ABSTRACT

BAA is used to evaluate the skeletal maturity of children. Evaluating BAA is a significant way of the diagnostic and organization path in the children with the growth and endo-crime disorder. BAA techniques are famous to evaluate the growth rate of the child. The Bone Age Assessment is used to search hormone issues like diabetes, thyroid and search the genes dis-orders like removing of genes, chromosomes abnormal. The main issue is growth is determined by the dissimilar between a SBA (Skeleton Bone Age) and the age from the birth. In this research work, BAA is different techniques are used to evaluate BA (bone age) such as SIFT (Scale Invariant Feature Transform), FCM (Fuzzy C mean Clustering) and Classification to detect the age based on the bones using Back propagation Neural Network. In this proposed work is utilized to extricate the element in view of standard segment examination. It removes the one of kind properties of the separated picture. It produces two sorts of the component separating in surface structures i.e. key focuses. At that point they arrange the separated element utilizing Back engendering Neural System. In BPNN calculation produces the two stage's i.e. preparing and testing stage, in preparing state we recognize the execution in light of ages, times and approval checks. Moreover, the related element examination for different stages is talked about to give a precise quantitative assessment of particular components for the last BAA. Evaluate the performance parameters like root means square error, mean square error and accuracy.

Keywords

BAA (Bone Age Assessment), Skeleton Bone Age, SIFT (Scale Invariance Feature Transformation) and Filtration Method (Median).

1. INTRODUCTION

The verification of BA (Bone Age) is used for the follow up, diagnosis, treatment of diseases and endo-crime dis-orders[1]. In judiciary case is most significant for determining the individual adults and has legal capacity. For illustration, “Turkish Law” and “Rules” separate individuals into dissimilar age clusters form both a Legal and Severe Perception. The crime is depending on the nature, a penalty and sentence might alter according to the age cluster of the perception. It is an especially significant to evaluation whether the single in Ques [2]. Is at least 6, 7, 12, 15 and 18 years of age. The individual growth, the Bone Age (BA) is most normally used area of biological growth and Age.

Bone Age Assessment is depending upon analysing the stage of growth associated with skeleton development through the calculation of hand wrist radiographics. The stage of skeleton maturity could determine based-on binary features: (i) The stage of growth in field’s under-going ossification and (ii) Calcium accumulation in those fields [3].

Bone age is the path of defining the degree of maturation of chid bones. As a person produces from life through childhood and finishes growth as an elder, the skeleton bones modify in shape and size. These modifications could be understood by X-RAY[4]. The bone age of the child is the sum of the age at which children reach this rule of bone maturation.

At birth, only the metaphases of the “Huge Bones” are present. The huge bones are those that grow normally by the elongation at on epiphysis at one end of the developing bone. The huge bone adds the tibias, femurs and fibulas of the less limb, radius and phalanges of the toes and fingers [5].

Skeletal Bone estimation of children is a normal process performed in paediatrics. The object is determined the Bone age assessment through a detailed study of left hand wrist radio-therapy, which add all relevant feature extracted and regions detect based in Fuzzy c mean clustering[6].

Normally, the system includes an imaginary study the circle, bones and tubular bone adding distal, centre and proximal based on clinical methods like Tanner and White House techniques. The classical technique, this methods study of bone features or clusters (FCM) in hand radio-graphic by first feature extracting using scale invariance feature transformation to skeleton development and classify the age based on the features like Epiphysis and Metaphysis start to combined from the centre and extend toward the region or edges [7].

2. LITERATURE REVIEW

Giordano et.al (2016) [8] presented a tool for automatic assessment of skeletal bone age according to a modified version of the Tanner and Whitehouse (TW2) clinical method. The tool is able to provide an accurate bone age assessment in the range 0–6 years by processing epiphyseal/metaphysial ROIs with image-processing techniques, and assigning TW2 stage to each 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. Thangam et.al (2012) [9] described the comparative study on four computerized skeletal Bone Age Assessment (BAA) methods using the partitioning method. The four systems studied work according to the renowned
The aim of this paper is to evaluate or compare the results obtained from every bone age estimation methods and suggests the best method based on the accuracy and efficiency. Aydoğdu et.al (2014) [11] described automatic assessment with computers is to render the decision procedure more objective, and to consequently permit more consistent results to be obtained. Studies in this area have drawn considerable attention to automatic assessment approaches, especially following the progresses in the area of image processing. In the current study, the Greulich-Pyle (GP) and the Tanner-Whitehouse (TW) methods used in computer-assisted bone age assessment were presented, & information was also provided regarding the mechanization of these methods. Hsieh et.al (2013) [12] observed that the Tanner and Whitehouse III (TW3) method for determining bone age involves detailed shape analyses of several bones of interest and assigning corresponding scores, but the complexity and time consuming nature make it hard to apply in clinic. Therefore, our project is to develop an easy-to-use graphical user interface which can automatically localize and segment the phalanx region of interests (PROIs) and the epiphyseal/ metaphysis region of interests (EMROIs) of the left-hand radiogram, and then a TW3 scoring system is provided to the user to make a decision. Based on this structure, a set of image processing processes was proposed for the segmentation of PROIs and EMROIs, and then 8 EMORIs were consecutively popped up for the evaluation of TW3 scores.

3. DIFFICULTIES IN BONE AGE ASSESSMENT

This study aims to develop an automated method for BAA based on combined method. This method tries to overcome the problems of conducting BAA in manual methods. The work motivated the increasing awareness of the need for bone age assessment (BAA) schemes featuring an appropriate methodology for skeletal age estimation. The endocrinological problems in youngsters are already evident in many countries worldwide, varying in scale and intensity for different age groups and sexes[13]. Change in lifestyles and eating habits of people also contribute to endocrine disorders, increasing the need for a system that predicts such problems well in advance. Skeletal bone age assessment is a procedure often used in the management and diagnosis of endocrine disorders. It also serves as an indication of the therapeutic effect of treatment. It is of much significance in paediatric medicine in the detection of hormonal growth or even genetic disorders. Bone age is assessed from the left-hand wrist radiograph and then compared with the chronological age[14]. Although much research has been carried out, the problem of estimating accurately the bone age of an individual is far from being solved. While this method suffered from the classical “infancy” problems (e.g. image quality, reproducibility etc..), it can be considered as one of the first steps towards more complex and accurate systems for bone age assessment. Since then, many other methods for assessing skeletal bone age, especially based on the BPNN method, have proposed [15].

4. SIMULATION MODEL

The bone age assessment of skeletal age development is normally used process in radiography. The difference between biological age and bone maturity defines the existences of some irregular in skeletal growth. The bone age assessment is normally evaluated using radiography of the left hand, due to the relatively tiny patient study and the high degree of normal of the test case. The hand presents a huge number of centres which could be used to obtain an accurate estimation of the degree of maturity. The methodology diagram defines that the system composed of a graphical user interface for input hand radiography some steps: Image Acquisition followed by an image pre-processing process like noise check, filtration, segmentation methods, which locations the FCM for further processing, which extract the features from each SIFT and Clusters and Neural Network (BPNN) classifier which observed the bone difficulties and assign suitable bone age as it was knowledge set trained during its training phases.

Step 1: First, we collect the dataset from the http://www.ipilab.org/BAAweb/ site.

Step 2: 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.

Fig 1. (i) Original Image and (ii) Noisy Image

Step 3 Edge detection: We apply the canny edge detection means detect the edge based in minimum, maximum and average value. After edge approach, we remove the distortion and apply median filter used to create the image noise free.

Fig 2. (i) Filtered Image and (ii) Edge Detection
Step 4 Segmentation: to detect region based on FUZZY C-MEANS methods. Otsu technique is used to automatically perform clustering-based image thresholding, or, the reduction of a gray level image to a binary image.

Step 5 Feature Extraction: We implement the feature extraction technique using SIFT algorithm. A method of analysis which involves finding the linear combination of a set of variables that has maximum variance and removing its effect, repeating this successively.

Step 6 Classification: We proposed a classification using the Back propagation neural network. In this approach classify the data in two phases:

(i) Training Phase
(ii) Testing Phase

Step 7: After classification, we evaluate the performance parameters based on Novel approach (BPNN+SIFT) i.e accuracy, false acceptance rate , false rejection rate and mean square error rate and compare the base paper performance parameters.

5. RESULTS
The back propagation neural network is used to classify in this research to detect the bone age radiography. The characteristics obtained in the existing model is given as the input to the BPNN in the training phase along with the hidden neurons = 10 and the given trained network is tested with the testing radiography and the calculated bone age is displayed.

Fig 6. Back Propagation Neural Network

The above figure represents that the neural network means applying the classification. It generates the two phase’s i.e training and testing phase. We defined that the 100 epochs mean training iterations, but the system will use the 7 iterations. Calculate the time, performance, gradient and mutation.

Fig 7. (i) Best Performance (ii) Training State

The above figure 7(i) and (ii) 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. The training state parameters i.e gradient means calculated the line slope of the training phase. Mutation is what changes required in changes state and validation check means split the data into two phases.

The below figure 8 represents that the regression phase means calculated the average performance with the training, testing and validation check.
The table below defines that the values considered from the extracted features of both. The value defines that the ratio between age group is 1-7 age.

**Table no. 1 Mean Square Error Rate (Proposed Work)**

<table>
<thead>
<tr>
<th>Age</th>
<th>Mean Square Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.001941</td>
</tr>
<tr>
<td>2</td>
<td>0.004852</td>
</tr>
<tr>
<td>3</td>
<td>0.007521</td>
</tr>
<tr>
<td>4</td>
<td>0.009462</td>
</tr>
<tr>
<td>5</td>
<td>0.00123</td>
</tr>
<tr>
<td>6</td>
<td>0.001456</td>
</tr>
<tr>
<td>7</td>
<td>0.001698</td>
</tr>
</tbody>
</table>

**Fig 8. Regression**

**Fig 9. Means Square Error Rate (Proposed Work)**

The Mean Squared Error (MSE) is a measure of how close a fitted line is to data points. For every data point, you take the distance vertically from the point to the corresponding y value on the curve fit (the error), and square the value. Then you add up all those values for all data points, and, in the case of a linear fit, divide by the number of points minus two.

The squaring is done so negative values do not cancel positive values. The smaller the Mean Squared Error, the closer the fit is to the data. The MSE has the units squared of whatever is plotted on the vertical axis.

**Table 2. Accuracy in Proposed Work**

<table>
<thead>
<tr>
<th>Age</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>49</td>
</tr>
<tr>
<td>3</td>
<td>58</td>
</tr>
<tr>
<td>4</td>
<td>69</td>
</tr>
<tr>
<td>5</td>
<td>80</td>
</tr>
<tr>
<td>6</td>
<td>89</td>
</tr>
<tr>
<td>7</td>
<td>99</td>
</tr>
</tbody>
</table>

**Fig 10. Accuracy with BPNN and FCM**

It shows the best accuracy result. As False Acceptance Rate and False Rejection Rate decrease, Accuracy increases. The above figure defined that the accuracy, performance parameters, it is a description of the system error, a consider of statistic bias as these cause a dissimilar between a consequence and a true values.

**Table 3. Comparison between RMSE (Proposed and Existing Work)**

<table>
<thead>
<tr>
<th>Age</th>
<th>Root Means Square Error (PP)</th>
<th>Root Means Square Error (Base Paper)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.001402</td>
<td>0.0022</td>
</tr>
<tr>
<td>2</td>
<td>0.003116</td>
<td>0.04886</td>
</tr>
<tr>
<td>3</td>
<td>0.004518</td>
<td>0.0684</td>
</tr>
<tr>
<td>4</td>
<td>0.006387</td>
<td>0.09771</td>
</tr>
<tr>
<td>5</td>
<td>0.007633</td>
<td>0.1221</td>
</tr>
<tr>
<td>6</td>
<td>0.009191</td>
<td>0.1441</td>
</tr>
<tr>
<td>7</td>
<td>0.00109</td>
<td>0.1661</td>
</tr>
</tbody>
</table>

**Fig 11. Comparison Proposed and Existing Work (RMSE)**

The above figure shows that the comparison between Root Mean Square Error Rate in Existing and Proposed work. We enhance the performance of the proposed work used in BPNN. This means Average of the training section and testing section error. The effect of each error on RMSD is proportional to the size of the squared error, thus larger errors have a disproportionately large effect on RMSD. Consequently, RMSE is sensitive to outliers.
6. CONCLUSION AND FUTURE SCOPE

In conclusion, our study aims to develop an automated method for BAA based on combined method. This method tries to overcome the problems of conducting BAA in manual methods. Artificial Intelligence overcomes the segmentation problem as suffered by existing systems. We implement the Sobel approach to detect the edges based on maximum values. After edge approach, we remove the distortion and apply a median filter used to create the image noise free. To detect region based on FCM methods. Otsu technique is used to automatically perform clustered-based image segmented, or, the reduction of a gray level image to a clustered i.e component image. We implement the feature extraction technique using the SIFT algorithm. A method of analysis which involves finding the linear combination of a set of variables that has maximum variance and removing its effect, repeating this successively. Then they classify the extracted feature using Back propagation Neural Network. In BPNN algorithm generates the two phase’s i.e training and testing phase, in training stage we identify the performance based on epochs, times and validation checks. We can find the result in Bone age assessment with the enhance of the accuracy value is 99 and RMSE value is 0.0152.

In future scope, we 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. It can use Deep Neural Network for the training and testing process which will have high response time and high reaction time with less error probabilities. The future work can be the comparative analysis of two machine learning algorithms for bone age assessment.

7. REFERENCES


