International Journal of Intellectual Advancements and Research in Engineering Computations (IJIAREC)

IJIAREC |Vol.12 | Issue 1 | Jan - Mar -2024

www.ijiarec.com

ISSN: 2348-2079

DOI : https://doi.org/10.61096/ijiarec.v12.iss1.2024.1-12

Research

A CNN Based Approach for the Prediction of Knee Osteoarthritis

Billa Suvarna Latha*, Dr. G. Prathibha

**M Tech Student, Department of ECE, Dr YSR ANUCET, Acharya Nagarjuna University, Guntur, Andhra Pradesh-522510.*
Assistant Professor, Department of ECE, Dr YSR ANUCET, Acharya Nagarjuna University, Guntur, Andhra Pradesh-522510.

*Author for Correspondence: Billa Suvarna Latha
Email: suvarnalatha.billa@gmail.com

Published on: 20 Jan 2024

Published by:
DrSriram Publications

Abstract

Radiology takes place a crucial part in various medical applications like methods used for earlier diagnosis, observation, and medication assessment of numerous medical conditions. Osteoarthritis (OA) is a degenerative joint condition brought on by changes to the bones and cartilage loss in the joints. The examination of bone texture to predict early OA of the knee is a challenging task in processing of medical image. It's better for viewing severity conditions in medical field rather than to listening. Therefore, it is essential for early prediction and treatment of Knee OA by examining the X-ray images which are medically categorized by experienced doctors by Kellgren and Lawrence (KL) scoring method. The present work suggests a strategy for automated osteoarthritis of the knee classification based on Deep Convolutional Neural Networks (DCNN).The X-ray pictures from Osteoarthritis Initiative (OAI) Dataset are utilized for assessment. Then, a strategy is proposed to extract the features using pretrained Efficient Net architectures such as Efficient Net B0, Efficient NetB1, Efficient Net V2B0, Efficient Net V2B1, Efficient Net V2B2 and Efficient Net V2B3. These eradicated characteristics are then decreased in dimension by Principal Component Analysis (PCA). The reduced features are classified with Basic Convolution Neural Network (CNN) architecture which resulting in a testing accuracy of 95.71% and an imbalanced accuracy of 86.41% using the features of Efficient Net V2B1.

Keywords: Pre-Trained Networks, Imbalanced Accuracy, Testing Accuracy.

INTRODUCTION

Osteoarthritis of the knee is a deteriorated joint disorder that damages the joints in the knee. It is a frequent ailment that occurs when the cartilage in the ends of the knee joint bones softens and wears away over time, which leads to rub the bones against one another. It causes pain, stiffness, and mobility loss in the damaged knee. It could result in knee replacement if not tackled early. There are various reasons that bring out the advancement of osteoarthritis in the knee, including age, obesity, genetics, joint space reduction and cartilage end hardening and previous injuries to the knee joint. The manifestation of osteoarthritis in the knee may differ according to the severe condition, but general symptoms like pain, stiffness in the knee, swelling, and a grinding sensation when moving the knee.

Knee osteoarthritis is a significant health problem in India, particularly as the population ages and becomes more sedentary. However, there is a lack of comprehensive data on the prevalence and impact of knee osteoarthritis in India. Some information based on the available data considering some factors are Prevalence: Studies have estimated that the prevalence of knee osteoarthritis in India varies from 22% to 39%, based on the population analysis and the exploited diagnostic criteria. Age: Knee osteoarthritis is the most frequent problem in older adults in India, along higher incidence in persons having the age of 50. Gender: Knee osteoarthritis is the most prominent problem in women compared to men in India, with a female-to-male ratio ranging from 1.5:1 to 2:1. Healthcare utilization: Osteoarthritis in the knee is a serious cause of disability in India also it is a major reason for visits to primary care physicians and orthopedic surgeons. Economic burden: Knee osteoarthritis imposes a significant economic burden on individuals and families in India, particularly with reference to costs of healthcare and lost effectiveness.

Based on the Centres for Disease Control and Prevention (CDC) **[1]**, the most common form of arthritis is osteoarthritis (OA) that influences around 32.5 million adults in the United States. Knee osteoarthritis is the generally occurring OA and is the primary cause of disability in older adults. Some statistical records on knee osteoarthritis in the US are Prevalence: older adults are mainly affected by knee osteoarthritis, with an incidence of 37.4% in persons having the age of 60, compared to 13.8% in those aged 25-74. Gender: Women is highly affected by knee osteoarthritis when compared to men, with an incidence of 19.2% in women and 14.5% in men. Ethnicity: The prevalence of knee osteoarthritis varies by ethnicity, with higher rates in white American adults (16.8%) and non-Hispanic Black adults (11.4%) and Mexican American adults (10.2%). Healthcare utilization: Knee osteoarthritis is a leading cause of visits to primary care physicians and orthopedic surgeons, and it is also a major reason for joint replacement surgery. Economic burden: Knee osteoarthritis is a financial burden significantly in the United States, along with an estimated annual expenditure of $128 billion in medical care and lost productivity.

With an advancement of Machine Learning (ML) and Deep Learning (DL) algorithms that produces an hindrances in disease progression detection at a starting stage and offers a fascinating perspectives for automation of medical image analysis. Deep Learning techniques help to support the identification, classification and quantification of Medical Images patterns.

The literature on CNN based approach for knee osteoarthritis prediction is presented in Section II. The Methodology and the Architecture are examined in III - Section. The Results of the experiments are discussed in IV - Section. The Conclusion of the work along with the discussions is given in Section V. The reference works used in this study are represented in the final section.

LITERATURE REVIEW

Wang, Yu, et al. [2] proposed an automated osteoarthritis in the knee classification strategy based on deep neural networks using OAI dataset. The x-ray pictures are pre-process i.e. the frequency domain and the histogram filter is assimilated to accentuate the trabecular bone texture properties and enhance the recognition accuracy. The AMSGrad approach is employed to balance between accuracy and repetitive exploration effectiveness for joint centre searching with JC-RegNet according to the VGG neural network and it achieved an accuracy of 96% which is higher than SVM method. This classification achieved an accuracy of 81.41%.

Jain, Rohit Kumar, et al. [3] proposed an effective deep CNN OsteoHRNet for predicting the knee OA KL grades severity from X-ray pictures of OAI dataset built on High-Resolution Network (HRNet), among the most new deep models that capture the multi-level properties of X-rays of the knee. The recommended method lowered the computations by using the attention mechanisms only once in the overall network and the counterproductive features are filtered adaptively prior to classification. Further, the optimization of the proposed method is done using ordinal loss instead of the traditional entropy based minimization. As compared to other networks like VGG 19, DenseNet 161 the proposed method Osteo HRNet has attained the best multiple class precision of 71.74% and MAE of 0.311.

Abedin,Jaynal,etal. [4] Developed anticipated models using Elastic Net (EN), Random Forests (RF) and Linear Mixed Model to obtain the interrelation among the two knees and a trained convolution neural network (CNN) which utilizes just X-ray pictures from the OAI dataset. For the purpose of the model relationship among the two knees, linear mixed effect models (LMM) were used which has equal total precision prognosis for the EN regression, which exactly considered the hierarchical structure of the data, results in high accurate deduction. The respective root mean squared errors of CNN, EN, and RF models' were 0.77, 0.97 and 0.94 that suggests that modelling X-ray pictures and information of the patient achieves equivalent outcomes by training the models for prognosticate the KOA severity levels.

Chen,Pingjun,et al. [5] proposed two deep Convolutional Neural Networks (CNN) that are employed to measure the knee OA severity automatically found by the Kellgren-Lawrence (KL) grading system. Knee Joints are identified by a specialised one-stage YOLOv2 network by taking the knee joints size seperated in X-ray pictures with less changeability. The detected results are compared with manual annotations using the metric known as Jaccard index that resulted in mean of 0.858 and recall of 92.2%. The detected knee joints are classified with a new ordinal loss modification, using the CNN models like changes in ResNet, VGG and Dense Net also Inception V3.

Thomas, Kevin A., et al. [6] proposed to create an automatic model to assess the knee osteoarthritis severity from X-Ray pictures and to assess how well it performs in comparison to musculoskeletal radiologists. The Kellgren-Lawrence (KL) technique was used to automatically normalize and enhance the radiographs from the Osteoarthritis Initiative (OAI) before being used as input and to prognosticate the KL score of every single image a 169-layer Convolutional Neural Network (CNN) along with a dense architecture was employed and Saliency maps were created to illustrate the features of the model utilised to calculate KL grades. The Accuracy and F1 score for the scores of the Committee as a ground truth is 0.71 and 0.70 whereas for the 50-image subset the Accuracy and F1 score of 0.60.

Mahum,Rabbia,etal. [7] Proposed DL-based eradicated features and categorization to found out a unique KOA findings at a starting stage. Then utilising mixed property descriptors like Convolutional Neural Network (CNN) via Local Binary Patterns (LBP) and CNN by Histogram of Oriented Gradient (HOG), features are recovered from pre-processed X-ray pictures having width of knee joint space. Finally multi-level classifications like Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbour (KNN), are employed for the KOA classification based on the Kellgren–Lawrence (KL) system. The photos are subjected to rotation estimation and 5-fold validation gives an accuracy of 97.14% and 98%.

Yunus, Usman, et al. [8] proposed the classification and localisation of the KOA technique utilising radiographic images from OAI and MOST dataset. This approach extracts LBP (Local Binary Pattern) features, which are then used to classify distinct KOA grades using PCA on the best features and the extensive properties are retrieved by Alex-Net and Dark-net-53 with proportions. For the KOA grades classification the retrieved features are fused serially and transferred to the 10-fold cross-validation classifiers which gives 90.6% accuracy. YOLOv2-ONNX (open exchange neural network) combination model is then used to localize the categorised images and it attained 0.96 IOU and 0.98 mAP on distinguished images by adopting ONNX model as the foundation of YOLO-v2.

Harrar, Khaled, Khadidja Messaoudene, and Mohammed Ammar [9] this study introduces a rapid and efficient method for categorising knee X-ray images from OAI dataset utilises LogitBoost, wavelet-based Gray Level Co-occurrence Matrix (GLCM),and Local Binary Patterns (LBP) so that improve classification of picture accuracy and reduce the time of training and testing. The suggested method improves the picture enhancement proceeded by Haar wavelet transformation. K-fold cross-validation technique is used for validation of the classification. The approaches GLCM and LBP results an accuracy of 77% and 82.5% but the estimation of accuracy is increased to 91.16% with the LogitBoost model by the combination of these two techniques LBP-GLCM compared to other classifiers.

Alexos, Antonios, et al. [10] the primary objective of the study is development of a prognostic tool using baseline data from OAI dataset to prognosticate the pain severity level in KOA patients. This is accomplished by using a feature importance ranking system to determine the significant risk factors and a variety of ML algorithms to predict whether a patient's KOA pain would stable, increase, or decrease. In order to determine which Machine Learning model delivers the best results, six models (Decision Trees, k Nearest Neighbors, Support Vector Machines, Random Forest, XGBoost and Naïve Bayes) were tested for their effectiveness in predicting the pain on characteristic divisions with different proportionality levels. With minimal number of features, up to 84.3% results have been obtained when these models are applied to various combinations of feature subsets.

Guan,Bochen,etal.[11] proposed to create risk assessment models using Deep Learning (DL) for prognosticate progression of pain which is a knee osteoarthritis (OA) risks. Using standard knee radiographs, a DL model was created to predict the evolution of pain and with demographic, medical and medical imaging grievance indicators; an Artificial Neural Network (ANN) was employed for creating standard grievance assessment model to prognosticate the pain distress. The AUC for the traditional model was 0.692 and DL model was 0.770, which was higher. In comparison to the conventional and DL models, the combined model's AUC was considerably higher at 0.807.

Liu, Bin, JianxuLuo, and Huan Huang [12] presented a model for continuous DL-based automatic knee OA diagnosis. Faster R-CNN is used as standard contains region proposal network (RPN) which is instructed to region proposals generation that holds knee joint by Fast R-CNN for processing input images for localization and classification. Modified model works better than Fast R-CNN, obtaining an average precision of about 0.82 with susceptibility over 78% and selectivity above 94% and it holds 0.33s for testing every single image, which attains a good trade-off among precision and speed.

Abdullah, S. Sheik, and M. Pallikonda Rajasekaran [13] proposed how an Artificial Intelligence (AI)-based DL approach can detect and identify the knee OA severity in digitalized X-ray pictures effectively. The width of knee joint space (JSW) region in digitalized X-ray pictures was instructed to be detected by the Fast RCNN architecture and ResNet-50 with transfer learning is employed to eradicate the characters. After comparing the output with the existing approaches, the recommended model detects the decreased knee JSW precision of 98.516% and severity of knee OA type precision of 98.90%. In future they intended to work on MRI data to grade knee OA.

Norman, Berk, et al. [14] suggested a fully automated model that employs KL grading and a modernized neural network for the prognostication of OA. From OAI dataset, bilateral PA fixed-flexion knee X-ray images were used for six various points of time and a U-net model is used to localized the right and left knee joints. For the severity of OA prediction, DenseNet architectures are used to train using these localized images. To examine the features of input images Saliency maps are used for decision making. The sensitivity and specificity levels of without OA, mild, moderate and severe OA are 83.7, 70.2, 68.9, and 86.0% and 86.1, 83.8, 97.1, and 99.1%.

METHODOLOGY

Dataset

Osteoarthritis Initiative (OAI) **[15]** dataset, a standard valuable resource for researchers who are interested in creating and evaluating CNNs and other machine learning algorithms for forecasting knee osteoarthritis development or treatment effectiveness. The dataset made available to the public contains clinical, imaging, and demographic information on approximately 4,796 participants. The OAI is a panel study of osteoarthritis in the knee that collects data over a period of up to 12 years at various time periods. The collection contains data on knee radiographs, MRI scans, clinical evaluations of knee function and pain and population statistics on sex, age and body mass index (BMI).Numerous research studies on knee osteoarthritis, including those looking at risk factors, treatment effectiveness, and disease progression, have made extensive use of the OAI dataset. A database means various types of data collected and stored in a digitalized format and it primarily contains images, text, audio, video, numerical data points etc. among the above datasets, image dataset is used to extract features using different CNN architectures.

From kaggle, OAI database is extracted. The database consists of 9786 images including the right and left knees. The pictures are manually categorized based on Kellgren and Lawrence (KL) classification standard and distribution of each category is shown in Table1. The KL system of grading is a medical imaging type of knee osteoarthritis. It starts from grade 0 to grade IV and also depending on x-rays. Osteoarthritis in the knee is the major problem occurs in all parts of society. Many changes are relevant to age, weight is a alternate factor.

The definitions of the original grade KL scale are: Grade 0: without pathological characteristics; Grade 1: doubtful joint space narrowing and possible lipping of osteophyte; Grade 2: specific osteophytes and possible joint space narrowing; Grade 3: moderated multiple osteophytes.

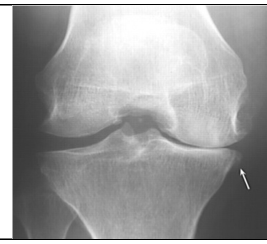
Table 1: According to Kellgren Lawrence grading system - distribution of each grade in dataset.

Kellgren Lawrence grading's	No. of Images in dataset
Grade 0	3857
Grade 1	1770
Grade 2	2578
Grade 3	1286
Grade 4	295

The automatic assessment of knee OA severity from radiographs has been approached as an image classification problem. According to the literature and in the machine learning approach to automatically assess knee OA severity, the first step is to localize the region of interest (ROI) that is to detect and extract the knee joint regions from the radiographs, and the next step is to classify the localized knee joints. First, the different approaches for detecting(or localizing) the knee joint regions in the radiographs are outlined.

Knee images digital analysis (KIDA) is a tool to analyse knee radiographs interactively, proposed by Marijnissen et al. KIDA quantifies the individual radiographic features of knee OA like medial and lateral joint space width (JSW) measurements, subchondral bone densities and osteophytes. However, this interactive tool can only be used by experts for quantitative measurements and requires expert intervention for objective quantitative evaluation.

The images which are used for feature extraction and classification of predicting knee osteoarthritis according to the Kellgren Lawrence grading system adopted from the dataset are shown in figure 1.

		
Grade 0 Normal No feature of OA	**Grade 1** Doubtful Minute Osteophyte	**Grade 2** Mild Definite Osteophyte

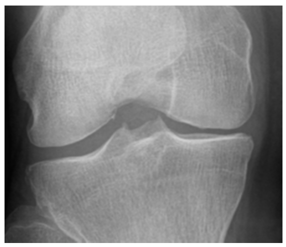
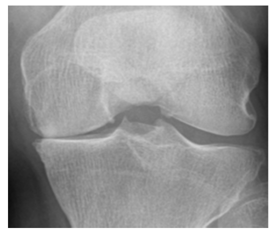
	
Grade 3 Moderate Moderate joint space reduction	**Grade 4** Severe Joint space greatly reduced

Fig 1: Images from the Dataset of KL Grades 0, 1, 2, 3, 4.

Convolutional Neural Networks

In deep learning, CNN stands for Convolutional Neural Network, which is a type of neural network commonly, used for image recognition and classification tasks. CNNs are specifically designed to process images, and they use a special type of layer called a convolutional layer to extract features from the input image. These features are then fed into one or more fully connected layers, which perform the final classification. The convolutional layer in a CNN applies a set of filters to the input image, which essentially performs a mathematical operation on the pixel values in the image. The result of this operation is a set of feature maps that represent different aspects of the image. These feature maps are then passed on to the next layer in the network for further processing. CNNs have been used to achieve state-of-the-art results on a wide range of image recognition and classification tasks, such as object detection, facial recognition, and medical image analysis.

A Convolutional Neural Network (CNN) proposed by Le Cunn et. al. **[16]** incorporates three key architectural principles to ensure robustness against shifts and distortions: local receptive fields, shared weights, and spatial/temporal subsampling. The structure of a typical CNN for image recognition is depicted in Figure 2.

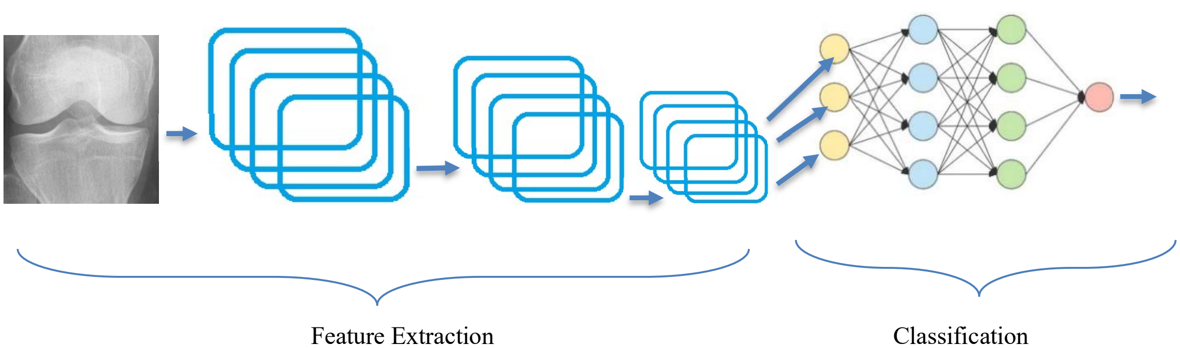


Fig 2: Architecture of Convolution Neural Network

Input images, which have been roughly standardized in size and centred, are fed into the initial layer. Every single unit within a layer collects inputs from a cluster of units in a small neighbourhood from the preceding layer. The Perceptron introduced the concept of associating components with local receptive fields in the input data. This idea of localized connections has been extensively utilized in Neural Models of Visual Learning. Neurons with these local receptive fields are capable of extracting fundamental visual attributes like aligned edges, corners, and endpoints. Subsequent higher layers then combine these features, whose positional variations can be accounted for by input shifts or distortions. Moreover, it's plausible that elementary feature detectors performing well in one image area will exhibit similar efficacy across the whole image.

Enforcement of a group of units generated basic features, each with receptive fields positioned at various locations across the pictures, to share similar weight vectors. The collective output of these units forms what is known as a working model. For each working model, the input image is scanned using an individual neuron with a localized receptive field that captures the neuron states at corresponding positions on the working model. This performance is akin to applying a small-sized kernel convolution succeeded by a flattening function. Representing the feature map as a plane of neurons with a single shared weight vector allows this process to be executed concurrently.

The convolutional layer is constructed using multiple feature maps, enabling the capture of numerous features from specific locations. Subsequent to each convolutional layer, there exists another layer that carries localized sub sampling and averaging. This reduces the decision of the working model and lessens the impact of shift-induced distortions on the output. Convolution and pooling constitute the initial stages of the CNN workflow, segmenting the image into distinctive features for individual analysis. The outcome of this process is then inputted into a fully connected neural network arrangement, employed to arrive at the ultimate classification determination.

Proposed Method

The key purpose in this study is to prognosticate the osteoarthritis using the x-ray pictures from the Dataset. The raw x-ray pictures are given to a pre-trained network as input to extract the features, an Efficient Net series such as EfficientNetB0, EfficientNetB1, EfficientNetV2B0, EfficientNetV2B1, EfficientNetV2B2, EfficientNetV2B3 are used. The extracted characteristics are decreased to 100 components by PCA and then these reduced features are classified using CNN with testing accuracies…..

Convolution Neural Networks, an engineering concept influenced by biology that produces competitive engineering solutions that outperform alternative methods. Despite the fact that manually derived features are not extracted, CNN still requires normalisation and orientation of pictures for image recognition. New architectures were created as a result of their greater classification capacity over classical feature-based categorization. Using the provided dataset to train the CNN from scratch is a typical deep learning strategy. The training period lengthens with a larger dataset. The trained model might not be universal and might over fit for a specific train, validation, and test split. In the transfer learning method, a model that has already been instructed on one database can be instructed on other database by fixing and/or freezing a few chosen layers. Even this strategy is not widely applicable. One can use a pre-trained CNN as a feature extractor by using the transfer learning approach.

A pre-trained CNN is used in the eradicated characteristics method. The model for this pre-trained CNN has already accomplished to categorise the 1000 classes in Image Net, which is a larger dataset on which it was trained. The pre-trained CNN is now fed the photos from the dataset for the Knee Osteoarthritis. The last pooling layer of this pre-trained CNN is where features are extracted. Principal Component Analysis (PCA) is used to minimise these characteristics, and 100 features are extracted.

Figure 3 shows the block diagram of proposed method. Transfer learning assures faster generalisation and less computational time. Actually, any layer of the pre-trained CNN can have its features retrieved. Lines are extracted from the initial layers, which are low level characteristics. The literature contains numerous Pre-Trained CNN architectures. There is no defined standard for which Pre-trained CNN should be used with our dataset. The literature has information on a number of CNNs, including ResNet, OsteoHRNet, DenseNet161, VGG19, InceptionV3, etc.

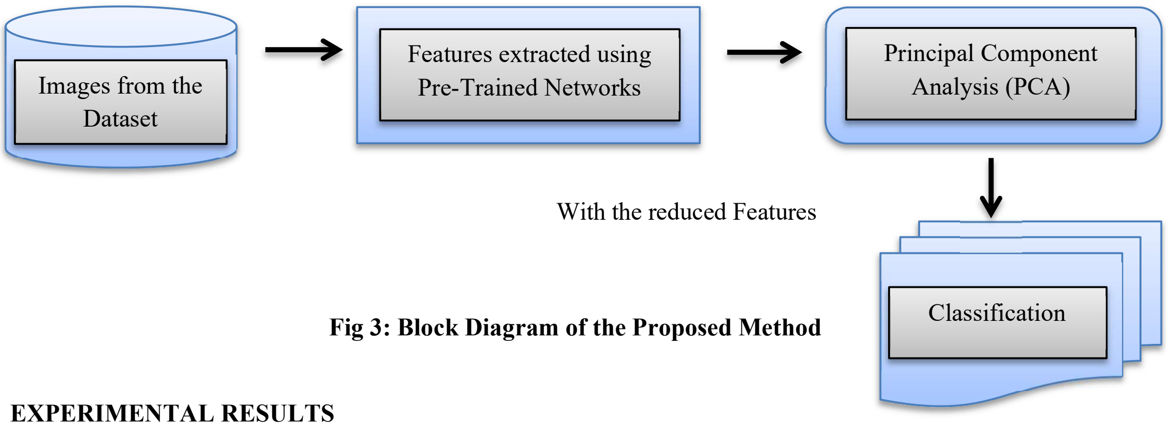


Fig 3: Block Diagram of the Proposed Method

EXPERIMENTAL RESULTS

Since, Deep Convolution Neural Networks require less pre-processing than conventional features extraction methods, CNNs are employed in this work to extract features. The Pytorch framework is used to run simulations in the Google Colab environment. Several Pre-trained Networks are utilised to extract characteristics from the OAI Dataset images that were taken from the Kaggle Dataset. Several Pre-Trained Networks NASNET Mobile, DenseNet121, EfficientNetB0, EfficientNetB1, EfficientNetV2B0, EfficientNetV2B1, EfficientNetV2B2, EfficientNetV2B3 are utilised in the study. These models were all developed to categorise thousands of distinct photos using the ImageNet dataset.

Each of these models is fine-tuned using transfer learning after being trained on the data to categorise the severity of knee osteoarthritis. The weights of the convolution layers are derived from ImageNet during feature extraction using pre-trained networks. For each Pre-Trained Network, 100 epochs are taken into account for extracting features. Extracted features from these Dataset using Pre-Trained Networks are given as input to CNN for classification of Knee Osteoarthritis using Pre-Trained network features. The Test accuracy, Imbalanced accuracy, F1-Score, Precision, Recall and Specificity for the features of Pre-Trained networks are depicted in below tables.

A study was conducted on around 9786 images that have been obtained from OAI dataset which is extracted from kaggle. Among that Grade 0 traced 3857 images, Grade 1 traced 1770 images, Grade 2 traced 2578 images, Grade 3 traced 1286 images and Grade 4 traced 295 images from the dataset.

The raw X-ray images from the dataset are taken for the feature extraction using EfficientNet series such as EfficientNetB0, EfficientNetB1, EfficientNetV2B0, EfficientNetV2B1, EfficientNetV2B2, EfficientNetV2B3 are used. The extracted features which are reduced to 100 components using principal component analysis (PCA) are documented in Comma Separated Values (CSV) format shown in figure 4.

No.of Images	Extracted and Reduced Features										
	0	1	2	3	4	5	....	95	96	97	98	99
0	86.89317	7.111241	1.523778	37.79704	3.714347	8.49867	....	2.086631	3.0322	1.17317	10.5626	4.809922
1	76.40237	16.9922	13.58995	26.70956	36.52913	60.32117	....	2.541385	8.041723	3.822281	3.560188	0.223493
2	9.846663	69.41037	13.28009	66.63351	9.631724	5.302103	....	7.137882	1.414879	6.464643	3.212858	0.685964
3	67.21386	6.357019	33.63565	18.2524	9.992669	29.46953	....	9.885207	0.757575	2.39514	4.741027	12.35205
4	24.8454	48.12676	58.87936	15.70093	5.780748	33.13005	....	3.054728	9.825717	4.973448	5.435844	20.69223
5	15.65875	68.45328	72.26937	26.52235	45.41634	2.026242	....	2.873447	1.729279	2.403016	5.970461	3.655284
6	5.873059	40.7977	69.71472	19.31055	35.77981	1.359265	....	4.497804	7.957124	12.36049	0.28619	4.213182
7	21.10344	97.29174	28.10702	5.077344	5.959489	0.015067	....	6.040334	3.458922	18.00581	1.289004	1.003467
8	32.72321	28.41789	13.16846	25.42854	60.8297	35.00518	....	4.389877	4.476263	0.12942	1.550716	0.494133
9	24.47932	100.5778	40.64927	37.29841	15.65002	17.52407	....	17.34803	5.736306	5.161637	2.225614	13.70536
10	5.261414	33.00422	15.50761	31.14962	36.73311	17.80625	....	12.03196	24.74897	8.136937	4.8177	3.232628
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
9777	11.3248	64.70799	104.2869	17.86425	19.1014	8.470965	....	16.92168	4.992651	17.95927	4.23269	0.430258
9778	91.84917	33.82237	28.80064	53.18865	28.66905	5.814065	....	18.28596	10.44783	2.108706	17.50891	13.51164
9779	42.25148	63.02115	10.77495	14.51803	19.73616	15.0564	....	8.217985	8.51172	2.858231	3.354967	8.588274
9780	63.31557	10.96186	37.27722	17.35105	13.25327	6.867685	....	6.348662	10.05507	0.441264	10.59484	0.744036
9781	1.452288	52.43272	35.2562	23.00954	10.8798	16.17604	....	0.869474	10.89716	8.7753	6.900725	7.512285
9782	4.864947	67.32475	36.74111	13.67762	6.583973	5.986907	....	9.103082	30.85594	2.132544	6.185744	12.52038
9783	52.90133	105.4607	28.52467	23.7197	60.95672	18.26211	....	6.550372	10.89932	14.40822	18.77006	12.10346
9784	38.23254	51.37384	16.29781	19.4767	20.9463	3.166865	....	21.50077	5.499319	3.711446	18.98902	4.663988
9785	9.636672	73.80967	23.61747	18.58813	4.205303	0.668265	....	1.951803	8.069853	14.24357	5.00771	13.29485
9786	11.63027	49.34647	44.23312	64.16068	5.378846	4.887088	....	8.02508	13.01226	4.47753	58.86121	24.56706

Fig 4: Image showing Extracted and reduced features from EfficientNetV2B1.

Then the reduced features are used for classification with basic Convolution Neural Network (CNN). All 9786 images with grades 0,1,2,3 and 4 are scattered into train, test and validation. To perform classification, 80% images from grade 0, 1, 2, 3, 4 are trained and remaining 20% images from grade 0, 1, 2, 3, 4 are tested. After classification the performance metrics described below are obtained.

Table 2 : Results obtained after classification of features using EfficientNet series.

Network	IBA	G Mean	F1 score	Precision	Recall	Specificity	Test accuracy
EfficientNetB0	0.7823	0.7274	0.8637	0.8495	0.8852	0.9847	0.9362
EfficientNetB1	0.7991	0.6812	0.8809	0.8983	0.8675	0.9829	0.9326
EfficientNetV2B0	0.8003	0.6969	0.8731	0.8695	0.8772	0.9873	0.9479
EfficientNetV2B1	0.8515	0.8229	0.9148	0.9053	0.9265	0.9893	0.9566
EfficientNetV2B2	0.7919	0.7338	0.8667	0.8525	0.8895	0.9866	0.9459
EfficientNetV2B3	0.7074	0.7153	0.7898	0.7757	0.8772	0.98	0.9168

The above table describes that EfficientNetV2B1 obtained good Imbalanced accuracy (IBA) of 85.15% and test accuracy of 95.66%. The resulted performance metrics represented in the formof graph is show in figure 5.

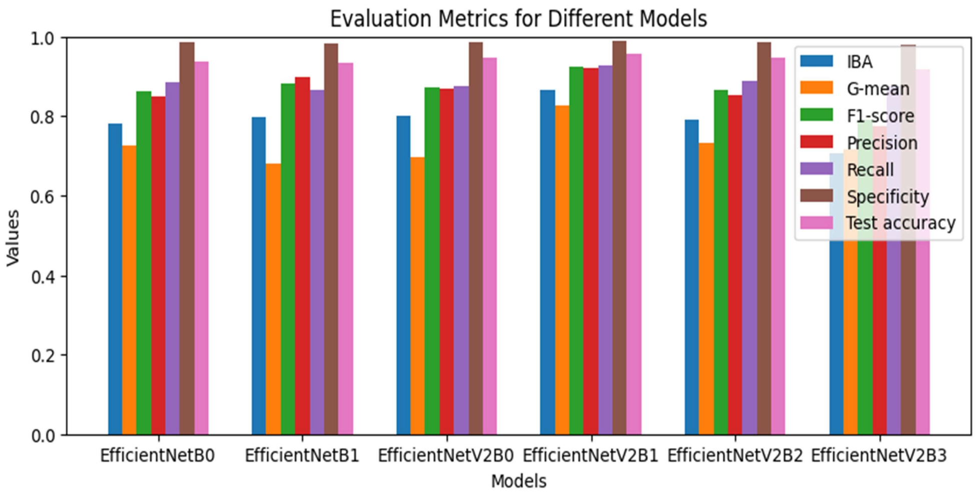


Fig 5 : Bar graph obtained after classification of results using EfficientNet series.

As comparison to above results, other two networks DenseNet121 and NASNet Mobile are used for feature extraction to concatenate the features with EfficientNet series. The concatenated features of EfficientNetV2B1 and DenseNet121 are shown in figure 6.

No.of Images	Extracted and Reduced Features											
	0	1	2	3	4	5	....	195	196	197	198	199
0	86.89317	7.111241	1.523778	37.79704	3.714347	8.49867	....	6.192691	16.13536	1.649609	2.755603	3.6265
1	76.40237	16.9922	13.58995	26.70956	36.52913	60.32117	....	6.745921	15.08164	4.00969	7.686093	2.483837
2	9.846663	69.41037	13.28009	66.63351	9.631724	5.302103	....	8.599255	4.886036	0.513941	7.974325	2.106714
3	67.21386	6.357019	33.63565	18.2524	9.992669	29.46953	....	5.409113	2.344352	12.18337	13.37451	1.00309
4	24.8454	48.12676	58.87936	15.70093	5.780748	33.13005	....	7.757468	1.070221	7.54495	17.58813	21.7243
5	15.65875	68.45328	72.26937	26.52235	45.41634	2.026242	....	9.92721	4.361092	8.297538	0.914552	3.627136
6	5.873059	40.7977	69.71472	19.31055	35.77981	1.359265	....	1.945822	13.33316	7.182663	6.331054	4.685277
7	21.10344	97.29174	28.10702	5.077344	5.959489	0.015067	....	4.120065	15.82494	1.949505	1.385637	15.10359
8	32.72321	28.41789	13.16846	25.42854	60.8297	35.00518	....	8.930031	2.878747	0.900903	9.310188	5.511904
	:	:	:	:	:	:	:	:	:	:	:	:
	:	:	:	:	:	:	:	:	:	:	:	:
9779	42.25148	63.02115	10.77495	14.51803	19.73616	15.0564	....	3.402669	13.67275	12.43401	8.134214	2.524627
9780	63.31557	10.96186	37.27722	17.35105	13.25327	6.867685	....	6.745518	4.63598	3.322214	3.166185	1.409871
9781	1.452288	52.43272	35.2562	23.00954	10.8798	16.17604	....	5.642975	1.346436	0.526858	3.222818	17.19198
9782	4.864947	67.32475	36.74111	13.67762	6.583973	5.986907	....	14.5035	13.57608	11.3106	9.216263	12.78564
9783	52.90133	105.4607	28.52467	23.7197	60.95672	18.26211	....	14.39859	7.977106	2.5724	15.85856	7.243069
9784	38.23254	51.37384	16.29781	19.4767	20.9463	3.166865	....	2.452324	0.304461	8.477932	12.66878	8.127594
9785	9.636672	73.80967	23.61747	18.58813	4.205303	0.668265	....	4.934235	3.133203	2.360641	1.034608	11.26004
9786	11.63027	49.34647	44.23312	64.16068	5.378846	4.887088	....	4.846457	1.491713	2.160197	0.968762	13.5813

Fig 6: Image showing concatenate features from EfficientNetV2B1+DenseNet121.

With the concatenate features of EfficientNet + DenseNet121, the training and testing of features for classification is done with the CNN and resulted performance metrics are shownin table 3.

Table 3 : Results obtained after classification of features using EfficientNet + DenseNet121.

Network	IBA	G mean	F1 score	Precision	Recall	Specificity	Test accuracy
EfficientNetB0 +DenseNet121	0.7745	0.6629	0.8571	0.8542	0.8608	0.9835	0.9341
EfficientNetB1 +DenseNet121	0.742	0.687	0.8244	0.8117	0.8668	0.9828	0.9285
EfficientNetV2B0 +DenseNet121	0.796	0.7093	0.8708	0.8635	0.8805	0.9867	0.9454
EfficientNetV2B1 +DenseNet121	0.7687	0.6352	0.8441	0.8378	0.8528	0.9853	0.9387
EfficientNetV2B2 +DenseNet121	0.7416	0.6397	0.8229	0.8115	0.8496	0.983	0.9295
EfficientNetV2B3 +DenseNet121	0.7375	0.6852	0.8205	0.8075	0.866	0.9822	0.9265

The above table describes the performance metrics, which are obtained by extracting and reduced features using DenseNet121 and concatenated the obtained features with EfficientNet series and are classified using CNN. After concatenate, the features doesn't shows the improved accuracy than EfficientNetV2B1. The resulted performance metrics represented in the form of graph is show in figure 7.

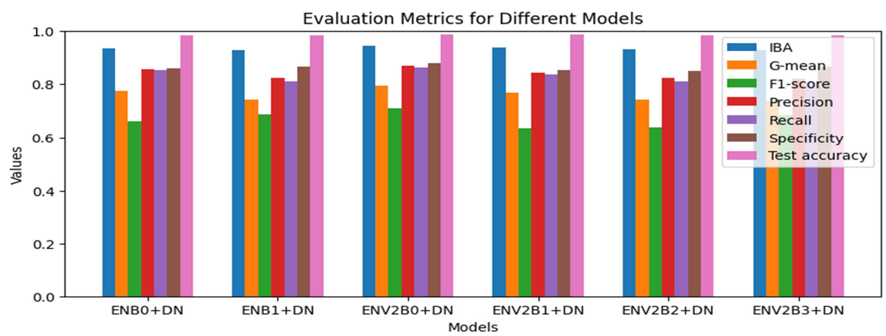


Fig 7: Bar graph obtained after classification of results using EfficientNet+DenseNet121.

As comparison, another network i.e. NASNetMobile is used to extract the features for the same 9786 images from the dataset. And these features are reduced same as the above networks by PCA. Then the reduced features of NASNetMobile are concatenated with the features of EfficientNet series. As an example, concatenated features of EfficientNetV2B1+ NASNetMobile are shown in figure 8.

No.of Images	Extracted and Reduced Features										
	0	1	2	3	4	5	....	195	196	197	198	199
0	86.89317	7.111241	1.523778	37.79704	3.714347	8.49867	....	0.007218	4.848192	13.75185	12.70793	8.427545
1	76.40237	16.9922	13.58995	26.70956	36.52913	60.32117	....	17.11696	19.01428	9.39362	15.5028	10.76162
2	9.846663	69.41037	13.28009	66.63351	9.631724	5.302103	....	21.19241	1.938293	8.091696	1.244822	30.82304
3	67.21386	6.357019	33.63565	18.2524	9.992669	29.46953	....	1.85221	7.719502	1.521982	4.477375	1.007084
4	24.8454	48.12676	58.87936	15.70093	5.780748	33.13005	....	6.970739	1.943976	2.949122	0.280095	8.618093
5	15.65875	68.45328	72.26937	26.52235	45.41634	2.026242	....	7.308731	4.173625	0.811308	1.760992	11.88092
6	5.873059	40.7977	69.71472	19.31055	35.77981	1.359265	....	7.435507	6.02172	7.927633	10.9429	6.878473
7	21.10344	97.29174	28.10702	5.077344	5.959489	0.015067	....	2.632315	0.593003	4.260919	3.530352	2.264951
8	32.72321	28.41789	13.16846	25.42854	60.8297	35.00518	....	8.908362	6.432305	1.082774	1.479107	8.482455
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
9778	11.3248	64.70799	104.2869	17.86425	19.1014	8.470965	....	5.907228	2.392583	11.63423	2.707019	7.427662
9779	91.84917	33.82237	28.80064	53.18865	28.66905	5.814065	....	3.179285	3.026833	3.229126	0.662875	1.554999
9780	42.25148	63.02115	10.77495	14.51803	19.73616	15.0564	....	9.370766	3.865982	6.039444	1.903202	4.157375
9781	63.31557	10.96186	37.27722	17.35105	13.25327	6.867685	....	0.502258	0.611665	6.986821	3.86307	4.492676
9782	1.452288	52.43272	35.2562	23.00954	10.8798	16.17604	....	15.77673	16.44485	10.39027	2.072461	6.670919
9783	4.864947	67.32475	36.74111	13.67762	6.583973	5.986907	....	2.746535	2.77558	0.313434	5.841945	2.531026
9784	52.90133	105.4607	28.52467	23.7197	60.95672	18.26211	....	1.77239	3.700873	8.078981	5.048048	11.11565
9785	38.23254	51.37384	16.29781	19.4767	20.9463	3.166865	....	4.897248	3.586852	4.752152	4.349573	4.063131
9786	9.636672	73.80967	23.61747	18.58813	4.205303	0.668265	....	6.119466	0.866665	1.037914	3.644482	9.144694

Fig 8: Image showing concatenate features from EfficientNetV2B1+ NASNetMobile.

With the concatenate features of EfficientNet + NASNetMobile, the training and testing of features for classification is done with the CNN and resulted performance metrics are shownin table 4.

Table 4 : Results obtained after classification of features using Efficient Net +NAS NetMobile.

Network	IBA	G mean	F1 score	Precision	Recall	Specificity	Test accuracy
EfficientNetB0 + NASNetMobile	0.7789	0.6354	0.8624	0.8784	0.8512	0.9825	0.929
EfficientNetB1 + NASNetMobile	0.7657	0.7073	0.8864	0.8839	0.8804	0.9581	0.9396
EfficientNetV2B0 + NASNetMobile	0.7868	0.7524	0.8569	0.841	0.8974	0.9878	0.9484
EfficientNetV2B1 + NASNetMobile	0.8164	0.7424	0.8856	0.8723	0.895	0.9711	0.9442
EfficientNetV2B2 + NASNetMobile	0.8038	0.7372	0.8916	0.8896	0.8937	0.9789	0.9345
EfficientNetV2B3 + NASNetMobile	0.8061	0.7571	0.8789	0.8661	0.8993	0.9877	0.9279

The above table describes the performance metrics, which are obtained by extracting and reduced features using NASNetMobile and concatenated the obtained features with EfficientNet series and are classified using CNN. After concatenate, the features doesn't shows the improved accuracy than EfficientNetV2B1. The resulted performance metrics represented in the form of graph is show in figure 9.

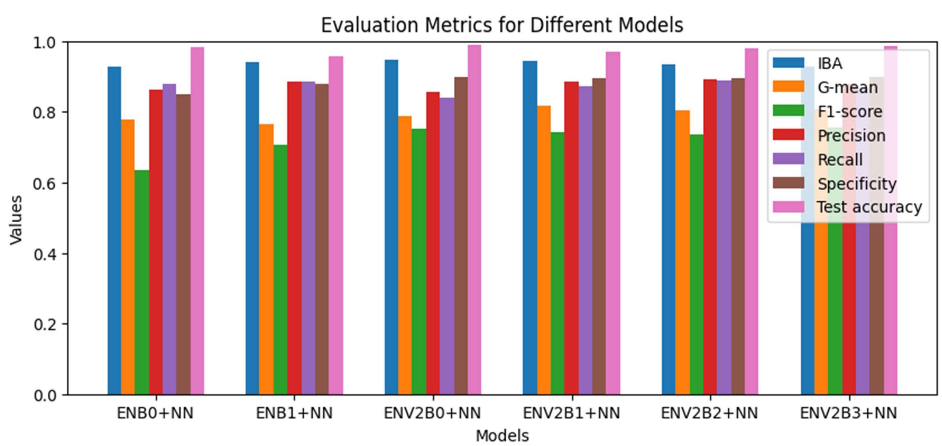


Fig 9: Bar graph obtained after classification of results using EfficientNet+NASNetMobile.

The confusion matrix, show the results obtained after classification of EfficientNetV2B1 features using CNN architecture for the dataset. The final outcome of the confusion matrix is shown below figure 10.

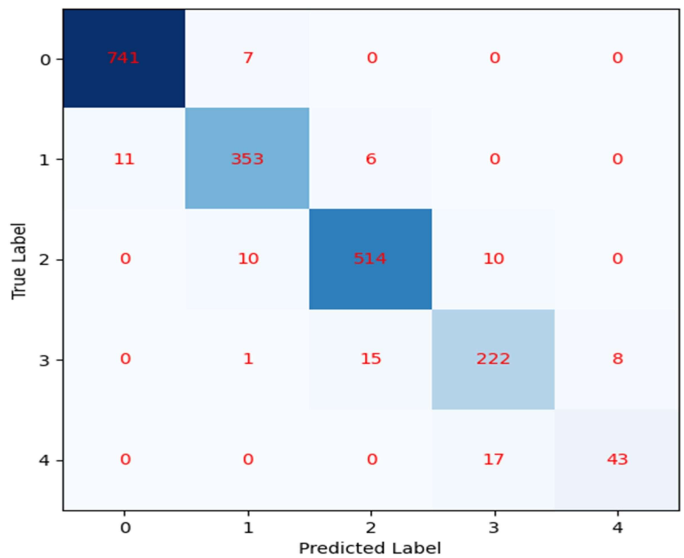


Fig 10: Confusion matrix obtained after classification of EfficientNetV2B1features.

Receiver Operating Characteristic (ROC) curve resulted after the classification of EfficientNetV2B1 with False positive rate Vs. True positive rate is shown in figure 11.

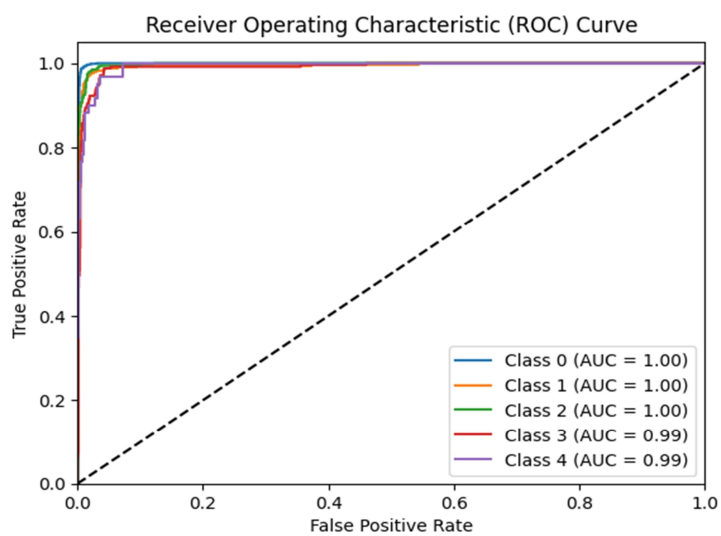


Fig 11: ROC curve obtained after classification of EfficientNetV2B1features.

CONCLUSION

In the present work, Deep Convolution Neural Networks are utilized to categorize the 5 classes of knee osteoarthritis images from the OAI Dataset. Pre-Trained Network elements that are categorized to obtain Imbalanced Accuracy are taken into account. The OAI Datasethas been used to extract features by the Pre-Trained Networks used in this present work.

The raw X-ray images from the dataset are taken for the feature extraction using EfficientNet series such as EfficientNetB0, EfficientNetB1, EfficientNetV2B0, EfficientNetV2B1, EfficientNetV2B2, EfficientNetV2B3 are used. The extracted features which are reduced by using principal component analysis (PCA) are documented in Comma Separated Values (CSV) format. Then the reduced features are used for classification with basic Convolution Neural Network (CNN). All 9786 images with grades 0, 1, 2, 3 and 4 are scattered into train, test and validation. To perform classification, 80% images from grade 0, 1, 2, 3, 4 are trained and remaining 20% images from grade 0, 1, 2, 3, 4 are tested. Apart from the various Pre- Trained Networks are used in the work out of which EfficientNetV2B1 is effectively compared to the other networks achieving an imbalanced accuracy of 85.15% and testing accuracy of 95.66% with the dataset.

To improve the accuracy, EfficientNet features are concatenated with the features of DenseNet121 and NASNetMobile is performed. It results; the concatenate feature doesn't show the improved accuracy than Efficient NetV2B1.

REFERENCES

1. Centers for Disease Control and Prevention (CDC). Available from: https://www.cdc.gov/index.htm.
2. Wang Y, et al. A ResNet-based approach for accurate radiographic diagnosis of knee osteoarthritis. CAAI Trans Intell Technol. 2022.
3. Jain RK, et al. 'Knee osteoarthritis severity prediction using an attentive multi-scale deep convolutional neural network.' *arXiv preprint arXiv*: 2106.14292 (2021).
4. Abedin J, Antony J, McGuinness K, Moran K, O'Connor NE, Rebholz-Schuhmann D, et al. Predicting knee osteoarthritis severity: comparative modelling based on patient's data and plain X-ray images. Sci Rep. 2019;9(1):5761. doi: 10.1038/s41598-019-42215-9, PMID 30962509.
5. Chen P, Gao L, Shi X, Allen K, Yang L. Fully automatic knee osteoarthritis severity grading using deep neural networks with a novel ordinal loss. Comput Med Imaging Graph. 2019;75:84-92. doi: 10.1016/j.compmedimag.2019.06.002, PMID 31238184.
6. Thomas KA, Kidziński Ł, Halilaj E, Fleming SL, Venkataraman GR, Oei EHG, et al. Automated classification of radiographic knee osteoarthritis severity using deep neural networks. Radiol Artif Intell. 2020;2(2):e190065. doi: 10.1148/ryai.2020190065, PMID 32280948.
7. Mahum R, Rehman SU, Meraj T, Rauf HT, Irtaza A, El-Sherbeeny AM, et al. A novel hybrid approach based on deep cnn features to detect knee osteoarthritis. Sensors (Basel). 2021;21(18):6189. doi: 10.3390/s21186189, PMID 34577402.
8. Yunus U, Amin J, Sharif M, Yasmin M, Kadry S, Krishnamoorthy S. Recognition of knee osteoarthritis (KOA) using YOLOv2 and classification based on convolutional neural network. Life (Basel). 2022;12(8):1126. doi: 10.3390/life12081126, PMID 36013305.
9. Harrar K, Messaoudene K, Ammar M. Combining GLCM with LBP features for knee osteoarthritis prediction: data from the osteoarthritis initiative. EAI Endorsed Trans Scalable Inf Syst. 2021:9.35. doi: 10.4108/eai.20-10-2021.171550.
10. Alexos A, Kokkotis C, Moustakidis S, Papageorgiou E, Tsaopoulos D. Prediction of pain in knee osteoarthritis patients using machine learning: data from osteoarthritis Initiative 11th International Conference on Information, Intelligence, Systems and Applications IISA. IEEE Publications; *2020*. doi: 10.1109/IISA50023.2020.9284379.
11. Guan B, Liu F, Mizaian AH, Demehri S, Samsonov A, Guermazi A, et al. Deep learning approach to predict pain progression in knee osteoarthritis. Skelet Rad. 2022;51(2):363-73. doi: 10.1007/s00256-021-03773-0, PMID 33835240.
12. Liu B, Luo Jianxu, Huang H. Toward automatic quantification of knee osteoarthritis severity using improved Faster R-CNN. Int J Comput Assist Rad Surg. 2020;15(3):457-66. doi: 10.1007/s11548-019-02096-9, PMID 31938993.
13. Abdullah SS, Rajasekaran MP. Automatic detection and classification of knee osteoarthritis using deep learning approach. Radiol Med. 2022;127(4):398-406. doi: 10.1007/s11547-022-01476-7, PMID 35262842.
14. Norman B, Pedoia V, Noworolski A, Link TM, Majumdar S. Applying densely connected convolutional neural networks for staging osteoarthritis severity from plain radiographs. J Digit Imaging. 2019;32(3):471-7. doi: 10.1007/s10278-018-0098-3, PMID 30306418.
15. NIH. The Osteoarthritis Initiative. https://nda.nih.gov/oai
16. LeCun Y, Bengio Y. 'Convolutional networks for images, speech, and time series', The handbook of brain theory and neural networks."(1998). Available from: https://dl.acm.org/doi/10.5555/303568.303704