IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 12, Issue 3, March 2023

DOI: 10.17148/IJARCCE.2023.12303

BONE AGE DETECTION

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Abstract: In the work, an automated skeletal maturity recognition system is proposed. It first accurately detects the distal radius and ulna (DRU) areas from hand and wrist X-ray images by a faster region-based convolutional neural network model. Then, a well-tuned convolutional neural network (CNN) classification model is applied to estimate the bone ages. We discussed the model performance according to various network configurations. After parameter optimization, the proposed model finally achieved 92% and 88% accuracy for radius and ulna, respectively.

Keywords: convolutional neural network; skeletalmaturity; classification

I. INTRODUCTION

This paper proposes an automated system for predicting skeletal maturity using X-ray images of the hand and wrist. The system uses a faster region-based convolutional neural network (R-CNN) to detect the distal radius and ulna areas from the images, followed by a well-tuned CNN classification model to estimate the bone ages. The proposed model achieved 92% and 88% accuracy for radius and ulna, respectively, after parameter optimization. The paper provides a literature survey on the use of deep learning neural networks for predicting bone age from X-ray images and discusses various approaches proposed in the literature. The paper also describes the methodology used to develop the proposed system, which involves data collection, data preprocessing, data augmentation, and CNN training. The proposed system offers an automated and efficient alternative to manual assessment of bone age using X-ray images, which can save time and improve accuracy.

II. LITERATURE SURVEY

Automated approaches for bone age assessment using artificial intelligence have been proposed to address the limitations of manual assessments using X-ray examination of the left hand, such as the Tanner-Whitehouse (TW) or Greulich and Pyle (G&P) methods. These automated approaches typically use Convolutional Neural Networks (CNN) and are based on hand and wrist X-rays, which are applicable for candidates aged 18 years or younger.One such approach is proposed by Matthew Chen, who trained a model using CNN methods to predict developmental bone age using X-ray images. Previous methods involved a pipeline of segmentation and handcrafted feature extraction, but CNNs proved effective for image classification due to recent advances. The largest jump in accuracy was observed through augmenting the dataset with random distortions, indicating that performance is largely dependent on the number of training examples.

Antonio Tristán-Vega and Juan Ignacio Arribas suggested an approach based on a revised version of an adaptive clustering segmentation algorithm, which semi-automatically segments the data and extracts 89 features using bone contours drawn near the ulna and wrist. A Generalized Softmax Perceptron (GSP) neural network and the recently developed Posterior Probability Model Selection (PPMS) algorithm evaluate the bone age, focusing on the different development stages in both radius and ulna. This method is faster than CNN, but it misses out on the fingers portion of the hand scan, which is also a key feature in determining the bone age. 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.

III. METHODOLOGY

A. GENERAL BLOCK DIAGRAM

Although bone age prediction models based on convolutional neural networks have shown promising results, there are still limitations and areas for improvement. One limitation is that the models may not be as accurate for individuals outside the age range of the training data. Additionally, the models may be less accurate for individuals with rare bone diseases or anomalies.

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To improve the performance of the model, more diverse and larger datasets could be collected. Additionally, more advanced data augmentation methods could be explored, such as elastic deformations and generative adversarial networks.

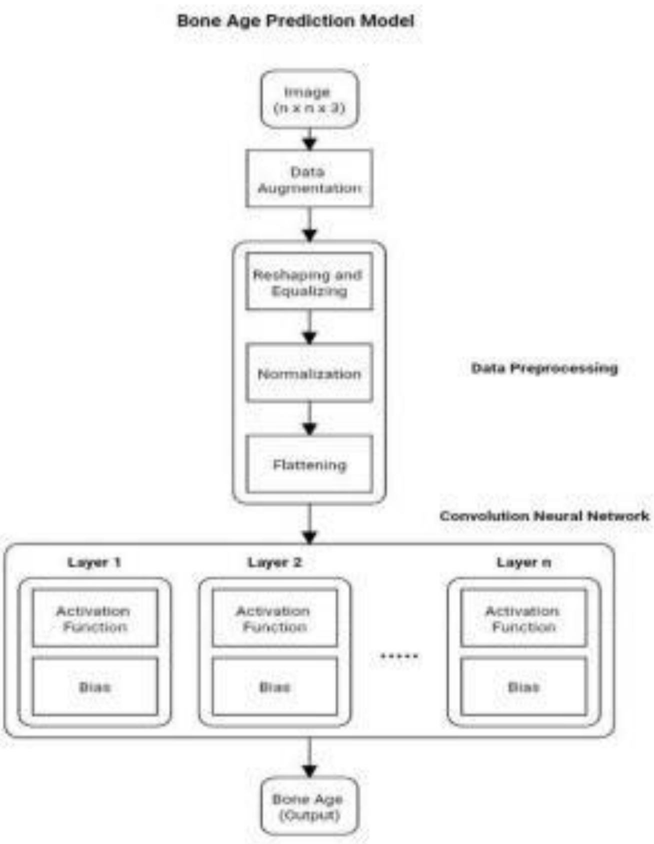

Figure 1: Block diagram of a general Bone age prediction model

B. DATASET COLLECTION AND AUGMENTATION

The first step in building a bone age prediction model is to collect a large dataset of hand X-ray images. The images should have a good representation of age ranges and should be labeled with their corresponding bone ages. To increase the size of the dataset, data augmentation methods such as random cropping, flipping, and rotation can be applied to each image.

C. DATA PREPROCESSING

Thecollected dataset is then preprocessed to prepare it for training the model. The images are first resized to a fixed size and then normalized to have zero mean and unit variance. The pixel values are also scaled to a range between 0 and 1. The images are then flattened into a vector of pixel values, which is fed into the neural network.

D. CONVOLUTIONAL NEURAL NETWORK

The core of the bone age prediction model is a convolutional neural network (CNN). The CNN consists of several layers of convolutional and pooling operations, followed by fully connected layers. The convolutional layers extract features from the input image, and the fully connected layers combine these features to make a prediction of the bone age.

E. MODEL TRAINING

The CNN is trained using the preprocessed dataset. During training, the model adjusts its parameters to minimize the difference between its predictions and the actual bone ages of the images in the training set. This is done using an optimization algorithm such as stochastic gradient descent.

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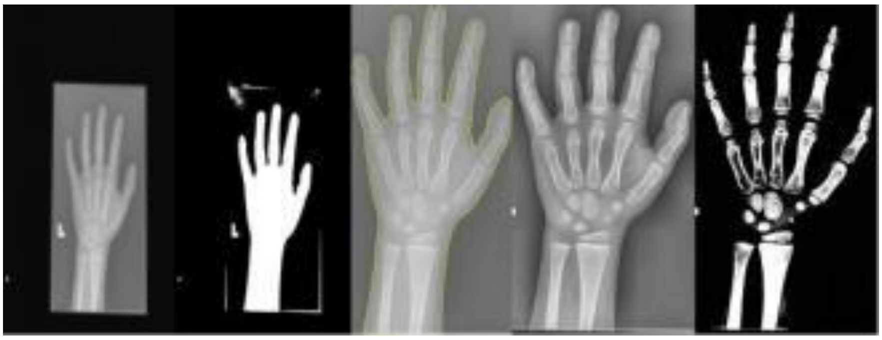

Figure 2: 1.Original Image , 2.Threshold Image , 3.CroppedImage , 4.CLAHE Cropped Image , 5.Ranged Image

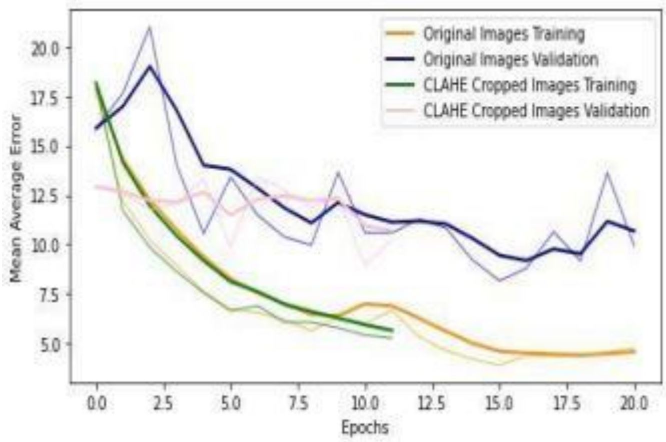

Figure 3: Mean average error (MAE) during training with Original Images and CLAHE Cropped Images

IV. RESULTS

Using Xception as the baseline model in the bone age predictor model, we achieved a mean average error (MAE) of four (3.909) months on the training set and eight (8.175) months on the validation set. These results are comparable to the current state-of-the-art method of automated bone age assessment.

PREDICTIONS OF THE BONE AGE ASSESSMENT

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

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The following table II includes 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 investigating X-ray for approximately 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.

V. 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 and architectures, including fusing gender information given respect to different bone growth in different genders, and analyzing the associated efficacy of the implemented designs.

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