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A Novel Approach for Bone Age Assessment using Deep Learning

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ABSTRACT

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In this paper, we propose a detailed approach to create a Bone age assessment model. Bone age assessment is a common medical practice in the assessment of child development, who are less than 18 years of age. In this proposed model, the Xception architecture is being used for transfer learning. Using feature extraction and transfer learning, the pre-trained convolutional neural network were custom trained. The dataset used for training the model is obtained from the Kaggle RNSA Bone Age dataset containing 12811 male and female bone images of different age groups. Finally, we were able to attain a mean absolute error (MAE) of 8.175 months in male and female patients, which aligns with our initial goal of achieving MAE in under a year.

Keywords : Bone Age Prediction, Convolutional Neural Network (CNN), Deep Learning, Transfer Learning, Image Processing, Histogram Equalization, Mean Average Error (MAE)

I. INTRODUCTION

In today's era, the radiologist and doctors need a good amount of time and expertise to predict the bone age of a person through hand scan X-ray. The automated bone age assessment system will save not only time but also it can be used by any person without having any expertise to predict bone age. The key idea is to predict a person's bone age automatically (below 19 years) by using the hand scan X-ray. This can be achieved by training deep learning neural network to predict the person's age and its accuracy can be improved using CNN (Convolutional Neural Networks) and Transfer Learning techniques.

II. LITERATURE SURVEY

The manual assessment of the bone age is generally performed by X-ray examination of the left hand by using either the Tanner-Whitehouse (TW) or the Greulich and Pyle (G&P) method, which shows several limitations. To address these issues, several automated approaches have been proposed, which includes different techniques of Artificial Intelligence. Most of these proposed automatic bone age assessment systems uses Convolutional Neural Networks (CNN) and are based on hand and wrist X-rays, which are mostly applicable for the candidates having age less than or equal to 18.

Matthew Chen [1], have approached the use of Convolutional Neural Network methods to train a model to predict developmental bone age using X-ray images. Previously, the methods used for this task was generally involved a pipeline of segmentation and handcrafted feature extraction, but the convolutional neural networks proved effective for image classification, due to its recent advances.

The largest jump in accuracy of predictions were observed through augmenting dataset with random distortions, indicating that the performance is largely dependent on the number of training examples [1].

Another approach proposed by Alexander Bilbily and Mark Cicero [3], uses both the pixel and sex information in the same network enabling the network to learn the relationship between pixel and sex information. The pixel information was passed through the Inception V3 architecture, which was concatenated with the sex information. The combination of multiple high performing models in an ensemble approach improved overall performance. Each of the best three models achieved mean absolute difference (MAD) of 5.99 months on the validation set and 4.265 months on the 200 image test set [3].

Antonio Trist´an-Vega and Juan Ignacio Arribas [2] have suggested an approach based on a revised version of an adaptive clustering segmentation algorithm, which semi-automatically segments the data and 89 features are extracted through it using the bone contours drawn near the Ulna and Wrist. A Generalized Softmax Perceptron (GSP) neural network, and recently developed Posterior Probability Model Selection (PPMS) algorithm evaluates the bone age, which focuses on the different development stages in both radius and ulna [2].

This method is quite faster than CNN, but as the algorithm focuses only on the ulna and wrist portion of the hand scan, it misses out the fingers portion of the hand scan, which is also a key feature in determining the bone age. Also the semi-automatic nature of contour plotting in this method, might decrease the chances of the algorithm to predict the bone age correctly, due to the fact that sometimes the contours might not be drawn accurately [2].

III. METHODOLOGY

A. GENERAL BLOCK DIAGRAM

For a general bone age prediction model shown in figure 1, the data set consisting of a good amount of hand scan images is to be collected. Each image in the dataset is augmented by a data augmentation method, which relatively increases a small data set. The data preprocessing block reshapes, equalizes, normalize and then flattens an image so that it can be fed into a convolutional neural network. The convolutional neural network consists of many different layers of various parameters, required to model a hypothesis from the incoming image pixel values, outputting the bone age.

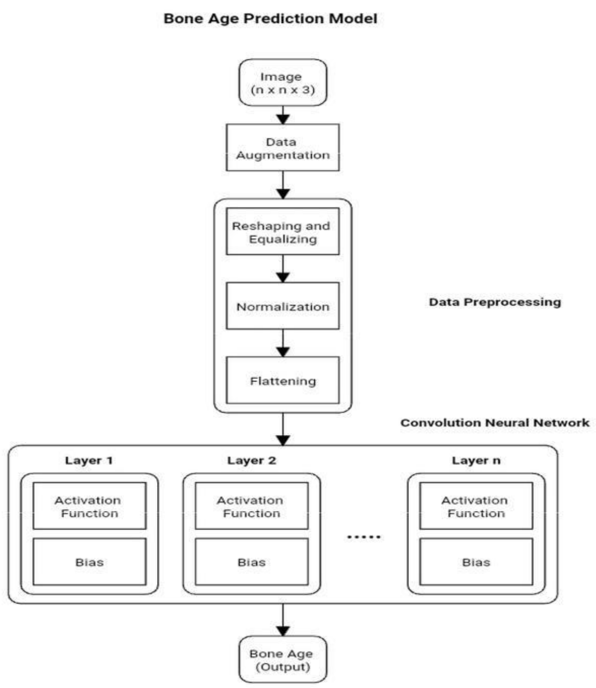


Figure 1. Block diagram of a general Bone age prediction model

B. DATA COLLECTION

Given a problem statement in Machine Learning, the most important thing is to gather data for training a model. This step is crucial because the quality and quantity of the data collected will directly determine the accuracy of your predictive model. After collecting the data there are various data preparation tasks viz. cleansing, aggregation, augmentation, labeling, normalization and transformation as well as any other activities for structured, unstructured and semi structured data. For designing the bone age prediction model, the data set of hand scans dataset is to be used.

C. DATA AUGMENTATION

The deep learning neural networks often improves its performance with the amount of available data. So to expand a relatively small training dataset, the process of data augmentation is used to improve the model's performance and its ability to generalize. The various methods can increase the dataset by using functions like rotation, zoom, rescale, flip. intensity variations, etc. Various libraries provide the process of data augmentation on the go during training the model, without affecting the original dataset.

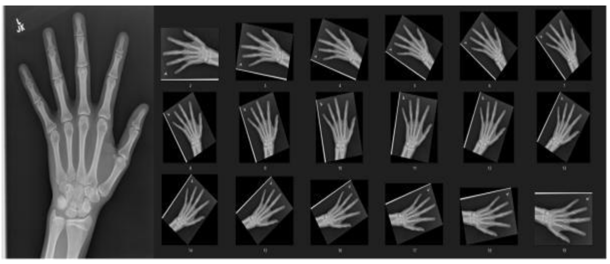


Figure 2. Data Augmentation Process

D. DATA PROCESSING

In the data pre-processing step, the features of the data are highlighted, encoded or transformed into a state, which can be easily parsed by the machine.

1) HISTOGRAM EQUALIZATION: To improve the quality of the images and to enhance the features of the images, histogram equalization is used. When the usable information of the image is addressed by close contrast values, the standard method normally increases the global contrast of the images, leaving behind a brighter image, which is undesirable, leaving behind distinctive features.

Figure 3. Original Image and its Histogram Equalized Image

2) CLAHE (CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION): As the standard histogram equalization usually increases the global contrast of the images, leaving behind distinctive features of the image. CLAHE is an improvement to standard equalization, which divides the image into small blocks, called *"tiles"* and apply histogram equalization to these blocks.

So the histogram would limit confine to a smaller region and if (unless there is noise is present in that area), which would then it would be amplified. To tackle this issue, the contrast limiting is applied to those pixels whose histogram bin is above the specified contrast limit, and those pixels are clipped and distributed uniformly to other bins before applying histogram equalization.

Figure 4. Original Image and its CLAHE pre-processed Image

3) CROPPING AND RANGING: The process of cropping results in the removal of some of the peripheral areas of an image so as to isolate the subject matter from its background. The image is cropped into the desired Region of Interest (ROI), which is achieved by threshing image, taking largest contour and obtaining the extreme points in it. The resulting cropped image will have a rectangular border along these extreme points.

In the ranging process, pixels within a specific range of intensities are retained while the remaining pixels in the image are filtered (black end) out, highlighting the important features in an image required for training a model.

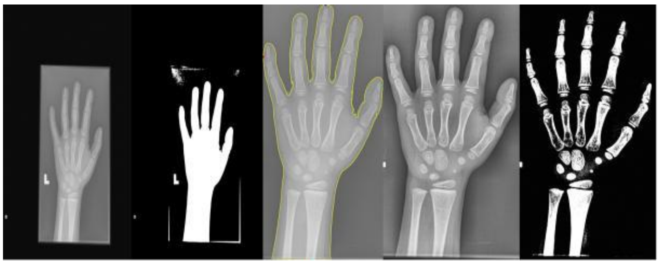


Figure 5. 1. Original Image, 2. Threshold Image, 3. Cropped Image, 4. CLAHE Cropped Image, 5. Ranged Image

IV. IMPLEMENTATION DETAILS

A. BLOCK DIAGRAM

The method as illustrated in figure 6 uses a convolutional neural network replacing a pipeline of segmentation and hand crafted feature extraction. The RSNA Bone Age dataset was used, contributed by Stanford University, the University of California - Los Angeles and the University of Colorado during RNSA Pediatric Bone Age Challenge, which composed of around 12811 hand scans, out of which 12611 (6833 male, 5778 female) as seen in figure 7, are training hand scan images and 200 test hand scan images, across 19 years of ages and stages of bone development.

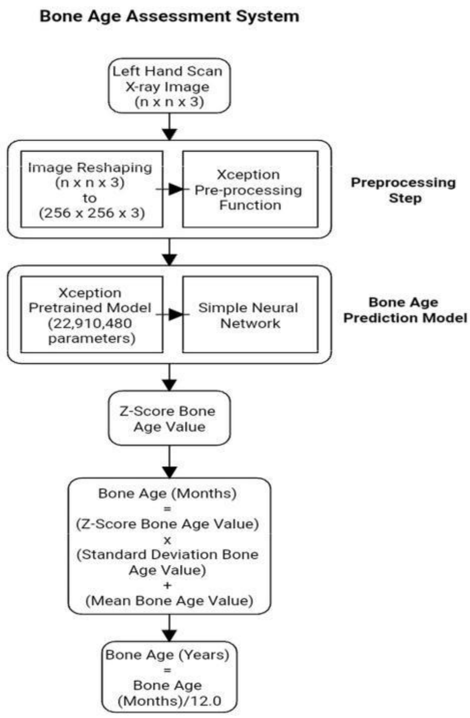


Figure 6. Block diagram of Bone age assessment system

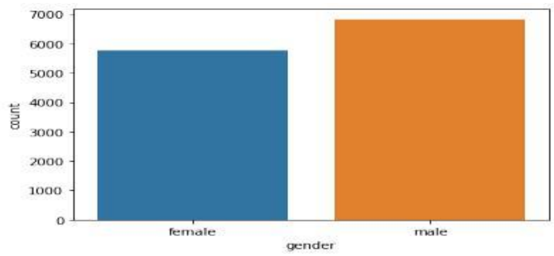


Figure 7. Distribution of Male and Female X-rays Images

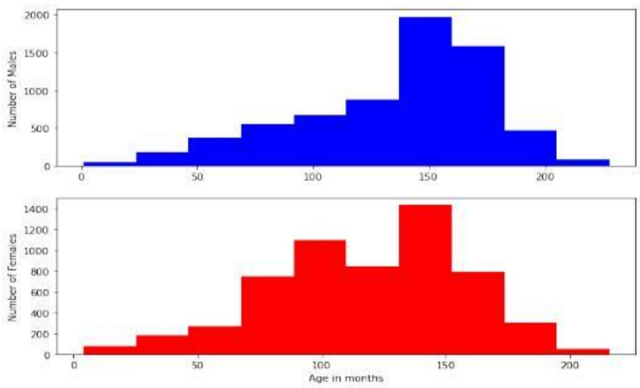


Figure 8. Histogram distribution of Male and Female X-rays Images

B. TRANSFER LEARNING

Transfer learning in machine learning is the process of reusing a pre-trained model on a new problem. In transfer learning, a machine exploits the knowledge gained from a previous task to improve generalization about another. Using Xception architecture as our baseline model and training each layers, we were able to exploit its knowledge to increase the accuracy of bone age prediction model. The Xception architecture has top-1 accuracy of 0.790 and top-5 accuracy of 0.945, which is better than other pre-trained model architectures.

C. BONE AGE PREDICTION MODEL

The bone age prediction model predicts the bone age from hand X-ray images. The model uses the transfer learning technique, where Xception pre-trained model is used as a baseline model clubbed with a simple neural network consisting of dense layers, which yields a Z-score value of the predicted age. The predicted age is further calculated using the mean and standard deviation of the dataset.

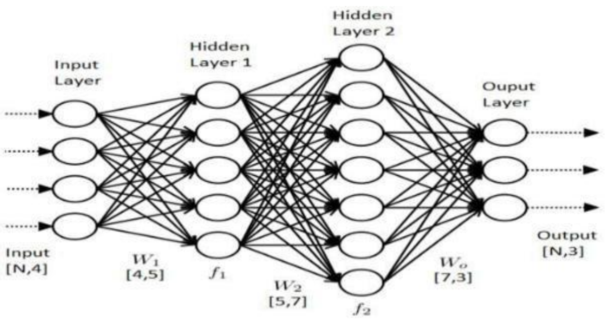


Figure 9. Neural Network's Skeleton

D. TRAINING WITH ORIGINAL DATA SET IMAGES

The training is done with the original images from the RNSA Pediatric Bone Age Challenge Dataset. These images are passed through a neural network consisting of a pre-trained Xception Model attached to a simple neural network outputting a raw numerical value. During training process only the best fit model is saved, which is evaluated on lowest validation loss. The best fit model has a mean average error (MAE) of around 4 months on training data and around 8 months on validation data, as seen in figure 10 and 11.

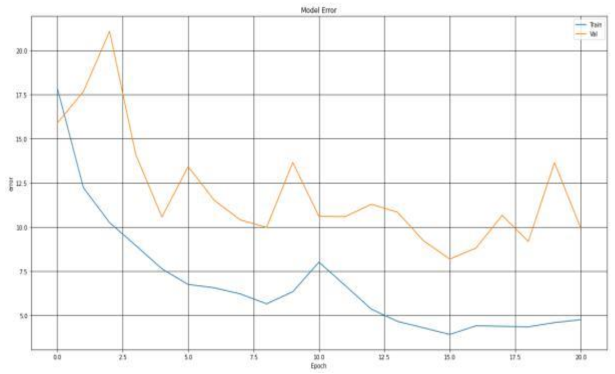


Figure 10. Mean average error (MAE) during training with Original Images

E. TRAINING WITH CLAHE CROPPED DATA SET IMAGES

In this operation, the CLAHE Cropped Images achieved using the cropping and equalizing processes on the original images are used for training. These images as well are passed through a neural network consisting of a pre-trained Xception Model attached to a simple neural network outputting a raw numerical value. During training process only the best fit model is saved, which is evaluated on lowest validation loss. The best fit model has a mean average error (MAE) of around 4 months on training data and around 9 months on validation data, as seen in figure 11.

From the following graph, we can draw the conclusions that the training and validation MAE were nearly equal while training with original and CLAHE cropped images across the epoch. During training the model with CLAHE cropped images the validation MAE at the start was lower as compared to that of original images, but gradually the MAE's engulfed.

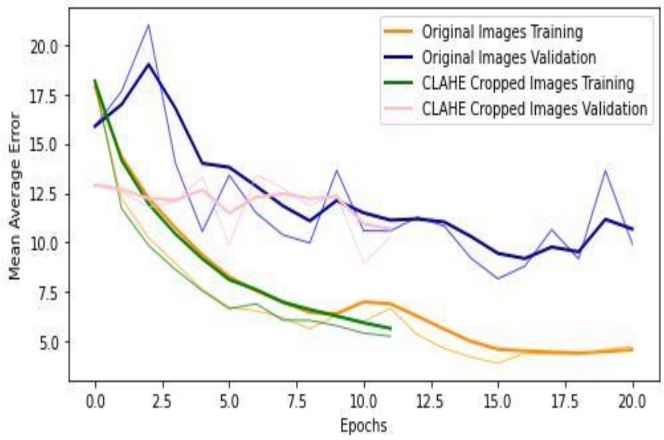


Figure 11. Mean average error (MAE) during training with Original Images and CLAHE Cropped Images

V. RESULTS

Using Xception as our baseline model in the bone age predictor model we were able to achieve the mean average error (MAE) of four (3.909) months on training set, eight (8.175) months on the validation set. We were able to produce results that are comparable to the current state of the art method of automated bone age assessment [3].

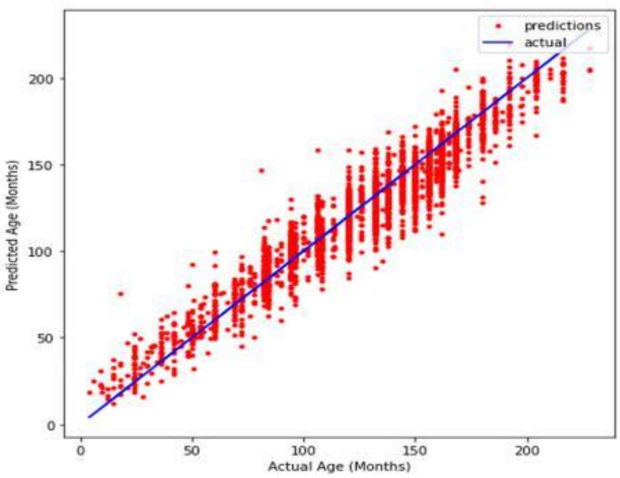
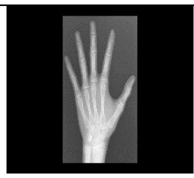


Figure 12. Prediction Graph

TABLE I

PREDICTIONS OF THE BONE AGE ASSESSMENT SYSTEM

Fig No.	Bone X-ray	Chronological Age	Model Predicted Age
1.		10 Years	9.78 Years
2.		14 Years	13.80
3.		15 Years	14.429

The following table II concludes the model's accuracy by comparing it with an Expert's prediction. The radiologist predicts the bone age using the Tanner-Whitehouse (TW) method, by closely investing in X-Ray for approximately around 5 minutes. This manual method also requires gender information and the chronological age of the patient. The highlighting feature of the Bone age assessment system is that it predicts the bone age within seconds without any dependency on gender information.

TABLE II
PREDICTIONS OF AN EXPERT AND THE BONE AGE ASSESSMENT SYSTEM

Fig No.	Bone X-ray	Chronological Age	Gender	Expert's Predicted Age	Model Predicted Age
1.		10 Years	Male	10.6 Years	9.6 Years
2.		11 Years	Male	11.4 Years	10.7 Years
3.		10.5 Years	Female	9.4 Years	9.97 Years
4.		31 Years	Male	-	-

Age of the last patient is above 18 years so hand X-Rays alone are not enough, other X-Rays with hand X-Rays cumulatively are required to predict the age.

VI. ANALYSIS

A. FILTERS

As it is evident that image processing can be used to alter the image as per our needs, analysis using various filter was the next step. The seven different filters are analyzed for their assistance in the accuracy of the models predictions, viz. Sharpening, CLAHE, Noise Reduction, CLAHE with Sharpening, Sharpening with Noise Reduction, Averaging CLAHE and Noise Reduction with Sharpening of higher intensity. The analysis was done on random images found on internet, which were unfamiliar to the model. The analysis in the table III shows the effect of filters on the mean average error.

Averaging CLAHE was derived from CLAHE where the clip limit of the image is varied between a specified range. These filters were implemented before feeding them to the trained machine learning model. The MAE of the model IV-C without any filter was greater than that of with filter. Noise filter with Sharpening reaches a MAE equal to the that of our normal predictions. Thus we can conclude that no filter is required to be applied to increase the accuracy of the Model any further.

TABLE III
MAE OF DIFFERENT FILTERS

Sr No.	Filters Used	MAE (In Years)
1.	Without any Filters	0.715
2.	Sharpening	0.808
3.	CLAHE	0.945
4.	CLAHE with Sharpening	1.146
5.	Averageing CLAHE	1.29
6.	Noise Reduction	0.785
7.	Noise Reduction with Sharpening	0.77
8.	Noise Reduction with Sharpening (Level- 2)	0.947

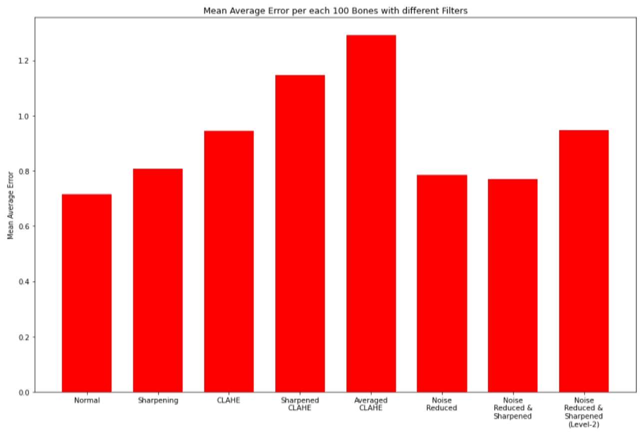


Figure 13. MAE using different filters

B. MAE OF MALE AND FEMALE BONES

As there is difference in the growth of bones in males and females, the predictions of the bone age prediction model will vary. To analyze these variations, 1000 male and female hand scans across 19 years of ages and stages of bone development are passed through the bone age prediction model and mean average error (MAE) is obtained. The mean average error for the male bone's hand scan is 2.99 months and that of female bone's hand scan is 1.957 months, as shown in figure 14.

By fusing the gender information in the bone age prediction model, the gender specific features can be enhanced and the accuracy of the model can be improved.

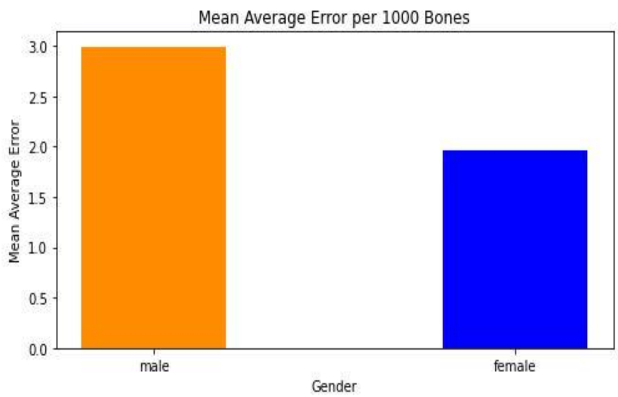


Figure 14. MAE of male and female bones

VII. CONCLUSION

We achieved an MAE of 8.175 months using the Xception architecture. The result is similar to the other full bone age assessment model using the similar dataset [3]. The bones found in the center of the hand and wrist are distinctly the most salient features for predicting the bone age of an individual. Future work can include trying different filters; architectures including fusing gender information given respect to different bone growth in different genders and analyzing the associated efficacy of the implemented designs.

VIII. REFERENCES

[1] M. Chen,"Automated Bone Age Classification with Deep Neural Networks", Stanford University, 2016.

[2] A. Tristan-Vega and J. Arribas, "A Radius and Ulna TW3 Bone Age Assessment System", IEEE Transactions on Biomedical Engineering, vol. 55, no. 5, pp. 1463-1476, 2008. Available: 10.1109/tbme.2008.918554.

[3] S. S. Halabi, L. M. Prevedello, J. Kalpathy-Cramer, A. B. Mamonov, A. Bilbily, M. Cicero, I. Pan, L. A. Pereira, R. T. Sousa, N. Abdala, F. C. Kitamura, H. H. Thodberg, L. Chen, G. Shih, K. Andriole, M. D. Kohli, B. J. Erickson, and A. E. Flanders, "The RSNA Pediatric Bone Age Machine Learning Challenge," Radiology, vol. 290, no. 2, pp. 498–503, 2019.

[4] X. Pan, Y. Zhao, H. Chen, D. Wei, C. Zhao and Z. Wei, "Fully Automated Bone Age Assessment on Large-Scale Hand X-Ray Dataset", International Journal of Biomedical Imaging, vol. 2020, pp. 1-12, 2020. Available: 10.1155/2020/8460493.

[5] A. Gertych, A. Zhang, J. Sayre, S. Pospiech-Kurkowska and H. Huang, "Bone age assessment of children using a digital hand atlas", Computerized Medical Imaging and Graphics, vol. 31, no. 4-5, pp. 322-331, 2007. Available: 10.1016/j.compmedimag.2007.02.012.

[6] H. Thodberg, S. Kreiborg, A. Juul and K. Pedersen, ”The BoneXpert Method for Automated Determination of Skeletal Maturity”, IEEE Transactions on Medical Imaging, vol. 28, no. 1, pp. 52-66, 2009. Available: 10.1109/tmi.2008.926067.

[7] ”Bone age prediction through x-ray images”, Medium, 2021. [Online]. Available: https://medium.com/techlabsms/bone-age-prediction-through-x-ray-images-6e181d900a7a.

[8] L. Morris, ”Assessment of Skeletal Maturity and Prediction of Adult Height (TW3 Method)”, Australasian Radiology, vol. 47, no. 3, pp. 340-341, 2003. Available: 10.1046/j.1440-1673.2003.01196.x.

[9] J. Kim et al.,”Computerized Bone Age Estimation Using Deep Learning Based Program: Evaluation of the Accuracy and Efficiency”, American Journal of Roentgenology, vol. 209, no. 6, pp. 1374-1380, 2017. Avail-able: 10.2214/ajr.17.18224 [Accessed 18 April 2021].

[10] M. Nadeem, H. Goh, A. Ali, M. Hussain, M. Khan and V. Ponnusamy,”Bone Age Assessment Empowered with Deep Learning: A Survey, Open Research Challenges and Future Directions”, Diagnostics, vol. 10, no. 10, p. 781, 2020. Available: 10.3390/diagnostics10100781.

[11] M. Zulkifley, S. Abdani and N. Zulkifley,”Automated Bone Age Assess-ment with Image Registration Using Hand X-ray Images”, Applied Sciences, vol. 10, no. 20, p. 7233, 2020. Available: 10.3390/app10207233.

[12] F. Cao, H. Huang, E. Pietka and V. Gilsanz,”Digital hand atlas and web-based bone age assessment: system design and implementation”, Computerized Medical Imaging and Graphics, vol. 24, no. 5, pp. 297-307, 2000. Available: 10.1016/s0895-6111(00)00026-4.

[13] E. Pietka, A. Gertych, S. Pospiech, Fei Cao, H. Huang and V. Gilsanz, ”Computer-assisted bone age assessment: image preprocessing and epiphyseal/metaphyseal ROI extraction”, IEEE Transactions on Medical Imaging, vol. 20, no. 8, pp. 715-729, 2001. Available: 10.1109/42.938240.

[14] ”OpenCV: Histograms - 2: Histogram Equalization”, Docs.opencv.org, 2021. [Online]. Available: https://docs:opencv:org/master/d5/daf/tutorial_py_histogram_equalization:html.

[15] A. Polesel, G. Ramponi and V. Mathews, ”Image enhancement via adaptive unsharp masking”, IEEE Transactions on Image Processing, vol. 9, no. 3, pp. 505-510, 2000. Available: 10.1109/83.826787.

[16] M. Kazubek, ”Wavelet domain image denoising by thresholding and Wiener filtering”, IEEE Signal Processing Letters, vol. 10, no. 11, pp. 324-326, 2003. Available: 10.1109/lsp.2003.818225.

[17] R. Gonzaelez ́ and R. Woods, Digital image processing. Reading (Mass.) [etc]: Addison-Wesley, 1993.

[18] S. Agaian, K. Panetta and A. Grigoryan, ”Transform-based image enhancement algorithms with performance measure”, IEEE Transactions on Image Processing, vol. 10, no. 3, pp. 367-382, 2001. Available: 10.1109/83.908502.

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