Bone Age Estimation Using ResNet34

This presentation delves into the development and evaluation of a ResNet34-based system for automated bone age estimation in pediatric healthcare.

Introduction to Bone Age Assessment

What is Bone Age?

Bone age refers to the skeletal maturity of a child, which is not necessarily the same as their chronological age.

Importance of Assessment

Bone age assessments are essential for diagnosing growth disorders and monitoring growth patterns in children.

Challenges with Manual Bone Age Assessment

Subjectivity

Manual assessments can be subjective, leading to variations between different radiologists.

Time-Consuming

Manual assessments require significant time and expertise from trained radiologists.

Scalability

Manual assessments are not scalable for large datasets, limiting their effectiveness in clinical settings.

Importance of the Project

This project on automated bone age estimation holds significant value for both pediatric healthcare and the advancement of AI in medical imaging.

1 Pediatric Healthcare

Accurate bone age assessment is crucial for diagnosing and monitoring various growth disorders in children, such as growth hormone deficiencies, thyroid disorders, and precocious or delayed puberty. By automating this process, clinicians can quickly identify abnormal growth patterns and initiate appropriate treatment plans to ensure optimal physical and hormonal development for their young patients.

2 Modern Automation

Implementing AI-powered bone age estimation systems can significantly streamline the assessment process in busy pediatric clinics. These automated tools can analyze X-ray images and provide fast, reliable results, reducing the workload on healthcare professionals and enabling them to focus more on patient care. This improved efficiency can lead to faster diagnoses, timely interventions, and better long-term outcomes for children with growth-related conditions.

Broader Impact

> Beyond the direct benefits to pediatric healthcare, this project also contributes to the ongoing advancement of AI in medical imaging. The successful development and deployment of an accurate, reliable bone age estimation model can serve as a blueprint for applying deep learning techniques to other diagnostic imaging tasks, ultimately improving patient outcomes and enhancing the capabilities of modern healthcare systems.

Problem Statement

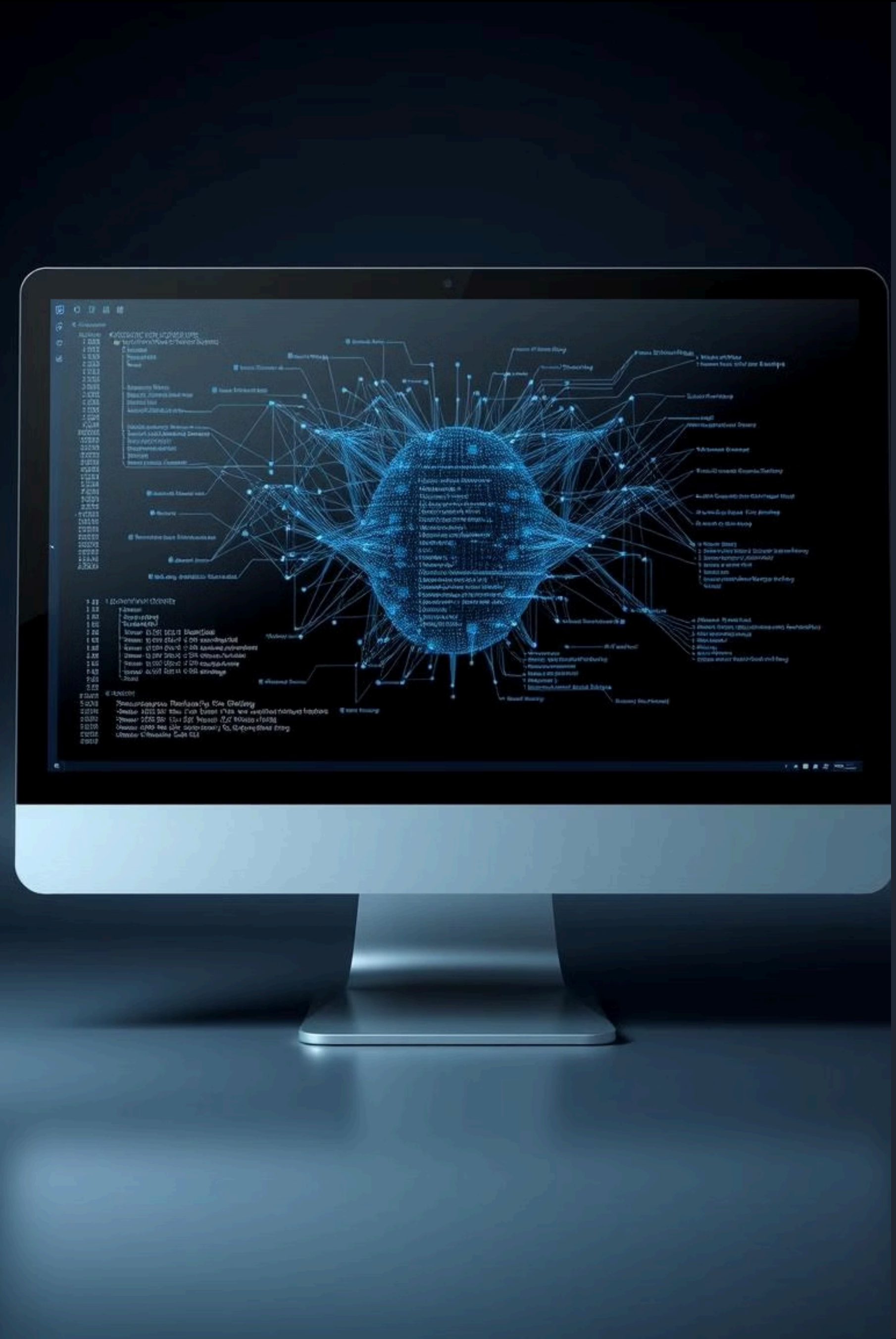
The limitations of traditional bone age estimation methods necessitate the development of automated solutions.

Manual Interpretation

Traditional methods rely heavily on manual interpretation of X-ray images, which is prone to inter-observer variability and is often time-consuming and subjective.

Objective Automation

This project aims to automate the bone age estimation process using deep learning, specifically ResNet34, to provide objective, consistent, and scalable results.



Project Motivation

The choice of ResNet34 and the need for automation are key driving forces behind this project.

ResNet34

ResNet34 is a powerful deep learning architecture well-suited for medical image analysis due to its efficiency in handling complex patterns and extracting relevant features from X-ray images.

Automation

Automating bone age estimation reduces human error, improves scalability, and ensures consistent results, ultimately leading to more accurate and reliable diagnoses.

Project Objectives

This project aims to develop and evaluate a robust automated bone age estimation system based on ResNet34.

1. **Development**

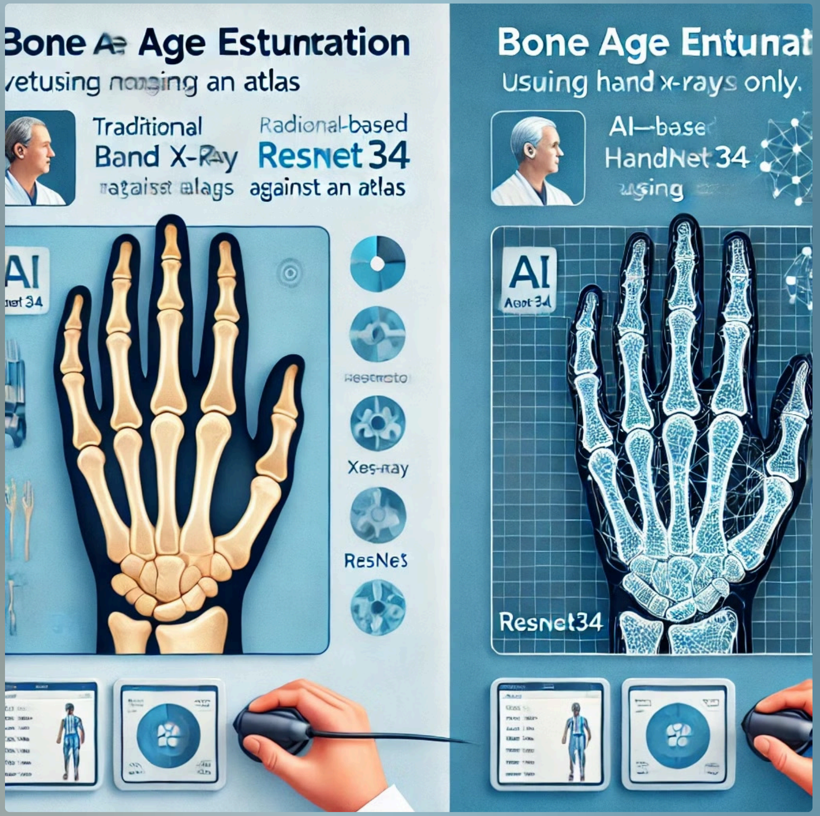
   The primary objective is to create a ResNet34-based system for automated bone age estimation, capable of accurately predicting bone age from X-ray images.

2. **Preprocessing**

   Thorough preprocessing of X-ray images is crucial to prepare high-quality inputs for the ResNet34 model, ensuring optimal performance and accuracy.

3. **Validation**

   The system's performance will be rigorously validated against traditional methods using accuracy and MAE metrics, demonstrating its effectiveness and reliability.



Comparison with Traditional Methods

1

Manual Methods

Subjective, time-consuming, and prone to variations between experts.

2

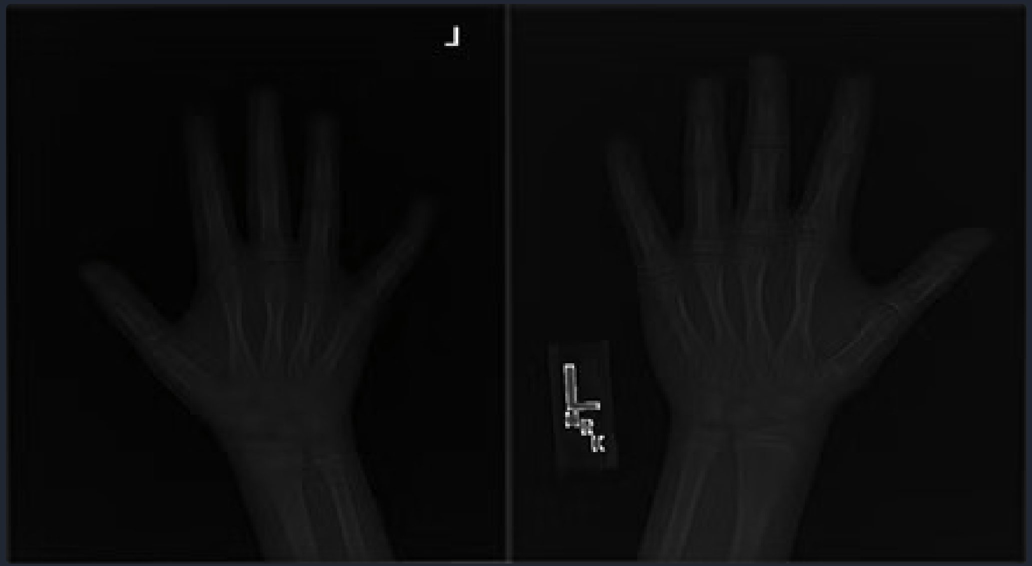
AI Model

Consistent, scalable, objective, and readily available for clinical use.

Data Preprocessing

1.Excluding Low Contrast Images

the first step we did is excluding low contrast images from the RSNA dataset, and the reason behind this process is to ensure that the model receives the most relevant data, leading to better performance and more reliable results

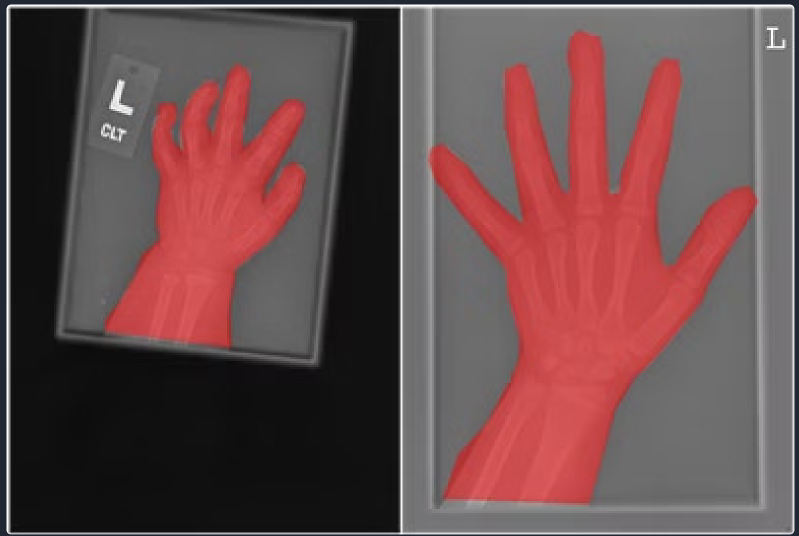


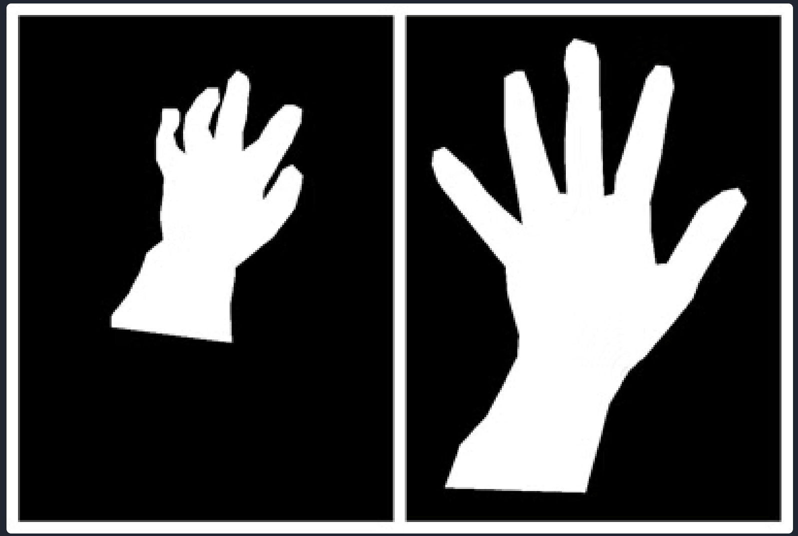
2.Draw Masks Manually

Improved Model Focus

Enhanced Accuracy

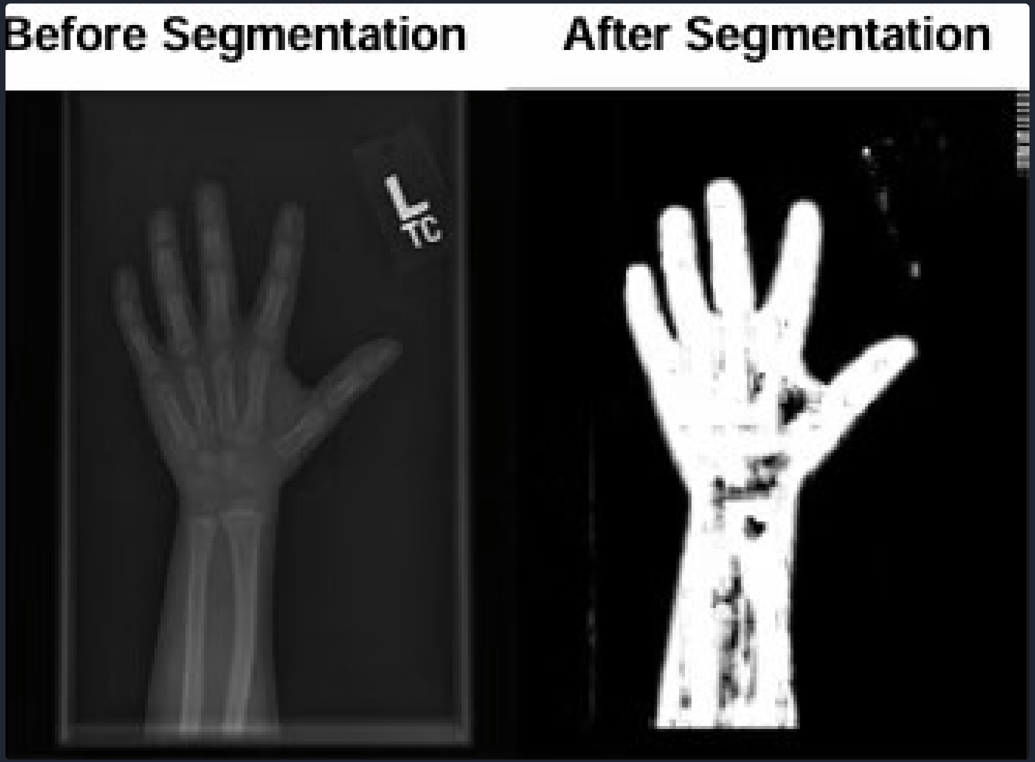
Faster Training





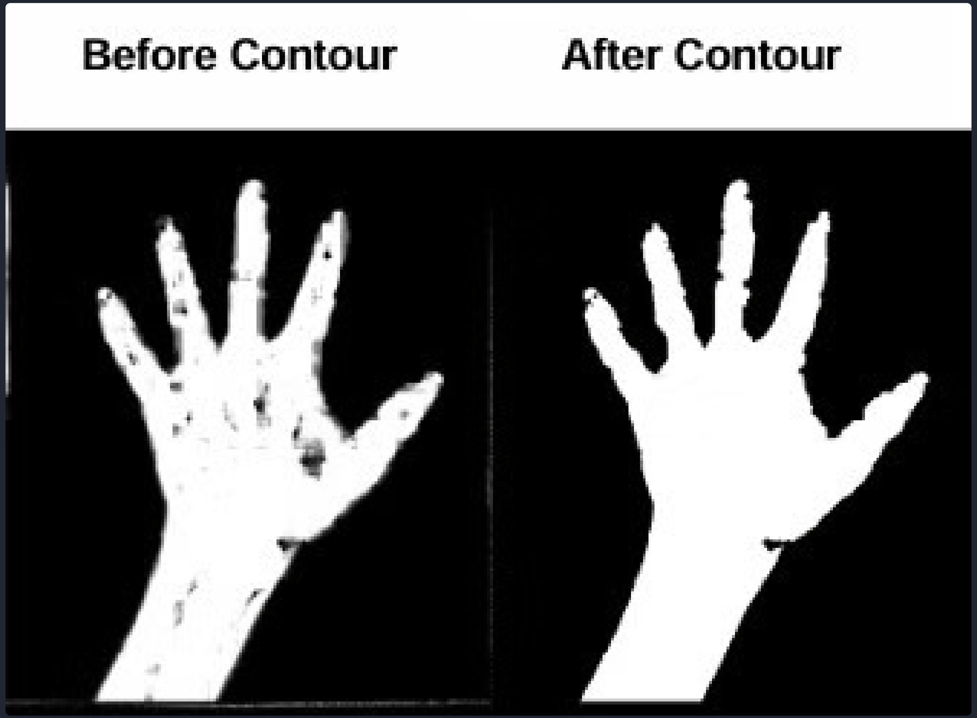
3.Create a Segmentation Model

we use patch extraction because our images are big (high width and length), and we have just 100 images. Patch extraction is a crucial strategy in this scenario for several important reasons when dealing with high-resolution images and small dataset (100 image)



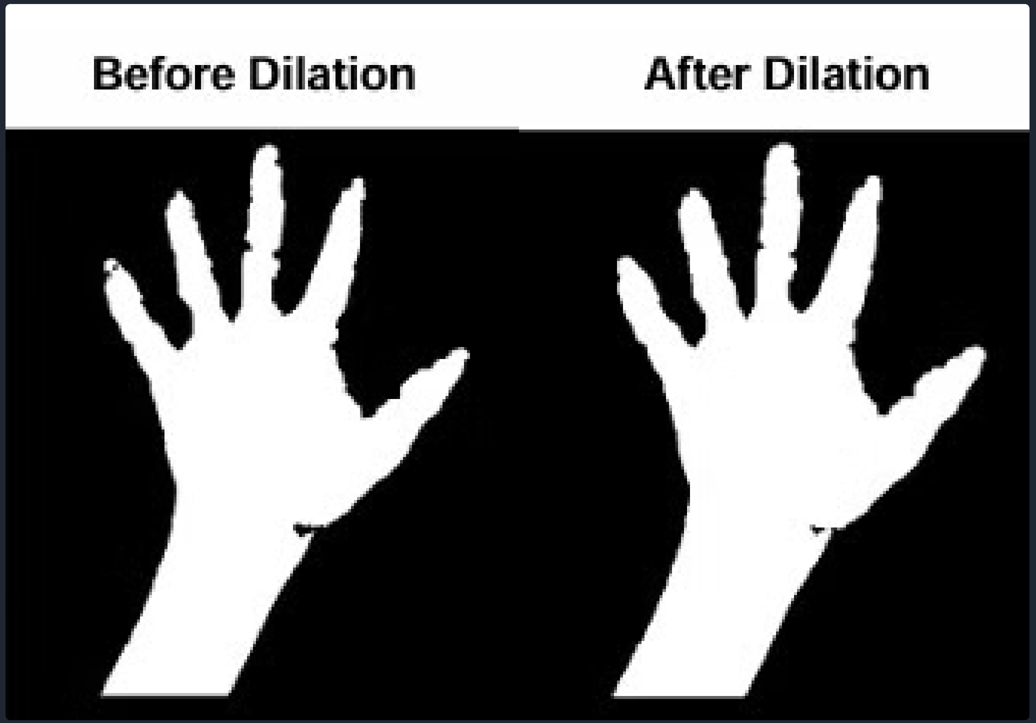
4.Applying Contours to Resulted Masks

To resolve unintended black regions within the segmented area, we apply contour method to the images.



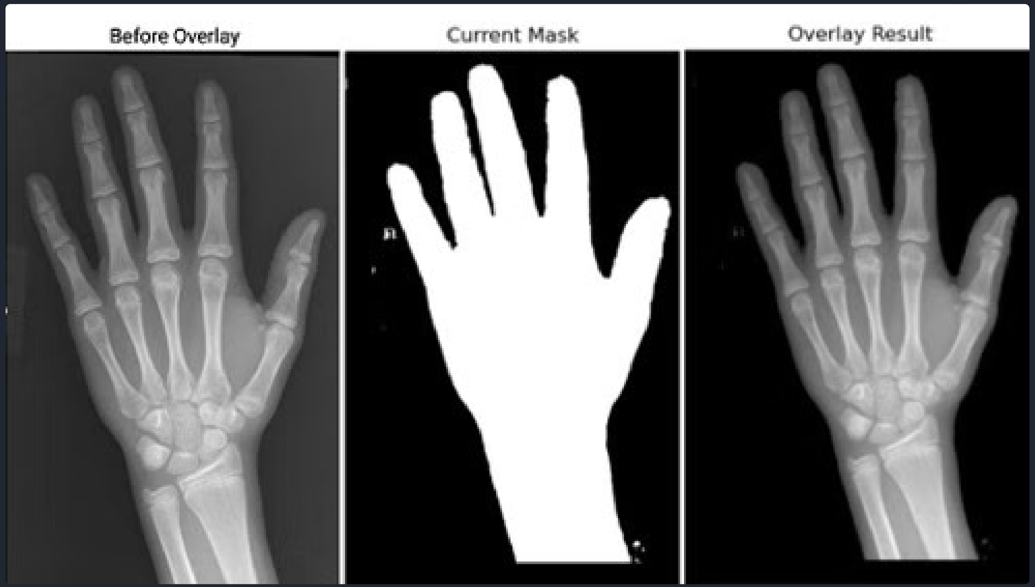
5.Apply Dilation to Images

This operation expands the boundaries of white regions (foreground) in a binary image, which is particularly useful for enhancing features such as skeletal structures, making regions like bones or growth plates more pronounced.



6.Apply overlay to images

By removing irrelevant regions, it reduces noise, allowing the model to learn more effectively.

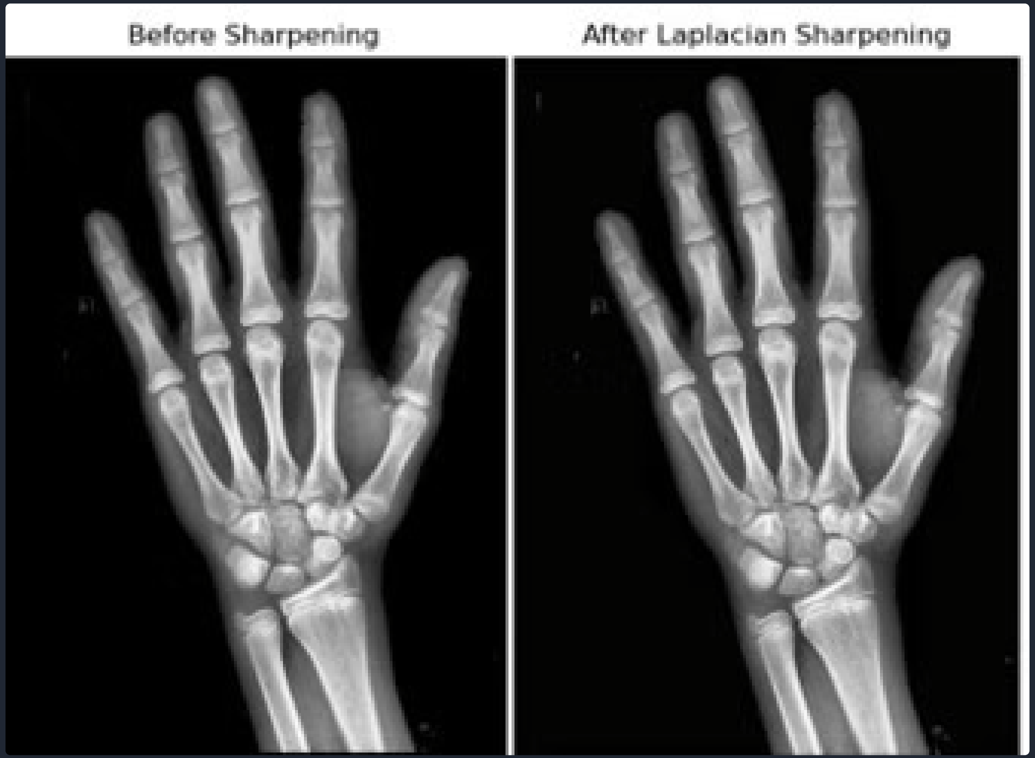


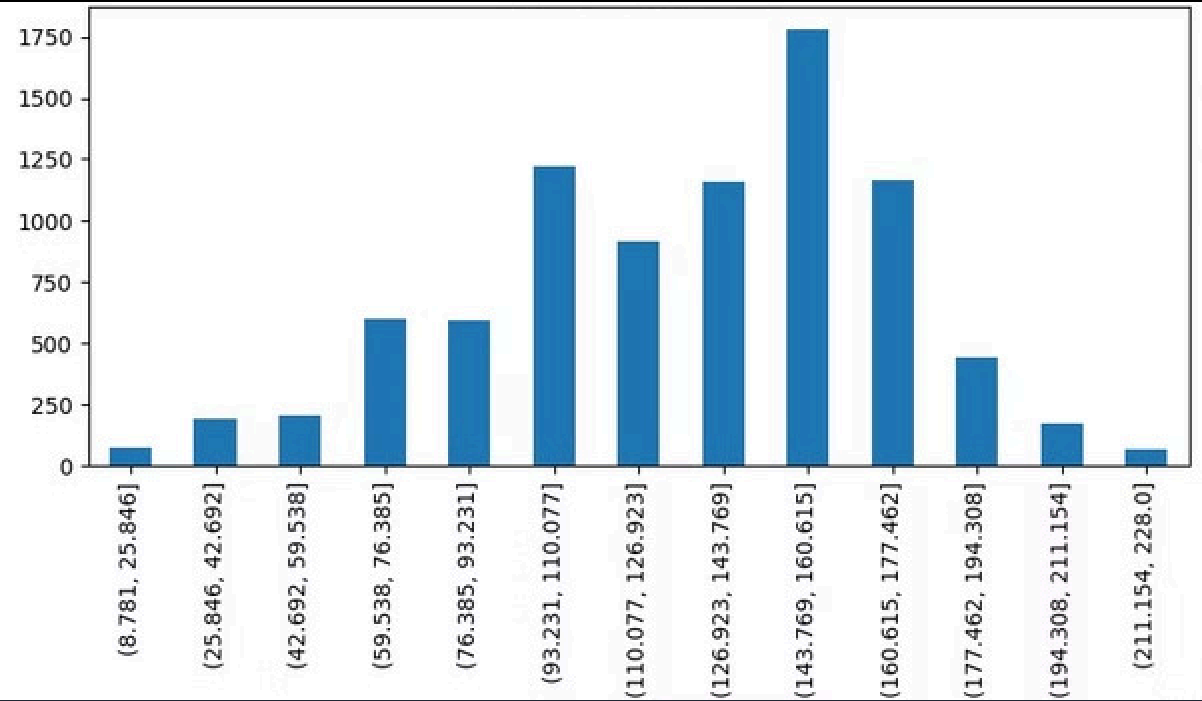
7.Apply CLAHE to Images (Histogram Equalization)

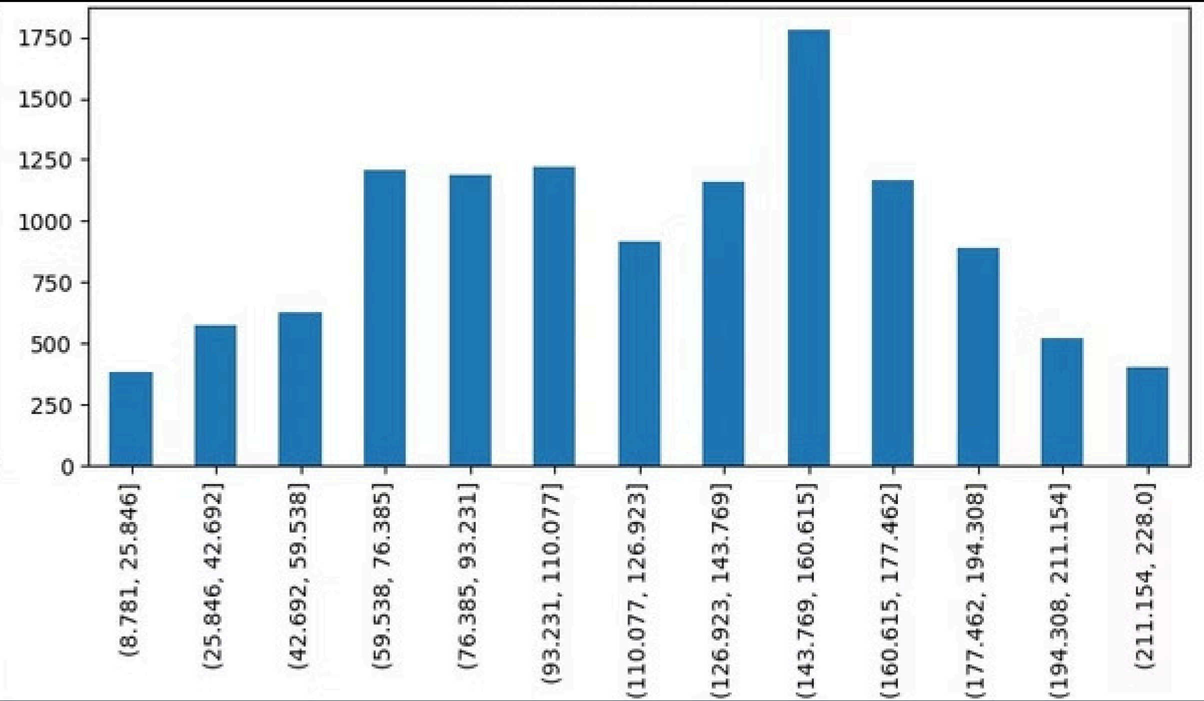
Contrast Limited Adaptive Histogram Equalization (CLAHE) is a preprocessing technique used to enhance the quality of X-ray images by improving the visibility of finer details in localized regions.

8.Apply Sharpening to Images

Applying Laplacian sharpening on CLAHE-processed images to further enhance their visual clarity and accentuate edges.







9.Weighted Augmentation

we calculate category weights inversely proportional to the frequency of each bone age category. Categories with fewer samples receive higher weights, which are then normalized so that the sum of all weights equals 1.

Evaluation and Validation of the Model

Accuracy

8.7

The model achieves high accuracy in predicting bone age, with a high accuracy rate.

8.7 Months

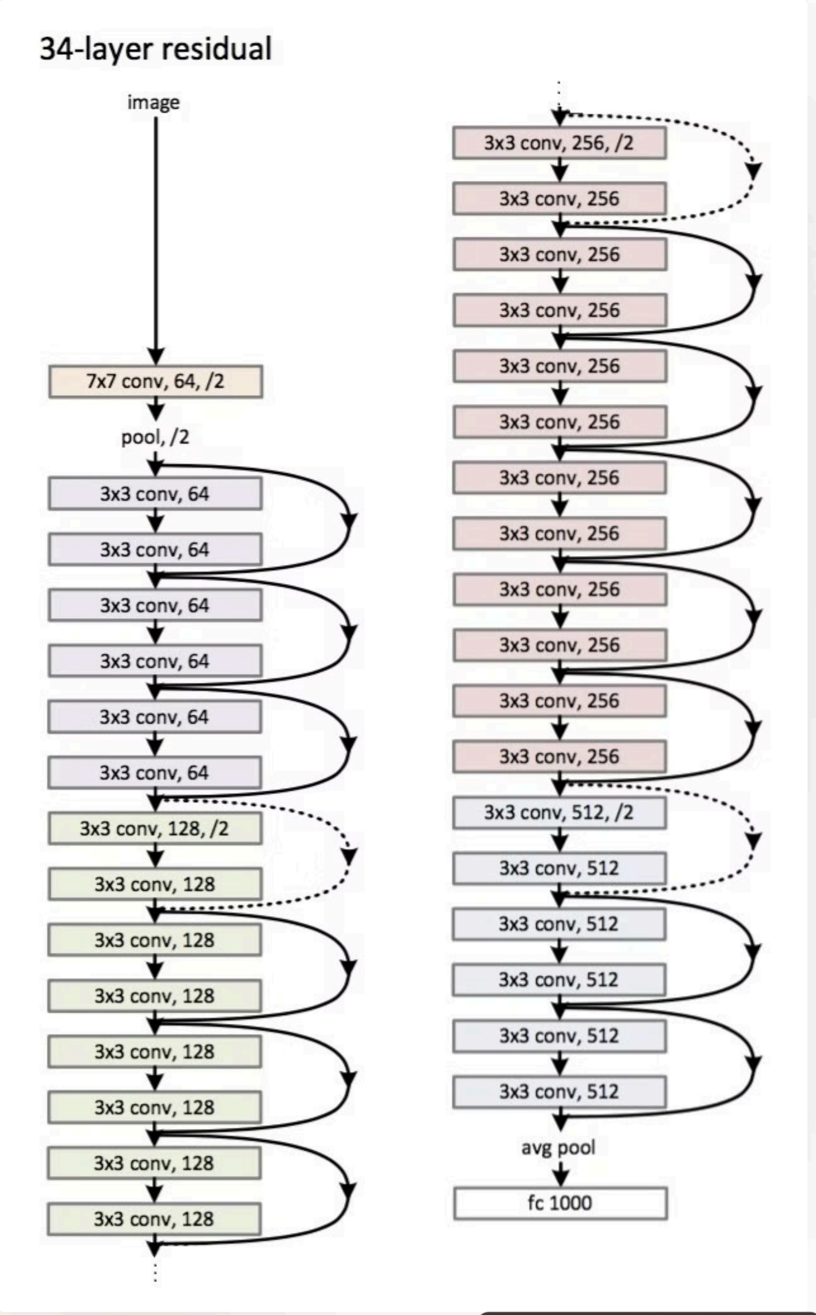
Mean Absolute Error

The model has a low error rate of 8.7m, demonstrating its reliability and precision.

10,000

Data Size

The model was trained on a large dataset of over 100,000 x-ray images.



Model Architecture

The core of the automated bone age estimation system is the ResNet34 deep learning model.

1

ResNet34

ResNet34 uses residual connections to effectively handle deep layers, enabling it to capture complex features from X-ray images and learn intricate patterns related to bone development.

2

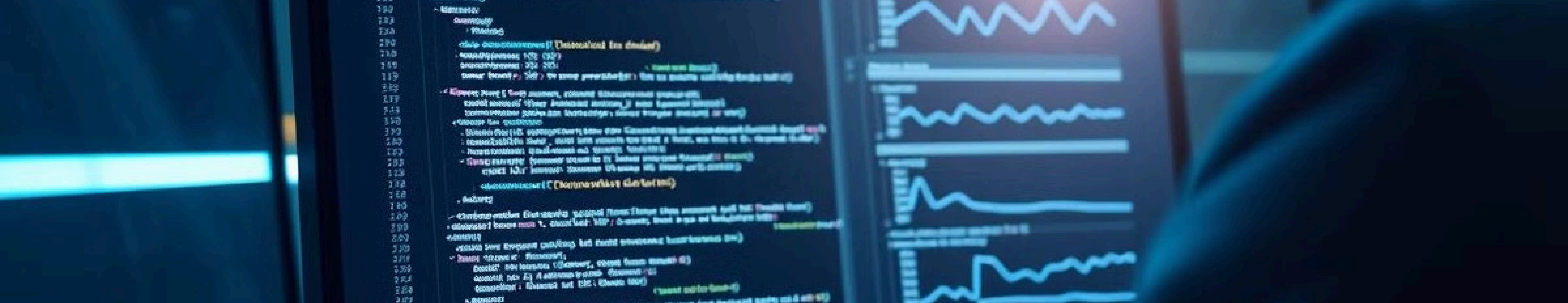
Feature Extraction

The model extracts skeletal features, such as bone length and growth plate size, to make accurate predictions about bone age.

3

Gender Input

Gender information is included as an auxiliary feature in the model, as bone development can vary slightly between genders.



Training the ResNet34 Model for Bone Age Estimation

1

Loss Function

A loss function measures the difference between the predicted bone age and the actual bone age.

2

Optimizer

An optimizer adjusts the model parameters to minimize the loss function, improving accuracy.

3

Epochs

The model is trained over multiple epochs, iteratively updating weights to improve performance.

4

Validation Set

A validation set is used to monitor the model's performance during training, preventing overfitting.

Training Process

Training the ResNet34 model involves optimizing its parameters to achieve accurate bone age predictions.

1

Optimizer

The Adam optimizer is used with learning rate tuning to adjust model parameters effectively and minimize the loss function.

2

Loss Function

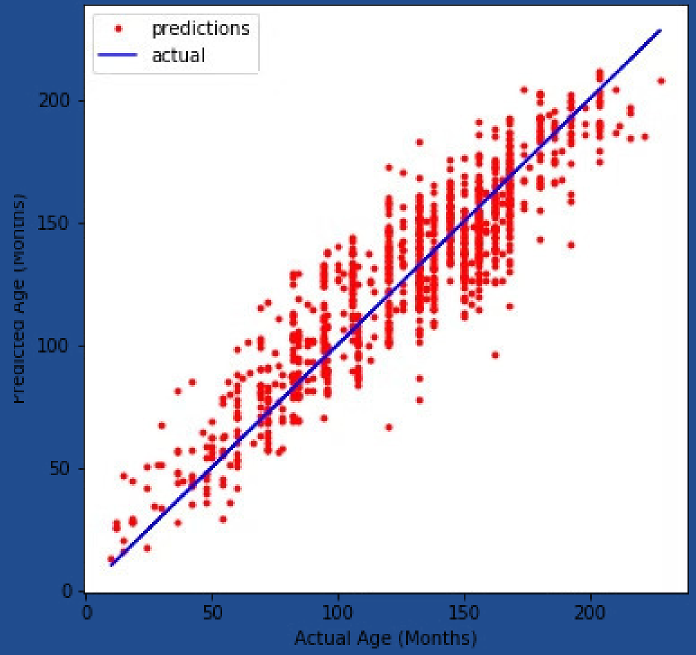
Mean Absolute Error (MAE) is employed as the loss function, measuring the average difference between predicted and actual bone ages.

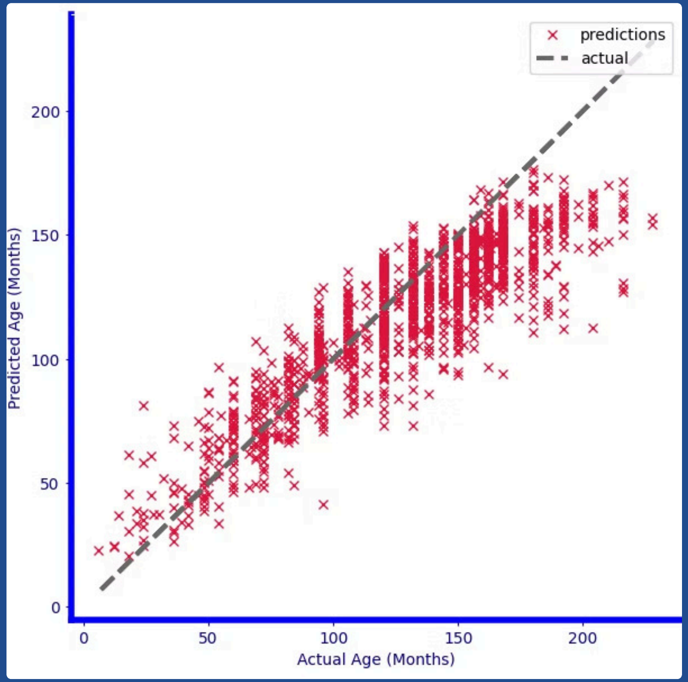
3

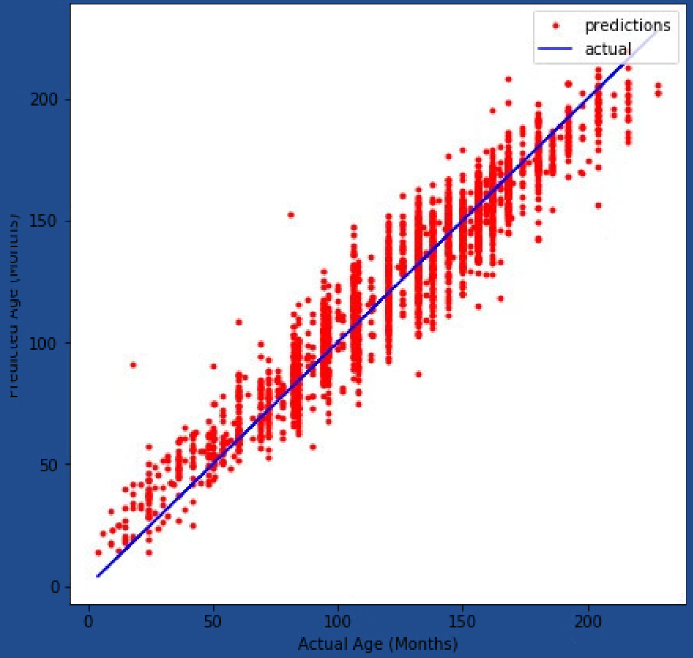
Callbacks

Callbacks are implemented to enhance the training process. ReduceLROnPlateau dynamically adjusts the learning rate based on performance, and EarlyStopping prevents overfitting by stopping training when performance plateaus.

Best UpVoted Kaggle Results







Results

Accuracy

Demonstrates high accuracy in predicting bone age from hand radiographs.

Efficiency

Effectively handles diverse data with minimal errors and reliable performance.

Visualization

Scatter plots show close alignment between predicted and actual bone ages.