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Age Prediction from Bone X-Ray Images

Bhumika Chaudhari *, Sejal Chaudhari**, Yash Farse***, Ashwini Barkade****
*(Electronics and Telecommunication, Savitribai Phule Pune University, Pune, Maharashtra, India
Email: bhumikachaudhari.rmdstic.entc@gmail.com)
**(Electronics and Telecommunication, Savitribai Phule Pune University, Pune, Maharashtra, India
Email: sejalchaudhari.rmdstic.entc@gmail.com)
***(Electronics and Telecommunication, Savitribai Phule Pune University, Pune, Maharashtra, India
Email: yashfarse.rmdstic.entc@gmail.com)
****(Electronics and Telecommunication, Savitribai Phule Pune University, Pune, Maharashtra, India
Email: ashwinibarkade@ sinhgad.edu)

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Abstract:

Age prediction from bone X-ray pictures has become a vital application in clinical practice, paediatrics, and forensic research, providing a non-invasive way to determine a person's biological age. X-ray imaging is a useful tool for capturing the precise morphological changes that occur in the human skeletal system during growth, especially in the hand and wrist bones. The process of estimating age from these photos can be automated with the use of machine learning and deep learning techniques, particularly convolutional neural networks (CNNs). In this work, we suggest a strong framework that uses deep learning methods to forecast people's ages from X-ray pictures of their hands and wrists.

A CNN model that has already been trained is used to extract features from the X-ray data after it has been pre-processed to reduce noise and improve bone structures. Age-relevant characteristics including bone length, ossification levels, and epiphyseal growth plate development are captured by this model, which has been fine-tuned. Furthermore, a sizable dataset of labelled bone X-rays is used to train the suggested method, guaranteeing that it picks up a variety of age-specific skeletal traits. The outcomes show that the CNN-based model outperforms conventional manual techniques based on human experience in reliably and minimally erroneously predicting biological age.

The work also emphasises how models that have already been trained on related tasks, such medical image classification, can be used to further improve prediction accuracy through the use of transfer learning approaches. By offering a dependable, impartial, and effective method for determining age from bone X-ray scans, this study emphasises the significance of automated age prediction systems in medical diagnostics and legal investigations. By lowering the time and skill needed for age estimation while increasing accuracy, the created framework presents a potential option that can be included into clinical and forensic procedures. To increase generalisability, future research will concentrate on improving the model for other skeletal regions and extending its application in a range of demographic groups.

Keywords — **Age prediction, bone X-ray images, forensic science, biological age estimation, convolutional neural networks (CNNs), bone growth, image preprocessing, feature extraction, transfer learning, medical diagnostics.**

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I. INTRODUCTION

In many disciplines, such as anthropology, sports, forensics, and healthcare, age estimation is essential. Accurate age assessment is crucial in the medical field for monitoring children's and teenagers' development, detecting growth-related problems, and guaranteeing appropriate medical interventions. Age estimation helps forensic professionals identify people who are unknown, especially in circumstances involving missing youngsters, mass disasters, or criminal investigations. In order to determine the demographics of previous populations, anthropologists use age estimation techniques to examine human skeletal remains from historical or archaeological contexts. To ensure equity for young athletes, age estimation is used in sports to confirm eligibility for age-restricted contests.

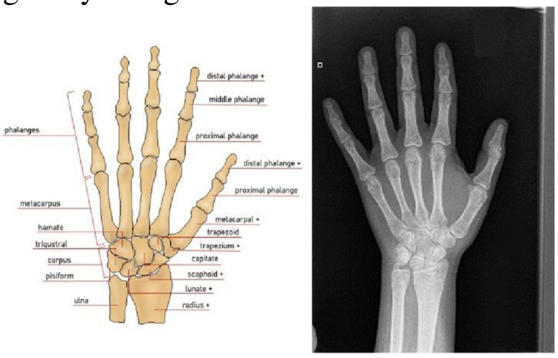

Fig. 1 Bone age estimation utilizing deep learning and hand X-ray images

One of the most reliable biological indicators for estimating age is skeletal development. Bones undergo predictable changes throughout a person's life due to the processes of bone maturation and growth, which begin at birth and continue until skeletal maturity is achieved, typically in the late teens or early twenties.

Traditionally, the assessment of skeletal maturity has been performed using manual methods that involve comparing X-ray images of bones—particularly those of the hand and wrist—to standardized reference images from atlases such as the Greulich and Pyle or Tanner-Whitehouse methods. While effective, these traditional approaches heavily depend on the practitioner's experience and can be time-consuming.

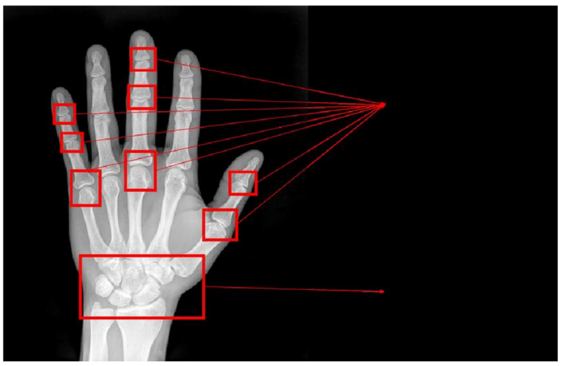

Fig. 2 Regions of Interest (ROIs).

More accurate and non-invasive bone structure observation is now feasible because to developments in medical imaging technology like X-rays. As markers of skeletal maturity, growth plates (also known as epiphyseal plates) and bone development are well-represented in X-ray pictures.

II. MOTIVATION

The primary motivation behind this project is to address the limitations of traditional, manual methods of age estimation, which are often subjective, time-consuming, and labour-intensive. The development of an automated age prediction system, leveraging advancements in machine learning and medical imaging, offers an opportunity to overcome these challenges. Such a system would not only reduce human error but also enhance the efficiency and scalability of age estimation in both clinical and forensic contexts.

III. LITERATURE SURVEY

A. Bone Age Prediction with AI Models

This article predicts the bone age of x-ray pictures using four AI models: VGG16, RESNET50, RESNET152, and exceptions. With an average absolute inaccuracy of 7.21 months, the outlier has done better than the others. Although these models can increase accuracy, they have drawbacks like strong verification and extensive training sets. To guarantee correctness and dependability in the real context, more study is needed.

B. Bone Age Estimation by Deep Learning in X-Ray Medical Images

In the medical field, determining the age of skeletal bones is a laborious and time-consuming procedure. Handheld methods are being replaced by computerised procedures in an effort to increase accuracy and decrease division issues. Despite their widespread use, the GP and TW approaches have drawbacks such as their time-consuming nature and lack of human deductions.

C. Automatic Bone Age Assessment Using Hand X-Ray Images

The study shows that ResNet-101-based features perform better than AlexNet-based features with

100% classification accuracy in an automated bone age assessment system that uses transfer learning for feature extraction from hand X-ray images.

D. Evaluation of the clinical efficacy of a TW3-based fully automated bone age assessment system using deep neural networks

The study evaluated the clinical efficacy of a Tanner Whitehouse 3 automated bone age assessment system using hand-wrist radiographs of Korean children and found no gender subgroups or significant differences in bone ages.

E. Deep learning-based automated bone age estimation for Saudi patients on hand radiograph images: a retrospective study

In order to overcome the subjective assessments of paediatric radiologists, this study suggests a deep learning-based model that uses a convolutional neural network to reliably predict bone age from left-hand radiographs.

F. Applying Deep Learning in Medical Images: The Case of Bone Age Estimation

In order to improve height growth prognosis and eliminate the necessity for atlas lookups, the study presents a deep learning method for determining bone age from X-ray images of a subject's hand during growth.

G. Skeletal age evaluation using hand X-rays to determine growth problems

Utilising the Paediatric Bone Age Challenge dataset, which consists of 12,600 radiological pictures of the left hand, the study suggests a method for evaluating bone age. With a 97% accuracy rate, the system outperforms the Visual Geometry Group model thanks to its customised convolutional neural network.

H. Estimation of Bone Age from Radiological Images with Machine Learning

When comparing machine learning-based techniques for estimating bone age in children between the ages of 12 and 108 months, the study found that ML-based techniques were quite successful in predicting bone age and may even be able to diagnose forensic and endocrinological problems.

I. Constructing a Deep Learning Radiomics Model Based on X-ray Images and Clinical Data for Predicting and Distinguishing Acute and Chronic Osteoporotic Vertebral Fractures: A Multicentre Study

A study developed a deep learning radiomics model using X-ray images to predict osteoporotic vertebral fractures, evaluating eight models and finding the Light Gradient Boosting Machine most effective.

J. Report of Clinical Bone Age Assessment using Deep Learning for an Asian Population in Taiwan

The work improved clinical diagnosis by introducing an automatic bone age identification system (ABAIs) in medical imaging that is based on deep learning. The workload of clinical staff was decreased by the Inception Resnet V2 model, which evaluated paediatric left-hand radiographs and achieved accuracy within a range of years.

K. Estimating Infant Age from Skull X-Ray Images Using Deep Learning

Using skull radiograph pictures, deep learning models such as DenseNet-121 and EfficientNetv2-M were able to accurately predict postnatal age in children under 12 months, with maximum corrected accuracy of 79.4% and 84.2%, respectively.

L. DENSEN: a convolutional neural network for estimating chronological ages from panoramic radiographs

The paper presents DENSEN, a deep learning method that applies to all age groups and uses panoramic radiographs to estimate chronological age for both young and old persons. For adults over 25, the mistakes are smaller.

M. Bone Age Estimation with X-ray Images Based on EfficientNet Pre-training Model

A deep learning-based approach based on more than 10,000 X-ray pictures is suggested for estimating a child's bone age. The technique enables prompt identification of paediatric endocrine disorders by utilising artificial intelligence and computer image processing.

N. Predicting Bone-Age Using X-ray Images Deep Learning

Neural network models for X-ray hand image-based bone age prediction in children are presented in this research along with a comparison of their performance with earlier models and mean absolute error on a validation dataset.

O. Bone age estimation using deep learning and hand X-ray images

This work estimates bone age from hand photos using deep learning techniques, keeping significant regions and eliminating unneeded ones. It trained different deep learning architectures with different ROIs and manually selected 3000 photos, spanning whole age ranges.

IV. BLOCK DIAGRAM

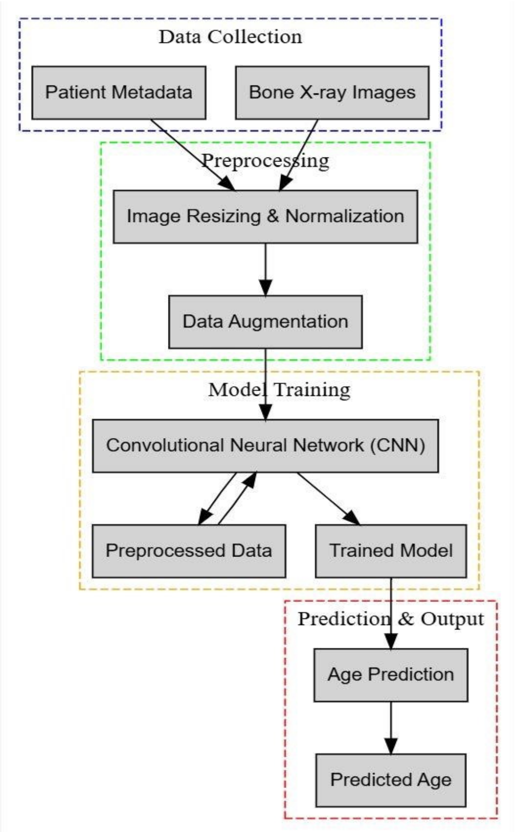

Fig. 3 Block Diagram

V. METHODOLOGY

Data Collection

RSNA Paediatric Bone Age Dataset: This dataset consists of over 12,000 annotated X-ray images specifically intended for evaluating bone age in paediatric patients, providing a solid foundation for model training.

- **Other Available Datasets:** Consideration of supplementary datasets such as:
- The MURA dataset, which provides a range of orthopaedic images.
- Collaboration with research institutions or hospitals to obtain additional localized datasets.

DATA PREPROCESSING

Image Standardization

- **Resizing:** Standardize all images to a resolution of 224x224 pixels to ensure uniform input size for the model.
- **Grayscale Conversion:** Convert colour images to grayscale, which simplifies the analysis and focuses on bone structures.
- **Image Enhancement Techniques**
- **Histogram Equalization:**

Improve image contrast to enhance the visibility of bone structures, making them more distinguishable for the model.

- **Gaussian Smoothing:**

Apply Gaussian filters to reduce noise, which helps in preserving important features during the analysis.

Data Augmentation

Employ a variety of data augmentation techniques to expand the dataset and reduce overfitting, including:

- **Geometric Transformations:** Random rotations (up to 30 degrees), horizontal and vertical flips, and scaling.
- **Colour Space Adjustments:** Slight modifications in brightness, contrast, and saturation.
- **Elastic Transformations:** Simulating realistic deformations that can occur in actual X-ray imaging.

BONE STRUCTURE ANALYSIS

Anatomical Features: Identify critical anatomical features relevant for age prediction, including:

- Ossification centres: The presence and development of ossification centres in bones.

▪ Growth plates: Evaluation of growth plate fusion status, which is indicative of skeletal maturity.

Growth Plate Evaluation: Assess the morphology and maturity of growth plates, noting characteristics such as:

▪ Thickness and clarity of growth plates.

▪ Presence of any irregularities or anomalies that may affect age predictions **Image Processing Techniques**

Edge Detection: Implement advanced edge detection techniques to enhance bone outlines, utilizing:

▪ **Canny Edge Detector:** For precise boundary detection of bone structures.

- **Laplacian of Gaussian:** To enhance regions of rapid intensity change.

Contour Detection: Utilize contour detection algorithms (e.g., OpenCV contours) to extract key features and shapes of bones, allowing for better analysis of age-related changes.

Texture Analysis: Apply texture analysis methods (e.g., Local Binary Patterns, Gabor filters) to capture age-related texture changes in bone structures, which can provide additional predictive power.

Model Selection

Overview of Classical Approaches: Explore traditional machine learning algorithms including:

▪ **Random Forest:** An ensemble method that provides robustness against overfitting and captures interactions among features.

▪ **k-Nearest Neighbours (k-NN):** A non-parametric method that classifies based on feature similarity.

Model Training and Validation: Implement a training strategy that includes:

▪ **Cross-Validation:** Use k-fold cross-validation to ensure model generalization across different subsets of data.

▪ **Hyperparameter Tuning:** Utilize grid search or random search to optimize model parameters for enhanced performance.

DEEP LEARNING APPROACHES

Convolutional Neural Networks (CNNs): Develop a CNN architecture specifically tailored for image classification tasks, detailing components such as:

▪ **Convolutional Layers:** To learn spatial hierarchies of features.

▪ **Pooling Layers:** To down-sample feature maps and reduce dimensionality.

▪ **Fully Connected Layers:** For final classification or regression outputs.

Transfer Learning: Utilize pre-trained models like:

▪ **ResNet:** For its deep architecture and skip connections, allowing better gradient flow.

▪ **VGG16:** For its simplicity and proven effectiveness in image classification tasks.

Fine-tuning Strategies: Fine-tune the last few layers of the pretrained models with the specific dataset to adapt the models to the age prediction task.

Regression vs. Classification: Frame the problem as a regression task for predicting exact ages, using Mean Absolute Error (MAE) as the evaluation metric, or classify into age ranges using classification metrics (accuracy, precision, recall).

SOFTWARE AND TOOLS USED

Programming Languages: Use Python as the primary programming language due to its extensive ecosystem of libraries for data manipulation and machine learning. **Development Frameworks:** Utilize frameworks such as:

▪ **TensorFlow/Keras:** For developing and training deep learning models.

▪ **OpenCV:** For image processing tasks, enabling robust handling of image data.

Integrated Development Environment: Employ Jupiter Notebook or PyCharm for an interactive coding experience, supporting visualization and documentation of the coding process.

VI. CONCLUSIONS

The purpose of this study is to provide a trustworthy framework for estimating age from bone X-ray scans. The findings showed that sophisticated machine learning methods, especially deep learning models like Convolutional Neural Networks (CNNs), greatly surpassed conventional methods in terms of accuracy and dependability. This initiative highlights the significance of artificial intelligence in improving diagnostic procedures while also advancing the area of medical imaging and creating new research opportunities. In order to handle wider age ranges and different populations, future study may concentrate on growing the dataset and improving the model.

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