A Transfer Learning Approach for Classification of Knee Osteoarthritis

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***Abstract* — Artificial intelligence is a concept that is extremely popular in the realm of healthcare and medical imaging. It strives to generate experimental findings that are beyond the capacity of humans and encourages consistent outcomes in assisting clinical specialists. Doctors that rely substantially on pictures, such as radiographers profit greatly from medical X-ray image analysis. Early-stage Knee Osteoarthritis detection is one such imaging prognosis. Wear and tear along with the slow degeneration of the articular cartilage are the main causes of knee osteoarthritis. Due to sophisticated technology, osteoarthritis detection employing X-ray pictures demands professionals who are technically proficient. Long examination periods and erroneous outcomes might stem from a lack of professional expertise. Thus, in this paper, a rapid and effective technique of utilizing Artificial Intelligence, medical image processing, and Machine Learning, has been suggested, to aid clinicians in making proper conclusions in classifying Knee Osteoarthritis at its early stages. The intricacies of Artificial Intelligence will surely aid in the faster adoption of technology in healthcare.**

Keywords — Artificial Intelligence, Medical Imaging, Machine Learning, Transfer Learning, Knee Osteoarthritis

I. INTRODUCTION

Human bodies have 360 joints that link one bone to another. The knee joint is among the strongest and most crucial joints in the human body. Many common tasks, such as walking, sitting, and standing, rely on efficient knee joint movements. However, as humans age, the articular cartilage begins to wear and tear, thus reducing the quality of everyday important actions. Arthritis is a disorder that includes discomfort, swelling, and abrasion in the knee joints, and the prevalent type of this is 'Osteoarthritis (OA)'.

In Knee OA, the cartilage in the knee corrodes, and the protecting area between the bones shrinks. This results in painful bone spurs as bones tend to rub against one another. A common imaging test called an X-ray enables doctors to look inside the body without the need of surgical incisions. This can help with the evaluation, observation, and management of a number of joint conditions. The drawback is that diagnosing OA through X-ray pictures by a clinical specialist is challenging and may result in incorrect judgments due to the disorder's complexities.

While determining the stage of OA may be a helpful option, early diagnosis of OA is critical for both the patient and the medical professional treating him. Computer-aided analysis and artificial intelligence imaging approaches are now blooming and producing excellent results in X-ray image analysis. The same method may be used to diagnose knee OA by running image processing and machine learning algorithms on a well-curated dataset of X-ray knee images.

This paper provides an automated strategy, using DenseNet-201 for the early diagnosis of OA in elderly individuals, permitting them to seek immediate medical attention. Transfer learning is used to train the DenseNet-201 model on the dataset curated from [1] and [2]. The deep learning technique called transfer learning uses a model developed for one task as the basis for a model on another task. Since building neural networks for a given task requires a significant amount of computer resources pre-trained models are frequently used as a foundation in deep learning. A pre-trained model with initial training on a different dataset would include weights that closely match the features of that dataset. It is then possible to apply these learnt features to different types of data. Hence the concept of transfer learning is highly efficient with regards to image classification tasks.

II. LITERATURE REVIEW

For the classification problem, a deep learning model that delivers the most accurate results with the fewest inconsistencies is necessary. After looking through numerous approaches for the classification problem as ennumerated by Schiratti et al. [3] and Ningrum et al. [4], the decision of using X-rays images for training the model was taken. Kokkotis et al. [5] reviews machine learning algorithms used for the classification of Knee Osteoarthritis. Instead of relying solely on techniques like logistic regression, K-Nearest Neighbors

(KNN), Support Vector Machines (SVMs), or tree-based algorithms used in [7][8][10], a transfer learning approach using deep learning provides a better result.

Yeoh et al. [6] examines 3D Convolutional Neural Networks (3D CNNs) to identify Knee Osteoarthritis. The main drawback of employing the use of 3D CNNs is the cost of computation. The images used have a larger size and a higher resolution. Making use of elementary adaptations of different network architectures could be inadequate in accurately classifying the images. Apart from this the cost of computation and large training time associated with training multiple 3D convolutional layers, makes the use of 2D convolutional layers a better choice.

Nasser et al. [12] makes use of Discriminative Regularized Auto-Encoders (DRAEs) and manages to achieve an accuracy of 69.83% for classification of Grade-0 and Grade-1 images in accordance with the Kellgren Lawrence (KL) scale. Tiulpin et al. [13] proposes a multiclass classification model with an average accuracy of 66.71%. The proposed methodologies fall short in obtaining a high accuracy for the classification task.

Eliminating the shortcomings of the above references our proposed solution makes use of Transfer Learning to classify X-ray images as ‘0’ (healthy) or ‘1’ (suspected OA) and achieves an overall accuracy of 82.48% on the test set.

III. System Architecture

The process begins with the creation of a well defined Knee Osteoarthritis dataset. The dataset consists of 2 classes: ‘0’ indicating a healthy knee and ‘1’ indicating suspected Knee Osteoarthritis. RandomOverSampler is used to correct the class imbalance issue present in the images of the training set. The images are augmented and normalized. The training set images are fed into the DenseNet-201 model. With the help of feed-forward connections, a DenseNet links every layer to every other layer. Conventional CNNs containing L layers possess L connections. DenseNets on the other hand have $L(L+1)/2$ direct connections. Each layer’s feature map serves as an input to layers after that particular layer. The DenseNet architecture provides advantages, such as better feature propagation and the removal of vanishing gradients. DenseNets obtain significant improvements over many models, because they require lesser computation, but still provide a better performance. DenseNet-201 is a CNN that consists of 201 layers. Images can be categorized into 1000 distinct classes using a pre-trained DenseNet-201 model that was trained on more than 1 million images. The model is subsequently trained on X-ray images using early stopping and an exponential learning rate scheduler. After the training is over, a random image from the test set is selected and passed to the model. The image is assigned to that class which has a higher probability score. Once the final classification is performed by the model a graph is generated indicating the probability of the classification by the model. The final system architecture is shown in Fig. 1.

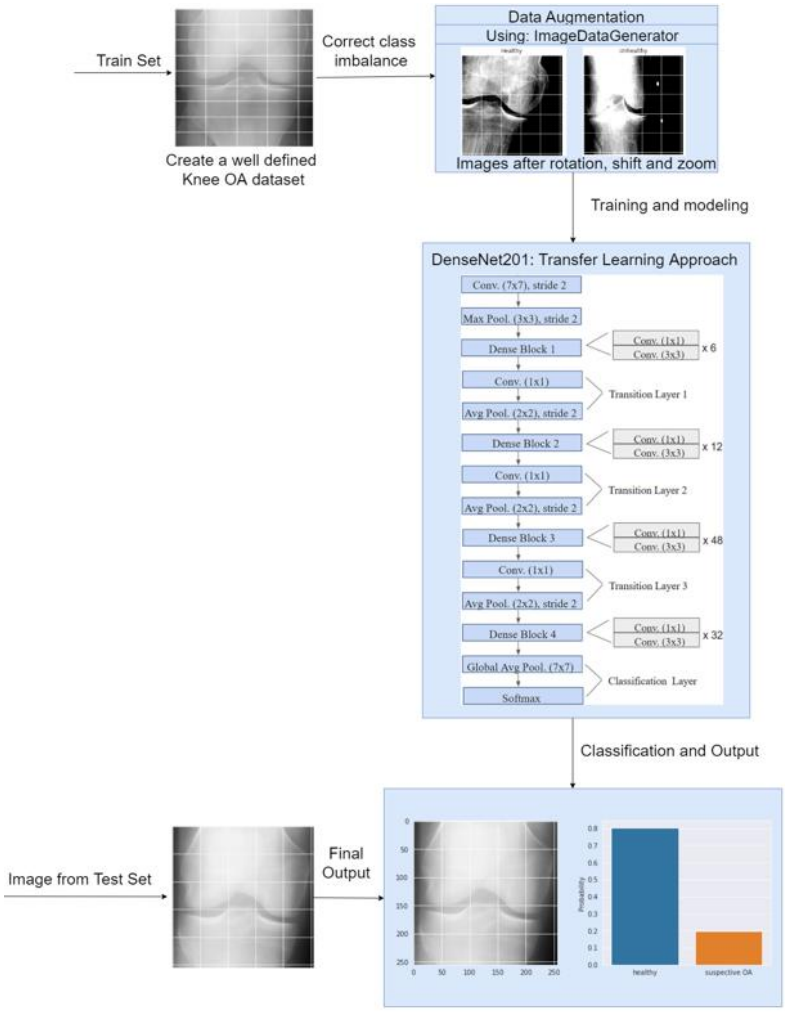

Fig. 1. System Architecture

IV. Methodology

A. Data Collection

Creating a robust dataset is the first step in training the model to classify images. The Knee Osteoarthritis (KOA) dataset, which contains a total of 5478 images (as shown in Fig. 2), served as the data for training the deep learning model employed in this system. The images of the dataset are either labelled as ‘0’ (healthy) or ‘1’ (suspected OA). The dataset contains 3473 images from class 0 and 1457 images from class 1. The dataset was split into 3 different parts as follows:

i. **Training Data**: Comprises 4930 images.
ii. **Validation Data**: Comprises 274 images.
iii. **Testing Data**: Comprises 274 images.

	Filepaths	Labels
0	drive/MyDrive/KOA NEW/0/9691359L.png	0
1	drive/MyDrive/KOA NEW/0/9677286R.png	0
2	drive/MyDrive/KOA NEW/0/9679111R.png	0
3	drive/MyDrive/KOA NEW/0/9679705L.png	0
4	drive/MyDrive/KOA NEW/0/9683366L.png	0
...	...	...
5473	drive/MyDrive/KOA NEW/1/9091337L.png	1
5474	drive/MyDrive/KOA NEW/1/9085790L.png	1
5475	drive/MyDrive/KOA NEW/1/9126014L.png	1
5476	drive/MyDrive/KOA NEW/1/9087863R.png	1
5477	drive/MyDrive/KOA NEW/1/9081306R.png	1

5478 rows × 2 columns

Fig. 2. Example of images that have labels '0' (healthy) or '1' (suspected OA).

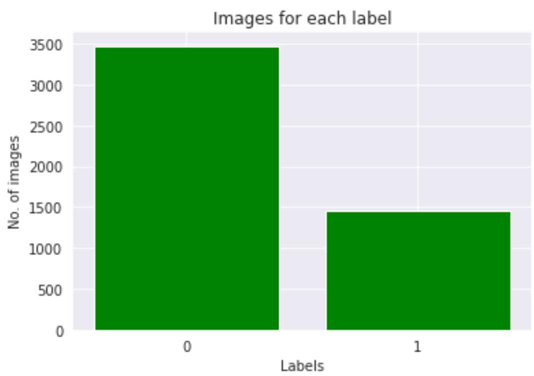

Fig. 3. Class count for all the images present in the dataset.

B. Data Preprocessing

The dataset contains a high class imbalance, shown in Fig. 3, with there being 2016 more images of class 0 in the dataset as compared to class 1. Prior to preprocessing the class imbalance of the dataset is corrected using RandomOverSampler. The classes were balanced so that the dataset contains 3473 images of class 0 and 3473 images of class 1. The class balancing after over-sampling can be seen in Fig. 4.

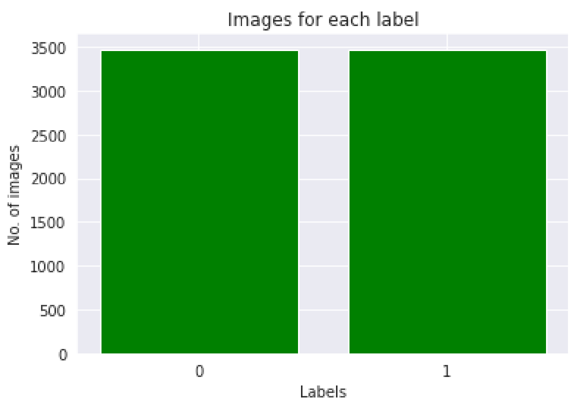

Fig. 4. Images of both the classes were balanced using RandomOverSampler

The following steps were applied as part of the preprocessing step using ImageDataGenerator from TensorFlow:

i. **Rotation**: This setting ranges from 0º to 180º and can be used to rotate images in the dataset at random.
ii. **Width and Height Shift**: With this parameter, images can be translated at random, either in the vertical direction or the horizontal direction.
iii. **Zoom**: This controls the amount of random zoom applied to each image.
iv. **Shear**: Using this shear transformations can be applied at random.
v. **Fill Mode**: This method is employed to fill in new pixels that may be produced due to image processing transformations such as a width shift.

The images were also scaled and normalized as neural networks yield optimum outputs when all their features are at the same scale. Similar to this, optimization techniques like Gradient Descent excel when the features are distributed uniformly around a mean having a value of zero and a standard deviation having a value of one. The images after completion of the preprocessing step are shown in Fig. 5.

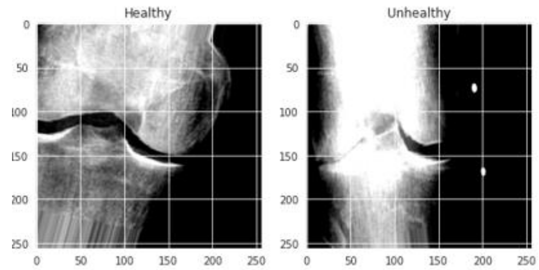

Fig. 5. Results obtained after successful completion of the preprocessing stage.

C. Training the Model

To classify the images as '0' (healthy) or '1' (suspected OA), the concept of transfer learning was utilized. Transfer learning is a deep learning technique that stores knowledge obtained from solving a specific problem and uses it on another similar problem. DenseNet-201 initialized with ImageNet weights was used for the binary classification task. Convolutional neural networks find their applications in different biomedical imaging tasks as proposed in [9] and [11]. DenseNets are CNNs that employ Dense Blocks connecting layers with corresponding feature-map sizes to one another. Kwon et al. [9] makes use of Inception-ResNet-v2 to extract features from the images. The key advantage of using DenseNet over ResNet is that DenseNet concatenates preceding feature maps, whereas ResNet uses summation to join them. Each layer of the neural network takes inputs from layers above it and transmits its feature maps to layers below it, thus maintaining the feed-forward structure of the network. Early stopping and a learning rate scheduler with exponential decay was used while training the model. As the model training advances the learning rate scheduler modifies the learning rate in order to improve model accuracy and minimize the loss. The learning rate scheduler used to train the model uses an exponential decay to adjust the learning rate resulting in faster convergence. A regularization technique called early stopping was applied to prevent overfitting, while the learner was being iteratively trained. These techniques update the learner after each epoch in order to improve its fit with the training data.

V. Results

The deep learning model is successfully able to classify images as ‘0’ (healthy) or ‘1’ (suspected OA). To understand the performance of our model, accuracy and loss were selected as the model evaluation metrics. Model evaluation assists in examining the performance of a model (as shown in Fig. 6 and Fig. 7), to identify its benefits and drawbacks by making use of multiple assessment measures. This is beneficial for evaluating the effectiveness for trained models.

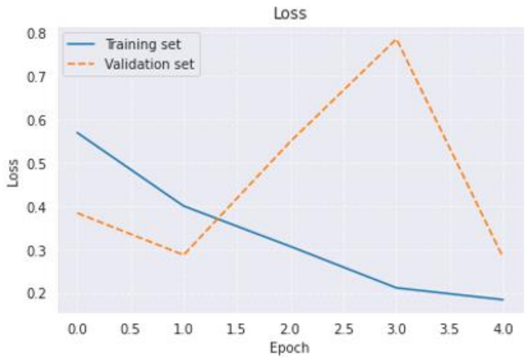

Fig. 6. Model loss during each epoch for the training and validation sets.

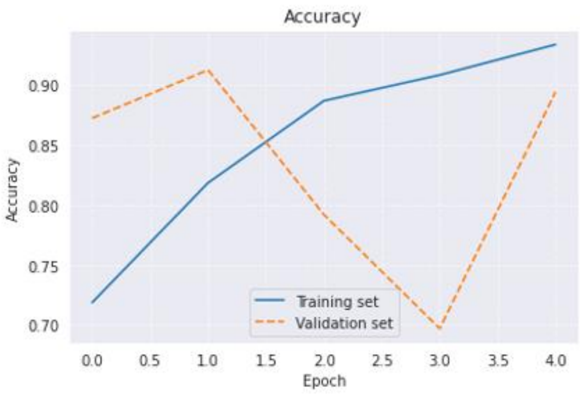

Fig. 7. Accuracy obtained for the DenseNet-201 deep learning model.

A random image (represented by Fig. 8) is selected from the test set and fed into the model. The output (shown in Fig. 9) is displayed in the form of the input image and the probability scores of the two classes the model is trained on. A higher probability score of one class indicates that the image belongs to that particular class.

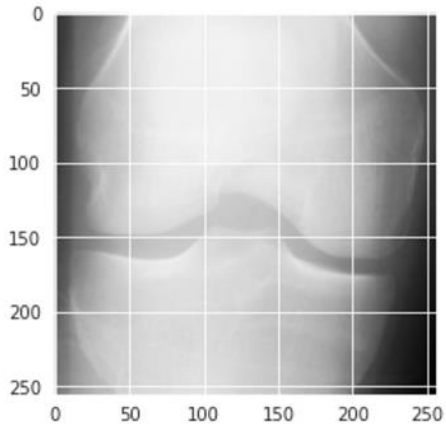
Fig. 8. The above image belongs to class ‘0’ (healthy).

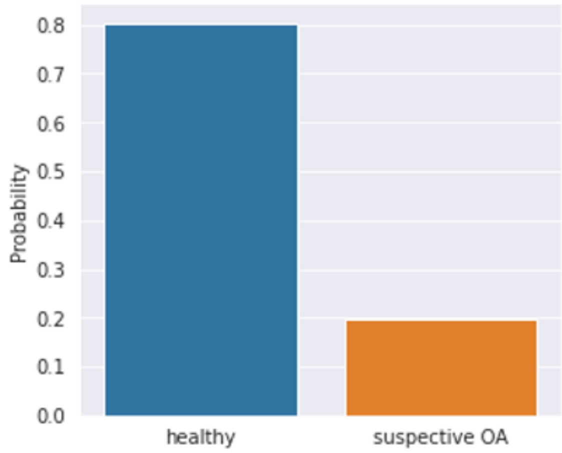

Fig. 9. The probability score of the classification is 0.8 (i.e, 80%)

To evaluate and summarize the performance of the DenseNet-201 model on the test set a confusion matrix is generated.

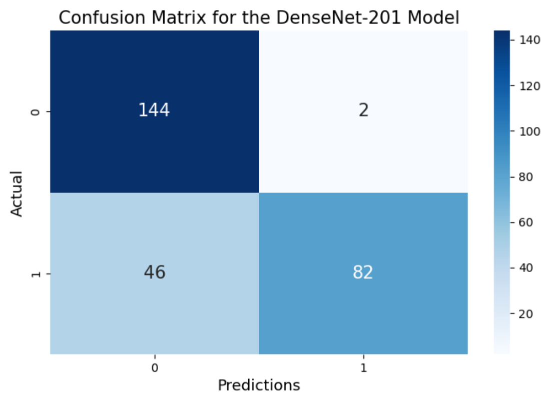

Fig. 10. Classification results in the form of a confusion matrix for DenseNet-201

The accuracy for the model can be obtained from the confusion matrix (shown in Fig. 10) as follows:

$$\text{Accuracy} = \frac{144 + 82}{144 + 2 + 46 + 82} = 82.48\%$$

The precision, recall and F-score of the DenseNet model are calculated as follows:

$$\text{Precision} = \frac{82}{82 + 2} = 97.62\%$$

$$\text{Recall} = \frac{82}{82 + 46} = 64.06\%$$

$$\text{F} - \text{Score} = \frac{2 \text{ x } 97.62 \text{ x } 64.06}{97.62 + 64.06} = 77.36\%$$

VI. Conclusion

Determining whether or not a person develops Knee Osteoarthritis from an X-ray scan is a critical task. Furthermore, creating a model that can reliably foresee the disease's KL-Grade is challenging. Our methodology relies on appropriately displaying whether or not an individual has Knee OA, with the model inferring an individual's knee as 'healthy' or 'suspective OA' based on the data. This was accomplished by curating a dataset, preparing the data, modeling the results, and finally achieving an accuracy of 82.48%. This approach proves to be a valuable resource for medical experts, as it allows them to further assess the degree of damage and provide appropriate surgery or treatment once the patient has been diagnosed with the correct condition. The outcomes are obtained using a probabilistic graph by employing a neural network technique and modeling the data into the DenseNet-201 model. Since, the condition is severe, knowing what proportion of a person is healthy or unwell helps individuals accept the statistics better. To recapitulate, Artificial Intelligence (AI) in medical imaging is a burgeoning and promising technology, specifically to identify knee osteoarthritis. It may compensate for a lack of professional competence and assist clinicians in easing, speeding up, and thus upgrading existing medical technologies through the use of AI.

VII. References

[1] Chen, Pingjun (2018), "Knee Osteoarthritis Severity Grading Dataset", Mendeley Data, V1, doi: 10.17632/56rmx5bjcr.1

[2] Tiwari, S. "Knee Osteoarthritis Dataset with Severity Grading", Kaggle. https://www.kaggle.com/datasets/shashwatwork/knee-osteoarthritis-dataset-with-severity (accessed Jul. 2, 2022).

[3] Schiratti, JB., Dubois, R., Herent, P. et al. A deep learning method for predicting knee osteoarthritis radiographic progression from MRI. Arthritis Res Ther 23, 262 (2021). https://doi.org/10.1186/s13075-021-02634-4

[4] Ningrum DNA, Kung WM, Tzeng IS, Yuan SP, Wu CC, Huang CY, Muhtar MS, Nguyen PA, Li JYC, Wang YC. A Deep Learning Model to Predict Knee Osteoarthritis Based on Nonimage Longitudinal Medical Record. J Multidiscip Healthc. 2021;14:2477-2485. https://doi.org/10.2147/JMDH.S325179

[5] Kokkotis, Christos & Moustakidis, Serafeim & Papageorgiou, Elpiniki & Giakas, Giannis & Tsaopoulos, Dimitrios. (2020). Machine Learning in Knee Osteoarthritis: A Review. Osteoarthritis and Cartilage Open. 2. 100069. 10.1016/j.ocarto.2020.100069.

[6] Pauline Shan Qing Yeoh, Khin Wee Lai, Siew Li Goh, Khairunnisa Hasikin, Yan Chai Hum, Yee Kai Tee, Samiappan Dhanalakshmi, "Emergence of Deep Learning in Knee Osteoarthritis Diagnosis", Computational Intelligence and Neuroscience, vol. 2021, Article ID 4931437, 20 pages, 2021. https://doi.org/10.1155/2021/4931437

[7] Brahim A, Jennane R, Riad R, Janvier T, Khedher L, Toumi H, Lespessailles E. A decision support tool for early detection of knee OsteoArthritis using X-ray imaging and machine learning: Data from the OsteoArthritis Initiative. Comput Med Imaging Graph. 2019 Apr;73:11-18. doi: 10.1016/j.compmedimag.2019.01.007. Epub 2019 Jan 29. PMID: 30784984.

[8] Kumar, A. & Saxena, P. Quantification of cartilage loss for automatic detection and classification of osteoarthritis using machine learning approach. In 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 1–6, 10.1109/ICCCNT45670.2019.8944538 (2019).

[9] Kwon SB, Han HS, Lee MC, Kim HC, Ku Y, Ro DH. Machine Learning-Based Automatic Classification of Knee Osteoarthritis Severity Using Gait Data and Radiographic Images. IEEE Access. 2020; 8:120597-120603. 9130657. doi: 10.1109/ACCESS.2020.3006335

[10] Jamshidi A, Pelletier JP, Martel-Pelletier J. Machine-learning-based patient-specific prediction models for knee osteoarthritis. Nat Rev Rheumatol. 2019 Jan;15(1):49-60. doi: 10.1038/s41584-018-0130-5. PMID: 30523334.

[11] Banerjee, S., Bhunia, S., & Schaefer, G. Osteophyte detection for hand osteoarthritis identification in x-ray images using CNNs. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2011, 6196–6199. https://doi.org/10.1109/IEMBS.2011.6091530

[12] Y. Nasser, R. Jennane, A. Chetouani, E. Lespessailles and M. E. Hassouni, "Discriminative Regularized Auto-Encoder for Early Detection of Knee OsteoArthritis: Data from the Osteoarthritis Initiative," in IEEE Transactions on Medical Imaging, vol. 39, no. 9, pp. 2976-2984, Sept. 2020, doi: 10.1109/TMI.2020.2985861.

[13] A. Tiulpin, J. Thevenot, E. Rahtu, P. Lehenkari, and S. Saarakkala, "Automatic knee osteoarthritis diagnosis from plain radiographs: a deep learning-based approach," Scientific Reports, vol. 8, no. 1, pp. 1727–1810, 2018.