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Proposed Osteoarthritis Detection Algorithm Using CNN and Image Processing Techniques

Hanafy Ali[1],

[1] Computers and Systems engineering Depart., Faculty of Engineering, Minia University, El Minia, Egypt, hmali@mu.edu.eg.

ABSTRACT This paper presents a fully developed computer aided diagnosis (CAD) system for early knee Osteoarthritis (OA) detection using knee medical imaging and machine learning algorithms. The medical images are first pre-processed in the Fourier domain using a circular Fourier filter. Osteoarthritis (OA) is a chronic disease prevalent worldwide. There are two primary forms of osteoarthritis, affecting mainly the fingers, thumbs, spine, hips, knees, and big-toes, while secondary occurs with pre-existing joint anomalies. OA most commonly occurs in older individuals, but it can occur in adults of any age. OA is also known as degenerative joint disease, degenerative arthritis, and arthritis with wear and tear. Diagnosis of such disease is normally rendered by examining the joint scan of the Image with X-ray of knee. MRI analyzes are conducted by well-trained radiologists and orthopedists. The other side of this study is that it requires time and can be subject to loss of precision. The manual segmentation of images from a great number of scan images is a tedious and time-consuming procedure. Automatic segmentation and interpretation of joint MRI scans is therefore needed to increase the precision of clinical outcomes and bone calculation. In recent years, the advent of deep-learning technologies within medical systems is causing a transition. This can process a large volume of data to have greater precision. Deep learning methods can thus be used effectively for the automatic segmentation of MRI scans. This paper offers an overview of the different models and their output using deep learning and image processing techniques. Diagnosis of the illness is conferred from the image data. The state-of-the-art analysis is then discussed on Convolutional Neural Network (CNN) and Image Recognition. Finally, a comparative overview of the proposed model with other state-of-the-art techniques are presented based on the performance metrics. In the proposed detection algorithm, we found that all the suggested models achieved a higher level of predictive accuracy, greater than 90%, in detecting osteoarthritis. However, the best-performing model was the pretrained VGG-16 model with edge detection, which achieved a training accuracy of 99% and a testing accuracy of 92%.

KEYWORDS: *Osteoarthritis, CNN, X-ray, Deep Learning, Classification, feature extraction, knee osteoarthritis detection.*

I. INTRODUCTION

Recent technology developments indicate that Deep Learning is a growing area of research in health and for practical applications. The possible uses are enormous, ranging from low-tech industries to high-tech industries with massive data chunks [1]. The number for data will have tripled by 2025, and a trillion-dollar global market will surround it. Yann [2], defined Deep Learning as, enables computational models composed of multiple layers of processing to learn data representations with multiple levels of abstraction, as it will shift the computing paradigms of today and cause new models to fulfill the needs of health, society and education.

Osteoarthritis [3] is among the most severe of all types Of arthritis mainly seen in female, the elderly along with the overweight. More than 27 million Americans are projected to have the condition [4], which mainly affects people who are 60 years and older. OA is called Arthritis [5] "wear-and-tear." It typically comes with aging and results from the use of joints over time. The cartilage Osteoarthritis (OA) is a joint disease with knee OA which mostly affects cartilage. Cartilage is the protective connective tissue that protects the ends of bones in a joint. During Osteoarthritis, the upper layer of cartilage is expelled due to which the bones touch each other creating extreme discomfort. A standardized method for classifying individual joints into 5 groups is the Kellgren-Lawrence (KL) scheme [6].

Symptoms may vary from person to person. For the most part, over several years the joint injury happens slowly, and the pain generally increases as it does. But it can also be making fast progress. OA is fairly mild in some individuals, and does not significantly interfere with everyday life. Others can suffer severe disability and pain. There are 2 types of OA, primary OA seen in the elderly due to genetic or aging causes. Secondary OA, attributable to some illness, diabetes, obesity, athletics, or rheumatoid arthritis patients, appears to develop early in life. The key symptoms of OA are pain and joint motion difficulties [7], diminished mobility and restricted participation; joint morning or after prolonged rest stiffness The present OA assessment is based on clinical examination, signs and unique radiographic evaluation (MRI) techniques [8].This method increases image quality and the speed of acquisition. Nevertheless, numerous methods of biomedical imaging have been used recently to improve the speed and efficiency of image acquisition. The scheme of the operation of the computer-aided system is shown in figure 1.

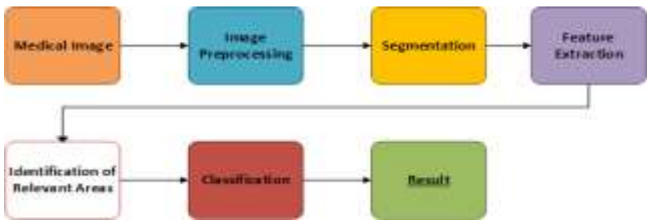


Figure 1.**Computer Aided Medical Image Diagnosis.**

The paper is organized as follows. Section 2 presents the state-of-the-art literature survey. Section 3 describes the proposed methodology. Experimental setup and dataset details are provided in section 4. Results and analysis are discussed in section 5. Finally, section 6 concludes the paper.

II. Literature Survey

According to the previous study, researchers have examined various ways of detecting and analyzing osteoarthritis using specific photographs of the knee such as X-ray, MRI, etc. For most medical imaging systems, the image segmentation process is of considerable significance.

In [12] Multicenter Osteoarthritis Study and validated it on randomly selected 3,000 subjects (5,960 knees) from Osteoarthritis Initiative dataset, diagnosis method based on the Deep Siamese CNN, with 66% accuracy. To determine the thickness of the joint area, Image segmentation and edge detection method was applied with 65% accuracy. Deokar et al. [13], The input datasets are collected from various Hospitals and diagnostic centers with required specifications which are MRI images, The different features GLCM texture, statistical, shape etc. is extracted by using different image processing algorithms, With 95.24% accuracy.

In [14], Discrete step algorithm for X-Ray bone image segmentation. Reference [15], Dataset generated and collected locally 3D MRI Scans, Artificial neural network (ANN) was employed to learn the mapping function between the CDI feature space and OA severity, With 70.6% accuracy. Aprilliani et al [16], Prediction Based on Random Forest The data of 33 patients with osteoarthritis National Hospital of Indonesia were used. Have used random forest algorithm with 86.9% accuracy

In [17], Dataset of X-ray images and KL grades from the Osteoarthritis Initiative (OAI) have used deep convolutional neural networks (CNN). With 53.9% accuracy. In reference [18], Dataset of X-ray images and KL grades from the Osteoarthritis Initiative (OAI) through fractal analysis of trabecular bone (TB) textures on radiographs. Still under progress. In [16], the Osteoarthritis Initiative (OAI). MRI data Machine Learning Techniques with 75% accuracy. Yaodong et al. [19] proposed an Adept Edge Detection Algorithm for Human Knee Osteoarthritis Images, Proposed an edge detection algorithm for joints. In reference [20], Knee X-rays of different ages, and various socio-economic blood groups. The experiment is performed on 200 Knee X-ray images, Effective contour segmentation technique for diagnosing the disease by segmenting the portion / part of the knee X-ray image. The numerous functions such as Haralick, Statistical, First Four Moments, Texture and Shape are calculated and confidentially analyzed using Random Forest classifier, With 87% accuracy

III. Proposed Methodology

Deep Learning (DL) techniques based on the Artificial Neural Network (ANN) have been applied successfully in recent years for disease diagnosis and detection. The basic process within the networks developed in these techniques is designed to motivate the human brain 's work. Using many signals entering the system, nonlinear operations are applied, and output signals are generated. They show representative learning. Because these models do not employ an explicit method when extracting data features. The method of extraction of the functionality is carried out using secret data layers from the data [21]. As in the machine learning technique [13], it is not mandatory to extract features separately for the extraction process of features in deep learning models. Techniques such as supporting vector machine, k-tools, and neural network have been used in the diagnosis of neurological disorders in previous studies. Additionally, the techniques used in the diagnosis of certain disorders that cause diseases in humans were inspired by nature and provided significant achievements [22][23]. Early diagnosis of Arthritis disease (AD) is very important in preventing the disease from progressing and in ensuring its treatment. Features derived from MR photos of the knee are rated and classified for AD detection [24]. Features should accurately represent AD-related stages.

A. Model-1: Inception v3

Inception-v3 is a deep convolutional, 48-layer wide, neural network. You can load a pretrained version of the qualified network from the ImageNet database on more than one million images [25]. The pre-trained network is capable of classifying images into 1000 categories of objects, such as keyboard, mouse, pencil and many animals. As a result, the network has learned rich representations of features for a large array of images. The Network has a 299-by-299 picture scale for input.

B. Model-2: Model-2: VGG16

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual competition and is an international challenge to computer vision. Every year teams work on two projects. The first is to identify objects moving from 200 levels into an image, which is called location of objects the second is image classification, each labeled with one of 1000 groups, which is called image classification.

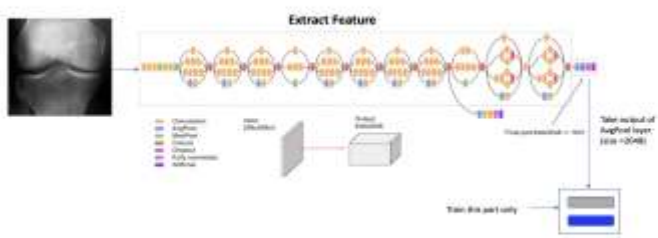


Figure 2. **Inception V3 Architecture.**

The feedback from the network is an image in dimension (224, 224, 3). The first two layers have 64 3 * 3 filter size channels, and the same padding. Then, with a max pool stride layer (2,2), two layers which have 256 filter size and filter size convolution layers (3,3). A max pooling stride line (2, 2) followed, which is the same as previous base Then, there are two filter sizes (3, 3) and 256 filter convolution layers available. This is accompanied by 2 sets of 3 layers of convolution, and a sheet of max. On 512 (3, 3) spaced filters each have the same padding. This image is then transferred to two layers of convolution row The filters we use are type 3 * 3 instead of 11 * 11 in AlexNet and 7 * 7 in ZF-Net, in these convolution and max pooling layers. It also uses 1 * 1 pixel in some layers which is used to control the number of input channels. A 1-pixel padding (same padding) is done after each layer of convolution, to avoid the image 's spatial function.

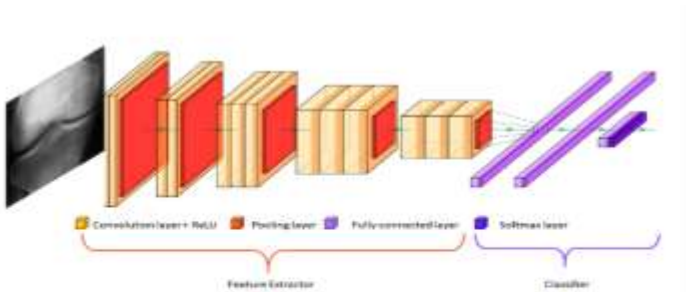


Figure 3. **VGG16 Architecture.**

C. Model-3: VGG16(Edge Detection)

Edge detection includes a variety of mathematical methods which aim to identify points in a digital image where the brightness of the image changes sharply or has discontinuities, more formally.

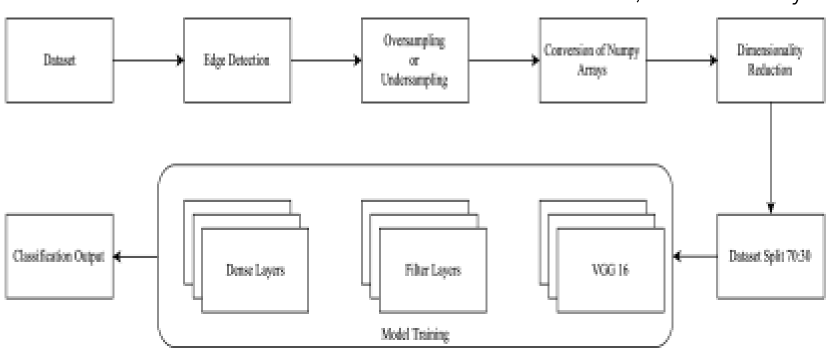


Figure 4. **Proposed Model Architecture for Edge Detection.**

Typically, the points at which image brightness changes sharply are structured into a set of curved line segments called edges. The same problem of finding discontinuities in one-dimensional signals is known as phase detection, and shift detection is known as the problem of finding discontinuities in signal over time. Edge detection is an important tool for image processing, machine vision and computer vision, particularly in the fields of feature detection and extraction.

D. Model-5: VGG19

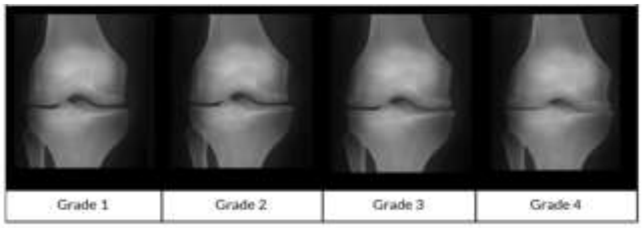
VGG19 is a 19-layer VGG layout version (16 layers of convolution, 3 Fully connected layers, 5 layers of MaxPool and 1 layer of SoftMax). Many versions of VGG include the VGG11, VGG16, and others. As an input to this network, a fixed size of (224 * 224) RGB image was given, indicating that the matrix was form (224,224,3). The only pre-processing completed were that they subtracted the mean RGB value from each pixel, calculated in the whole training set.

Used (3 * 3) size kernels with a 1-pixel phase scale, this allowed them to cover the whole notion of image.

Spatial wrapping helped to maintain spatial resolution of the image. The total pooling was carried out over a 2 * 2 pixel side frame 2. This was accompanied by Rectified linear unit(ReLu) adding non-linearity to allow the model better discriminate and improve the computational time as previous simulations using tanh or sigmoid functions proved much better than commonly used models. Applied three totally connected layers from which the first two were 4096 heights, then a layer with 1000 channels for classification of ILSVRC 1000-way and the final layer is a SoftMax feature.

IV. Experimental Setup

In this paper we used the grades of OAI Dataset and Kellgren-Lawrence (KL) as ground reality to characterize OA X-ray photographs of the knee. The KL classification scheme is now considered the gold standard for initial determination of the extent of knee osteoarthritis in X-rays. This uses five classes which is to show seriousness of OA x-ray knee. .'Grade 0' is standard, 'Grade 1' is doubtful, 'Grade 2' is minor, 'Grade 3' is mild and 'Grade 4' is extreme. Figure 2 indicates the method for rating the KL. The rating scheme Kellgren Lawrence is a radiological assessment of osteoarthritis of the hip. This progresses from grade 0 to grade IV which is focused on x-rays. There are a range of rating schemes developed for knee osteoarthritis, the rating scheme Kellgren-Lawrence is the most commonly used and accepted method for the treatment of knee osteoarthritis.



Classification	Normal	Doubtful	Mild	Moderate	Severe
Description	No Features of OA	Minute Doubtful	Definite Normal joint space	Moderate joint space	Joint space greatly reduced

FIGURE 5: Kellgren-Lawrence Grading Scheme

A. Edge Detection using Image Processing

Figure 6. Depicts Image Processing for detecting the edges of the image and separating it from the other images based on the Kellgren-Lawrence grading scheme.

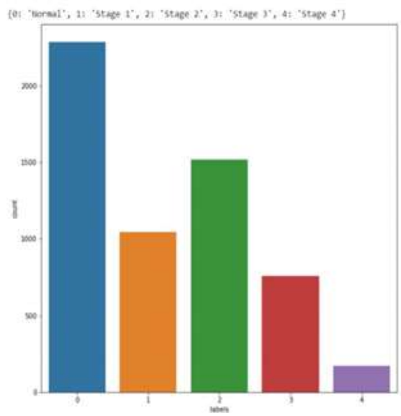


FIGURE 7. (a) Dataset Before Normalization

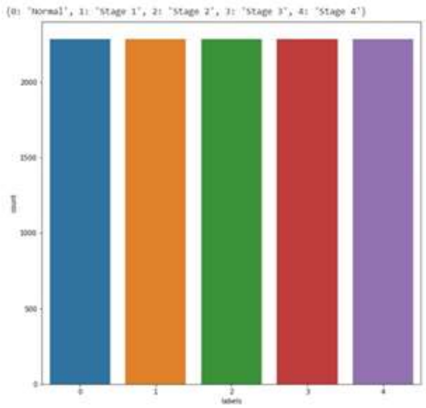


FIGURE 7. (b) **Dataset After Normalization (Oversampling)**

V. Results and Analysis

In this section, the experimental results and performance analysis of the proposed model is discussed.

At first, the performance of the proposed transfer learning model for OS detection is analyzed through model accuracy and model loss. Figure 8 shows the VGG19 transfer learning model for the OS detection. Figure 8 (a) shows the graph of epochs vs accuracy and figure 8 (b) shows the epochs vs loss graph. The graph shows that the model loss is minimized through various regularization techniques and overfitting is avoided through dropouts and L1 and L2 regularizations. Hence the accuracy of the model is improved. The difference between the training and testing accuracy and loss shows the model is performing well.

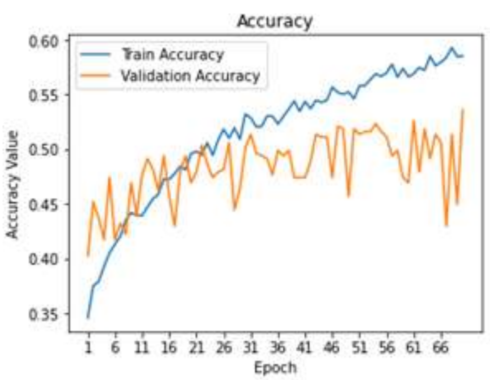


FIGURE 8-a. **Epoch vs Accuracy of the Proposed Model Performance using Transfer Learning VGG19**

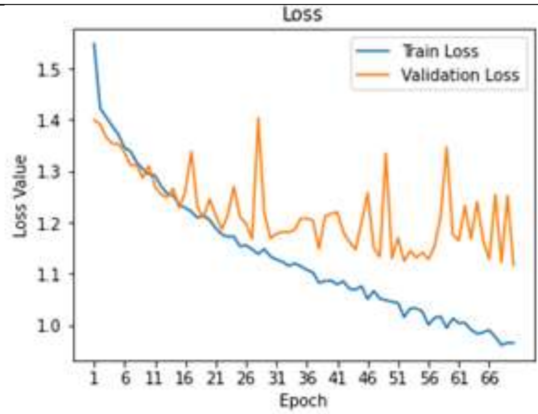


FIGURE 8-b. **Epoch vs Loss of the Proposed Model Performance using Transfer Learning VGG19**

The transfer learning VGG19 model is then evaluated through confusion matrix. Confusion matrix is generally used to evaluate the performance of a classifier. Figure 9 shows the confusion matrix of the proposed transfer learning model. The higher values in the matrix shows that the model classifies the OS appropriately.

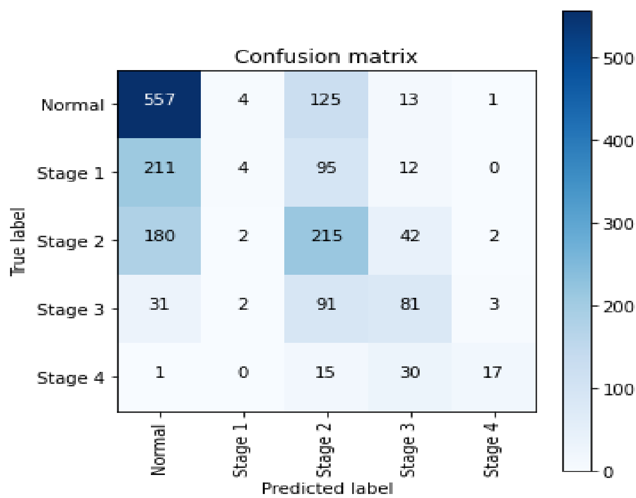


FIGURE 9. **Confusion Matrix Plot of the Proposed Model (VGG19).**

Table 1 shows the performance of the VGG19 model with respect to performance metrics: Precision, Recall, F1-score and Support. The model is classified and tested under five stages. The normal stage has higher values compared to the other stages. The table compares the performance of the different stages of the model.

Table 1.**Performance of VGG19 Model**

VGG19	Performance Metrics			
	Precision	**Recall**	**F1-score**	**Support**
Normal	0.57	0.80	0.66	700
Stage 1	0.33	0.01	0.02	322
Stage 2	0.40	0.49	0.44	441
Stage 3	0.46	0.39	0.42	441
Stage 4	0.74	0.27	0.40	63

A. Performance Evaluation

In this section, the performance of the proposed transfer learning model is compared with the performance of other pretrained models such as Inception V3, VGG16, VGG16 (Edge Detection), and Inception V3 (Edge Detection). Figure 10 shows the comparison graph of VGG19 with other pretrained models. It is evident from the graph that the accuracy of the pretrained models is having high variation with the validation accuracy. Such variations in the accuracy are acceptable and it means the model is not performing well. But the proposed VGG19 model shows minimal difference between the validation and real-time accuracy of the model.

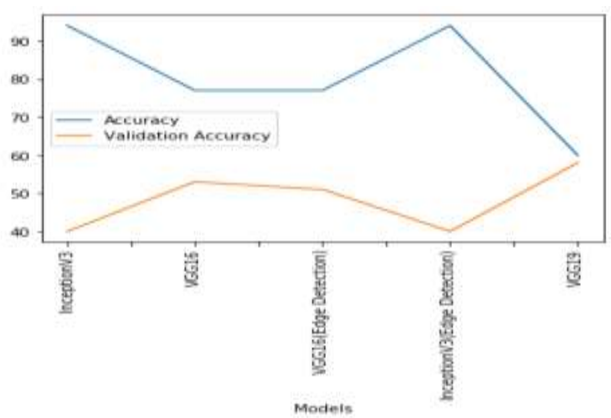


FIGURE 10. **Performance Evaluation of the Proposed model.**

Table 2 shows the model accuracy comparison of VGG19 model with other pretrained models for OS detection. Hence it is obvious that the proposed transfer learning model has high accuracy with less overfitting and it is efficient for detecting and classifying OS.

Table 2. **Model Accuracy Comparisons of VGG19.**

Models	Model Accuracy	
	Accuracy %	Validation Accuracy %
Inception V3	94	40
VGG16	77	53
VGG16 (Edge Detection)	77	51
Inception V3 (Edge Detection)	94	40
VGG19	60	58

V. CONCLUSION

Chronic diseases have a detrimental impact on human life, and may endanger future human life. DL approaches have also been improved in recent years with the advancement of computer-aided technologies, which were commonly used in developing chronic diagnoses. The data used in disease diagnosis are the MRI image data which are stored in large amounts in substantially higher storage environments. The preparation and teaching of a vast amount of data is one of the problems that strategies can face. A list of the DL approaches used for the treatment of chronic OA disease typically observed from cartilage degeneration is provided in this report. MRI image images have been found to be used successfully in the treatment of OA.

In paper, five learning models are used to diagnose this disease by generating and resulting for each, out of which are checked on the pre-trained models. Thanks to the addition of the dropout and L1,L2 layers to the network to prevent overfitting, VGG19 has achieved the high precision values of these DL approaches. MRI photos are exceptional in treatment of the disease. The network needs to be more checked with other pre-trained models such as Deeplabv3 and Res Net that will be carried out in more progress, the diagnostic accuracy of these methods is now approaching human standard and could also outperform human experts in the future; hence patients will gradually get more accurate diagnoses.

Adding these approaches to the diagnostic chain will concentrate less on repetitive tasks such as grading images and more on unexpected observations by radiologists and other clinical experts. We believe that the use of clinical evaluation could significantly improve the diagnosis of knee OA from plain radiographs for all the learning-based methods along CAD (Computer-aided detection) machine aforementioned reasons.

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