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An Enhanced Pediatric Bone Age Estimation Model Based on CNN and Metaheuristic Group Learning Algorithm

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Abstract: Pediatric Bone Age estimation is done in the medical field to diagnose the abnormal growth and development in the children. In the recent few years, machine learning algorithms are gained popularity in the field due to better accuracy and overcome human error. In this paper, we have designed an enhanced pediatric bone age estimation model using the convolutional neural network (CNN) and metaheuristic group learning algorithm (GLA) to enhance the assessment accuracy of the model. The group learning algorithm is a metaheuristic algorithm which searches the best region of interest (ROI) in the database images based on the objective function. In this research, k-mean clustering algorithm is taken as the objective function. After that, convolutional neural network is trained and tested with the ROI database images. The proposed model is evaluated on RSNA 2017 database images which contains pediatric bone images. Further, its evaluation is done using three performance metrics such as MAE, RMSE, and RMSPE. The result shows that the proposed model provides minimum value of these performance metrics over the existing models.

Keywords: Bone Age, Clustering, CNN, Deep Learning, Filtering, GLA, Machine Learning, Metaheuristic, Optimization, Pediatric, Segmentation.

1. Introduction

The term "pediatric bone age assessment" (BAA) is a clinical tool that is often used in the diagnosis and treatment of endocrine problems, pediatric radiography, and child growth assessment [1]. The BAA approach typically evaluates bone skeletal maturity using left-hand radiographs, since bone ossification levels in the non-dominant hand reflect bone maturity. The Greulich-Pyle (G&P) technique and the Tanner Whitehouse (TW) method are the traditional standard methods for assessing bone age [2]. By comparing the radiographs with the reference atlas, the G&P approach determines which atlas is the most comparable to the radiographs. The estimated bone age is represented by the labeled age of the chosen atlas. The TW approach is more complicated than the G&P method [3]. It doesn't depend on the complete radiograph to estimate bone age; instead, it examines particular areas of interest (ROIs), which include the carpal, phalanx, metacarpus, and radius bones. A numerical scoring method is used to evaluate each ROI, and the final bone age is computed by taking the average of all ROI scores. This is done because the ROIs include necessary anatomical elements that play significant roles in BAA. However, the traditional evaluation process involves visual inspection and manual annotation by skilled radiologists or pediatricians. This process is challenging, time-consuming, and subject to the influence of various physicians with varying standards. Therefore, automatic pediatric bone age estimation models based on machine learning is getting attention due to less time consuming and better accuracy [4].

The main contribution of this research is to enhance the accuracy of the pediatric bone age estimation model based on deep learning and metaheuristic group learning algorithm. In the deep learning algorithm, convolutional neural network is utilized for pediatric bone age estimation whereas metaheuristic group learning algorithm is used for determine the region of interest based on k-mean clustering as the objective function. The group learning algorithm is an optimization algorithm and its main motive is to find the best clustering based on the objective function. Besides that, median filter is applied in the pre-processing step in order to remove the noise. The proposed approach is evaluated using simulation on the standard RNSA dataset. The findings indicate that the suggested model offers minimum error between the actual and predicted value of the bone.

The rest of the paper is as follows. Section 2 shows the related work is done in the pediatric bone age estimation model using the machine learning and metaheuristic algorithms. Section 3 shows the preliminaries in which different algorithms are explained which are required to design the proposed pediatric bone age estimation model. Section 4 explains the proposed pediatric bone age estimation model is based on CNN and metaheuristic group learning algorithm. Further, Section 5 shows the simulation evaluation and comparative analysis with the existing models. Finally, Section 6 shows the conclusion and future scope of the work.

2. Related Work

In this section, we have studied and analysed the pediatric bone age estimation models are designed using the deep learning and machine learning algorithms. Wang et al. [5], designed a dual attention dual-path network for bone age estimation and evaluated the model on the standard RSNA dataset. Besides that, region based CNN is utilized for segmentation purposes in the pre-processing step. Further, Ren et al. [6], utilized the regression CNN algorithm for bone age estimation. The regression CNN follows the monitoring of the dynamic attention loss while training and accurately estimate the bone age. Next, Chandran et al. [7], designed a bone age estimation model using the metaheuristic golden eagle optimization (GEO) and dual channel capsule generative adversarial network. The GEO algorithm is utilized for optimal tuning of the DCCGAN. Moreover, Hemand et al. [8], utilized the metaheuristic group teaching optimization algorithm to enhance the performance of AlexNet-based Deep CNN by determining their weight values. Finally, we have analysed that Sonal Deshmukh and Arti Khaparde [9], used the two-metaheuristic algorithm class and whale optimization for segmentation purposes and deep CNN algorithm for bone age estimation.

From the above studies, we have found that convolutional neural network is the most preferred algorithm for pediatric bone age estimation. Further, metaheuristic algorithms are utilized in the segmentation and optimal tuning of the neural network in order to enhance the accuracy. However, in the literature, a number of metaheuristic algorithm is available and selection of most optimal metaheuristic algorithm reduces the model complexity and quickly find the best solution. Therefore, in this research, an enhanced pediatric bone age estimation model is designed using the metaheuristic group learning algorithm and CNN.

3. Preliminaries

3.1 Database: The authors established the RSNA Pediatric Bone Age Challenge 2017 dataset to demonstrate the use of artificial intelligence (AI) and machine learning (ML) in the medical imaging field [10]. The total number of radiographs is 14,236 (12,611 samples were there in the training set, 1,425 samples were in the validation set, and 200 samples were in the test set). The main goals of the study were to discover medical imaging innovators, facilitate cooperation for the creation of AI models, and reliably detect skeletal age in paediatric hand radiographs by using machine learning approaches. The training and validation sets in the dataset, which came from Children's Hospital Colorado and Lucile Packard Children's Hospital at Stanford, were labeled with estimates of skeletal bone age (months) and sex. The algorithm's performance was assessed using an extra test set. The ground truth estimates were developed using the Greulich and Pyle standard and feedback from several professional reviewers.

3.2 Median Filtering: The median filter's primary objective is to make images less noisy. The median filter evaluates every pixel in the image separately. It helps in determining whether or not it is common in its surroundings by examining its close neighbors. It replaces the value of each pixel with the median of given numbers rather than just the mean of the values that are nearby. To determine the median, all of the nearby neighborhood’s pixel values are first sorted into numerical order. Then, the pixel under review is replaced with the middle pixel value [11].

3.3 K-Mean Clustering: A common issue that arises when processing hand radiographs digitally is uneven background contrast variations. The method of digitally acquiring radiographs has an inherent impact. The issue of overlapping pixel intensities between the soft tissue area and bone presents a significant barrier to the segmentation algorithm. Many techniques for pre-processing radiographs have been developed to eliminate the background [12]. Eliminating the soft tissue area is the most difficult step. Image segmentation methods are needed to overcome the issue. There are many types of image segmentation techniques: hybrid, edge-based, region-based, thresholding, deformable models, clustering, and so on. For the aim of segmentation, this study uses the k-mean clustering approach. The process of clustering involves assembling comparable patterns into groups, much as in unsupervised learning. Based on a distance metric like Euclidean distance, pixels are grouped into k clusters using the most widely used clustering approach for segmentation, k-means clustering. The clustering method is based on optimizing an objective function, such as minimizing a squared error function.

3.4 Metaheuristic Group Learning Algorithm: The GLA exhibits how managers and group leaders influence their members' abilities, as the name indicates. This method differs significantly from previous algorithms in that it splits the population into many equal groups. Then, it chooses a subset of people as group leaders (based on fitness), and then identifies the manager, or the person with the highest overall fitness. The following are the GLA algorithm's key features [13]:

• The initial population is generated at random.

• The most fit person within the population assumes the role of manager for every individual.

• Several groups are represented by the whole population (four groups were considered for this study).

• The leader of every group is the best member (the one with the greatest level of fitness within the group).

• Each group's leader has an impact on its fellow members.

• Group leaders and other people are impacted by the manager.

• Mutations are used to randomly alter an individual's basic structure.

The manager influences the group leader. Leaders of groups also have a big impact on how the next projects of the groups are initiated, run, and managed. Eq. 1 is used mathematically to illustrate how the manager affects the group leaders.

$$LA = (x - y) * r \quad (1)$$

In this case, x represents the leader of the group (the person with the greatest fitness inside the group), y denotes the manager (the person with the best fitness throughout the whole population), and r is a random integer between 0 and 1. LA is the group's new leader after the manager has influenced it.

The project's execution should benefit from the manager's and group leaders' discussions over the implementation techniques. Additionally, group members should be informed of the plans and how they will impact their work. Typically, the groups will be informed by the group leaders of the methods that the manager and they have decided upon. This is mathematically shown by Equation 2. This algorithmic behavior is indicative of the exploitative stage.

$$new\ pop(i) = \big(LA - pop(i)\big) * r \quad (2)$$

Here, new Pop(i) represents the group's individual, r represents a random integer in the [0,1] range, i [n, here n is the group size], and LA represents the leader established in Eq. 1. Pop(i) is the new individual after its impact from the LA identified in Eq. 1.

Periodically, the population leader meets with every member of the population and issues instructions directly to them. The managers will thus have an effect on the workers. The following is how this behavior is assessed in the GLA.

$$new\ individual(i) = (pop(i) - y) * r \quad (3)$$

In this case, y is the leader, r represents a random integer in the interval [0, 1], and new Pop(i) represents an individual. Once an individual is influenced by the leader of the whole population, it becomes a fresh individual. Additionally, sometimes a sudden action or information from outside the group affects a member's skill set. To demonstrate this random impact from outside the organization, certain individuals' positions have been swapped at random. This characteristic of the algorithm is shown by the mutation operator.

3.5 Convolutional Neural Network (CNN) Algorithm: A kind of neural network that is feedforward with depth convolution and structure computation is called a convolutional neural network (CNN). This method is a good example of a deep learning representation [14]. Typically, a CNN has three layers: input, hidden, and output. A CNN's input layer is capable of handling multidimensional data. The output layer's design and operation are comparable to those of a conventional feedforward neural network. The result of an image classification task might be a classification label. The output of an object recognition problem may include the item's size, classification, and center coordinates. Here are several common types of hidden layers: convolutional, fully connected, and pooling. The convolutional layer's primary job is the input data's extraction. Convolution output channel count is dependent on the number of convolution kernels. The previous convolutional layer's feature map should be moved and rotated by the set step size. The position elements should then be multiplied and added up to get the feature map of the next layer. Convolution operation results may be non-linearly mapped by the activation function layer in the convolution layer, which can also map pooled or convolution output results to a specified range, usually between 0 and 1.

Because of this, it is often used with the convolution process. The activation functions that are most often utilized include the leaky relu (lrelu), sigmoid function, hyperbolic tangent function, corrector linear unit (relu), etc. Lower sampling layer is pooling layer. The pooling function is the most crucial component. The distinctive graph statistics of a single point's neighbouring areas may be used to substitute the outcome of that single point. When a feature map with local correlation is obtained after the convolution layer, a lot of features are obtained. If these features are utilized straight for training, overfitting will occur. By representing the large-size feature map by the small-size feature map, the pooling layer may eliminate redundant features for object identification, decrease feature dimension, and simplify network computation. Every network node is connected to every other network node in the preceding field via the entire connection layer. In order to create a feature vector, the features that were taken from the front may be combined. The output might be classification or regression based on feature vectors and distance.

3.6 Performance Metrics: The evaluation of the pediatric bone age estimation model is done by comparing the actual bone age with the predicted bone age by model. Therefore, various error matrices are determined to evaluate the proposed model and compare with the existing models. Table 1 shows the performance metrics are evaluated for the proposed model [15].

Table 1 Performance Metrics

Performance Metric	Equation
Mean Absolute Error (MAE)	$\text{MAE}=\frac{1}{N}\sum_{i=1}^{N}\lvert a_i-\hat{p}_i\rvert$
Root Mean Square Error (RMSE)	$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i-\hat{p}_i)^2}$
Root Mean Square Percentage Error (RMSPE)	$\text{RMSPE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\frac{a_i-\hat{p}_i}{a_i})^2}$

4. Proposed Pediatric Bone Age Estimation Model

In this section, the proposed pediatric bone age estimation model is explained which is designed to accurately measure the bone age based on the gender factor. Figure 1 shows the flowchart of the proposed pediatric bone age estimation model. In the proposed model, initially, standard dataset is read. In the standard dataset, two files are available. The first file is .csv file which contains the image Id, age, and gender factor. On the other hand, the second file contains the images based on the Id number. Therefore, based on information of both files, the image dataset of bone age is read. After that, the image is pre-processed using the median filter in order to noise and smooth the images based on median value. Next, ROI (region of interest) is determined in the dataset images based on segmentation process. In order to accomplish this goal, clustering method is taken into consideration and optimal clusters in the dataset images is find out using the metaheuristic group learning algorithm. Further, the CNN is utilized for estimate the bone age based on the available information of the standard dataset. In order to accomplish this goal, the segmentation image is trained along with the information of gender and age factor. Based on trained images, the CNN model predicts the bone age. Finally, performance evaluation of the proposed model is done using the three metrics such as MAE, RMSE, and RMSPE.

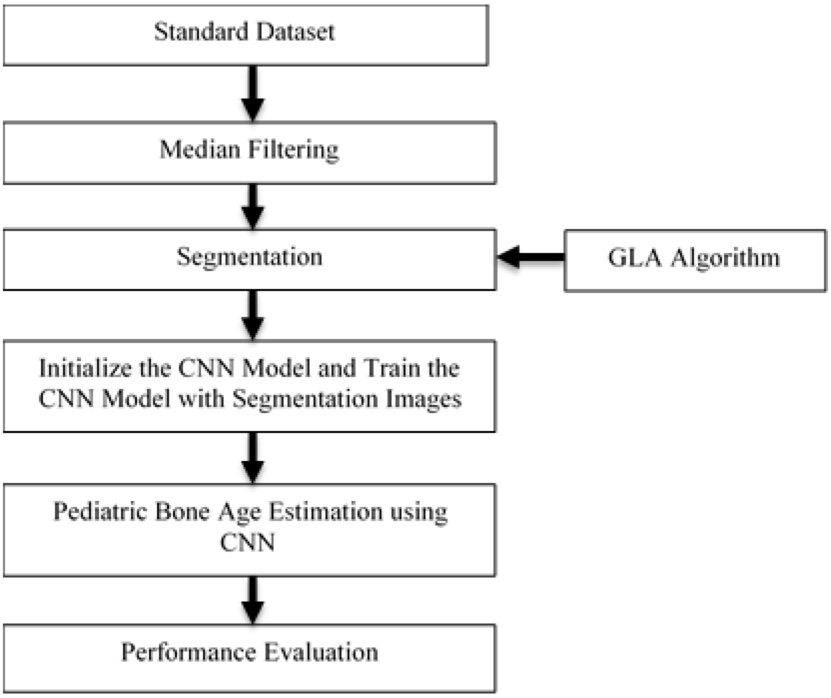


Figure 1: Flowchart of the Proposed Pediatric Bone Age Estimation Model

5. Result and Discussion

This section shows the simulation evaluation of the proposed pediatric bone age estimation model on the standard RSNA 2017 dataset and compare with the existing models based on various performance metrics. In the proposed model, CNN, and metaheuristic GLA algorithm is utilized. Therefore, these algorithms are need to initialized for simulation purposes. Table 1 shows the simulation setup configuration.

Table 1: Simulation Setup Configuration for CNN and GLA Algorithm

Parameter	Value
Max Epochs	20
Learn Rate Drop Factor	0.1
Initial Learn Rate	0.1
No of Layer	50
Learn Rate Drop Period	15
Min. Batch Size	256
Input Layer	64 x 64

Table 2 shows the subjective analysis of the proposed pediatric bone age estimation model in which bone age is shown by evaluating the different dataset images.

Table 2: Subjective Analysis of the Proposed Pediatric Bone Age Estimation Model

Age :120

Age :150

Age :69

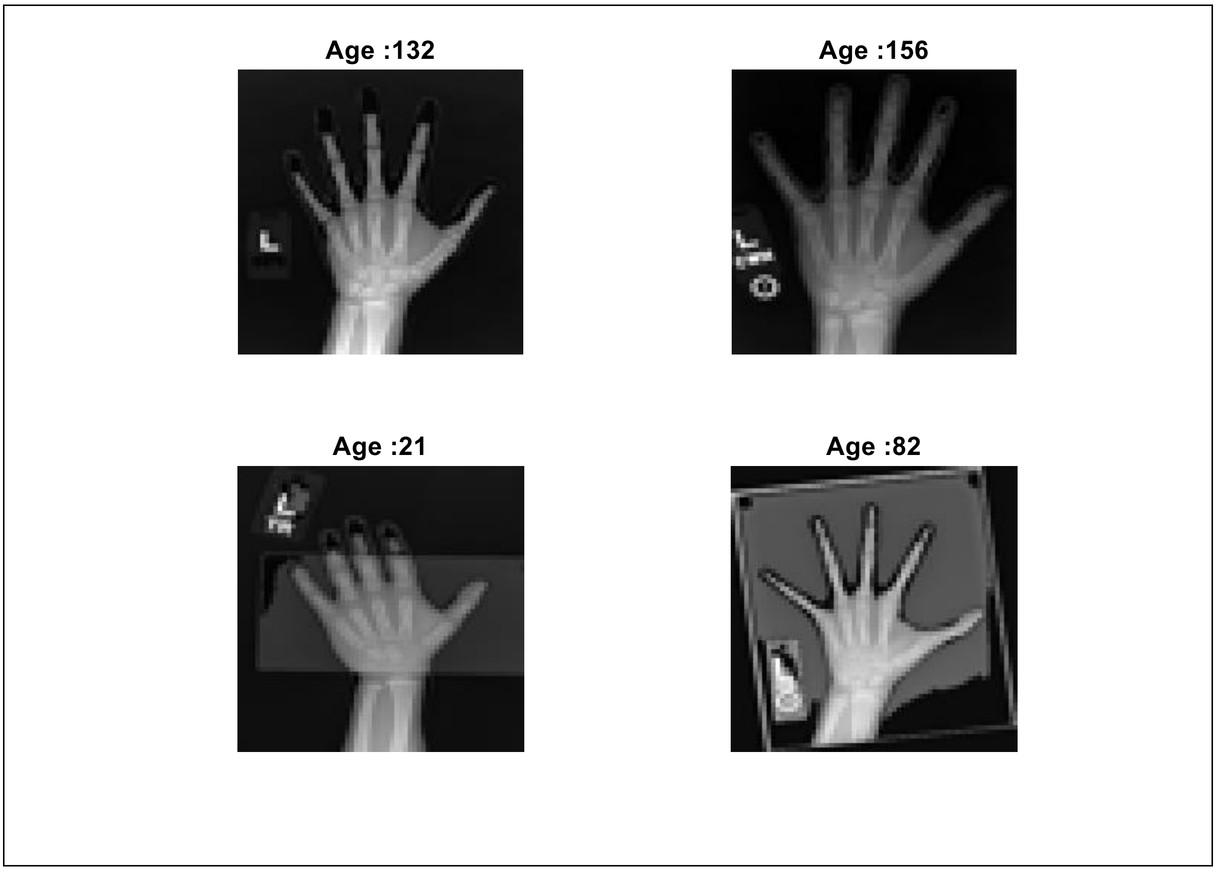
Age :180

Age :144

Age :75

Age :132

Age :180



Further, Figure 2 shows the convergence rate graph which is plotted for group learning algorithm. This graph is plotted between objective function vs. iteration. The graph shows in how many iterations the group learning algorithm achieves the desired objective function. The results shat that the group learning algorithm is quickly search the best parameter value of segmentation method in the initial iterations.

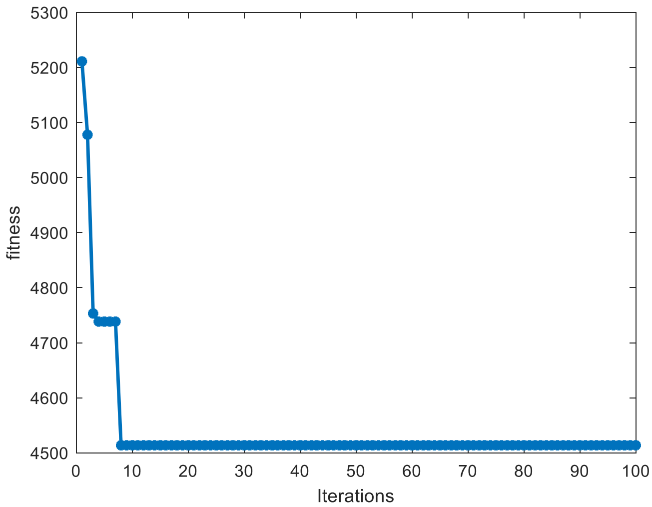


Figure 2 Convergence Rate Graph

Table 3 shows the objective analysis of the proposed pediatric bone age estimation model based on the various performance metrics such as MAE, RMSE, RMSPE. The result shows that the error factor is minimum between actual and predicted age by CNN model for different cases are taken into consideration, as shown in Figure 3.

Table 3: Objective Analysis based on Various Performance Metrics for Pediatric Bone Age Estimation Model

	Both	Male	Female
MAE	2.7927	3.0629	2.5
RMSE	14.12	15.04	13.051
RMSPE	2.3634	2.4751	2.2361

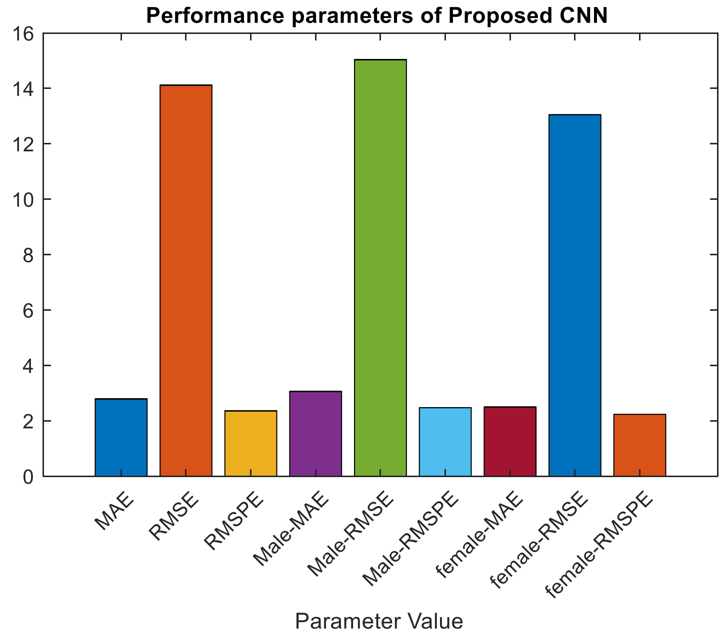


Figure 3: Performance Parameters for the Proposed Model

Finally, the proposed pediatric bone age estimation model is compared with the existing models based on various performance metrics [5]. Table 4 shows the comparative analysis based on the parameter of MAE. The results reveal that the suggested model achieves the minimum MAE (2.7927) over the existing models (refer to figure 4).

Table 4 Comparative Analysis based on MAE Parameter (Both)

Algorithm	MAE
Inception-V4 (Incep-V4)	9.02
EfficientNet-B4 (EB-4)	7.79
ResNet-50 (Res-50)	8.31
ResNet-101 (Res-101)	8.79
Inception-ResNet-V2 (I-R-V2)	8.49
DenseNet-201 (Dense-201)	8.53
DADPN	7.38
Xception	7.61
Proposed Method	2.7927

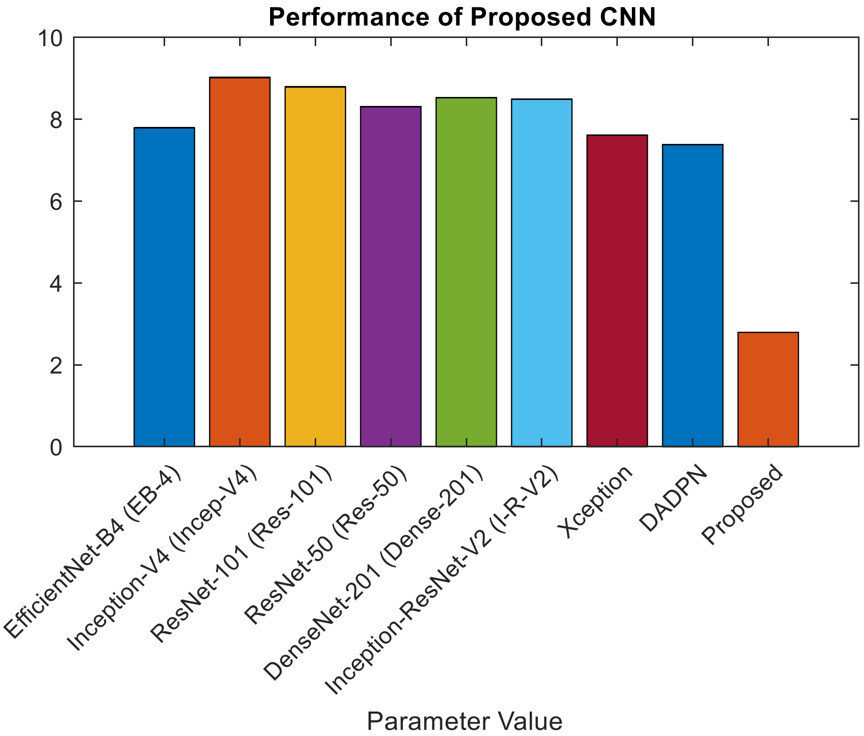


Figure 4: Comparative Analysis based on MAE Parameter

From the simulation evaluation, following key points are analysed.

- The addition of group learning algorithm in the proposed bone age estimation model enhances the accuracy to find the region of interest. However, this process increases the time complexity of the algorithm because GLA algorithm is an optimization algorithm which searches the best solution based on the predefined population and iteration size.

6. Conclusion and Future Scope

In this research, we have developed an enhanced pediatric bone age estimation model in order to predict the bone age with minimum error with respect to actual age. In order to accomplish this goal, initially, standard dataset is read which contains the images of bone age, their ID, age and gender factor. Based on this information, the pre-processing of the image is done using the filtering and segmentation method in order to remove noise and to find out the region of interest. Besides that, in this research, group learning algorithm is utilized to find out optimal clusters in order to accomplish the segmentation. After that, CNN model is trained with region of interest images along with the age and gender factor. Based on this information, the CNN model predicts the bone age with respect to actual bone age. The results indicate that the suggested model achieves the minimum MAE over the existing models. In the future, pre-processing method is enhanced by deploying the image enhancement method. The primary motivation of the image enhancement method is to enhance the brightness of the dataset images by analysing the various characteristics of it. Besides that, lightweight deep learning method is designed for human bone age estimation.

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