DeepBone: Predictive Bone Age Assessment through Image Processing and Deep Learning

Github Link: https://github.com/Sonikaabigail/DeepBone-Predictive-Bone-Age-Assessment-through-Image-Processing-and-Deep-Learning

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Abstract :

The use of this study aims to determine the bone vocation of children by applying deep learning algorithms and advanced image processing methods. On putting convolutional neural network(CNN) ResNet50 to use, together with other methods: histogram equalization, Sobel edge detection, Prewitt operator, gradient magnitude thresholding and CLAHE, the study aimed to boost bone age assessment. Results have shown the impact of the impact of these preprocessing processes that make prediction more accurate, most of all in an integrated way. However, while Sobel edge detection and gradient magnitude thresholding showed considerable enhancement in their feature extraction and classification, Canny edge detection performed better and allowed for more detailed CCTV surveillance footage interpretation. This study shows how the kind of preprocessing techniques can improve the application of medical imaging data for research purpose both in terms of accuracy and interpretation. Unfortunately, their effectiveness should be taken with a pinch of salt as further details need to be ironed out and the models need to be more robust for those complex enough datasets. Moreover, the study points to the difficult issues caused by genders and races as relevant to the age assessment, pointing out the essentiality of more future studies in this area.

Introduction :

The expression "bone age," or "skeletal age" in a short form, denotes the level of the development of a child's bones. It is confirmed by measuring the development of bones through X-ray examination accompanied by contrasting the developed bones with the picture reference. Mobile field X-ray generates data on leg bones that together with the Harman and Throws-Djernes' formula predicts an optimum time for developmental growth and pubertal stage of the child.

The commonness of bone age assessment in pediatric endocrinology and orthopaedics together with such disorders as growth abnormalities, renders it critical. Bone age inspection is a tool used by pediatric endocrinologists to study and identify the effect of growth hormone deficiency or sex hormone delay, either early or late puberty as well as other conditions of skeletal dysplasias. It implies essential health data for appraising the efficacy of therapeutic projects like growth hormone treatment and forming treatment packages. Bone age determination is a medical procedure applied for bone development monitoring in children with skeletal abnormalities, fractures or congenital anomalies, concerning the determination of skeletal maturity. It speeds up the decision process of the orthopaedic doctor by studying the results and picking up the time for surgical operation.

The objectives of the study are to demonstrate a system that will be based on deep learning algorithms, and complex image processing technologies, and, of course, will be both accurate and precise for determining bone age. We intend to build an application that by using machine learning models that have been trained on large sets of pediatric radiological images, can automatically determine bone age and X-ray pictures efficiently with minimal human intervention. This method will divert the path to efficient diagnosis by clinical experts in the field of pediatric endocrinology and orthopaedics. This step will in turn reduce the time taken to assess the bone age and enhance the accuracy as well as reliability of diagnosis. In the meantime, this approach features both scalability and efficiency as well as fills up the gaps in the conventional methods. This way, we intend to move towards solving these problems.

[1] In a paper by Greulich and Pyle, a study has figured out the skeletal age estimation of a mixed population of youngsters. There were some differences found: whereas, both the Black girls and Hispanic girls were ahead of the average age of the individuals from late childhood to adolescence by some margin, the white and Asian girls tended to be, if not better at, the same as that given age. The black guys in the hoods were the improved minority teens. Young Asians presented a contradictory pattern and matured early in adolescence but late in middle childhood, whereas White boys experienced no such pattern till the onset of puberty. With skeletal age standards, scepticism should be high in late childhood and adolescence, particularly in Asian and Hispanic boys and females, and Black and Hispanic females. The fact is they can differ by nine to eleven months from the chronological age during this period.

[2] Gender and race occupy a prominent place in this field of research and must be included when considering recommendations, interventions and studies focusing on bone age. The traditional Greulich-Pyle and Tanner-Whitehouse 2 bone age assessment methods, as well as the newer methods of ultrasonography and automated systems such as BoneXpert, are covered in the discussion. One of the functions of bone age is the evaluation of the maturity state of the girl to determine the beginning of menarche, the peak height velocity, the adult height as well as the onset of puberty. Clinical characterizations include paediatric endocrinology and orthodontics. Bone formation is led by sex hormones (mainly estrogen) obviously. However, lately, the BoneXpert is coming up as a more accurate method and bone age is still considered a valid predictor in pediatric medicine.

Methods:

ResNet50 (CNN) :

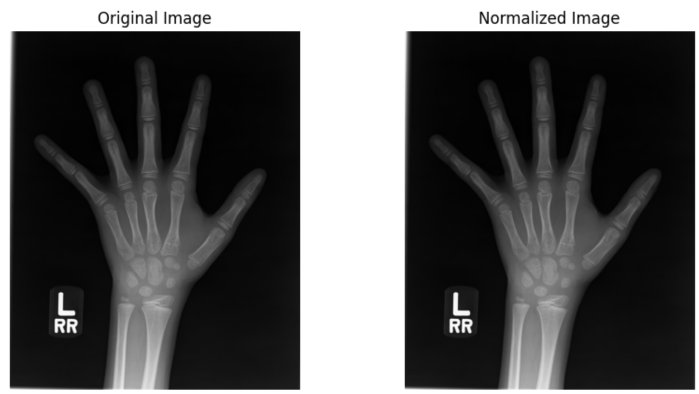
CNNs, which is a group of deep learning approaches with an ability to process data organized on grids in order (such as images), stand for “Convolutional Neural Networks”. CNNs consist of depth-wise feature learning, namely convolutional layers, pooling layers, and fully connected layers. Convolutional training filters, the network receives lessons on how to automatically extract hierarchical representations of features like edges and textures out of the training images. Convolution with a pooling layer decreases the spatial dimensions of the feature maps therefore these representations will be less sensitive to small variations in spatial translations. Fully linked layers fuse the basic data into a result of the model’s prediction.

Transfer learning is a machine learning maintenance strategy where a model is trained originally for a particular task and then adapted to another task with the same features. For this purpose, transfer learning does not focus on training the model on the entire data from the beginning rather it uses the insights gained from training on a large dataset to handle a problem that is pretty similar to the previous one. Even, this approach is beneficial when the target tasks have a small data size or a simple structure compared to the other complex tasks. As feature extractors and through fine-tuning, transfer learning dramatically shortens training time and increases the likelihood of accurate indoor navigation.

ResNet50 is a well-known CNN architecture designed by Microsoft Research in 2015. It is one of the first instances of residual networks. It is **the abbreviation for Residual Network (ResNet) with 50 layers, that is, a deep network. ResNet50 tries the relinquishing gradient challenge faced by very deep networks by adding residual connections or skipping connections between layers. These interactions direct gradients to flow consistently faster as compared to deeper nets that are trained, thereby made possible to train complex architectures deeper than before. ResNet50 Blocks composite each block consisting of several conv layers, from which a shortcut referred to as an identity connection is drawn to proceed. We have used the transformer-based architecture, which had been pre-trained on the ImageNet dataset - a large-scale image recognition task. The architecture is capable of performing transfer learning, hence a powerful feature extractor for computer vision tasks.

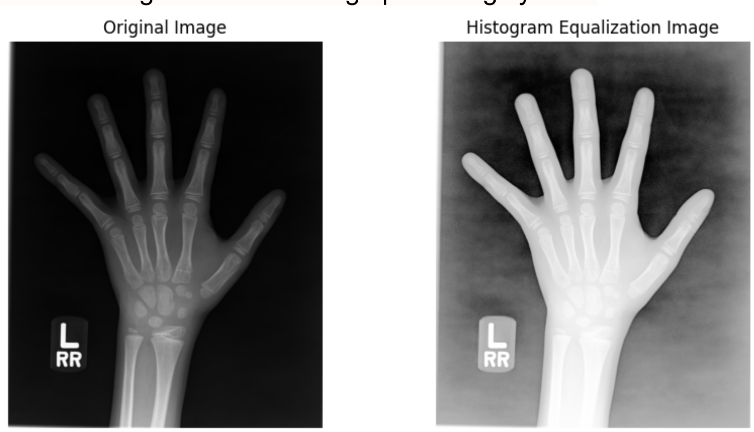
Normalization:

[3] During image data processing, this method does have a specific technique, which is known as histogram equalisation, they are used to help adjust the images so that it gives more brightness and high contrast levels. Histogram equalisation, which is usually used for lightening an X-ray picture for the evaluation of the degree of bone maturity, is a technique that adjusts the number of outlines of the picture by making pixel values broadly distributed throughout the whole dynamic range. The usage of deep learning for the computerized age determination of bones thus involves better visualisation of the features and structures of bones, which facilitates the analysis and the determination of age through deep learning algorithms. Histogram equalization as quantile transformation is a technique that proves to be an improvement in the distinctiveness of the X-ray movies and increases their readability by the practitioners for bone maturation phase determination. The pre-processing stage is a critical aspect of the input data enhancement process which boosts predictability and system reliability in the overall process of bone age assessment.



Histogram Equalization:

[4] An image processing technique called histogram equalization that can be applied to images of the various aspects of brightness and contrast is used. Particularly, the kernel operator, which is used mathematically for greening consideration and for mapping, allows us to distribute pixel values as uniformly as possible over the whole dynamic range in X-ray pictures evaluated in bone age assessment. Consequently, digital technology enables a better perception of the characteristics and proportions of bones and through AI makes it possible to calculate an age of bone. Histogram equalization is a rather pivotal tool for obtaining the needed clarity in X-rays and providing a correct interpretation of bone maturation phases due to the redistribution intensities of pixels in the histogram. Preparing data for input is crucial since it significantly improves the precision and reliability of predictive mapping of bone age, which is one of the basic stages of the bone age predicting system.

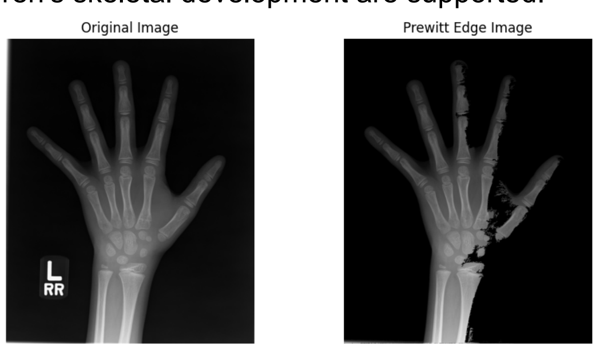


Sobel Edge Detection :

[5] The main approach in image processing, and largely utilized in medical imaging (for example X-ray scans), is the Sobel Edge Detection technique. This is achieved through a gradient-edged feature whereby the gradient magnitude of pixel intensity is used to represent edges (lines and boundary separations) in a given picture. This edge detection method will be performed through convolution with Sobel kernels in both, the X and Y, axes. It makes features, that are necessary for the analysis further, more expressive by pointing out immediate abrupt changes in intensity. Edge detection by Sobel aids in the proper picking out of bone structures during computational X-ray image preparation, which will be significantly helpful in the accurate classification of bone age. The fact that the separation of bones reduces the chances of interpretation errors among experts is one of the benefits of the approach. Having Sobel Edge Detection with a good computational approach and clarity to highlight important object features is a useful technique before handing over X-ray images for further deep learning-based analysis.

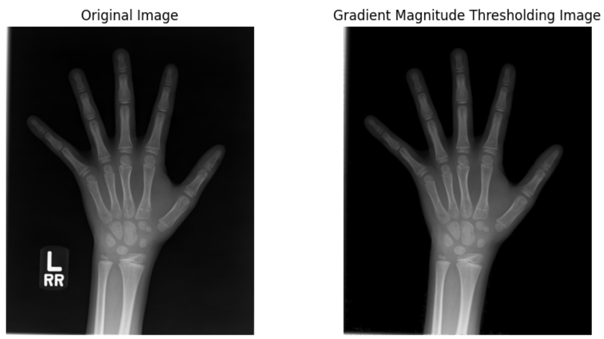
Prewitt Operator

[5] In image processing, specifically for the images derived from X-rays, the popular operator is the Prewitt operator. It implies that the edge detection technique is one of the techniques for detecting gradient intensity within the image. The Prewitt Operator makes the image's edges stand out by employing a set of filters to convolve them using a horizontal and vertical kernel We can see the areas where intensity is changing in a fast way through these lines. In this way, the process enhances the explanation of the contours in X-ray pics and increases the effectiveness of future diagnostic tools. The Prewitt Operator is famous even outside the academic world due to its popularity for medical image processing applications, especially Bone Age (BA), as it is quite easy to implement and provides efficient edge recognition. Its usage will assist in the X-ray images deficient in information this is the reason why the accurate diagnosis and evaluation of children's skeletal development are supported.



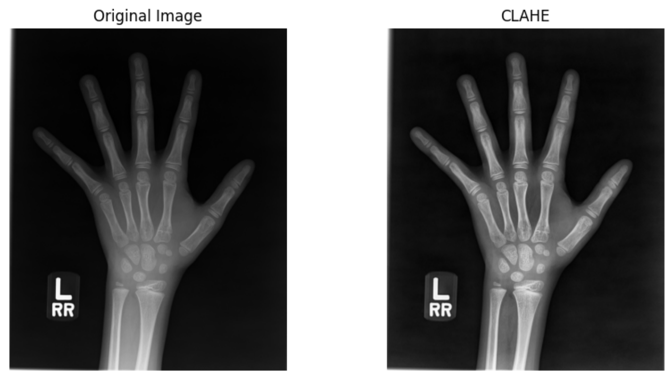
Gradient Magnitude Thresholding

[6] A preprocessing method is used, i.e., gradient magnitude thresholding, which is used for evaluating X-ray images and helps in visualizing the bones better in order to determine bone age. In the image, nasty bone edges are represented by points of irregular fluctuation of intensity in the pixels. One can note the difference in magnitude by measuring the magnitude of the gradients. Following that step, the thresholding technique is applied to secrete interests and the anatomical bone structure is examined in more detail. In combination with the system of highlighting traits and decreasing background noises, this method allows the accurate bone age diagnosis. The Gradient Magnitude Thresholding has proven useful as part of image preprocessing in the deep learning world. It helps in gaming the input data clean which later on leads to better performance of deep learning models and more precise and consistent predictions of skeletal age.



Contrast Limited AHE (CLAHE)

[7]The image processing technique, also known as Contrast Limited Adaptive Histogram Equalization (CLAHE) is the most common way of bringing out details by increasing the contrast of X-ray images. In contrast to the common histogram equalization techniques, CLAHE does not extend the level of contrast development by which it may increase the noise, especially in the cases of low contrast. The image is split into various sections, and every subdivision by itself gets the processing of histogram equalization. Developed this method, it is rightly said that an image suffers a slight drop in the overall brightness but has an admirable improvement in the local contrast intensification. For example, in situations where medical radiology, including the radiography of X-rays, where the minute contrasts are the only factor for the precise diagnosis could play a role. CLAHE provides the investigation and detection facility of a plethora of medical disorders that can be revealed by improving the clarity of images taken with X-ray devices to have more accurate results of the investigations.



Results:

Pre-Processing Methods	**MAE**	**MSE**
Normalization	5.2799	48.3337
Histogram Equalization	3.8843	24.7598
Sobel Edge Detection	3.7681	23.5154
Prewitt Operator	3.8905	24.4489
Gradient Magnitude Thresholding	3.7263	23.1090
CLAHE	3.6696	22.7856

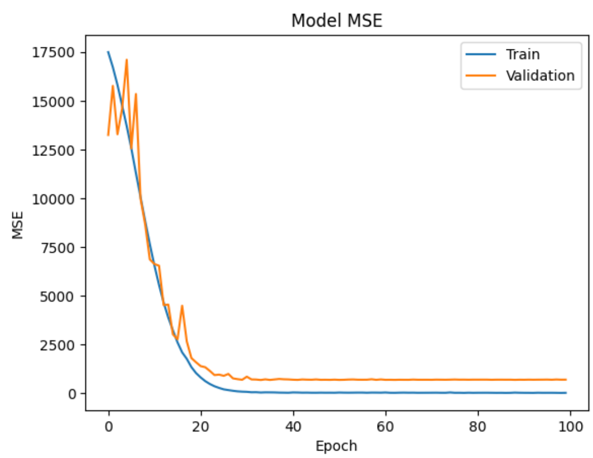
The ResNet50 model which has the process of image processing integrated as one of its methodologies has proved to give better estimates of bone age in the different experiments that have been conducted so far. For 78 epochs at the beginning, while being trained on normalized images, it got good but not impressive results: its losses were 57.3576, its MAE was 5.2799, and its MSE was 48.3337. These processes are being detailed in a strategic plan, which will also contain specific plans for improving the accuracy of the system.

Histogram equalization was subsequently used and it led to the improvement of the results since the loss was reduced by 32.4145 and also the MAE reduced by 3.8843. However, the model displayed resistance for the average of MAE as equaling 23.5716 on validation data depicting. The addition of Sobel Edge Detection to the deep learning model aided in its separation of bone age, the result being an MAE of 3.77 and an MSE of 23.52 on the training set. Generalization was overestimated in the validation set, and hence, there is a requirement for better extensive learning.

In the case of calibrating the deep dog breed classifier with ResNet50 using Prewitt filtering, the best results are achieved, with MAE = 3.89 and MSE = 24.45 thus showing a good performance. Whilst the errors are lower for the validation set as compared to the training set, it does show a strong presence of model overfitting which illustrates the need for further refinement.

Squashing the Gradient Magnitude Thresholding into the training cycle, we have seen significant improvement: with very small MAE and MSE (3.73 and 23.11 respectively) for the training dataset. While further validation with a larger dataset may be necessary to achieve better predictive power, the lower MAE and MSE values in that set are a good indicator of overfitting, requesting that more attention be given to the issue.

In the end, we tested ResNet50 with CLAHE histogram equalization, and the result was shown to have a strong prediction potential, with a training loss of 29.9731 and 708.0649 of the validation loss. Obtained was the model error MAE equal to 3.6696 in the training set and 20.5618 in the validation set, which might signify a possibility of bone age assessment in a precise and accurate way.



Conclusion:

The main purpose of this research was to come out with the most precise and systematic way of identifying the age of the bones by using deep learning algorithms and complex image processors. The ResNet50 architecture, a CNN (recurrent neural network) is which together with various preprocessing techniques such as histogram equalization, Sobel edge detection, Prewitt operator, gradient magnitude thresholding, and CLAHE (Contrast Limited Adaptive Histogram Equalization) contribute to remarkable achievements towards this objective. The results proved that those methods were appropriately combined into the ResNet50 model and thus performance in the age prediction was boosted. At first, the model learned on images that had been normalized and yielded decent results. Enhancements came, especially, involving histogram equalization, Sobel edge detection and other pre-processing methods, drastically reducing errors and increasing predicting accuracy. Specific changes that showed up in the system of Sobel edge detection and gradient magnitude thresholding presented big differences in both training and validation sets, which is a sign of those two techniques being much better in feature extraction and classifying.

Also, the article points out that the preprocessing methods are crucial in improving the two indicators: the interpretability and the accuracy of medical imaging data, which stands at the forefront in bone age assessment. Techniques like histogram equalization and CLAHE have given us lots of leeway in improving image clarity and contrast, leading us to more accurate diagnosing and interesting evaluation of human skeletal development. While, promising results we obtained, the obstacles that require re-consideration and more refinement were also observed, thus, the large dataset is necessary for further validation. Last but not least, the possibility of gender and race variations in bone age assessment constitutes the major barrier entrenched in the present-day process and has been well illustrated by past studies.

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