A Deep Learning Framework for Skeletal Maturity Evaluation

Mokkala Kiran Moni[1], *K Neelima[2], P Rajat Kumar[3], V Prashanth Kumar[4], R Leelavathi Bai[5]

[1, 2, 3, 4, 5]Department of CSE, Annamacharya Institute of Technology and Sciences, Tirupati, Andhra Pradesh, India
[1]kiranmonireddy@gmail.com
[2]neelimadrishti9392@gmail.com
[3]prajatkumar2004@gmail.com
[4]mrprasanth192@gmail.com
[5]leelalucky7729@gmail.com

Abstract. The paper proposes a web-based implementation for a bone age classification system that assists clinicians in interpreting skeletal maturation in children using pediatric hand X-ray images. The system is implemented using the Django framework and incorporates a convolutional neural network (CNN) architecture to automatically predict bone age from the input images. The proposed image classification system supports multiple image formats, including DICOM, which contains embedded patient information such as gender, birth date, and study date. These details are automatically extracted to compute the chronological age of the patient. The system processes images using deep learning–based feature extraction and predicts bone age based on learned skeletal patterns. The performance of the proposed model is evaluated using standard evaluation metrics, including accuracy, precision, recall, and F1-score. Experimental results demonstrate that the CNN-based bone age prediction model achieves an accuracy of 82%, precision of 82%, recall of 79%, and an F1-score of 81%, indicating the effectiveness of the proposed system for automated skeletal maturity assessment.

Keywords: Bone Age Assessment, Convolutional Neural Network, X-ray Imaging, DICOM, Deep Learning, Django Web Application, Pediatric Growth Analysis

1 Introduction

Bone Age Assessment, or BAA, is an important clinical process by which the bone ages of children can be determined. BAA is an important factor in diagnosing various bone development disorders, hormonal disorders, and developmental problems, and selecting an appropriate bone development process. Estimating bone ages precisely helps clinicians track the progress of bone development, check whether a specific bone development process is successful, and, in turn, make appropriate bone development decisions. Normally, bone ages can only be determined by a radiologist by examining different bone structures of a child, as presented in an X-ray report of a child's hands,

B. Singh et al. (eds.), *Proceedings of the International Conference on Advances in Computing Technology and Artificial Intelligence (COMPUTATIA 2026)*, Atlantis Highlights in Intelligent Systems 18,
https://doi.org/10.2991/978-94-6239-713-2_7

by referring to various growth charts. Even though this is the most widely practiced bone development process, this traditional bone development procedure is highly subjective in nature, which causes problems in an increasing number of cases in a busy clinical environment.

Recent advancements in artificial intelligence and deep learning have significantly improved medical image analysis, including automated bone age assessment from hand X-ray images [7], [10]. Several studies have demonstrated that machine learning and convolutional neural network (CNN) models can effectively estimate bone age from pediatric hand radiographs with improved prediction accuracy [9], [10]. All models and concepts proposed for this purpose have focused more on accuracy enhancement and have apparently failed or ignored formulating user-friendly models. Unfortunately, the lack of user-friendly models, along with growth ranges and percentiles, can limit the utility and applicability of proposed models as effectively as possible. Predicting and showing effective output as mere numerical values without any additional detailing can reduce the efficacy and applicability of proposed models.

To overcome the problem, this project is planned to facilitate a web-based automated bone age classification system utilizing the Django platform and pre-trained CNN architectures. The proposed system is anticipated to process pediatric hand image data using both standard image formats and the DICOM medical image standard, enabling better compatibility with real-world clinical image data. In the context of DICOM image processing, key patient information such as gender, birth date, and date of study is extracted from image headers and used to calculate the accurate chronological age from the image data. For standard image data, it is planned to let the user manually provide the patient information to meet practical needs towards maximum flexibility and compatibility with different clinical applications.

Once the image is processed, it utilizes gender-based pre-trained models of CNNs to make direct predictions of bone ages from the processed image of the X-ray. The gender-based models ensure that individuals understand that each gender develops differently during growth. To ensure that the predictions can be used, the prediction of bone age is fitted against existing data on gender-based growth patterns. Cubic spline interpolation is used to ensure that expected values of bone ages, along with upper and lower confidence limits, can be interpolated for a given chronological age. Additionally, statistical analysis using a normal distribution curve is conducted to obtain percentile values, which permit an interpretation of the bone growth either as abnormal, delayed, or advanced growth patterns rather than a mere numerical value.

The system also employs a robust method of authenticating users, a user-friendly interface through a web interface, and a structured output display method showing chronological age, predicted bone age, percentile score, and classification of growth status. The system integrates deep learning-based bone age prediction with statistical growth modeling and a scalable web platform. Model performance is evaluated using standard metrics, including accuracy, precision, recall, and F1-score, enabling a reliable assessment of skeletal maturity and improving the efficiency of clinical decision support.

2 Related Work

In clinical settings, bone age assessment (BAA) has long represented an important tool in the study and assessment of skeletal maturity, growth disorders, and endocrine abnormalities among pediatric cohorts [1]. Traditional methods of bone age estimation depend on radiographic analysis of hand–wrist images with standardized atlases [2]. Examples include the Greulich-Pyle method [3], and others based on a scoring approach, such as the Tanner-Whitehouse method [4]. Even though these approaches have been widely employed and clinically validated, they are highly dependent on expert interpretation and have a number of shortcomings concerning inter-observer variability and inefficiency [5]. A number of review studies have critically analyzed the above traditional methods and discussed their drawbacks regarding different ethnic and demographic groups [6].

To overcome the limitations of manual assessment methods, several automated techniques based on artificial intelligence have been proposed for bone age analysis, including machine learning models, convolutional neural networks (CNNs), and transformer-based deep learning approaches [7], [9], [10]. Although the initial application of machine learning techniques for bone age analysis from hand radiographs was limited to handcrafted feature extraction [8], recent advances in deep learning have enabled end-to-end bone age analysis directly from X-ray images [9]. Systematic reviews have proved the effectiveness of deep learning techniques, like convolutional neural networks and transformers, with better accuracy than the evaluation of radiologists [10]. Lightweight deep learning models have also been proposed for improving efficiency with maintained accuracy [11].

Evidently, several studies have been conducted and implemented to validate AI-aided bone age assessment systems in practical clinical scenarios [12]. A wide range of studies on comparative evaluation of commercial and academic-grade AI systems revealed improved reconciliations with better reading speed and better agreements with GP-based assessments carried out by domain experts [13]. A number of studies also highlight the significance of ethnic and geographical variations to make bone age estimates more credible and correct [14]. A recent line of studies using multimodal approaches like large language models and fusion models aims to incorporate improved interpretability with bone age estimation using AI [15].

Apart from the traditional X-ray technique, alternative imaging methods involving ultrasound imaging and MRI scans have also been explored for the purpose of radiation-free or multisite bone age estimation [16]. However, these imaging methods could not gain popularity for bone age estimation by virtue of the increased costs involved and the unavailability of these methods [17]. In conclusion, the overall literature clearly emphasizes the use of automated deep learning-based bone age classification methods instead of the traditional bone age estimation methods involving the use of atlases [18].

3 Result

The proposed bone age estimation system is implemented as a web application using the Django framework and Python deep learning libraries. The proposed system is designed to automatically predict the bone age of children from hand X-ray images. First, the user is required to upload the hand X-ray images. The proposed system supports standard image formats such as JPG and PNG, as well as DICOM medical images. For DICOM images, the patient details such as gender, date of birth, and date of study are automatically extracted from the image metadata, while for other images, the details are entered by the user.

After the image is uploaded, the resizing and normalization steps are performed to ensure that the input requirements for the convolutional neural network models are satisfied. Gender-specific pre-trained convolutional neural network (CNN) models are employed to predict the bone age in months from the X-ray images. The CNN model automatically extracts skeletal features from the input images and learns patterns associated with different stages of bone development. To make the output more relevant to the clinical scenario, the predicted bone age is compared with the growth reference data. Cubic spline interpolation is employed to compute the mean bone age and confidence limits for the patient's chronological age. Furthermore, statistical analysis employing a Gaussian distribution is utilized to compute the percentile values, which enable the classification of bone development as normal, delayed, or accelerated. The final assessment results are provided using an intuitive web interface. The flowchart is shown in Fig. 1.

3.1 List of Materials Used in Experiments

- The Pediatric hand X-ray images collected from publicly available medical datasets were used for experimental validation. The dataset contains pediatric hand–wrist radiographs used for bone age assessment and includes images stored in standard formats such as JPG and PNG as well as DICOM medical image format containing patient metadata.
- A standard desktop or laptop computer with enough processing power and storage capacity for smooth execution.
- Python programming environment with Django web framework and deep learning libraries such as Keras and TensorFlow
- Pre-trained convolutional neural network models for bone age prediction.
- File storage system for managing uploaded medical images and associated metadata.

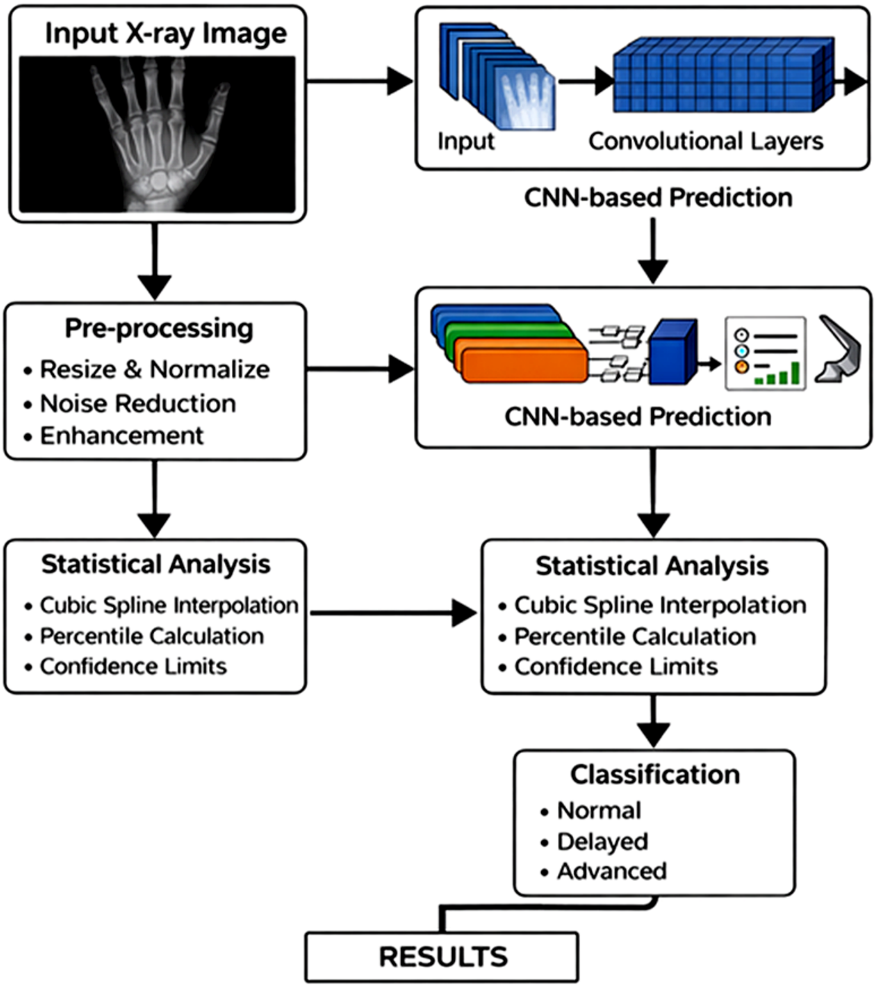

Fig. 1. A deep learning framework for skeletal maturity evaluation workflow.

3.2 Step-by-Step Procedure

3.2.1 Load Hand X-ray Images into the System

The process can therefore be initiated by uploading pediatric hand X-ray images via a web interface. The system is designed to accommodate various image formats, such as JPG, PNG, as well as DICOM medical image formats, making it useful in different environments, i.e., clinical and non-clinical environments.

3.2.2 X-Ray Image Preprocessing

After uploading the X-ray images, preprocessing steps, including image resizing, pixel normalization, and image enhancement, are applied to ensure that the input images satisfy the requirements of the convolutional neural network model and improve prediction consistency.

3.2.3 Calculate Patient Chronological Age

A basic Perl code may be used to determine the chronological ages in months by using the patient's birthday and the study date, which is extracted using images in the DICOM format or by inputting the data using conventional images. Apply a Convolutional Neural Network for Bone Age Prediction. A processed X-ray image may be input to a pre-trained, gender-specific CNN to automate the calculation of the patient's bone age, owing to the difference in the growth rate of the bones between males and females.

3.2.4 Application of Convolutional Neural Network for Prediction of Bone Age

The pre-trained gender-specific convolutional neural network analyzes the processed X-ray images to estimate bone age. The model was trained on previously available pediatric bone age datasets and is used in the proposed system for predicting bone age from new input images. The bone age of the patient will then be automatically calculated. Gender-specific models will be used, i.e., different models for different genders, because development is different for both genders.

3.2.5 Perform Statistical Growth Analysis

For appropriate clinical interpretations, the bone age thus determined is compared with growth reference tables appropriate for each gender. Cubic spline methods of interpolation and Gaussian analysis can be utilized.

3.2.6 Store and Display Results

Lastly, after predicting the bones, the system displays the prediction results to the user in an organized fashion using an interactive interface on a webpage. This includes the prediction results like the percentage result, age prediction, etc., with regard to the development of the bone, i.e., early, normally developed, or advanced development. This image illustrates the whole process of the automated bone age assessment system used in this project. First, the pediatric hand X-ray image is taken as the input image. Then the image passes through various preprocessing techniques such as resizing, normalization, and enhancement. Next, the pre-trained convolutional neural network model examines the image and determines the bone age from it. The output is then further examined using statistical analysis techniques such as determining the percentile value and confidence interval. Finally, based on the output, the bone development status is obtained as normal, delayed, or accelerated. The performance of the proposed system is evaluated using standard evaluation metrics, including accuracy, precision, recall, and F1-score, which are calculated during the experimental analysis.

3.3 Procedure to Implement the Process

The methodology adopted in implementing the proposed system in assessing bone development in children follows a well-structured and systematic method. At the outset, pediatric hand x-ray images are fed as input in the proposed system through the user interface facility offered by the system. The proposed system supports various image formats such as JPG and PNG images, as well as DICOM medical images in particular. After the image is uploaded, there is an image preprocessing step. In this step, image resizing to the required input image size by the convolutional neural network is conducted. Additionally, the pixel normalization is performed to enhance image quality.
For the case of DICOM image data, the system automatically retrieves vital patient data such as gender, birth date, and study date. However, in situations involving the use of non-DICOM image data, the user is required to manually enter the data. This data is then used in calculating the chronological ages in months. The processed image is fed into a pre-trained convolutional neural network that analyzes skeletal features and produces an accurate prediction of the patient's corresponding bone age. The system compares the patient's calculated bone age with reference growth information for different genders in order to determine the percentile values as well as create the confidence limits. Following the analysis, the bone development status is categorized based on the statistics obtained, determining whether it is normal, delayed, or advanced development. Finally, the calculated bone age, percentage, and growth status are saved for easy display and interpretation using the interface provided to the user.

4 Results

4.1 Output

The proposed bone age estimation system is capable of analyzing the pediatric hand X-ray images based on the patient information provided, such as gender, date of birth, and date of the study. The system is capable of processing the input information and automatically estimating the bone age based on the learned patterns. The experimental results demonstrate that the proposed system can effectively estimate bone age from pediatric hand X-ray images, achieving an accuracy of 82%, precision of 82%, recall of 79%, and an F1-score of 81%. The system processes pediatric hand X-ray images along with patient information such as gender, birth date, and study date to estimate bone age and evaluate skeletal maturity across different input samples. The bone age values estimated enable further analysis of skeletal maturity by comparing the results with the expected growth patterns. Especially when one is doing screening, one would want few, if any, incorrect predictions because these would lead to further, unnecessary tests. The value for recall, i.e., 79%. This demonstrates that the system is effective, since it is able to pick up most bone age patterns that actually exist.

Moreover, with an F1-score of 81%, precision is equally important as recall, thereby indicating that the model is performing well without any prejudice towards one of them in particular. Furthermore, with regard to the results of "Area Localization," they clearly highlight certain areas of focus in X-ray images of bones, thus further substantiating the classification results provided by such an approach in validating its potential as an effective system for decision-making in the assessment of bone age in an automated manner. Table 1. Shows the bone age model.

Table 1. Performance of Pretrained CNN-based Bone Age Model

Model	Accuracy	Precision	Recall	F1-Score
CNN–based Bone Age Model	82%	82%	79%	81%

4.2 Output

The experimental verification of the proposed bone age assessment system, moreover, yields consistent performance results across a given set of images related to a human hand X-ray. The bone age classification model achieved an accuracy of 82%, indicating that the proposed deep learning approach can correctly classify bone age patterns for the majority of input X-ray images. The proposed image classification approach has the ability to efficiently classify bone ages in most of the given input images Precision value, i.e., 82%. This indicates that, according to the system, bone age prediction categories that have been labeled are mostly correct, signifying that the system has few false positives, as shown in Fig. 2.

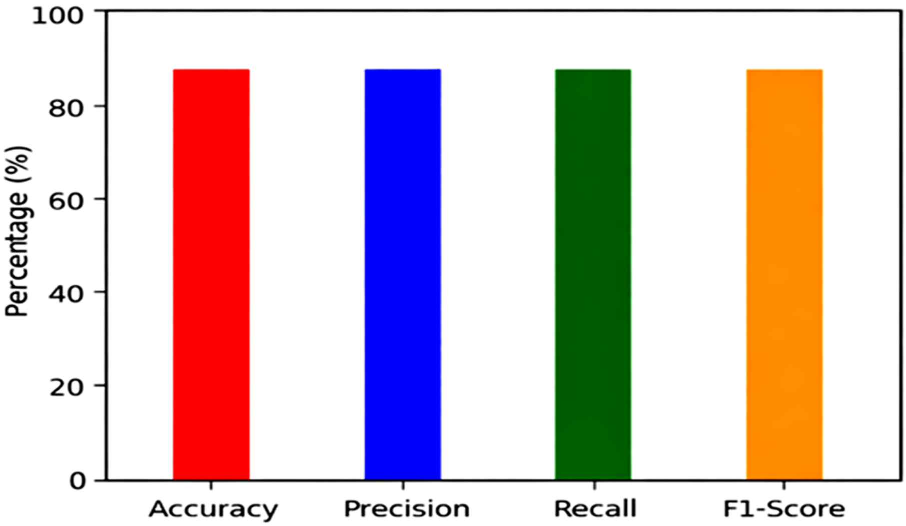

Fig. 2. Performance Metrics of Bone Age Assessment Model

5 Discussion

From the outcomes of the proposed bone age assessment system, the effectiveness of integrating deep learning and statistical analysis for skeletal maturity evaluation can be clearly observed. In the proposed system, bone age prediction from pediatric hand X-ray images can be performed in a reliable manner compared to traditional manual assessment methods. The automated approach helps reduce subjectivity in radiological interpretation and improves consistency in bone age estimation using a convolutional neural network–based analysis. These findings are consistent with previous studies that have demonstrated the effectiveness of deep learning techniques for automated bone age estimation from medical images [9], [10]. The performance of the deep learning model demonstrates reliable prediction capability, achieving an accuracy of 82%, precision of 82%, recall of 79%, and an F1-score of 81%. These evaluation metrics indicate that the proposed system can effectively identify bone age patterns from pediatric hand X-ray images while maintaining a balanced trade-off between precision and recall. The results highlight the potential of deep learning models to support clinical decision-making by providing consistent and reproducible bone age predictions. Another important feature of the proposed system is its ability to provide contextual interpretation of prediction results. The use of cubic spline interpolation and Gaussian distribution-based percentile analysis enables the classification of bone development as normal, delayed, or advanced relative to the patient's chronological age. This statistical analysis enhances the interpretability of the predicted bone age and provides additional clinical insight into the skeletal growth status of pediatric patients.

6 Conclusion

This paper presented an automated framework for bone age assessment that utilizes deep learning techniques to estimate skeletal maturity from pediatric hand–wrist radiographs. The proposed system analyses radiographic features associated with bone development stages and reduces reliance on traditional atlas-based assessment methods such as the Greulich–Pyle and Tanner–Whitehouse approaches, which often require expert interpretation and may introduce inter-observer variability. Experimental evaluation of the proposed system demonstrated that the deep learning–based model can effectively predict bone age from pediatric hand X-ray images, achieving an accuracy of 82%, precision of 82%, recall of 79%, and an F1-score of 81%. These results indicate that the proposed approach can support automated bone age estimation and assist clinicians in evaluating skeletal maturity more consistently. The results suggest that integrating deep learning–based prediction with statistical analysis methods such as cubic spline interpolation and Gaussian distribution–based percentile estimation can improve the interpretability of bone age predictions by categorizing skeletal development as normal, delayed, or advanced relative to chronological age. Future work may focus on improving prediction performance through the use of larger datasets, advanced deep learning architectures, and multi-modal medical imaging techniques. Further research may also explore integrating the system into clinical environments to support decision-making in pediatric growth assessment.

References

1. G. Boitsios, T. Saliba, and P. Simoni, "Comparative study of the performance of two versions of the same AI tool for pediatric skeletal maturation assessment," Eur Radiol, Jan. 2026, doi: 10.1007/s00330-025-12265-x.
2. W. Yuan, P. Fan, L. Zhang, W. Pan, and L. Zhang, "Bone Age Assessment Using Various Medical Imaging Techniques Enhanced by Artificial Intelligence," Diagnostics, vol. 15, no. 3, p. 257, Jan. 2025, doi: 10.3390/diagnostics15030257.
3. Q. Lou, H. Yang, and F. Lu, "A two-stream network with global-local feature fusion for bone age assessment," 2025, arXiv. doi: 10.48550/ARXIV.2512.18331.
4. P. Hai, Z. Bin, L. Kesheng, L. Cong, and X. Fei, "Lightweight deep learning system for automated bone age assessment in Chinese children: enhancing clinical efficiency and diagnostic accuracy," Front. Endocrinol., vol. 16, Jul. 2025, doi: 10.3389/fendo.2025.1604133.
5. J. Pape, M. Rosolowski, R. Pfäffle, A. B. Beeskow, and D. Gräfe, "A critical comparative study of the performance of three AI-assisted programs for bone age determination," Eur Radiol, vol. 35, no. 3, pp. 1190–1196, Nov. 2024, doi: 10.1007/s00330-024-11169-6.
6. H. W. Jung et al., "Comparison of adult height prediction using bone age and body composition for growth assessment in Korean children," Sci Rep, vol. 15, no. 1, Mar. 2025, doi: 10.1038/s41598-025-94685-9.
7. A. M. Simões, J. P. Meneses, P. G. Oliveira, and J. Abrantes, "Clinical validation of an Artificial Intelligence software for bone age assessment based on Greulich and Pyle method in a Portuguese paediatric cohort," European Journal of Radiology Artificial Intelligence, vol. 3, p. 100029, Sep. 2025, doi: 10.1016/j.ejrai.2025.100029.
8. R. E. Büyüktoka and A. Salbas, "Multimodal Large Language Models for Pediatric Bone-Age Assessment: A Comparative Accuracy Analysis," Academic Radiology, vol. 32, no. 11, pp. 6905–6912, Nov. 2025, doi: 10.1016/j.acra.2025.07.058.
9. H. Wu et al., "Construction of a Simplified Bone Age Assessment Model in Chinese Children Aged 3 to 18 Years," The Journal of Clinical Endocrinology & Metabolism, vol. 110, no. 10, pp. 2926–2937, Jan. 2025, doi: 10.1210/clinem/dgaf022.
10. I. M. Martín Pérez, S. Bourhim, and S. E. Martín Pérez, "Artificial Intelligence-Based Models for Automated Bone Age Assessment from Posteroanterior Wrist X-Rays: A Systematic Review," Applied Sciences, vol. 15, no. 11, p. 5978, May 2025, doi: 10.3390/app15115978E.
11. E. Ozkan and M. Koyun, "Atlas-Assisted Bone Age Estimation from Hand–Wrist Radiographs Using Multimodal Large Language Models: A Comparative Study," Diagnostics, vol. 16, no. 3, p. 487, Feb. 2026, doi: 10.3390/diagnostics16030487.
12. R. Minty, N. Mahomed, N. van Wyk, G. Mndebele, Z. Lockhat, and A. Ranchod, "Comparison of bone age assessment using manual Greulich and Pyle method versus automated BoneXpert method in South African children," South African Journal of Radiology, vol. 29, no. 1, Apr. 2025, doi: 10.4102/sajr.v29i1.3033..
13. S. E. Martín Pérez et al., "Precision and Accuracy of Radiological Bone Age Assessment in Children among Different Ethnic Groups: A Systematic Review," Diagnostics, vol. 13, no. 19, p. 3124, Oct. 2023, doi: 10.3390/diagnostics13193124.

14. Y. Zhang, X. Yang, L. Zhang, Z. Zhao, and Y. Yang, "Ultrasound-based bone age assessment in children and adolescents: a mini-review," Front. Pediatr., vol. 13, Aug. 2025, doi: 10.3389/fped.2025.1615923.
15. L. Wan et al., "Deep Learning-Based Bone Age Assessment Using Multi-Site MRI Epiphyseal Imaging: A Retrospective Study." Springer Science and Business Media LLC, Nov. 12, 2025. doi: 10.21203/rs.3.rs-6599801/v1
16. N. Pei et al., "Automated Bone Age Assessment and Adult Height Prediction from Pediatric Hand Radiographs via a Cascaded Deep Learning Framework," J Med Syst, vol. 49, no. 1, Nov. 2025, doi: 10.1007/s10916-025-02306-9.
17. M. Satoh, "Bone age: assessment methods and clinical applications," Clin Pediatr Endocrinol, vol. 24, no. 4, pp. 143–152, 2015, doi: 10.1297/cpe.24.143.
18. H.-J. Choi, D. Na, K. Cho, B. Bae, S. T. Kong, and H. An, "Self-accumulative Vision Transformer for Bone Age Assessment Using the Sauvegrain Method," 2023, arXiv. doi: 10.48550/ARXIV.2303.16557.