# AGESCAN: DEEP LEARNING FOR SKELETON GROWTH

**[1]Poojari Manish Lokanath, [2]Sowmya, [3]Abdul Ahad, [4]Abahy S, [5]Gopal Krishna Naik**

*[1]Third year B.E. Student, [2]Associate Professor, [3] Third year B.E. Student, [4]Third year B.E. Student, [5]Third year B.E. Student*

*[1]Department of Computer Science & Design Engineering,*
*[1]Srinivas Institute of Technology, Mangaluru, India*

**Abstract:** AgeScan is an intelligent skeletal maturity estimation an AI-driven approach utilizing cutting-edge neural network architectures techniques to skeletal maturity assessment using children's hand radiographs. Built on the Xception model architecture, AgeScan processes medical images and outputs precise bone age estimations, supporting clinicians in the diagnosis of growth disorders. The system is trained on a publicly available RSNA bone age dataset and fine-tuned using data augmentation and hyperparameter optimization techniques. With a mean absolute error of 5.56 months in internal testing, AgeScan demonstrates clinical potential for improving accuracy and consistency in bone age interpretation, reducing dependency on manual evaluations.

**Index Terms – Bone age, AI, Xception, deep learning, pediatric radiology, skeleton growth, RSNA dataset, medical imaging**

## I. INTRODUCTION

Bone age determination is a critical task in pediatric radiology, supporting diagnoses related to endocrine function, developmental anomalies, and final height prediction. Traditional methods such as the Greulich and Pyle atlas rely on manual image comparison, introducing subjectivity and inconsistencies. **AgeScan** addresses these limitations by providing an automated deep learning-based solution for assessing skeletal maturity from hand X-rays. The system is designed to operate within clinical workflows, offering fast and reliable age estimation with minimal human input.

**AgeScan** addresses these long-standing challenges by introducing an automated, deep learning–powered solution that estimates skeletal maturity from hand radiographs with high accuracy. Built on the robust Xception architecture, the system can capture subtle patterns in bone morphology that may be overlooked by the human eye. AgeScan has been trained on a diverse dataset for reliable performance across a big range of age groups and patient demographics.

Designed to integrate into existing workflows, AgeScan offers a faster, more consistent alternative that reduces dependence on manual interpretation—empowering healthcare providers to make timely and confident decisions with minimal effort. Beyond speed and precision, the system enhances equity in healthcare by offering standardized results, even in settings where pediatric radiology expertise may be scarce. With AgeScan, clinicians can shift focus from tedious image analysis to personalized patient care, rapidly improving results for children undergoing growth evaluation.

## II. LITERATURE REVIEW

Research in skeletal growth analysis has evolved from manual chart-based techniques to intelligent systems powered by artificial intelligence. Traditional approaches like the Tanner-Whitehouse and GP methods, while widely accepted, suffer from variability due to observer judgment. Studies have shown mean inter-observer differences of up to 6 months in some cases.

In recent years, machine learning, and especially convolutional neural networks (CNNs), have gained traction in medical imaging. Models such as BoneXpert, 16Bit, and Deeplasia have delivered promising results on hand radiographs. However, such frameworks commonly lack the ability to robustness across different imaging conditions.

A pediatric skeletal maturity dataset from the RSNA's open-source repository dataset has become a benchmark for model training and evaluation, encouraging reproducibility and comparison. AgeScan builds on this foundation, employing the Xception model— a highly efficient CNN known for its depthwise separable convolutions. This architecture offers superior feature extraction while maintaining lightweight computation, ideal for clinical use.

## III. METHODOLOGY

1. Data Collection:Images were sourced from the RSNA Bone Age dataset, including 12,611 anonymized pediatric hand radiographs labeled with bone age and sex. The dataset spans ages 1 to 18 years and includes a balanced gender distribution.

2. Image Preprocessing:Radiographs were resized into 256×256 pixel images and normalized for uniformity prior to use in model training. The normalization step ensures consistent input size and intensity values for improving model performance and training robustness.

3. Model Architecture:AgeScan is built on the Xception model, Preferred because it strikes an effective balance between accuracy and computational efficiency. The model uses pretrained ImageNet weights and is fine-tuned using medical imaging data.

4. Hyperparameter Optimization:The Hyperband algorithm was utilized to optimize the learning rate, dropout values, and dense layer size. The Adam optimizer was selected for its adaptive learning rate during backpropagation.

5. Training and Evaluation: The sentence is too short for the paraphrasing tool, which needs at least 30 words. Try adding more detail—for example, why the data was split or how it supports model evaluation—and I can humanize it for you. Would you like a suggested expansion?

## IV. SYSTEM ARCHITECTURE

The AgeScan system architecture is designed to provide a seamless and accurate bone age estimation workflow. It begins with an image upload interface that accepts standard medical imaging formats such as DICOM and PNG. Once uploaded, the images pass through a preprocessing pipeline that enhances contrast and normalizes pixel intensity to ensure uniformity and improve model input quality.

The core of the system is the Xception model, a deep convolutional neural network known for its efficiency and high accuracy, which extracts key features from the radiograph that are indicative of skeletal maturity. These features are then passed to the age prediction layer, which generates an estimated bone age in months.

To support clinical decision-making, a report generator compiles the prediction along with a reference chart and displays a confidence level for interpretability. Additionally, an optional feedback module allows radiologists to review and correct the system's predictions, enabling continuous model improvement through real-world input.

## V. MODEL TRAINING

The model was trained using the RSNA pediatric bone age dataset, which includes over 12,000 labeled hand radiographs of children aged 1 to 18. During training, the dataset was divided into training, validation, and testing sets to ensure robust performance evaluation. The validation process yielded a mean absolute error (MAE) of 5.56 months, while the model demonstrated a similar external test MAE of 6.00 months, indicating its reliability across unseen data. To enhance accuracy　　　and generalization, data augmentation techniques were employed alongside hyperparameter optimization using the Hyperband　　algorithm, which finetuned key parameters such as learning rate, dropout, and dense layer sizes. The model used ImageNet- pretrained weights and was further refined with medical images for domain specificity. The Adam optimizer was chosen for its ability to adapt learning rates during backpropagation, further boosting performance.

The final model showed a strong correlation exceeding 0.97 with expert radiologist assessments and retained prediction stability even under common image transformations, underscoring its clinical robustness and utility.



*Fig. Bone age predictions vs actual ages.*

## VI. CONCLUSION

AgeScan successfully leverages the power of deep learning to automate paediatric skeletal growth evaluation. It minimizes human bias and accelerates diagnosis, offering a scalable solution for clinical environments. Future enhancements include support for skeletal dysplasia, real-time PACS integration, and multilingual UI support for global deployment.

## VII. ACKNOWLEDGMENT

## REFERENCES

[1] RSNA Pediatric Bone Age Challenge Dataset

This dataset, made publicly available by the Radiological Society of North America (RSNA), consists of over 12,000 anonymized pediatric hand radiographs.

[2] Eshika Jain et al., "Advancing Bone Age Estimation with Xception"

In this study, the authors explored the application of the Xception model—known for its depthwise separable convolutions—in the context of bone age assessment.

[3] Rassmann et al., "Deeplasia: Deep Learning in Skeletal Dysplasias," Pediatric Radiology (2024)

This paper introduces Deeplasia, a deep learning framework tailored to the diagnosis of skeletal dysplasias in children.

[4] Santomartino et al., "Robustness of Deep Learning Bone Age Models"

The authors focus on evaluating the stability of bone age models under various image perturbations, such as contrast shifts and rotations.

[5] Haghnegahdar et al., "Automated Bone Age Estimation," Journal of Dentistry, Shiraz University of Medical Sciences (2024)

This research investigates automated bone age estimation using deep learning models, comparing their performance to traditional manual methods.

[6] Alzyoud et al., "Epiphyseal Fusion and Chronological Age," Medicina (2024)

This study examines the relationship between the fusion of epiphyseal growth plates and chronological age, providing valuable data for bone age prediction models.