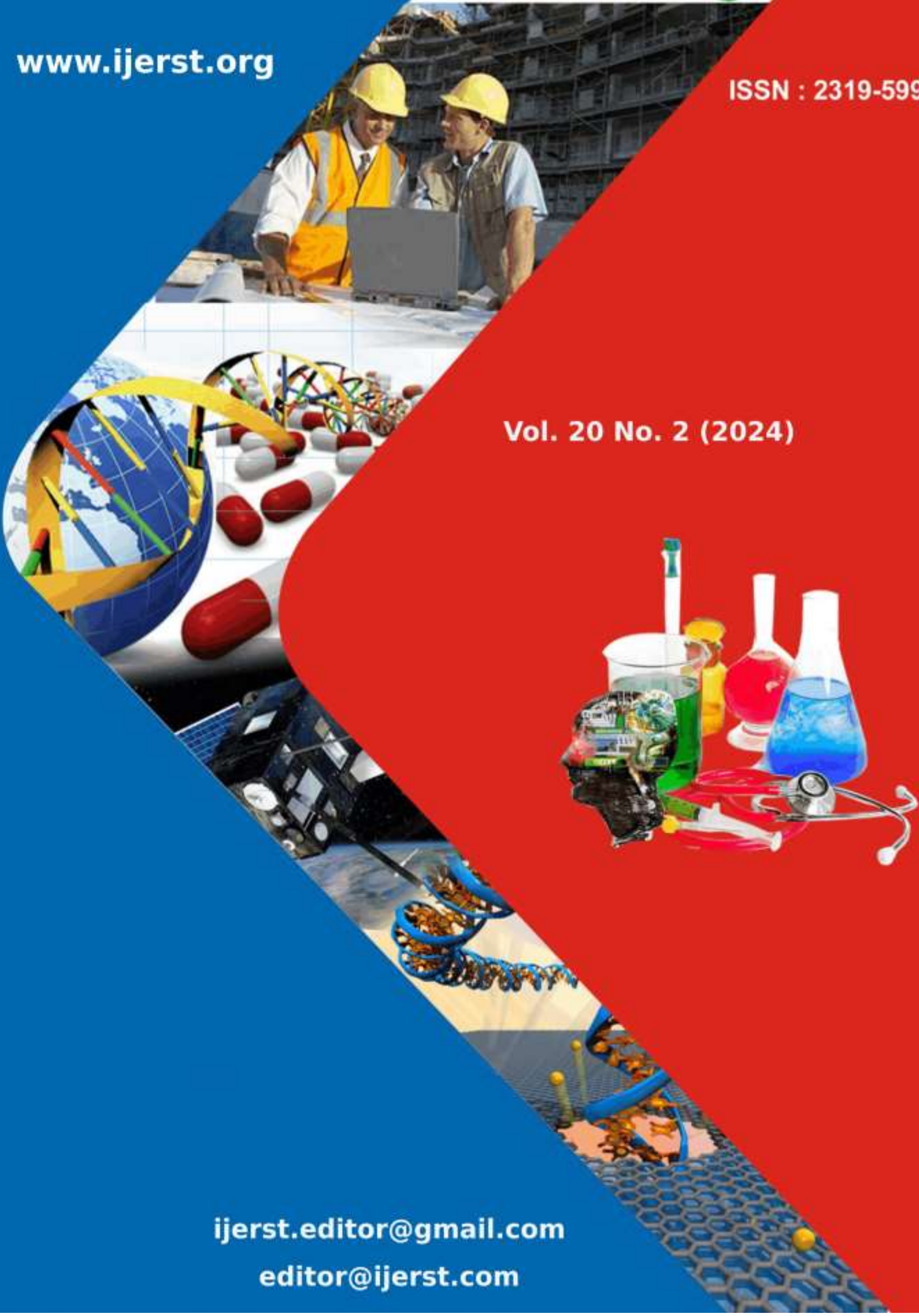
International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991



Vol. 20 No. 2 (2024)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 20, No. 2, 2024

Research Paper

DEEP LEARNING-BASED PREDICTION OF KNEE OSTEOARTHRITIS PROGRESSION USING 3D MRI: AN ANN APPROACH

Dr.X.S.AshaShiny[1], Bavanolla Vaishnavi[2], Valalahally Sukanya Shreya[2], Katikala Siddarth[2], Daftharbandh Harika[2]
[1]Professor, [2]UG Student, [1,2] Department of Information Technology
[1,2]CMR Engineering College (UGC-Autonomous), Medchal Rd, Kandlakoya, Telangana 501401

Received: 07-3-2024 Accepted: 12-4-2024 Published: 22-4-2024

ABSTRACT

Knee osteoarthritis (OA) is a progressive degenerative disease that disproportionately affects older adults, leading to significant morbidity, disability, and socioeconomic burden. Despite its high prevalence, the pathology of OA remains poorly understood, and no effective disease-modifying interventions currently exist. Medical imaging, particularly magnetic resonance imaging (MRI), plays a crucial role in diagnosing OA and assessing disease progression by measuring cartilage changes. However, manual segmentation of knee cartilage from 3D MRI scans is labor-intensive, time-consuming, and requires specialized expertise, making it impractical for large-scale clinical applications. To address these challenges, this study leverages deep learning techniques to predict OA progression using 3D MRI data. We computed the Cartilage Damage Index (CDI) from 36 key locations in the tibiofemoral cartilage compartment and applied principal component analysis (PCA) for feature extraction. A supervised learning model, support vector machine (SVM), and an artificial neural network (ANN) were implemented to predict OA progression, as measured by changes in Kellgren and Lawrence (KL) grade, medial joint space narrowing (JSM), and lateral joint space narrowing (JSL). By integrating artificial intelligence with MRI-based biomarkers, this approach aims to enhance the accuracy, efficiency, and reproducibility of OA progression prediction, offering a promising tool for early intervention and treatment evaluation.

KEYWORDS : Knee Osteoarthritis (OA), Artificial Neural Network (ANN), Cartilage Damage Index (CDI), Joint Space Narrowing (JSN), Support Vector Machine (SVM)

1.INTRODUCTION

The most common form of joint disorder in the United States is osteoarthritis (OA). Knee OA can cause pain and is the number one disease at causing loss of ability to perform daily activities such as walking and stair climbing. [1]Knee OA is associated with age and is characterized by the loss of articular cartilage volume. OA is viewed as a "whole-organ" disorder, manifesting damage to a range of articular structures, especially the hyaline cartilage, meniscus, periarticular bone, ligaments, and tendons. [2] Despite its importance for public health. Among the major weight-bearing joints, knee joint that comprises three compartments (medial tibiofemoral, lateral tibiofemoral, and patellofemoral) is most frequently affected by OA. The global prevalence of knee OA is 16% in the population aged 15 and above where the elders are the most affected subpopulation. [3] Primary knee OA occurs in elders due to wear and tear of cartilage tissues. However, younger individuals could develop secondary knee OA as a result of joint overuse or trauma.

[4] The risk factors for knee OA include age, gender, obesity, injury, joint abnormalities, diet, excessive physical activity, physical inactivity, and genetic factors. People with symptomatic knee OA will suffer from debilitating knee pain, joint stiffness, joint swelling, physical disability, and difficulty in conducting activities of daily living (ADLs). [5] Those symptoms are presented in a heterogeneous pattern, indicating that knee OA is a whole joint disorder instead of simple cartilage problem. The uptrend of knee OA prevalence is forecast due to increasing life expectancy and the rise of risk factors, such as obesity and ageing. It will gradually add burden to the healthcare resources, giving rise to a major economic burden in societies. Thus, action must be taken to relieve this future burden. Knee OA disease management consists of two key elements: diagnosis and treatment. Both diagnosis and treatment work conjunctly to provide optimal disease management outcomes. The diagnosis identifies the existence of disease in patient itself based on signs and symptoms, whereas treatment works specifically to deal with the disease to trigger curative and palliative effects. The goal of treatment is to delay disease progression and to avoid the worst disease stage. The diagnosis can be done at multiple time points to monitor disease progression. By extending the fundamental knowledge of disease progression, the prognosis could be performed to predict future disease events and future treatment outcomes. Currently, the unknown correlation between covariates has made knee OA prognosis remains unpractical. Medical experts hardly predict the right disease progression to formulate plan for disease prevention. To the best of our knowledge, there is no prognostic tool available in clinical practice. Recently, diagnostic and prognostic prediction models are conceptualized for the healthcare industry, and this idea could be adapted to upgrade the current knee OA management system.

2. LITERATURE SURVEY

Guida et. al [6] utilizes a 3D CNN model to analyze sequences of knee magnetic resonance (MR) images to perform knee OA classification. An advantage of using 3D CNNs is the ability to analyze the whole sequence of 3D MR images as a single unit as opposed to a traditional 2D CNN, which examines one image at a time. Therefore, 3D features could be extracted from adjacent slices, which may not be detectable from a single 2D image. The input data for each knee were a sequence of double-echo steady-state (DESS) MR images, and each knee was labeled by the Kellgren and Lawrence (KL) grade of severity at levels 0–4. In addition to the 5-category KL grade classification, we further examined a 2-category classification that distinguishes non-OA (KL $\leq$ 1) from OA (KL $\geq$ 2) knees. Clinically, diagnosing a patient with knee OA is the ultimate goal of assigning a KL grade. On a dataset with 1100 knees, the 3D CNN model that classifies knees with and without OA achieved an accuracy of 86.5% on the validation set and 83.0% on the testing set. We further conducted a comparative study between MRI and X-ray. Compared with a CNN model using X-ray images trained from the same group of patients, the proposed 3D model with MR images achieved higher accuracy in both the 5-category classification (54.0% vs. 50.0%) and the 2-category classification (83.0% vs. 77.0%). The result indicates that MRI, with the application of a 3D CNN model, has greater potential to improve diagnosis accuracy for knee OA clinically than the currently used X-ray methods.

Kijowski et. al [7] provided a review of current applications of DL in osteoarthritis (OA) imaging, including methods used for cartilage lesion detection, OA diagnosis, cartilage segmentation, and OA risk assessment. DL techniques have been shown to have similar diagnostic performance as human readers for detecting and grading cartilage lesions within the knee on MRI. A variety of DL methods have been developed for detecting and grading the severity of knee

OA and various features of knee OA on X-rays using standardized classification systems with diagnostic performance similar to human readers. Multiple DL approaches have been described for fully automated segmentation of cartilage and other knee tissues and have achieved higher segmentation accuracy than currently used methods with substantial reductions in segmentation times. Various DL models analyzing baseline X-rays and MRI have been developed for OA risk assessment. These models have shown high diagnostic performance for predicting a wide variety of OA outcomes, including the incidence and progression of radiographic knee OA, the presence and progression of knee pain, and future total knee replacement.

Joseph et. al [8] focuses on AI applications in OA research, first describing machine learning (ML) techniques and workflow, followed by how these algorithms are used for OA classification tasks through imaging and non-imaging-based ML models. Deep learning applications for OA research, including analysis of both radiographs for automatic detection of OA severity, and MR images for detection of cartilage/meniscus lesions and cartilage segmentation for automatic T2 quantification will be described. In addition, information on ML models that identify individuals at high risk of OA development will be provided. The future vision of machine learning applications in imaging of OA and cartilage hinges on implementation of AI for optimizing imaging protocols, quantitative assessment of cartilage, and automated analysis of disease burden yielding a faster and more efficient workflow for a radiologist with a higher level of reproducibility and precision. It may also provide risk assessment tools for individual patients, which is an integral part of precision medicine.

Imtiaz et. al [9] provides a survey of recent and the most representative deep learning techniques (published between 2018 to 2020) for the diagnosis of osteoarthritis and rheumatoid arthritis. The paper also reviews traditional machine learning methods (published 2015 onward) and their application for the diagnosis of these diseases. The paper identifies open problems and research gaps. We believe that deep learning can assist general practitioners and consultants to predict the course of the disease, make treatment propositions and appraise their potential benefits.

Han et. al [10] investigated the variation in tibial plateau STB microarchitecture in end-stage knee OA patients and their association with knee alignment (hip-knee-ankle, HKA, angle) and OA severity.

Kashyap et. al [11] provided contextual feature to the second-level RF classifier that also considers local features and produces location-specific costs for the layered optimal graph image segmentation of multiple objects and surfaces (LOGISMOS) framework. Double-echo steady state MRIs used in this paper originated from the OA Initiative study. Trained on 34 MRIs with varying degrees of OA, the performance of the learning-based method tested on 108 MRIs showed significant reduction in segmentation errors (p <; 0.05) compared with the conventional gradient-based and single-stage RF-learned costs. The 3-D LOGISMOS was extended to longitudinal-3-D (4-D) to simultaneously segment multiple follow-up visits of the same patient. As such, data from all time-points of the temporal sequence contribute information to a single optimal solution that utilizes both spatial 3-D and temporal contexts. 4-D LOGISMOS validation on 108 MRIs from baseline, and 12-month follow-up scans of 54 patients showed significant reduction in segmentation errors (p <; 0.01) compared with 3-D. Finally, the potential of 4-D LOGISMOS was further explored on the same 54 patients using five annual follow-up scans demonstrating a significant improvement of measuring cartilage thickness (p <; 0.01) compared with the sequential 3-D approach.

Matzat et. al [12] discusses the biochemical basis and the advantages and disadvantages associated with each of these techniques. Recent implementations for these techniques are touched upon, and future considerations for improving the research and clinical power of these imaging technologies are also discussed.

3. PROPOSED SYSTEM

Knee osteoarthritis (OA) is a disease that increases in incidence and prevalence with advancing age, such that in those over the age of 60, about 10% of men and 13% of women have symptomatic knee OA. With the aging of the population, the number of people in the age range with the greatest severity of OA continues to increase. Furthermore, OA is a leading cause of morbidity and disability, and thus carries high socioeconomic costs. In 2004, arthritis was estimated to cost the United States $336 billion, or 3% of the gross domestic product, with OA as the most common form of arthritis. The pathology of OA disease is still unclear and there are no interventions that effectively modify the OA disease process. In clinical studies, OA is mainly diagnosed through medical images. Measurement of cartilage change is a primary assessment of structural progression of OA and is used to evaluate the effectiveness of new treatments. Magnetic resonance (MR) imaging is a non-invasive technology that can generate 3-dimensional images of intra-articular soft-tissue structures, including cartilage. However, obtaining accurate and reproducible quantitative measurements from MRI scans is burdensome due to the structure and morphology of the knee as well as the nature of MR imaging. It may take up to six hours for a reader to manually segment each series of 3-dimensional (3D) knee MRI. Furthermore, operators who use cartilage segmentation software often need extensive training which further contributes to the time and cost.

Over the past decade, researchers have developed different approaches to reduce the burden of measuring knee cartilage on MR images. These includes segmenting alternate MR slices or confining measurements to partial regions of cartilage. Computer-aided algorithms (e.g., active contours, B-splines) have also been developed to assist with cartilage segmentation for MR images. Unfortunately, these methods lack sufficient accuracy and reliability to detect small cartilage changes. Thus, there remains a need among researchers for a quantification method that can be rapidly computed and has good reproducibility, validity, and sensitivity to change. Therefore, this project explored the hidden biomedical information from knee MR images for OA prediction. We have computed the Cartilage Damage Index (CDI) information from 36 informative locations on tibiofemoral cartilage compartment from 3D MR imaging and used PCA analysis to process the feature set. Here a supervised learning model called support vector machine (SVM), and an artificial intelligence model known as ANN are employed to predict the progression of OA, which was measured by change of Kellgren and Lawrence (KL) grade, joint space narrowing on medial compartment (JSM) grade and joint space narrowing on lateral compartment (JSL) grade.

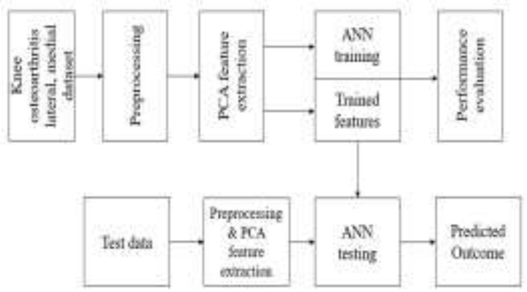


Figure 1: Block diagram of proposed system.

4. RESULTS AND DISCUSSION

The Python code is Tkinter library to develop a graphical user interface (GUI) application aimed at predicting knee osteoarthritis (OA) progression from 3D MRI data. The GUI features buttons for key functionalities like uploading datasets, building predictive models, and comparing model accuracies. Users can interact with the application seamlessly, aided by informative labels and text boxes that convey the status of operations and display prediction results.

Upon dataset upload, the application processes the data, splitting it into training and testing sets. It then proceeds to train various machine

International Journal of Engineering Research and Science & Technology

learning algorithms, including Support Vector Machine (SVM), Random Forest, Naive Bayes, and an Artificial Neural Network (ANN). Each model undergoes evaluation on the test set, with metrics like accuracy, precision, recall, and confusion matrix being displayed. Additionally, there's provision for feature engineering through Principal Component Analysis (PCA), although this aspect is currently commented out in the code.
The GUI facilitates model comparison by offering a graphical representation of accuracy scores using a bar graph. This feature enables users to assess the performance of different algorithms quickly. Furthermore, the application allows for real-time prediction on new data, enabling healthcare professionals and researchers to make informed decisions regarding knee OA progression based on MRI data. Overall, the implementation combines ease of use with robust functionality, catering to the needs of medical practitioners and researchers involved in knee OA analysis and prediction.

Figure 2: Displays the GUI of Knee Osteoarthritis Progression Prediction.

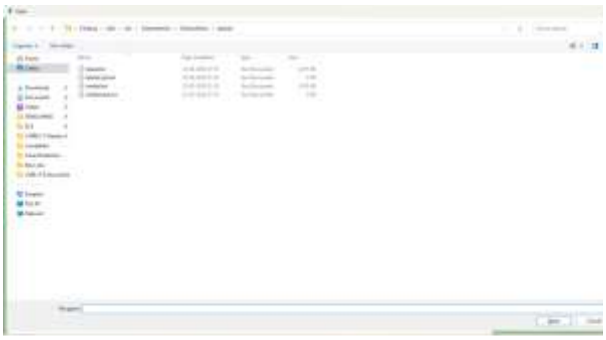


Figure 3: Uploading the Knee Dataset.

Figure 4: Successful Dataset Reading Confirmation.

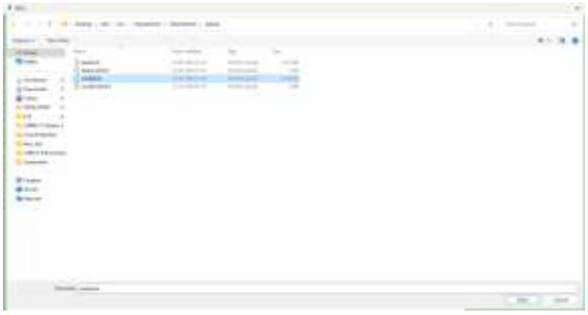


Figure 5: Uploading Medical test dataset for prediction.

Figure 6: Proposed Model Predicted on applied test dataset

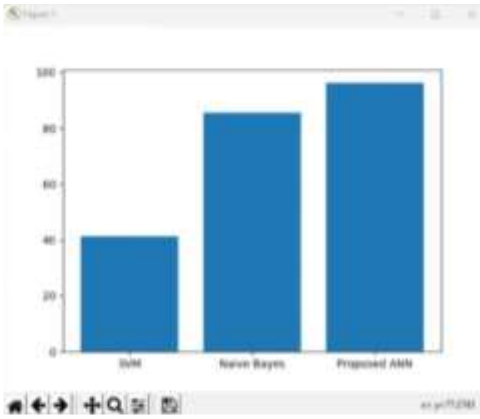


Figure 7: Accuracy Comparison Graph of each Models.

5. CONCLUSION

Using dataset preprocessing, principal component analysis feature reduction, and artificial neural network classification are the three steps involved in predicting knee osteoarthritis from 3D-MRI data. The following is a possible summary of the procedure at a high level. The step of cleaning and preparing the dataset for analysis is referred to as the dataset preprocessing step. It is possible that this will require removing duplicates, filling in missing values, and normalizing the data. It is absolutely necessary for accurate classification to obtain the relevant features hidden within the 3D-MRI data. In this step, the knee joint may be segmented, regions of interest may be identified, and features of texture, shape, or intensity may be extracted. In certain circumstances, the high dimensionality of the extracted features might make classification performance less effective or lengthen the amount of time needed for computation. PCA is a method that can be utilised to lessen the dimensionality of the feature space while still maintaining the majority of the data's variability. On the basis of the condensed set of features, a neural network model can be educated to perform knee osteoarthritis classification. In order to achieve the highest possible classification accuracy, the architecture of the ANN as well as its hyperparameters will need to be optimized using cross-validation and/or grid search. The trained ANN model needs to be evaluated with the help of an independent test set so that its precision, sensitivity, and specificity can be determined, along with other performance metrics. It is essential to keep in mind that each of these steps requires careful consideration and, depending on the particular dataset and research question, may involve several sub-steps or variations. In addition, the accuracy and generalizability of the model are dependent on the quality and representativeness of the dataset, as well as the selection of feature extraction and reduction methods, as well as the robustness of the ANN architecture and training algorithm.

REFERENCES

[1] Jones, G.; Ding, C.; Scott, F.; Glisson, M.; Cicuttini, F. Early radiographic osteoarthritis is associated with substantial changes in cartilage volume and tibial bone surface area in both males and females. Osteoarthr. Cartil. 2004, 12, 169–174.

[2] A. Cui, H. Li, D. Wang, J. Zhong, Y. Chen, and H. Lu, "Global, regional prevalence, incidence and risk factors of knee osteoarthritis in population-based studies," EClinicalMedicine, vol. 29-30, 2020.

[3] M. T. Mardini, S. Nerella, M. Kheirkhahan et al., "The temporal relationship between Ecological pain and life-space Mobility in Older Adults with knee osteoarthritis: a Smartwatch-based demonstration study," JMIR Mhealth Uhealth, vol. 9, no. 1, Article ID e19609, 2021.

[4] M. van Smeden, J. B. Reitsma, R. D. Riley, G. S. Collins, and K. G. M. Moons, "Clinical prediction models: diagnosis versus prognosis," Journal of Clinical Epidemiology, vol. 132, pp. 142–145, 2021.

[5] V. L. Kronzer, L. Wang, H. Liu, J. M. Davis, J. A. Sparks, and C. S. Crowson, "Investigating the impact of disease and health record duration on the eMERGE algorithm for rheumatoid arthritis," Journal of the American Medical Informatics Association, vol. 27, no. 4, pp. 601–605, 2020.

[6] Guida, C.; Zhang, M.; Shan, J. Knee Osteoarthritis Classification Using 3D CNN and MRI. Appl. Sci. 2021, 11, 5196. https://doi.org/10.3390/app11115196

[7] Kijowski, R., Fritz, J. & Deniz, C.M. Deep learning applications in osteoarthritis imaging. Skeletal Radiol (2023). https://doi.org/10.1007/s00256-023-04296-6

[8] Joseph, G.B., McCulloch, C.E., Sohn, J.H. et al. AI MSK clinical applications: cartilage and osteoarthritis. Skeletal Radiol 51, 331–343 (2022). https://doi.org/10.1007/s00256-021-03909-2

[9] Maleeha Imtiaz, Syed Afaq Ali Shah, Zia ur Rehman, A review of arthritis diagnosis techniques in artificial intelligence era: Current trends and research challenges, Neuroscience Informatics, Volume 2, Issue 4, 2022, 100079, ISSN 2772-5286, https://doi.org/10.1016/j.neuri.2022.100079.

[10] Han, X., Cui, J., Xie, K. et al. Association between knee alignment, osteoarthritis disease severity, and subchondral trabecular bone microarchitecture in patients with knee osteoarthritis: a cross-sectional study. Arthritis Res Ther 22, 203 (2020). https://doi.org/10.1186/s13075-020-02274-0

[11] S. Kashyap, H. Zhang, K. Rao and M. Sonka, "Learning-Based Cost Functions for 3-D and 4-D Multi-Surface Multi-Object Segmentation of Knee MRI: Data from the Osteoarthritis Initiative," in IEEE Transactions on Medical Imaging, vol. 37, no. 5, pp. 1103-1113, May 2018, doi: 10.1109/TMI.2017.2781541.

[12] Matzat, S.J., Kogan, F., Fong, G.W. et al. Imaging Strategies for Assessing Cartilage Composition in Osteoarthritis. Curr Rheumatol Rep 16, 462 (2014). https://doi.org/10.1007/s11926-014-0462-3