

# Knee Osteoarthritis Detection and Classification using X-Ray with CNN Algorithm

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**Abstract**-An enriched machine learning technique called Knee Osteoarthritis Detection and Classification Using X-Rays with CNN Algorithm (KOD). The proposed system (KOD) automatically detect the Knee Osteoarthritis using X-Rays. In our proposed system we focuses on an enriched machine learning techniques for a classification of Knee Osteoarthritis. The Proposed system contains five stages. In the 1st stage appropriate data type and source are selected for collecting the data. In the second phase the proposed system will undergo preprocessing which improves the performance by handling missing values, normalizing features. In the third stage the data set is split into test and training data. The data selected for training is used to train the CNN model. Following the previous stage the fourth stage is about classifying the data. The final stage is about testing the model, fine tuning and deploying our system for betterment in health care.

**Keywords:** *Convolution Neural Networks (CNN), Feature extraction*

## I. INTRODUCTION

Osteoarthritis (OA) is a multifactorial disease that is challenging to identify, diagnose, and manage. It is a long-term degenerative condition marked by cartilage degradation, which ultimately effects in the deterioration of bones. One kind of osteoarthritis that affects the knee joint is called knee osteoarthritis (KOA). Pain, stiffness, edema, and restricted joint movement are examples of physical symptoms. Age, gender, race, heredity, obesity, injuries, low vitamin D levels, and lifestyle are risk factors. The diagnosis of osteoarthritis in the knee is typically made using arthroscopy, X-rays, magnetic resonance imaging, and symptoms (MRI). But OA's early phases are frequently obscured. Furthermore, there is only a slight correlation between the image-represented severity level of OA and the 35-degree pain and disability. Therefore, there's a need. The other method is fine tuning this network to specialize for a particular dataset.

These network are also applied for KOA classification .Many Automated method and physicians grading system are less reliable as they misclassify a KL grade

to its nearby grade. In addition, since there are very few morphological and feature changes in successive KL grades, it becomes difficult to differentiate different grades. In most studies, the initial stages of KOA have little accuracy while, in some studies, the most difficult stages are merged for classification . At the same time, some methods try combining X-ray features with other clinical data to improve performance. As a result, the earlier it can be diagnosed, the earlier it can be treated, and knee degeneration leading to total knee replacement can be avoided .

When moving their joints, a patient with OA symptoms will experience severe pain, stiffness, and a grating feeling. Based on its severity, OA is categories into five , ranging from 0 to 4. We are collecting datasets of X-ray images for this specific work from Kaggle. Applied the data pre-processing technique to reduce noise and improve the knee X-ray image quality, and it also uses a Wiener filter for noise reduction with a histogram modelling-based image enhancement approach. The results of several classifiers, including the convolutional neural network (CNN), are compared after classifying the

images as normal or abnormal. Osteoarthritis (OA) pathology has long required research because of the disease's significant effects on a patient's lifestyle, high economic cost, and incapacity. Osteoarthritis (OA) goes beyond anatomical and physiological alterations (joint degeneration with gradual loss of joint cartilage, bone hypertrophy, changes in the synovial membrane, and loss of joint function) because cellular stress and the breakdown of the extracellular cartilage matrix start with micro- and macro-injuries [1]. In general, OA is linked to aging. Nevertheless, there are other risk factors, including gender, trauma, genetic susceptibility, obesity, inactivity, and bone density.

This is one of the 50 most prevalent diseases in the world, affecting around 250,000 people globally. The Kellgren-Lawrence (KL) grading system is the industry standard used by medical professionals to group the degree of KOA on radiographs. Even with the advent of alternative medical imaging technologies, radiographs are still employed for imaging because they are readily obtainable and reasonably priced. The World Health Organization (WHO) recognized the KL grading system as the norm in 1961. It divides the severity into five progressive levels: 0 for healthy, 1 for questionable, 2 for minimal, 3 for moderate, and 4 for severe. The care and expertise of the doctor have a significant impact on how accurately the severity diagnosis is made.

We need an assisting tool to prevent the development and worsen the disease. In this project, Our goal is to close this gap by raising the accuracy of our predictions for every KL grade. The primary signs of osteoarthritis (OA) include joint stiffness in the morning or after rest, decreased function and participation limitations, and pain and trouble with joint motion. At the moment, OA is assessed using a clinical examination, symptoms, and basic radiographic methods like X-rays, MRIs, and CT scans. The Kellgren-Lawrence (KL) system is a recognized approach for grading individual joints into

five categories, despite the fact that numerous extra methods have been offered.

According to published research, OA in the hips and knees ranks as the tenth most common cause of disability worldwide<sup>1</sup>. This places a significant financial burden on society. According to reports, the annual anticipated total expenditures per patient for OA treatments are as high as 19,000 €<sup>2</sup>. A portion of these expenses result from the current clinical incapacity to methodically identify the illness early on, when there may still be hope for halting its advancement or at the very least lessening the severity of its eventual handicap. The only ways to extend a patient's healthy years of life are behavioral therapy and early diagnosis, as there is currently no viable treatment for severe OA other than total joint replacement surgery. Clinically, OA can be diagnosed at an early age; nevertheless, at this time, it requires the use of expensive magnetic resonance imaging (MRI) available only at specialised centres or in private practice.

Common X-ray findings of osteoarthritis (OA) include bone spur growth, reduced joint space between neighboring bones, and degradation of joint cartilage. When x-rays suggest that other types of joint tissues may be damaged or when they do not clearly explain the cause of joint pain, MRI scans may be ordered. The accuracy with which osteoarthritis is now diagnosed clinically is insufficient for effectively tracking the condition's progression and quality. Because of this, we need more sophisticated, multifactoral techniques and algorithms to access the parameters and course of osteoarthritis..

Detection and Grouping of Osteoarthritis in knee from medical images is one of the active fields in computer vision. Image classification is one of the most commonly studied problems in computer vision. The goal of this field is detecting all the objects of a given image. Since the Convolution Neural Networks (CNN) can detect the objects with more than 90% of accuracy, we can use a fine- tuned neural network to

detect an object. In the respective for above-mentioned issues, this work will implement Deep Features techniques to detect and classify the Osteoarthritis from medical images and also incorporate a large database for better accuracy. This project focuses on the various machine learning techniques for the grouping of OA disease from the medical images.

Musculoskeletal diseases and articular disorders are one of the main health problems in recent years and affect especially the aging population. The human knee joint is commonly affected by osteoarthritis (OA), a degenerative disease that is the primary cause of chronic disability. Osteoarthritis (OA) is a commonly occurring joint disease, often leading to pain and reduced function in older individuals. It is marked by the gradual deterioration of diarthrodial joint tissue. It can affect many joints, such as the hips, knees, fingers, thumbs, spine, and toes, however it most commonly affects the hip and knee joints.

Detection and progress monitoring of knee OA can be done by measuring biochemical and The anatomical alterations linked to the tissues include articular cartilage, ligaments, meniscus, synovial fluid, and subchondral bones

## II. RELATED WORKS

In [1], The author Tayyaba Tariq et al have reported a deep learning-based ordinal classification approach to grading knee osteoarthritis X-rays. This Project implemented a new state-of-the-art result in automated KOA classification for all KL grades. In addition, they enhanced the performance of the models by making an ensemble of fine-tuned models. The implemented method provides a quick, early, and reliable evaluation of input knee X-rays, and medical practitioners can use it as an alternative option to save time. Ordinal classification improved the performance of our system significantly. Further Ensemble has also shown significant improvement for all evaluation metrics.

The author Maryam Tamadon et al [2] have implemented Osteochondral tissue repair in osteoarthritic joints: clinical challenges and opportunities in tissue engineering. This paper implemented one of the priorities for the Bone and Joint Decade, is one of the most prevalent joint diseases, which causes pain and disability of joints in the adult population. The implemented system contains the OC tissue structure and the design, manufacturing and performance of current OC scaffolds in treatment of OA. The findings demonstrate the importance of biological and biomechanical fixations of OC scaffolds to the host tissue in achieving an improved cartilage fill and a hyaline-like tissue formation.

Detection of Osteoarthritis using Knee X-Ray Image Analyses: A Machine Vision based Method was created by Shivanand Sharanappa Gornale et al. [3]. This study used a variety of medical imaging modalities in addition to a clinical assessment to evaluate osteoarthritis. Unwanted distortions in a knee X-ray image can make it difficult to analyze the bone structures. The authors have employed a semi-automated strategy to address these issues, which offers a rapid and effective way to examine any anomalies or issues related to the bone structures. The authors of the work segmented a knee x-ray picture that was subjected to a number of feature extraction approaches using the Active Contour algorithm.

In [4], The authors Joseph Humberto Cueva et al. described the diagnosis and classification of osteoarthritis in the knee in [4]. This study used a refined ResNet-34 and a semi-automated CADx model based on Deep Siamese convolutional neural networks to identify OA lesions in both knees simultaneously based on the KL scale. With an average multi-class accuracy of 61%, the implemented project findings show higher performance outcomes for categorizing KL-0, KL-3, and KL-4 than KL-1 and KL-2. Physicians use visual evaluation of X-ray or MR images to assess the severity of knee OA using the Kellgren and Lawrence

(KL) scale.

The author Abdul Sami Mohammed et al [5] We used a Residual Neural Network to identify and categorize Knee Osteoarthritis from X-ray images. Our goal was to create a fast and accurate automated system to assist physicians in diagnosing this common condition in older adults. Our method aims to reduce manual work for doctors and prevent misdiagnosis.

Malathi S Y et al [6] have designed Automatic Inception V3 Neural Network for Diagnosis of Knee Osteoarthritis from X-Ray Images automatic. This paper applied new methods to automatically localize knee joints using a fully convolutional network and quantified knee The level of OA intensity across a network that was jointly trained for multi-class classification and regression, with both networks being initially trained from the ground up. The FCN-based approach is significantly more precise than the methods that came before it. The method that was used demonstrates that the classification outcomes attained with the automatically localized knee joints are on par with those from the manually segmented knee joints.

In [7], The author Mahima Shanker Pandey et al have reported Computer Assisted Automated Detection of Knee Osteoarthritis using X-ray Images. This paper implemented an automated method for the detection of OA using knee X-rays. The automated approach leads to accurate results in contrast to manual approaches (prone to mean errors for test to test). The implemented approach is a complete automated system including the pre-processing, ROI segmentation, thresholding, distance calculations and decision making. The automated system worked well on clear images of knee.

The author Insha Majeed Wani et al [8] have successfully integrated the detection of Osteoporosis in knee X-ray images through the application of transfer learning, utilizing a Convolutional Neural Network (CNN). The X-ray images utilized were

sourced from a specially curated dataset, which was classified into three groups: normal, osteopenia, and osteoporosis, using a widely recognized medical test called the Quantitative Ultrasound system. This system, which is approved by medical authorities, calculates the T-score by evaluating the bone mineral density (BMD) of the bone. The dataset we used included a total of 381 knee X-ray scans. The project we undertook evaluates the effectiveness of several well-known CNN models, including ResNet-18, VggNet-16, AlexNet, and VggNet-19, in identifying osteoporosis from knee X-ray images.

D. Pavithra [9] have designed A Survey on Computer Aided Methods for Diagnosis and Assessment of arthritis in the knees. In order to automatically estimate the severity of knee osteoarthritis from X-ray pictures, this article employed machine learning methods. Grading of OA and also implemented the task of automatically extracting the knee-joint region from the X-ray images and quantifying their severity by training a faster region convolutional neural network (R-CNN). The executed project assesses the performance of several machine learning models like transfer learning, support vector machines and fully connected neural networks based on their grouping accuracy.

In [10], The author Yashas C et al have reported Knee Osteoarthritis Detection and Severity Prediction Using Convolutional Neural Network. This project implemented a new transparent computer-aided diagnosis method based on the Deep Siamese Convolutional Neural Network to automatically score knee OA severity according to the Kellgren-Lawrence grading scale. The implemented project is trained by the method using the data solely from the Multicenter Osteoarthritis Study and validated it on randomly selected 3,000 subjects (5,960 knees) from Osteoarthritis Initiative datasets. This paper executes a semi-automatic CADx model based on Deep Siame CNN.



### III. PROPOSED METHOD

#### A. Proposed System Architecture

The proposed system (KOD) automatically detects the Knee Osteoarthritis using X-Rays. In our proposed system we focus on an enhanced machine learning techniques for a classification of Knee Osteoarthritis. The Proposed system contains five stages. In the 1st stage appropriate data type and source are selected for collecting the data. In the second phase the proposed system will undergo preprocessing which improves the performance by handling missing values, normalizing features. In the third stage the data set is split into test and training data. The data selected for training is used to train the CNN model. Following the previous stage the fourth stage is about classifying the data. The final stage is about testing the model, fine tuning and deploying our system for betterment in health care. It is as shown in Fig 1.

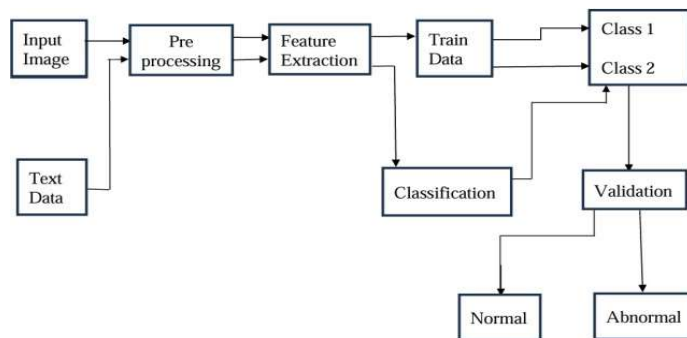


Fig 1: Proposed System Architecture

#### B. Data Flow Diagram

A data-flow diagram is a way of representing the flow of data of a process or a system (usually an information system). The data flow diagram also helps us to monitor what data we are feeding to a given component of the program and what output data it generates after processing. A data-flow diagram doesn't have any control flow as there are no decision statements or loops. The data flow diagram is just a graphical depiction of the flow of data through the information system. The Data Flow Diagram is very useful in understanding a system and can be efficiently used during analysis and is shown in Fig 2.

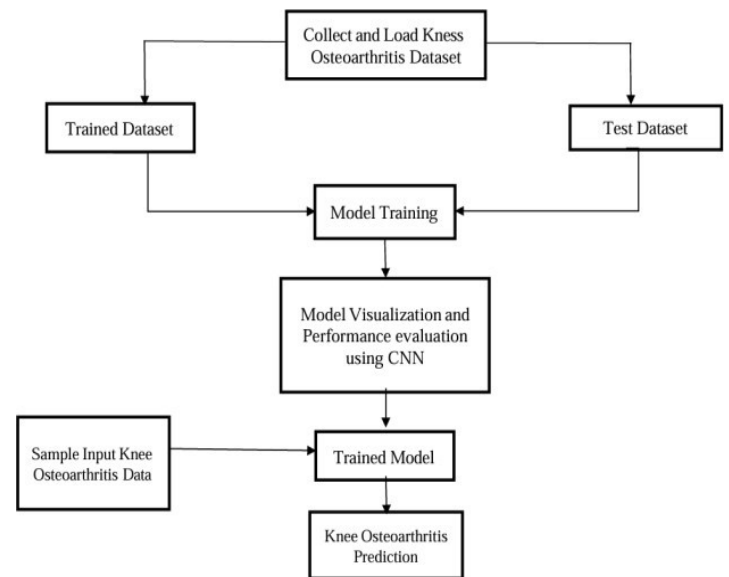


Fig 2: Dataflow Diagram for Proposed System

#### C. Data Collection

The dataset which is collected from Kaggle is taken into account. The dataset contains knee X-ray data for both knee joint detection and knee KL grading. These collected data can be taken from the hard copy of X-ray or directly from the computerized data from the machine. Let us consider the X-ray input as  $X$ , where  $X$  is the X-ray dataset.  $X = x_i$ , where  $i = 0, 1, 2, 3 \dots n$ . This X-rays can be represented in the  $X_{irj}$  is the  $r$ th row and  $j$ th Column in the  $i$ th image frame  $X_i$ .

#### D. Pre-Processing

The procedures and methods used on raw data prior to feeding it into machine learning algorithms for testing and training are referred to as data preparation. Pre-processing aims to improve the image data by reducing unwanted distortions or enhancing certain image properties that are significant for tasks involving additional processing and analysis. The data preprocessing will mainly contain 3 techniques mainly: Resizing an Image, Conversion of grayscale Image, Reducing Noise. In resizing of the image the given X-ray will be resized the frames that they are upscaled and downscaled as per our requirements. In

conversion of the grayscale images will be converted to grayscales with the range of 1 and 0 (Black and white). In the noise reduction processes we will take the image from the grayscale and later it will remove the unwanted items in the image (X-ray) given as an input dataset. Consider the collected data  $X = x_i$ , where  $i = 0, 1, 2, 3 \dots n$ . as an input of preprocessing. In the data preprocessing the given X-ray image will be sent to above mentioned stages and the output of this will be  $X^*$ . where  $X^* = X^*i$  where  $i = 0, 1, 2, 3 \dots n$ .

### E. Feature Extraction

Feature extraction in image processing is a technique of redefining a large set of redundant data into a set of features reduced dimension. This transformation of the input data into the set of features is called feature extraction. Feature extraction refers to the process of identifying and extracting important characteristics or features from raw data. It helps to focus on the most relevant information and discard irrelevant or redundant data.

Feature extraction aims to extract significant information while eliminating superfluous or unnecessary data. Facilitating more efficient and accurate analysis by machine learning algorithms. It helps improve model performance, reduce computational complexity, and enhance the interpretability of the data. Feature extraction is crucial for building effective and efficient models, especially when dealing with high-dimensional datasets.

A convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the several types of artificial neural networks which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and jobs that need pixel data processing.

$X^*$  is the image data set that has been preprocessed.  $X^*$  is converted into the set of images  $X^*i$  that where  $X^*i$  represent the preprocessor image, where  $i$  is equal to  $1, 2, 3, \dots, n$ . Each of this preprocessed image is broken into small individual blocks of size  $3 \times 3$ . consider the  $b$  is the block data set and  $b_i$  represents the  $i$ th block of the image data set  $b_i = b_{irk'}$  for  $r = 1, 2, 3, \dots, h$ ,  $k = 1, 2, 3, \dots, w$ . Consider the kernel or the optimal value  $U = U_{pq}$  where  $p = 1, 2, 3 \dots m$   $q = 1, 2, 3, \dots, n$ . In convolution layer the the matrix multiplication will be done between block value  $b_{irk'}$  and optimal value  $U_{pq}$  and the result will be summation of this matrix  $b_{irk'} \times U_{pq} = b_{irq'}$  finally it can be written as  $b_{fi}$  where  $b_{fi}$  is the final result after the summation of the matrices multiplication result. this process will continue till all the blocks are slid over the all the pixels finally, the output looks same as the input but the size of the pixels will be decreased. This result will be sent to max pooling  $[2 \times 2]$  in which each  $2 \times 2$  matrices of the  $b_{fi}$  is max polled. We need to apply max pooling for the given input.

That is  $b_{fi} = \max(b_{fu}, b_{fv}, b_{fw}, b_{fx})$  where  $u, v, w, x$  belongs to  $i$ . The main aim of this max pooling is to reduce the size of the image image features. The process will continue with many filter applied again and again until the resulting frame will be of minimal size.  $FB$  is the final block of the values.  $FB = FB_{mn}$  where  $m = 1, 2, 3, \dots, h$ ,  $n = 1, 2, 3, \dots, w$ . This  $FB$  will be flattened into 1 Dimensional vector. This flattened values are sent to the fully connected layer, The main aim of using the fully connected layer is to connect the information extracted from the previous steps (i.e. Convolution layer and Pooling layers) to the output layer and eventually classifies the input into the desired label. This fully connected layer will associate features to a particular label.  $X = X_t$  where  $t = 1, 2, 3, \dots, d$  with  $d$  features.

### Algorithm for Feature Extraction:

Input: Preprocessed image data set  $X^* = X^*i$ , for  $i = 1, 2, 3, \dots, n$  with  $n$  Images

Output: Image feature set  $X_t$ , for  $t=1,2,3,\dots,d$  with  $d$  Features

Begin

1. image data set  $IM'$  is first broken down into blocks  $B_i$  where  $i=1,2,3,4,\dots,n$  blocks
2. ch block  $B_i$  can be written as  $B_i=B_{irk}$  (3) where  $r=1,2,3,\dots,h$  and  $k=1,2,3,4,\dots,w$ .
3. ch block is sent to convolution layer and will perform the matrix multiplication with the kernel value with can be  $(3*3)$  or  $(5*5)$  based on our requirements.
4. result is sent to max polling and this process will continue till the matrix is converted to single 1D vector using flattening layer
5. peat the above steps until to generate feature  $X_t$  vector o to all image frames in the image set  $X$ .

End

## F. Training

The training phase in machine learning involves teaching a model to make predictions or perform a task by exposing it to a labelled dataset. The goal is to train a model that can make precise estimation on new, unseen data by learning patterns and relationships from the training set. In this stage, the proposed APWS system iteratively splits the input plant monitoring dataset ( $X$ ) into  $K$  dissimilar clusters based on K-Means technique and it represents each individual cluster into separate plant monitoring data for analysis process. The clustering stage consists of four steps.

In the first step, it select the  $k$  centroid vectors  $V = \bar{v}r$ , for  $r = 0,1,\dots,k$ ,  $V \subseteq X$ ,  $\forall \bar{v}r \in X$  the actual plant monitoring dataset  $X = x_i$  for  $x_i = x_{ij}$ , for  $i=0,1,\dots,n$ ,  $j=0,1,2,\dots,d$  over based on predetermined knowledge, where  $k$  denotes the number of clusters or centroid values,  $V$  is the centroid vector set with  $k$  vectors,  $\bar{v}r$  denotes the  $r$ th centroid vector with  $d$  plant monitoring data which belongs into the centroid vector set  $V$ , vectors and  $d$  represents the size of the vector.  $X$  is the plant monitoring data vector set with  $n$ .

In the second step, it measures the dissimilarity  $D(, V)$  between the plant monitoring data set vector set  $X = x_i$ , for  $i=0,1,\dots,n$  and centroid vector set  $V = \bar{v}r$  for  $r = 0,1,\dots,k$  based on Euclidean distance and is defined in the Equation (1).

Where,  $d(X_{ij}, \bar{v}r_j)$  denotes the Euclidean distance  $D(\bar{X}, \bar{V}) = \{ \{ d(\bar{X}_{ij}, \bar{V}_j) \}_{r=0,1,\dots,k}^{k-1,n-1,d-1} \} \forall \bar{V} \subseteq \bar{X} \forall x_i \in \bar{X}, \forall x_{ij} \in x_i \}$  ..... (1) between  $j$ th plant monitoring data of the  $r$ th centroid vector and  $i$ th input plant monitoring dataset and is defined in the equation (2).

$$d(x_{ij}, \bar{v}r_j) = \{ \{ \sum_{j=0}^{d-1} (x_{ij} - \bar{v}_{rj})^2 \}^{1/2} \} \dots \dots \dots (2)$$

Next step, it place the each individual  $i$ th vector  $x_i$  in the  $X$  into their closed centroid vector  $\bar{v}r$  of its respective cluster in the  $cr$  cluster set  $C = cr$  for  $r = 0,1,\dots,k$  based on the highest similarity and is defined in the equation (3).

$$c_r = \text{Min} \{ \{ d(x_i, \bar{v}r_j) \}_{r=0,1,\dots,k}^{k-1,n-1} \} \forall c_r \subseteq \bar{X} \} \dots \dots \dots (3)$$

Where,  $C$  denotes the predetermined cluster with  $k$  clusters,  $cr$  represents the  $r$ th cluster in the cluster set  $C$  and in the last step, it updates the  $r$ th centroid vector value  $V = \bar{v}r$  of each individual cluster  $C = cr$  based on vectors in their respective  $r$ th cluster and is defined in the equation (4) as

$$\bar{v}r = \{ \{ \frac{1}{|c_r|} \times \sum_{e=1}^{|c_r|} c_{re} \} \} \forall c_{re} \in c_r \} \dots \dots \dots (4)$$

Where,  $|c_r|$  denotes the number of similar plant monitoring data vectors and  $c_{re}$  represents the  $e$ th vector in the  $r$ th cluster which belongs into cluster set  $C$ . The process of updating centre is iterated until a situation where centres do not change anymore or criterion function becomes lesser and the clustering stage algorithm is described in the below sub section.

### Algorithm for Training:

Input: Plant monitoring dataset  $X = x_{ij}$  with  $n$  vectors, centroid vector set  $V = \bar{v}r$  with  $k$  vectors

Output: Produced  $k$  distinct clusters  $C = \{c_1, c_2, \dots, c_k\}$

Begin

1. Randomly select k number of centroid vectors over the plant monitoring dataset  $X$  with n vectors and assigned into  $V = \bar{v}_r$  for  $r = 1, 2, 3, \dots, k$
  2. Iteratively computes the Euclidean distance between centroid vector set  $V = \bar{v}_r$  and plant monitoring data vector  $X = x_i$  using Equations (2) and (3)
  3. Place the each individual vector in the plant monitoring data vector set  $X = x_i$  into its closest cluster centroid cluster based on higher similarity using Equation (4)
  4. Update the each individual rth cluster centroid ( $\bar{v}_r$ ) based on elements or vectors of the rth cluster by Equation (5)
  5. Repeat the steps from 2 to 4 until the present iteration cluster centroid is similar to previous iteration.
- End.

### G. Classification

In the classification stage we need classify in which stage of the Osteoarthritis (OA) does the given image (X-ray belongs to. Here we are taking two inputs, one with the clusters  $C$  and the Test image data set image data set. Here it will under go XOR operatin between these two data sets. If the values of the cluster and test set is same then the value will be 1, which indicates the human is present in the room. else the value will be 0, which indicates the human absent in the room.

$$d(C, T) = (C_i \oplus T_j) \mid d(C, T) = \begin{cases} 1, & C_i \neq T_i \\ 0, & C_i = T_i \end{cases} \quad \forall C_i \in C, \forall T_i \in T \quad (6)$$

Grade 0-No Radio-graphic features of OA present  
 Grade 1-Doubtful OA (narrowing of joint space)  
 Grade 2-Mild OA (definite narrowing of joint space)  
 Grade3-Moderate OA (multiple osteophytes, sclerosis)  
 Grade4-Severe OA (large osteophytes, sever sclerosis, bone deformity)

### Algorithm for Classification:

Input: The data set  $T = \{T_1, T_2, \dots, T_m\}$  and clusters  $C = \{c_1, c_2, \dots, c_k\}$

Output: which stage of the Osteoarthritis (OA).

Begin

1. Compare the input test dataset with clusters

2. Find out which cluster does the dataset belong to using hamming distance formula as defined in equation (6)
  3. Based on the cluster, decided whether to human present in the room or not present in the room.
- End

## IV. RESULTS

The below Fig 3 shows the Home Page.

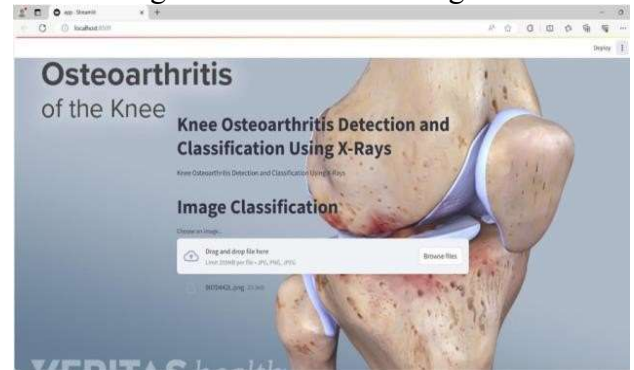


Fig 3: Home Page

The Fig 4 shows Normal Data Sets

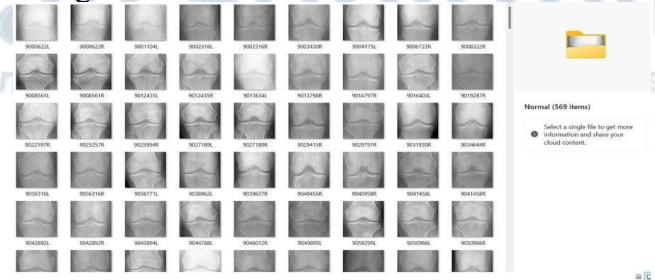


Fig 4: Normal Data Sets

The Fig 5 shows Osteoarthritis Data Sets

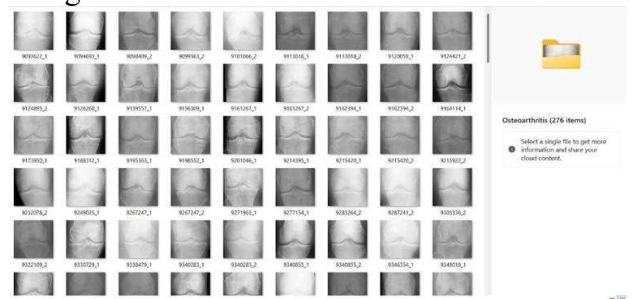


Fig 5: Osteoarthritis Data Sets



The Fig 6 shows *Program Execution*

```

C:\Users\insp> python -X +v
WARNING: I/O: http://192.168.13.166:8501

2024-05-09 11:32:35.722531: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from computation order. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
WARNING:tensorflow: From C:\Users\insp\anaconda3\lib\site-packages\keras\sources\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

WARNING:tensorflow: From C:\Users\insp\anaconda3\lib\site-packages\keras\sources\backend.py:1398: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

WARNING:tensorflow: From C:\Users\insp\anaconda3\lib\site-packages\keras\sources\layers\pooling\max_pooling2d.py:161: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool_2d instead.

2024-05-09 11:32:40.531509: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: SSE42 SSE43 SSE41 SSE42 AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

I/I/ (=====) - 2s 2s/step
I/I/ (=====) - 3s 3s/step
I/I/ (=====) - 4s 4s/step
I/I/ (=====) - 4s 4s/step
WARNING:tensorflow: out of the last 5 calls to <function Model.make_predict_function.<lambda>.predict_function at 0x00000366E97ECC0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_tracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.
I/I/ (=====) - 4s 4s/step

```

### Fig 6: Program Execution

The Fig 7 shows Backend Program Output.

[illegible]

### Fig 7: Backend Program Output

The Fig 8 shows Prediction Result– Normal

# Osteoarthritis

## of the Knee

### Knee Osteoarthritis Detection and Classification Using X-Rays

Knee Osteoarthritis Detection and Classification Using X-Rays

### Image Classification

Choose an image...

 Drag and drop file here  
Limit 20MB per file • JPG, PNG, GIFS

Browse files

903658.png 23.6KB

Prediction: Normal





**Fig 8: Prediction Result – Normal**

The Fig 9 shows Prediction Result – Osteoarthritis (Moderate)

# Osteoarthritis

## of the Knee

### Knee Osteoarthritis Detection and Classification Using X-Rays

Knee Osteoarthritis Detection and Classification Using X-Rays

### Image Classification

Choose an image...



Drag and drop file here  
Limit: 20480 per file • JPG, PNG, JPEG

9003827L.png 12.64K

Predicted: Osteoarthritis



**Fig 9: Prediction Result – Osteoarthritis (Moderate)**

The Fig 10 shows Prediction Result – DR (severe)

The image shows a web application interface for knee osteoarthritis detection. The main title is "Knee Osteoarthritis Detection and Classification Using X-Rays". Below it, a subtitle reads "Knee Osteoarthritis Detection and Classification Using X-Rays". The application is titled "Image Classification". A file upload section shows a file named "9005899.jpg" (12.0 KB) has been uploaded. The prediction result is "DR". The background of the interface features a 3D anatomical model of a human knee joint.

**Fig 10: Prediction Result – DR (severe)**

## V. CONCLUSION

In this paper, we have applied a deep learning-based ordinal classification approach to grading knee osteoarthritis X-rays. We present new state-of-the-art results in automated KOD classification for all KL grades. In addition, we enhanced the performance of our models by making an ensemble of fine-tuned models. Our method provides a quick, early, and reliable evaluation of input knee X-rays, and medical practitioners can use it as an alternative option to save time. Ordinal classification improved the system's performance has shown remarkable improvement and Ensemble has exhibited significant enhancement across all evaluation metrics

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