

Hand Wrist X-Ray Images in Bone Age Assessment Using Particle Swarm and Convolutional Neural Network Algorithm

Akanksha Sharma, Prabhjeet Kaur

Abstract: - Bone age assessment is method of analyzing the maturity of bones of an individual using x-ray images. Generally, left hand wrist is used for imaging for the reason that calcium deposit in the ossification area of the bones recognizes the organic growth of the bones. Bone age assessment (BAA) is method of checking ossification maturity level in left hand wrist using x ray images for bone age assessment using graphical approach. In early stage; two main techniques used for bone age assessment are Greulich-Pyle (GP) and Tanner Whitehouse (TW2) technique. The radiograph bone of the patient is matched with standard radiographs using graphics and results are determined in Greulich-Pyle method, whereas in Tanner Whitehouse method scoring approach is used for assessment of bone age. In last developed method, maturity level of bone age of ulna and radius was analyzed utilizing convolutional neural network. Medical technologist determine the age of person through radiograph technology of hand wrist of the person and that process of recognizing age is known as bone as assessment. In this research, two algorithms are congregated for prediction of particle using convolutional neural network. The main research section defined that to search the BAA (Bone Age Assessment) from the UCI machine learning repository site and reviewed the various BAA techniques. To develop a filtration and optimized feature vector extraction and selection method to smooth the hand wrist X-ray images. To implement deep learning approach using CNN to classify the assessment rate based on the X-ray Bone Images. After that evaluation of the performance metrics such as error rate, PSNR (Peak Signal to Noise Ratio) and Accuracy Rate and compared with the various methods

Keywords: -Bone age assessment, Convolutional neural network, Radiograph technology, Tanner Whitehouse method.

I. INTRODUCTION

Bone age assessment is investigation by pediatrics and by radiologist for recognizing the divergence between age skeleton of child (age of bones) and consecutive age (age by birth). Bone age assessment is method of the indication of the skeleton age and maturity of bones of an individual. Bone age is differentiated from the sequential features based on age of an individual. Bone age is determined by pediatricians and endocrinologists for diagnosis of various diseases. Main applications areas of bone age assessment are clinical, medical field[1].

Revised Manuscript Received on June 05, 2019

Akanksha Sharma, Dept. of CSE, Sachdeva Engineering College For Girls, Gharuan, Mohali, India.

Prabhjeet Kaur, Dept. of CSE, Sachdeva Engineering College For Girls, Gharuan, Mohali, India.

Bone age assessment is done by comparing chronological age based on radiological investigation of skeleton development of left hand wrist. Divergence between two standards recognizes the abnormal values of skeleton growth. Maturity is evaluated using ossification center and less radiation coverage [2]. Patients having global digenesis and metacarpal sign are acquiring for diagnosis of bone age assessment. Analyzing of ossification centers in the carpal human bones and epiphyses of tube-shaped bones including distal, central, and proximal phalanges as well as radii and ulna used for bone age assessment. With increase in age, bone penetration done in very directional way. Metaphysis show in penetration. Band among the shaft and the ossification center is destroyed. Epiphysis and metaphysis fuse into one adult bone [3]. Background of bone age assessment is determined in various stages. From pre-processing stage, there is extraction of the bones using rate of interest for specific bones. The characteristics mass, figure and organization of bones are extracted from picked bones. Cropped bones used for training purpose and organization of contribution image related to bone age class[4]. Figure 1 demonstrate about the left hand include region of interest present in hand and wrist.



Fig.1 Hand image radiograph apply to regions of interest [5]

Skeleton bone age can be estimated using clinical approaches which are Greulich and Pyle technique and other is Tanner & Whitehouse (TW) Technique. Greulich and Pyle technique is graphics match technique and Tanner & Whitehouse is score assign method. Greulich and Pyle technique is simple and fast technique than Tanner & Whitehouse. In Greulich and Pyle technique is left hand wrist radiograph which is compared to sequence of radiograph in graphics on basis of age and gender. Detailed analysis of bone assigned for group of objects recognizes stage of development. Every bone described by number of scores. Average score determine the bone age assessment.



Hand Wrist X-Ray Images in Bone Age Assessment Using Particle Swarm and Convolutional Neural Network Algorithm

Evaluation of bone age considered through region of interest(ROI).Region of interest is described by three stages which are Epiphysis, Metaphysis and Diaphysis and helps in identification of ossification centers. Establishment of region of interest described in different stages which are stage A, stage B,... Stage I. Stages are described as, in stage A- absenteism, Stage B- solitary average of calcium, Stage C- central distinction, Stage D- high dm is half of meta-physis, stage E- edge of epi-physis, Stage F- wider epiphysis, Stage G- epiphysis caps the meta-physis, stage H- start union of epi-physis and meta-physis, Stage I- ending epiphysis. Maturity scoring is determined through sum of region of interest. In Existing work, maturity of bone age was analysed using automatic approach using convolutional neural network. Firstly, detection of distance radii and ulna surface was analysed in x-ray images. In addition, classifier with convolutional neural network was used to assess the bone age. Performance was analyzed on basis of network arrangement to improve accuracy of radius and ulna. In proposed approach, detection of bone age assessment is done using UCI machine learning repository site. Hand x-ray images were acquired for extraction and selection of feature vector of images for assessment of bone age. Deep learning method was implemented using Particle Swarm optimization and convolutional neural network for classification of assessment of age of x- ray images. Performance is evaluated based on accuracy rate, PSNR (Peak Signal to Noise Ratio) and error rate. Section 1 described about an overview of bone age assessment using convolutional neural network. Section 2 explained about literature survey of bone age assessment. Section 3 determined about the proposed methodology for detection and classification of bone age assessment. Section 4 illuminated about experimental results using various performance parameters. Section 5 described conclusion and future scope.

II. LITERATURE SURVEY

Bian, Z. and Zhang, R et al., 2018[11] proposed a research on extraction and classification of features of x ray images and assessment of bone using deep learning method. In this research, 301 x ray images was acquired based on Google net convolutional neural network. Using data extraction technique, data set was extended 30 times .Accuracy was achieved during training and testing approach. Firstly, x ray data sets are presented through information gathering approach. After that, classification method was used with training data set. In final approach, there is an enhancement in accuracy in proposed research. **Birhade, P and Khaparde, A. et al., 2017[12]** implemented different extraction methods for extraction of bones like as radius,ulna,distal using snake algorithm. In this research, images are detected in different stages. Firstly, radiological images are taken as input and then segmentation is done. After that, data base contain 50 digital images. In final approach, various segmentation methods are applied like as dynamic contour, snake theory and detachment instruction leveling group (DSLRL).

ÇELİK, H. et al., 2018 [13] proposed a research on Greulich Pyle method in assessing bone of children and compared age with Gilanz- Ratib Atlas . Using innovative artificial neural network method data was compared with

intellectual organization. Bone age is assessed using with distance radius, ulna, and epiphysis. In addition, it was demonstrated that Greulich-Pyle method and Gilsanz-Ratib method was required for definite ages, because there is mean square inaccuracy acquired was 0.17year for male and 0.43 for females. **Mansourvar M and Kareem S A et al.,2014[14]**researched on establishment of an involuntary approach for assessment of bone age. In this research, main aim was to discriminate the issues of manual methods of bone age assessment. In University of Malaya Medical Centre (UMMC),in department of medicine, there was survey based on feedback polling mainly done by radiologists for identification of bone and extraction of features that have an impact on age of bones. **Arsalan Manzoor Mughaletal ., 2014[15]** proposed a research on bone age using various methods and different skeleton elements. Mainly bone age was biological maturity of an individual. Bone age of child indicates maturity of an individual, using radiography of hand or wrist was commonest modality techniques. Non radiation based techniques of visualizing hand & wrist bones such as ultrasonography for bone age calculation have theorized but are not as accurate as radiographic methods. By the age of 18 years, bone age cannot be computed from wrist or radiographs, there medical test is done between age 18-22 years of age. Bone age is an indicator of the skeletal and biological maturity of an individual. That was different from chronological age, which is calculated using the date of birth of an individual. Bone age is often requested by pediatricians and endocrinologists for comparison with chronological age for diagnosing diseases which result in tall or short stature in children. Serial measurements are also used to assess the effectiveness of treatments for these diseases. In this paper formulae had also been designed for computing the final adult height of children from bone age values in normal healthy children. In order to compute bone age various methods have been developed using different skeletal elements and various visualization techniques. **Hans HenrikThodberg et al., 2009[16]** proposed a research on Bone age rating was associated with a considerable variability from the human interpretation, and this is the motivational new method for automated determination of bone age (skeletal maturity). The method, called BoneXpert, reconstructs, from radiographs of the hand, the borders of 15 bones automatically and then computes “intrinsic” bone ages for each of 13 bones (radius, ulna, and 11 short bones). Finally, it transforms the intrinsic bone ages into Greulich Pyle (GP) or Tanner Whitehouse (TW) bone age. The main motive of this paper was to change the status of bone assessment by introducing a new, computerized, and 100% automated approach called Bone Xpert. Common Problem of these systems is the ability to reconstruct the bone orders and to automatically locate each bone relevant locations. The systems are not fully automate and able to process 90% of the case , a technique has been developed to supervise by Xpert. **A.T. Al-Taani et al ., 2007[17]** proposed a research on new approach classifying bones of the hand wrist images in to pediatric stages of maturity using point distribution module.

This method consists two phases: the training phase and classification phase. During training, examples of bones from each class are collected to allow shape deformations for each class are learnt. A model representing each class is generated. These models are subsequently used to classify new examples of the bones. During classification all models was compared to the input image and the object is assigned to the class whose model is the closest match. In this paper experimental results obtained using 120 images of the third distal and middle phalanxes showed the usefulness of the method for classifying these bones in to their proper stages of maturity.

PradnyaBirhade et al., 2017[18] proposed a research on different segmentation techniques that can be used to extract different bones in the wrist like distal, middle, radius and the results shows in snake algorithm. Estimation of age is one the emerging topic in medical imaging. Bone age assessment is a semi-automated method based on radiological examination of left-hand wrist which was used to find the age of skeletal and it further compared with chronological age(actual age from birthdate). A difference between these two values indicates abnormalities in the skeletal development. In order to get better results of BAA segmentation of the desired bone is necessary. In this paper Edge Based Segmentation Algorithms was used as there is multiple ossification centers available for the evaluation of the bone maturity. In the paper, they basically based on measuring bone length, angles and shape variations and variation may occur from person to person and observer to observer. **Chih-Yen Chen, Chi-Hung Hwang et al 2014[19]** proposed research on children's bone analysed on the histogram of epiphyseal region of interests(EMRIO). Firstly, in this paper 9 EMROIs was taken from ring finger, middle finger and index finger into our analysis and then extract the 13 geometrical features for each of them. And then they utilized the KNN classification under the binary decision tree structure for determining the bone age. In the classification phase, two algorithms were considered. For the first one, features from the 9 knuckles were concatenated into one before the classification. Secondly it had been analyzed the features of the individual 9 knuckles to produce 9 bone age results, and then to choose their mode as the final bone age. In this paper it had been demonstrated that the proposed algorithm approaches the accuracies of about 60% in 1 year error and 80% in 2 year error for the first algorithm, and the accuracies of about 65% in 1 year error and 80% in 2 year error for the second algorithm, respectively. In this paper the bone age of an individual had been evaluated to get the appropriate result. **P.Thangam et al., 2013 [20]** proposed a research on contribution of various wrist boners in different stages of growth and four techniques for bone age assessment process. Bone age is a reliable indicator of growth and skeletal BAA is used in the management and diagnosis of endocrine disorders. Bone age can be estimated from the left-hand wrist radiograph of the subject. The strength of BAA procedure was greatly influenced by the quality of the features exploited and the contribution of the wrist bone employed. In this paper four systems presented according to renowned of Interest taken from wrist bones. In this paper accurate and robust BAA(Bone Age Assessment) ensured from age 0-10 years to ensure accurate result. In this paper it was indicated that the

growth of a patient is accelerating or decreasing, based on which the patient can be treated with growth hormones. Normally manual methods suffer from severe inter and inter rather variability, so limitation of these manual methods was necessary to make automation desirable. Researchers had recognized the importance of automating the assessment of bone age. Some research has resulted in computerized bone age assessment systems that have been used in clinical research. So BAA is computerized to automate the better results. In this section, define that the bone age assessment using various methods such as deep learning concepts with CNN and calculate the accuracy rate. In various paper studied and find the major issue 1 to 18 year bone are changed and then high complexity rate and maximum time consuming and less accuracy rate as compared to existing one. But in proposed work, implement a novel approach to verify the performance analysis and bone assessment in right and left hand wrist X-Ray images.

III. PROPOSED METHODOLOGY

The main research section defined that to search the BAA (Bone Age Assessment) from the UCI machine learning repository site and reviewed the various BAA techniques. To develop a filtration and optimized feature vector extraction and selection method to smooth the hand wrist X-ray images. To implement deep learning approach using CNN to classify the assessment rate based on the X-ray Bone Images. After that evaluation of the performance metrics such as error rate, PSNR (Peak Signal to Noise Ratio) and Accuracy Rate and compared with the various methods.

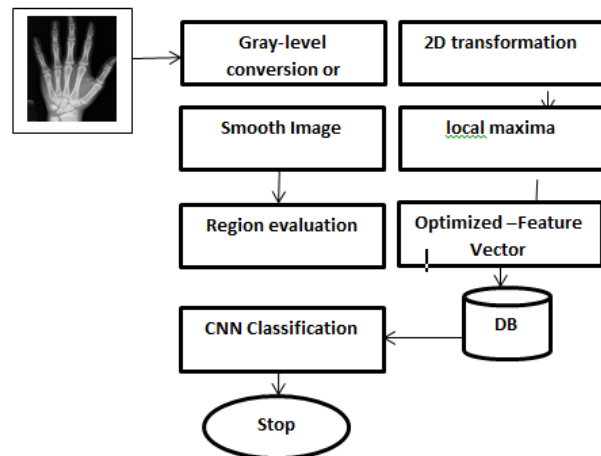


Fig 2. Research Methodology

The research work implementation steps are:

Step 1:- Dataset Searching (X-Ray Images)

Total of 35 x-ray images were retrieved which also contain label data. Sample Dataset (MURA) image is defined in fig 2. It is a great database of Hand Bone X-rays. Methods are mainly tasked with considering whether an X-ray Study is Assessment of the Bone Age. Dataset can lead to vital developments in Medical Imaging Technology which can assess at the bone radio logistic images. "Mura" is the largest PUBLIC radiographic image database.



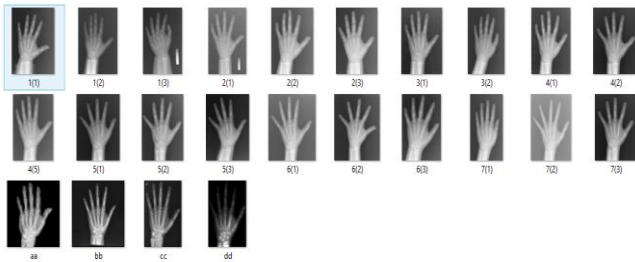


Fig 3. Hand Wrist X-Ray Images

Step 2:-Conversion (Gray level) or dimension reduction.

In this second phase, image is one value of individual pixel is a single sample re-presenting only quantity of light, i.e., it carries only Image Intensity Information. It images a type of black and white are composed completely of shades of gray. The X-ray Image contrast ranges from black at the minimum intensity to white color at the maximum.

Step 3:-2d transformation to calculate the smooth X-ray images and local maxima.

Major idea of median filter is to execute through signal entry-by-entry, removing each entry with the median of nearing entries. In this method is used to calculate the smooth hand wrist X-Ray images.

Pseudo Code in 2D transformation Filter Method [21]

```

Assign output_x_ray_image_pixval[ ImgWid] [Imght]
Assign window_img [win_img_wid*win_img_ht]
Edge_x = round(win_img_wid/2)
Edge_y = round(win_img_ht/2).
For x from edge to ht_img – edge_y
For y from edge_y to img_htedge_y
ii = 0;
forFxx from 0 to win_img_wid
forFyy from 0 to win_img_ht
win[i] = input_pixval[xx+fxx – edge_x][yy+fyy-edge_y]
ii= ii+1;
shuffle entries in window[]
output_x_ray_image_pixval [xx][yy] = win [win_img_wid
*win_img_ht/2];
    
```

Step 4:- Region calculation using Sobel Operator

It is used in digital image processing and CV, normally within edge detection method, where it generates an image edges.

Sobel operator uses 3*3 matrixes which are convolved with the real hand wrist X-Ray image to evaluate the approx. of the derivations one for horizontal alters and one for vertical. It define A1 as the source image and Gx1 and Gy1 two binary x-ray images which at individual point contain the vertical and Horizontal derivative approx. correspondingly, the evaluations are as follows:

-1	0	+1
-2	0	+2
-1	0	+1

-1	-2	+1
0	0	0
-1	+2	+1

Gx1 = * A and Gy1 = *A

Where * here signifies 2D signal processing operation.

Step 5:- Optimized Feature vector means fetch the features based on the optimized Eigen values and vectors.

It is defined of a radiographic image or patch that easier the image by extracting useful data. It converts X-Ray image of size wid*ht*3 channel (3D) to feature set length of array n. Otherwise HOG feature descriptor, given input image is of size 64*128*3 and output feature vector is of length 3780.

The main Steps are:

- (i) Pre-processing
- (ii) Gradient Image
- (iii) Histogram of gradient 8*8
- (iv) Block Normalize 16*16.
- (v) Compute HOG feature vector

Step 6:- CNN classification method to classify the age assessment and evaluate the performance metrics.

Novel approach (PSO-CNN) implements to select the unique properties based in velocity and position and age assess the hand wrist X-Ray image. It is a various layer of network. It comprises an input layer, hidden layer and output layer. Typically HLs consist of one or several CLs (Convolutional Layers) and Pooling Layers successively surveyed by 1 or various fully associated layers. Input feature images can be extracted by CLs and PLs can optimize data size and enhance the feature in-variants. Fully associated layers are utilized to choose unique properties to construct mapping relations between prior layers and outputs.

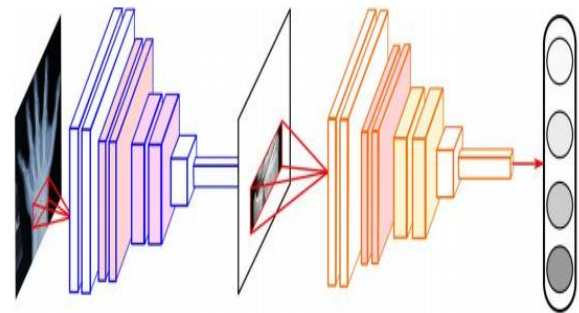


Fig 4. Block Diagram of Deep Learning Method (CNN)

Step 7:- Comparison.

After that all processing has been completing and evaluate the performance metrics Accuracy rate, PSNR and error rates etc and compare it existing methods and metrics.

IV. EXPERIMENTAL ANALYSIS

In this research experiment was designed on MATLAB 2016a tool. Bone Assessment was depending on Graphical User Interface (GUI) framework and classification was depending on P-CNN deep learning method. Training Phase used the Particle Swarm optimization and reduced the various classification methods. It has various metrics which incomplete the design performance like as number_of_neurons in fully connected layers, the extents of Kernel Convolutional, the amount of CN layers and techniques.



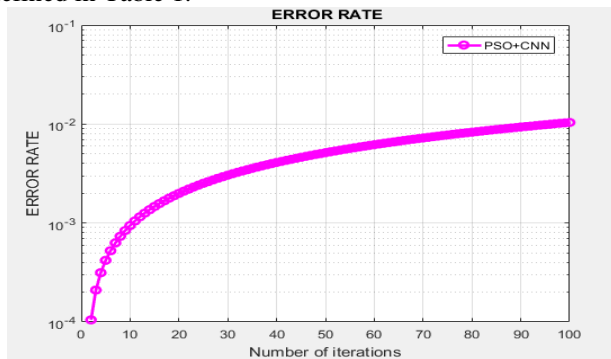
Then we related with the several different network performances of assessment accuracy and select the fit value one.

The research results are recorded in TABLE 1.

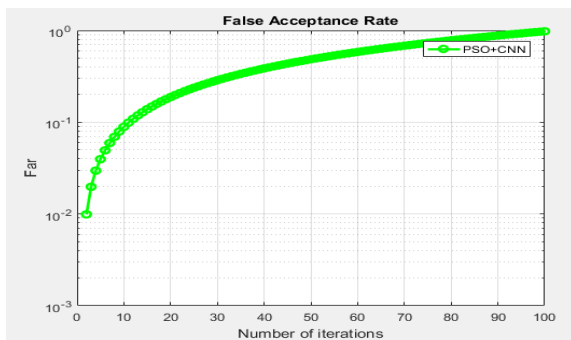
Table 1: Performance Analysis in Our Proposed work

Performance Metrics	Values
Accuracy Rate (%)	96.88
Error Rate	0.014
False Acceptance Rate	0.989
False Rejection Rate	0.9792
PSNR (%)	77.61

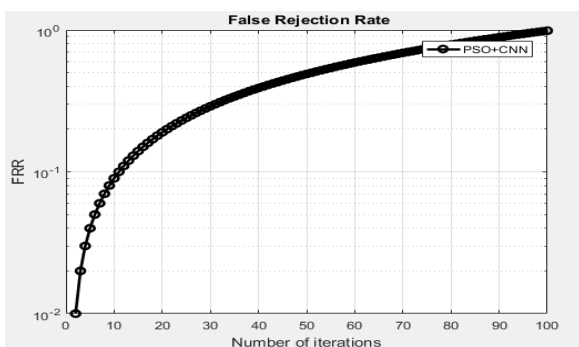
Training phase, we designed the nature inspiring optimization algorithm to reduce the total sum of error. Performances of various models are calculated on metric, as defined in Table 1.



(i)



(ii)

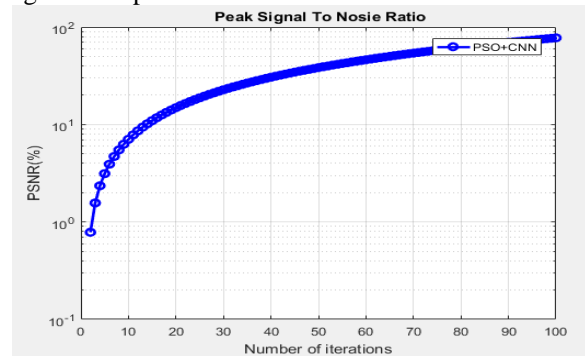


(iii)

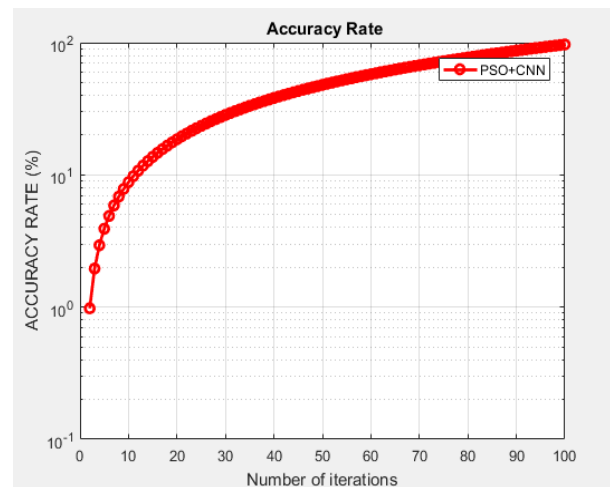
Fig 5 (i) Error Rate (ii) False Acceptance Rate and (iii) False Rejection Rate

Fig 5 shows that the performance of the proposed algorithm. In this work calculate performance metrics (i) error rate means training error and testing error calculated is equal to

sum is also known as mean square error rate. (ii) False Acceptance rate and (iii) False Rejection Rate means acceptable wrong data in less format and reject the false data is high as compared to FAR.



(i)



(ii)

Fig 6(i) Peak Signal To Noise Ratio (PSNR) and (ii) Accuracy Rate in Per cent

Fig 6 (i) and (ii) defines that the image quality based on PSNR (Peak Signal to Noise Ratio) parameters based and all error rates is minimum and system accuracy rate is high as compared to the other parameters. Below Fig 6. defines that the comparison based on accuracy rate with CNN and PSO-CNN (New Model). In proposed method using in BAA to improve the parameter and decreases the error rate, FAR and FRR rate. Studied the various papers and analyses the performance metric performance based on deep learning approaches. After that found the accuracy rate already improved with deep learning method but quality not consider in bone assessment. In recent work has implemented the novel algorithm to measure the image quality parameter based on error rate.

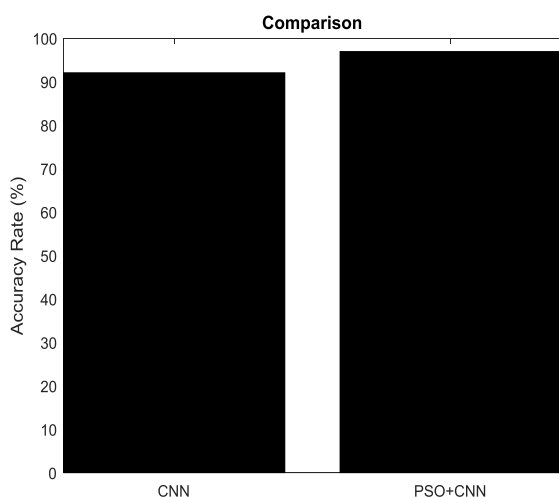


Fig 6. Comparison

Table 2. Comparative Study with Existing Work

Performance Metrics	Proposed Work	Existing Work
Accuracy Rate (%)	96.88%	92%

Table 2 defines that the comparison between PSO-CNN with CNN methods. In proposed algorithm accuracy value is 96.8% and existing approach accuracy rate is 92 per cent.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, a novel approach PSO- convolutional neural network was implemented to problem of automation bone age assessment. Convolutional neural network use testing and training on data set namely MURA image database for extraction of 35 x-ray images. Extraction of features of x-ray images are done through convolution layer and pooling layer in proposed method. Bone age assessment is analyzed from UCI instrument knowledge depository site and studied different bone age assessment method. Feature vector are selected and extracted from hand wrist x-ray bone images through filtration and optimization method. Overall performance was analyzed on basis of true positive, true negative, false positive, false negative that determine specificity, sensitivity and accuracy level. After that evaluation of the performance metrics such as error rate, PSNR (Peak Signal to Noise Ratio) and Accuracy Rate and compared with the various methods.

Though wide research has been done by several researchers for recognizing maturity of bone, still an issue of accuracy factor exists. Various structures on spitting image strength must be implemented in future for estimation of bone age of person with accurate results.

REFERENCES

1. Thangam, P., Saravanan, R., &Thanushkodi, K. (2013, July). Robust techniques for automated Bone Age Assessment. In *2013 International Conference on Current Trends in Engineering and Technology (ICCTET)* (pp. 92-94). IEEE.
2. Chu, M., Liu, B., Zhou, F., Bai, X., &Guo, B. (2018, December). Bone Age Assessment Based on Two-Stage Deep Neural Networks. In *2018 Digital Image Computing: Techniques and Applications (DICTA)* (pp. 1-6). IEEE.

3. Pietka, E., Gertych, A., Pospiech, S., Cao, F., Huang, H. K., & Gilsanz, V. (2001). Computer-assisted bone age assessment: Image preprocessing and epiphyseal/metaphyseal ROI extraction. *IEEE transactions on medical imaging*, 20(8), 715-729.
4. Wang, Y., Zhang, Q., Han, J., &Jia, Y. (2018, December). Application of Deep learning in Bone age assessment. In *IOP Conference Series: Earth and Environmental Science* (Vol. 199, No. 3, p. 032012). IOP Publishing.
5. Gertych, A., Zhang, A., Sayre, J., Pospiech-Kurkowska, S., & Huang, H. K. (2007). Bone age assessment of children using a digital hand atlas. *Computerized medical imaging and graphics*, 31(4-5), 322-331.
6. Thangam, P., Mahendiran, T. V., &Thanushkodi, K. (2012). Skeletal Bone Age Assessment-Research Directions. *Journal of Engineering Science & Technology Review*, 5(1).
7. Tanner, J. M., Whitehouse, R. H., Cameron, N., Marshall, W. A., Healy, M. J. R., & Goldstein, H. (1975). *Assessment of skeletal maturity and prediction of adult height (TW2 method)*(Vol. 16). London: Academic Press.
8. Roche, A. F., Davila, G. H., &Eyman, S. L. (1971). A comparison between Greulich-Pyle and Tanner-Whitehouse assessments of skeletal maturity. *Radiology*, 98(2), 273-280.
9. Milner, G. R., Levick, R. K., & Kay, R. (1986). Assessment of bone age: a comparison of the Greulich and Pyle, and the Tanner and Whitehouse methods. *Clinical radiology*, 37(2), 119-121.
10. Khan, K., &Elayappen, A. S. (2012). Bone growth estimation using radiology (Greulich-Pyle and Tanner-Whitehouse methods).In *Handbook of Growth and Growth Monitoring in Health and Disease* (pp. 2937-2953).Springer, New York, NY.
11. Bian, Z., & Zhang, R. (2018, June). Bone Age Assessment Method Based on Deep Convolutional Neural Network. In *2018 8th International Conference on Electronics Information and Emergency Communication (ICEIEC)* (pp. 194-197).IEEE.
12. Birhade, P., Khaparde, A., &Deshmukh, S. (2017, August). Performance Analysis of Snake Algorithm for Bone Age Assessment.In *2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA)* (pp. 1-5).IEEE.
13. ÇELİK, H. (2018, September). Comparison of Greulich-Pyle and Gilsanz-Ratib Atlases Through An Intelligent Bone Age Assessment System. In *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)* (pp. 1-4).IEEE.
14. Mansourvar, M., Kareem, S. A., Ismail, M. A., &Nasaruddin, F. H. (2014, June). Automatic method for bone age assessment based on combined method. In *2014 International Conference on Computer and Information Sciences (ICCOINS)* (pp. 1-5).IEEE.
15. Mughal, ArsalanManzoor, Nuzhat Hassan, and Anwar Ahmed."Bone age assessment methods: A critical review." *Pakistan journal of medical sciences* 30, no. 1 (2014): 211.
16. Thodberg, Hans Henrik, Sven Kreiborg, Anders Juul, and Karen Damgaard Pedersen. "The BoneXpert method for automated determination of skeletal maturity." *IEEE transactions on medical imaging* 28, no. 1 (2009): 52-66.
17. Al-Taani, A. T., I. W. Ricketts, and A. Y. Cairns. "Classification of hand bones for bone age assessment." In *Electronics, Circuits, and Systems, 1996.ICECS'96., Proceedings of the Third IEEE International Conference on*, vol. 2, pp. 1088-1091. IEEE, 1996.
18. Birhade, Pradnya, Arti Khaparde, and SonalDeshmukh. "Performance Analysis of Snake Algorithm for Bone Age Assessment."In *2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA)*, pp. 1-5.IEEE, 2017.
19. Chen, Chih-Yen, Chi-Hung Hwang, Chi-Wen Hsieh, Tai-Lang Jong, Hsian-Chuan Liu, Chui-Mei Tiu, and Yi-Hong Chou. "A study of bone age evaluation based on hand knuckles radiogram." In *Instrumentation and Measurement Technology Conference (I2MTC) Proceedings, 2014 IEEE International*, pp. 68-71. IEEE, 2014.
20. Thangam, P., R. Saravanan, and K. Thanushkodi. "Robust techniques for automated Bone Age Assessment."In *Current Trends in Engineering and Technology (ICCTET)*, 2013 International Conference on, pp. 92-94.IEEE, 2013.
21. Qiu, G.,"An improved recursive median filtering scheme for image processing", *IEEE Transactions on Image Processing*, 5(4), 646-648,1996.

AUTHORS PROFILE



Akanksha Sharma is an M.tech Student at Department Of C.S.E, Sachdeva Engineering College for Girls, Gharuan(Mohali) ,Punjab, India. She has received her B.Tech degree in Computer Science And Engineering from Sachdeva Engineering college for girls Gharuan(Mohali) in the year of 2016 and she is pursuing her M.tech from SECG, gharuan presently.

She is doing her research in the field of Image Processing ,titled as “Hand Wrist X-Ray Images in Bone Age Assessment Using Particle Swarm and Convolutional Neural Network Algorithm”.Beside this , her other research interests include data mining, network security, ,web-designing and development and data analytics. She has research publication in UGC also.



Er. Prabhjeet Kaur is an Assistant Professor in Dept. of Computer Science And Engineering, at Sachdeva Engineering College for Girls, Gharuan. She has completed her B.Tech from Rayat and Bahra Engineering College(IKGPTU),Kharar(Mohali),Punjab ,India and M.Tech from Punjabi University ,Patiala. Her

Specialization is in Machine Learning and Data Mining. She has research publications in reputed journals.