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Original Research Article

Hyper-tuned convolutional neural network based pediatric skeletal bone age estimation model

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ABSTRACT

Background: The pediatric skeletal bone age estimation model is developed to estimate the bone age in order to investigate the genetic and growth disorders of children's. In this paper, a deep learning-based is presented for it.
Method: Initially, in this model, the standard RSNA dataset of hand X-ray images is read. Followed by median filtering to remove noise and segmentation of the hand bone region using k-mean clustering. After that, the Convolutional Neural Network (CNN) algorithm is used to estimate the bone age. In this article, the CNN algorithm is used over other deep learning algorithms due to its automatically extracting the features from the hand X-ray images and estimating the bone age. Furthermore, in this research, the hyper-parameter optimization of the CNN algorithm is done by finding the best parameter values using the metaheuristic algorithm to enhance the performance of it. The metaheuristic walrus optimization algorithm is used, and it determines the general hyperparameters, such as the learning rate of the CNN algorithm, based on the objective function.
Results: The simulation evaluation was done on MATLAB 2018b software. The standard RSNA dataset of hand X-ray images was used. The performance evaluation is done by splitting the same dataset into training and testing ratios and evaluated using the error metrics. The result indicates that the proposed model accomplishes the lower values of these error metrics over the previous approaches.
Conclusion: The proposed method efficiently measures pediatric skeletal bone age by processing hand X-ray images with the CNN algorithm, which has been optimized through hyperparameter tuning.

Keywords: CNN, Deep Learning, Hyper-parameter, Metaheuristic, Pediatric skeletal bone age, Walrus optimization, RSNA

INTRODUCTION

Estimating the age of a child's skeletal bones is a common clinical procedure used to examine endocrinology, genetics, and growth issues.[1] Using the difference between the bone age reading and the numerical age, doctors can correctly identify children who aren't developing normally. Nowadays, the left-hand X-ray image is frequently used to determine the age of the bones, and the morphological characteristics of several bone components, including the phalanx and wrist, have significant reference value. Popular bone age assessment (BAA) standards include the Greulich and Pyle (G&P) standard and the Tanner-Whitehouse (TW) standard. Each uses a different set of specific bone parts as regions of interest (ROIs) for evaluation.[2] Conventional manual evaluation procedures, which use diverse standards as a guide, mostly rely on the physicians' opinions and personal experiences. These approaches have the inherent drawbacks of being time-consuming, inefficient, and inaccurate. Deep learning methods have done extremely well in the last several years, due to significant amounts of data. As a result, several deep learning methods have been suggested for BAA.[3-5] A skeletal bone age estimation model was developed using the MLP algorithm by Li et al.[6] In addition, the dataset images were prepared for the deep learning model using the CNN-based feature extraction, cropping to segment the bone region, and histogram equalization to enhance the contrast. They have accomplished the lowest MAE value of 6.2 for the RSNA dataset. Next, a method for bone age estimation by determining the ROI using the masked RCNN algorithm and the attention-based inception V3-based regression method to determine the bone age was designed by Liu et al.[7] Similar to the previous approaches, the evaluation was done for the RSNA dataset and accomplished the lower value of MAE. A dual-attention dual-path network by considering the single structure of the CNN algorithm to estimate the pediatric skeletal age was designed by Wang et al.[8] The RSNA dataset was considered for evaluating their model. The dataset images were segmented to separate the bone region from the original image using the segmentation method. The result indicates that they have accomplished the MAE of 4.76 months.

Similar to the previous approach, the U-Net multi-tasking algorithm was used for bone age estimation purposes for the RSNA 2017 dataset and achieved the MAE value of 8.190 months.9 The performance of various deep learning algorithms, namely, Inception V3, MobileNetV2, XceptionNet, and DenseNet201, and hyper-tuned the parameters of it using the various optimizers (Adam, Adamax, SGD, RMSprop, and Nadam) evaluated by Nivedita et al, Solanki et al.[10]

Out of these optimizers, Adam outperforms the others for hyper-tuning the performance of deep learning algorithms. The faster RCNN algorithm used to select the region of interest from the dataset images and the inception v3 regression algorithm for estimating bone age by Saadi et al.[11] The result indicates that the best value of MAE was accomplished for 7.5 and 8.3 months for the male and female genders, respectively. Finally, the Chinese children left hand radiograph images (8242 images) are used for predict the bone age and adult height using the RESNET-18 network by Pei et al.[12] Besides that, they have used the Yolact algorithm for segment the images. The result indicates that have accomplished the Pearson correlation value of 0.98 and 0.94 for bone age and height prediction.

In the deep learning algorithms, the CNN algorithm has gained popularity in the pediatric skeletal bone age estimation method due to automatically extracting the features from the dataset images and helping in determining the bone age in an efficient way.[13,14] However, the performance of the CNN algorithm is highly dependent on the hyperparameters that are used in it for training purposes. The hyperparameter optimization is done to determine the best parameter values to enhance the performance of the CNN algorithm. However, this process is very computationally expensive because it involves evaluating the CNN algorithm multiple times.[15] Therefore, optimization approaches are utilized to accomplish this goal. In the previous studies, grid search, random search, Bayesian optimization, and metaheuristics are the most popular approaches. Out of these approaches, the metaheuristic algorithms have gained popularity due to finding the best parameter based on the objective function in the solution space of the parameter in the time-constraint environment.[16] In the previous studies, the CNN algorithm is optimized at three levels: hyper-parameters of the convolution layer (such as convolution layer and kernel size), the fully connected layer (such as connectivity pattern and dropout), and general hyper-parameters such as learning rate and batch size.[17] In this article, the general hyperparameter of the CNN algorithm is optimized to enhance the performance of the proposed method. The main contribution is summarized as follows.

A pediatric skeletal bone age estimation model is presented by hyper-tuning the parameters of the CNN algorithm using the metaheuristic walrus optimization algorithm to enhance the performance of it. A preprocessing approach is designed using the median filtering and k-means clustering algorithm to remove the noise and segment the bone region from the original image. The evaluation on the standard RSNA dataset shows that the proposed model accomplishes the lower value of error metrics, such as MAE, RMSE, and RMSPE.

The remaining research manuscript has four sections. Section 2 presents the method section in which a detailed description of the proposed model, which is designed by hyper-tuning the CNN algorithm. Section 3 shows the results. Finally, the discussion and conclusion are presented in section 4-5.

METHODS

The proposed model is designed to estimate the pediatric skeletal age by processing the hand bone radiographs using the CNN algorithm. The main novelty of the presented model is that the learning parameters of the CNN algorithm are hyper-tuned using the metaheuristic walrus optimization algorithm to enhance its performance. The flowchart of the proposed pediatric skeletal age model is shown in (Figure 1).

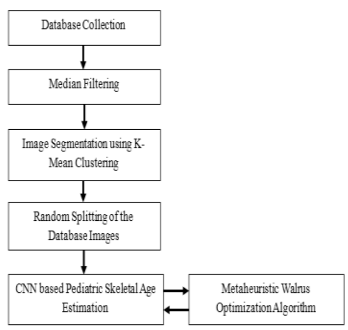

Figure 1: Illustrating the steps involved in the proposed pediatric skeletal age estimation model.

Database collection

To estimate the pediatric skeletal age, the hand radiograph data was collected from the publicly available database, such as RSNA 2017.[18] This database contains two files. The first file is a .csv file that contains the ID, bone age, and gender factor, whereas the second file contains the hand radiograph images. The data contains a total record of 550, and the images are available in png format.

Median filtering

In this step, the database images were read, and the noise from them is removed using the median filtering. The benefit of the median filtering method over other filtering methods is that it effectively removes the salt and pepper noise and preserves the edge information.

Image segmentation using K-mean clustering

This step was performed to segment the hand bone region from the original database image. In order to accomplish this goal, the k-means clustering algorithm was used. Unsupervised learning is used in K-means clustering to arrange data into clusters. In K-means clustering, the number of clusters (k) must be known. In the dimensional space, "k" centroids are first chosen at random. Each data point and each center position were given a squared Euclidean distance. The data is then clustered to a particular centroid using the minimal distance. The position of each centroid is modified by calculating the average of all data points assigned to a particular cluster. The distance measure is calculated, and the centroid location is updated. This process is continued until the centroid location doesn't change.[19]

Random splitting of the database images

In this step, the segmented images were randomly split into training and testing ratios. The training ratio was used to train the CNN algorithm, whereas the testing ratio was used to validate the performance of the CNN algorithm to estimate the pediatric skeletal age. In the proposed model, a 70:30 ratio was used.

CNN based pediatric skeletal age estimation

In this step, the CNN algorithm was employed for pediatric skeletal age estimation purposes. The CNN algorithm has three main layers: convolution, pooling, and a fully connected layer.[20] The convolution layer extracts features from the dataset images by applying filters to them. Followed by the pooling layer that down samples the features of the previous layer while preserving the essential features of the image. Finally, the fully connected layer is used to flatten the features in a vector form to estimate the bone age. However, in the CNN, the hyperparameter needs to be set before training the model. The filter size, type of pooling, learning rate, batch size, epoch size, and optimizers are the hyperparameters of it. Therefore, in this research, we have hyper-tuned the learning parameter for better performance using the metaheuristic algorithm. In this research, the walrus optimization algorithm was used. The walrus algorithm uses the feeding, migration, and predator evasion strategy of walruses to search for the optimal solution in the solution space of the learning parameter.[21] In this optimization, RMSE was taken as the objective function.

RESULTS

This section presents the simulation evaluation of the proposed model and comparative analysis with the previous approaches. The simulation evaluation was done on MATLAB 2018b software. The system configuration was an Intel (R) Core (TM) i7-7500 CPU, a 64-bit Windows operating system, and 16 GB RAM.

Evaluation criteria and performance indices

To evaluate the proposed model, the standard dataset images and .csv file were read. The dataset images were resized to the resolution of 256×256. Thereafter, these images were filtered using the median filter. The window size of the file was 3×3. The filtered image was given to the k-means clustering algorithm to segment the bone region from the entire region. In addition, the segment images were resized into 64×64 size from 256×256 to give them to the CNN algorithm. After that, 4D data (.csv file and segmented images) was given to the CNN algorithm, and its layers were initialized, as shown in Table 1.

Finally, the hyper-tuning of the learning parameter of the CNN algorithm was done using the metaheuristic walrus optimization algorithm before the final estimation of the pediatric bone using the CNN algorithm. In the WO algorithm, the RMSE was chosen as the objective function, and the population and iteration size were 5 and 30. The evaluation of the proposed pediatric bone age estimation model was done using the error metrics, namely, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Root Mean square Absolute Percentage Error. The description of these metrics is given below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|G_i - P_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(G_i - P_i)^2} \quad (2)$$

$$RMSPE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{G_i - \hat{p}_i}{G_i}\right)^2}$$

In the above formulas, the G_i,P_i represents the ground and predicted value by the proposed model. Furthermore, n denotes the total number of records were taken into consideration for evaluation purposes. A lower value of these error metrics reflects that the proposed model is efficiently determining the pediatric bone age. The original image, the image after median filtering, and the segmentation using the k-means clustering algorithm is presented in (Figure 2-4).

Figure 2: Original pediatric bone age image.

Figure 3: Pediatric bone age image after median filtering.

Figure 4: Segmented pediatric bone age image after k-mean clustering algorithm.

The error metrics that were measured for the proposed pediatric bone age estimation model for different cases is presented in (Table 1). This table presents the error metrics with and without optimization of the CNN algorithm. The result indicates the proposed model with optimization of the parameter of the CNN algorithm achieves lower error metrics than without optimization. This reflects that the proposed model efficiently predicts the bone age with respect to the ground value.

Table 1: Performance evaluation of the proposed pediatric bone age estimation model.

Category	MAE	RMSE	RMSPE
Both	2.7	13.343	2.846
Male	2.014	13.816	2.458
Female	3.4432	12.81	3.214

DISCUSSION

The proposed pediatric bone age estimation model was compared to the previous approaches based on machine learning and deep learning algorithms such as EfficientNet-B422, Inception-V4, Resnet-V223, ResNet-101 and ResNet5024, DenseNet-20125, Xception26, DADPN13. To accomplish this goal, the same dataset was considered that was utilized in the previous studies. The result indicates that Inception-V4 (Incep-V4)23 accomplishes the highest MAE and proposed model achieves lower error metric values compared to previous approaches, due to hyper-tuning the parameters of the CNN algorithm and preparing the dataset images using median filtering and segmentation methods.

Table 2: Comparative analysis with the previous approaches.[13,22-26]

Models	MAE value
EfficientNet-B4 (EB-4)[22]	7.79
Inception-V4 (Incep-V4)[23]	9.02
ResNet-101 (Res-101)[24]	8.79
ResNet-50 (Res-50)[24]	8.31
DenseNet-201 (Dense-201)[25]	8.53
Inception-ResNet-V2 (I-R-V2)[23]	8.49
Xception[26]	7.61
DADPN[13]	7.38
Proposed pediatric bone age estimation model	2.7

The time complexity of the proposed pediatric bone age estimation model is increased due to employing the metaheuristic walrus optimization algorithm for hyper-tuning the parameters of the CNN algorithm. Furthermore, this time complexity is highly dependent on the parameter values of walrus optimization, such as population and iteration size. In addition, the dataset was limited for evaluation purposes, and the same dataset was utilized for training and testing purposes. So, the proposed model outperforms because it learns the maximum characteristics of the testing images in the training phase.

CONCLUSION

In this article, a deep-learning-based pediatric bone age estimation model is presented. In this model, initially, the standard dataset images were read, and it was prepared for the deep learning algorithm by performing the median filtering to remove noise and segmentation using the k-means clustering algorithm to segment the hand bone region. The prepared dataset images, along with information of the dataset, such as gender, ID number, and bone age information, were given to the deep learning algorithm. In this model, the deep learning CNN algorithm was used, and hyper-tuning of the learning parameters of it was done using the metaheuristic walrus optimization algorithm. The simulation evaluation on the standard dataset on RSNA 2017 shows that the proposed model accomplishes the lower MAE value over the previous approaches. The main limitation of the presented model is that the data is limited, and the same data is utilized for training and testing purposes. In the future, a large amount of data will be collected by combining the multiple databases or generated using the data augmentation method to evaluate the robustness of the proposed model.

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