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Inception V3 Neural Network For Automatic Diagnosis Of Knee Osteoarthritis From X-Ray Images

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Abstract: Osteoarthritis is a common condition affecting the knee joint that is characterized by the progressive and irreversible loss of articular cartilage. Patients' lives are greatly impacted by this degenerative disorder, so prompt and accurate diagnosis is essential. The primary diagnostic tool for osteoarthritis, traditional knee X-rays, frequently depend on the experience of seasoned doctors, which adds to the burden and increases the risk of making mistakes in judgment because slight variations in disease stages exist.This work uses artificial intelligence (AI) and machine learning to create a state-of-the-art medical diagnosis support system in response to these issues. The technique of transfer learning, which makes use of neural network models that have already been trained, is the foundation of the system. It minimizes reliance on large datasets and facilitates effective learning for the diagnosis of knee osteoarthritis.

Index Terms **– Inception V3, Knee Osteoarthritis, X-Ray Images**

I. Introduction

Osteoarthritis of knee joints is a disease, which affects joints and surrounding areas of the joints. OA occurs mainly due to progressive destruction of articular cartilage, still suitable medical therapy and medications lessen the pain related with this condition. It is commonly seen in elder population. In the body knee is the most multiplex structure. As stated by WHO data (2017) the frequency of OA is incrementing yearly in most developed countries [1]. Global statistics show that 15% of women and 10% of men 60yrs and older have syndrome of knee osteoarthritis. The generality is high as 40%. The most frequent OA is knee OA. The pain that comes up from KOA diminishes the quality of life and limit the daily activities. Additionally, KOA cause the depression and anxiety, along with it substantial economic burden. For example, in the United States (US) the health related expenditure related with this condition inferred at US$186 billion annually [2].

Generally physician and researchers are utilizing the information from imaging acquired with multiple modalities for evaluation of KOA. Whereas high resolution MRI has rapidly emerged as a popular method, it has low accessibility and costly. As a consequence, radiography is considered as another norm to access the severity of KOA, as it is non or least invasive, suitable and can be carried out quickly [2,3,4].

The key issue in knee OA is confirming the hardness and pain associated with the disease. The Kellegren-Lawrence [5] classification for identifying stages of KOA is fixed on five variables: the existence of osteophytes on the joint boundary; the existence of periarticular ossicles, largely in relation to distal and proximal interphalangeal joints; tightening of joint cartilage related with subchondral bone; the modified shape of the bone ends, particularly in the head of femur. Consequently, the severity of KOA which is fixed on Kellegren-Lawrence is divided into five phases. Phase 0 represents normal and healthy knees, phase 1 represents doubtful OA, phase 2 is indicative of mild OA, phase 3 represents moderate OA, and phase 4 is indicative of severe OA. Several analyses have illustrated successful techniques to establish the severity of KOA [4,5,6,7,8]. But, there is no precise method for computing severity of KOA in scientific practice.

OA knee is characterized by cartilage loss that can be captured by imaging modalities and translated into imaging features. Plain radiography images (X-rays), ultrasound, and MRI are examples of common image modalities. Among the three procedures mentioned above, X-ray is the most practical and cost-effective modality, making up a sizeable share of clinical practice. Radiographs have historically been used to evaluate bony changes in OA. This technique allows for clear visualisation of early disease processes such osteophytes, subchondral sclerosis, and subchondral cysts. As OA worsens, radiography is utilised to evaluate Joint space width, which gives a de facto indication of how well hyaline and fibrocartilage are doing. Since the 1970s, the standard view for radiographic assessment of the tibiofemoral joint has been the extended-knee radiograph, which is a bilateral anteroposterior image acquired while the patient is weight-bearing, with both knees in full extension. OA severity is often classified by subsequent Joint space narrowing and the simultaneous appearance of subchondral bone abnormalities such as cysts or sclerosis.

With the passage of time and the advance in computing and AI, Researchers have used complex computer-assisted techniques to study X-ray interpretation and diagnosis for a number of years and there has been a huge leap in analysis and interpretation of OA Knee.

In our study we aim to minimise the human interaction in interpretation of knee radiographs by using a simple type of learning algorithm that performs supervised learning on the standardised Knee AP radiographs and obtain Grading of Kellgren and Lawrence (KL), the OA Research Society International (OARSI) joint space narrowing score, and measurement of joint space width (JSW)

i. Developing simple, cost effect, rapid, reliable X-ray analysis software for the grading of OA Knee in adults using Plain Radiographs
ii. To correlate the obtained results with Knee Injury and Osteoarthritis Outcome score (KOOS)

II. Review of Literature

In the alignment of the research goal, the very first requirement is to bring the enhancement into the input Knee osteoarthritis images from the dataset that supports computationally optimized diagnosis of KAO especially for segmentation and classification with the grading of the diseases by means of preserving clinically important feature by avoiding the possible distortion [**9**]. Working on the image resolution and its size are the important factors to deal with image enhancement techniques (IET). One of the traditional and popular method for the IET is the histogram equalization (HE), that distributes the histogram evenly so that the contrast of the image becomes better visible [**10**]. In the work of (**Anifah et al, 2013**) a special form of the HE namely contrast-limited adaptive histogram equalization (**CLAHE**) is used as a pre-processing step for Osteoarthritis classification, where they claim that CLAHE is applicable for the normalizing the intensities of the images of OA dataset. However, it suggests further process after CLAHE implementation [11]. In the work of (**Kuran et al, 2022**), further evolution is found, where the enhanced super resolution generative adversarial network (ESRGAN) along with the CLAHE is used for enhancing the knee-x-ray. This method adopts three stage computation, where ESRGAN is used for upsampling of the dataset images then the up sampled images are enhanced by the CLAHE then finally, the enhanced image is down sampled as original size so that both intrinsic and size is maintained without much distortion as it provides entropy of 6.98 and 7.30 for original and the enhanced image [9]. The optimal methods of the image enhancement help to detect the changes in the shape of the cartilage. The figure 1 illustrates the localization of the cartilage as well as the shape of the degenerated cartilage in the knee joints.

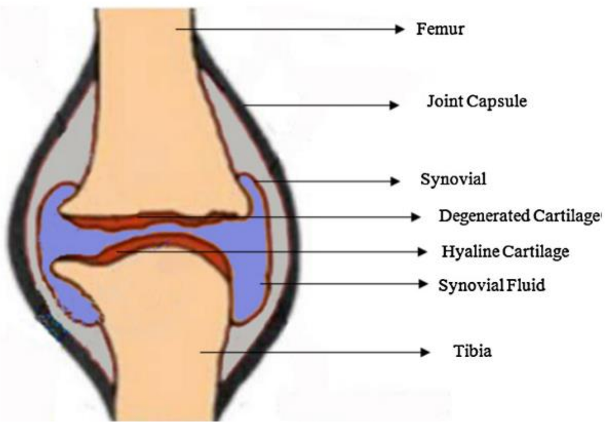

Figure-1: the shape of the degenerated cartilage in the knee joints.

However, the visual perception is more widely useful for the human vision system also in the computer vision systems. The table 1 describes the variants of the fundamental HE based image enhancement-based methods.

Table-1: Evolution of the HE variants

Cite No	Method Name	Findings
Gonzalez et al, 2002[12]	Conventional HE or Global HE	From the PDF of input image CDF is constructed and then each pixel intensity is mapped in dynamic range that causes changes in the brightness.
Zuiderveld et al, 1994[13]	Contrast Limited Adaptive Histogram Equalization (CLAHE)	It exploits local image statistics based on the block operation that overcomes the peak problem in histogram that causes the problem of artefacts and noises in CHE / GHE
Kim et al, 1997[14]	Brightness Preserving Bi-Histogram Equalization (BBHE)	It takes threshold of separation of the input histogram and forms many bi-histogram equalization. This helps to preserve the image original brightness.
Wang et al, 1999[15]	Dualistic sub-image histogram equalization (DSIHE)	It extends BBHE by selecting the threshold separating point at the median of the histogram. However, both BBHE and DSIHE fails to preserve the original brightness in some conditions
Chen et al, 2003[16]	(Minimum mean brightness error bio-histogram equalization (MMBEBHE)	It is an extension of the method BBHE, it uses a absolute mean brightness error as a performance metrics. Though it gives better result that BBHE, however this method too gives undesirable effects.
Chen, et al,2003[17]	Recursive Mean Separate Histogram Equalization (RMSHE)	It operates in recursive manner by partitioning the image histogram. Then segments are equalized one by one and finally, the contrast enhanced output image is obtained using unification of all the segments.

Very similar to RMSHE, Recursive sub-image histogram equalization (RSIHE) was proposed in the work of (Sim et al. 2007) [18]. In RMSHE, the mean is used as the separating point, and RSIHE uses median as the separating point. Further evolution was proposed by (**Wang et al, 2007**), as Weighted Threshold HE (WTHE) [19]. Basically, WTHE, uses adaptive method to control the enhancement which is easy to control and adapt different formats of images. Another, weight-based techniques are: i) Recursive Separated and Weighted Histogram Equalization (RSWHE) (**Kim et al, 2008**) [20] and Wight Clustering Histogram Equalization (WCHE) (**Sengee et al, 2008**) [20]. In the work of (**Ibrahim et al, 2009**) namely Sub Region Histogram Equalization (SRHE) which uses Gaussian filter for the purpose of partitioning of the input image [21]. Another work by (**Zuo et al, 2013**) , namely Range Limited Bi-Histogram Equalization(RLBHE) uses a threshold that minimizes the intra class variance is used as the separating point[22].

III. Materials and Methods

3.1 Dataset

We trained a neural network model to identify radiographic features indicative of osteoarthritis (OA) severity. We used a specific set of images for training and a separate set of images for testing the model's performance on unseen data. The test set was not included in the training process to evaluate the model's generalization ability. To enhance generalization, we replicated each training image into multiple altered versions, increasing the effective diversity of the training set. This augmentation technique aims to improve the model's recognition of relevant features. After training, we assessed the model's performance on the test set by predicting Kellgren-Lawrence (KL) scores, which quantify OA severity. To determine whether the model focused on similar features as radiologists, we analyzed the regions of each image that were most influential for the model's predictions.Comparing the model's identified influential regions with expert radiologists' assessments allows us to evaluate the model's interpretability and its alignment with human expert knowledge.

3.2 Convolutional neural networks

Convolutional neural networks (CNNs) are a class of advanced machine learning models specifically designed to process and analyze images. These powerful algorithms have the capability to automatically extract meaningful features from images, eliminating the manual effort required to create custom feature extractors[23]. Over the years, CNNs have been successfully employed in numerous image classification tasks, and their application in medical image analysis has gained considerable attention in recent research endeavors.

The typical architecture of a CNN, as depicted in Figure 2, comprises various specialized layers. Constructing a Convolutional Neural Network always entails three key layers, each serving a distinct purpose. These layers are:

Convolution Layer: This layer applies convolutional filters to the input data, enabling the network to learn and extract features from images.

Pooling Layer: The pooling layer reduces the dimensionality of the extracted features while preserving their essential characteristics. It helps in improving the network's efficiency and handling scale variations.

Fully Connected Layer: The fully connected layer connects every neuron from the previous layer to the subsequent layer. It enables the network to learn complex patterns and make predictions based on the extracted features.

These three layers play a fundamental role in the construction and functioning of a CNN, facilitating effective image analysis and classification tasks.

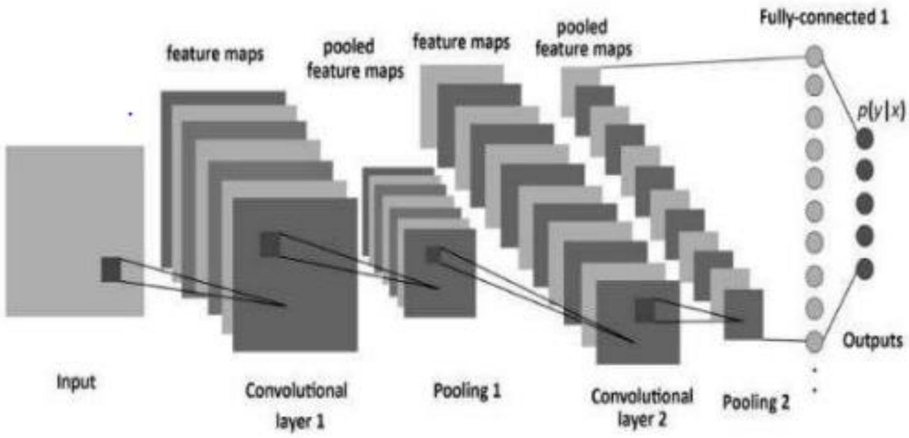

Fig 2:General architecture of CNN

Deep Neural Network (DNN) Architecture:

Utilizing a DNN with reverse forward propagation, our approach involves tailoring hyperparameters for each training iteration. The most effective DNN configuration identified comprises layers with 90 and 20 neurons. Positioned within the realm of Machine Learning, Reinforcement Learning (RL) emerges as a contemporary topic, focusing on adaptable decision-making in complex, uncertain environments. The RL method follows a Markov decision process, incorporating key elements such as rewards, goal values, and a strategy defined by a probability function.

RL Methodology and Optimal Policy:

The RL approach centers on determining the optimal policy in the absence of a prior model. Q-learning, a prominent RL technique, operates as a model-free method for discovering optimal actions within a Markov decision process. The method involves an action-value function, guiding the predicted effectiveness of actions in a given state when following the optimal policy.

Training Process and Model Evaluation:

After training, the DNN model is systematically evaluated, adjusting Q-values based on learning rates. The approach incorporates a declining learning rate (denoted as 'a') to enhance stability. The training system, encompassing both DNN and vector models, aims to produce stable features. The proposed technique demonstrates efficacy in early identification of knee osteoarthritis with limited data, addressing challenges posed by the condition's variability.

Outcomes and Performance Analysis:

The study's outcomes are based on actual treatment center data, ensuring consistency between training and testing datasets. Performance metrics, including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), categorize outcomes. Sensitivity, Specificity, and Prognostic Cost metrics are employed to gauge system performance. The RL approach surpasses existing methods, as illustrated in Figure 3, with significant improvements in accuracy, sensitivity, and specificity.

Graphical Representation and Model Comparison:

Figure 3 provides a visual interpretation of affected zones, depicting the performance analysis of the RL method against other methods such as CNN, DNN, ResNet 150, and Dense VoxNet. The RL-based strategy consistently outperforms existing methods, showcasing superior accuracy and precision ratios.

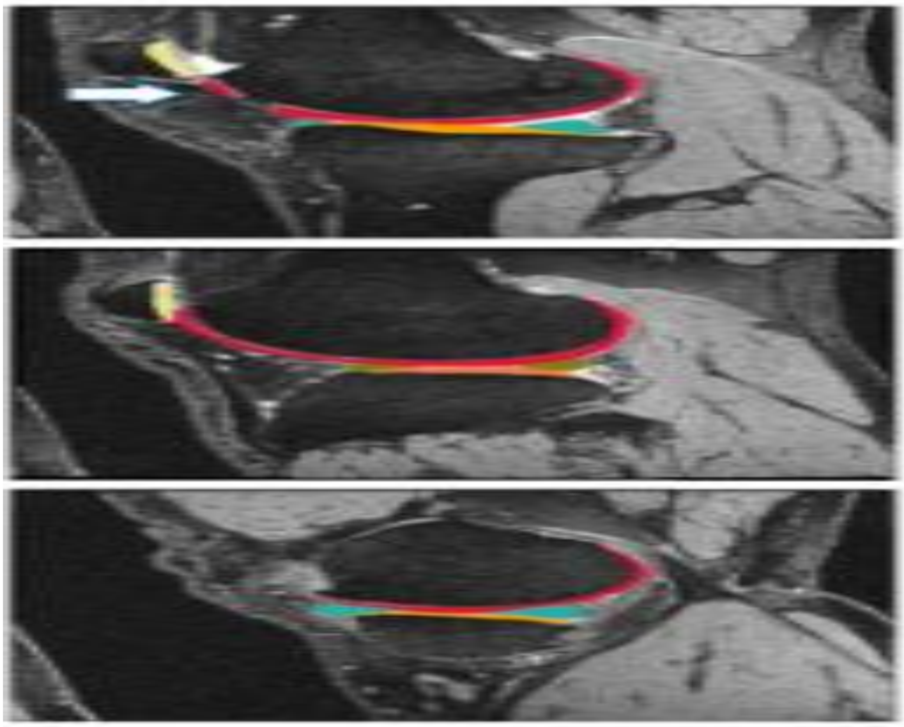

Figure 3:Visual representation of effected KOA Images.

Neural Network Structure and Vector Preprocessing:

Neural network architecture considerations involve optimal configurations without specific mention of neurons in DNNs. Training parameters, including batch sizes and epochs, are determined. Vector preprocessing, uncertainty matrix outcomes, and ROC curve analysis contribute to understanding DNN performance.

Precision and Sensitivity Evaluation:

The suggested RL-based algorithm is evaluated for precision, sensitivity, specificity, and precision ratio. Performance analysis, as depicted in Figure 6, indicates that vector scaling yields the highest accuracy among tested approaches.

Correlation Analysis and Parameter Relationships:

Exploring relationships between quantitative skin texture parameters and knee osteoarthritis. The RL-based algorithm's precision, sensitivity, specificity, and prediction ratios are evaluated, with a focus on key parameters such as the indecision template, accurate prediction, and incorrect prediction.

This comprehensive approach showcases the effectiveness of the proposed RL-based strategy in enhancing diagnostic capabilities for knee osteoarthritis, particularly in scenarios with limited data and variable conditions.

A. Preprocessing Stage

The initial phase of image data processing is crucial in preparing for the construction of a diagnostic model. To begin, we must gather knee X-rays for training purposes and collaborate with a medical professional to annotate the X-rays based on the Kellgren-Lawrence classification. This classification will serve as valuable labeled data for training the model.

Subsequently, we engage in the pre-processing of the knee X-rays. Recognizing that the model's focus is solely on diagnosing the joints of the knee, we opt to discard irrelevant information by cutting the knee X-rays, retaining only the knee joints. To facilitate this process, we employ the LabelImg tool for image labeling. The positions of the knee joints are marked using LabelImg, and the tool stores this information in XML format.

B. Model Building

In order to efficiently crop all knee X-rays based on the marked positions, we employ Python. The coordinates extracted from the XML files are utilized to precisely crop the X-rays, leaving only the pertinent knee joint information. This set of cropped knee joint X-rays becomes the dataset for training the diagnostic model. This meticulous preparation lays the foundation for developing an accurate and effective knee joint diagnostic model. Upon completing the data preprocessing stage, the next step involves the construction of a diagnostic model for osteoarthritis. To achieve this, transfer learning is employed in this research, leveraging the capabilities of five well-established neural network models: Inception V3, ResNet, DenseNet, MobileNet, and EfficientNet. These models have garnered acclaim for their performance in the ILSVRC classification competition.

While accuracy stands as a fundamental metric in AI-based systems, this research delves deeper by considering recall and precision to comprehensively assess system performance. Given the nature of the diagnostic task, where type I error holds more significant implications than type II error, decisions are influenced by recall when accuracy is consistent across models.The diagnostic process is stratified into three stages, each involving the training of a distinct model. During the initial phase of model training, the first step involves classifying Kellgren-Lawrence (K/L) grades 0, 1, and 2 as mild categories, while grades 3 and 4 are grouped as severe categories for the training of the diagnostic model. With this categorization in place, the training of the first-stage model commences.

III. Results

To construct the diagnostic model, five pre-trained models—Inception V3 are employed.The results are illustrated in figure 4. Post-training, the task is to identify the most suitable pre-trained model among them. A comprehensive evaluation is conducted by comparing the accuracy and recall metrics across all five models, utilizing the same dataset. This comparison aids in the selection of the optimal pre-trained model for further refinement and enhancement of the first-stage diagnostic model.

precision	recall	f1-score	support
0.8	0.67	0.73	73
0.64	0.69	0.67	36
0.93	0.79	0.86	34
0.8	0.9	0.84	78
0.78	0.88	0.82	32

Figure 4:Results of Inception V3.

Conclusion:

This study underscores the applicability of Convolutional Neural Networks (CNNs) in the analysis of knee X-ray images. Notably, the models proposed in recent years exhibit commendable performance throughout the research. At each stage of our system, the diagnostic model outperforms its counterparts, particularly in distinguishing between severe and non-severe knee osteoarthritis.

The primary focus of this research is on the differentiation between severe and non-severe cases of knee osteoarthritis, aiming to aid physicians in prioritizing less severe cases for examination. This strategic approach not only alleviates the burden on healthcare professionals but also ensures that patients with more critical conditions receive prompt medical attention. The model developed in this study exhibits superior performance in successfully discerning various joint conditions.

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