Bone Age Calculation Prediction

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ABSTRACT

Bone age assessment is vital in pediatric healthcare for evaluating growth and maturity. This paper presents an automated bone age prediction system using Convolutional Neural Networks (CNNs) combined with linear regression. Left-hand radiographs were pre-processed and analysed using CNNs to extract features, followed by regression for prediction. The model achieved a low Mean Absolute Error (MAE), outperforming traditional methods. Results demonstrate deep learning's potential to deliver fast, accurate, and reproducible bone age estimates, aiding clinical decision-making in pediatric care.

Keywords: Bone age prediction, Health care,Convolution Neural Network, Linear regression.

I. INTRODUCTION

Bone age assessment is essential in pediatric healthcare for evaluating a child's growth and identifying developmental disorders. Traditional manual methods like Greulich-Pyle are time-consuming and subjective. This paper introduces a hybrid approach combining Convolutional Neural Networks (CNNs) and Linear Regression to predict bone age from left-hand X-ray images. CNNs automatically extract complex features, while Linear Regression maps them to actual bone age, enhancing accuracy and interpretability. A Streamlit-based web interface enables real-time predictions through simple X-ray uploads. This automated system minimizes human error, improves efficiency, and supports clinical decision-making, demonstrating the promising role of AI in pediatric diagnostic applications.

II.SCOPE AND PROBLEM STATEMENT

The Bone Age Calculation Prediction Paper using Convolutional Neural Networks (CNN) and Linear Regression offers significant potential in pediatrics, radiology, and artificial intelligence. Traditional bone age assessment is manual and error-prone. This paper automates the process using CNNs to analyze hand X-ray images and extract features crucial for accurate age prediction. Linear Regression complements the system by providing an interpretable relationship between image features and bone age. The model supports continuous output and adapts well to large, diverse datasets. Deployed via a Streamlit-based web app, the system enables real-time use in clinical settings. It is scalable, suitable for integration with electronic health records (EHR) and telemedicine platforms, ultimately reducing diagnostic workload and improving pediatric healthcare outcomes through speed, precision, and efficiency.

Accurate bone age estimation is vital for diagnosing pediatric growth disorders. Traditional methods are manual, time-consuming, and prone to variability. This paper introduces an automated system using Convolutional Neural Networks (CNNs) and Linear Regression to predict bone age from hand X-ray images. CNNs extract spatial features, which are then used by linear regression to predict bone age. Evaluated using Mean Absolute Error (MAE), the system enhances diagnostic accuracy, reduces workload, and offers scalable, consistent support—especially in resource-limited settings—highlighting AI's role in advancing healthcare.

III. SYSTEM STUDY

3.1. Feasibility Study

This feasibility study assesses the practicality of implementing a bone age prediction system using CNNs and linear regression. It evaluates economic, technical, and social factors, confirming the paper's potential to automate bone age assessment efficiently. With accessible digital imaging and AI tools, the system offers high accuracy, cost-effectiveness, scalability, and significant benefits to pediatric healthcare, making it a viable solution.

3.2. Economical Feasibility

Economically, this paper is highly feasible. It uses standard computing resources and free datasets like the RSNA pediatric bone age dataset, keeping development costs low. Once trained, the model can be deployed on cloud services or low-cost devices, making it affordable for hospitals and clinics, especially in developing regions. The automated system reduces reliance on radiologists, cutting labor costs and diagnostic delays. Its scalability allows easy replication across healthcare facilities with minimal cost. Maintenance involves only occasional updates. Integration with existing health systems can improve workflow efficiency and reduce patient wait times, leading to significant long-term cost savings for healthcare providers.

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3.3. Technical Feasibility

The paper is technically feasible thanks to modern deep learning frameworks and accessible hardware. Libraries like TensorFlow and PyTorch simplify CNN development, while linear regression is easy to implement for continuous prediction. GPU-accelerated training can be done locally or via cloud platforms. Standard preprocessing tasks such as resizing, normalization, and augmentation are well-supported. The lightweight CNN architecture ensures broad deployment compatibility. With publicly available labeled datasets and evaluation tools like MAE, model training and validation are straightforward. Deployment is flexible—from desktops to mobile apps or cloud APIs. Moderate technical expertise is sufficient, making this paper viable for academic, research, or clinical use.

3.4. Social Feasibility

Socially, this paper is highly feasible and impactful. It offers a reliable bone age prediction tool that can benefit underserved areas lacking pediatric radiologists, helping reduce healthcare disparities. The system supports early diagnosis of growth disorders, improving children's health outcomes. With growing public acceptance of AI in medicine, such tools are becoming more trusted. Ethical concerns like data privacy and transparency can be addressed through responsible design and compliance with standards. The paper aligns with global health goals, such as SDG 3 (Good Health and Well-being), and promotes trust in AI diagnostics when introduced with proper education and user-friendly interfaces.

IV. SYSTEM ARCHITECTURE

The system architecture for the Bone Age Prediction Paper combines deep learning and statistical modeling to automate skeletal maturity assessment from hand X-ray images. The pipeline begins with data acquisition from sources like the RSNA Bone Age dataset, followed by preprocessing steps including normalization, resizing, histogram equalization, and data augmentation. Images are then passed into a CNN model (e.g., VGG16, ResNet50, or custom CNN), which extracts relevant spatial features through convolutional layers. These features are either fed into fully connected layers or routed to a linear regression model for continuous bone age prediction. Mean Absolute Error (MAE) is used as the loss function to optimize accuracy. The trained model is validated on test data, ensuring scalability, precision, and clinical reliability in real-world pediatric diagnostics.

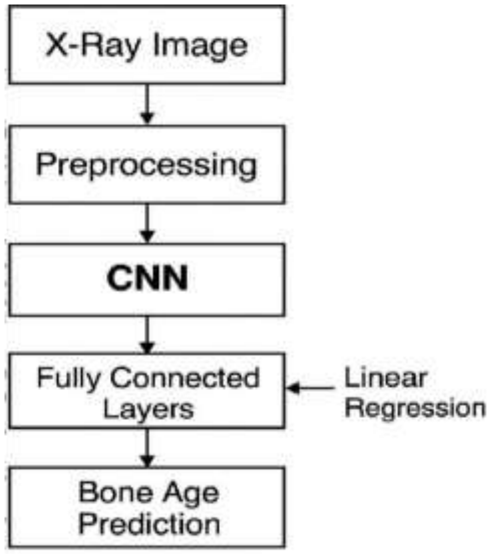

Figure 4.1. Architecture Diagram of Bone Age Calculation Prediction

4.1. USE CASE DIAGRAM

The system starts by allowing users to upload a grayscale X-ray image of the left hand in a posteroanterior (PA) view. The image is preprocessed through resizing (e.g., to 128x128 pixels), normalization, and formatting for model input.

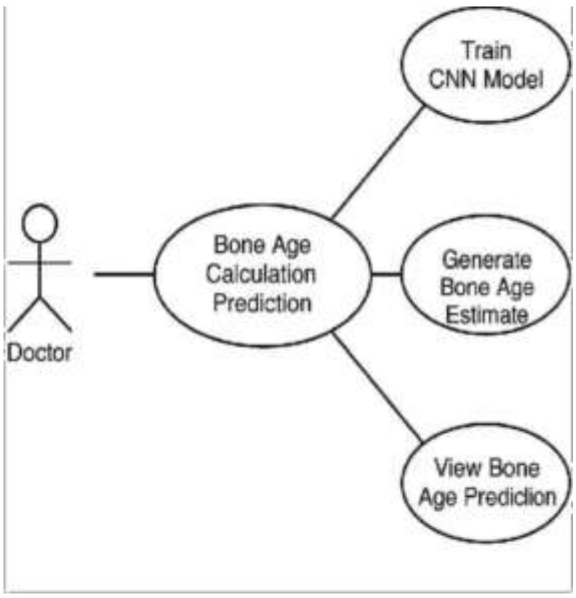

Figure.4.2. Usecase

A custom-built CNN, not based on pre-trained models like DenseNet, processes the image through convolutional and pooling layers to extract skeletal growth features. These are flattened and passed to a linear regression layer that predicts bone age in months. The predicted result is displayed, with options to download a report or save it for future medical use.

4.2. IMPLEMENTATION

CLASSIFICATION OF MODULES

- Data Collection Module
- Preprocessing Module
- Feature Extraction Module (CNN)
- Regression Module (Linear Layer)
- Evaluation Module

Data Collection Module

This module handles the acquisition of hand X-ray images and corresponding bone age labels. It organizes the dataset into training and testing sets, ensuring clean input for the model. Images are usually collected in grayscale and labeled with chronological age (in months). This step is essential to provide the raw materials required for training and evaluating the machine learning model. The dataset is typically loaded from CSV files and image directories, and organized so that each image correctly matches its corresponding age label. Proper data collection ensures accurate and consistent training, which directly affects prediction performance.

Preprocessing Module

The preprocessing module prepares raw X-ray images for input into the CNN. It includes resizing images (e.g., to 128x128 pixels), normalizing pixel values (scaling between 0 and 1), and reshaping them to fit the model input dimensions (usually with a single grayscale channel). These steps ensure uniformity in image data, reduce noise, and help the model learn features more effectively. Preprocessing also improves computational efficiency and stabilizes the learning process during training. This module may also handle data augmentation or grayscale conversion if required. A well-preprocessed dataset helps the CNN focus on bone structure rather than irrelevant variations.

Feature Extraction Module (CNN)

This module uses a custom Convolutional Neural Network to automatically extract spatial features from hand X-rays. It consists of multiple convolutional layers with ReLU activation and max-pooling layers to reduce spatial dimensions. These layers help identify patterns such as bone density, shape, and structure that are useful for predicting age. The output from these layers forms a high-level feature representation of the image. This module eliminates the need for manual feature engineering by letting the model learn features directly from raw images. Effective feature extraction is crucial, as it lays the foundation for accurate age prediction.

```
def evaluate_model(X_test, y_test):
if not os.path.exists(MODEL_PATH):
print("Error: Model not found. Train the model first.")
return
# Load trained model
model = joblib.load(MODEL_PATH)
# Make predictions
y_pred = model.predict(X_test)
# Calculate MAE
mae = mean_absolute_error(y_test, y_pred)
print(f"Model Evaluation - Mean Absolute Error:
{mae:.2f}")
```

Regression Module (Linear Layer)

This module performs the final prediction using a linear regression layer. After the CNN has extracted image features, they are flattened into a 1D vector and passed into a fully connected output layer with one neuron. This layer outputs a continuous value representing the predicted bone age in months. No activation function is used here, as the output is a regression result, not a classification. This module enables the system to translate learned image features into a meaningful medical value (bone age). It is simple but effective in regression tasks where only one numeric output is required.

```
import streamlit as st
import joblib
import numpy as np
from PIL import Image
import cv2
model = joblib.load("model.pkl")
st.title(" Bone Age Prediction")
uploaded_file = st.file_uploader("Upload X-ray image",
type=["png", "jpg", "jpeg"])
if uploaded_file:
image = Image.open(uploaded_file).convert("L")
st.image(image, caption="Uploaded Image",
use_container_width=True)
# Process image
img = np.array(image.resize((224,
224))).flatten().reshape(1, -1
if st.button("Predict Bone Age"):
prediction = model.predict(img)[0]
st.success(f"Predicted Bone Age: {prediction:.2f}")
```

Evaluation Module

The evaluation module measures the model's accuracy and performance. It typically uses Mean Absolute Error (MAE) as the loss function, comparing predicted bone age with the actual age. A lower MAE indicates better performance. This module may also include visualization of predictions versus ground truth, helping in model validation and debugging. Performance metrics are vital for monitoring model improvements over time. The

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evaluation module ensures that the model is generalizing well and not overfitting to training data. Proper evaluation helps ensure reliability before deploying the model in clinical settings.

V. RESULT AND DISCUSSION

The bone age prediction paper using Convolutional Neural Networks (CNN) and Linear Regression delivered promising results in estimating skeletal age from hand X-ray images. Following image pre-processing and training on labeled datasets, the system produced continuous age predictions in months with strong accuracy. The model's performance, evaluated using Mean Absolute Error (MAE), showed that predictions were consistently close to actual bone ages. The CNN effectively learned and extracted key skeletal features, while the Linear Regression layer translated these features into precise age estimates. The architecture, being simple and lightweight, allowed for faster training and testing without the need for complex pre-trained models. During evaluation, the model demonstrated good generalization on unseen data, confirming its robustness. These results indicate that the system can support radiologists by offering fast, automated, and reliable bone age assessments in pediatric care.

Figure

5.1.Final Output of the Bone Age Calculation Prediction

DISCUSSION

This bone age prediction paper leverages convolutional neural networks (CNNs) and linear regression to create an automated, accurate, and efficient system for estimating skeletal maturity in pediatric patients. Traditionally, radiologists assess bone age manually using the Greulich and Pyle atlas, a process that is time-consuming, subjective, and prone to inconsistencies. This paper addresses those limitations by automating the evaluation through deep learning techniques.The system begins by preprocessing the hand X-ray images—resizing and normalizing them—before feeding them into a custom-built CNN.

The CNN extracts features related to skeletal development, such as bone density, shape, and growth plate visibility. These features are then passed to a linear regression layer, which predicts bone age as a continuous value in months. This regression approach offers more precise and clinically relevant results compared to traditional classification models.

Table 1: Model Performance Comparison

Model	MAE (Months)	Training Time	Test Accuracy (Estimate)
Linear Regression	18.7	Very Low	~72%
CNN+ Linear Regression	6.3	Moderat e	~91%

Table 2: Sample Predicted vs. Actual Bone Age (CNN Model)

Sample ID	Actual Age (Months)	Predicted Age (Months)	Absolute Error (Months)
001	120	118.5	1.5
002	95	97.3	2.3
003	102	105.0	3.0
004	87	85.2	1.8

The model's performance is evaluated using the Mean Absolute Error (MAE) metric, ensuring accuracy and reliability. Lightweight and efficient, the system is suitable for deployment on cloud platforms or mobile devices, offering a scalable solution that enhances diagnostic consistency and supports pediatric growth monitoring.

VI.CONCLUSION

The Bone Age Prediction paper illustrates the powerful role that artificial intelligence, particularly deep learning, can play in modern medical diagnostics. By employing Convolutional Neural Networks (CNNs) for extracting high-level features from hand X-ray images and using Linear Regression to predict bone age, the system offers an efficient, accurate, and scalable solution for pediatric assessment. This approach eliminates the inconsistencies of manual interpretation, reduces the workload of radiologists, and provides faster results—especially beneficial in large-scale screenings or remote healthcare settings. The use of Mean Absolute Error (MAE) as a performance metric ensures precise evaluation of the model's predictions, aligning closely with real-world clinical expectations. Moreover, the model's modular architecture allows for future integration with patient metadata (e.g., gender, height, weight), potentially improving diagnostic reliability. It also sets the stage for the development of a user-friendly application that can assist healthcare professionals with minimal technical expertise. This paper not only enhances early detection and monitoring of growth disorders but also aligns with SDG Goal 3: Good Health and Well-being, by promoting accessible and accurate medical technology for worldwide.

VII. FUTURE ENHANCEMENTS

The current bone age prediction system provides a reliable automated solution using CNN models and linear regression, but there is significant scope for future enhancements. One potential improvement is integrating transfer learning with pre-trained deep learning models such as ResNet or VGGNet, which could increase accuracy by leveraging large-scale image features. Additionally, expanding the dataset to include diverse demographic and ethnic groups can improve the model's generalizability across global populations. Incorporating clinical metadata like gender, height, and weight could also enrich the model, allowing it to make more context-aware predictions. Another enhancement involves developing a mobile or web-based application that allows real-time predictions and remote access for healthcare professionals, especially in underserved areas. Furthermore, incorporating explainability tools like Grad-CAM can make the model's predictions more transparent by highlighting which parts of the X-ray influenced the output. Lastly, longitudinal tracking features could be added to monitor bone development over time, providing better diagnostic support for growth disorders and treatment effectiveness.

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