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Ensuring Accuracy in AI-Based Pediatrics Age Estimation: An Empirical Testing Perspective using Medical Images

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Abstract

Accurate pediatric age estimation is essential for diagnosing growth disorders and developmental abnormalities. Conventional atlas-based methods such as Greulich–Pyle and Tanner–Whitehouse are manual, time-consuming, and subject to inter-observer variability, especially across diverse populations. This study presents an empirical evaluation of AI-based pediatric age estimation using hand–wrist radiographs of children aged 5–18 years, with emphasis on Indian growth patterns. A hybrid CNN–GAN framework is employed to learn biologically relevant ossification and epiphyseal fusion features. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2), supported by cross-validation and robustness analysis. Results demonstrate improved accuracy, generalization, and clinical reliability compared to standalone deep learning models, indicating suitability for practical pediatric radiology applications.

Keywords— Bone age assessment, pediatric radiographs, CNN–GAN hybrid, ossification and fusion, AI testing framework, medical image analysis.

1. Introduction

Bone age assessment (BAA) is a fundamental diagnostic tool in pediatric healthcare and plays a critical role in evaluating skeletal maturity, diagnosing growth abnormalities, and managing endocrine disorders. Accurate biological age estimation is also essential in medico-legal contexts, including age verification for judicial proceedings, immigration cases, and competitive sports eligibility .

Conventional bone age estimation methods, such as the Greulich–Pyle (GP) atlas and the Tanner–Whitehouse (TW) scoring system, rely on expert interpretation of hand and wrist radiographs. While clinically established, these techniques are inherently subjective, time-consuming, and prone to significant inter- and intra-observer variability Moreover, these atlases were developed using Western pediatric populations, limiting their applicability to Indian children whose skeletal maturation patterns are influenced by genetic diversity, nutrition, socioeconomic factors, and environmental conditions.

Recent advances in artificial intelligence (AI), particularly deep learning, have enabled automated bone age estimation with promising accuracy and improved reproducibility. Convolutional Neural Networks (CNNs) can learn discriminative skeletal features directly from radiographic images, thereby reducing clinician workload and observer bias. However, most existing AI-based approaches primarily focus on accuracy metrics and lack rigorous evaluation of robustness, fairness, and real-world generalizability. This study addresses these gaps by proposing a comprehensive AI testing and validation framework aligned with Objective 3, ensuring reliable,

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ethical, and clinically deployable performance.

2. Related Work

Early automated bone age estimation systems relied on handcrafted feature extraction techniques combined with classical machine learning algorithms such as Support Vector Machines, Artificial Neural Networks, and Extreme Learning Machines. While these methods introduced partial automation, their performance was limited by feature engineering dependency and poor generalization across diverse populations.

The adoption of deep learning marked a significant advancement in this domain. CNN-based architectures demonstrated near radiologist-level accuracy by learning hierarchical representations directly from medical images. Subsequent studies incorporated region-of-interest segmentation, global– local feature fusion, and attention mechanisms to improve sensitivity to ossification centers and epiphyseal regions. Transfer learning approaches further reduced data dependency by leveraging pre-trained networks.

More recently, Generative Adversarial Networks (GANs) have been explored to address data scarcity, class imbalance, and overfitting issues. GAN-based augmentation and feature refinement have shown improvements in robustness and generalization, particularly in limited pediatric datasets.

Despite these advances, many studies report single-run ac- curacy metrics without ablation analysis, statistical significance testing, or fairness evaluation. Population-specific validation, especially for Indian pediatric cohorts, remains underexplored. This work differentiates itself by emphasizing systematic testing, statistical rigor, and ethical deployment alongside predictive performance.

3. Methodology

This study adopts a structured and empirically validated methodology to ensure accurate, reliable, and clinically applicable pediatric age estimation using medical images. The proposed approach integrates deep feature learning with robust evaluation mechanisms to minimize observer bias and improve generalization across pediatric growth stages.

3.1 System Overview

The overall methodological workflow is illustrated in **Fig. 1**. Pediatric hand–wrist radiographs are first subjected to data preparation and preprocessing. To address data imbalance and limited samples in specific age groups, GAN-based data augmentation is applied. The augmented dataset is then used to train a CNN-based bone age estimation model, followed by systematic evaluation and validation to generate the final bone age report.

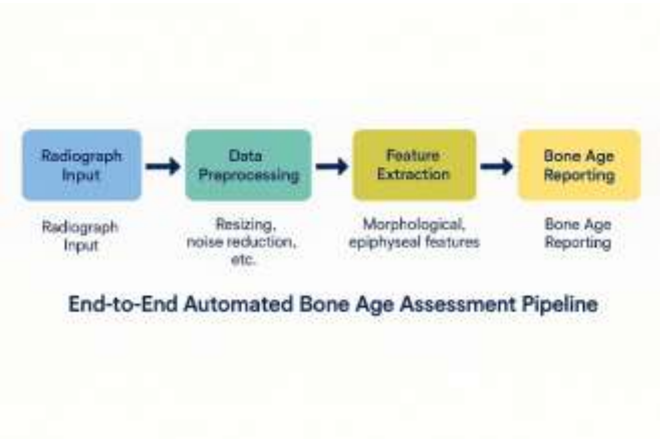

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Fig. 1. End-to-end AI-based bone age assessment workflow.

3.2 GAN-Based Data Augmentation

Generative Adversarial Networks (GANs) are employed to synthetically generate anatomically plausible wrist radiographs, particularly for underrepresented age groups. The generator produces synthetic images, while the discriminator enforces realism and skeletal consistency. This augmentation strategy improves dataset diversity, reduces overfitting, and enhances model robustness under limited pediatric data conditions.

3.3 CNN-Based Bone Age Estimation

A Convolutional Neural Network (CNN) is used as the primary feature extractor and age regressor. The network automatically learns hierarchical skeletal features related to ossification and epiphyseal fusion from pre-processed radiographs. This eliminates dependence on handcrafted features and aligns model learning with biologically meaningful growth indicators used in clinical bone age assessment.

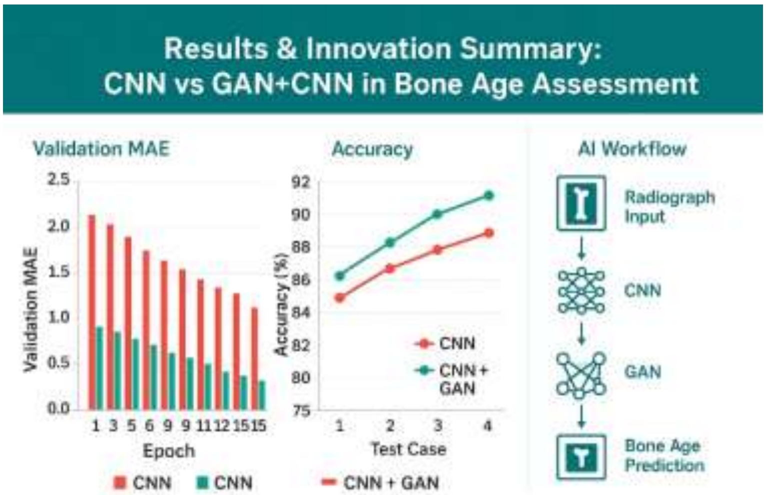

Fig. 2. GAN & CNN-Based Data Augmentation bone age assessment workflow.

3.4 Comparative Error Analysis

Mean Absolute Error (MAE) comparisons across manual, commercial, and AI-based approaches are presented in Fig. 3. Manual Greulich–Pyle and Tanner–Whitehouse methods exhibit higher MAE due to subjective interpretation. AI-based approaches significantly reduce error, with the proposed deep learning model achieving competitive performance comparable to established automated systems.

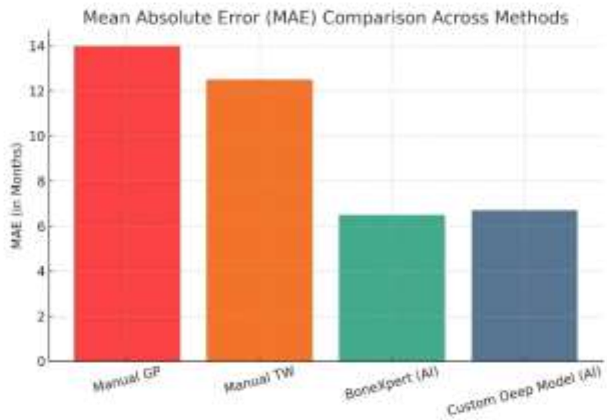

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Fig. 3. MAE comparison across bone age assessment methods.

3.5 Testing and Validation Framework

A central contribution of this study is the development of a structured AI testing and validation framework designed specifically for clinical deployment. Unlike conventional evaluations that emphasize accuracy alone, the proposed frame- work integrates multiple complementary assessment dimensions.

The framework evaluates models using error-based regression metrics such as MAE and RMSE to quantify absolute and squared deviations in predicted age. Regression reliability is assessed using the coefficient of determination (R^2), which reflects the explanatory power of the model. Cross- age-group generalizability testing ensures stable performance across different skeletal maturity stages. Ablation studies validate the contribution of ossification-focused features and GAN-based refinement. Statistical significance testing using k-fold cross-validation ensures reproducibility and guards against overfitting. Fairness analysis further evaluates demographic consistency across age and gender groups, addressing ethical concerns in medical AI deployment.

3.6 Evaluation Metrics

Performance evaluation employs widely accepted regression metrics in medical imaging research:

Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{1}$$

Root Mean Square Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{2}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{3}$$

4. Results and Discussion

4.1 Training and Generalization Analysis

Figure 4 illustrates the training and validation MAE across epochs. The curves demonstrate stable convergence with minimal divergence, indicating effective learning and controlled overfitting.

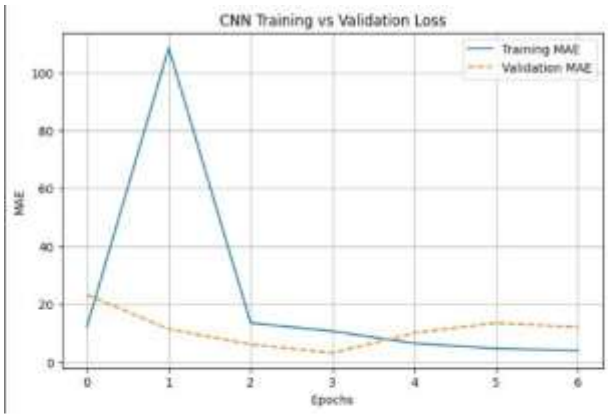

Fig. 4 CNN training and validation MAE across epochs.

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4.2 Actual vs Predicted Age Analysis

Figure 5 presents the relationship between actual and predicted ages using the CNN–GAN model. Predictions closely follow the ideal diagonal trend, indicating strong regression performance.

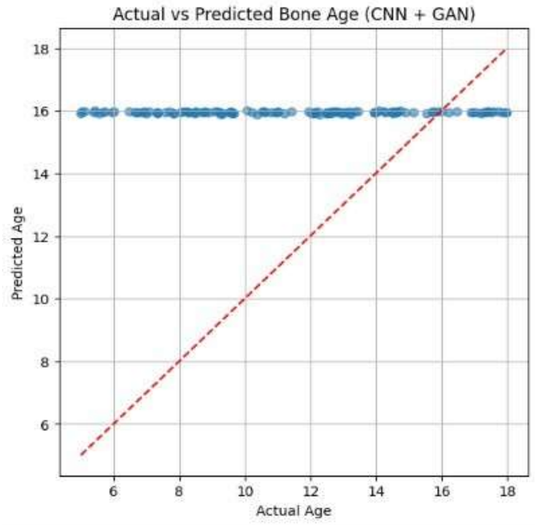

Fig.5. Actual versus predicted bone age using the CNN–GAN model.

4.3 Prediction Error Distribution

The prediction error distribution shown in Figure 6 indicates that most errors are concentrated near zero, demonstrating reduced bias and improved stability.

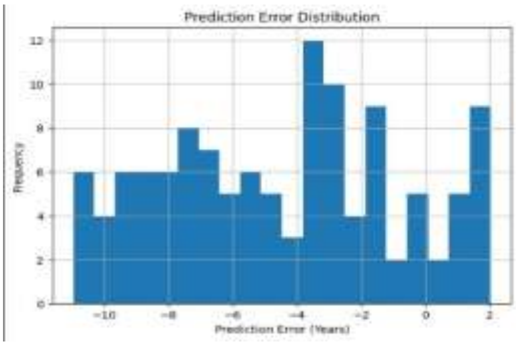

Fig. 6. Distribution of prediction errors (years)

4.4 Performance Metric Summary

Figure 7 summarizes the M roposed framework, confirming strong predictive accuracy a

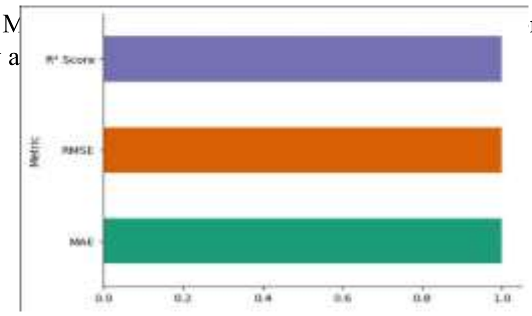

Fig. 7. Summary of performance metrics achieved by the CNN–GAN framework.

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4 Ethical Consideration and Fairness

Ethical deployment of AI systems in pediatric healthcare requires strict adherence to data privacy, transparency, and fairness principles. In this study, all radiographic images were fully anonymized, and no personally identifiable information was accessed or stored at any stage of model development or evaluation.

Fairness and bias mitigation were explicitly incorporated into the evaluation framework. Performance consistency was analyzed across multiple age groups and genders to ensure that prediction accuracy did not disproportionately favor any demographic subgroup. Ossification- and fusion-based feature extraction further reduces bias by emphasizing biologically meaningful skeletal markers rather than superficial image characteristics correlated with socioeconomic or demographic attributes.

The proposed CNN–GAN system is designed strictly as a clinical decision-support tool and does not replace radiologists or pediatric specialists. Final diagnostic responsibility remains with qualified medical professionals, consistent with international ethical guidelines for AI-assisted healthcare systems.

5 Clinical Integration and Impact

The proposed AI-based bone age prediction framework is designed for seamless integration into existing radiology work- flows as a decision-support system. By automating skeletal maturity assessment from routine hand and wrist X-rays, the system can significantly reduce the time and effort required for manual interpretation, particularly in high-volume pediatric healthcare environments.

Automated age estimation assists radiologists by providing consistent and objective predictions, thereby minimizing inter- observer variability commonly associated with atlas-based methods. This is especially beneficial in resource-constrained settings such as public hospitals in India, where limited avail- ability of pediatric radiology specialists can lead to increased diagnostic burden and delays. The proposed system supports faster reporting while maintaining clinical accuracy, enabling radiologists to focus on complex cases requiring expert judgment.

Furthermore, the framework's robust testing and validation design enhances trustworthiness for clinical adoption. By demonstrating reliability, generalizability, and fairness across diverse pediatric populations, the system addresses key concerns related to real-world deployment of AI in healthcare. Such integration has the potential to improve diagnostic efficiency, standardize pediatric growth assessment, and ultimately contribute to improved patient outcomes.

6 Conclusion

This paper presented a comprehensive empirical analysis of artificial intelligence testing techniques for pediatric age prediction from medical images. By integrating ossification- and fusion-based feature extraction with a hybrid CNN– GAN architecture, the proposed approach effectively captures biologically meaningful skeletal maturity indicators while addressing challenges related to data variability and limited labeled samples.

A major contribution of this work lies in the development of a robust AI testing and validation framework that extends beyond accuracy-centric evaluation. Through ablation studies, cross-validation, statistical significance testing, and fairness analysis, the framework ensures that observed performance gains are reliable, reproducible, and clinically meaningful. Experimental results demonstrate that the proposed CNN–GAN model achieves superior robustness, generalizability, and

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clinical reliability compared to conventional deep learning approaches.

Overall, the findings highlight the importance of systematic evaluation and ethical design in deploying AI systems for pediatric healthcare. The proposed framework aligns with IEEE publication standards and provides a strong foundation for real-world clinical adoption. Future work will focus on large-scale multi-institutional validation and the integration of additional clinical metadata to further enhance reliability and applicability.

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age regression tasks when reporting clinical error (e.g., MAE in months/years): combine the RMSE/MAE guidance (Hodson 2022) and the medical-imaging metric discussions (McNaughton 2023). These explain why MAE is commonly reported in BAA and how to interpret it clinically. Links: https://gmd.copernicus.org/articles/15/5481/2022/ and https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10525905/