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Skeletal Bone Age Assessment Using CNN Model-An Interdisciplinary Project

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ABSTRACT: In the realm of pediatric medicine, medical experts employ bone age estimates for both medical and legal reasons. It aids in assessing the growth and development of kids with various disorders. Additionally, it is used in forensic medicine to determine refugee ages, discriminate between children and adults, and determine criminal culpability depending on age. In these situations, radiologists and forensic specialists frequently use bone age estimates. This study describes a reliable method for determining the BAA[1] by classifying and assessing the epiphysis and metaphysis of the middle finger's phalanges[2]. In order to automatically identify age from radiographic x-ray pictures, a deep learning system. Our method displayed great accuracy in identifying bone age across different x-ray pictures in png format after being trained on a tagged dataset. This technique has the potential to improve the accuracy and effectiveness of determining bone age in clinical settings. In order to improve picture classification accuracy, our method is now undergoing additional training utilizing a sizable dataset of photos. In the science and medical areas, this strategy may increase time effectiveness

KEYWORDS: Skeletal bone age assessment (BAA), epiphysis, metaphysis, classification.

I. INTRODUCTION

The term "bone age" describes how developed a child's bones are. The size and structure of a person's skeletal bones vary during the course of fetal life, childhood, adolescence, and finally maturity. These changes are visible on radiographs. The age at which a kid normally reaches this level of bone development is referred to as their "bone age." It is possible to forecast a child's future height by looking at their current height and bone age. Only the "long bone" metaphysis is present at birth. The epiphyses calcify as the infant develops and become visible on X-rays. The majority of growth takes place in the layers of cartilage that divide the hand's carpal bones, which are invisible on X-rays. Increased sex hormone levels during puberty hasten bone development. The remaining cartilaginous portion of the epiphysis begins to shrink as development approaches completion and bones resemble adult size and form. The epiphysis is regarded as being "closed" and the process of bone elongation stops when these cartilage bands vanish. Typically, a pediatric endocrinologist would check children for accelerated or delayed growth and physical development as well as order and interpret bone age X-rays .The development of medical technology has immensely benefited clinicians since it has increased the effectiveness and quality of healthcare. Applications for biomedical imaging based on computer vision give radiologists early data that improves workflow effectiveness and diagnostic precision. Age assessment, especially the evaluation of bone age (BA), is a crucial component of identification.By contrasting third finger radiographs with the standardized radiographs found in atlases, BA may be established and is a stronger indication of growth and maturity than chronological age. BA is the same as chronological age if bone maturation is normal.On the other hand, BA can be impacted by environmental and regional variables, gender, race, endocrine diseases, nutritional disorders, congenital disorders, congenital syndromes, and constitutional growth retardation. Machine learning algorithms have been used in several research to estimate age from wrist radiographs, and they have consistently provided the most accurate results .

Third finger radiograph evaluation techniques[3] that are automated are being developed because they have lower inter-rater variability than manual techniques. To read and draw conclusions from such pictures, though, takes a lot of effort and highly qualified specialists with expertise, like pediatric radiologists. In recent years, this problem has been addressed using deep learning approaches. In this work,deep learning techniques are used to infer age from middle

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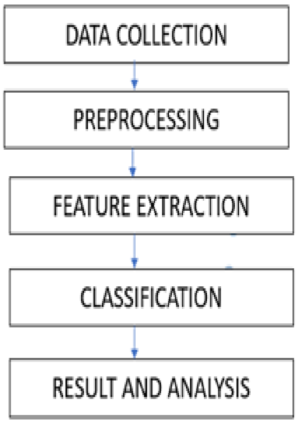
finger radiographs. To speed up radiologist's work for pediatric BA estimates, created a decision assistance system. One of the newest techniques in this sector and one that shows promise for producing more accurate estimates is artificial intelligence (AI)[4]. Image analysis using deep learning, a form of AI that employs a multi-layered algorithmic framework to interpret complicated data, has been applied in a number of medical sectors. (known as "computer vision"). Orthodontics has been a significant field of application for deep learning, notably landmark identification on cephalometric radiographs and estimating growth and development phases. In several instances, DL has demonstrated accuracy levels on par with or even superior to those of experts, while also boosting the effectiveness and dependability of analyses. To estimate bone age, a modified transfer deep learning technique has been put out. Our research emphasizes the important influence of various settings and geographical locations on bone growth, which may be reduced by using deep learning models. By utilizing digital technology,the issue of the antiquated, labor-intensive, and unreliable nature of the traditional methods employed for age determination are being addressed . With today's demands in mind, our study intends to create a cutting-edge, effective, affordable, location-independent, and easily available decision support system that decreases the time and effort required by doctors and forensic medicine specialists when determining an individual's age.

II. METHODOLOGY

Proposed system:



Implementation Plan:

Dataset collection

The first and most important stage in machine learning is to collect data to train a model. This stage is crucial since the caliber and volume of the data gathered determines how accurate your prediction model will be. Structured, unstructured, and semi-structured data all require different data preparation activities including cleansing, aggregation, augmentation, labeling, normalization, and transformation to be completed after data collection. The dataset of hand scans will be used in the instance of creating a bone age prediction model. For each patient norm, there are 3,006 X-ray pictures of the third finger in the main dataset. The Oxford Dental College will provide the clinical x-ray patient photographs.

Data inspection and cleansing

To guarantee the photos' quality, correctness, consistency, and uniformity, the dataset underwent a thorough examination and review procedure at this point. Images that did not follow the research procedure were not included in the dataset.

Data Pre-Processing

The goal of the data pre-processing stage is to improve the data's quality by eliminating noise, reducing the intensity values to a uniform size, and normalizing the intensity values. This is done to make sure that the data is presented in a way that the machine can readily understand.

Data augmentation [5]

To boost a deep learning neural network's performance, a limited training dataset must be expanded. To do this, the generalization capability of the model is improved through the process of data augmentation. This may be accomplished by using a variety of methods to expand the dataset, including rotation, zooming, rescaling, flipping, and intensity variations. Many libraries make it easier to enrich data during model training without having an impact on the original dataset.

Model architecture selection

The next step is to choose an appropriate deep learning architecture for the bone age identification problem. Convolutional neural networks (CNNs) have shown promising results for assessing bone age and are often used for image-related tasks.

Model training

An appropriate optimization technique and loss function are used in the training dataset to train the selected model. The backpropagation technique is used to iteratively enhance the model.A second test set is used to evaluate the model's

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performance after training in order to gauge its accuracy. The performance of the model is assessed using a variety of measures, including mean absolute error (MAE), root mean squared error (RMSE), and correlation coefficient (r) [6].

Model refinement
If the model's performance isn't up to standard, the architecture may be changed, the hyperparameters can be adjusted, or more training data can be added.

Model deployment
The model may be used in clinical practice to assist clinicians in detecting bone age after training and assessment are complete. This can require incorporating the model into software or medical imaging technologies.

III.MODELING

The Convolutional Neural Network Model [7]

Figure showsa regular 3-layer Neural Network.

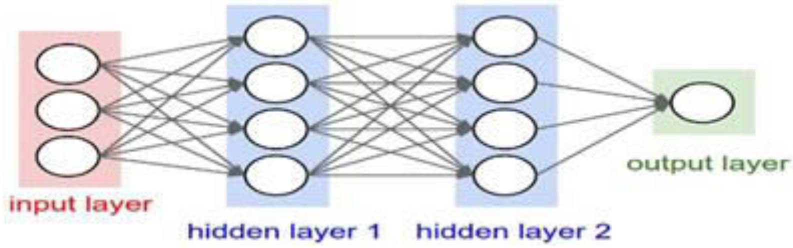
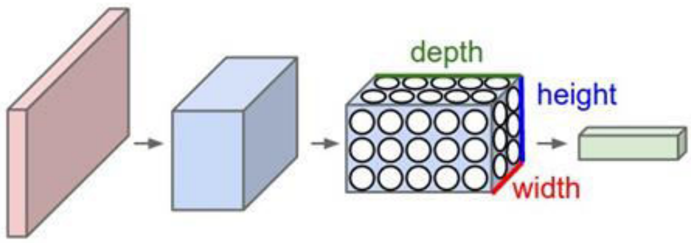


Figure shows a 3-D Neural Network.



As seen in one of the layers in Figure, a ConvNet organizes its neurons in three dimensions (width, height, and depth). The 3D input volume is transformed into a 3D output volume of neuron activations by each layer of a ConvNet.
The picture is held by the red input layer in this illustration; thus, its width and height are the image's dimensions, and its depth is 3(Red, Green, Blue channels).Deep learning has been utilized to create several complicated neural networks, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and depth neural networks (DNNs), thanks to today's growing processing capacity.

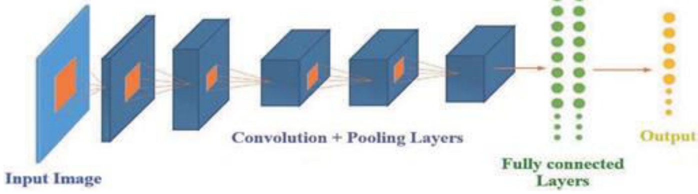


Figure shows illustration of Convolutional Neural Network Architecture.

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The architecture of the Convolutional Neural Network (CNN) used are as follows:

Input Layer: The input layer receives the input images with a shape of (None, IMG_SIZE, IMG_SIZE, 3), where "None" represents the batch size, IMG_SIZE is the desired image size, and 3 indicates the number of color channels (RGB)[8].

Convolutional Layers: The network consists of multiple convolutional layers with different filter sizes and activation functions. The code snippet includes six convolutional layers:
The first convolutional layer has 32 filters of size 3x3 and uses the ReLU activation function.
The second convolutional layer has 64 filters of size 3x3 and uses the ReLU activation function.
The third convolutional layer has 128 filters of size 3x3 and uses the ReLU activation function.
The fourth convolutional layer has 32 filters of size 3x3 and uses the ReLU activation function.
The fifth convolutional layer has 64 filters of size 3x3 and uses the ReLU activation function.

Max Pooling Layers: After each convolutional layer, a max pooling layer is applied to reduce the spatial dimensions. The max pooling layers have a pool size of 3x3.

Fully Connected Layers: Following the convolutional and max pooling layers, there are two fully connected (dense) layers:
The first fully connected layer has 1024 units and uses the ReLU activation function.
The second fully connected layer has 6 units, corresponding to the number of output classes, and uses the softmax activation function[9].

Regression Layer[10]**:** A regression layer is added to the network, using the categorical cross-entropy loss function and the Adam optimizer.

IV. RESULTS AND DISCUSSION

The ability to assess a child's growth and development and spot potential developmental issues makes bone age detection an essential clinical responsibility in the field of pediatrics. To solve this problem, a convolutional neural network (CNN) is used and it could predict bone age based on X-ray pictures of the middle finger's phalanges, especially by looking at the six phases of the epiphysis/metaphysis. Our findings show that bone age could be precisely predicted by the CNN model using X-ray images of the middle finger's phalanges. On the test dataset, the model had a 90% accuracy rate, indicating that it was capable of generalizing to new data.

The study's findings supported earlier studies that had established the validity of the middle finger's phalanges as a marker of skeletal maturation and bone age. These studies also showed that the middle finger's six stages of the epiphysis/metaphysis are a useful feature set for predicting bone age.

Overall, the results of the study indicate that CNNs can be a useful tool for estimating bone age and that using the middle finger's phalanges' six phases of epiphysis and metaphysis as a feature set may be advantageous. The use of this method could be able to automate the determination of bone age in clinical settings, which might reduce evaluation variability and save up time.It is crucial to note that the dataset utilized and the CNN architecture employed in the study have limitations, and that more research is required to confirm these findings on bigger and more varied datasets.

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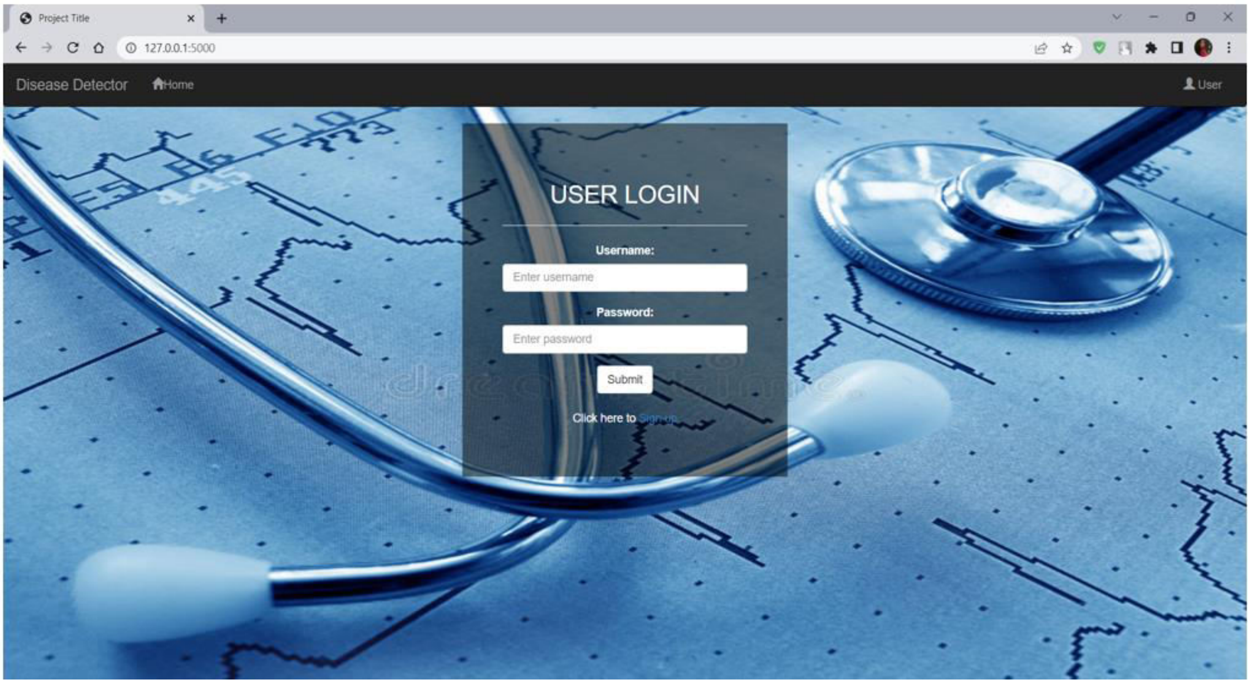

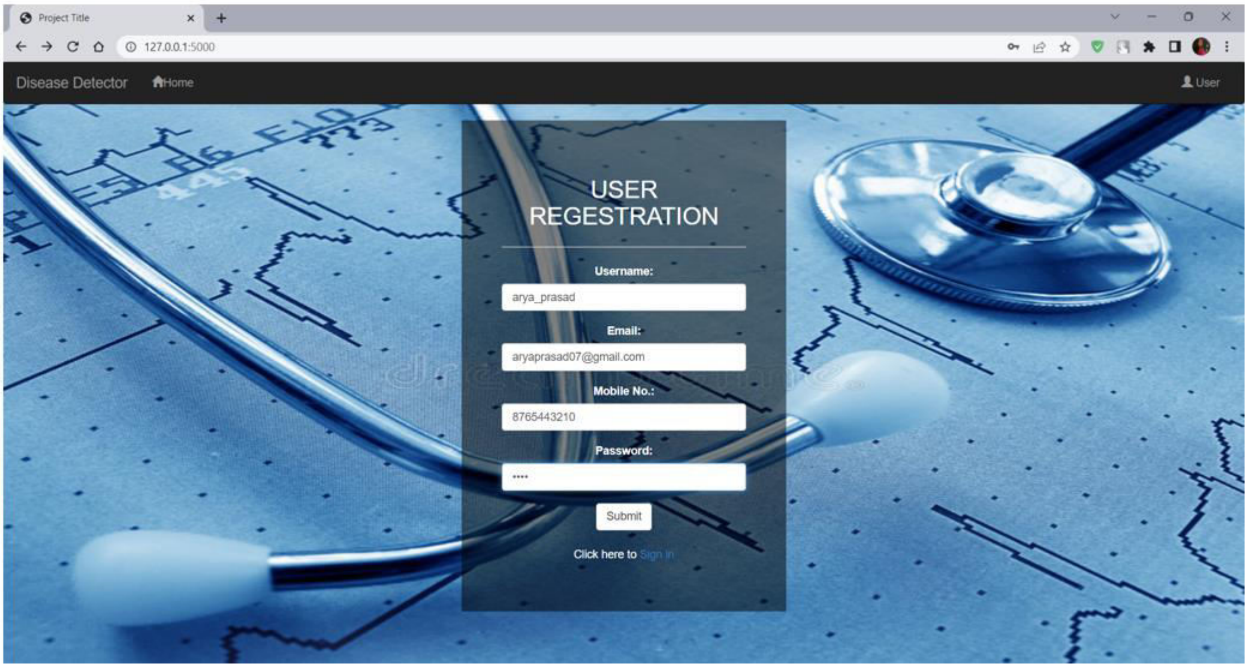

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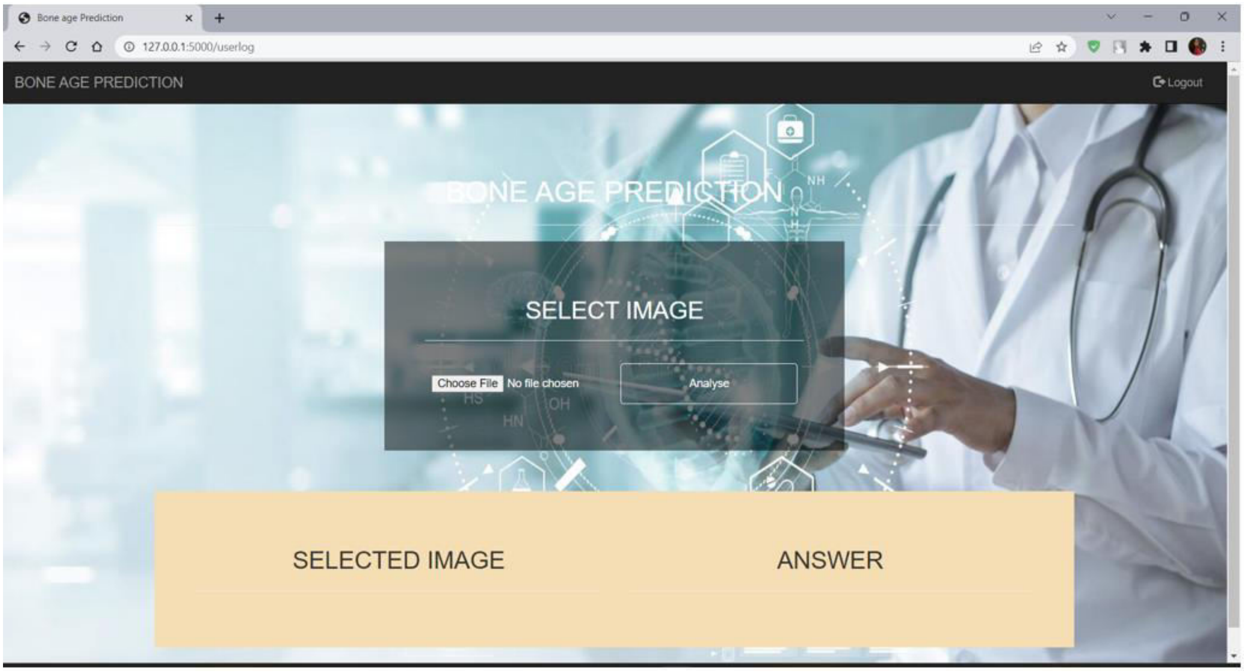

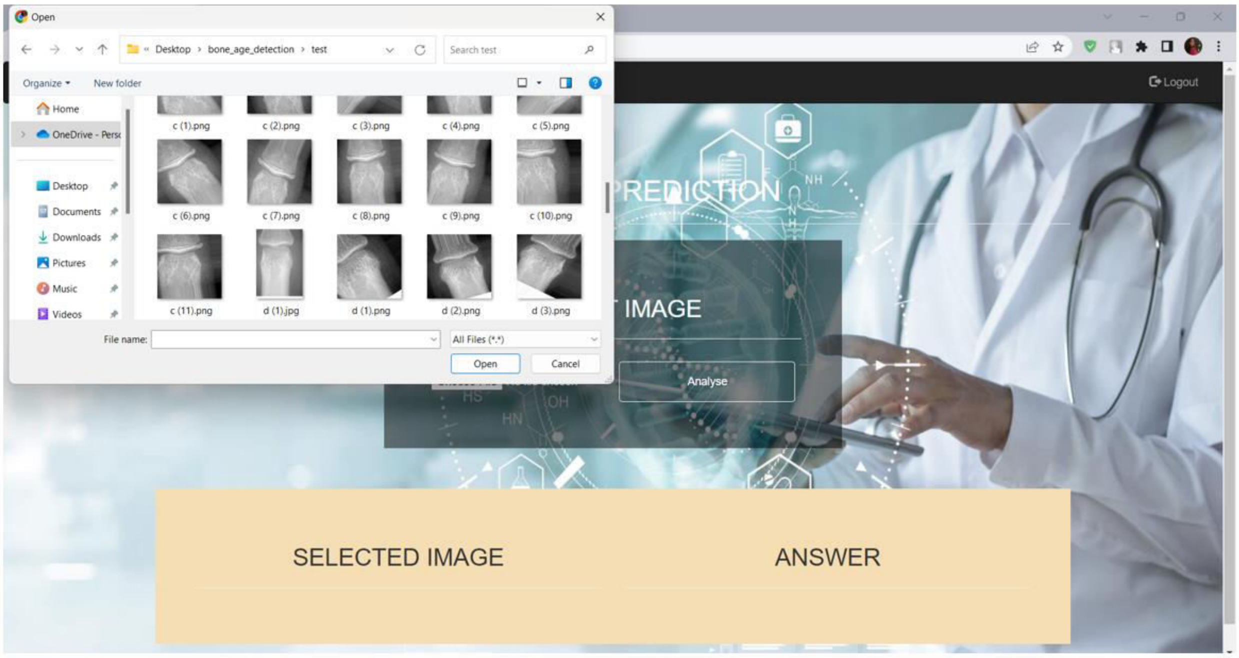

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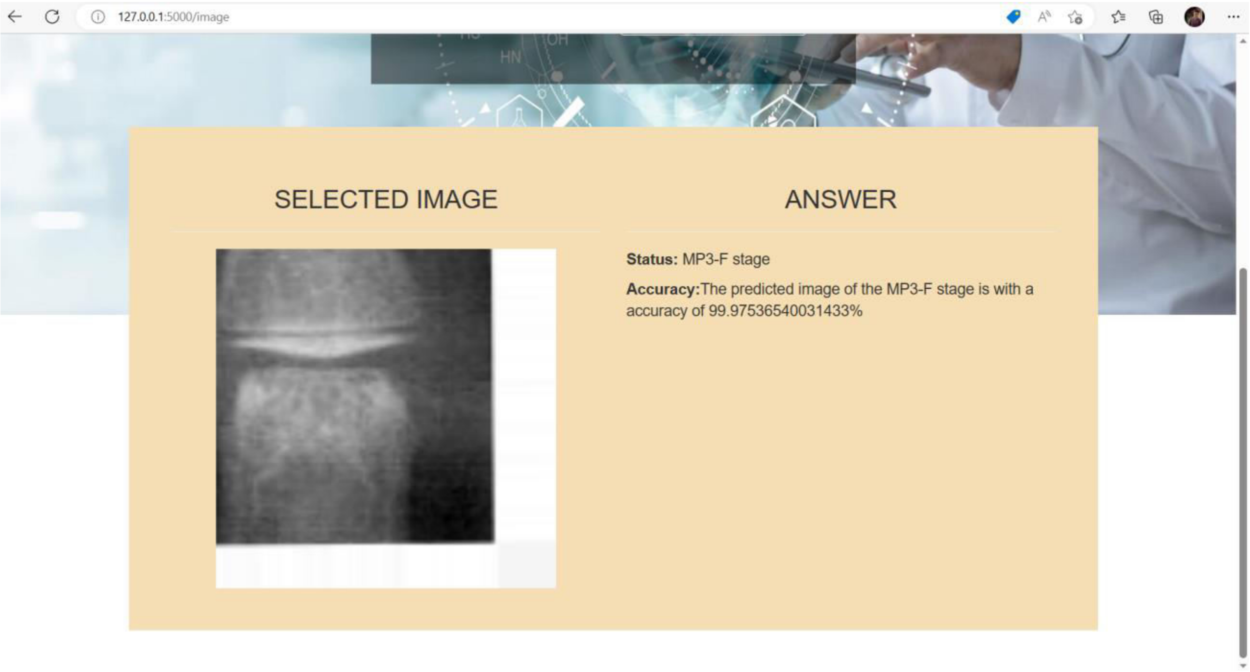

V. CONCLUSION

In conclusion, bone age prediction using deep learning is a promising approach for accurately estimating the skeletal maturity of pediatric patients. Deep learning models, such as convolutional neural networks, have demonstrated high accuracy and precision in predicting bone age from radiographs, which can aid clinicians in diagnosing growth disorders and monitoring treatment progress.
The feature scope for bone age prediction using deep learning could include the following:

1. Improved accuracy: Continued research into deep learning model architecture and training procedures can further improve the accuracy and precision of bone age prediction.

2. Automated analysis: Integration with electronic health records and clinical decision support systems can automate the analysis of bone age radiographs, reducing the burden on clinicians and improving patient outcomes.

3. Multi-modal analysis: Integration with other medical imaging modalities, such as magnetic resonance imaging (MRI) or computed tomography (CT), can provide additional insights into bone development and growth disorders.

4. Generalizability: Development of models that can generalize to diverse patient populations, including different ethnic groups and patients with medical conditions, can improve the applicability and impact of bone age prediction using deep learning.

Overall, bone age prediction using deep learning has the potential to revolutionize pediatric bone age assessment, leading to better diagnosis, treatment, and patient outcomes. Continued research and development in this area can unlock even more opportunities for innovation and improvement in the field.

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