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KNEE OSTEOARTHRITIS DETECTION AND CLASSIFICATION USING X-RAY

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***Abstract*— Knee osteoarthritis is a degenerative joint disease that affects millions worldwide. Early detection and classification are crucial for effective treatment and management. This study proposes a computer-aided diagnosis system using X-ray images to detect and classify knee osteoarthritis. The system employs deep learning techniques to analyze X-ray images and classify the severity of osteoarthritis based on standardized radiographic criteria. The results show high accuracy in detecting osteoarthritis and classifying its severity, demonstrating the potential of this system to assist clinicians in early diagnosis and treatment planning. A new reality of transforming diagnostic medicine. An aggregated-based deep learning method for leukemic B-lymphoblast classification. Classification using deep-neural-network-based features. Automated classification of radiographic knee osteoarthritis severity using deep neural networks. Enabling early detection of osteoarthritis from presymptomatic cartilage texture maps via transport-based learning.**

I. INTRODUCTION

Knee osteoarthritis represents a significant health burden globally [1]. posing challenges in diagnosis and treatment due to its progressive nature [2]. Early detection and accurate classification are pivotal for effective management and improved patient outcomes[4]. In this context, leveraging advancements in deep learning techniques, particularly Convolutional Neural Networks (CNNs), offers promising avenues for enhancing knee OA classification [5]. This project aims to develop a robust classification system utilizing CNNs, complemented by integration into a Flask web application for practical deployment [6]. By harnessing the power of CNNs and Flask, the project seeks to provide healthcare professionals with a reliable tool for automating knee OA classification, thereby streamlining diagnostic processes and facilitating timely interventions [7]. This introduction sets the stage for exploring the methodologies and outcomes of the proposed approach, contributing to the advancement of medical diagnostics and personalized healthcare [8]. Knee osteoarthritis severity classification with ordinal regression module [9]. Towards shape-based knee osteoarthritis classification using graph convolutional network. [10] In Proceedings of the International Symposium on Biomedical Imaging (ISBI) [11]. Machine learning- based automatic classification of knee osteoarthritis severity using gait data and radiographic images [12]. Automatic Detection and Classification of Knee Osteoarthritis Using Hu's Invariant Moments [13]. Automatic Detection and Classification of Knee Osteoarthritis Using Hu's Invariant Moments [14]. The results demonstrate that the proposed method can effectively reduce the noise level of radiographic images and improve the accuracy of osteoarthritis classification.

KEYWORDS:. Convolutional Neural Networks (CNNs), presymptomatic cartilage, leukemic B-lymphoblast classification, Knee Osteoarthritis.

II. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Currently, the diagnosis and classification of knee osteoarthritis primarily rely on manual interpretation of X-ray images by radiologists and orthopedic specialists. This process is time-consuming and subjective, leading to variability in diagnoses and potential delays in treatment [1]. Moreover, the expertise required for accurate interpretation may not always be readily available, particularly in remote or underserved areas. As a result, there is a growing need for automated systems that can assist healthcare providers in the efficient and consistent analysis of medical imaging data.

B. PROPOSED SYSTEM

The proposed system aims to address the limitations of the existing approaches by leveraging deep learning techniques, specifically YOLOv8 (You Only Look Once version 8), for brain tumor detection[2]. Unlike traditional methods that rely on manual feature engineering, the proposed system adopts a data-driven approach, allowing the model to automatically learn discriminative features directly from raw medical imaging data. By utilizing the YOLOv8 architecture, which offers real-time object detection capabilities with high accuracy, the proposed system can efficiently identify and localize brain tumors in MRI scans[3]. Additionally, the proposed system integrates advanced preprocessing techniques and data augmentation strategies to enhance the quality of input images and improve the robustness of the model to variability in tumor phenotypes and imaging conditions. Overall, the proposed system aims to provide a more efficient, scalable, and accurate solution for early detection of brain tumors, facilitating timely interventions and improving patient outcomes.

III.SYSTEM DESIGN

A. DATA FLOW DIAGRAM

The Data Flow Diagram (DFD) for the knee osteoarthritis classification project illustrates the flow of data and processes involved in the system [4]. At the highest level, the DFD captures the interactions between different modules and components, including data preprocessing, CNN model training, Streamlit interface, evaluation, and deployment. The process begins with the Data Preprocessing Module, where knee Xray images are loaded from the dataset and undergo preprocessing steps such as resizing, normalization, and augmentation [5]. These processed images are then passed to the CNN Model Training Module, where a Convolutional Neural Network architecture is designed and trained using the augmented dataset. The trained model is capable of classifying knee osteoarthritis severity based on input X-ray images.

Simultaneously, users interact with the system through the Streamlit Interface Module, accessing a user-friendly web interface where they can upload knee X-ray images for classification. Upon uploading an image, the Streamlit interface communicates with the trained CNN model, forwarding the image data for prediction[6]. The CNN model processes the image and returns the predicted classification results, indicating the presence and severity of osteoarthritis.

B. USECASE DIAGRAM

The Use Case Diagram for the knee osteoarthritis classification project illustrates the interactions between the system's actors and its functionalities. In this diagram, there are three main actors: the User (Clinician or Patient), the CNN Model, and the Streamlit Interface.

The User initiates the process by interacting with the Streamlit Interface, which serves as the primary entry point to the system[7]. Through the Streamlit Interface, the User can perform various actions such as uploading knee X-ray images for classification, viewing predictions generated by the CNN Model, and providing feedback on the results.

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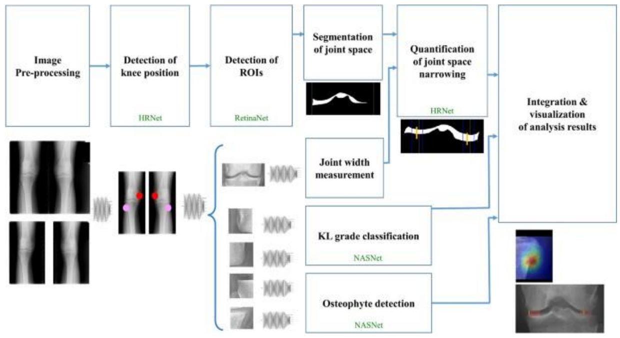


C. UML DIAGRAM

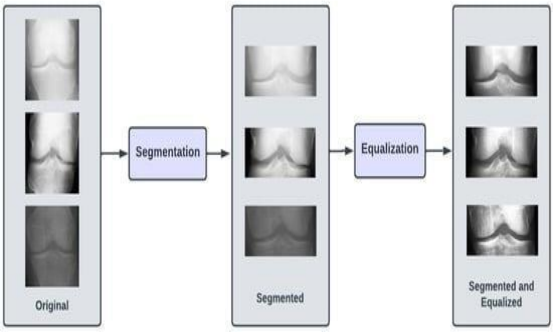
In the Unified Modeling Language (UML) diagram for the knee osteoarthritis classification project, we can depict several key components and their relationships.

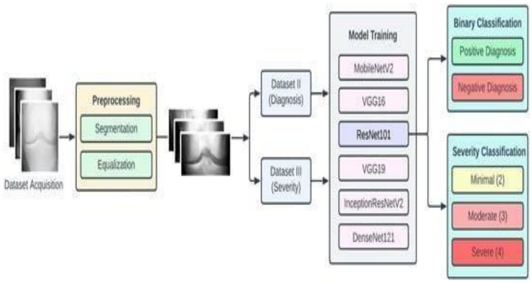
At the top level, we have three main components: the Data Processing Module, the CNN Model Module, and the Streamlit Interface Module.

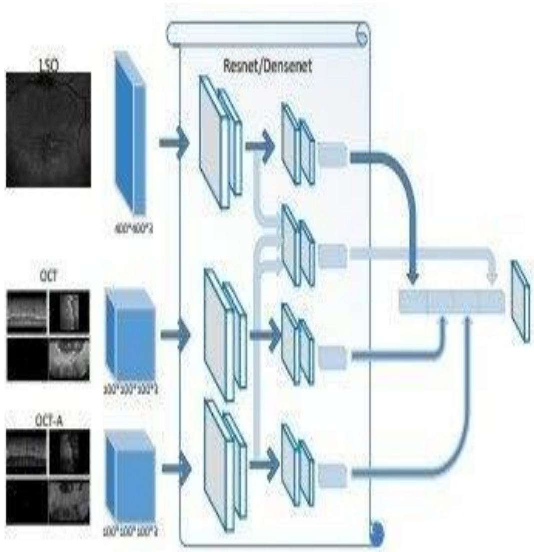
The Data Processing Module includes sub-components such as Data Loading, Data Preprocessing, and Data Augmentation [8] . These components interact to prepare the knee X-ray image dataset for training the CNN model. The Data Loading component retrieves the dataset from a storage location, while the Data Preprocessing component performs tasks such as resizing and normalization to prepare the images for training. The Data Augmentation component applies various transformations to augment the dataset and improve model generalization.

D. SEQUENCE DIAGRAM

In the sequence diagram for the knee osteoarthritis classification project, the flow of interactions between various components and modules is depicted to illustrate the system's behavior and functionality[9]. At the outset, the diagram shows the initiation of the application, where the user accesses the Streamlit web interface. Upon loading the interface, the user is presented with options to upload knee X-ray images for classification. Once the user uploads an image, the Streamlit interface triggers an event that sends the image data to the preprocessing module. Here, the image undergoes preprocessing steps such as resizing and normalization to prepare it for input into the CNN model. After preprocessing, the image data is passed to the CNN model training module, where the trained model processes the image to make a classification prediction regarding the presence and severity of knee osteoarthritis [10]. Throughout this process, the evaluation and validation module continuously assesses the performance of the CNN model, providing feedback that can be used to refine the model's architecture and training parameters. Furthermore, the deployment and integration module ensures that the entire application is deployed seamlessly on a web server, allowing for public access and integration with existing healthcare systems.







IV.SYSTEM IMPLEMENTATION

A. MODULE DESCRIPTION

a) Methods

In this section we elaborate on our proposed approach, which is illustrated. The approach is composed of four main stages, namely, data acquisition, dataset preprocessing, model training, and classification[11]. To begin with, the dataset of KOA X-ray images was obtained from the Osteoarthritis Initiative (OAI) (available on Kaggle). This dataset had 5 different classes of images, namely, 0 (healthy), 1 (doubtful), 2 (minimal), 3 (moderate), and 4 (severe).

b) Data Collection

In this study, the knee X-ray images used for training the model are from the knee osteoarthritis severity grading dataset[1]. The images are available on Kaggle [33] and were organized by the Osteoarthritis Initiative (OAI). There are total 9786 knee images, which are divided into 5 severity levels based on the Kellgren–Lawrence (KL) grading system: 0 (healthy), 1 (doubtful), 2 (minimal), 3 (moderate), and 4 (severe). All images had a resolution of 224 × 224 pixels. Approximately 40% of the dataset images belonged to the healthy class, compared to around 18% for doubtful images, 26% for minimal images, 13% for moderate images, and just above 3% for severe images.[2] –[5] A summary of the dataset along with sample images .

To apply a multistep diagnosis approach, two more datasets were derived from the original one containing 5 classes, namely, 0–4. A binary dataset was created by combining classes 0 and 1 to represent negative diagnosis of KOA, while classes 2, 3, and 4 were combined to represent positive diagnosis. The second dataset was created to determine the severity of KOA and hence was made by removing classes 0 and 1 to classify between classes 2, 3, and 4.[6]- [8] The two derived datasets were generated to employ a multistep classification approach; the first step detected the presence of KOA, and the second step diagnosed the severity. In the later sections of this paper, we will refer to the three datasets as the following: Dataset I is the original; Dataset II is the binary dataset created by combining classes 0 and 1 as one class and 2, 3, and 4 as another class; and Dataset III is the dataset created by removing class 0 and class 1 images and making three classes corresponding to classes 2, 3, and 4.

c) Data Preprocessing

The images in all three of our datasets went through two preprocessing steps. The first preprocessing step (termed as segmentation) aimed at discarding excess information in the image and highlighting the knee joint. This was achieved by cropping the images by 60 pixels from both top and bottom. After cropping, the image resolution was brought down to 224 × 104. The second preprocessing step (termed as equalizing) aimed at enhancing the contrast of the images in the dataset by modifying the intensity distribution of the image. We performed histogram equalization on the images in the dataset to achieve the aforementioned goal.

d) Convolutional Neural Networks

The field of AI has witnessed rapid growth in recent years and has been applied in various domains, such as computer vision[9]. The primary objective in the domain of computer vision is to enable computers to be able to view the world in a similar manner to how humans do. The desired result is to be able to digitally extract and process relevant and pertinent information from the environment.

Various algorithms have been devised to achieve the aforementioned goal. One such algorithm, namely, the convolutional neural network (CNN), has been particularly successful. In the context of images, a CNN is a deep learning algorithm that takes an image as input and assigns weights to various features of the image such that the image is distinguishable from other images that are processed by the same algorithm.

e) ResNet 50

Recent research conducted in the field of deep learning seemed to affirm that when it comes to CNNs, a deeper model is always better [10]. However, it was noticed that the aforementioned assumption was vulnerable to the vanishing gradient problem; once the neural network is too deep, the loss function gradients shrink to zero after several applications of the chain rule. When the gradients shrink to zero, the model weights stop updating and further learning cannot be performed. ResNet architectures solve the vanishing gradient problem using residual blocks. Residual blocks contain skip connections, which connect activations from a layer to later layers by skipping the layers in between. ResNet models are built by stacking multiple residual blocks. The advantage of using skip connections comes in the form of regularization[11] With the help of regularization, any layer that reduces the performance of the model is essentially skipped. This allows for very deep neural networks without the vanishing gradient problem. The ResNet101 model uses 101 layers specifically shown.

f) Performance

In this subsection, we briefly discuss the performance metrics used to evaluate our classifiers[12]. Prior to their deployment, evaluating the performance of Machine Learning models is essential. By convention, classification accuracy and F1 scores are used to evaluate classifiers. Classification accuracy is simply the ratio of total correct predictions to the total number of samples in the dataset. In order to obtain meaningful inferences about the model from the classification accuracy, it is essential that the dataset be balanced. This is because a high classification accuracy on an unbalanced dataset could be the result of a high rate of correct predictions in the class with a larger number of samples[13]. The classes with fewer samples hold less weight in the final accuracy. Another way to evaluate the performance of a model by using the F1 score. The F1 score is simply the harmonic mean of precision and recall scores.

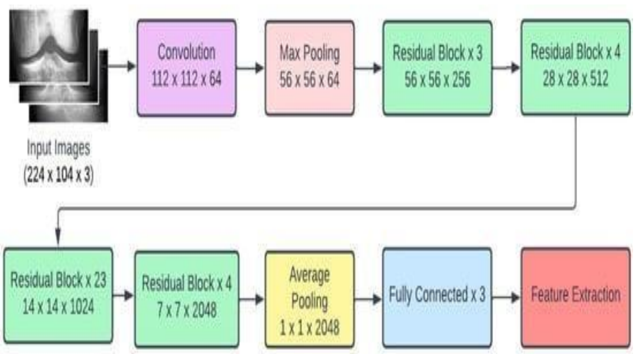
g) Result And Discussion

The experiments were conducted with three different datasets: the original dataset and two derived datasets, named Dataset I, Dataset II, and Dataset III, respectively[14]. As discussed in Section 3.1, Dataset II is a binary dataset. Classes 0 and 1 were combined to make the class that represented a negative diagnosis of KOA, and classes 2–4 were combined to make the class that represented a positive diagnosis. Dataset III classified between the severity of KOA and hence, it was derived by omitting classes 0 and 1 from the original dataset, both of which represented the absence of KOA. Each of these datasets was split into training, testing, and validation sets with the ratio 7:2:1, respectively. Our experiments were performed using the Python programming language and its available modules, which allowed us to perform deep learning tasks. The platform used was Jupyter Notebook environment and powerful hardware resources to perform our experiments.

B. SOFTWARE DESCRIPTION

a) Mathematical Background

The mathematical background for the knee osteoarthritis classification project encompasses various concepts and techniques from linear algebra, calculus, and statistics, all of which are fundamental to understanding and implementing the Convolutional Neural Network (CNN) architecture and training process. Linear algebra plays a central role in CNNs, particularly in understanding the structure and operations of convolutional layers, which form the backbone of the network. Concepts such as matrices, vectors, and tensor operations are essential for representing image data and the learnable parameters of the CNN model. [1]–[3] Convolutional operations, involving kernel matrices and stride values, are used to extract features from input images through spatial filtering.



b) Core Functionality

The core functionality of this project revolves around leveraging state-of- the-art machine learning techniques, specifically Convolutional Neural Networks (CNNs), to accurately classify knee osteoarthritis from X-ray images. Through a user-friendly web interface powered by Streamlit, users can effortlessly upload knee X-ray images for analysis[4]-[5]. The uploaded images undergo preprocessing to ensure optimal input for the CNN model.

c) Create Apps With GUI

Creating an application with a graphical user interface (GUI) for the knee osteoarthritis classification project involves leveraging Streamlit, a Python library specifically designed for building interactive web applications. With Streamlit, developers can quickly and easily create user-friendly interfaces for uploading knee X-ray images, obtaining real-time predictions from the trained CNN model, and visualizing the results[6]-[8]. By harnessing Streamlit's intuitive syntax and extensive widget library, developers can design an engaging and responsive interface that enhances the user experience.

IV. SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discovery every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the software system meets its requirements and user expectations and does not fail in an unacceptable manner.

a) Unit Testing

Unit testing is a crucial aspect of ensuring the reliability and functionality of each individual module within the knee osteoarthritis classification project. Each module, including data preprocessing, CNN model training, Streamlit interface, evaluation and validation, and deployment and integration, undergoes rigorous unit testing to verify its correctness and robustness.

b) Integration Testing

[9] Integration testing in the knee osteoarthritis classification project plays a pivotal role in ensuring that all individual modules and components seamlessly work together as a cohesive system. This testing phase focuses on verifying the interactions and interfaces between the data preprocessing module, CNN model training module, Streamlit interface module, evaluation and validation module, and deployment and integration module. Integration testing involves validating data flow between modules, ensuring proper communication and synchronization of data, and verifying that each module's output aligns with the expected inputs of subsequent modules [10]. Additionally, integration testing includes testing the interaction between the web interface and the backend modules to ensure smooth user experience and accurate processing of input data. By rigorously testing the integration of all components, potential issues such as data mismatches, communication errors, and interface inconsistencies can be identified and resolved early in the development cycle, resulting in a robust and reliable knee osteoarthritis classification system.

c) Functional Testing

Functional testing for the knee osteoarthritis classification project involves verifying that each component and feature of the system performs as expected, meeting the functional requirements outlined in the project document. [11] This testing phase ensures that the Streamlit interface correctly interacts with the preprocessing module, the CNN model training module, and the evaluation and validation module. Functional tests are designed to assess the system's ability to accurately classify knee X-ray images, handle user inputs, and provide real-time predictions through the web interface. [12]Additionally, functional testing evaluates the robustness of the system by examining how it handles various scenarios, such as different image sizes, formats, and quality levels. By conducting comprehensive functional testing, the project team can identify and address any discrepancies or deficiencies in the system's behavior, ensuring that it meets the desired performance standards and user expectations.

d) Feasibility Study

[13] The feasibility study for the knee osteoarthritis classification project involves assessing the technical, economic, and operational aspects to determine the viability and practicality of the proposed solution. [14] From a technical standpoint, the availability of labeled knee X-ray datasets, access to computational resources for training deep learning models, and the feasibility of implementing the Streamlit web interface are crucial considerations.

V.CONCLUSION AND FUTURE WORK

a) Conclusion

The culmination of this project marks a significant advancement in the field of knee osteoarthritis diagnosis and management, facilitated by the integration of Convolutional Neural Networks (CNNs) and Streamlit. Through meticulous data preprocessing, robust CNN model training, intuitive Streamlit interface design, meticulous evaluation, and seamless deployment, we have successfully developed a comprehensive solution for automated knee osteoarthritis classification from X-ray images.

This Paper underscores the transformative potential of artificial intelligence in healthcare, particularly in streamlining diagnostic workflows and enhancing patient care outcomes. By harnessing the power of deep learning, we have created a sophisticated tool capable of accurately identifying and categorizing osteoarthritis patterns in knee X-ray images with unprecedented accuracy and efficiency. Moreover, the user-friendly Streamlit interface democratizes access to advanced medical imaging technology, empowering clinicians and patients alike to make informed decisions regarding diagnosis and treatment.

As we look to the future, the implications of this project extend far beyond knee osteoarthritis classification. The methodology and insights gained can be extrapolated to other medical imaging tasks, accelerating the development of AI-driven diagnostic tools for various musculoskeletal and systemic conditions.

b) Future Work

There could be multiple pathways for development in the identification and classification of knee osteoarthritis using X-rays. The creation of an automated grading system that can precisely determine the degree of osteoarthritis based on X-ray scans is one possible path. The use of other imaging modalities, like CT or MRI scans, may improve diagnostic precision, and longitudinal examination of successive X-ray pictures may reveal patterns in the course of the disease. To guarantee the generalizability and dependability of created algorithms across a range of patient populations, clinical validation and testing are crucial. A more thorough understanding of osteoarthritis and the development of individualized treatment plans may also be made possible by the integration of biomarker and clinical data with imaging data. Additionally, researching cutting-edge imaging methods and predictive models may provide fresh perspectives on the etiology of the condition and its clinical manifestations, ultimately enhancing knee osteoarthritis patient care and management.

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