray of the left hand, wrist, and fingers. It is very simple, safe and painless that uses a small amount of radiation. The bone age is measured in years. The fingers and wrist of the child's radiographic images contain growth plates in growth zoning at both ends. The special cells in growth plates will determine the growth of the finger. Because of fewer minerals in radiograph images the growth plates can be finding easily in x-rays. As a person grows the growth plate of the radiograph will change in appearance on the X-ray images and become thinner, eventually the growth plates are closed. A doctor can assign a bone age based on the appearance of the bones and growth plates. A child's skeletal maturity is assigned by using digital atlas which determining standard X-ray images with the atlas which is most closely related to the appearance of the child's bones on the X-ray [1].

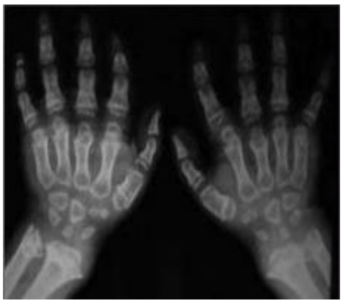

Fig 1. Bone Age Assessment

Bone age assessment is a procedure frequently performed in paediatric radiology. Based on a radiological examination of skeletal development of the left-hand wrist, bone age is assessed and then compared with the chronological age. A discrepancy between these two values indicates abnormalities in skeletal development. The procedure is often used in the management and diagnosis of endocrine disorders and it can also serve as an indication of the therapeutic effect of treatment [2]. Since these people usually don't have identity papers, determination of the skeletal maturity can help in the determination of the true age of such a person. This examination is universally used due to its simplicity, minimal radiation exposure, and the availability of multiple ossification centres for evaluation of maturity. Automatic skeletal age assessment has the potential to reduce the time required to examine the image and to increase the reliability of the analysis.

II. RELATED WORK

Daniela Giordano et al., 2016 [9] defined a tool for automatic assessment of skeletal bone age according to a modified version of the Tanner and Whitehouse (TW2) clinical method. The tool was able to provide an accurate bone age assessment in the range 0–6 years by processing epiphyseal/metaphysical ROIs with image-processing techniques, and assigning TW2 stage toeach ROI by means of hidden Markov models.The system was evaluated on a set of 360 X-rays (180 for males and 180 for females)achieving a high success rate in bone age evaluation (mean error rate of 0.41 ± 0.33 years comparable to human error) as well as outperforming other effective methods. They described the graphical user interface of the tool, which is also released, thus to support and speed up clinicians' practices when dealing with bone age assessment. **Mohamed Uvaze et al., 2013 [10]** defined that the Skeletal age assessment is a common and time consuming task in pediatric radiology. There are different feature selections in a bone age assessment (BAA) system for various stages of skeletal development. For example, diameters of epiphysis and metaphysic are used as sensitive factors during the early stage. Once the epiphyseal fusion has started, an additional feature such as the degree of fusion is extracted at the later stage. Image analysis is a critical point for feature selections to get a fine BAA, which includes ROI processing and feature extraction. Radius (R) and Ulna (U) bones are also considered for bone age calculation or assessment using Neural Network (NN). This system includes two parts. The first part gathers the features from the middle fingers Epiphysis / Metaphysis of Phalangeal region, which satisfy feature development of epiphysis and metaphysis. The second part gathers information from the Radius / Ulna bones by splitting-up ROI into quadrants and calculating the length of the bone in each quadrant. Experimental results reveal that the presented NN system provides a very good ability to assign a hand radiograph to an appropriate bone age. Furthermore, the related feature analysis for various stages is discussed to provide an accurate quantitative evaluation of specific features for the final BAA. **D. Giordano, C. Spampinato et al., 2009[11]** proposed a fully automatic system for bone age evaluation, according to the Tanner and Whitehouse method, based on the integration between EMROI and CROI analysis, which ensures accurate bone age assessment for the entire age range (0-10).

For both approaches novel segmentation techniques will be proposed. In detail, for the CROI analysis the bones extraction has been carried out by integrating anatomical knowledge of the hand and trigonometric concepts, whereas the TW2 stage assignment is implemented by combining the active contour models (ACM) and derivative difference of Gaussian (DrDoG) filter. For the EMROI analysis, image processing techniques and geometrical features analysis, based on difference of Gaussian (DoG), are proposed. **M. Krithika et al., 2015 [12]** used to estimate the skeletal maturity of children. Performing bone age assessment is an important path of the diagnostic and management pathway in children with a variety of growth and endocrine disorder. Bone age assessment methods are popular to estimate the growth rate of children. BAA is used to find hormone problems such as thyroid, diabetes, obesity and also finds genetic disorders such as deletion of genes, chromosome abnormalities. The growth problem is determined by the difference between a skeletal bone age and chronological age (The age from the birth). But such differences are not to always mean there is a skeletal maturity problem, because sometimes healthy kids can have the differences between bone ages and the birth age. The Appearances of the carpal bones, metacarpal bones, phalanges, radius and ulna of left hand wrist is used to calculate the bone age efficiently. **Arkadiusz Gertych et al., 2007 [13]** developed an automated method to assess bone age of children using a digital hand atlas. The hand Atlas consists of two components. The first component is a database which is comprised of a collection of 1,400 digitized left hand radiographs from evenly distributed normally developed children of Caucasian (CA), Asian (AS), African-American (AA) and Hispanic (HI) origin, male (M) and female (F), ranged from 1 to 18 year old; and relevant patient demographic data along with paediatric radiologists' readings of each radiograph. This data is separate into eight categories: CAM, CAF, AAM, AAF, HIM, HIF, ASM, and ASF. In addition, CAM, AAM, HIM, and ASM are combined as one male category; and CAF, AAF, HIF, and

ASF are combined as one female category. The male and female are further combined as the F & M category. The second component is a computer-assisted diagnosis (CAD) module to assess a child bone age based on the collected data. The CAD method is derived from features extracted from seven regions of interest (ROIs): the carpal bone ROI, and six phalangeal PROIs. The PROIs are six areas including the distal and middle regions of three middle fingers. These features were used to train the eleven category fuzzy classifiers: one for each race and gender, one for the female, one male, and one F & M, to assess the bone age of a child. The digital hand atlas is being integrated with a PACS for validation of clinical use.

III. CLINICAL METHODS

The main clinical methods for skeletal bone age evaluation are the Greulich and Pyle (GP) method and the Tanner e Whitehouse (TW2) method [3]. There are several differences between the two methods. The G&P method is most widely used in the Netherlands. This is mainly because the G&P method is faster and easier to use than the TW2 method. However, research has shown that the two methods produce different values for skeletal age and that these differences are significant in clinical practice. According to Bull the TW2 method is the more reproducible of the two, and also potentially more accurate. Although he states that it has never actually been shown to be more accurate. [14]

a) Greulich and Pyle Method

In 1929 preliminary studies were started at the Western Reserve University School of Medicine in Ohio. These studies were the base for a long-term investigation of human growth and development. A large number of children of different ages were enrolled in the study. These children had radiographs taken of their left shoulder, elbow, hand, hip and knee. In the first postnatal year an examination was conducted every three months, from twelve months to five years they were examined each 6 months and annually thereafter. In total the study ran from 1931 until 1942[4]. In 1937 an atlas, [15]"Atlas of Skeletal Maturation of the Hand", was published by Todd. This atlas was based on a part of the data collected in such study. Greulich and Pyle based their atlas partly on the atlas by Todd. Since their atlas was first published in 1950 they were able to use all the radiographs obtained in the original study. In total they had at their disposal from two to twenty-one hand radiographs made at successive examinations of each of 1000 children. In their method for each of these bones an elaborate description of its developmental stages is included.[5]

b) T2W Method

The TW2 method doesn't use a scale based on the age, rather it is based on a set of bone's standard maturity for each age population. In details, in the TW2 method twenty regions of interest (ROIs) located in the main bones are considered for the bone age evaluation. Fig.2 shows some of the bones of interest. Each ROI is divided in three parts: epiphysis, metaphysis and diaphysis especially in young people, it is possible to identify these different ossification centres in the phalanx proximity [6].

The development of each ROI is divided into discrete stages and each stage is given a letter (A,B,C,D, . . ., I) as is shown in fig.2. A numerical score is associated with each stage of each bone (Table 1). By adding the scores of all ROIs, an overall maturity score is obtained. This score is correlated with the bone age differently for males and females by the function shown in fig. 2.2. The TW2 method has a modular structure which makes it suitable for automation. For the TW2 method, three score systems have been developed [6]:

- TW2 20 Bones: characterized by twenty bones including the bones of the first, third and fifth finger and the carpal bones.
- RUS: considers the same bones of the TW2 method except the carpal bones; [16]
- CARPAL: considers only the carpal bones.

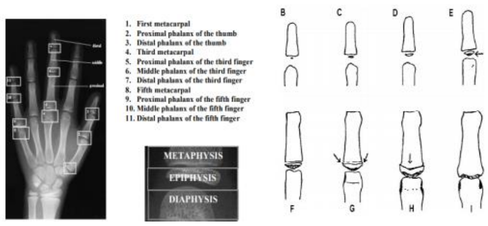

Fig 2 (i) Analysed ROIs in TW" method and (ii) Discrete Stages

IV. RESEARCH AIM AND PROPOSAL

The following are the objectives of the work to be done:

- To implement a proposed algorithm for bone age assessment using Artificial Neural Network.
- To develop a Pre-processing and ROI (Region of Interest) algorithm for feature extraction.
- To evaluate the accuracy in percentage performance parameter.

Step 1: First, we collect the dataset from the http://www.ipilab.org/BAAweb/ site.
Step 2: Pre-processing: Upload the image from the dataset to convert the original image to gray scale image. The gray scale image conversion means to reduce the original pixel size of the image.
Step 3: Extracted Feature: The categorized into specific stages labeled as (A, B, C, D, . . ., I). A numerical score is given to each stage of development for each bone individually. By summing up all these scores from the ROIs, a total maturity score is calculated.
Step 4: Classification: We proposed a classification using the Artificial Neural Network. In this approach classify the data in two phases:

(i) Training Phase

(ii) Testing Phase

Step 5: After classification, we evaluate the performance parameters based on Hidden Markov Model i.e. accuracy performance parameters.

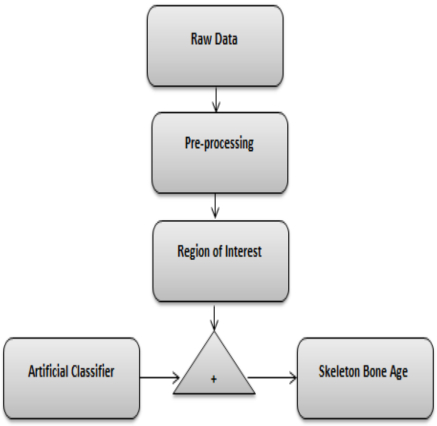

Fig 3. Proposed Flow chart

V. RESULT DISCUSSIONS

It shows that the central page defines the 0-4 age female dataset. After that the extract the features in the bone age based and classify the feature based on ANN algorithm. In testing section, we implement the analysis phase to identify the age based on bone detection and calculate the performance parameters like means and standard deviations.

Fig 4.Pre-processing Phase

The above figure shows that the upload the real image and then check the salt and pepper noise in the original image. We apply the median filter to remove the interference and distortion in the original image. In median filter implement the noisy image; convert the noise image after filtration process generates 2d transformation.

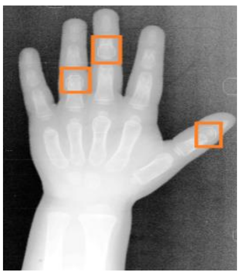

Fig 5 . Region of Interest

The above figure shows that the extraction, instead, has been carried out by taking into account, for each finger, the average gray-level of the segmented image depicting a finger. We then compute the first-order derivative of the average gray-level profile and search for local maxima: these values indicate the bone borders for metaphysis, epiphysis, and diaphysis and are used to extract the ROIs. We then apply, for reducing noise, smoothing filters on gray-level finger images. The first derivative is applied to the smoothed signal in order to enhance the identified ROIs. Finally, by thresholding the previous signal, we obtain a suitable filter to and using it extract the desired ROIs. In fact, based on the peaks of the obtained filter, the distance between the middle and the distal part of the finger and the one between the proximal and the middle part of the finger are calculated. If they are out of an anatomically plausible range, a warning message is displayed, and the procedure starts again by working on the derivative of the gray-level profile.

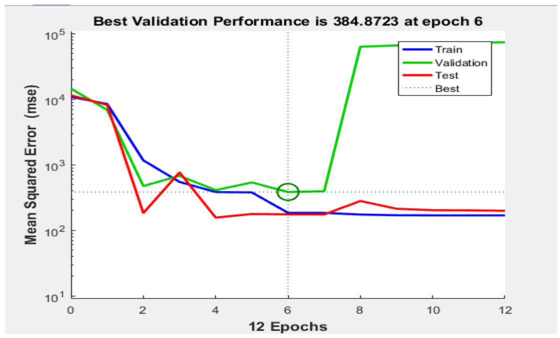

Fig 6. Performance

The above figure represents that the performance based on mean square error. That means we calculate the performance based on best validation performance. It defines that the train, test, validation and best position phase in the training stage.

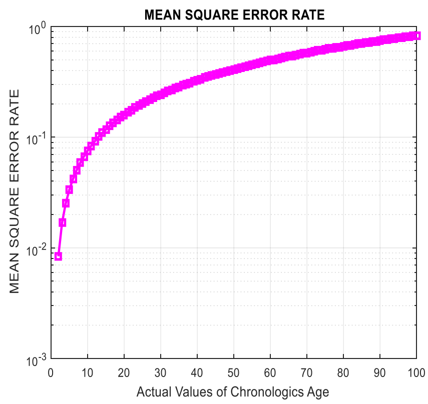

Fig 7. Means Square Error Rate

The above shows that the means square error rate means total error identifies the bone age assessment system.

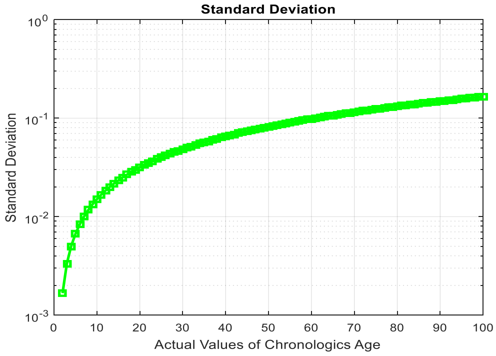

Fig 8. Standard deviation

The above figure defined that the standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values.[1] A low standard deviation indicates that the data points tend to be close to the mean of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values.

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, we study aims to develop intends to build up a computerized strategy for BAA in view of consolidated technique. This strategy tries to defeat the issues of leading BAA in manual strategies. Counterfeit consciousness beats the division issue as endured by existing frameworks. We execute the Sobel way to deal with distinguish the edges in view of most extreme esteems. After edge approach, we expel the contortion and apply a middle channel used to make the picture commotion free. To distinguish area in view of ROI and ANN (Artificial Neural Network) techniques. Otsu system is utilized to consequently perform thresholding - based picture fragmented, or, the decrease of a dark level picture to a parallel picture. We actualize the element extraction system utilizing the ROI calculation. A technique for examination which includes finding the direct mix of an arrangement of factors that has most extreme change and evacuating its impact, rehashing this progressively. At that point they arrange the separated component utilizing back propagation neural network. In ANN algorithm generates the two phase's i.e. training and testing phase, In training state we identify the performance based on epochs, times and validation checks. We can found the result in Bone age assessment with the enhance of the mean square error rate and standard deviation.

In future scope, BAA will identify the category of the MALE and FEMALE in bone age assessment. The second one we will implement the age detection is 3 year 5 month, 5 year 2 month of the bone images. Will Implement Deep Neural Network for the training and testing process which will have high response time and high reaction time with less error probabilities.

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