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Detection and Classification of Arthritis Severity based on Kellgren-Lawrence grading Using CNN models

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ABSTRACT
In adults, both Rheumatoid Arthritis (RA) and Knee Osteoarthritis (KOA) can result in joint pain and functional restrictions. While RA can affect anyone of any age, KOA primarily affects the elderly population. Using diverse imaging and clinical data, efforts have been made in recent years to create automated classification models for both KOA and RA. For instance, utilizing data from radiographic imaging and gait analysis, a study established an automated classification model based on the Kellgren-Lawrence (KL) grading system for KOA. The algorithm obtained great accuracy in multi-class Knee Osteoarthritis classification by using gait data and radiographic image features collected from a deep learning network. Similar to this, automated diagnostic models for Rheumatoid Arthritis have been developed using a variety of imaging modalities, including magnetic resonance imaging (MRI) and ultrasound. In terms of correctly diagnosing Rheumatoid Arthritis and forecasting the course of the disease, these models have produced encouraging results. Overall, the creation of automated diagnostic models for Knee Osteoarthritis and Rheumatoid Arthritis based on various imaging and clinical data holds great promise for increasing the precision and effectiveness of these diagnoses as well and facilitating prompt interventions to enhance patient quality of life.

Keywords: Deep Learning, CNN, Knee Osteoarthritis, Rheumatoid Arthritis, Kellgren Lawrence Grading Scale

I. INTRODUCTION

One particularly prevalent kind of osteoarthritis (OA), which is a debilitating condition that disproportionately affects the elderly population, is knee osteoarthritis (KOA). In the world, OA is estimated to affect 30% of people over 60, and the cost of treating OA-related conditions is estimated to be 1% to 2% of the global GDP[1-3].As the population ages, more people are anticipated to have KOA, which can significantly affect functional independence and quality of life due to joint range of motion and gait dysfunctions[4-6]. As the population ages, more people are anticipated to have KOA, which can significantly affect functional independence and quality of life due to joint range of motion and gait dysfunctions[4-6]. The Kellgren-Lawrence grading system is currently the standard for radiographic evaluation of KOA. However, the analysis of radiographic images based on the presence of sclerosis, osteophytes, bone deformities, and joint space narrowing is a time-consuming, highly specialized process that necessitates the assistance of qualified experts[7,8].In order to help clinicians provide rapid and accurate diagnoses, there is a need for more efficient and automated diagnostic approaches [10].

Rheumatoid arthritis is a chronic inflammatory disease that damages joints as well as body tissue. An effective system analysis is needed to recognize and detect rheumatoid arthritis by hand, especially in the early phases of development or pre-diagnostic stages. The purpose of this study is to develop a convolutional neural network and image processing techniques an intelligent system that can identify hand rheumatoid arthritis. The system contains two essential phases. The image processing phase is the first step in using image processing to process images. Some of these techniques include preprocessing, image segmentation, and feature extraction with the Gabor filter. In the second stage, the neural convolution network recognizes the hand images as normal using the extracted features as inputs. For classification, the CNN algorithm is employed, and images of both normal and abnormal hands are used to train the network. The system was tested using the same number of images as the testing set, and the investigation's findings showed an 83.5% recognition rate.

T. Chau[1] as proposed a review of gait data analysis methods. Statistical, fractal, and fuzzy approaches as numerous novel methods for analysing gait data have been investigated in recent years, including fuzzy systems, multivariate statistical methods, and fractal dynamics. This paper analyses the potential of these techniques to bolster the gait laboratory's analytical toolkit through a critical analysis of current gait investigations. It has been discovered that traditional multivariate statistical techniques are the most extensively used and comprehended. The entire potential of fuzzy and fractal analysis of gait data has not yet been fully realized, despite initial promise. Further study into the application of these two methods will help gait data analysis because of the tendency to combine multiple techniques in an analysis.

Elango Natarajan [2] A chronic, destructive condition known as rheumatoid arthritis (RA) affects and destroys the joints of the wrist, finger, and feet. One may lose the capacity to lead a typical life if mistreated. RA, which affects about 1% to 2% of the population, is the most common kind of inflammatory joint pain. Soft computing has played a significant role in aiding disease analysis in doctors' decision-making over the years. This study's primary goal is to look at the viability of using machine-learning methods to analyze RA characteristics. A reliable database has been found to be used for this research as a preliminary effort. The database contains array temperature measurements for the hand joints obtained via thermal imaging. Additionally, this database, which has 32 instances and 8 attributes, is used to assess the accuracy of performance for categorizing various algorithms.

J. Antony[3] as proposed Deep convolution neural networks for assessing the severity of the radiographic signs of knee osteoarthritis as Osteoarthritis (OA) is mostly brought on by damage to the cartilage's protecting tissue at its ends. It might happen in the hands, neck, lower back, knees, or hip joints. We suggest a technique for exploiting X-ray pictures to detect osteoarthritis in knee joints. The suggested method entails picture augmentation utilizing contrast- restricted adaptive histogram equalization, then locating the central portion of the synovial cavity region, which is present between the upper and lower knee bones.

II. METHODS AND MATERIAL

The architecture of our model is as below

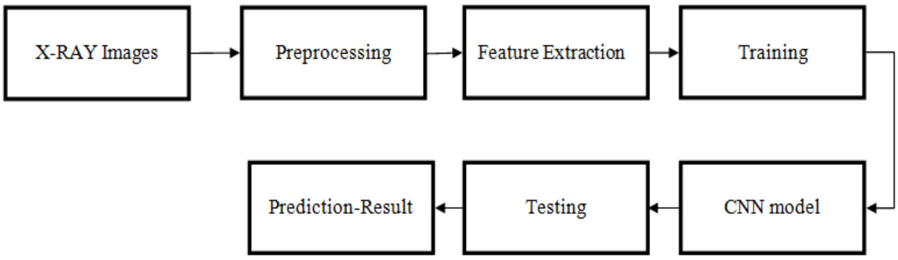

Fig.1 System Architecture

Artificial intelligence has made significant progress in recent years in bridging the gap between people and robots. Both academics and hobbists work on many facets of the topic to enable remarkable things and the field of computer vision is one such component. Through the use of the knowledge, they learn from seeing the world as humans do, this field aims to make it possible for machines to identify images and videos, categorize images, and recommend media. Convolution neural networks have been the subject of substantial research, leading to improvements in computer vision with deep learning.

CNN requires less preparation than other classification methods and has the capacity to learn features/characteristics. We created a straightforward CNN model that consisted of three convolution blocks. A convolution layer, a max- pooling layer, and a batch normalization layer make up a convolution block. Rectified Linear Activation Unit (Re Lu) activation. A second convolution layer immediately follows two convolution blocks with 64 filters. The two- dimensional arrays are flattened to create a single linear vector. Every neuron in a layer is connected to every other neuron in the layer above it, which is the definition of a layer with dense connections. The linear vector and dense layer with 128 units activation functions are used. We specify a number between 0 and 1 to randomly turn off the neurons in order to avoid the model from over fitting on training data. To indicate the output vector's dimensions, an additional dense layer of 1 unit is added. To provide binary output, the sigmoid activation function is used.

MobileNetV2: The following generation of mobile vision applications will be powered by MobileNetV2. In terms of classification, object detection, and semantic segmentation, MobileNetV2 advances the state-of-the-art for mobile visual recognition. It is a major improvement over MobileNetV1.TensorFlow-Slim Image Classification Library now includes MobileNetV2, or you may immediately begin using MobileNetV2 in Collaborator. You may also download the notebook and use Jupiter to explore it locally. Pretrained checkpoints can be found on GitHub, and MobileNetV2 is also accessible as modules on TF-Hub.

InceptionV3: The major goal of Inception v3 is to consume less computing power by altering the Inception architectures from earlier versions. Rethinking the Inception Architecture for Computer Vision, a 2015 article, made this suggestion. Christian Szeged, Vincent Vanhoucke, Sergey Ioffe, and Jonathon Shlens all contributed to its creation. Inception Networks (Google Net/Inception v1) have demonstrated to be more computationally efficient than VGGNet, both in terms of the amount of parameters created by the network and the economical cost (memory and other resources) incurred. It is important to take care not to lose the computational benefits while making changes to an Inception Network. Due to the unknown effectiveness of the new network, it becomes difficult to modify an Inception network for various use cases.

ResNet 50: ResNet-50's usage of residual blocks, which enables the network to have a lot of depth (up to 50 layers) while still performing well, is one of its primary advantages. The input and output of a residual block are combined, allowing the network to learn residual mappings rather than entire mappings. As a result, the gradient can pass right through the block, making it easier to train the network. To extract features from images, ResNet-50 also combines convolutional layers, pooling layers, and fully connected layers.

VGG 16/19: The VGG model, or VGGNet, supports 16/19 layers is also referred to as VGG16/19 CNN model.VGG16 consists of 13 convolutional layers and 3 fully connected layers. The architecture of VGG16 consists of input, convolutional layer, hidden layer and fully connected layers.

Kellgren-Lawrence Grading Scale

[5-7]Based on radiographic images, the Kellgren-Lawrence grading scale is a popular categorization system for determining the severity of osteoarthritis (OA). Dr. John Kellgren and Philip Lawrence created it in 1957, and since then it has grown to be one of the most widely used grade systems for Osteoarthritis assessment in clinical research and practice.

The degree of joint space narrowing, the presence of osteophytes (bone spurs), subchondral sclerosis (hardening of the bone beneath the cartilage), and the existence of bone abnormalities are based on the Kellgren-Lawrence grading system, which has a scale from 0 to 4.

Brief overview of the grades is as below:

- Grade 0: No signs of OA
- Grade 1: Possible osteophytes and/or a slight narrowing of the joint space
- Grade 2: Definite osteophytes and a moderate narrowing of the joint space
- Grade 3: Moderate to severe joint space narrowing, multiple osteophytes, and the possibility of sclerosis
- Grade 4: Severe joint space narrowing, large osteophytes, and marked sclerosis.

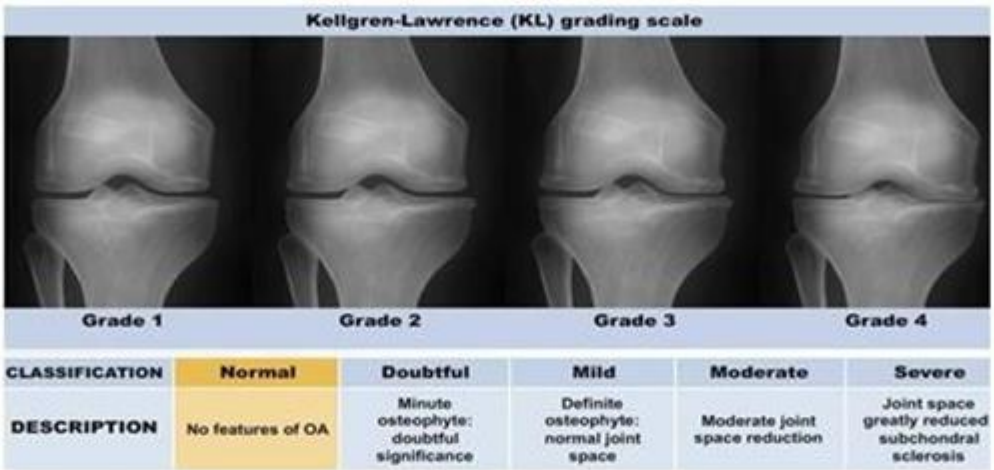

Fig. 2 Kellgren-Lawrence (Kl) Grading Scale

Fig. 3 Different Grades of Rheumatoid Arthritis

III. RESULTS AND DISCUSSION

The outcomes of this project illustrates how well pre-trained models for image processing and machine learning techniques can detect osteoarthritis and rheumatoid arthritis in X-ray pictures. The project tested the effectiveness of three well-known CNN models—MobileNetV2, InceptionV3, ResNet50 and VGG19—in identifying the presence of arthritis in X-ray pictures.

Machine learning methods were used to determine the models' accuracy ratings, and the results were displayed graphically. The MobileNetV2 model, followed by InceptionV3, ResNet50 and VGG19 had the greatest accuracy score (94.12%).

These findings show the potential of machine learning methods for osteoarthritis and rheumatoid arthritis early detection and diagnosis, which can significantly enhance patient outcomes. Additionally, the graphical display of the results offers a simple and informative way to present the performance of various models, which can aid healthcare providers in their decision-making processes. Overall, this project emphasizes the importance of combining image processing and machine learning approaches in the area of medical diagnostics and emphasizes the necessity of ongoing research in this field to further improve the precision and efficacy of arthritis diagnosis.

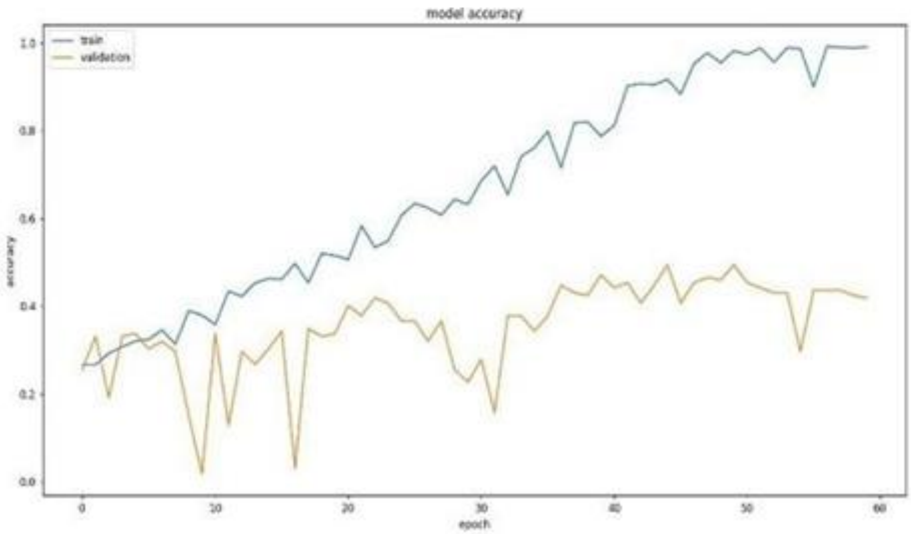

Fig. 4 Test and Train Accuracy

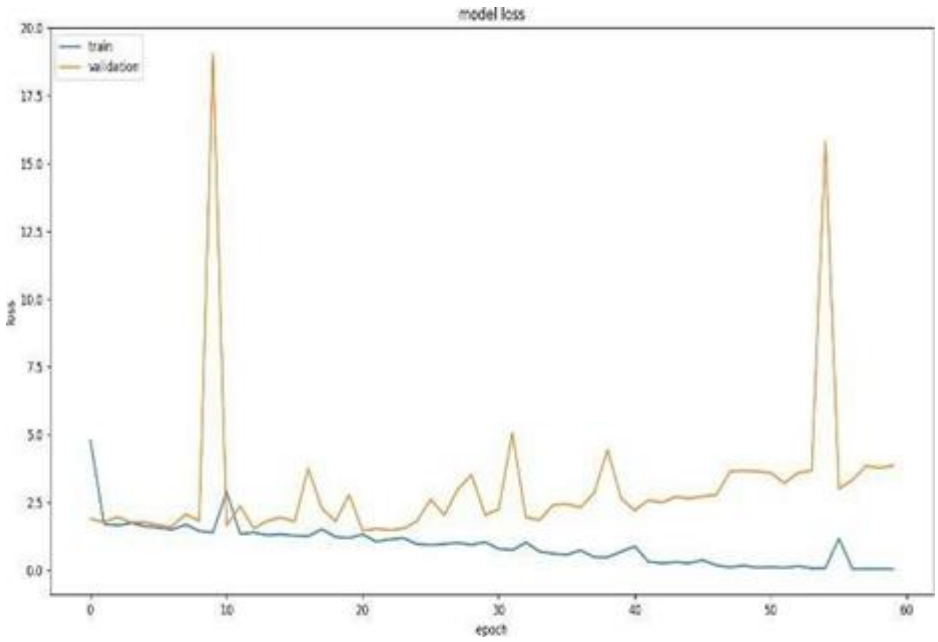

Fig. 5 Test and Train Loss

Fig 4 & Fig 5 depicts test and train accuracy & test and train loss.
The performance comparison of CNN models- Mobilenetv2, Inceptionv3, and Resnet50 is plotted Using line Graph refer Fig.5.

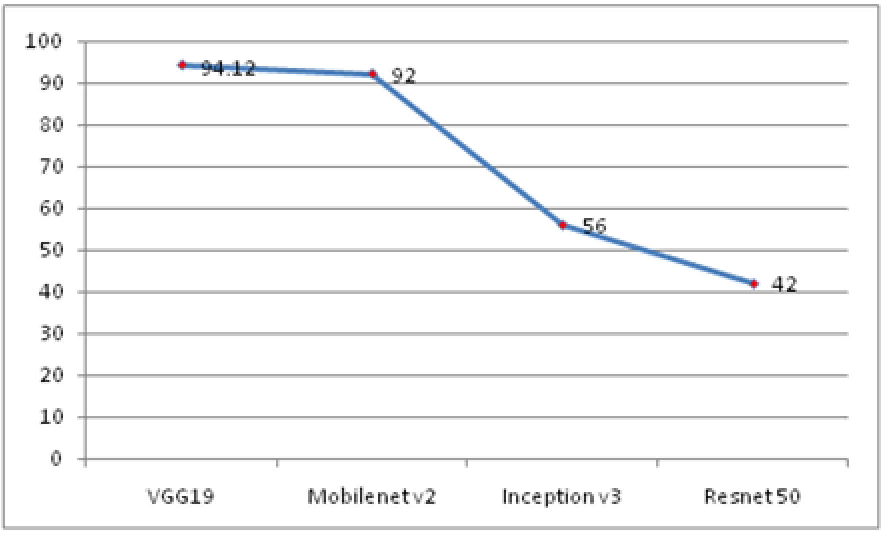

Fig. 6 Performance comparison of CNN Models-Mobilenetv2, Inceptionv3, and Resnet50 Using Line Graphs

IV. CONCLUSION

The availability of biological image capturing and storage equipment enables research that is based on in-depth analysis of huge biological image pipelines. However, despite the growing significance of image analysis in biological experiments, machine vision algorithms are typically created by specialists in pattern recognition and signal processing, and biologists frequently lack the resources and expertise to create these algorithms and software tools. Here, we describe a tool that experimental biologists can use and that has been demonstrated to work well for several real biological investigations using data from actual biological systems. The application can be used as a command line utility by academics with only a rudimentary understanding of computers, but advanced users can integrate the code andlibraries into their own software tools.

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