# Skeletal Bone Age Assessment Using Neural Network

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***Abstract—*** Bone age assessment (BAA) is a method of evaluating the level of skeletal maturation in children. The manual methods are prone to variability of observation, time consuming and limited to objective decisions. BAA is purely based on measuring the length and shape of various bones, so radiographs images are must. In this research work, a multi-scale structuring element is used to enhance the X-ray of a left hand-wrist using circular shape structuring element at different scales to extract bright and dark portions at all scales and its neighboring scales. The proposed algorithm is used to extract the features based on many important factors and its dimensions are reduced using principle component analysis. It extracts the unique properties of the filtered image. It gives two kinds of the feature extracting in texture forms i.e. eigenvectors and eigenvalues. Then the extracted features are classified using BPNN and this classification is used to classify the bone age and detects the age of the bone and then the performance parameters like FAR, FRR and accuracy are evaluated.

***Index Terms—*** Bone Age Assessment or Skeletal, left hand, wrist, Feature Extraction (PCA), classification Back propagation Neural Network (BPNN).

## I. INTRODUCTION

Skeletal maturation is a surrogate of developmental age or physiological maturity which represents more truthfully than chronological age or determines how far an individual has progressed towards full maturity and may hence be considered a sort of 'biological age'. Skeletal maturation is marked by an orderly and a reproducible sequence of recognizable variations in the appearance of the skeleton during childhood [1].

Bone age assessment is very significant in pediatrics, especially in the diagnosis of endocrine logical problems and growth disorders. Based on the skeletal improvement of the bones in the left-hand wrist [2], bone age is assessed and compared with the chronological age. A difference between these two values indicates irregularities in skeletal development. This is used in the diagnosis of endocrine disorders and also to monitor the therapeutic effect of the treatment. Bone age indicates whether the growth of a patient is accelerating or decreasing, based on which the patient can be treated with growth hormones. BAA is widely used due to its simplicity, minimum radiation exposure, and the availability of multiple Bone Disease Management centers for assessment of maturity [3].

The development of each ROI is divided into various stages, as shown in figure 1, and each stage is given a letter (A,B,C,D,…I), reflecting the development stage as:

- Stage A – Absent
- Stage B – Single deposit of calcium [4]
- Stage C – Center is distinct in the entrance
- Stage D – Maximum diameter is partial or more the width of metaphysics
- Stage E – Border of the epiphysis is dipped
- Stage F – Epiphysis is as varied as metaphysics
- Stage G – Epiphysis caps the metaphysis
- Stage H – Fusion of epiphysis and metaphysis has begun
- Stage I – Epiphysis fusion completed.

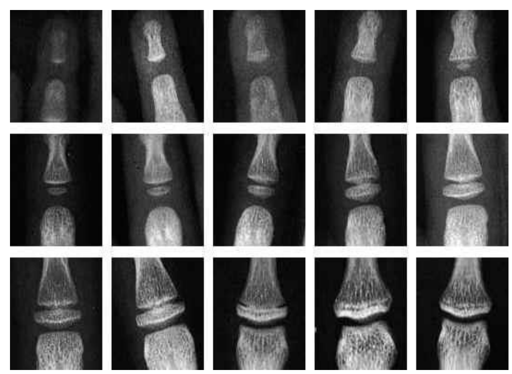


Fig.1. Different stages of Bone Development

BAA is a radiological inspection to determine the difference between the skeletal bone age and the chronological age (the real age since birth date) [5]. This discrepancy presents aberrations in the skeletal growing of children or hormonal problems. For a reliable assessment of bone age (BA) and reproducible method, it is not only a difficult process but also a time-consuming radiological procedure. BAA is based on three orders as follow; (a) entrance of primary and secondary middles of ossification, (b) growth of both centers, (c) timing of fusion of the primary and secondary centers.

## II. TYPES OF BONE AGE ASSESSMENT

**1. GP Method [6]**

The GP method is an atlas method in which bone age is assessed by comparing the radiograph of the enduring with the nearest standard radiograph in the atlas. The GP method was developed using radiographs of upper-middle class Caucasian kids in Cleveland, Ohio, United States, & the radiographs were obtained between 1931 and 1942. It has recently been reported that secondary sex characteristics in current boys & girls begin earlier than they did numerous decades ago in the United States, therefore, it may be difficult to assess bone age accurately in current children using the GP method.

**2. TW2 Method**

There are actually 3 different TW2 methods: the radius-ulna-short bones (RUS) method for appraising the 13 long or short bones (i.e., the radius, ulna and short bones of the first, third & fifth fingers), the carpal process for evaluating the 7 carpals and the 20-bones method for evaluating the 13 long or short bones and 7 carpals. For the purposes of this review, the TW2 techniques are referred to as the TW2 technique hereafter. The TW2 method is a scoring method. The maturity level of each bone is categorized into a stage (from stage A to H or I). Afterwards, every stage is replaced by a score and a total sore is calculated. Finally, the total score is transformed into the bone age value [7].

## III. RELATED WORK

C. Spampinato et.al (2017) [8] presented several deep learning methods to assess skeletal bone age automatically; the results presented an average discrepancy between manual & automatic assessment of about 0.8 years, which is state-of-the-art performance. Besides, this is the first mechanical skeletal bone age calculation work tested on a public dataset and for all age ranges, races & genders, for which the source code is obtainable, thus representing an exhaustive baseline for future research in the field. Beside the precise application scenario, the writer aims at providing answers to more general questions about deep learning on medical images: from the comparison between deep-learned features and manually-crafted ones, to the usage of deep-learning techniques trained on general imagery for medical difficulties, to how to train a CNN with few images. Daniela Giordano et.al (2016)[9] 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 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 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. P. Thangam et.al (2012) [10] did a comparative study on four computerized skeletal Bone Age Assessment (BAA) methods using the partitioning method. The four systems studied work according to the renowned Tanner & Whitehouse (TW2) method, based on the Region of Interest (ROI) taken from the wrist bones. The systems ensure accurate & robust BAA for the age range 0-10 years for both girls & boys. Assumed a left hand-wrist radiograph as input, they estimate the bone age by deploying remarkable procedures for preprocessing, feature extraction, and classification. The four BAA systems differ from each other in the type of ROI used, the feature extraction techniques and finally the classification. The systems output the age class to which the radiograph is categorized (Class A – Class J), which is mapped onto the final bone age. The systems were studied and their performances were compared by varying the partition of the train and test data sets. The systems were judged based on the results obtained from two radiologists. Nikhil Dharman et.al (2014) [11] presented methods for assessing bone maturity that include :

1) Greulich and Pyle

2) Tanner and Whitehouse and

3) Eklof and Ringertz.

The aim of this paper is to evaluate or compare the results obtained from every bone age estimation methods & suggests the best method based on the accuracy and efficiency [12].

Table 1. Computation between related papers in Bone Age Assessment

| Author Name | Title Name | Technique Used | Parameters or Results |
|---|---|---|---|
| C. Spampinato [2017] | Deep learning for automated skeletal bone age assessment in X-ray images. | Deep learning , ROI | Average in reading phase (1,2) |
| D. Giordano [2015] | Modeling skeletal bone development with hidden Markov models | Machine Learning , hidden Markov models | TW2 final score |
| P. Thangam [2012] | Comparative Study of Skeletal Bone Age Assessment Approaches using Partitioning Technique | Feature Extraction and classification | Accuracy, Recall, Precision |
| N. D. M. K and J. C. Moses[2014] | Survey on Different Bone Age Estimation Methods | ER method, GP and TW method | Accuracy |

## IV. ISSUES IN BONE AGE ASSESSMENT

Bone age assessment (BAA) is a method of evaluating the level of skeletal maturation of the population. Generally, it is applied manually by comparing an X-ray of a left hand-wrist with a standard samples as atlas in the clinical procedure. The manual methods however are prone to variability of observation, time consuming and limited to objective decisions. These are big motivations for an automatic method for 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 [13]. The work stimulated the growing awareness of the need for bone age assessment (BAA) structures featuring an appropriate methodology for skeletal age estimation. Bone age is assessed from the left-hand wrist radiograph and then compared with the chronological age. Although much research has been carried out, the problem of estimating accurately the bone age of an individual is far from being solved [14]. Then, it can be observed that use of machine learning in building automated BAA is limited although some researchers have used Deep Learning also. But the biggest disadvantage in using Deep learning is that it requires high grade hardware and huge dataset. Many researches have used Neural Networks for building BAA and it can be seen that this method seems to perform well in most cases .With advancement in medicine many new indicators can be used for age assessment and better feature vectors can be made having better discriminate power. Hence, new set of feature vector and feature processing is proposed (PCA) for its use in Neural network [15](Back propagation).

## V. PROPOSED MODEL

In this section, the implementation steps taken to solve the main issues (estimating accurately with help machine learning) in bone age systems have been explained.

Step 1: The images for building the proposed have been sourced from http://www.ipilab.org/BAAweb/ site.

Step 2: All the images undergo few pre-processing steps such as resizing for maintain aspect ratio and then were converted into gray scale. So that the image processing requires less resources.

Step 3: Segmentation & Edge detection: The next process was to remove noise (by using median filter ) if any in the images and then apply segmentation algorithm for getting prominent hand image on which edges need to made more clear with the help of sobel operator.

Step 4: In this step, each image is processed for extracting its feature with respect to its class. We have taken 10 classes: which include 6, 8...16 years old boys and these classes were coded as A, B, C respectively. For each class dataset, PCA was applied[16]. This removes not only useful information but precisely decomposes the X-ray hand image structure. This further involves transformation of number of possible correlated variables into a smaller number of orthogonal (uncorrelated) components known as Principal Components. Each hand X-Ray may be represented as a weighted sum (feature vector) of the Eigen faces which are stored in a 1D array. Finally, this step can be summarized as follows:

*a)* For each age, class $10 \times 15$ matrix was made available. The number of rows in the matrix dimension indicates the number of exemplars available for each class and the number of columns indicates the total number of features extracted as given in Table 2. The PCA-based preprocessing was then applied on 10 features in order to find the principal variables to be given as input for the ANN.

Table 2. Features Extracted from hand X-ray

| | |
|---|---|
| 1 | Standard deviation of Grey Levels $\sigma$ |
| 2 | Skewness of the Image matrix |
| 3 | Kurtosis of the Image matrix |
| 4 | Histogram tail length on the dark side $(q-p)$ |
| 5 | Histogram tail length on the bright side $(s-r)$ |
| 6 | Number of edge pixels after thresholding a segmented window at mean value |
| 7 | Number of pixels after thresholding at $\mu-2\sigma$ |
| 8 | Calculate the number of edge pixels for feature 14 |
| 9 | Number of pixels after thresholding at $\mu+2\sigma$ |
| 10 | Calculate the number of edge pixels for feature 16 |

*b)* Calculate the mean of the input X-Ray images

Subtract the mean from the input images to obtain the mean-shifted images

*c)* Calculate the eigenvectors and eigenvalues of the mean-shifted images

*d)* Order the eigenvectors by their corresponding eigenvalues, in decreasing order

*e)* Retain only the eigenvectors with the largest eigenvalues (the principal components)

*f)* Project the mean-shifted images into the Eigen space using the retained eigenvectors.

Step 5: Classification: A feed-forward ANN with a Back-Propagation learning algorithm has been chosen using 75% of the data-set for training and 25% for testing. The results were compared with those obtained using all the features as input for the ANN. Subsequently, several experiments have been conducted in order to find the best ANN configuration for the identification of bone age class. The experiments have been carried out using different number of hidden layers, different number of neurons in the hidden layers, different values of the Pearson coefficient and different numbers of input for the network. The implementation of neural network as classifier is as follows:

a) First, normalization of the input and output vectors. Using method that eliminates the insignificant principal components based on the threshold value. In our case, 0.02 values as threshold is used.
b) The output of the above step gives a transformed input vector and principal component of the transformed input matrix.
c) After the network has been trained, this matrix should be used to transform any future inputs that are applied to the network. It effectively becomes a part of the network, similar to the network weights and biases. The multiplication of the normalized input vectors by the transformation matrix, transformed input vectors are obtained.
d) Next step it to divide the dataset into training, validation and test sets and conduct evaluation.

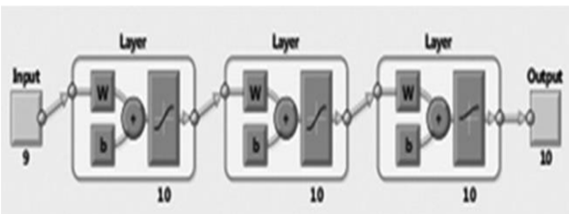



Fig.2. Network with an input layer of neurons

e) Figure 2 shows a network with an input layer of nine neurons representing the best selected features, two hidden layers with 10 and 10 neurons, respectively, and finally the output layer with 10 neurons, one for each age class ( 6,8,9,10,11,12,13,14,15,16 ) years .

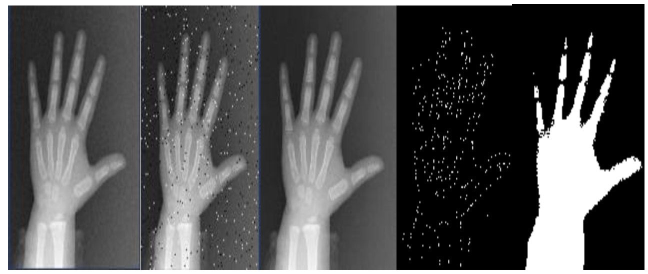
Step 6: After classification, we evaluate the performance parameters based on this approach (BPNN+PCA) i.e. accuracy, false acceptance rate, false rejection rate and mean square error rate and compared the base paper performance parameters.

Here, the network output and the corresponding targets to a function have been passed to the network that returns three parameters. The first two, m and b, correspond to the slope and the y-intercept of the best linear regression relating targets to network outputs. If we had a perfect fit (outputs exactly equal to targets), the slope would be 1, and the y-intercept would be 0.

## VI. RESULTS

In this research work, we have used Matlab 13a for image processing functions and its neural network toolbox for implementing the classification algorithm. Following are the results of the implementation.

The below figure 3(i) an (ii) show that the uploaded the original image in the software for checking if there is any kind of noise in the original image.



(i) (ii) (iii) (iv) (v)

Fig.3. (i) Original Image (ii) Noisy Image (iii) Noise Free Image(Filtration) (iv) Edge detection and (v)Segmentation

The above figure 3(iii) represents that the filtered 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 the filtration process generates 2d transformation. The fig (iv) and (v) represents that the edge detected by the single value in the filtered image. Sobel operator was used on the original images for identification of the edges of the bone parts. The segmentation method applied was ostu method. Finally the image was converted to extract ROI in terms of gray scale and finally into a binary image

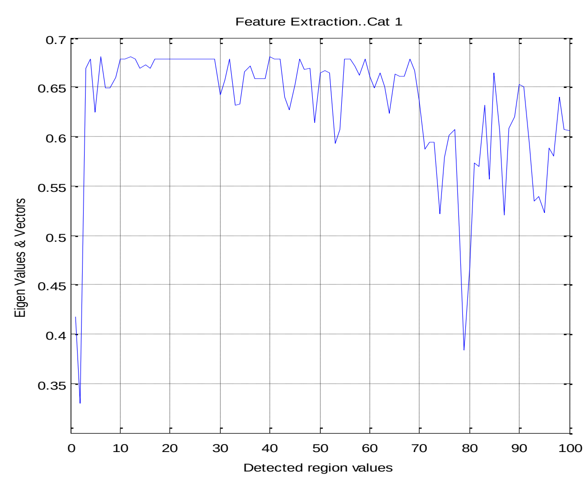



Fig.4. Features Extracted In Bone Age Images

The figure represents that the principle component analysis calculates the unique properties. In this feature data divides into two features i.e. Eigen values and Eigen vector.

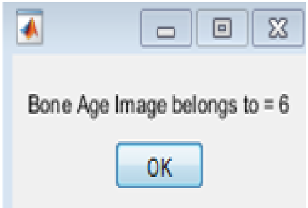
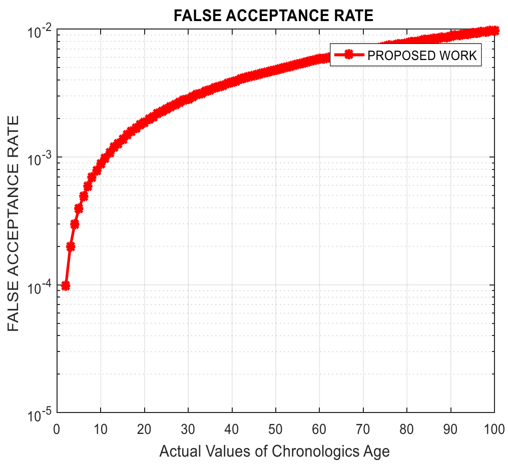
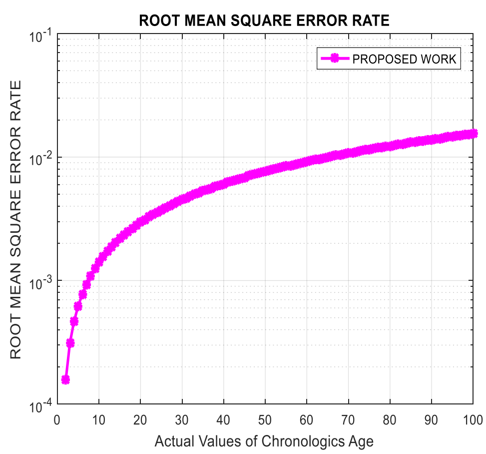



Fig.5. Detection of Age

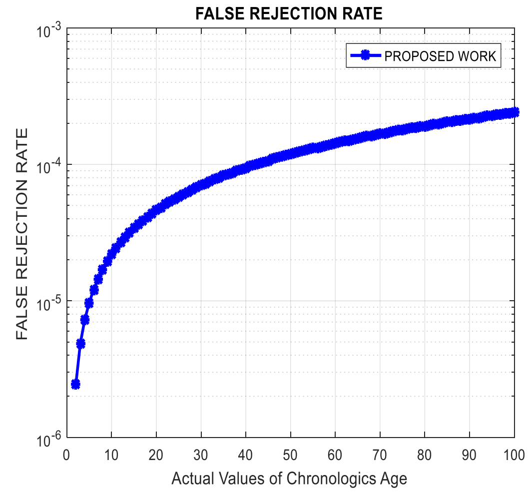
The above message box shows that the age detection of the bone based on features and region's data classification possible. To identify the age number is 6.




(i)




(ii)




(iii)

Fig.6. Performance Error Rate Parameters (FAR, RMSE anf FRR)

The figure 6(i) shows false acceptance rate, it can be seen that there is little likelihood that the system will accept wrong age class as per the values in the table. The figure 6(ii) defined that the Root Mean Squared Error, is a frequent measure of the dissimilarities between values considered by a model or estimator values actually considered. The FRR values also show similar terms as false acceptance rate. It clearly shows that system will not incorrectly reject the age class while predicting. It is, normally, expressed as %age following the FRR definition this is %age of valid input which are in-correctly wrong.

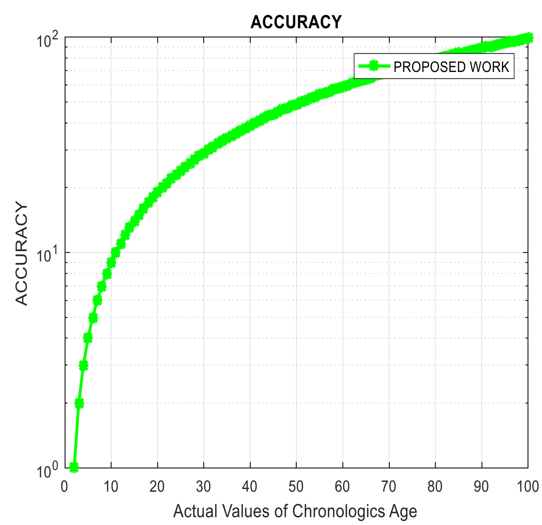



Fig.7. Accuracy in Proposed Work

The figure 7 defines the accuracy performance parameters. It is the description of system error, a consideration of statistic bias as these cause a dissimilar between a consequences and a true values.

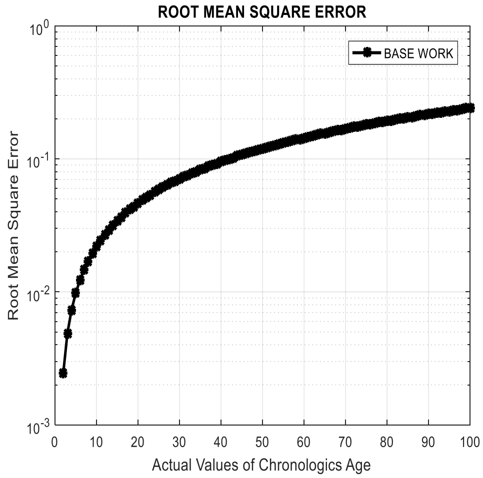



Fig.8. RMSE in Base paper

The figure 8 shows that the root means square error in base paper. In base paper RMSE increases but the performance of the RMSE has been improved i.e. reduce the parameter value based on BPNN.

Table 3. False Acceptance Rate (Proposed Work)

| Actual Value of Chronologic Age | False Acceptance Rate |
|---|---|
| 6 | 0.00788 |
| 8 | 0.001775 |
| 9 | 0.002958 |
| 10 | 0.003846 |
| 11 | 0.004733 |
| 12 | 0.005916 |
| 13 | 0.006804 |
| 14 | 0.00779 |
| 15 | 0.008973 |
| 16 | 0.009762 |

Table 4. Root Means Square Error Rate (Proposed Work)

| Actual Value of Chronologic Age | Root Means Square Error |
|---|---|
| 6 | 0.001402 |
| 8 | 0.003116 |
| 9 | 0.004518 |
| 10 | 0.006387 |
| 11 | 0.007633 |
| 12 | 0.009191 |
| 13 | 0.00109 |
| 14 | 0.001231 |
| 15 | 0.001386 |
| 16 | 0.01527 |

Table 5. False Rejection Rate (Proposed Work)

| Actual Value of Chronologic Age | False Rejection Rate |
|---|---|
| 6 | 0.001941 |
| 8 | 0.004852 |
| 9 | 0.007521 |
| 10 | 0.009462 |
| 11 | 0.000123 |
| 12 | 0.0001456 |
| 13 | 0.0001698 |
| 14 | 0.001965 |
| 15 | 0.0021591 |
| 16 | 0.0002402 |

Table 6. Accuracy in Proposed Work

| Actual Value of Chronologic Age | Accuracy |
|---|---|
| 6 | 9 |
| 8 | 20 |
| 9 | 29 |
| 10 | 31 |
| 11 | 49 |
| 12 | 58 |
| 13 | 69 |
| 14 | 80 |
| 15 | 89 |
| 16 | 99 |

Table 7. Root means Square Error Rate (Base Paper)

| Actual Value of Chronologic Age | Root Means Square Error (Base Paper) |
|---|---|
| 6 | 0.002198 |
| 8 | 0.04886 |
| 9 | 0.0684 |
| 10 | 0.09771 |
| 11 | 0.1221 |
| 12 | 0.1441 |
| 13 | 0.1661 |
| 14 | 0.1954 |
| 15 | 0.2174 |
| 16 | 0.2398 |

The table 6. defines that the performance of the implemented work parameters i.e. false acceptance rate, false rejection rate, root means square error rate and Accuracy. In Table 7 values shown in base paper.

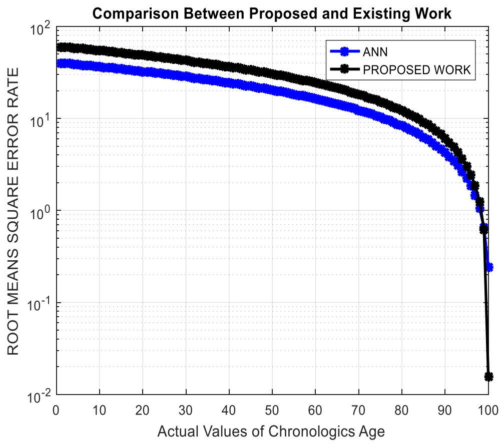



Fig.9. Comparison between Base paper and proposed work

Table 8. Comparison between Proposed and Existing work (RMSE)

| Actual Value of Chronologic Age | Root Means Square Error (Base Paper) | Root Means Square Error |
|---|---|---|
| 6 | 0.002198 | 0.001402 |
| 8 | 0.04886 | 0.003116 |
| 9 | 0.0684 | 0.004518 |
| 10 | 0.09771 | 0.006387 |
| 11 | 0.1221 | 0.007633 |
| 12 | 0.1441 | 0.009191 |
| 13 | 0.1661 | 0.00109 |
| 14 | 0.1954 | 0.001231 |
| 15 | 0.2174 | 0.001386 |
| 16 | 0.2398 | 0.001457 |

The figure 9 shows that the comparison between Root Mean Square Error Rate in existing [15] and implemented work. It can be seen that the values in implemented case also remains below 0.5 and close to 0.1 which means that there was not over or under data fitting in neural network while finding the age classes. It clearly shows that the predicted values and actual values have little difference hence higher degree of accuracy.

## VII. CONCLUSION AND FUTURE SCOPE

Bone Age Assessment (BAA) Systems have undergone multiple changes since, the usage of machine learning algorithms have come into main stream industry. From systematic reviews, it was found that most of these methods follow neural networks based algorithms for classification tasks. In this research, we have used well established methods for extracting feature of each bone part so that a reliable solution can be developed. The features extracted were based on image processing methods and were found have enough discriminate to provide ease for neural network for computing various classes of Ages. It is apparent for each actual class of age the algorithm was able to predict correct age class. Thus showing that there was high rate of true positive. From the results it can be seen that the average accuracy value remain close to 98.9% .But the root mean square values is below 0.5 which means the neutral network was able to fairly fit the data for finding age classes .

For future scope, this work can be extended by adding two more classes i.e. Male and Female. Separate feature vectors can be male and female classes with their age brackets. This extended feature row can be subjected to neural network and few parameterized loops to find most optimal configuration of neural network with same or higher degree of accuracy.

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