Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 7, No. 1, January 2025, pp: 80-90; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received August 27, 2024; revised September 22, 2024; accepted October 26, 2024; date of publication November 20, 2024
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v7i1.574

How to cite: Rahul N. Kadu, Sunil N. Pawar, "Advanced Bi-CNN for Detection of Knee Osteoarthritis using Joint Space Narrowing Analysis", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 7, no. 1, pp. 80-90, January 2025.

Advanced Bi-CNN for Detection of Knee Osteoarthritis using Joint Space Narrowing Analysis

Rahul N. Kadu[1], Sunil N. Pawar[2]

Department of Electronics and Telecommunication, MGM University, Maharashtra, India
Corresponding author: Rahul N. Kadu (e-mail: kadurahul24@ gmail.com)

ABSTRACT The prevalence of knee osteoarthritis is significantly increasing due to the expanding global ageing population and the rising incidence of obesity. Many researchers use artificial intelligence analytics for knee osteoarthritis (KOA) prediction and treatment. The majority of research is restricted to particular patient groups or attributes, such MRI, X-ray, or questionnaire groups. In our research we propose the use of advanced ortho bilinear convolutional neural network (CNN) classifier to enhance the precision of knee osteoarthritis detection through joint space narrowing analysis. Recognizing the critical need for accurate and early diagnosis in osteoarthritis, this study introduces a sophisticated approach leveraging the unique capabilities of bilinear CNNs (BiCNN). By integrating bilinear interactions within the CNN architecture, the model aims to capture convoluted spatial and channel-wise dependencies in knee radiographic images, thereby improving the capability to understated changes in osteoarthritis progression, particularly within the joint space. The proposed bilinear CNN classifier technique promises to refine the precision of knee osteoarthritis detection, providing clinicians with a powerful tool for identifying joint space narrowing with improved accuracy. Based on the experiment over unseen images, the recall was 93.04%, precision 96.33%, F1 Score was 95.46% and overall accuracy was 94.28%. Results show the superiority of the proposed method compared to other state-of-the-art methods. Hence the proposed method can be used for KOA diagnosis and KL grading in real time scenarios.

INDEX TERMS Bilinear Convolutional Neural Network (BiCNN), Joint Space Narrowing (JSN), Knee Osteoarthritis (KOA), KL Grades, Machine Learning.

I. INTRODUCTION

Osteoarthritis in the knee is a difficult condition that many adults worldwide suffer from. Knee Osteoarthritis (KOA) often takes place due to loss of articular cartilage due to wear and strain. Usually, KOA increases over time and potentially can cause disability. The severity on the clinical signs of KOA may vary from person to person. But over the period of time KOA usually worsens, and becomes more difficult to handle. Also, there is difference in each person's rate of advancement of disease. KOA is one of the most widespread and debilitating musculoskeletal disorders worldwide. It significantly reduces quality of life, produces pain, and hinders normal functionality. It is typified by the gradual deterioration of articular cartilage, along with inflammation, constriction of the joint space, and osteophyte formation.

It is anticipated that the prevalence of KOA will significantly increase in the upcoming years due to the expanding global ageing population and the rising incidence of obesity. Consequently, it is critical to identify KOA early in order to improve the management of this chronic condition overall, reduce suffering, and implement timely interventions. Enhancing the detection and diagnosis of KOA has been the focus of a recent wave of research and technological developments. Early identification is the only approach to slow the progression of osteoarthritis in the knee. Because of the ongoing growth in KOA medical data, researchers are incorporating artificial intelligence analytics for KOA prognosis [1] .

The majority of laborious and time-consuming image-based techniques are used in conventional ways to determine the risk variables for the prediction of KOA progression. Consequently, there is a need for more effective and transparent techniques that could aid in clinical decision-making and facilitate the early identification of KOA.

Clinical diagnosis of KOA is based on findings of stiffness or deformity in the knee, as well as subjective reports of pain or swelling in the knee. X-rays continue to be the most widely utilized radiographic test for KOA screening and pathological advancement of the illness. For the measurement of the progression of KOA, the Kellgren-Lawrence (K-L) grade based on X-ray findings is considered as a standard [2]. Joint space narrowing (JSN) on radiography is typically related to the osteoarthritic knee's loss of articular cartilage. The possible risk factors for osteoarthritic alterations in the knee and their connection to JSN is being studied [3]. Since KOA causes irreversible joint deterioration, total knee replacement is a solution with a high price tag and a short lifespan—especially for obese patients. Thus, it is essential to identify KOA in early stages [4]. The doctors are doing manual inspection of X-Ray images for detection of KOA. Also, the results may vary from physician to physician. The aim of the proposed work is to identify KOA in patients using Deep Learning and JSN analysis.

The most popular predictors of KOA progression include imaging, tests, results, biomechanical characteristics, laboratory biomarkers, and clinical factors. Deep learning models have been used in the field of KOA to forecast the beginning of KOA using MRI [5]

In order to improve the precision of KOA detection we propose to use Bilinear CNN to perform JSN analysis. Use of Leaky Relu activation function helps to improve the overall effectiveness of the model. Inclusion of LogSoftmax layer helps to provide clear and interpretable classification. With the use of Bilinear CNN overall Accuracy of the model is increased as compared to traditional CNNs.

II. RELATED WORK

Ntakolia et al. [1] suggested a machine learning method to use multimodal data from the osteoarthritis Initiative to forecast the course of JSN in each knee and in both knees together. The results of the ML models showed that the SVM model prevailed with a 77.7% accuracy for 88 and 90 features for the right leg, while the LR model performed best for the left leg with a 78.3% accuracy for 164 features. Bing-chen et al. [2] discussed the use of two new variables, average space width between joints (aJSW) and articulate angle (AA), for measuring KOA and evaluating disease progression. The study used a web-based radiology viewer to measure these variables in patients with KOA. Chan et al. [3] evaluated JSN in patients with KOA and its correlation with meniscal tears, anterior cruciate ligament (ACL) ruptures, articular cartilage erosion, and length of discomfort. Yeoh et al. [4] proposed the use of 3D CNN in detection of KOA. According to the study, using 3D CNN techniques based on MR images can provide superior outcomes in early detection of KOA.

Hu et al. [5] suggested the use of DeepKOA, a deep learning-based method, to forecast KOA advancement. Using automated software, the authors of this study measured the JSN, which is determined by variations in Joint Space Width. Ganesh Kumar et al. [6] Offered Automatic KOA severity classification using CNN and enhanced image sharpening. The severity is evaluated using deep convolutional neural networks (CNN) in combination with the Kellgren-Lawrence (KL) grading system. The mean accuracy of the improved images obtained with the application of image sharpening was 91.03%. Yunus et al. [7] suggested CNN-based classification and YOLOv2 recognition of KOA. With the KNN classifier, the suggested method obtained a precision rate of 0.95 on Grade-0, 0.85 on Grade-1, 0.82 on Grade-2, 0.85 on Grade-3, and 0.81 on Grade-4. Dhami et al. [8] suggested deep learning (VGG16) to use X-ray pictures to assess the degree of knee pain. Five grades are assigned to simple X-ray images that are analyzed and gathered from Kaggle. For knee osteoarthritis grading, this model achieved a mean precision of 0.858 and a recall of 92.2 percent. Patel et al. [9] proposed the study different loss functions using CNN. Sarvamangala et al. [10] proposed a multi scale convolutional blocks in convolutional neural network (MCBCNN) for automatic classification and grading of KOA. MCBCNN has been implemented using three pre-trained CNN models: mobileNet2, resNet50, and inceptionNetv3. Out of the three MCBCNNs that have been suggested, the MCB resNet50 performs better with an accuracy of more than 95% and an F1 score of 0.8.

Zhang et al. [11] proposed radiographic image based KL grade classification of KOA. The model performance showed a multi-class accuracy of 74.81%. Antony et al. [12] examined techniques for employing CNNs to automatically quantify the severity of KOA. After examining three pre-trained networks, the study concluded that the VGG-M-128 and CaffeNet BVLC reference networks functioned the best. Compared to the earlier methods, a linear SVM produced a noticeably higher classification accuracy. Ntakolia et al. [13] proposed a pipeline for machine learning to forecast JSN in KOA patients. In this study SVM, Naïve Bayes, Gradient Boosting, Logistic Regression and Random Forest Classification models are implemented to determine JSN in KOA patients. Sivakumari et al. [14] proposed the Implementation of AlexNet for Classification of KOA using X-Ray images. CNN was implemented to determine cartilage damage wherein severity of Grade 0 indicates no JSN and Grade 4 indicates big osteophytes with marked JSN. Sharma et al. [15] proposed the use of MRI images to predict JSN in KOA patients. The study was performed on a group of individuals for a period of 2 years to observe the changes in JSN. Abdullah et al. [16] proposed automatic categorization and detection of KOA using CNN and X-Ray imaging. Pretrained models such as ResNet-50 and AlexNet were used to determine the JSN in KOA patients. Gornale et al. [17] proposed to employ Random Forest classifier for detection of KOA using radiographic images. The authors of the work segmented a knee x-ray image that was subjected to a number of feature extraction approaches using the Active Contour algorithm. The accuracy of the used approach was 87.92%.

Harish et al. [18] proposed to employ CNN and VGG-16 models for detection of KOA. Overall accuracy of 67% was achieved using CNN and 93% was achieved using VGG-16. Wirth et al. [19] proposed prediction of JSN and subsequent cartilage loss using MRI images. Babatunde et al. [20] proposed the Combination of Tunnel View and Antero posterior Radiographs to improve the detection of KOA. Results demonstrate significant improvement in JSN when Tunnel view and AP view both are used. Cigdem et al. [21] performed a comprehensive review on use of various Artificial Intelligence based techniques in identification of KOA using JSN. Silverwood et al. [22] performed an orderly review and meta-analysis on risk indicators involved in KOA in adults. Wright et al. [23] proposed the use of Joint space width to determine the accuracy of Cartilage damage in KOA patients. Alshamrani et al. [24] suggested using transfer learning models for the identification of KOA using X-ray images. These models are based on sequential CNNs, VGG-16, and ResNet-50. Schiratti et al. [25] suggested the use of EfficientNet-B0 network, pre-trained on ImageNet for predicting KOA using MRI images. Imjabbar et al. [26] proposed the use of TBT-CNN model for identification of the JSN progression in KOA patients. The prediction model performed significantly better in estimation of KL grades of KOA patients. Antonio et al. [27] proposed a computer-aided diagnosis that uses the YOLOv3 algorithm with KOA MRI to automatically determine the KOA severity. Norman et al. [28] suggested a fully automated technique for KOA identification using a cutting-edge neural network and KL grading. The testing sensitivity rates of mild, moderate, severe, and no KOA for this ensemble of DenseNets were 83.7, 70.2, 68.9, and 86.0%.

Guan et al. [29] suggested deep learning (DL) models to use baseline knee X-rays to forecast the course of radiographic medial JSN. Tariq et al. [30] suggested using transfer learning to combine ResNet-34, VGG-19, DenseNet 121 and DenseNet 161 into an ensemble to improve the overall performance of the prototype. Scheepers et al.[31] assessed the sensitivity of fixed-flexion radiography over a two-year period in individuals with osteoarthritis to identify knee JSN. Stachowiak et al. [32] developed an automated decision support system to identify and forecast KOA based on TB texture regions selected from knee and hand radiographs. Khury et al. [33] examined how patients with knee osteoarthritis may use standardized-flexion (SF) radiographs to assess the clinical significance of JSN in identifying cartilage deterioration in certain sub regions shown on MRI sequences. Tack et al. [34] outlined an automated segmentation-based technique that makes use of 3D CNNs to quantify cartilage volume. Accurate automated cartilage volumetry supports both, diagnosis and progression of KOA. Yaodong et al. [35] measured the thickness of the cartilage using 3D MRI for knee joint. The machine learning technique used to determine the mapping function between the KOA severity and the CDI feature space was an ANN. Alexos et al. [36] suggested approach to determine KOA pain progression and the most illuminating criteria for the creation of prognostic machine learning models capable of predicting the course of long-term pain.

III. MATERIALS AND METHODS

KOA is characterized by the continuous deterioration of knee joint structures, including the loss of cartilage and the narrowing of the joint space. These structural changes are observable in X-ray images and serve as crucial diagnostic markers for assessing the severity of the condition. Joint space narrowing, in particular, is a pivotal indicator of OA progression, as it reflects the degree of cartilage degeneration and the extent of joint damage. Traditionally, clinicians and radiologists have relied on manual measurements and visual assessments to evaluate joint space narrowing, a process that is not only labor-intensive but also subject to human error and variability. As such, there is a pressing need for automated and precise techniques that can provide consistent and objective assessments of knee OA severity. In our research, we leverage the power of advanced Bilinear CNNs to analyze knee X-ray images with unprecedented precision.

A Bilinear CNN (BiCNN) is a powerful architecture for image classification, particularly excelling in fine-grained recognition tasks. It leverages the strengths of CNNs while introducing a unique way to capture image features and their interactions. Bilinear CNN employs two separate CNNs operating in parallel on the same image. Each CNN extracts distinct feature maps from the input. The outputs from both CNNs are combined using an outer product operation, creating a high-dimensional representation capturing feature interactions.

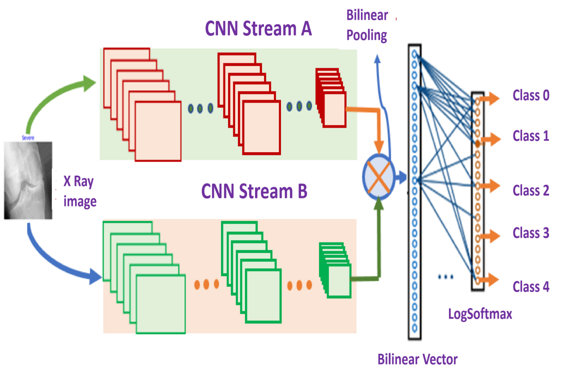


FIGURE 1. Architecture of Ortho Bilinear CNN Classifier

The Bilinear CNN classifier is a deep learning architecture designed for fine-grained visual recognition as shown in FIGURE 1. It excels at distinguishing subtle differences between visually similar objects, making it valuable in tasks like joint space narrowing. Here's a breakdown of its working:

1. Dual Feature Extraction: The core idea lies in using two separate CNNs to analyze the input image. These CNNs can be pre-trained on large datasets to learn general image features. Each CNN extracts its own set of features, potentially

focusing on different aspects of the image. For example, one might capture shape information while the other analyzes textures.

2. Bilinear Pooling: The key step involves combining the outputs from both CNNs. Instead of simply concatenating them, Bilinear CNNs use a technique called bilinear pooling. Imagine each feature map as a matrix. Bilinear pooling calculates the element-wise product of these matrices, capturing the interactions and relationships between individual features. This creates a new, richer representation of the image that incorporates information about how different features co-occur and relate to each other.

3. Classification: The resulting pooled representation is then fed into a final classification layer. This layer uses learned weights to classify the image into one of the predefined categories. By considering the intricate relationships between features, Bilinear CNNs can achieve better accuracy than traditional methods, especially in fine-grained tasks where subtle differences hold the key.

A. BILINEAR FEATURE MAP

Let f_A(x) and f_B(x) be feature vectors extracted by two independent CNN branches for input x. These vectors correspond to the characteristic features contained in the input image. Information represented by these vectors is distinct from each other. The bilinear feature map at location l is calculated as Eq. (1) [37]

$$\boldsymbol{bilinear(l,x) = f\_A(x)\hat{}T * f_{B(x)}} \qquad (1)$$

where ^T denotes the transpose and * denotes the matrix multiplication. This captures pairwise interactions between features from both branches.

B. BILINEAR POOLING

Bilinear pooling is used for fine grained image classification. Bilinear pooling aggregates the bilinear feature map across all locations. This simply means that we combine every feature from A with every feature from B by taking their inner product. It extracts relationship between features using the input feature vectors. Sum Pooling functions is used, the Eq. (2) shows pooled_features of bilinear pooling [37]

$$\boldsymbol{pooled\_features = sum\big(bilinear(l,x)\big)} \qquad (2)$$

These functions summarize the overall interaction patterns within the image.

C. Classification

The pooled features are used as input to a final classification layer with weights w_k. The score predicted is as given by Eq. (3) [37]

$$\mathrm{score(k)\ =\ w\_k\hat{}T * pooled\_features} \qquad (3)$$

D. Workflow of Proposed Model

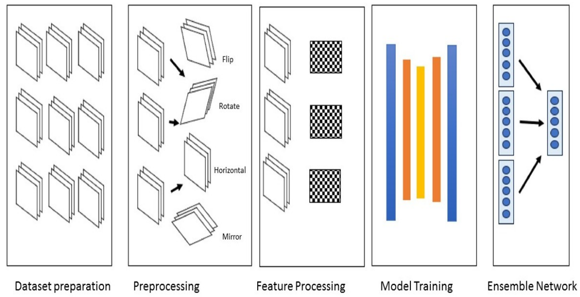


FIGURE 2. **Workflow of Proposed Methodology**

The workflow of proposed methodology is as shown in FIGURE 2. Our research focuses on enhancing the classification and determining the severity of KOA using X-ray images. We have used publicly available OSAIL Knee Osteoarthritis KL Scoring Dataset for training, validation and testing the proposed model. Data Preprocessing converts raw data to a labeled dataset. Feature processing helps to obtain information from raw data which is useful to predict the result in better way. Model training is the phase in which we provide machine learning algorithm along with data as input from which the model learns to predict possible outcome. Ensemble Network combines two or more CNNs to improve overall accuracy of the model.

E. RESEARCH CONTRIBUTION

We integrated attention layers within the CNN to enable the model to focus more on areas indicative of OA changes, such as osteophytes and JSN. The model was trained on images at multiple resolutions, allowing it to learn features at different scales, which is crucial for detecting both early and advanced stages of OA. We employed an ensemble of models, each trained on different portions of the data and using varied image processing techniques. This approach helped in improving the robustness and generalizability of our model.
In addition to basic augmentations, we implement geometric transformations and simulate various imaging conditions (like different X-ray exposure levels) to make our model robust against a wide range of imaging scenarios. We introduced a dual-path network architecture that processes images in parallel paths with different receptive fields. This approach allows the model to capture both fine-grained details and texture information. It helps to reduce the model's complexity without compromising its ability to learn rich feature representations. This technique is crucial for efficient training and inference. The Bilinear CNN Classifier Architecture detail is as shown in FIGURE 3. Details of the different layers used in architecture is as below:

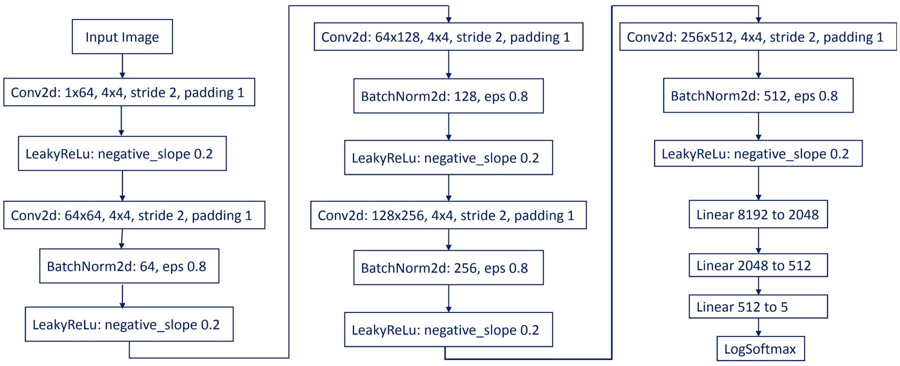


FIGURE 3. **Bilinear CNN Architecture**

Convolutional Layers (Conv2d): These layers are the core building blocks of the model, they extract features from the input images. The model includes multiple Conv2d layers, each with varying numbers of filters and kernel sizes. The first layer takes the input image, and subsequent layers receive the output from the previous layer. Different layers' capture different levels of details - While deeper layers recognize more intricate patterns related to osteoarthritis, earlier levels identify edges and textures. The Eq. (4) shows 2d convolution operation [37]

$$Conv2d(x) = W * x + b \tag{4}$$

Where, W is the weight matrix, x is the input to the layer and b is the bias term.

Activation Functions LeakyReLU: It introduces non-linearity into the model, allowing it to learn more complex patterns. After each convolutional layer, a LeakyReLU (Leaky Rectified Linear Unit) activation function is used. LeakyReLU is particularly effective in preventing the dying ReLU problem, where neurons stop participating in the learning process. To guarantee that every neuron continues to participate in the learning process, it permits a little, non-zero gradient while the unit is dormant. The operation performed by activation functions LeakyReLU is as shown in Eq. (5) [37]

$$LeakyReLU(x) = \begin{cases} x & if \quad x > 0 \\ 0.2 * x & otherwise \end{cases} \tag{5}$$

Batch Normalization (BatchNorm2d): This layer is used to normalize the inputs of each layer, stabilizing and speeding up the learning process. BatchNorm2d layers are placed after specific convolutional layers in the architecture. By normalizing the input layer by adjusting the mean and variance, batch normalization helps combat internal covariate shift.

The operation performed by batch normalization is as shown in Eq. (6) [37].

$$BN(x) = \frac{\gamma * ((x - \mu)}{\sqrt{\sigma^2 + \varepsilon}} \tag{6}$$

where, μ and σ^2 are the mean and variance of the batch, ε is a small constant added for numerical stability (0.8 in this case), γ and β are learnable parameters of the layer.

Linear Layers: These layers, also known as fully connected layers, are used to map the learned features into the final output. The architecture includes several linear layers towards the end, which progressively reduce the dimensionality of the feature space. These layers are crucial for classification, as they combine the features learned by the convolutional layers to make predictions about the presence and stage of osteoarthritis. The operation performed by linear layers is as shown in Eq. (7) [37]

$$Linear(x) = Ax + b \tag{7}$$

where, A is the weight matrix of the layer, b is the bias term.

LogSoftmax Layer: This layer is used for the final classification. It converts the output logits into probabilities that sum up to one, providing a clear and interpretable classification. The operation performed by LogSoftmax layer is as shown in Eq. (8) [38]

$$\text{LogSoftmax}(xi) = \log\left(\frac{\exp(xi)}{\Sigma_j(xj)}\right) \tag{8}$$

where, xi represents the input to the node, the denominator Σj exp(xj) is the sum of the exponential values of all inputs to the nodes in that layer.

IV. EXPERIMENTATION

The proposed algorithm Bilinear CNN Classifier is implemented using Intel Core i7-12th Gen Processor, NVIDIA GeForce RTX 3060 GPU, 32GB DDR4 RAM, Windows 10 operating system with CUDA-enabled for deep learning tasks. The software used for implementation of proposed model AWS Deep Learning AMIs with pre-installed frameworks such as TensorFlow and PyTorch. The Bilinear CNN Classifier is a deep learning model designed for the automated detection and classification of KOA using radiographic images. The flow diagram for training and testing the proposed model is as shown in FIGURE 4.

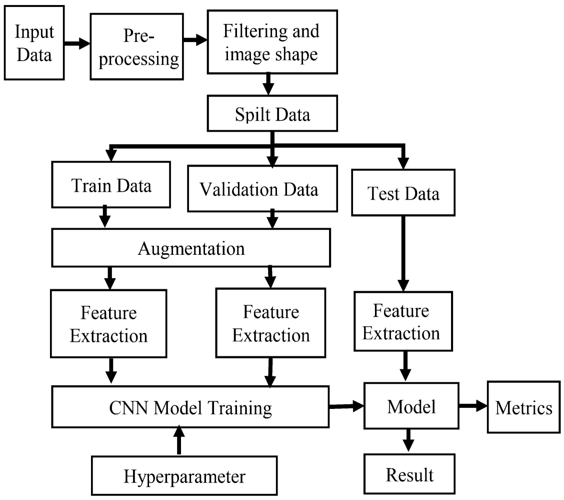


FIGURE 4. Flow diagram for training and testing of the proposed

Dataset Used: The OSAIL Knee Osteoarthritis KL Scoring Dataset is used for training, validation and testing the proposed model. The dataset is publicly available at- https://www.kaggle.com [39]. This dataset contains 9786 knee X-ray images with KL grades. The split of dataset training, validation and testing is- Training: 7829 images (80%), Validation: 979 images (10%) and Test: 978 images (10%)

V. RESULTS

A. PERFORMANCE METRICS

To evaluate the performance of proposed model we use the metrics: accuracy, precision, recall, F1 score. Equations (9) to (12) present the mathematical expressions of these metrics.

Accuracy, in Eq. (9), is the ratio of correctly predicted data samples of the total number of input samples [6]. In these equations, TP corresponds to true positive, FP to false positives, TN to true negatives, and FN to false negatives.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

Precision, described in Eq. (10) refers to the ratio between correctly predicted positive samples and the total predicted positive samples, high precision relates to the low false positive rate [6].

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

Recall, as seen in Eq. (11), is the ratio of correctly predicted positive samples to all samples in the actual class [6].

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

F1 Score, in Eq. (12), is defined as the Harmonic Mean between precision and recall [6].

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (12)$$

B. TRAINING OF PROPOSED MODEL ON DATASET

The proposed model is trained and tested on OSAIL Knee Osteoarthritis KL Scoring Dataset and Processor is Intel Core i7-12th Gen with GPU: NVIDIA GeForce RTX 3060. The Google Colab server was used to train and test the suggested model. The proposed model was trained for 10000 iterations (100 Epochs). The results obtained during training are as depicted in TABLE 1. Ablation experimentation is performed which shows the number of parameters, average size of output layer, BFLOPS and Frames per Second (FPS) of proposed model is depicted in TABLE 2.

TABLE 1
Results Obtained During Training

Type of model	Image Size	Recall (%)	Precision (%)	F1 (%)	Accuracy (%)	Training Time (Hrs)
Proposed BiCNN Classifier	320x320	95	97	96	98	80

TABLE 2
Ablation Experimentation Showing Parameters of Proposed Model

Type of model	Input Network Resolution	Respective Field size	Parameters (M)	Average size of Layer O/P (WxHxC)	BFLOPS 512x512	FPS
Proposed BiCNN Classifier	320x320	3x3	50	80 x 80 x 1024	20	33

C. Validation of trained model

TABLE 3 shows testing results of proposed model on unseen test images. Graphical representation of comparison of proposed model- BiCNN classifier with other models is as depicted in FIGURE 5. Figure 5 shows that Proposed BiCNN model has emerged as best performing model as there is significant improvement in performance parameters like Accuracy, Precision, Recall and F1-score. After completing the training of all models, it was found that Accuracy obtained using Proposed BiCNN Classifier is 94%. Accuracy obtained using ResNet-50 was upto 82% and Siamese CNN increased upto 88%. Our proposed model achieved a Precision of 97% which is far superior to 78% in ResNet-50 and 84% in Siamese CNN. This improvement is attributed to the use of Bilinear CNN in detection process. Overall accuracy obtained by VGG-16 is 80% and time required to train the model is about two weeks. It makes VGG-16 time consuming and less efficient as compared to BiCNN. Overall accuracy obtained by Resnet-50 is 82%. As Resnet-50 is susceptible to over fitting, it is less efficient than BiCNN. Overall accuracy obtained by Siamese CNN is 88%. As it compares similar images for classification, it is computationally very expensive. Overall accuracy obtained by Dense CNN is 78%. It has high memory usage and is susceptible to over fitting. Overall accuracy obtained by CNN with attention model is 86%. Attention mechanism increases complexity and reduces adaptability of the model.

TABLE 3
Testing Results of Proposed Model on Unseen Data

Type of model	Recall (%)	Precision (%)	Accuracy (%)	AP (%)	F1 (%)	FPS
CNN [6]	75	72	76	70	73	21
Dense CNN [7]	77	74	78	72	75	22
VGG-16 [8]	79	76	80	74	77	17
ResNet-50 [10]	81	78	82	76	79	15
CNN with Attention [11]	85	82	86	80	83	16
Siamese CNN [11]	87	84	88	82	85	14
Deep CNN [12]	83	80	84	78	81	19
Proposed BiCNN Classifier	93	96	94	91	95	29

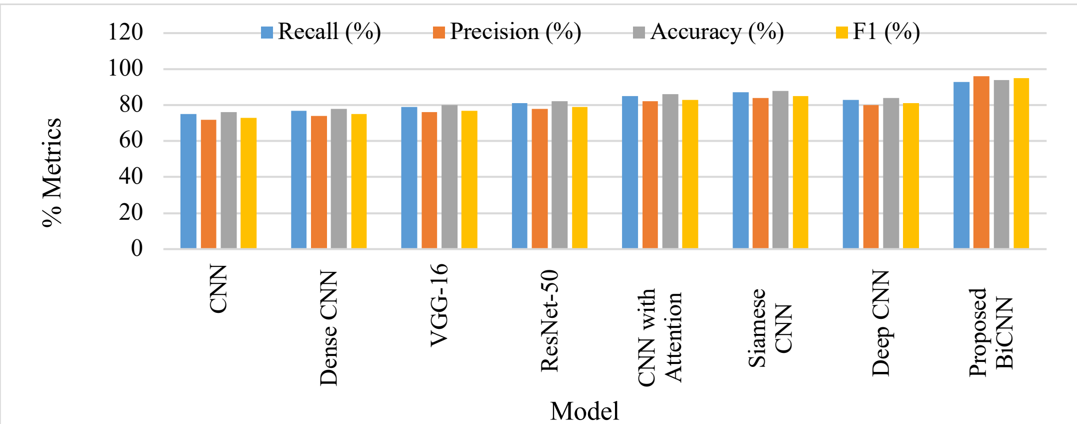
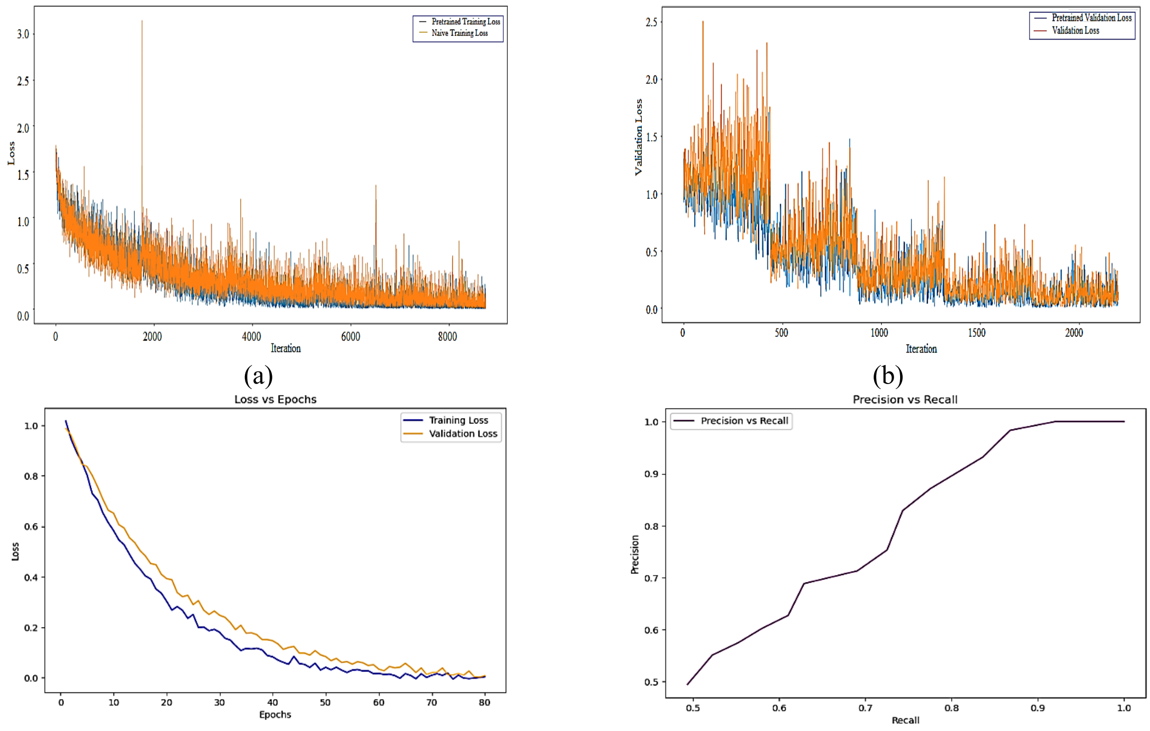


FIGURE 5. **Comparison of proposed model BiCNN classifier with other models**

VI. DISCUSSION

A. ANALYSIS OF TRAINING PHASE

FIGURE 6(a) shows graphical plot of training loss Vs iteration. The loss line appears to be decreasing which indicates model is training properly. This shows that the model is gaining knowledge from the training set and adapting to new input with ease. FIGURE 6(b) shows the graphical plot of validation loss Vs iteration of proposed model. It shows as number of iteration increases validation loss decreases. Model gains knowledge with each iteration, increasing the prediction accuracy of the model. This helps to reduce validation loss of the model. Decreasing training loss and validation loss is highly desirable. If the loss lines don't appear in decreasing pattern, indicates model is not trained correctly. Hence we will have to increase the number of iterations to train the model. FIGURE 6c shows graphical plot of training loss and validation loss Vs epochs. It demonstrates that the both loss decreases when number of epochs increases and there is very small difference between training and validation loss, indicates model is trained properly. This will result in higher prediction accuracy. FIGURE 6d shows graphical plot of Precision Vs Recall. As the curve is approaching the right corner of the graph that indicates the model can distinguish between classes well. It is highly desirable that the model has higher values of Precision and Recall. Higher values of Precision and Recall leads to larger Area under the Curve (AUC), which is essential to achieve higher accuracy of the model.



(c) (d)

FIGURE 6. Analysis of training phase (a) Plot of Loss vs. Iteration during Training (b) Plot of Validation Loss vs. Iteration (c) Plot of Training Loss and Validation Loss Vs. Epochs (d) Plot of Precision Vs. Recall

B. CONFUSION MATRIX

The confusion matrix shown in FIGURE 7 suggests that the machine learning model is able to make accurate predictions of knee OA severity based on JSN analysis. Diagonal cells (green) represent correct predictions. For example, 200 patients with normal OA were correctly classified as normal, 170 with mid OA were correctly classified as mid, and 18 with severe OA were correctly classified as severe. When accuracy is calculated, diagonal values represents True Positive, negative class outcomes predicted by the model correctly are True Negative, False positive and False negative refer to errors made by the model.

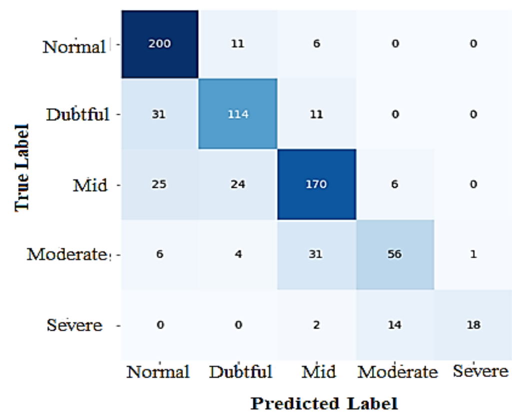


FIGURE 7. Confusion Matrix

C. COMPARISON OF PROPOSED MODEL:

Comparison of our proposed model with other models is shown in TABLE 4. Compared with research [1], the findings of this study show that the use of Logistic Regression produces a multi class classification accuracy of 78.30%. Research [1] uses Osteoarthritis Initiatives based dataset for detection of Knee OA. Research [6] uses Resnet V2 and demonstrates signifactly high accuracy of 91.03%. In Research [6] authors declare that they use Osteoarthritis Initiatives based dataset for detection of knee OA. Research [7] uses YOLO V2 for detection of Knee OA and demonstrates an classificaiton accuracy of 90.60%. In Research [7] authors declare that they use Radiopaedia based dataset for detection of knee OA. Research [11] uses Resnet-34 and demonstrates accuracy of 74.81%. In Research [11] authors declare that they use Osteoarthritis Initiatives based dataset for detection of knee OA. Research [18] uses VGG-16 and demonstrates accuracy of 93.45%. In Research [18] authors declare that they use Kaggles Knee OA based dataset for detection of KOA.Our BiCNN model produces a significantly high accuracy of 94.28% which outperforms other models in the field of KOA detection. The bilinear form makes gradient computation easier and enables both networks to be trained end-to-end using labeled images. BiCNN architecture demonstrates fine grain recognition that extracts two features at a time. The performance of the BiCNN model in this study is consistent and has demonstrated superior capabilities in handling complex dataset. This research can help in improving the clinical detection of KOA disease based on x-ray images

Despite the promising results, there are a several limitations.The use of Bilinear CNN increases the computation time with average requirement of 29 frames/sec. Also the training duration is upto 80Hrs in proposed BiCNN model.

TABLE 4
Comparison of Accuracy with previous Research

Research	Technique	Number of Classes	Accuracy
[1]	Logistic Regression	5 Classes	78.30%
[6]	Resnet V2	5 Classes	91.03%
[7]	YOLO V2	5 Classes	90.60%
[11]	Resnet-34	5 Classes	74.81%
[18]	VGG-16	5 Classes	93.45%
Proposed Model	BiCNN	5 Classes	94.28%

To enhance the performance of KOA detection, future research work should explore hybrid models and techniques to improve the computational efficiency of the BiCNN model. Another important aspect is the need for larger and more diverse datasets inorder to improve classification accuracy . Lastly, there is a need for further investigation into hyperparameter tuning specific to CNNs for improving classification accuracy. By addressing these aspects, future studies aim to achieve significantly improved accuracy in classifying KOA detection.

Sample X-ray images indicating the severity of Knee Osteoarthritis in the patients is shown in FIGURE 8. Depending on the severity of KOA in the patients X-ray

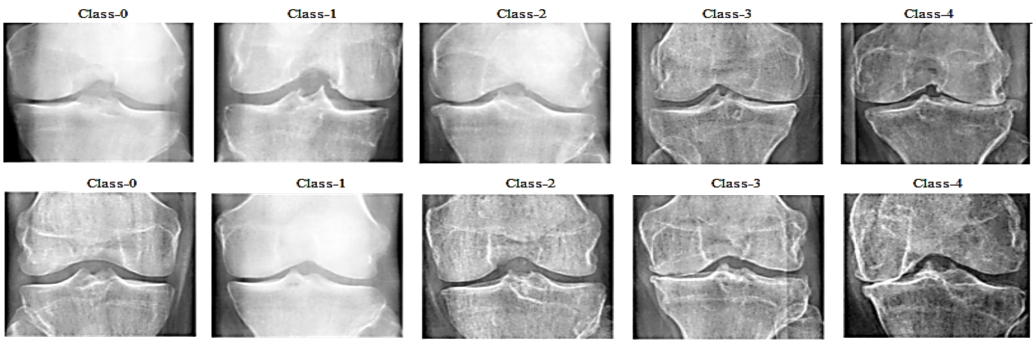


FIGURE 8. **Sample X-ray images showing classes**

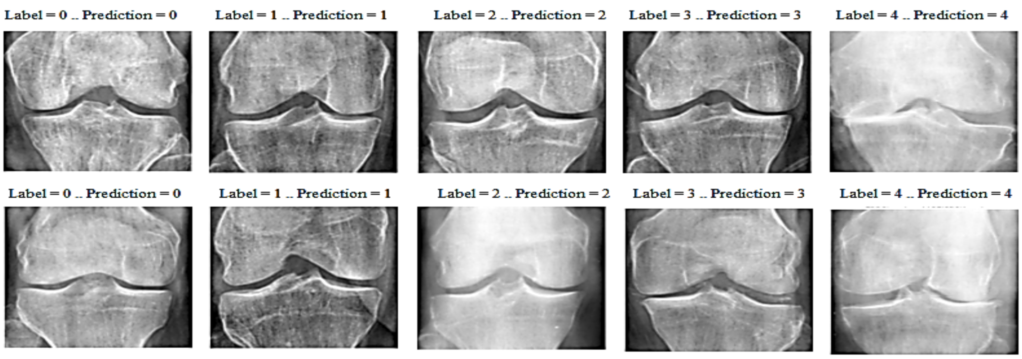


FIGURE 9. **Predicted X-ray images by model**

images are graded into classes ie-Class 0 to Class 4. Class 0 indicates healthy knee whereas Class 4 indiacates Knee with maximum KOA impact. These images serve as input to the BiCNN model. FIGURE 9 shows X-ray images with prediction from the model, for example- Label 0, Prediction 0 indicates our model predicted Class 0 for given image of a patient with Class 0 KOA.

VII. CONCLUSION

This study explores the potential of advanced bilinear CNN classifier technique for precise detection of knee osteoarthritis (KOA) through joint space narrowing (JSN) analysis. Our novel attention bilinear CNN classifier model combines bilinear pooling with attention to improve classification. The model is trained and tested on Intel Core i7-12th Gen Processor with NVIDIA GeForce RTX 3060 GPU. The proposed method achieved a significant improvement in accuracy compared to existing KOA detection techniques, demonstrating the effectiveness of bilinear CNNs classifier in capturing intricate feature interactions for fine-grained analysis. We compared the performance of our model with traditional CNN model, the bilinear CNN classifier outperformed traditional CNNs and baseline methods, achieving an accuracy of 94.28 %, Recall 93.04 %, F1 Score 95.46% and Precision of 96.33 % in detecting knee OA based on JSN analysis using unseen images. This improvement can be attributed to the proposed model's ability to effectively learn and exploit the subtle relationships between different image features, leading to more precise identification of subtle narrowing indicators of early-stage KOA. Bilinear CNNs are a powerful tool for fine-grained tasks, but they are computationally expensive due to the double feature extraction and bilinear pooling. Increase in computational expenses can be considered as the limitation of this work. The future work is to reduce computational cost by exploring different CNN architectures and hyper-parameter tuning could yield further accuracy gains.

REFERENCES

[1] C. Ntakolia, C. Kokkotis, S. Moustakidis, and D. Tsaopoulos, "Prediction of joint space narrowing progression in knee osteoarthritis patients," Diagnostics, vol. 11, no. 2, Feb. 2021, doi: 10.3390/diagnostics11020285.

[2] B. C. An, K. Fang, Y. Wang, Y. M. Zeng, and K. R. Dai, "New variables for measuring joint space width to evaluate knee osteoarthritis," Chin Med J (Engl), vol. 124, no. 23, pp. 3886–3890, Dec. 2011, doi: 10.3760/cma.j.issn.0366-6999.2011.23.010.

[3] W. P. Chan, G. S. Huang, S. M. Hsu, Y. C. Chang, and W. P. Ho, "Radiographic joint space narrowing in osteoarthritis of the knee: Relationship to meniscal tears and duration of pain," Skeletal Radiol, vol. 37, no. 10, pp. 917–922, Oct. 2008, doi: 10.1007/s00256-008-0530-8.

[4] P. S. Q. Yeoh et al., "Emergence of Deep Learning in Knee Osteoarthritis Diagnosis," 2021, Hindawi Limited. doi: 10.1155/2021/4931437.

[5] J. Hu et al., "DeepKOA: a deep-learning model for predicting progression in knee osteoarthritis using multimodal magnetic resonance images from the osteoarthritis initiative," Quant Imaging Med Surg, vol. 13, no. 8, pp. 4852–4866, Aug. 2023, doi: 10.21037/qims-22-1251.

[6] M. Ganesh Kumar and A. Das Goswami, "Automatic Classification of the Severity of Knee Osteoarthritis Using Enhanced Image Sharpening and CNN," Applied Sciences (Switzerland), vol. 13, no. 3, Feb. 2023, doi: 10.3390/app13031658.

[7] U. Yunus, J. Amin, M. Sharif, M. Yasmin, S. Kadry, and S. Krishnamoorthy, "Recognition of Knee Osteoarthritis (KOA) Using YOLOv2 and Classification Based on Convolutional Neural Network," Life, vol. 12, no. 8, Aug. 2022, doi: 10.3390/life12081126.

[8] B. S. Dhami, M. Mehra, and R. P. Singh, "VGG16 Based Knee Osteoarthritis Grading Using X-Ray Images," Int J Res Appl Sci Eng Technol, vol. 10, no. 10, pp. 678–683, Oct. 2022, doi: 10.22214/ijraset.2022.46994.

[9] V. Patel, S. Shukla, and M. Gyanchandani, "Analysis of Different Loss Function for Designing Custom CNN for Traffic Sign Recognition."

[10] D. R. Sarvamangala and R. V. Kulkarni, "Grading of Knee Osteoarthritis Using Convolutional Neural Networks," Neural Process Lett, vol. 53, no. 4, pp. 2985–3009, Aug. 2021, doi: 10.1007/s11063-021-10529-3.

[11] B. Zhang, J. Tan, K. Cho, G. Chang, and C. M. Deniz, "Attention-based CNN for KL Grade Classification: Data from the Osteoarthritis Initiative," in Proceedings - International Symposium on Biomedical Imaging, IEEE Computer Society, Apr. 2020, pp. 731–735. doi: 10.1109/ISBI45749.2020.9098456.

[12] J. Antony, K. McGuinness, N. E. O. Connor, and K. Moran, "Quantifying Radiographic Knee Osteoarthritis Severity using Deep Convolutional Neural Networks," Sep. 2016, [Online]. Available: http://arxiv.org/abs/1609.02469

[13] C. Ntakolia, C. Kokkotis, S. Moustakidis, and D. Tsaopoulos, "A machine learning pipeline for predicting joint space narrowing in knee osteoarthritis patients," in Proceedings - IEEE 20th International Conference on Bioinformatics and Bioengineering, BIBE 2020, Institute of Electrical and Electronics Engineers Inc., Oct. 2020, pp. 934–941. doi: 10.1109/BIBE50027.2020.00158.

[14] T. Sivakumari and R. Vani, "Implementation of AlexNet for Classification of Knee Osteoarthritis," in 7th International Conference on Communication and Electronics Systems, ICCES 2022 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 1405–1409. doi: 10.1109/ICCES54183.2022.9835835.

[15] R. Madan-Sharma et al., "Do MRI features at baseline predict radiographic joint space narrowing in the medial compartment of the osteoarthritic knee 2 years later?," Skeletal Radiol, vol. 37, no. 9, pp. 805–811, Sep. 2008, doi: 10.1007/s00256-008-0508-6.

[16] S. S. Abdullah and M. P. Rajasekaran, "Automatic detection and classification of knee osteoarthritis using deep learning approach," Radiologia Medica, vol. 127, no. 4, pp. 398–406, Apr. 2022, doi: 10.1007/s11547-022-01476-7.

[17] S. S., P. U., and R. R., "Detection of Osteoarthritis using Knee X-Ray Image Analyses: A Machine Vision based Approach," Int J Comput Appl, vol. 145, no. 1, pp. 20–26, Jul. 2016, doi: 10.5120/ijca2016910544.

[18] H. Harish, A. Patrot, S. Bhavan, S. Gousiya, and A. Livitha, "Knee Osteoarthritis Prediction Using Deep Learning," in 2023 International Conference on Recent Advances in Information Technology for Sustainable Development, ICRAIS 2023 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 14–19. doi: 10.1109/ICRAIS59684.2023.10367065.

[19] W. Wirth et al., "Lateral and medial joint space narrowing predict subsequent cartilage loss in the narrowed, but not in the non-narrowed femorotibial compartment - data from the Osteoarthritis Initiative," Osteoarthritis Cartilage, vol. 22, no. 1, pp. 63–70, Jan. 2014, doi: 10.1016/j.joca.2013.10.011.

[20] O. M. Babatunde, J. R. Danoff, D. A. Patrick, J. H. Lee, J. K. Kazam, and W. Macaulay, "The Combination of the Tunnel View and Weight-Bearing Anteroposterior Radiographs Improves the Detection of Knee Arthritis," Arthritis, vol. 2016, pp. 1–8, Jan. 2016, doi: 10.1155/2016/9786924.

[21] O. Cigdem and C. M. Deniz, "Artificial intelligence in knee osteoarthritis: A comprehensive review for 2022," Osteoarthritis Imaging, vol. 3, no. 3, p. 100161, Sep. 2023, doi: 10.1016/j.ostima.2023.100161.

[22] V. Silverwood, M. Blagojevic-Bucknall, C. Jinks, J. L. Jordan, J. Protheroe, and K. P. Jordan, "Current evidence on risk factors for knee osteoarthritis in older adults: A systematic review and meta-analysis," Apr. 01, 2015, W.B. Saunders Ltd. doi: 10.1016/j.joca.2014.11.019.

[23] J. Christopher Buckland-Wright, D. G. Macfarlane, J. A. Lynch, K. Jasani, and C. R. Bradshaw, "Joint space width measures cartilage thickness in osteoarthritis of the knee: high resolution plain film and double contrast macroradiographic investigation," 1995.

[24] H. A. Alshamrani, M. Rashid, S. S. Alshamrani, and A. H. D. Alshehri, "Osteo-NeT: An Automated System for Predicting Knee Osteoarthritis from X-ray Images Using Transfer-Learning-Based Neural Networks Approach," Healthcare (Switzerland), vol. 11, no. 9, May 2023, doi: 10.3390/healthcare11091206.
[25] J. B. Schiratti et al., "A deep learning method for predicting knee osteoarthritis radiographic progression from MRI," Arthritis Res Ther, vol. 23, no. 1, Dec. 2021, doi: 10.1186/s13075-021-02634-4.
[26] A. Almhdie-Imjabbar, K. L. Nguyen, H. Toumi, R. Jennane, and E. Lespessailles, "Prediction of knee osteoarthritis progression using radiological descriptors obtained from bone texture analysis and Siamese neural networks: data from OAI and MOST cohorts," Arthritis Res Ther, vol. 24, no. 1, Dec. 2022, doi: 10.1186/s13075-022-02743-8.
[27] P. J. A. Antonio, J. Aldwayne B. Delmo, R. V. Sevilla, M. Angelo D. Ligayo, and D. L. Montesines, "Deep Transfer Network of Knee Osteoarthritis Progression Rate Classification in MR Imaging for Medical Imaging Support System," in 2022 International Conference on Decision Aid Sciences and Applications, DASA 2022, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 285–289. doi: 10.1109/DASA54658.2022.9765065.
[28] B. Norman, V. Pedoia, A. Noworolski, T. M. Link, and S. Majumdar, "Applying Densely Connected Convolutional Neural Networks for Staging Osteoarthritis Severity from Plain Radiographs," J Digit Imaging, vol. 32, no. 3, pp. 471–477, Jun. 2019, doi: 10.1007/s10278-018-0098-3.
[29] B. Guan et al., "Deep learning risk assessment models for predicting progression of radiographic medial joint space loss over a 48-MONTH follow-up period," Osteoarthritis Cartilage, vol. 28, no. 4, pp. 428–437, Apr. 2020, doi: 10.1016/j.joca.2020.01.010.
[30] T. Tariq, Z. Suhail, and Z. Nawaz, "Knee Osteoarthritis Detection and Classification Using X-Rays," IEEE Access, vol. 11, pp. 48292–48303, 2023, doi: 10.1109/ACCESS.2023.3276810.
[31] S. Botha-Scheepers et al., "Fixed-flexion knee radiography: the sensitivity to detect knee joint space narrowing in osteoarthritis," Osteoarthritis Cartilage, vol. 15, no. 3, pp. 350–353, Mar. 2007, doi: 10.1016/j.joca.2006.09.006.
[32] G. W. Stachowiak, M. Wolski, T. Woloszynski, and P. Podsiadlo, "Detection and prediction of osteoarthritis in knee and hand joints based on the X-ray image analysis," Biosurf Biotribol, vol. 2, no. 4, pp. 162–172, Dec. 2016, doi: 10.1016/j.bsbt.2016.11.004.
[33] F. Khury et al., "Validation of joint space narrowing on plain radiographs and its relevance to partial knee arthroplasty RadiologiCal and MRi data FRoM the osteoaRthRitis initiative," Bone Joint Res, vol. 10, no. 3, pp. 173–187, 2021, doi: 10.1302/2046-3758.103.BJR.
[34] A. Tack and S. Zachow, "Accurate Automated Volumetry of Cartilage of the Knee Using Convolutional Neural Networks: Data From the Osteoarthritis Initiative," in 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), IEEE, Apr. 2019, pp. 40–43. doi: 10.1109/ISBI.2019.8759201.
[35] Y. Du, J. Shan, R. Almajalid, and M. Zhang, "Knee osteoarthritis severity level classification using whole knee cartilage damage index and ANN," in Proceedings - 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies, CHASE 2018, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 19–21. doi: 10.1145/3278576.3278585.
[36] A. Alexos, C. Kokkotis, S. Moustakidis, E. Papageorgiou, and D. Tsaopoulos, "Prediction of pain in knee osteoarthritis patients using machine learning: Data from Osteoarthritis Initiative," in 11th International Conference on Information, Intelligence, Systems and Applications, IISA 2020, Institute of Electrical and Electronics Engineers Inc., Jul. 2020. doi: 10.1109/IISA50023.2020.9284379.
[37] T.-Y. Lin, A. RoyChowdhury, and S. Maji, "Bilinear CNN Models for Fine-Grained Visual Recognition," in 2015 IEEE International Conference on Computer Vision (ICCV), IEEE, Dec. 2015, pp. 1449–1457. doi: 10.1109/ICCV.2015.170.
[38] K. Banerjee, V. C., R. Gupta, K. Vyas, A. H., and B. Mishra, "Exploring Alternatives to Softmax Function," in Proceedings of the 2nd International Conference on Deep Learning Theory and Applications, SCITEPRESS - Science and Technology Publications, 2021, pp. 81–86. doi: 10.5220/0010502000002996.
[39] "https://www.kaggle.com/datasets/peymannejat/osa il-knee-osteoarthritis-kl-scoring-dataset."

AUTHORS BIOGRAPHY

Rahul Nandkumar Kadu has completed bachelor's degree in Electronics and Telecommunication from Savitribai Phule Pune University in the year 2008. He earned his Master's Degree in VLSI and Embedded Systems from Savitribai Phule Pune University in the year 2013. He has 14 years of teaching experience as Assistant Professor at Pravara Rural Engineering College, Loni. Currently he is a Research Scholar in the Department of Electronics and Telecommunication at Jawaharlal Nehru Engineering College, MGM University. His research interests include Machine Learning, Computer Vision and Biomedical Electronics. He has published 16 research papers in international journals and presented 12 papers in international conferences. https://orcid.org/0000-0002-6879-0737

Dr. Sunil Nilkanth Pawar is Professor in the Department of Electronics and Telecommunication at Jawaharlal Nehru Engineering College, MGM University. He has completed his bachelor's degree and Master's Degree in Electronics Engineering. He has completed his PhD in Electronics and Telecommunication from SRT Marathwada University in 2015. He has a teaching experience of 28 years and currently working as the Head of Electronics and Telecommunication Department at Jawaharlal Nehru Engineering College. His research interest includes Communication Engineering, Network Security and Machine Learning. He has published 40 research papers in international journals. https://orcid.org/0009-0005-9955-199X.