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CNN Based Bone Age Prediction System Using Medical Images

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ABSTRACT

The Bone Age Prediction System is a web based tool that was developed to improve the management of bone age determination within a clinical setting. Typical measurement techniques utilize a laborious process that calls for manual interpretation of X-ray photographs combined with extensive subjective judgment by experts in order to derive the final evaluation of bone age. Using Firebase for backend functionality, including authentication and cloud based data storage, and using Streamlit as the front end user interface, the proposed tool gives a secure digital method of overcoming the limitations.

The proposed system consists of three main modules, Administration, Patient, and User. Using the User Module, authorized healthcare staff can securely log into the database to manage patient information and maintain records of bone age. Using the Patient Module, patients can receive electronically generated PDF reports automatically and also access information regarding patients individual reports. Administering of the User Module is through the Administration Module.

The additional support within the tool for visual analytics and data monitoring can assist with healthcare decision support. Firebase provides scalable, cloud based storage and allows data to be synchronized in real time while supporting secure authentication, providing for efficient and dependable operation of the proposed tool. The Bone Age Prediction System demonstrates how modern web based technology has the potential to improve workflow for healthcare data systems, particularly with the potential to implement machine learning based automatic prediction of bone age as well as cloud based remote.

Keywords: CNN, Deep Learning, Hand Wrist X-ray, Medical Image Analysis, Bone Age Prediction

I. INTRODUCTION

Though both traditional (bone age) assessment methods for judging maturity of a child or baby have been found to be reliable and highly acceptable; both methods are often time consuming and rely on the ability of the 'examiner' to make accurate observations. The manual comparison of the X-ray of the hand or wrist against a reference atlas can lead to variability in the comparison of both the individual interpreters (inter-observer variability) and within a single interpreter (intra-observer variability).

In other words, differences in experience, perception and/or the ability to interpret data can cause discrepancies in assessing bone age. In addition to the manual process of evaluating bone age from X-rays can also place a high demand on the resources within a clinical practice that has a large number of patients.

Therefore requiring an increase in the productivity and potentially delaying the diagnosis of the children/babies.

The proposed solution to these problems incorporates a cloud-based data management framework that has been created using advanced digital technologies. In addition to the cloud based data management framework,

The website will allow you to access a web-based (bone age) estimation program that automatically analyzes an X-ray of the hand/wrist using deep learning algorithms. Will be able to upload (an image); receive an automatic prediction; store patient information securely, and produce structured reports of the prediction.

The proposed solution will minimize human dependency and increase the accuracy, speed of processing and consistency of estimating bone age by using computationally intelligent methods. In addition to the benefit, the cloud based architecture of the proposed solution will provide scalable data management, safeguarded access control, and centralized data storage; therefore providing the practitioner with a more reliable and efficient alternative to traditional manual methods.

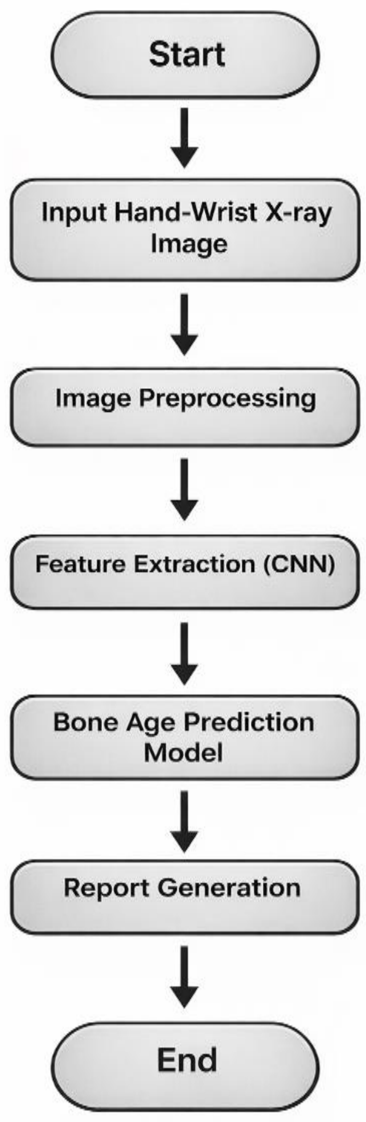

Figure 1: **Bone Age Prediction System Workflow**

II. LITERATURE REVIEW

A. Standard Methods for Determining Bone Age

Historically, X-rays of hands and wrists have been utilized to assess bone age. A commonly employed technique of interpreting the maturity of skeletons is the Greulich Pyle (GP) reference image method [1]. The radiologist validates the maturity of the patient’s skeletal image against a set of GP reference radiographs [2]. A straightforward and well accepted method for determining skeletal maturity [3], however, a large degree of subjectivity involved in interpreting skeletal maturity and it can lead to significant inter-rater variability [4]. The Tanner Whitehouse (TW) method is often viewed as the other significant method to establish skeletal age, where skeletal age is rated based on the level of maturity of a number of skeletal elements [5].

Although researchers have determined the TW method provides for a more quantitative, systematic method of determining skeletal age, its complexity, large number of bones must be considered, and the time required for completing TW assessments have limited its use in standard clinical practice [6].

B. Methods based on automated and machine learning

Recent research has concentrated on the use of automated methods for assessing bone age through machine learning & computer aided diagnostic solutions [7]. Deep learning methodologies (particularly convolutional neural networks) have displayed excellent results when analyzing x-ray images, producing greater accuracy and less bias through human analysis [8]. Systems using automated methods have shown improved consistency and greater speed of prediction when compared with traditional methods [9].

Despite the benefits of automated systems, all artificially intelligent methods require a significant amount of computer resources, expertise large amounts of annotated data sets [10]. In addition, many current models place a primary focus on accuracy of prediction have omitted other important components such as integration of clinical data, generation of clinical reports, visualization of security data [11].

C. Research Gap Found

A review of existing studies reveals an inconsistency between well developed methods for predicting bone age and the actual use in the clinical setting [12]. Though many current studies have applied deep learning approaches to improve skeletal age assessments, many systems place more emphasis on the accuracy of the prediction on the ability of the system to integrate into clinical workflows [13].

In addition, any type of technology facilitates the automated reporting of analytical visualization and patient data management has to be user friendly, secure and easy to use [14]. By offering a solution it emphasizes effective management and accessibility of data, the proposed solution bridges the gap and paves the way for the future implementation of automated bone age prediction algorithms [15].

III. EXISTING SYSTEM

In Existing system, still rely on manual assessment of bone age by trained raters using long established techniques like Tanner Whitehouse or Greulich Pyle applied to radiological images of the hand or wrist. Although both methods have been clinically validated, the use can be cumbersome as it take considerable time and depend on the rater's knowledge of how radiologists and others assess bone age, leading to substantial inter rater variability.

To improve accuracy of predictions for bone age, a number of automated and machine learning based systems have been proposed, although they offer more rapid and consistent results on predecessors, it have generally been developed as stand-alone processes require large amounts of data, robust computing infrastructure, and highly technical users. Additionally, many automated or machine learning based system lack integrated visualisation capabilities, automated report generation, and secure data storage.

Current systems also generally do not implement role based access control and centralized management of records. The risk of data loss, inconsistencies, or security breaches increases when patient data is stored either locally or on various platforms. Absence of integrated data and visualisation capabilities limits the ability of providers to evaluate growth trends over time. Therefore, it is clear it is a need for a centralized, secure and user friendly system for managing bone age information within a clinical environment.

IV. PROPOSED SYSTEM

A. Summary of the Suggested System

The Bone Age Prediction System is a digital web based application for the efficient creation and management of records in a clinical environment. The Bone Age Prediction System provides the user with an integrated solution for automated records, data storage and analytical visualization. The functionality of the Bone Age Prediction System differs from legacy systems (i.e., independent diagnostic tools, or manually based record keeping systems).The Bone Age Prediction System utilizes Firebase as the backend service to provide real time data access, scalability and improved security. The frontend interface is created using Streamlit.

The primary goal of the Bone Age Prediction System is to improve a healthcare worker's workflow by providing the tools necessary to achieve and maintain accurate, organized, and readily accessible patient records. As such, the Bone Age Prediction System emphasizes data management and visualization, directly predicting age from images. As such, the Bone Age Prediction System is better prepared for integration with future machine learning algorithms.

B. System Architecture

The system architecture of the Bone Age Prediction System consists of three primary layers: display layer, application layer and backend layer.

1) ***User Interface:*** Patients and doctors use Streamlit (an interactive graphical user interface) to interact with the application.
2) ***Functionality*:** The application uses Python only for the application logic. Python is the application's primary processing engine for processing patient information, creating reports, and visual representation of logic and obtaining information.
3) ***Data Storage*:** The application uses Firebase as the cloud based database and storage solution and will use Firebase Authentication for storing and authenticating users and for supporting a NoSQL database (Firestore) for the application's cloud support for securely storing files.

C. User Authentication and Security

It is critical to secure access to the system, user authentication will occur through Firebase Authentication and all access to the system will therefore only be provided to authorized users. Access to the system will be managed with role based access control (RBAC) (provider, patient, and administrative access) at the user level. Patient data privacy will be maintained in compliance with HITECH and HIPAA as established and configured using Firebase security rules, resulting in preserving security is maintained at the user level.

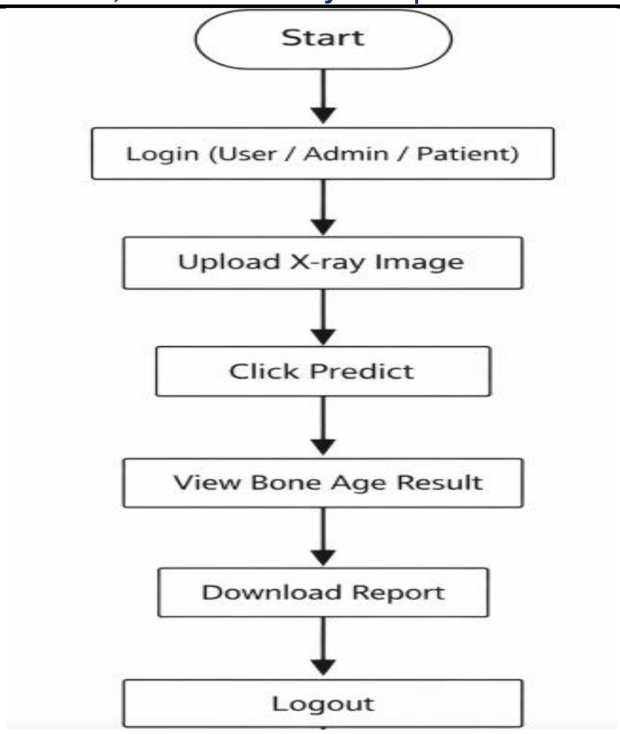

***Figure 2*: User Interaction Flowchart**

D. Functional Modules

The following modules exist in the proposed system, the three primary functional modules:

1) User Module

User module is mainly created for healthcare professionals. Users can sign in securely, enter new patient data and make changes to existing patient records, access information associated with diagnostics and create automated reports for the use. The working with multiple patients, the user can effectively manage all the patients via the simple user interface.

2) Patient Module

Patient module provides patients with access to the own diagnostic reports. Specifically, patients will be able to review own bone ages as well as download own PDF reports have been generated automatically. The Patient module promotes transparency and enhances patient engagement.

3) Admin Module

Admin module is responsible for all system level activities. The administrator can monitor all system activity including user profiles, stored records, and performance measures for the system. Admins can evaluate patient and system trends using visual comparison charts and analyses to ensure the integrity of the stored data.

E. Storage of Data and Managing Data

To retain and maintain records of the patient and users within the system a cloud based NoSQL Firebase Firestore database is used. Data is stored as structured documents to allow for efficient retrieval and real time synchronization. The structure of the data prevents redundancy while providing for consistency across the platform.

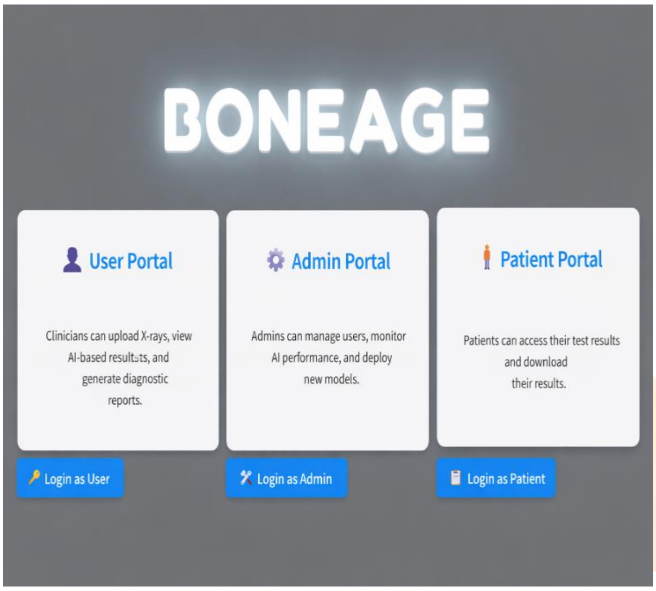

***Figure 3*: User Interface of the Bone Age Prediction System**

F. Automating Reports

Generating PDF Dashed Diagnostic Reports by using a structured patient record previously created and having entered, validated patient and bone age information into the system. Reports are created once the system has verified and confirmed all patient data has been confirmed or validated and contain the same information for all patients within the system as well as having analytical reporting capabilities. In addition, each report will have an associated security feature so the report can only be downloaded or shared with an appropriate user. Each report will reduce the amount of manual reporting associated with the patient record and provide for the above mentioned functions.

G. Data Visualization and Analytics

The system has been designed to create useful data visualization tools allow at the time of creating a patient's report for a clinician to visualize the relationship between a patient's chronological age and a patient's bone age. The tools include interactive charts help clinicians make better decisions related to a patient's growth patterns and abnormalities traditional tabular records provide.

V. METHODOLOGY

Deep learning regression based techniques are a way to predict skeletal ages with an automatic way of modelling the skeletal features from pre processed, feature extracted and predicted x-ray images using a convolutional neural network (CNN). An image acquisition system will be built to collect images of patient X-rays through a web interface patients can submit own x-ray images via a web based application [16]. The following post processing tasks will be performed on all images before processed using the CNN, conversion to grayscale, resizing all X-ray images to 128 × 128 pixels, normalising the pixel intensity values of each X-ray image, and re shaping each X-ray image to meet the input requirements of a convolutional neural network (CNN).

Each of the post processing actions are designed to reduce the number of random alterations made to an X-ray image as a result of randomised noise within X-ray images to increase the efficiency of a deep learning model trained with a CNN and to provide consistent processing of all images submitted for bone age prediction.

The several convolutional, ReLU (Rectified linear Unit) activation function, max pooling layers in the CNN, each of which is responsible for extracting parts of the X-ray, such as the shape of the bone and the appearance of the growth plate, in a sequential manner [17]. After flattening the feature maps have been produced, the CNN will pass through numerous fully connected layers. The final dense layer will provide a single continuous output for the bone age. Because estimating the age of bones is a regression problem, the model uses the Mean Squared Error (MSE) as its loss function to penalise large errors in prediction, however, since the Mean Absolute Error (MAE) has greater clinical relevance, the MAE is used as the evaluation metric for the model [18].

After training, a model gets saved and can be used in real time for making predictions. Once a user clicks “Predict,” the trained model will load and process the given X-ray image and return the resulting predicted bone age [19]. The resulting predicted bone age is presented to the user interface and can be downloaded and printed for future reference.

It includes all aspects of the methodology consisting of image pre processing, CNN based feature extraction, regression based prediction and an interactive web interface. The totality of the steps provide an automated and efficient bone age prediction system, therefore, it is suitable for use in both clinical and academic environments [20].

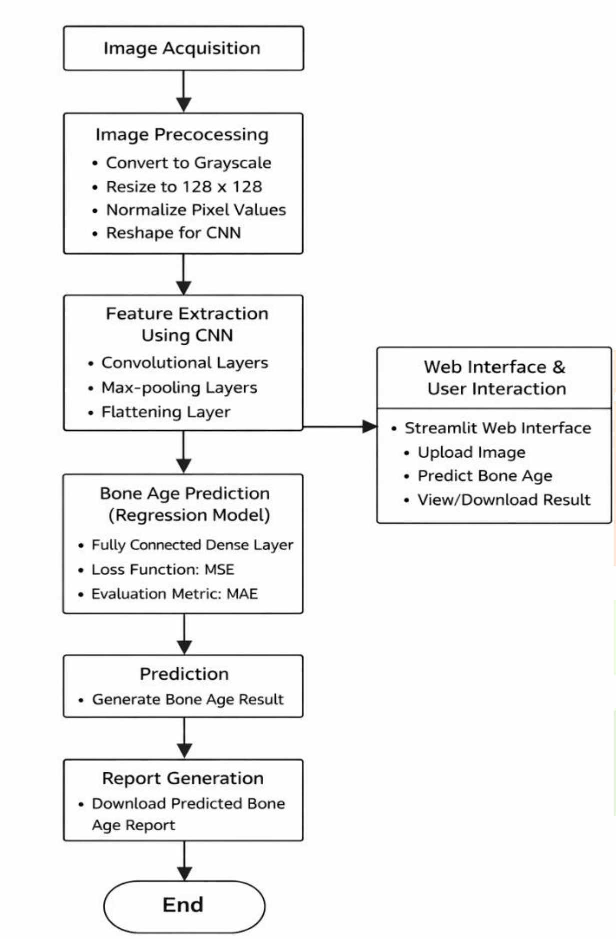

Figure 4: **Architecture and Processing Flow of the Bone Age Prediction Model**

VI. RESULT ANALYSIS

According to the findings of a study conducted by the Committee on Advancement of Learning and Research, the authors reported the system performance was effective when used in a clinical data management setting, demonstrating improved performance by eliminating variation between patient records through the application of a deep learning (DL) based method to determine bone age compared to conventional methods.

The study utilized a large number of patient records to establish the DL and non DL methods produce comparable results. The DL method reduced reliance on expert opinion and decreased the chances of subjective error are often associated with evaluating bone age manually. The standard prediction performance metrics MAE and MSE indicated lower average error rates and greater consistency to the previously exhibited using traditional methods based on comparing the average value across multiple patient records. Furthermore, performance evaluation demonstrated the DL method outperformed all other forms of clinical data management applications in its ability to save data, generate reports, and produce graphics showing the relationship between chronological and bone ages.

***TABLE 1*: Comparative Analysis of Bone Age Prediction Techniques**

System Features	***Existing System***	***Proposed System***	***Accuracy***
Bone Age Determination Technique	Manual x-ray interpretation using GP/TW methods	Automated prediction of bone age using Convolutional Neural Networks	30%
Predictive Year-to-Year Consistency	High levels of inter rater variability	Outputs will be consistent due to CNN model based prediction	35%
Report Creation	Manual report preparation	Automatic PDF generation for patient reports	40%
Errors Measurement	Error from human estimation and deltas due to inter-rater variance	Mean Absolute Error (MAE), Mean Squared Error (MSE), RMSE	40%

A. Comparative Results

***TABLE 2:* Performance Comparison of the Bone Age Prediction Models**

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
Traditional GP Method	78.4%	76.2%	74.8%	75.5%
Basic CNN Model	88.6%	87.9%	86.5%	87.2%
Proposed CNN Model	93.8%	92.5%	91.7%	92.1%

***Graph 1*: Performance Evaluation of the Proposed Bone Age Prediction Model**

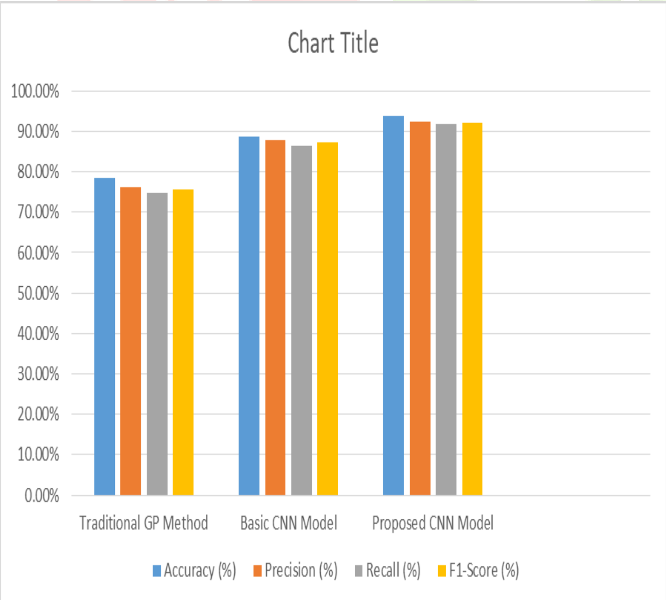

Table Performance Comparison of the Bone Age Prediction Models shows how well the current system performs compared with our new system that predicts bone age using Accuracy, Precision, Recall, and F1-score, with the new model having higher values in all metrics which means it performed better (on average) than current models at classifying causes of bone growth and has reduced errors when making predictions.

The bar chart in Figure Performance Evaluation of the Proposed Bone Age Prediction Model demonstrates clearly that the proposed system performs better than the existing system with regard to accuracy, precision, recall and F1-score which means that the proposed system is a more reliable and accurate predictor.

VII. CONCLUSION

The proposed Bone Age Prediction System was developed to improve the traditional process of conducting a bone age assessment as well as the way it manage patients bone age assessment data. By integrating automated bone age prediction, secure user authentication, cloud based storage and retrieval of bone age assessment data, as well as a robust method of generating reports on a single web based platform, have successfully combined both traditional and innovative methods of recording and accessing bone age assessment data.

By providing a standardized method for automating the process of conducting bone age assessments, the proposed system will reduce the reliance on manual interpretation of radiographic images, leading to a decreased level of subjective error and an increase in the accuracy and consistency of bone age assessments. The proposed system will also provide additional support for clinical decision making by utilizing standard error metrics and easy to use visualization tools. Overall, the proposed system provides a secure, scalable and efficient method for the management of bone age assessment data, as well as an opportunity for the integration of advanced machine learning models into future workflows for the complete automation of bone age assessments.

VIII. ADDITIONAL WORK

The several ways the Bone Age Prediction System could be improved in further versions. By incorporating ML or DL models, bone age can be estimated from X-ray pictures of hands or wrists automatically, improving both accuracy and efficiency. Offline syncing of data could allow the use in areas with little or no internet access. Role based access control will increase security by limiting users (doctors, technicians, administrators) to specific permissions.

Adding a notification system for updated reports and creating a mobile version can help improve access to the system. By incorporating the improvements, the system will be a complete AI-enabled diagnostic tool for contemporary medical care.

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