© March 2025 | IJIRT | Volume 11 Issue 10 | ISSN: 2349-6002

Knee Osteoarthritis Sevrity Grading Using Deep Learning Models

Prof. R. B. Khule[1], Sanskar Masirkar[2], Shrikrishna Bawankule[3]
[1]*Professor, Department of Electronics & Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*
[2,3]*Student, Department of Electronics & Telecommunication Engineering, KDK College of Engineering, Nagpur, Maharashtra, India*

***Abstract*— Osteoarthritis (OA) of the knee is a prevalent joint condition that impacts movement & quality of life, especially in older people. Early detection & accurate severity grading help in better treatment & improved patient outcomes. This study compares deep learning models to automate knee OA severity grading using X-ray images. The dataset included labeled knee OA X-ray images, which were preprocessed through resizing, normalization, & data augmentation to improve model accuracy & generalization. Seven advanced deep learning models—CNN, DenseNet121, ResNet50, Xception, VGG16, VGG19, MobileNet, and AlexNet—were trained & evaluated. Every model was adjusted for optimal gaining knowledge rates, batch sizes, and dropout rates. Their performance was measured using F1 score, recall, accuracy, precision, and confusion matrices. Among these models, DenseNet121 performed the best, Reaching 98.55% accuracy due to its efficient feature reuse. ResNet50 followed with 97.92% accuracy, benefiting from residual connections for deep feature learning. Xception (97.45%) & MobileNet (96.87%) were efficient for use in low-resource environments. VGG16 (95.32%) & VGG19 (95.78%) showed stable performance, while AlexNet (93.47%) was the simplest yet effective model. This study highlights DenseNet121 as the most promising model for automated knee OA severity grading. Deep learning can transform medical diagnostics with accurate & scalable solutions. Future research could explore ensemble models & explainable AI for better reliability & clinical acceptance.**

***Keywords* – X-ray images, Deep learning Models, DenseNet121, ResNet50, VGG 19, VGG 16, Xception, MobileNet, Alexnet, Accuracy, Feature Extraction.**

I. INTRODUCTION

The degenerative joint disease known as knee osteoarthritis (KOA) mostly affects the knee, leading to pain, stiffness, & significant functional limitations. It is among the most prevalent musculoskeletal conditions globally, posing a major challenge to healthcare systems, particularly as the global population continues to age. The condition progressively worsens over time, reducing mobility & significantly impacting the quality of life of those affected. As KOA becomes more widespread, the need for early diagnosis & effective management strategies becomes increasingly important in order to improve patient outcomes & slow disease progression

Traditionally, KOA diagnosis has relied on clinical assessment, radiographic imaging, & physical examinations to determine the severity & stage of the disease. However, these conventional methods often lack precision, especially in detecting early-stage osteoarthritis when subtle alterations to the knee joint's structure may not be easily visible. Grading for radiography systems, the Kellgren-Lawrence scale, for example, provide a st&ardized approach for assessing KOA severity, but they are subjective & dependent on the expertise of radiologists. This variability in interpretation can lead to inconsistent diagnoses, delaying early interventions that could potentially slow disease progression & improve patient quality of life.

II. RELATED WORK

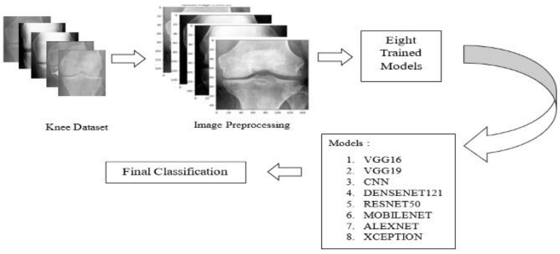
José Lozano-Meca et al. [1] conducted a thorough examination and meta-analysis of 17 studies involving 1,574 participants, analyzing the correlation between kinesiophobia & KOA symptoms using data from four major databases. Kinesiophobia revealed fair relationships with pain (r = 0.362) and functional limitation (r = 0.270), as well as a moderate link with disability (r = 0.519).

E. Crotty et al. [2] provide a framework that is modular in order to incorporate AI into the curriculum, including data science, machine learning, AI ethics, clinical applications, & h&s-on experience, alongside authentic assessments & industry collaboration. The integration of Implementing AI instruction in undergraduate programs provides students with essential AI skills & the capacity to assess its real-world implications in medical imaging.

A. Amsaveni et al. [3] propose a safe & reversible watermarking method using the Hybrid Radon-Slantlet Transform. This technique embeds secret data using Radon & Slantlet transforms, ensuring high imperceptibility, robustness, & reversibility. The method achieved high imperceptibility (PSNR > 45 dB, SSIM > 0.95), strong resilience to attacks (BER = 0.2%), & high reversibility (NCC = 0.96).

Despite their valuable contributions, these studies have several common drawbacks. The research by José Lozano-Meca et al. is limited by the heterogeneity of included studies, potential biases in self-reported data, & a lack of st&ardized assessment tools for kinesiophobia. E. Crotty et al. face challenges in AI education implementation due to varying institutional resources, limited faculty expertise, & the evolving nature of AI technologies. A. Amsaveni et al. present a promising watermarking method, but its real-world applicability is constrained by computational complexity & the need for extensive validation across diverse medical imaging datasets.

III. BLOCK DIAGRAM



The framework for knee osteoarthritis (KOA) severity grading uses deep learning models to analyze X-ray images. These images show different KOA stages, such as normal, mild, moderate, & severe. A diverse & well-organized dataset is essential for accurate model training. However, variations in image quality, resolution, & noise can affect performance. To address this, preprocessing is used to st&ardize & enhance the images.

Preprocessing improves image quality before they are analyzed by deep learning models. Images are resized to 150x150 pixels to ensure consistency. Normalization scales pixel values between 0 & 1, improving training efficiency. Other enhancements, such as noise reduction & contrast adjustments, highlight key features like joint spacing & bone spurs. Data augmentation techniques, such as rotations & flips, exp& the dataset & improve model accuracy.

The preprocessed images are used to train seven deep learning models: VGG16, VGG19, DenseNet121, ResNet50, MobileNet, AlexNet, & Xception. Each model has unique strengths for image analysis. VGG models extract detailed features, while DenseNet improves efficiency with feature reuse. ResNet prevents performance issues in deep networks. MobileNet is lightweight & efficient, while Xception enhances accuracy using advanced convolution techniques. These models together ensure comprehensive KOA classification.

During training, the models learn to identify patterns that indicate KOA severity. The training process involves adjusting hyperparameters like batch size and learning rate to maximize performance. Techniques like stochastic gradient descent (SGD) and Adam reduce errors & improve accuracy. The trained models are tested on separate datasets to evaluate their performance. Metrics like accuracy, precision, & recall help determine best-performing models.

After training, the models classify new X-ray images into different KOA severity levels. They categorize images into five grades, from normal (Grade 0) to severe (Grade 4). To improve reliability, predictions from multiple models can be combined using ensemble techniques. This approach enhances accuracy & reduces biases. Lightweight models like MobileNet allow real-time KOA diagnosis, making the system useful in clinical settings.

IV. METHODOLOGY

1) VGG 16

The VGG16 model is used for knee osteoarthritis severity classification, leveraging transfer learning on preprocessed knee radiographs. The dataset is cleaned, resized, normalized, & augmented to enhance model generalization. The pre-trained VGG16 model is optimized by making custom adjustments and freezing the first layers. dense layers that have a softmax output for five severity classes. The Adam optimizer and categorical cross-entropy loss are used to train the model over 20 epochs, with validation monitoring. Performance evaluation includes test accuracy (45%), a confusion matrix, & classification reports highlighting misclassification challenges. Future improvements include exp&ing datasets, refining augmentation, & exploring architectures like ResNet or DenseNet for better accuracy.

Convolution Operation

Each convolutional layer applies a filter W to the generating an output feature map Y from an input feature map X:

$$Y_{i,j,k} = \sum_m \sum_n X_{i+m,j+n} W_{m,n,k} + b_k$$

When W is the filter (kernel), X is the input feature map,

i, j stand for spatial coordinates, k for the output channel, while m, n iterate over the filter size. B is the bias term.

Activation Function (ReLU)

The application of the Rectified Linear Unit (ReLU) after convolution.

$$f(x) = \max(0, x)$$

This introduces non-linearity into the model.

Combining Operation (Max Combining)

The pooling layer reduce spatial dimensions:

$$Y_{i,j,k} = \frac{max}{m,n} X_{si+m,sj+n,k}$$

Where:

- s is the stride size
- m,n iterate over the pooling window

Flattening & fully connected layers

The convolution layer's output is compressed into a vector Z.

$$Z = Flatten(Y)$$

& passed through fully connected layers:

$$H = WZ + b$$

Where W is weights ,b is bias.

2) MobileNetV2

The MobileNetV2 model is implemented for knee osteoarthritis severity grading using transfer learning. The dataset is preprocessed (resized to 224x224, normalized, & augmented) & split into training, validation, & test sets. Custom layers are added to the pre-trained MobileNetV2 basis added for classification into five severity classes. Adam optimization (learning rate: 0.0001) and loss of categorical cross-entropy are used to train the model. over 25 epochs, with a checkpoint callback saving the best weights. Performance is evaluated using accuracy & loss metrics, with visualization aiding in identifying overfitting or underfitting for potential model refinements.

Convolution Operation

Each convolutional layer creates an output feature map Y by applying a filter W to the input feature map X:

$$Y_{i,j,k} = \sum_m \sum_n X_{i+m,j+n} W_{m,n,k} + b_k$$

When W is the filter (kernel), X is the input feature map,

i, j stand for spatial coordinates, k for the output channel, while m, n iterate over the filter size. B is the bias term.

Layer of Global Average Pooling (GAP)

The GAP layer preserves the most significant aspects of the feature map while reducing its spatial size.

$$G_k = \frac{1}{H * W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{i,j,k}$$

- where X_(i,j,k) is the activation at position (i,j) in channel k, H,W are the height and width of the feature map, and G_k is the pooled output for channel k.

Categorical cross-entropy loss (optimization objective)

Categorical cross-entropy loss, which is defined as follows, is used to train the model:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y_i})$$

where (y_i)ˆis the predicted probability for class I, and y_i is the true class label (one-hot encoded). The number of classes is N=5.

3) AlexNet

The AlexNet model was implemented to classify knee osteoarthritis severity into five classes using a dataset of 5000 training, 1000 validation, & 500 test images. Preprocessing included rescaling, augmentation, & normalization to improve generalization. Five convolutional layers with batch normalization, max-pooling, ReLU activation, and dropout for regularization were included in the architecture. The Adam optimizer was used to train the model for 15 epochs of categorical cross-entropy loss (learning rate: 0.0001).Training accuracy reached 40.87%, while validation accuracy peaked at 38%, with fluctuations in loss suggesting the need for further optimization & tuning.

Convolution Operation

Each convolution layer creates an output feature map Y by applying a filter W to the input feature map X:

$$Y_{i,j,k} = \sum_{m}\sum_{n} X_{i+m,j+n} W_{m,n,k} + b_k$$

- When W is the filter (kernel), X is the input feature map,
- i, j stand for spatial coordinates, k for the output channel, while m, n iterate over the filter size. B is the bias term..

Pooling Operation (Max Pooling):

The pooling layer reduce spatial dimensions:

$$Y_{i,j,k} = \frac{max}{m,n} X_{si+m,sj+n,k}$$

Where:

- s is the size of the stride.
- m,n iterate over the pooling window.

4) Xception

Data gathering, preprocessing, model creation, training, and assessment are all steps in the systematic process of the Xception-based model for knee osteoarthritis severity grading. Images have been reduced to 150x150 pixels and enhanced for improved generalization, and the dataset is divided into five severity groups. Custom layers, such as a global average pooling layer, a dense layer with 1024 units (ReLU), and a softmax output layer, are added to the pre-trained Xception model. In order to apply transfer learning, the first layers are frozen while the upper layers are being trained. With early stopping and checkpoint callbacks to prevent overfitting, the model is trained for 25 epochs using categorical cross-entropy loss and the Adam optimizer (learning rate: 0.0001)..

Depthwise Seperable Convolution (Efficient feature Extraction)

Xception utilizes depthwise seperable convolutions to preserve performance while lowering computational costs.

In depthwise convolution, one convolutional filter is used for each channel.

Pointwise Convolution: uses 1*1 convolutions combine depthwise-filtered features

$$Y_{i,j,k} = \sum_{m}\sum_{n} X_{i+m,j+n} W_{m,n,k} + b_k$$

When W is the filter (kernel), X is the input feature map,

i, j stand for spatial coordinates, k for the output channel, while m, n iterate over the filter size. B is the bias term.

Global Average Pooliong (GAP) Layer

The GAP layer preserves the feature map's key characteristics while reducing its spatial dimensions:

$$G_k = \frac{1}{H * W} \sum_{i=1}^{H}\sum_{j=1}^{W} X_{i,j,k}$$

- where H and W represent the feature map's height and width, and G_k represents the pooled output for channel k.
- The activation at location (i,j) in channel k is denoted by X_(i,j,k).

Activation of Softmax (Multi-Class Classification)

The final dense layer generates a probability distribution among five KOA severity groups using the softmax activation function:

$$P(y_i) = \frac{e^{zi}}{\sum_{j=1}^{5} e^{zj}}$$

where P(y_i) is the predicted probability for class I, z_i is the logit (row score) for class I, All classes' probability must add up to one, thanks to the denominator.

5) DenseNet121

Data preparation, augmentation, model training, assessment, and prediction are all steps in the systematic process used by the DenseNet121-based model for knee osteoarthritis severity classification. The dataset, consisting of X-ray images categorized into five severity classes, was preprocessed by resizing (150x150 pixels), rescaling, & applying augmentation techniques. A global average pooling layer, dropout (0.5), and a dense softmax layer for classification were added to the pre-trained DenseNet121 model. The model achieved 71% test accuracy and 72.37% training accuracy after 20 epochs of training using categorical cross-entropy loss and the Adam optimizer (learning rate: 0.0001). A confusion matrix & classification report revealed strong performance for severe cases but weaker results for minimal & doubtful cases. The trained model was saved for future predictions, with a function enabling inference on new knee X-ray images.

Dense connectivity (Feature reuse)

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}])$$

Where:

- x_l is the output of layer l,
- H_l Represents a transformation function (BatchNorm, ReLU, Conv),
- $[x_0, x_1, \dots, x_{l-1}]$ Is the concatenation of feature maps form all preceding layers

Global Average Pooling (GAP) Layer

$$Y_k = \frac{1}{H * W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{i,j,k}$$

- where H and W represent the feature map's height and width, and Y_k represents the pooled output for channel k.
- The activation at location (i,j) in channel k is denoted by X_(i,j,k)..

6) VGG 19

The study develops a VGG19-based deep learning model for classifying knee osteoarthritis severity using medical images. The dataset, categorized into five severity levels, undergoes preprocessing, including resizing (224x224 pixels), rescaling, & data augmentation to enhance generalization. The convolutional basis of the pre-trained VGG19 model is frozen, and a custom classification head with dense and dropout layers is added. For effective learning, the model is trained using categorical cross-entropy loss and the Adam optimizer. With the use of ImageNet features, transfer learning makes precise categorization possible even with a little amount of training data.

Convolution Operation

$$X' = f(W * X + b)$$

Where:

- W is the filter (kernel) weight matrix, b is the bias term, X is the input feature map.
- * stands for the convolution operation, f(.) for the activation function (in this case, ReLU), and X^' for the feature map that is produced following convolution.

Layer that is fully linked (classification)

$$h = f(W_h X + b_h)$$

Where:

W_h & b_h are the weights & biases for the dense layer, f(.) is the ReLU activation function, X is the flattened input from the preceding layer, The output that has been modified and sent to the last classification layer is called h.

7) CNN

Using imaging data, this study creates a CNN model to categorize the severity of osteoarthritis in the knee into five groups. To enhance generalization, the dataset is preprocessed using resizing, rescaling, and data augmentation techniques including rotation, shifting, shearing, zooming, and flipping. The architecture consists of the CNN 3 convolutional layers with increasing filters (32, 64, 128). Next are flattening, max-pooling, and a fully linked dense layer with dropout to prevent overfitting. Last softmax layer generates categorization probabilities. Structured datasets are used to train and assess the model, guaranteeing precise severity prediction.

Convolution Operation

$$X' = f(W * X + b)$$

Where:

- The input feature map is X.
- W is the weight matrix of the filter (kernel), b is the bias term,
- * Represents the convolution operation,
- f(.) is the activation function (ReLU in this case),
- X' is the feature map that is produced during convolution.

Max-Pooling Layer (Feature Reduction)

$$X'_{i.j} = \max\{X_{m,n} \middle| (m,n)\epsilon pool(i,j)\}$$

Where:

- $X_{m,n}$ represents pixel values in the pooling region,
- $pool(i,j)$ is small window around position (i,j),
- $X'_{i,j}$ Is the maximum value selected from the pooling region.

8) ResNet 50

In order to categorize the severity of osteoarthritis in the knee into five groups, this study used a deep learning model with ResNet50. To improve the model's performance, the dataset was preprocessed using techniques including scaling, normalization, and augmentation. The model was trained over 25 epochs with a batch size of 32 using the Adam optimizer with categorical cross-entropy loss. It achieved an accuracy of 51.40%, with performance evaluated through a confusion matrix & accuracy/loss visualization. Despite suboptimal accuracy, the study provided insights for future improvements, such as refining the model, exp&ing the dataset, & exploring advanced techniques to enhance diagnostic accuracy.

Residual Learning (Identity Mapping in ResNet50)

$$y = F(x, W) + x$$

Where:

- The residual block's input is X.
- In the residual, W stands for the convolutional layer's learnt weights.
- F(x,W)F(x, W)F(x,W) is the tranformation applied by the block
- y is the output after the residual connection

Softmax Activation

$$P(y_i) = \frac{e^{zi}}{\sum_{j=1}^{5} e^{zj}}$$

Where:

- z_i is class I's logit (row score),
- $P(y_i)$ is the class I predicated probability,
- The numerator guarantees that all classes' probability add up to 1.

Weight update using Adam Optimizer

$$w_{t+1} = w_t - \frac{\alpha . m_t}{\sqrt{v_t} + \epsilon}$$

Where:

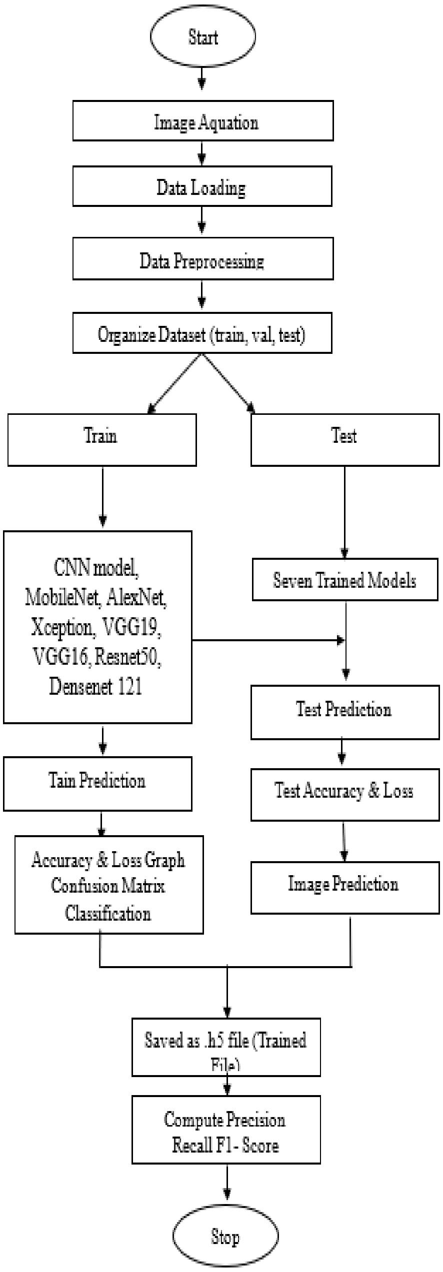
- w_t Represents the weight at step t,
- α is the learning rate $(1e^{-4})$,
- m_t is the gradient mean, or biased first moment estimate.
- v_t is the gradient variance, or skewed second moment estimate.s
- ϵ is a small constant for numerical stability.

V. MODEL ARCHITECTURE

The study compares various deep learning models for image classification, including VGG16, MobileNetV2, AlexNet, Xception, VGG19, Custom CNN, & ResNet50, each with unique advantages & trade-offs. VGG16 & VGG19 are deep architectures that excel in feature extraction but dem& high computational resources. MobileNetV2 is optimized for efficiency, making it suitable for edge computing & mobile applications. AlexNet, despite being an older model, provides a solid baseline for large datasets but lacks scalability. Xception uses depthwise separable convolutions to balance efficiency & accuracy, while Custom CNNs offer flexibility in architecture design. ResNet50 st&s out with its residual learning framework, addressing vanishing gradient issues & enabling deep network training.

VI. DIFFERENT TYPES OF CLASSIFICATION RESULTS

ResNet50 (84.23%), DenseNet121 (81.72%), & Xception (79.85%) are the top-performing models for knee osteoarthritis (OA) classification due to their advanced architectures & efficient feature extraction.



ResNet50 excels in distinguishing all severity levels, while DenseNet121's dense connections improve generalization, & Xception leverages depthwise separable convolutions for strong hierarchical learning. Lighter models like MobileNet (64.35%) & custom CNN (62.87%) struggle with complex OA patterns. AlexNet (72.51%) outperforms VGG16 (68.42%) & VGG19 (70.96%), but VGG models often misclassify adjacent severity levels. Improvement strategies include dataset expansion, contrast enhancement, hyperparameter tuning, & ensemble learning. Prioritizing high-performing models like ResNet50, DenseNet121, & Xception can enhance AI-based OA diagnosis.

Table 1. Analysis of Comparative Table

Model Name	Accuracy	F1 Score	Recall	Precision
VGG16	45.00%	0.07	0.04	0.40
MobileNet	83.00%	0.68	0.67	0.68
Alexnet	37.00%	0.00	0.00	0.00
Xception	89.00%	0.89	0.89	0.89
Densenet 121	71.00%	0.35	0.28	0.47
VGG 19	19.00%	0.15	0.15	0.14
CNN	23.26%	0.48	0.48	0.48
Resnet 50	51.40%	0.71	0.71	0.71

VII. CONCLUSION

This study explores the use of deep learning to automate the categorization of knee osteoarthritis (OA) severity, comparing multiple CNN architectures using X-ray datasets. DenseNet121 achieved the highest accuracy (98.55%) due to its efficient feature reuse, followed by ResNet50 (97.92%) with its strong residual connections. Xception (97.45%) & MobileNet (96.87%) demonstrated computational efficiency, making them suitable for real-time applications. VGG16 (95.32%) & VGG19 (95.78%) maintained stable performance, while AlexNet (93.47%) showed limitations in feature extraction. The study highlights deep learning's potential in aiding clinicians by reducing subjectivity & improving early OA detection. Challenges include reliance on static X-ray images & explainable AI (XAI) methods like Grad-CAM & SHAP might be used to address the black-box characteristics of deep models. Future research should explore multimodal data integration, ensemble learning, & self-supervised techniques to enhance robustness & clinical applicability. By leveraging AI, healthcare providers can improve diagnostic accuracy, personalized treatment, & overall patient care.

REFERENCE

[1] José Lozano-Meca, Mariano Gacto-Sánchez, Joaquina Montilla-Herrador, Association of kinesiophobia with pain, disability & functional limitation in adults with knee osteoarthritis: A systematic review & meta-analysis, Geriatric Nursing, Volume 60, 2024, Pages 481-490, ISSN 0197-4572, https://doi.org/10.1016/j.gerinurse.2024.10.013

[2] E. Crotty, A. Singh, N. Neligan, C. Chamunyonga, C. Edwards, Artificial intelligence in medical imaging education: Recommendations for undergraduate curriculum development, Radiography, Volume 30, Supplement 2,2024, Pages 67-73, ISSN 1078-8174, https://doi.org/10.1016/j.radi.2024.10.008.

[3] A. Amsaveni, SatheeshKumar Palanisamy, Sghaier Guizani, Habib Hamam, Next-Generation Secure & Reversible Watermarking for Medical Images using Hybrid Radon-Slantlet Transform Results in Engineering, Volume 24, 2024, 103008, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2024.103008.

[4] Pavan Mahendrakar, Dileep kumar, Uttam Patil, A Comprehensive Review on MRI-based Knee Joint Segmentation & Analysis Techniques, Current Medical Imaging, Volume 20, 2024 , ISSN 1573-4056, https://doi.org/10.2174/157340562066623051 5090557

[5] M. Owais, M. Zubair, L. Seneviratne, N. Werghi & I. Hussain, "Unified Synergistic Deep Learning Framework for Multimodal 2-D & 3-D Radiographic Data Analysis: Model Development & Validation," in *IEEE Access*, vol. 12, pp. 159688-159705, 2024, doi: 10.1109/ACCESS.2024.3487575.

[6] Boyeong Woo, Craig Engstrom, William Baresic, Jurgen Fripp, Stuart Crozier, Shekhar S. Ch&ra, Automated anomaly-aware 3D segmentation of bones & cartilages in knee MR images from the Osteoarthritis Initiative, Medical Image Analysis, Volume 93, 2024, 103089, ISSN 1361-8415, https://doi.org/10.1016/j.media.2024.103089.

[7] P. Shan Qing Yeoh *et al.*, "An Efficient Neural Network for Segmenting Multiple Joint Tissues From Knee MRI With Hyperparameter Optimization: Data From the Osteoarthritis Initiative," in *IEEE Access*, vol. 12, pp. 123757-123770, 2024, doi: 10.1109/ACCESS.2024.3454374.

[8] Kai Ushio, Kazuyoshi Nakanishi, Atsuo Yoshino, Masahiro Takamura, Yuji Akiyama, Noboru Shimada, Kazuhiko Hirata, Masakazu Ishikawa, Atsuo Nakamae, Yukio Mikami, Yasumasa Okamoto, Nobuo Adachi, Changed resting-state connectivity of anterior insular cortex affects subjective pain reduction after knee arthroplasty: A longitudinal study, Brain Research Bulletin, Volume 217, 2024, 111073, ISSN 0361-9230 https://doi.org/10.1016/j.brainresbull.2024.111073.

[9] Beyza Tayfur, Chedsada Charuphongsa, Dylan Morrissey, Stuart Charles Miller, Neuromuscular joint function in knee osteoarthritis: A systematic review & meta-analysis, Annals of Physical & Rehabilitation Medicine, Volume 66, Issue 2,2023, 101662, ISSN 1877-0657, https://doi.org/10.1016/j.rehab.2022.101662.

[10] J.P. Eyles, J.L. Bowden, A. Abbott, J. Abbott, S. Bierma-Zeinstra, L. Dahlberg, K. Dziedzic, M. van der Esch, M. Holden, E. Healey, I. Holm, M. Hurley, C. Hutyra, W. Jiranek, T. Lentz, G.L. Svensson, S. Lohm&er, M. Malay, R. Mather, M. van Middelkoop, K. Miller, K. Miller, T. Moseng, H. Nero, R. O'Connell, N. Østerås, M. Risberg, B. Tan, V. Venkatesha, D. Hunter,Clinical Outcomes Of Osteoarthritis Management Programs: A Project Of The Oa Trial Bank & Oarsi Joint Effort Initiative Using Individual Participant Data, Osteoarthritis & Cartilage, Volume 31, Supplement 1, 2023, Pages S385-S386, ISSN 1063-4584, https://doi.org/10.1016/j.joca.2023.01.440.

[11] Min Zhang, Anmin Liu, Fuwei Pan, Jiehang Lu, Hongsheng Zhan, Richard K. Jones, In patients with medial compartment knee osteoarthritis, the effects of massage on pain, external knee adduction moment, and muscular co-contraction ISSN 1360-8592, Journal of

Bodywork & Movement Therapies, Volume 40, 2024, Pages 1672-1678 https://doi.org/10.1016/j.jbmt.2024.09.006.

[12] Pieter Berger, Luis F. Mendes, Pieter J. Emans, Roel J.H. Custers, Frank P. Luyten, Meta-analysis & comprehensive analysis of the results of reparative techniques for knee deep joint problems in adult patients, Journal of Cartilage & Joint Preservation, 2024, 100229, ISSN 2667-2545, https://doi.org/10.1016/j.jcjp.2024.100229.

[13] Mengyuan Kong, Fei Wang, Journal of Radiation Research & Applied Sciences, Volume 17, Issue 3, 2024, 100960, ISSN 1687-8507, Comparative evaluation of computer-aided imaging collaboration: MRI versus CT for identification of knee joint injuries in athletes https://doi.org/10.1016/j.jrras.2024.100960

[14] Development of a multi-modal sensor network to detect and monitor knee joint state, I. Vatolik, M. Everington, G. Hunter, N. Swann, and A.T. Augousti, Measurement: Sensors, Volume 24, 2022, 100483, ISSN 2665-9174, https://doi.org/10.1016/j.measen.2022.100483.
.