



Hybrid model for Classification of Osteoarthritis Grading using Deep Learning

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Abstract

Osteoarthritis in knee (KOA) is the most solitary foundation for movement restraint and corporal incapacity for grown-ups. It produces pain, soreness and makes it hard to stride, run or live energetically. KOA also recognized as Joint Destructive Disorder originates when joint cartilage becomes rigid and loses its flexibility. It almost affects all joints in our body. Early discovery and intervention can assist to slow down the deterioration of Knee Osteoarthritis. Physicians categorizing the grades grounded on their optical assessment is different across interpreters and extremely dependent on their skill. Innumerable frameworks in deep learning are being proposed for automatic recognition of osteoarthritis, but most of them consider only the images of the patients and don't combine the response and indicators of the patients. There is a compulsion to propose a new hybrid machine learning model capable of detecting and stating the severity of disease and diminishing the problem of specialists in classifying the grade of Knee Osteoarthritis.

Key Terms—Osteoarthritis, KL-grading, Deep-Learning, Adam Optimization.

I. Introduction

The most severe type of arthritis and the leading contributor to physical disability and activity restriction in older people is knee osteoarthritis (KOA) [1]. By 2030, most Americans over 65 will have symptoms of developing KOA [3]. A senior person's eminence in life is expressively crushed by soreness and additional joint KOA indicators. The deteriorating physical variations act as a source for KOA development and cannot be stopped by any treatment. Elderly people can, slow down the progression of KOA and improve their value of life by getting early

discovery and rehabilitation treatments. KOA is categorized by osteophyte growth, subchondral sclerosis, and joint space narrowing. MRI scans can be used to grasp the three dimensional structure of knee joints. The expensive tests and inadequate availability of MRI make it an unsuitable choice to make a diagnosis routine in KOA. Due to cost-effectiveness and availability x-ray has been accepted as the standard input. KL grading system, which was approved by WHO in 1961 [4] is most commonly used to grade KOA. From grade 0 to grade 4, the KL method splits KOA severity into five groups. Figure 1 table shows the sample's grade based on their criteria.

DIFFERENT KL GRADES AND THEIR CRITERIA.

OA Grading	Indication
Grade 0	No visible presence of Osteoarthritis in the joint
Grade 1	Doubtful presence, low possibility of joint space narrowing and possible osteophytic lipping.
Grade 2	Visible presence and possibility of joint space narrowing and presence of osteophytes.
Grade 3	Moderate joint space narrowing is visible, multiple osteophytes and presence of sclerosis and possibility of bone end deformation.
Grade 4	Large Joint Space Narrowing, large osteophytes, severe sclerosis and definite bone end deformation.

Fig 1: Diverse grade and their measures

The KL scoring standard has a lot of gray areas. As an illustration, potential osteophytic lipping and questionable JSN is used to find grade1. The doctor could possibly disperse dissimilar grades to the similar knee joint while investigating at different times. According to research by Culvenor et al.[5], the KL rating reliability is between 0.67 and 0.73. Due to the uncertain criterion, we hypothesize that the low trustworthiness of doctors' classification results, incorrectly, nearby grades are assigned to the knee joints. In medical analysis, misclassification of knee joint's grade as its nearby grade is less severe than misclassification of the grade as being distant.



Grading accuracy plays an exclusive role in measuring grade assessment is important. To solve this issue mean absolute error, a different evaluation metric to grade the knee joint was influenced by age estimation [6].

Risk Factors of KOA:

Pain, Tenderness, Stiffness, Swelling, Crackling, Changes in the shape of the joint are the common symptoms of KOA.

Age - age is one of the resilient threat issues for KOA. It infrequently happens in people less than 40 years of age.

Sex - It is inevident that females are more susceptible and have pain than males to cultivate OA.

Obesity - Due to the increased strain on joints, obesity can contribute to KOA. Weight loss might lower this risk.

Lifestyle - Smoking and inactivity will raise the risk of developing arthritis.

Genetic factors: It has been discovered that an individual's chance of developing knee, hip, and hand OA is increased by an increasing number of common genetic variations. Your risk is also raised if one of your parents or siblings has (or has had) OA.

Occupation: Osteoarthritis of the knee has been linked to jobs that regularly require crouching and kneeling, including dock labor, shipyard work, mining, and carpentry. Farm labor, construction work, and other activities requiring heavy lifting, extended standing, or daily distances of walking have all been linked to hip OA.

Injury: A significant joint injury or trauma raises the likelihood of OA in a particular joint in the future.

Competitive sports: Those who take part in competitive sports that put them at risk for joint damage have a higher risk of developing OA. The sports include wrestling, boxing, baseball pitching, cycling, gymnastics, soccer, and football.

II. Literature Review

For the KOA grade classification, various types of approaches have been developed in the past. Shamir et al [7] proposal for the knee joint detection uses a sliding window strategy and a templates matching technique. Euclidean distances between the present lifted window on the down-scaled knee picture and 20 predetermined knee joint images of size 15×15

are computed. The detected knee joint is considered to be the window with the least Euclidean distance. The Sobel horizontal gradients are used for feature extraction by Antony et al. [8], who also employ linear SVM based on the sliding window technique, to detect knee joints. This work was prompted by the fact that photographs of knee joints have horizontal edges.

Throughout the decades, different approaches have been used to classify KOA grades. The knee joint detection method proposed by Shamir et al. [7] combines a sliding window approach with a template matching methodology. Using 20 previously selected knee joint images of size 15×15, the present lifted window on the down-scaled knee image is calculated in terms of Euclidean distances. It is expected that the joint in a knee is located in the Euclidean window with the smallest length. According to Dr. Deny [9], In order to diagnose arthritis, it is essential to gauge how much or how thick the knee cartilage is. It had been done to examine knee MRI scans. The image is preprocessed by creating B-Splines prior to segmentation. Next, canny and log facet detectors are employed to extract borders, sharp edges in the gray values of the image. The extracted cartilage thickness play a major role in predicting KOA, according to the suggested approach. Calculating thickness involves comparing the range of pixels along edges. Based on the cartilage's thickness, it is then determined whether or not arthritis is abnormal. The Joint Space Width measured is compared to the fixed joint space width value, which is 5.7mm for men and 4.8mm for women. This makes it possible to tell the osteoarthritic knee apart from a healthy knee. By focusing on the thickness /viscosity of the cartilage, this method for evaluating arthritis is quick and easy. Vashishtha et al. have examined osteoarthritis definition, symptoms for diagnosis, types, and grades of osteoarthritis, as well as human knee anatomy and medical imaging methods. They provided methods for determining the severity of osteoarthritis utilizing imaging techniques including texture classification. [10] According to Saleem et al, the space width in a joint can discriminate among a healthy knees from unhealthy knee. The MRI input image has been altered by different image processing methods. Using template matching, the knee area has been removed [11]. Using image processing methods, Chan et al. showed early OA detection. To find the sick knee, authors used quad tree analysis. They put a particular emphasis on



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analyzing the morphology of the input knee with database knees which was simple to differentiate healthy and unhealthy knee joints [12].

After deciding on the ROI with a feature extraction technique, Chan et al. Authors created a classifier that can separate OA and non-OA. High accuracy of 92% was attained through their efforts. [13] In order to obtain an accurate position by taking into account the 8-neighborhood, Xie et al designed edge detection algorithm using sub-pixel while keeping Robert's gains of location accuracy and speediness. For high threshold selection efficiency, they substituted Otsu's Zernike's method. [14] For diagnosing OA, Raju et al, suggested many approaches. In order to distinguish OA from non-OA, they used image processing approaches. Eight of them described various techniques for separating osteoarthritis images from regular photos and for extracting operations. [15] A system for automatically detecting osteoarthritis that uses the Kellgren-Lawrence technique of grading has been developed by Kwon et al. They employed a vector machine to distinguish between photos with and without OA using gait analysis data and radiographic imaging. [16] A deep learning convolution network based on readings from the Kellgren-Lawrence grading technique has been proposed by Tiulpin et al. to automatically create the output. 3000 knee pictures of random participants were used to train their approach. [17] To demonstrate how obesity and overweight are contributing to the rise in osteoarthritis, Liukkonen et al. employed FE modeling in conjunction with an algorithm for cartilage deterioration. Using joint geometrics that were derived from magnetic resonance imaging, the authors of this paper developed 41 distinct models.

High body mass has been linked to a greater rate of OA, according to the algorithm. [18] For the purpose of determining the cartilage thickness from an image, Wagaj et al used an MRI image as input. Using segmentation based on pixels, the cartilage thickness has been estimated. For image segmentation, they used the texture filter [19]. In a number of research [8, 11, 13], deep learning-based techniques are used to analyze KOA. The knee analysis performance was enhanced through effective loss function in the KL grading assignment.

To automatically grade KOA severity and achieve cutting-edge performance, Pingjun Chen [20] applied two CNN models successively. In order to identify knee joints, he first customizes YOLOv2 detection architecture [21], to improve the KL grade classification, a unique ordinal loss is used. Experiments demonstrates the VGG-19 network model with ordinal loss achieves greatest KOA classification accuracy compared to the majority of popular CNN models. In comparison to all other CNN models, the suggested ordinal loss outperforms well in all terms of knee KL grading. DeepKneeExplainer is a novel explainable method that Md. Rezaul Karim [22] proposes diagnosing KOA based on x-rays and magnetic resonance imaging. MRIs and radiographs should first undergone a preprocessing step using the deep-stacked transformation technique to remove any potential noise in images. The region of interests are extracted using a U-Net and ResNet act as backbone. To train DenseNet we use the identified ROIs and to categorize the cohorts VGG architectures are used. Our system produces up to 96% classification accuracy. Radiographs have the potential to show osteoarthritis bone shape features, which are more obvious OA characteristics.

There are several methods for extracting features from data that are reported. For instance, Yoo et al, [23] used kinematic factors and as features to classify KOA using support vector machines (SVM), giving precision of 96.4%. Also an achieving equivalent classification accuracy are produced by Naive Bayes (NB) and Random Forest (RF) [24].

III. Methodology

A CNN is a generous network architecture and specifically used for image classification tasks involves in the processing of image pixel data. Human observation is not needed for the identification of important features in an image. CNN is very precise at image recognition and classification. Convolutional neural networks reduce computation as compared to a normal neural network. CNN may be divided into two different networks like Feature learning (eyes) and Classification (brain). These two nets work together to pretend the classification of images.

Convolutional and pooling layers play a



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major role in feature extraction. Images are broken down into different types of feature maps by different filters in **Convolution Layer**. The resultant Feature Map is created from our original input image that retains all of the critical elements of the original image while discarding the unnecessary data. The Pooling Layer, the following layer in our network, is in charge of roughly approximating the feature maps produced by the Convolutional layers. Any spatial variation that can have an impact on how well our network performs in image recognition is also taken into consideration by the pooling layer. Feature Learning component retrieved (generated) from the image, the classification component assigns the images to the appropriate categories. In classification part we have flatten and fully connected layers. Flatten layer converts two dimensional array into one dimensional array which was feed as an input to the next layer. The Fully connected layers, which would be utilized for classification, are a network of dense layers that are serially connected. In a network with complete connectivity, every layer 1 neuron is linked to every layer 2 neuron. To increase the accuracy of our predictions, the dense layers in computer vision applications typically comprise many neurons (256, 128 etc.).The last output layer has 1 neurons to complete a multiclass classification problem.

The iterative gradient descent process is performed to find the least optimal loss value for a function. Generally speaking, the parameters are initialized to random values, and after that, incremental steps are taken towards the "slope" at each iteration. To decrease the loss function and recognize the perfect parameter values, supervised learning heavily utilizes gradient descent. Adam uses the mean of first moment and the variance of the second gradient moments to adjust network weights during training. The parameters beta1 and beta2 control how quickly this happens. Adam optimizer adjusts the learning rate for weights of each network weight separately. Adam extracts the greatest aspects of AdaGrad and RMSProp algorithms and produce an optimization tool that can handle sparse gradients on noisy problems. Early stopping would be very helpful to address Adam optimizer's tendency to over fit very quickly. In general, Adam needs a lower learning rate: begin with 0.001, then increase/decrease as you see fit. Varying learning rate **between 0.0001 and 0.01** is considered optimal in most of the cases.

To compile the model we have to pass optimizer used to update weights, loss function (In

case of multiclass classification "categorical_crossentropy" is used) and metrics are used as parameters. To fit the model, we must choose the batch size, or the quantity of images will be utilized to train our CNN model prior to update the weight with back propagation and epoch's (an epoch is a quantity of how many times all the training images will be used once to update the weights). A multi-class problem is solved by Softmax by allocating chances to each class. Training converges more quickly due to this added limitation.

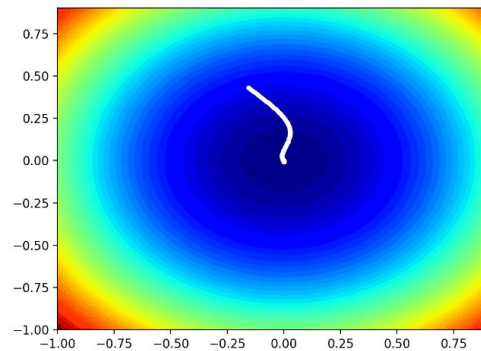
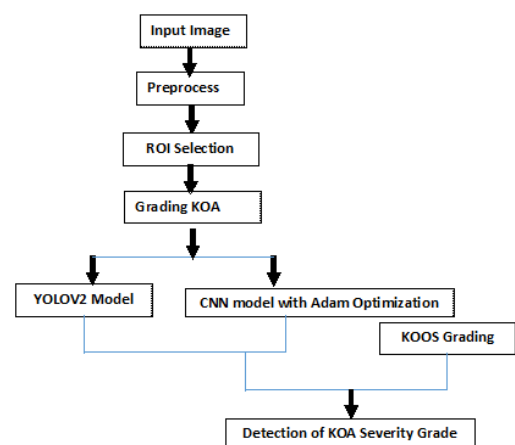


Fig 2: Contour plot with Adam

3.1 Proposed Framework Flowchart



3.2. KOOS Questionnaire



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The following formulas are used to calculate each subscale score

$$\text{KOOS Symptoms: } 100 - \left[\frac{\text{mean score symptoms} \times 100}{4} \right]$$

$$\text{KOOS Pain: } 100 - \left[\frac{\text{mean score pain} \times 100}{4} \right]$$

$$\text{KOOS ADL: } 100 - \left[\frac{\text{mean score ADL} \times 100}{4} \right]$$

$$\text{KOOS Sport/Recreation: } 100 - \left[\frac{\text{mean score sport/recreation} \times 100}{4} \right]$$

$$\text{KOOS Quality of life: } 100 - \left[\frac{\text{mean score QOL} \times 100}{4} \right]$$

The KOOS questionnaire was developed to evaluate the level of knee arthritis in patients based on their level of pain, symptoms, ability to carry out daily tasks, ability to participate in sports and leisure activities, and overall quality of life. To determine a final score out of 100, it can be self-administered. It is commonly used since it is simple to use, and calculating the result takes about 10 minutes. The ultimate result is displayed by adding the individual scores after each of the five characteristics has been evaluated. Each item in the five dimensions is evaluated separately using a Likert scale. Possible

KL Grades	0	1	2	3	4
Train	2286	1046	1494	724	174
Validation	317	153	212	106	27
Test	650	287	447	223	54

responses range from 0 (No problem) to 4 for each item (Dangerous).

$$KOOS = \sum_{i=1}^9 P_i + \sum_{i=1}^6 S y_i + \sum_{i=1}^{17} A_i + \sum_{i=1}^5 S p_i + \sum_{i=1}^4 Q_i$$

3.3. Fine Tuned CNN with Adam Optimization Adam Optimization Algorithm

- Input: Images
- Output: KOA Grade
- Start: Image size [i, j]
- ROI detection - Yolov2 Network
- KL Grading - Fine Tuned CNN with Adam
- Optimization Adam Optimization Update Rule

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * \nabla w_t$$

$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * (\nabla w_t)^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} * \hat{m}_t$$

[Train, validation, test] - Proportion of training, validation and testing knee samples
 For \forall image x in training data
 Compute of ROI \rightarrow KL Grade
 End For
 Final Grade Estimation \leftarrow Mean (CNN + KOOS)
 End

IV. Results:

The final grade will be calculated by taking the mean of KOOS Questionnaire and CNN model with Adam optimization algorithm. The suggested methodology considerably reduce the misclassification of KOA grades and increases classification accuracy.

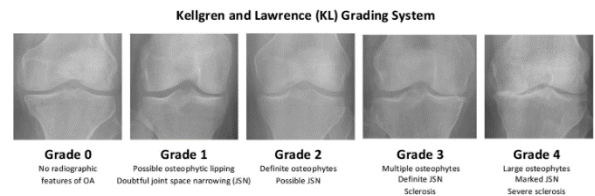


Figure 3: Knee joint grades

The images are distributed among various phases like training, validation and testing to categorize KOA Grade.

Table 1. Grading distribution among various phases

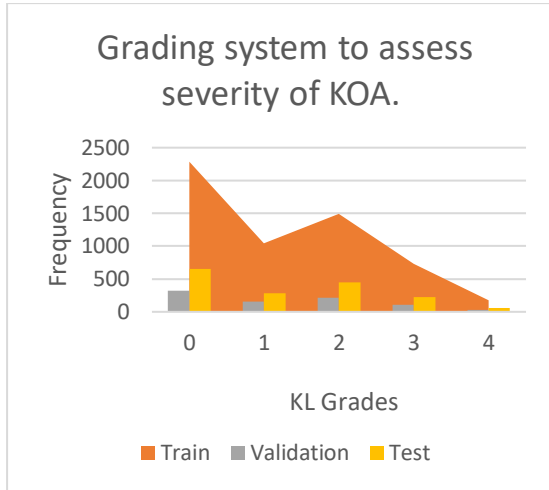
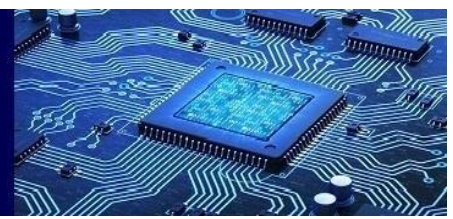


Fig 4: Grading system to assess severity of KOA

Metrics

On the road to evaluate performance of the suggested system several metrics, like Precision, Recall, Accuracy, and F1 Score, have been used. Metrics are determined using accurate and inaccurate forecasts. Images that the proposed model accurately classified are indicated by the letters TP, FP, FN, and TN. Images that were misclassified as normal images are indicated by the letters FN, and those that were correctly classified are indicated by TN. Precision is the proportion of TP over all pictures that have been categorized as positive. The proposed system's accuracy shows that the photos were appropriately categorized. Recall is calculated by taking the ratio of correctly identified class images and all positive class images, regardless of the system incorrectly identified them as belonging to a negative class. The better model has the closest recall value 1 .F1-score is a well-liked statistic that combines recall and precision.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1 - score} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$$

Optimization algorithms in deep learning can make a difference in time complexity of the suggested model. The Adam algorithm is an extension to SGD, can be used as an alternative algorithm to update network weights. The Adaptive Moment Estimation

algorithm is really efficient while working with large problems containing a lot of parameters. 'Gradient descent with momentum' and 'RMSP' are combined to create this technique, which uses less memory

Grade	Accuracy	Precision	Recall	F1-Score
0	96.63	96.63	97	97.31
1	96.46	97	96.46	97.22
2	96.47	96.66	96.66	96.66
3	96.46	96.46	96.46	96.46
4	98.12	98.63	98.46	98.22

Table 2. Performance evaluation of the proposed model

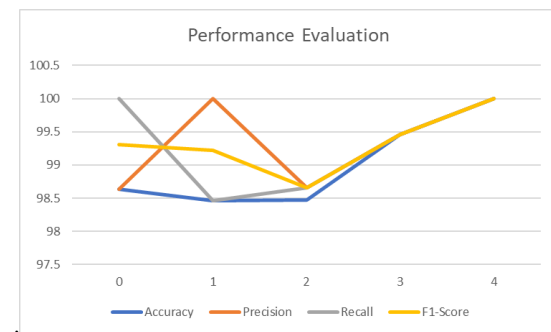


Fig 5: Performance Evaluation

V. Conclusion

In this paper, we provide a trustworthy architecture to identify KOA and categorize severity levels grounded on KL grading using deep learning. The recommended approach is grounded on fine-tuning CNN models utilizing Adam optimization algorithm and a customized YOLO model for detecting knee joints. Modern performance is reached in knee joint detection as well as knee grading. The performance of the one-stage detector YOLO on the detection of the knee joint demonstrates how well-suited it is to detection tasks with little fluctuation in object size. We applied the transfer learning awareness to streamline our architecture without increasing its computing price. In the proposed study, we employed two datasets: 1) the Mendeley Dataset, which was used for testing and training, and 2) the OAI Dataset, which was used for testing. The efficiency of the suggested model has been evaluated different kind of experiments. All changes are performed internally



and raw X-ray images can be immediately given as an input into our suggested model.

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